How Deceptive are Deceptive Visualizations?: An Empirical Analysis of Common Distortion Techniques

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ABSTRACT
In this paper, we present an empirical analysis of deceptive visualizations. We start with an in-depth analysis of what deception means in the context of data visualization, and categorize deceptive visualizations based on the type of deception they lead to. We identify popular distortion techniques and the type of visualizations those distortions can be applied to, and formalize why deception occurs with those distortions. We create four deceptive visualizations using the selected distortion techniques, and run a crowdsourced user study to identify the deceptiveness of those visualizations. We then present the findings of our study and show how deceptive each of these visual distortion techniques are, and for what kind of questions the misinterpretation occurs. We also analyze individual differences among participants and present the effect of some of those variables on participants' responses. This paper presents a first step in empirically studying deceptive visualizations, and will pave the way for more research in this direction.

Author Keywords
Deceptive Visualization; Empirical Analysis; Evaluation.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

INTRODUCTION
In recent years, data visualization has gained popularity as a powerful communication tool to support arguments with numbers while still making messages accessible. In fields as disparate as business, policy analysis, human rights, and journalism [14, 35], specialists and laypersons are using data to shape compelling, informative, and convincing narratives, conveyed through or supported by visualizations. While the use of such visual depictions as persuasion devices is not new, the popular use of visualizations has undoubtedly increased due in part to user-friendly software that allows non-experts to create visualizations. As such practices become more widespread and accessible, important new challenges and questions arise. If visualizations can make messages more accessible, comprehensible and persuasive [27, 37], visual representations can also be easily misused and misunderstood - even by their creators.

This problem has been known for a long time and it is not limited to visual representations but more to the general problem of communicating through numbers and statistics. Darrell Huff's "How to Lie with Statistics", published in 1954, popularized the problem and warned against the many traps of using statistics and charts in communication [15]. In the 1980s, Edward Tufte introduced the concept of *graphical integrity* in his classic "Visual Display of Quantitative Information" and succinctly explained the many subtle ways in which data graphics can distort information [38].

Despite their influence, these seminal works have not prevented distortion through data visualization. If anything, the heightened popularity of data visualization may have actually increased the prevalence of such cases and the impact they have on the population at large. Examples abound in popular media, TV and the Internet [4]. Some examples collected from popular sources [3, 1, 2] involve notorious distortions, such as manipulation of axis orientation/scale (Figure 1[a,c]), use of disproportionate sizes (Figure 1[f]), incorrect representation (Figure 1[d]) and non-linear scales (Figure 1[b,e]).

Misrepresentations may result from a lack of expert knowledge, as appears to be the case in distorted representations collected from human rights organizations. However, the possibility of influencing the audience can also create an incentive to use distortions intentionally - either in a zeal to convince, in the case of advocates, or in an attempt to mislead, in the case of unethical marketing firms. While jour-

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Figure 1. Some of the real-world data visualization examples which might lead to misinterpretation of message, hence to deception.

nalists may run the risk of accidentally distorting visualizations due to their significant time constraints, some very obvious examples of media misrepresentations suggest that distorted visualizations are sometimes used intentionally. While the motives behind these types of distortion differ dramatically from an ethical point of view, their visual characteristics and perception by the audience are largely the same. In this work we take a step toward understanding the extent to which audiences are deceived and whether there is a relationship between deception and individual differences among people. While the literature cited above, and many newly available works [4], warn against the danger of deceptive visualizations, we are surprisingly not aware of any empirical work aimed at assessing the severity of deception. To close this gap, we designed and ran a series of crowdsourced studies aimed at understanding the deceptive effect of distortion techniques.

Our studies stem from a preliminary analysis of existing deceptive visualizations which led us to (1) categorize deceptive visualization effects and focus on two main classes: *message reversal* and *message exaggeration/understatement* and (2) derive synthetic examples to reproduce these effects in a controlled environment.

