# A Lie Reveals the Truth

## Quasimodes for Task-Aligned Data Presentation

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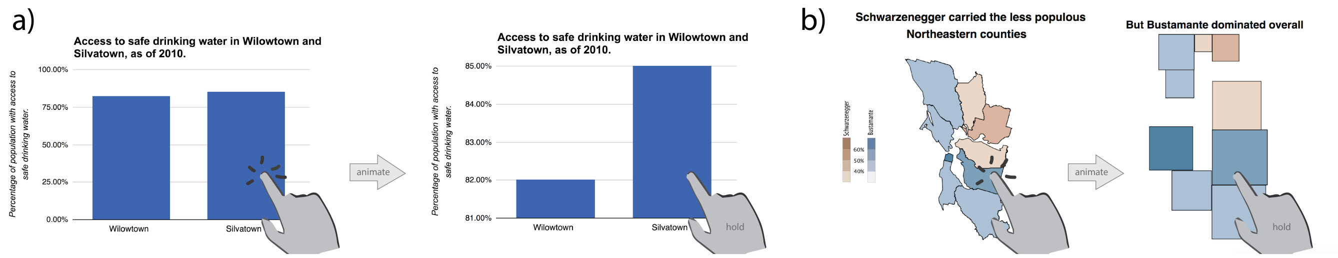


**Figure 1: The Perceptual Glimpses interaction technique allows for potentially deceptive views to be presented in context, by animating to a secondary view while the user presses and holds a control. a) A truncated axis [43] reveals the precise difference between two quantities. b) A misleading choropleth map transforms into a cartogram [20] to give insight into election results.**

## ABSTRACT

Designers are often discouraged from creating data visualizations that omit or distort information, because they can easily be misleading. However, the same representations that could be used to deceive can provide benefits when chosen to appropriately align with user tasks. We present an interaction technique, Perceptual Glimpses, which allows for the transparent presentation of so-called 'deceptive' views of information that are made temporary using quasimodes. When presented using Perceptual Glimpses, message-level exaggeration caused by a truncated axis on a bar chart was reduced under some conditions, but users require guidance to avoid errors, and view presentation order may affect trust. When Perceptual Glimpses was extended to display a range of views that might otherwise be deceptive or difficult to understand if shown out of context, users were able to understand and leverage these transformations to perform a range of low-level tasks. Design recommendations and examples suggest extensions of the technique.


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## CCS CONCEPTS

• **Human-centered computing → Empirical studies in visualization**.

## KEYWORDS

Animation, Perception, Deceptive Visualization

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## 1 INTRODUCTION

Many visualization researchers strongly discourage the use of some types of visualizations because they violate what Tufte calls graphical integrity: the notion that visual proportions should match the true proportions of the data [54]. An example of this is a truncated vertical axis on a bar chart. Setting the baseline to a higher value results in a perceptually exaggerated view of the difference between the plotted values (Figure 1a), which often causes misinterpretation [43]. This is a case of deceptive visualization: visualizations that can mislead viewers by distorting the size of the trend communicated by a graph, often by concealing important information from the viewer. Choropleth maps are another well-known example of a potentially deceptive visualization. Larger, less population-dense regions can occupy more visual real-estate than smaller, more populated areas, resulting in a counterintuitive view where size does not reflect count [38] (Figure 1b).

Although such practices can encourage misleading interpretations, they also have oft-overlooked benefits. A truncated axis on a bar chart increases the visual bandwidth available, allowing a viewer to estimate the difference between two bars more accurately (Figure 1a). Similarly, regions in a choropleth map are easier to recognize than those in a tiled cartogram, which do not align with a reader's mental map of space (Figure 1b). "Everything is best at something and worst at something else" [13], and visualizations are no exception. In this work, we argue that a subset of potentially deceptive views can be just as useful as other representations when correctly aligned to a specific, low-level user task.

The degree to which the viewer identifies and understands the transformation that was performed by the author of the visualization is what separates a useful view from a deceptive one. Deceptive views, just like views of derived information, can be difficult to understand out of context, so care must be taken to present them properly and transparently to avoid the possibility of misinterpretation. In this work, we investigate novel ways to achieve this goal.

We introduce Perceptual Glimpses, an interaction technique that allows a user to switch from a canonical view, which is typically an undistorted view of the data, to one or more secondary views, which are typically more prone to misinterpretation, or more difficult to decode. Perceptual Glimpses leverages quasimodes [45] (i.e., kinesthetically-held modes) to trigger animated transitions between different views of the same dataset. By showing a secondary view only for the duration of the user's touch, we seek to maintain awareness of the transformation, ensuring that the user knows the meaning of the current view, how it relates to the canonical view and how to return to the canonical view. Perceptual Glimpses could thus be useful for data presentation [32] and storytelling [33], where a designer can designate a small number of secondary views that highlight specific messages present in the underlying data.

To validate our approach, we performed a large-scale crowdsourced experiment that showed that the message exaggeration effect of a truncated-axis bar chart can be significantly reduced by showing context using Perceptual Glimpses. However, this was only confirmed for the variant where the canonical view was presented second, the opposite of the expectation which underlay the technique.

Investigating further, an in-person laboratory study (again focused on truncated axes) found that some participants made errors when applying Perceptual Glimpses that prevented them from recognizing deceptive claims. We gained qualitative insights into why seeing a canonical bar chart first appears to *decrease* its perceived trustworthiness. The study also found that Perceptual Glimpses can facilitate understanding of the existence of small but important trends (e.g., year-to-year changes in gross domestic products, which can have wide-reaching impacts). To investigate the suitability of the technique for a wider range of secondary views, participants also completed tasks with a more complex prototype. Results were encouraging in that participants could effectively perform a range of low-level tasks.

Perceptual Glimpses represents a first attempt at solving the difficult problem of presenting potentially deceptive visualizations in a manner that is useful and not harmful. However, our evaluation uncovered problems that prevent application of the technique without further modification. We hope that the insights gained through this process are useful in deepening knowledge of deceptive visualization, and in inspiring further techniques that investigate the associated design space.

Specifically, this work makes the following contributions:

(1) Results from a large-scale perceptual study of crowdworkers, confirming previous research on truncated-axis bar charts, and offering insight into the utility of presenting paired views using quasimodes
(2) Results from a laboratory study, which provide qualitative insights into how users may make errors with the technique in the context of a truncated axis.
(3) A series of design recommendations to inform the development of future techniques aimed at utilizing potentially deceptive views while mitigating harm.

## 2 RELATED WORK

### Perception, Bias and Deception in Visualization

There is a large body of research that seeks to determine which data representations are perceptually optimal for specific tasks [17, 27, 52, 61]. The findings of this work can be harnessed to effectively match data views to tasks during visualization authoring. Interestingly, visualizations that admittedly violate graphical integrity are rarely, if at all, put forward as possibly useful representations, since they are associated with a devilish intent to mislead the viewer [18, 29].

Researchers have also investigated how bias and perception intersect to create deceptive views [8, 19, 47, 60], with Pandey et. al. developing a method to quantify and compare the exaggeration caused by misleading representations [43]. It has been established that the framing of a visualization also has significant impact on the message communicated to viewers [31, 42] but that deception can persist even when charts are paired with accurate explanatory text [40].

In parallel, there has been significant graphical perception research examining perceptual [16, 52] and cognitive [21] biases that can lead audiences to systematically misinterpret visual information. Recent work has examined anchoring bias in visualization [59]. Anchoring effects and ordering effects, which have been studied extensively in other research domains [39, 55], describe how the order in which information is presented can affect the perceived size of an effect, with subjects across a wide range of domains [6, 14, 25] tending to assign more rhetorical weight to evidence that comes near the beginning of a sequence. Our work aims to leverage anchoring effects to minimize deception by grounding users in an initial, undistorted estimate.

### Connecting Multiple Views in Visualizations

Our work builds on the premise that no single view of data suits all tasks, which calls for mechanisms to display several different representations of the same data. One option is to present multiple views in parallel [46]. Interactive methods such as brushing and linking [7] are effective in supporting users in understanding connections between views, though juxtaposed views can require large amounts of space.

Animated transitions allow for the preservation of resolution, and are useful for linking sequentially-presented views, and increasing user understanding during data presentation [28]. Comparison between views is more difficult than with juxtaposed views, because users have to rely on their working memory [56]. However, our focus is on increasing user understanding of how a secondary view is derived from the canonical view. Congruent animation [56] might help preserve awareness of graphical distortion by providing a visual explanation, and in particular, animation has been shown to aid in understanding axis rescaling [28].

Sequential presentation requires mechanisms to navigate between representations. In mainstream visualization platforms, different views of the same data can be generated on demand, typically by selecting options through menus [37], or re-running commands with different parameters [35]. Tableau shortens the feedback loop for comparing different views with a drag-and-drop feature [51]. Similarly, there are countless systems in the visualization literature, that, informed by the mantra “Overview First, Filter, and Details-on-Demand” [50], provide multiple views of a dataset. Some of these systems allow more direct user control [24, 41] or higher levels of curation [4, 36, 63], or leverage touch interactions to allow for selection of different views [23, 30].

These tools typically support exploratory data analysis, where the user can generate many possible representations. We focus on the presentation [32] of a smaller set of curated views, and therefore do not require a particularly advanced form of user-driven interaction. We do, however, require a navigation approach that maintains a viewer’s awareness of whether they are looking at a canonical or secondary view, which quasimodes can help support.

### Quasimodes

Quasimodes are system states that require that the user actively maintain them (e.g., pressing and holding a SHIFT key), and that the user receive kinesthetic feedback for the duration of the quasimode (e.g., they feel their finger pressing against the key) [45, 49]. Quasimodes have been found to lead to fewer mode errors (i.e., forgetting that a mode is active) than persistent modes [49]. This benefit has led to their inclusion in many systems [5, 22, 45]. Many recent interactive touch-based visualization systems integrate quasimodes. Tangere [48] makes use of quasimodes that are triggered by the user’s non-dominant hand to disambiguate between selection types. TouchViz and TouchPivot present a preview of the next view that persists until the user lifts their finger [23, 30]. Tominski et. al. [53] used quasimodes to compare superimposed views in a desktop environment. To our knowledge, the effectiveness of quasimodes for triggering the presentation of transformed views has not been directly studied in the visualization literature.

## 3 THE PERCEPTUAL GLIMPSES TECHNIQUE

Perceptual Glimpses leverage quasimodes to allow users to navigate from a canonical view, selected to give an overview of the data without exaggerating any particular aspect of it (e.g., a well-normalized bar chart), to one or more secondary views, designed to facilitate specific perceptual tasks (e.g., a truncated-axis bar chart that provides greater resolution to evaluate a difference between bars).

When the user provides kinesthetic input by clicking or touching either the chart or a dedicated control, the canonical view smoothly morphs into the secondary view via an animated transition that interpolates between initial and final shapes and positions. When the user stops providing input, the visualization reverts back to the original view.

The secondary views described in this paper fall into one of two categories: potentially deceptive views, which could be misleading if presented out of context, and views of derived values, which are difficult to understand out of context. Potentially deceptive views may create a distorted belief about the message conveyed by the underlying data, regardless of the author’s intent [43]. However, if a user understands the process by which these views are generated, they may not necessarily be deceptive in practice. For example, filtering is a common feature used within many visualization tools, but selective filtering of data can produce spurious insights or be deceptive if it is not transparent to the user. Derived values are calculated from the data in the canonical view (e.g., through the aggregation of values or explicit encoding [26] of differences between values).

By transitioning between views, a user can identify at a glance what information is present in one view and absent in another. Thus, for potentially deceptive views, having access to the canonical view allows a user to understand the transformation that the canonical view underwent to produce it. In the case of views of derived information, the information provided by the canonical view allows viewers to better understand the quantities that are presented (e.g., by seeing both raw and aggregated values).