In the studies, we selected a set of common misrepresentation techniques from the classes we identified as frequent and created deceptive and non-deceptive versions of the same charts. We also collected personal traits of participants related to *education*, *chart familiarity* and *visual ability* to examine whether these traits play a role as co-factors on deception. Our results show that deceptive charts have a major impact on how people interpret a message and that in some cases this effect is modulated by some personal attributes we included in the study.

The main contributions of our work are: (1) the definition and classification of deceptive methods in visualization; (2) the empirical confirmation and measurement of some of the well-known graphical distortion techniques; and (3) the empirical analysis of the effect of personal attributes on the deceptive effect.

We believe this is an important first step toward a better characterization and understanding of how visualizations impact their readers. By studying the deceptive effect we expand some of the recent research on the cognitive and social effects of visualization, including research on bias [16], memorability [7, 9], literacy [11], and persuasion [27].

RELATED WORKS

The fact that it is possible to "lie" with statistics and visual representations has been known for a very long time in areas related to data analysis and representation. The 1950s classic "How to Lie with Statistics" introduced numerous methods through statistical communication can lead to misinformation [15]. In the 1980s, Tufte developed the concept of *graphical integrity* and the *lie factor* to describe how visual representation can distort information and deceive the reader [38]. Similar in spirit, and building upon them, are two more recent books on the same topics: "How to Lie with Charts" [17], which focuses mostly on the use of charts in business environments, and "How to Lie with Maps" [24], with focuses on geographical visual representations. While all of these works expose common deception patterns and provide guidelines to spot and avoid them, we are not aware of studies that test the deception effect in a controlled experiment.

Visualization researchers have, however, studied how visual encoding can distort information at level of perception. Particularly relevant is research on visual encoding which establishes how data is perceived and compared when represented with different visual channels such as position, size, color, angle. Bertin [8] introduced the concept of visual encoding and visual channels and provided guidelines on how to best use them. Cleveland and McGill in their famous experiments on *graphical perception* discovered that some visual channels lead to more accurate comparisons of quantitative information than others [13] (e.g., position along a common scale being the best one and area a poor one). Color, if not used properly, can lead to numerous distortions. The seminal work “How not to lie with visualization" [33], the more recent "Rainbow color map (still) considered harmful" [10] and numerous experiments on the topic show how poor color selection can lead to numerous distortions [12, 21]. The perception of correlation in scatter plots and parallel coordinates can also be problematic: when asked to estimate correlations, participants typically underestimate the positive correlations and overestimate the negative correlations in parallel coordinate plots [22, 31]. Mapping a numeric quantity to the radius of a circle rather than area is another popular technique that leads to distortion, and the use of area size has been found to be problematic also when rectangles are used [19].

All these studies focus mostly on visual effectiveness and are based on the careful selection and testing of specific perceptual tasks. For instance, Cleveland and McGill asked participants to compare two bars marked with a dot in a bar chart. While this is of course useful, we are more interested in studying deception effects at the *message level* of visualization because it better simulates what happens in the real world when a reader is presented with a new chart (e.g., in a newspaper, book, or presentation). Therefore, rather than asking participants to compare two bars in a chart, our studies ask participants to compare quantities between real-world objects using the domain language, as described in the User Study section. This, as explained in graph comprehension theory [36], is a crucial difference as part of the tasks the reader will need to perform is the translation between the question and the mapping between the domain concepts and the graphical representation (what Pinker calls *graphical schemata* [30]). Since the deceptive effect may well happen during this translation and mapping phase of graph comprehension, we determined it would be important to run studies that focus on the message level of data visualization.

DECEPTION AND DECEPTIVE VISUALIZATIONS

In data visualization, the classic adage "*do not lie to your users*" [34] is fading fast. Designers and communicators are utilizing the power of data visualization to augment their messages, which in turn has an effect on how users perceive the original message. While we are not aware of any study which discusses the trade-off between how much augmentation is good enough, or what is the maximum extent to which a communicator may augment through additional information without distorting the underlying message, there are strong proponents and opponents of deceptive designs that we would classify as deceptive.