In developing the technique, we were inspired by work on visual anchoring effects [59], and the "Overview First" mantra [50]. We hypothesized that showing the canonical view first would lead users to form an initial impression of the data using that view, which may be adjusted based upon any insights they garnered from the secondary view, but would still remain closer to their initial estimate. We also considered variants of Perceptual Glimpses where the secondary view was presented before the canonical view, to investigate this hypothesis. These variants suffer from a key drawback; if the user does not interact with the chart, as is common [10], they will see only the deceptive view.

## 4 STUDY 1: PERCEPTUAL STUDY OF CROWDWORKERS

Considering the truncated-axis view of a categorical bar chart, we sought to verify that access to the canonical view would reduce the likelihood that a user would be misled by the visualization. To this end, we conducted a large-scale empirical study to determine the change in message-level deception that results from presenting this potentially deceptive view in context using Perceptual Glimpses. Our preregistered plan of analysis for this study, as well as all questionnaires and charts used in the paper, are available at https://github.com/perceptual-glimpses/chi2019.

### Procedure

The experiment was implemented in a web browser and conducted through the Amazon Mechanical Turk (mTurk) crowdworking platform. The study replicates and extends the work of Pandey et al. [43], who derived a methodology for quantifying the extent of this message-level exaggeration. We replicate only the truncated-axis experiment. Users were asked to perform a deception test, in which they were shown a bar chart with or without a truncated axis (Figure 1a) and asked to estimate the size of the difference depicted by the chart (i.e., How much better do you think the condition of safe drinking water access in Silvatown is as compared to that in Wilowtown?) on a 5-point Likert scale from "slightly better" to "substantially better". All users were shown the same chart. In the control condition, the difference appears insignificant, so higher answers to the question reflect higher levels of message-level exaggeration. Users also answered an attention check question about the chart.

To assess whether individual differences between participants affected the degree to which they were affected by the message-level exaggeration effects, participants were also asked to complete the Need For Cognition (NFC) questionnaire [44], and two additional questionnaires to measure visual ability and self-reported chart familiarity. The deception test and questionnaires were reproduced from [43].

Participants were assigned to one of 4 conditions. The first two conditions, control (C) and deceptive (D), came from [43]. In the control condition, a bar chart with zero-normalized y-axis was displayed. In the deceptive condition, a bar chart with a truncated y-axis was displayed. The remaining two conditions made use of Perceptual Glimpses. The first displayed the control and then deceptive view (i.e., C to D condition or C→D), and the second displayed the deceptive and then control view (i.e., D to C condition or D→C). To ensure that participants in these conditions would see the information provided by Perceptual Glimpses, the deception test and attention check questions were disabled until participants had interacted with the chart.

We had the following hypotheses for this study:

- **H1.** The two interactive conditions (C→D, D→C) will have lower message-level exaggeration than the deceptive condition.
- **H2.** Due to anchoring effects, (C→D) will have lower message-level exaggeration than (D→C).

Participants were compensated USD $0.90 for completing the experiment, which was designed to take 5 minutes to complete. Similar inclusion criteria to [43] were used (i.e., 99% task approval rate, residence in the US or Canada).

A total of 368 responses were recorded. Participants who failed the attention check, used unsupported browsers or reported uncorrected vision problems were excluded. To increase answer quality, we also enforced a minimum response time for the NFC questionnaire, which was lowered from 45 seconds (stated in the preregistration) to 23 seconds (i.e., the bottom 5% of responses) because 101 participants (i.e., 27%) took less than 45 seconds, which was too high a proportion to practically exclude. We continued gathering responses until we had 75 per condition.

### Preregistered Analysis

Figure 2 shows the results of the deception test question. The data shows that the number of people answering "substantially better" was reduced for both the C→D condition (6.7%) and the D→C condition (4%) compared to the deceptive condition (25%). A Kruskal-Wallis test confirmed a significant difference between conditions for responses to the deception test question ($\chi^2(3) = 24.74$, $p < 0.0001$). Mann-Whitney U tests with Bonferroni-Holm correction were used as post hoc tests. Significant differences were found between the control (M = 1.61, 95% CI [1.41, 1.84]) and deceptive (M = 2.81, 95% CI [2.61, 3.04]) conditions (U = 1671.5, $p < 0.0001$), the control and C→D (M = 2.12, 95% CI [1.92, 2.35]) conditions (U = 2061, $p < 0.01$) and the deceptive and D→C (M = 1.88, 95% CI [1.68, 2.11]) conditions (U = 3611.5,

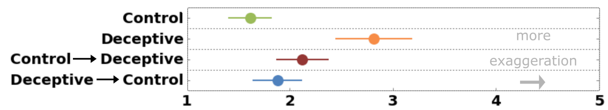


**Figure 2: Mean response to deception test question. Error bars are 95% CIs.**

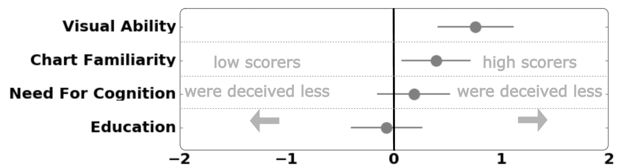


**Figure 3: Mean difference in deception test question response between individuals with low vs. high scores on visual ability, chart familiarity, NFC and education. Error bars are 95% CIs.**

p < 0.01). There was no significant difference between the C→D and D→C conditions (U = 3143.5, p= 0.19), between the C→D and deceptive conditions (U = 3355.5, p = 0.10) or between the control and D→C conditions (U = 2383, p = 0.14) after the multiple test correction. (A Dunn post hoc test with Bonferroni-Holm correction found the same significant differences between conditions). We binned the responses to the deception test question across all conditions based on the thresholds from [43] for low and high values of education, NFC, chart familiarity, and visual ability (Figure 3). Mann-Whitney U tests with 4-way Bonferroni-Holm correction were used to evaluate the effects of individual differences across each variable. Significant differences were found for chart familiarity ($M_{low}$=2.39, $M_{high}$=1.99, U=11377, p < 0.01) and visual ability ($M_{low}$=2.67, $M_{high}$=1.91, U=11464, p < 0.0001) - high scorers gave lower answers. No significant difference was found for education level or NFC.

### Discussion

The results confirm **H1**, that the deceptive effect of the truncated axis was reduced when presented using Perceptual Glimpses, but only for the D→C condition, where the deceptive view was shown first. Figure 4 shows the difference in deception test responses between the control and all other conditions. The difference from the control is smaller for D→C compared to the deceptive condition. The top row shows the difference between the three deceptive visualizations reported in [43] and the relevant controls, which are all clearly larger than that of D→C.

The results provide a replication of previous estimates for the magnitude of the exaggeration introduced by the truncated axis (point estimates lie within the 95% CIs from [43]). We also confirm the effect of individual differences in chart familiarity and visual ability on interpretation of the truncated axis - high scores are associated with less deception (this was suggested by observations in [43] but

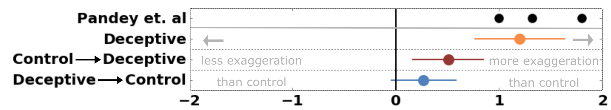


**Figure 4: Mean difference from the control condition. Top: Differences from the relevant controls for the three message-exaggeration deceptions from [43]. Error bars are 95% CIs.**

not confirmed statistically). Contrary to **H2**, no anchoring effect was observed, i.e., C→D did not result in lower values of message-level exaggeration compared to D→C. This was surprising, since the anchoring effect is robust in many domains when information is presented sequentially [39, 55]. To investigate why the anchoring effect did not hold in our context, and to better understand why some users made errors using Perceptual Glimpses, we planned an in-lab experiment where we could gain qualitative insights on participants' experiences.

## 5 STUDY 2: IN-LAB STUDY

We conducted a laboratory experiment to answer the following research questions: 1) how users might use Perceptual Glimpses applied to truncated-axis bar charts to investigate claims, deceptive or not, compared to static charts, 2) how presentation order affects user perceptions of the canonical and truncated-axis views. This study also included a third, exploratory phase involving views other than truncated-axis bar charts, discussed in a later section.

### Procedure

Twenty participants were recruited through public Facebook groups. All were current undergraduate or post-graduate students at a local university (ages 20-28, mean = 22, 16 female). All were fluent in English and had normal or corrected-to-normal vision. The experiment lasted about 90 min. (~60 min. for Phases I and II, ~30 min. for Phase III). Phase I consisted of a critical evaluation of claims based on truncated-axis bar charts and was conducted on an iPad with a 9.7" display. Phase II consisted of an interview about users' impressions of the charts used in the first experiment, and was conducted on a laptop computer.

## 6 PHASE I: CRITICAL EVALUATION OF CLAIMS

In the first phase, participants were presented with 10 written claims, each of which was accompanied by a bar chart. This phase was between-subjects, with 5 participants assigned to each of the conditions from the online experiment (i.e., control, deceptive, C→D, D→C). In this phase participants with interactive charts only had access to a single truncated-axis view, as in the online study

### Critical Evaluation Questions

The questions (Table 1 and supplementary material) consisted of three types. Four questions (Q1a-Q4a) presented a claim regarding the existence of an effect (e.g., "rapid decline", "gradual decline", or "peak"). Another four questions (Q1b-Q4b) presented a claim that the magnitude of an effect was small compared to the overall quantities involved in the question. Two deceptive questions (D1, D2) asked about a misleading claim, which implied a difference was large, when it was actually small enough to be considered insignificant. The eight non-deceptive visualizations were paired, with one of each type of question for four separate charts. Question order was randomized, with questions about the existence of an effect always shown before the paired question asking about the magnitude of the same effect. Most questions used synthetic data to reduce the possibility that knowledge of real-world trends would affect interpretation of the effects; the chart from Q1 (Figure 5) was adapted from an article about truncated axes that used real data on U.S. GDP during the 2009 recession, with obfuscated dates [62].

At the end of the phase, participants answered two Likert scale questions about perceived levels of trust and usefulness of the two views (for interactive conditions) or the charts overall (for static conditions) and verbal follow-up questions.

It was impractical to ask a large number of deceptive visualization questions, since participants may have guessed that something was amiss. Due to the nature of the truncated axis deception, we refrained from asking questions about numerical values, which might have led participants to examine the axes and notice the visual exaggeration. The non-deceptive questions were intended to gauge participant's ability to correctly characterize effects that were small in comparison to the overall magnitude of the quantities involved, but perhaps significant in absolute terms.

**Table 1: Example questions for critical evaluation task.**

| | |
|---|---|
| Q1a | As the result of a recession, in July 2030, the United States suffered a rapid decline in GDP. |
| Q1b | Despite claims of a recession, the effect on GDP in July 2030 was small compared to the size of the U.S. economy. |
| Q4a | People in Texas drink more white wine than red wine |
| Q4b | Compared to total wine sales, the difference in sales between red wine and white wine is relatively small. |
| D1 | Candidates from Party B received a much larger percentage of campaign contributions from small donors |

Participants were asked to evaluate how effectively the chart supported each claim, using a four-point Likert scale. We chose not to include neutral value, to encourage participants to explicitly decide whether a claim was supported. Participants were also required to provide a written justification and to annotate a screenshot with a circle to indicate which chart feature they used to make their judgment.

### Critical Evaluation Results

The experiment confirmed the hypothesis that users would find some benefit to being able to access the truncated-axis view of the visualization. Most participants (70%, 14/20) were concerned about the potential of the cut axis to deceive or mislead, but a large number (60%, 12/20) were also concerned about the opposite - that the scale of the graphs could be chosen to understate or suppress the existence of an important effect. Most (80%, 4/5) of the participants in the control condition indicated that they could not read some values as clearly as needed, due to the axis resolution.

In general, all participants correctly identified the existence of the effect in the non-deceptive questions (see Figure 6). An exception was Q1a, where 60% (3/5) participants in the control condition found that the chart definitely did not support the claim of a rapid decline in GDP, compared to 93% (14/15) in the other three conditions who found that the claim was at least somewhat supported. A participant from the control condition stated, *"I guess even a fraction of a percent of the U.S. economy is a huge amount, but that graph doesn't really do that justice" (P9)*. The responses to this question support the hypothesis that Perceptual Glimpses can aid identification of small but important effects.