Webster's Dictionary describes deception as "*the act of making someone believe something that is not true*" [5], which implies that deception necessarily involves an intent to mislead. However, as Adar et al. [6] maintain, "*deceptive(ness)* does not require intent", i.e., one may induce deception without lying. There are numerous examples of data visualizations and infographics which are deceptive, but which may not have involved an intent by the communicator to deceive. For example, while omitting outliers and other data points to show a best-fit regression line leads to a deceptive visualization with intent by a statistician, such poor practice may also result from novice use of statistics. Similarly, not following best practices of visualization design, such as truncating the axes, may lead to a deceptive visualization either *with* or *without* intent, depending on the level of sophistication of the creator.

To shed some more light on the origins of these problems in one particular field we conducted interviews with experts working at the intersection of data and human rights. These interviews suggested that while statistical literacy remains relatively low within the human rights advocacy world, the power of data-driven advocacy exerts an increasing pull to use data visualization. Human rights experts readily agree that there is little tailored evidence to guide decisions about how best to design data visualization to support human rights messages. Further, human rights organizations frequently lack sufficient personnel with specialist training in data analysis and visualization. This mismatch between strong incentives to use visualization and gaps in capacity can lead to the accidental construction of distorted visualizations, which can in turn mislead target audiences.

Based on these findings and the definitions introduced in the previous work [32], we put forth a working definition of deceptive visualization as "**a graphical depiction of information, designed with or without an intent to deceive, that may create a belief about the message and/or its components, which varies from the actual message**". Instead of focusing on the intent of the creator, we are interested in analyzing aspects of deceptive visualization such as distortion techniques, deception severity, etc., and thus do not explore the boundary of intentional vs. unintentional deceptiveness.

In visualization, deception may occur at two levels - the *chart level*, where the user reads the chart incorrectly, and/or processes an incorrect estimate of the data presented; and the *message level*, where users interpret the message incorrectly. Chart level deceptions occur at the visual encoding level, and are mostly modulated by the ability or inability of the user to read the chart correctly. The user's visual literacy, ability, and chart familiarity play an important role in neutralizing the deceptive effect of the visualization. Message level deceptions occur at message interpretation level, and may lead to creating false beliefs about the message and/or its components.

In the real world, visualizations are usually accompanied by a message, hence, it is interesting to study how visualizations lead to a message level deception. As this is the first experimental study that explores visualization deceptiveness, we chose to narrow our scope to focus only on message level deceptions. There are various ways to visually deceive viewers even at the message level, e.g., presentation of deliberate misinformation, distractions, information overload, or through deceptive techniques applied on the level of visual encoding. In our study, we decided to start from the common types of graphical distortions without including deceiving effects that do not stem from choices made at the visual encoding level (e.g., we excluded deliberate data manipulation). Starting with complete data, we identified two broad classes of message level deception - Message Exaggeration/Understatement, and Message Reversal, as described below.

Message Exaggeration/Understatement

This kind of deception happens when the fact is not distorted, however, but the extent of the presented fact is tweaked, i.e., the fact is exaggerated. For example, if a chart compares two quantities - A and B, where *A is bigger than B*, but the users are presented with the fact that *A is bigger than B*, but the extent is exaggerated. This type of deception affects the "**How**

much" type of questions, such as "*How much do you think is quantity A bigger than quantity B?*"

Message Reversal

This type of deception happens when a visualization encourages users to interpret the fact in the message incorrectly. For example, if a chart compares two quantities - A and B, where *A is bigger than B*, the users perceive the message as *A is smaller than B*. Thus, users perceive the incorrect message due to a distorted visualization, even though the actual data is presented. This type of deception affects the "**What**" type of questions, such as "*What does the chart show?*".