Answers to questions regarding magnitude varied tremendously, making it hard to identify a clear trend across conditions, so we could not verify the hypothesis that Perceptual Glimpses would permit better understanding of the magnitude of small effects. Questions that referred to dollar amounts (i.e., GDP decrease in Q1, housing price increase in Q2) were interpreted as small in comparison to the overall quantities, but large when participants placed them in

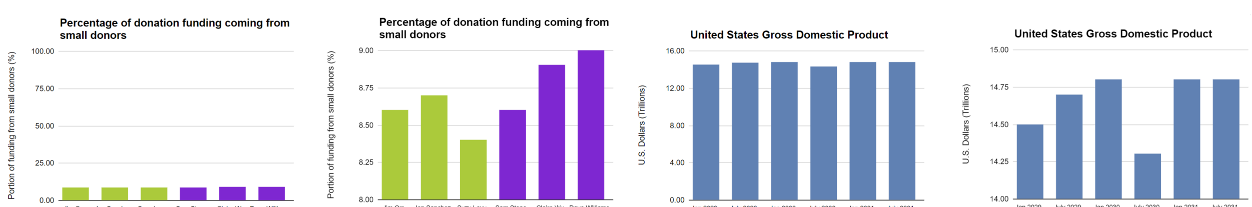


**Figure 5: Examples of bar charts (canonical and truncated-axis views) used in critical evaluation questions (D1 and Q1).**

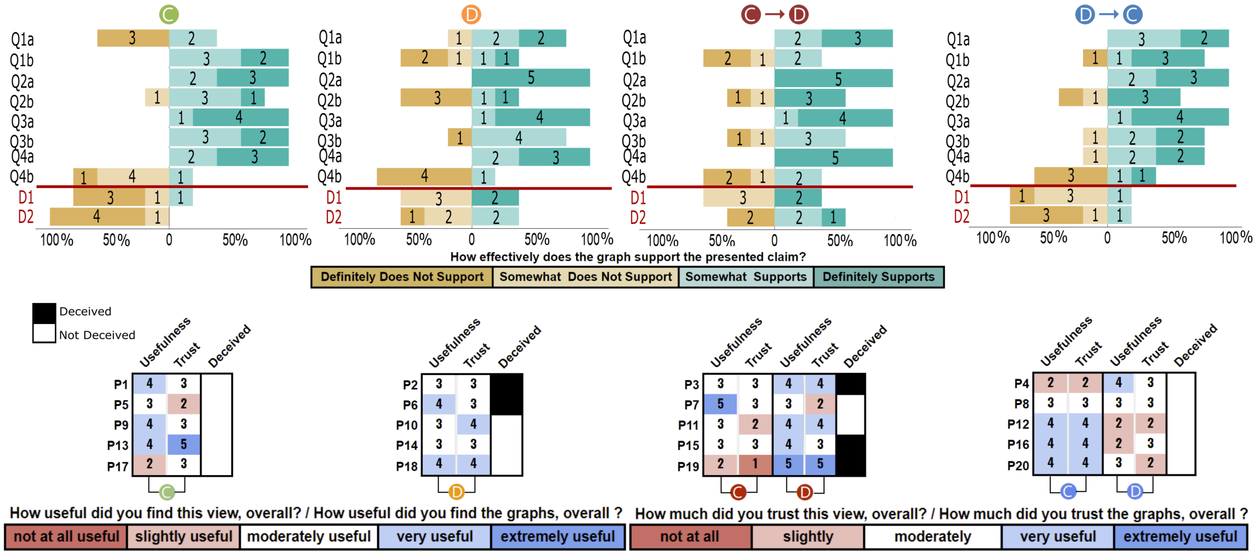


**Figure 6: Top: Answers to the 10 critical evaluation questions for each experimental condition. Bottom: Participants' ratings of trust and usefulness for each view (or the charts overall, in static conditions), and whether they were deceived at least once.**

the context of real life values. *"That's somewhat significant, because 150k could be somebody's down payment" (P3).* Participants in the truncated-axis and interactive conditions were more likely to consider these effects large. Several participants (10/20) commented that questions were ambiguous because they asked for subjective judgements rather than numerical quantities, or because they were unfamiliar with the subject. *"I don't have any knowledge of what is the average [for] car sales, what is a lot, what is a little... it's a little more difficult to make those calls" (P10).* Participants who felt more familiar felt more comfortable making these judgments: *"I, of course, have read a lot of news and have formed my own idea of what is significant and what is not. Say, losing half a trillion over a fourteen trillion GDP - that is significant" (P8).*

### Detecting Deceptive Claims

Participants were considered to have been deceived if they answered 'definitely supports' for at least one deceptive question, or if they answered 'somewhat supports' and it was clear from their written justification that they interpreted the difference as 'much larger' for D1 or a 'significant increase' for D2. Zero participants in the control or D→C conditions were deceived, compared to 40% (2/5) in the deceptive condition and 60% (3/5) in the C→D condition.

The two who were deceived in the deceptive condition (P2, P6) both indicated that they focused on the shape of the graph, instead of the axis values - *"I didn't actually read the figures" (P2).* Of those in the C→D condition, P3 indicated that he trusted the zoomed-in view more (see Figure 6) because he could see the exact numbers - however, his lack of trust in the zoomed-out view led him astray and he was deceived by D1. P19 also indicated higher levels of trust in the zoomed-in view because the truncated-axis view seemed uninformative *"you needed to see the changes between the bars, which you couldn't see when it was zoomed-out, so that's why I trusted more the zoomed-in one."* Though she gave identical numerical ratings, P15 found the truncated-axis view more trustworthy because she perceived it to be "more accurate" - she confirmed that she did not take the axis scale into account when deceived by D2.

## 7 PHASE II: FOLLOW-UP TO STUDY 1

To collect richer qualitative data about participants' reasoning process as they examined the charts using Perceptual Glimpses, in the second phase all 20 participants were shown the two interactive charts from the C→D and D→C conditions in the mTurk study, side-by-side, and allowed to investigate both freely. Participants were then asked the deception test question about safe drinking water access.

Participants gave lower answers compared to the mTurk experiment (M =1.75, 95% CI [1.45, 2.1]). When asked which presentation orders they preferred, participants were divided, with 45% (9/20) preferring to see the truncated-axis view first, usually (5/9) because it provided precise, numerical information on the difference, compared to the canonical view, i.e., *"I prefer to see the zoomed-in view, although this is very deceiving" (P8)*; *"It's important to know what the difference is too, rather than just having that ambiguous value" (P2).* Half (10/20) of the participants indicated that they would prefer to be presented with the canonical view first, often because they thought showing the truncated-axis view first would be deceptive (6/10). However, 85% (17/20) perceived some benefit to seeing the truncated-axis view and stated that they wished to see both views.

Since deception was discussed at the end of Phase I, participants were primed to consider it, likely affecting their deception test responses. However, the insight that users thought that Perceptual Glimpses was useful despite the possibility of deception was unaffected by priming. Phase III was also unaffected, as it did not directly investigate deception.

## 8 PHASE III: USABILITY EVALUATION

We included a third phase, to evaluate whether users could understand a wider range of views (these were not selected systematically, but chosen to illustrate the two categories of secondary views). To this end, a software prototype was implemented in D3 [9], for use on a 9.7” iPad.

### Description of the Prototype

The system (Figure 7) integrates eight secondary views. Each view can be selected by clicking the corresponding view button and can be applied by pressing and holding the transform button to trigger the quasimode transformation.

Four of the secondary views display derived values: deviations from a least-squares trendline (TD), values renormalized with respect to a specific bar (R; e.g., the difference in sales from 2003), finite differences between successive bars (FD; e.g., the year-to-year change in sales), and cumulative values (C). The other four views remove or distort information to provide a clearer view of the subset that remained. In addition to a truncated-axis (or cut-axis) view (CA), the user can filter categories (FC), zoom in on a range of successive bars, removing all other bars (Z), or fold the x-axis to bring two bars closer together, removing the bars in between and allowing for more accurate comparison (FA) [17, 52].

Some views can be parameterized prior to transformation. For example, the user can select one (R) or more (FC) bars by tapping them. The user can also select a range to zoom in on (Z) or exclude by folding (FA) by dragging two handles beneath the outermost bars of the range. The level at which the axis is truncated (CA) can be adjusted by dragging the cut line. For simplicity, all animations between canonical and secondary views used a simple interpolation of bar heights. For views that change the x-axis (FA, FC, Z), bars that are removed in a secondary view disappear by shrinking vertically. The TD, C, FD, Z views are only meaningful for time series data, and FC only for categorical data - disabled views for a given dataset are shown in grey.

### Procedure

Participants completed an informal user evaluation of the prototype system. Participants performed eight tasks derived from Amar et al.’s taxonomy of analytic, low-level user tasks [2]. Questions (Table 2) were selected such that each task was intended to match a specific view, which would allow it to be answered effectively. We wished to observe whether

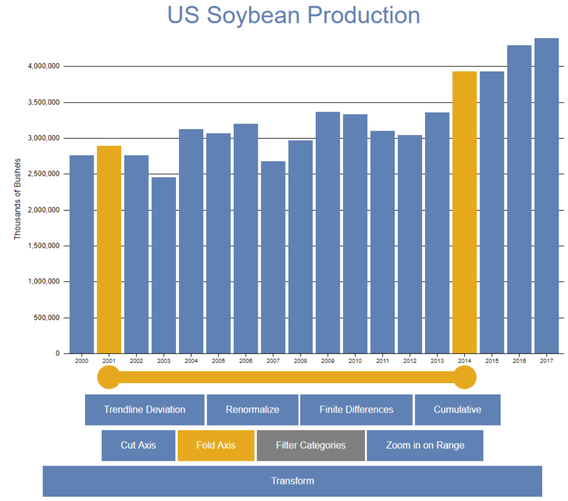


**Figure 7: Prototype System, showing canonical view, view buttons and transform button. The Fold Axis (FA) view is selected, but not active. Filter Categories (FC) is disabled.**

participants could correctly use each of the eight views to answer these questions, which would indicate a level of understanding of the view and its potential uses. Three datasets from Statista were used, two time series datasets (yearly soybean production [57] and quarterly iPhone sales [3]) and one categorical dataset (soybean imports for 9 countries [58]]). At the beginning of the phase, we demonstrated how to use the quasimode control and explained each view. Participants were allowed to explore all eight views freely on a test dataset, and then completed the tasks serially, entering answers into a text field and taking a screenshot to demonstrate their choice of secondary view. After all tasks were completed, we solicited qualitative feedback on the system. Not all views were active for all questions, as described above. (TD was also disabled for the iPhone sales questions due to a bug).

### Usability Evaluation Results

Generally, participants chose the intended view, with some exceptions. For Q3 all participants chose the correct view. For Q2 95% (19/20), and for Q1 and Q8 90% (18/20) chose the correct view. For Q4, all participants correctly chose the FD view, but two gave an incorrect numerical answer to the question and one could not determine how to answer.