STUDY RATIONALE AND METHODS

Given the limited empirical literature on deceptive visualization, we set out here some of the design rationale that made up the groundwork of this study. The main experiment design choices that are necessary for this kind of study include the selection of distortion and affected visualization techniques, the mechanism to create deceptive visualizations to study the effect, a way to detect/measure the deceptive effect, and a measure of additional attributes that might impact users' responses.

Selecting Distortion and Visualization Techniques

In "How to lie with Charts" Jones says: "Almost all visualizations are prone to distortion or lie" [17]. However, distortion techniques are visualization specific: one type of distortion technique may not affect all visualizations. For some visualizations, colors play a role in deception, for others truncated axes or missing labels add the deceiving layer. This research focuses on some of the visualization techniques that are widely used. Our focus on those techniques that reach broad audiences allowed us to exclude complex visualization techniques such as heatmaps or network maps in favor of focusing on simpler charts used extensively by journalists, human rights activists, and policy makers. We chose four distortion techniques: *truncated axis, area as quantity, aspect ratio, and inverted axis* that we identified as having been used in these realms.

Creating Treatments

Based on the distortion and visualization techniques, we created two set of treatments or visualizations, one control and one deceptive, for each of the distortion techniques mentioned above. In the following, we present the illustration of treatments we created for each of the distortion techniques.

Truncated Axis

In the truncated axis visual distortion, one or more of the axes of a chart are altered by changing the minimum and maximum values presented on the scale, as shown in Figure 2. Such alteration of the axis range leads to exaggeration or understatement of the quantities presented, thus directly affecting the user's response to the "how much" type of questions. For example, in Figure 2, users' responses to the question "*How much do you think Y is bigger than X?*" is likely to be dependent on the type of chart (control/deceptive) presented. It is important to note that all chart types that are axis-based are susceptible to this type of distortion. In this research, we use this distortion technique with bar-charts only.

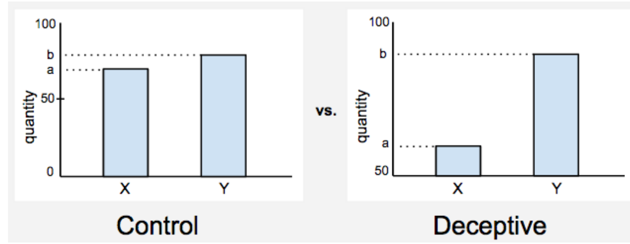


Figure 2. Illustration showing Truncated Axis distortion, which leads to message exaggeration/understatement type of deception.

Area as Quantity

Encoding quantitative data with size has faced serious criticisms in the visualization community, and is a process that requires careful mapping of data with graphics. Although no guidelines are available about how to map the actual data with graphical area, it is believed that a one-to-one mapping between the data and the graphical area is least prone to distortion. This is also one of the six graphical integrity principles suggested by Tufte [38]. However, it is not uncommon to see data mapped with one of the variables in the graphics that affect the graphical representation exponentially. This induces the message exaggeration/understatement type of deception. For example, from Figure 3 one may conclude that Y is "a lot" bigger than X, when the quantity is mapped to the radius of the circle (in the deceptive visualization). Other area-based charts are also prone to this type of distortion. When the quantity is mapped to the area, as in the control condition, the visualization is less susceptible to deception.

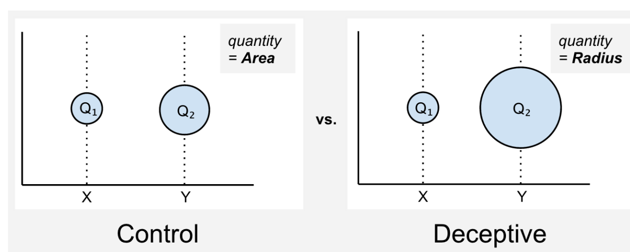


Figure 3. Illustration showing Area as Quantity distortion, which leads to message exaggeration/understatement type of deception.