In some cases, participants chose a view that was different than intended, but still perceptually useful. For Q7 only 7 participants (35%) chose to use FA, but most others used F (50%, 10/20), which gave the same result, only with more steps required to select the two bars of interest. Many participants chose FA (40%, 8/20), R (10%, 2/20), or Z (10%, 2/20) instead of CA (40%, 8/20) for Q5, which required comparing two values near the top of the chart; these views were all more helpful than the canonical view for this task, but unlike the cut axis

**Table 2: Questions for prototype usability evaluation, and corresponding perceptually effective view.**

| # | Question (and task type from [2]) | View |
|---|---|---|
| Q1 | What is the range of production volumes for the period 2001-2003? (Determine Range) | Z |
| Q2 | Which year deviates the most from the linear trend? (Find Extremum) | TD |
| Q3 | In what year did all-time iPhone sales surpass 600 million? (Compute Derived Value) | C |
| Q4 | How many quarters had lower sales than the previous quarter? (Compute Derived Value) | FD |
| Q5 | How many more iPhones were sold in Q1'2018 than in Q1'2015? (Retrieve Value) | CA |
| Q6 | Which Asian countries have > one billion metric tons in soybean imports? (Filter) | FC |
| Q7 | What is the difference in imports between Indonesia and Thailand? (Retrieve Value) | FA |
| Q8 | Which country is closest to Japan in import volume? (Cluster) | R |

did not increase the resolution of the y-axis, making answers less precise. Participants also generally used CA (65%, 13/20) instead of FC (35%, 7/20) for Q6, indicating that they found it more useful to focus on the countries above the reference point of 1 billion bushels than on the Asian countries.

Participants reported greater difficulty understanding the views of derived values, with 40% (8/20) reporting that they had difficulty understanding the FD view, and 30% (6/20) the TD view. This may be because these represent more complex mathematical operations, or because animated interpolation of bar heights was not sufficiently congruent [56].

When probed, 65% of participants, (13/20) said they thought that the animated transitions improved their understanding of the transformations, e.g., *"It made it easier to see what was happening… you actually know when you fold axis these three categories are gone... if you just click it and see the next picture you won't know what happened, like what left (P14)."* or prevented errors of interpretation *"It's a visual cue like 'Hey, keep in mind how this information is changing' For example with cut axis, that's a clear hint that like, don't take the bottom of the graph to be zero (P10)"*. This provides support for our initial hypothesis that the animation could help maintain awareness of potentially deceptive distortions.

The subjective responses provided less support for the hypothesis that quasimode control would be particularly useful. A small number of participants (3/20) stated that they thought the quasimode control would prevent them from making mode errors; e.g., P3 said that if he didn't have to hold to maintain the FC view he *"might just forget it's transformed and just forget about all the other years"*. No participants expressed confusion about how to apply transformations after the initial exploratory period. However, participants' feedback made it clear that quasimode control has limitations that render it ill-suited for detailed analysis - the most common being that it made it difficult to perform parallel tasks (7/20), like writing down values. Some participants stated that needing to remember the exact values from the chart was difficult, since the transformed view disappeared when they released the quasimode to report their answer.

These results reinforce the fact that the intended use case for Perceptual Glimpses is data presentation, where the user is not performing detailed analysis but rather observing insights curated by a designer, who has created a mapping between a secondary view and the low-level task required to appreciate its message.

## 9 DISCUSSION

### Benefits to Users

Results from all three phases of the second study provide evidence that users derived benefits from being able to access secondary views using quasimodes, including those that were potentially deceptive. The first phase showed that users could integrate information from both views to critically evaluate visualizations, showing a clear benefit for allowing users to recognize small but important effects, namely a change in GDP. In the second phase, even though most participants correctly identified the difference in drinking water access as quite small, almost all felt that they would be missing something if they were to see only the canonical view. In the third phase, users could comprehend and make use of the technique for a wide range of secondary bar chart views. The fact that users showed a degree of understanding is encouraging. Though they did not always use the view we intended, they almost always found a view that was better than the canonical view, identifying some overlap between views (specifically F and FA for comparing distant bars). To compare values near the top of the chart, users preferred other views over CA, indicating that setting the cut level may not be intuitive.

However, it is unclear to what degree these observed benefits come from quasimode control, compared with merely having access to the secondary view. We do not compare with alternative methods of presenting truncated-axis views (e.g., interactive juxtaposed views or static call-outs), and whether these solutions may perform equally well is left to future investigation.

### Errors in Detecting Deception

The crowdworker study provides evidence that presentation using Perceptual Glimpses can reduce the effects of truncated axis deception. However, in the second study it failed to show a clear-cut benefit for allowing users to detect deceptive visualizations. Thirty percent of users who used Perceptual Glimpses were deceived, compared to 40% of users in the deceptive condition. Given the possibility of misinterpretation, modifications are clearly necessary before the technique can be applied for truncated axes in general.

The errors we observed might be explained by our observation that for the truncated axis deception, individual differences in chart familiarity and visual ability (proxies for visualization literacy [11, 43]) played a significant role, and previous work which suggested that education level may have similar effects [40]. Unlike other deceptions such as a misleading choice of visual encoding, all the information required to notice a truncated axis deception is displayed to the user by the values on the axis. Highly literate users, who may already be aware of truncated axes, can already correctly interpret information from this view. Animated cues, and the ability to transition between the two views using quasimodes, will increase the likelihood that these users will notice the axis start point. However, other users may fail to grasp the ramifications of the transformation - this appears to have been the case for the three participants in the interactive condition who were deceived, and stated higher levels of trust in the truncated-axis view. This suggests a need for greater support to ensure users trust and make use of the data from the canonical view.

### Presentation Order

While our initial hypothesis was that we would observe an anchoring effect, this was not observed in either experiment. Interestingly, participants also consistently reported that they thought seeing the potentially deceptive view first might cause a user to be misled. In the online experiment, we could only confirm the effectiveness of the D→C presentation order, where the deceptive view was shown first, and the canonical view was revealed by a quasimode.

In the second experiment, participants appeared to assign greater value to the information that was presented in the second view that they saw. Participants in the C→D condition reported lower levels of trust and usefulness for the canonical view compared to the truncated-axis view, and were more likely to be deceived, while participants in the D→C condition were generally less trusting of the truncated-axis view. If this is the case, this is an instance where the "Overview First" design heuristic [50] leads to undesired behavior. One possible explanation for this counterintuitive result is that the information provided by the canonical and truncated-axis views were perceived as so different that they provoked the participants to employ a strategy known as 'considering the opposite' [34, 39], i.e., to completely rethink the validity of their initial assumption, rather than adjusting their initial estimate as with anchoring [55]. Many participants in the second experiment (11/20) explicitly described thought processes that were consistent with this strategy, i.e., *"The zoomed-out view, it's very very clear that the data is almost the same… then looking at the zoomed-in view for a minute, you think, 'Oh, maybe it's not.'"* (P12).

Another possible issue is that participants found the well-normalized view uninformative. In our deceptive questions the difference between bars was quite small, to make it unambiguous that the effect in the truncated-axis view was not large in magnitude. However, this was perceived by some not as evidence that an effect was insignificant, but that the canonical view was flawed. Participants who saw this view first may have dismissed the insights provided by the less information-dense chart in favor of the misleading, but obvious, insights from the truncated-axis view, e.g.,*"from an ambiguous amount, it goes to three percent change - which is a lot (P2)"*. In contrast, participants in the D→C condition were able to digest information from the truncated-axis view before reconsidering it relation to the overall magnitude. This relates to a core research question in data-driven storytelling - how interactivity, and the narrative structure in which data is presented, can affect interpretation [15].

### Need for Context

A consistent theme in the interviews was that participants felt that they lacked the information required to make subjective judgements about the magnitude or significance of the presented difference, e.g., *"maybe small to that field is a different meaning than small to me"* (P9). While participants who had access to both views had more precise information about the magnitude of the effect and how it related to the overall values, not all of them could correctly characterize effects as either significant or insignificant. Thus, explanation of the quantities involved in a visualization is another area where users should be given direct support. This should go further than a simple restatement of the content of the visualization, which has been shown to be insufficient to overcome the effects of deception [40].

## 10 RECOMMENDATIONS FOR DESIGN

The challenges we encountered suggest considerations for employing Perceptual Glimpses. The effectiveness of the recommended solutions can be confirmed with further work.

**Explicitly mark any views that could be misleading or deceptive**. If users are not given explicit guidance about whether a view is potentially deceptive, they must rely on their own visualization literacy. A small marking such as a caution symbol, or a red outline, may be sufficient to adjust participant's relative level of trust in the two views.

**Ensure every view is informative**. One reason participants disregarded information from the canonical view was that they found it uninformative. Annotations showing exact values or explaining unfamiliar quantities could make the view more useful and thus increase trust.

**Carefully consider presentation order**. Users may react very differently to two identical views presented in a different order. In the case of the truncated axis on a bar chart, they may value information more when it is presented later. This should be investigated on a case-by-case basis.

## 11 DESIGN EXAMPLES

To illustrate how Perceptual Glimpses might be extended beyond the bar charts evaluated in this study, we augment two existing visualizations using quasimodes. (See video figure and https://github.com/perceptual-glimpses/chi2019).

### Choropleth Maps

Choropleth maps exaggerate the importance of large geographical areas [38]. To improve this, designers sometimes employ cartograms, where each region is represented by a simple shape, scaled by relative population. In Figure 1b, we see a choropleth map and cartogram (reproduced from [20]) showing the results of the 2003 Californian election in the Bay Area. The choropleth map gives the impression that Schwarzenegger received a fairly large portion of the vote, while in reality the region, and especially the most densely populated counties, mostly voted for his opponent. By presenting this pair of maps using Perceptual Glimpses, the visual information in the second (canonical) view can be used to communicate that some aspects of the first view may be misleading. We add explicit narration to highlight the possibility of deception.

### Route Maps

LineDrive maps show a distorted "route map" view similar to hand-drawn maps to communicate a set of driving directions. They are designed to allow straightforward navigation [1] and are an instance of perceptually beneficial distortion [18]. However, they remove the context surrounding the route, abstracting it to a series of straight roads and turns. If a user is not already familiar with the area, they must blindly follow the directions. Using Perceptual Glimpses, an undistorted route map (adapted from [1]) is presented first, with the more abstract LineDrive map revealed by a quasimode. This allows users to get an overview of how a route is situated before viewing the task-specific LineDrive map.

## 12 LIMITATIONS & METHODOLOGICAL CONSIDERATIONS

The presented evaluation has a number of limitations. Our second study focused on obtaining qualitative insights into user experiences with Perceptual Glimpses and the effects of presentation order. This precluded the sample sizes necessary for statistical significance, and so further research must be done to confirm our findings. Since we did not explicitly control for visualization literacy, variation in individual abilities also may have affected our observations.

The work also raises broader methodological questions for the design of evaluations to gauge the impact of deceptive visualizations. Deception often occurs due to inattention, when viewers quickly or uncritically consume graphical information (e.g., skimming a news story). As such, the mere act of asking a question about a chart may put a participant on guard, rendering it difficult to tell whether they would have been deceived in other circumstances. The more deceptive questions one asks, the more suspicious subjects become, lowering the chance of successfully measuring deception.

A further complication is that, if a viewer who has been misled by a truncated axis is asked about specific numerical values, the process of re-expressing their subjective impression of a trend in numerical terms may cause them to uncover the deception. As in previous work [43], we attempt to circumvent this by asking questions using subjective phrases such as "significant increase". As work on interpretation of probabilistic phrases has shown, different people have wildly different interpretations of the same adjectives [12]. The lack of a precise definition for these terms makes calibration (e.g., showing users an example of a "slightly better" difference) difficult to justify. As a result, in Study 1, we required a large sample size to mitigate the effects of individual differences.

And, as we found in Study 2, what is considered 'large' is heavily dependent on the context of the question and the quantities used. Though we reduced possible bias by using synthetic data, it is possible that users preferred views that appeared to align with their existing domain knowledge, which may have affected self-reported trust. These factors combine to make it difficult to validate the effectiveness of tools intended to mitigate deception.

## 13 CONCLUSION

Perceptual Glimpses allows for the presentation of task-aligned views in context, including some views that might previously have been avoided due to the possibility of misleading a user. Two studies identified design considerations for this quasimode-triggered transformation, including possible order effects. Failure modes for the technique were also discovered, inviting future work that modifies Perceptual Glimpses to increase its effectiveness, or determines whether other techniques, such as coordinated views, might offer effective solutions to the problem space we introduce.

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