Aspect Ratio

This type of distortion primarily affects line-charts as it directly impacts the rate of increase or decrease of one quantity over another. While one may argue that aspect ratio may impact other visualizations such as bar-charts where the width-to-height ratio of the bars may create a similar effect, we apply this distortion to only line-charts as they appear more frequently with this type of charts. Another way of looking at this type of distortion is the angle of inclination/declination of the lines that are affected because of the changes in the aspect ratio. As shown in fig 4, by widening the scales on one of the axes, the angle can be distorted. Hence, the rate at which the quantity appears to increase seems slower in the deceptive visualization condition as compared to the control condition. This type of distortion also leads to message exaggeration/understatement.

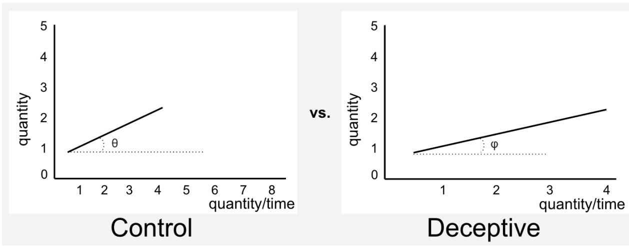


Figure 4. Illustration showing altered angle of the trend responsible for "rate of increase/decrease" due to Aspect Ratio distortion, which leads to message exaggeration/understatement type of deception.

Inverted Axis
Human beings relate directions with trends, such as: upwards - increase, downwards - decrease, right - front/progress, left - back/receding [17]. This directional interpretation makes *inverted axis* one the most common distortion techniques that leads to reversal of the message, and makes the users susceptible to drawing *false* conclusions. In other words, here deception occurs due to reversal of the message instead of exaggeration or understatement. This type of distortion also affects almost all visualization techniques that are axis-dependent. Figure 5 shows two chart conditions (control and deceptive) showing an increase in the quantity on the y-axis by quantity on the x-axis, however, the latter gives an impression that the quantity is decreasing because of the inverted y-axis.

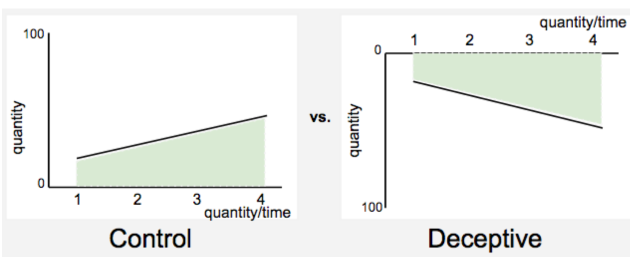


Figure 5. Illustration showing Inverted Axis distortion, which leads to message reversal type of deception.

Detecting Deception
In the scope of this research, we are only concerned with the deception that occurs through visual misrepresentation of information, which has an effect at the message level. As mentioned earlier, we categorized two types of message level deceptions - Message Exaggeration/Understatement, and Message Reversal, as follows:

Message Exaggeration/Understatement
These questions were created to detect whether the participants received the message in its original or exaggerated/understated form. As mentioned earlier, in this type of deception the fact of the message is not distorted, but is exaggerated. We detect this exaggeration/understatement by asking the "*how much*" type of question with a context, such as "*How much better do you think the condition of safe drinking water access in Silvatown is as compared to that in Wilowtown?*", where the users would reply on a 5-item Likert scale ranging from *slightly better* to *substantially better*. As this type of deception is unidirectional, i.e., it is extremely rare that the user would find smaller quantity bigger, the question and scale were designed to capture the single-tailed effect. To detect and study the extent of exaggeration/understatement, we compared the results of the correctly represented and misrepresented charts through a between-subject analysis.

Message Reversal
These questions were created to detect whether the users received the fact in the message correctly or not. Unlike *message exaggeration* where the fact in the message is not distorted, here the deceit occurs at the message level, distorting it. Instead of asking the "*how much*" question, we ask a multiple-choice "*what*" type of question, such as "*What can you say about the access to safe drinking water by the majority ethnic group in Silvatown, between 1995 and 2010?*". We provide three answer choices to the participants, including two interpretations of the message (one correct, and one incorrect, which the visual distortion would lead to), and "uncertain" as the third answer choice. A comparison of accuracy and between-subject analysis of the response gives an estimate of whether or not there is an effect of distortion.

Measure of Individual Differences
One of the most important aspects of studying visualization impact on human perception is understanding the ability of the target population to read and process the information presented, and form an interpretation of the underlying message. We included this aspect by using a two stage process to analyze participant's familiarity with basic charts, and their ability to process the information. To quantify familiarity, we used a 5-Likert scale question: "*How familiar are you with the chart shown below?*", with responses ranging from "not familiar at all" to "very familiar", presuming that higher chart familiarity means better ability of the participant to detect deception.

Another important variable to determine individual differences is "Need for Cognition". Need for cognition is a personality trait studied in social psychology to characterize the extent to which individuals are inclined towards effortful cognitive activities. This factor goes hand-in-hand with visual ability in profiling an individual based on his cognitive abilities and desire to process graphical information. Petty and Cacioppo define it as: "*the tendency to engage in and enjoy effortful cognitive endeavors*". In our study, we use their short 18-item test [29], which is one of the most popular scales to measure need for cognition. Apart from these, participants' demographic information, such as *age*, *gender* and *education* were recorded, while we primarily analyzed *education* as higher education may lead to higher visual literacy and ability to reason with statistics and graphs.

USER STUDY
We started our analysis by conducting two pilot studies. The first study was aimed at identifying whether or not there is a noticeable effect of distortion techniques on participants' responses, leading to deception. We used a real world deceptive visualization example (Figure 1[a]) and asked questions to detect any misinterpretation of the presented information. We found that such distorted visualizations can deceive users.

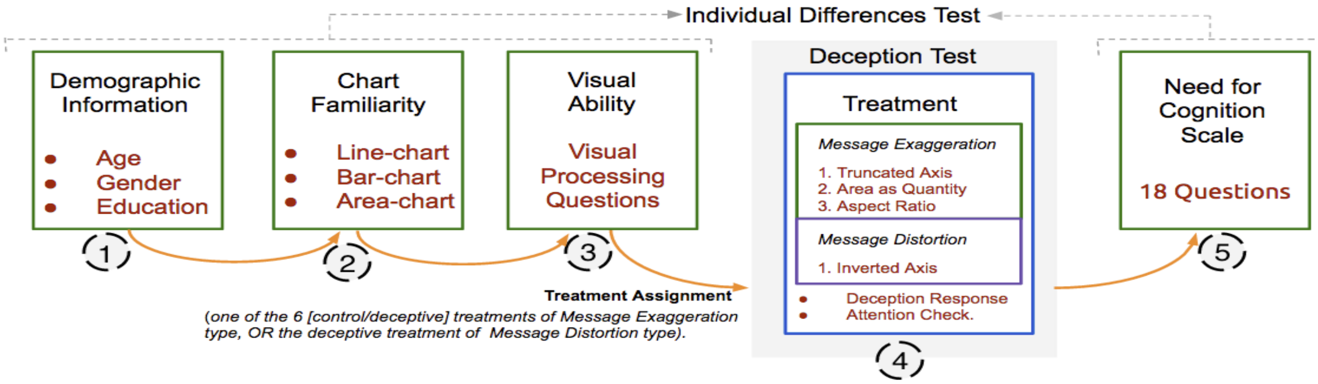


Figure 6. Various stages of the experiment. Stages 1, 2, 3 and 5 correspond to the individual differences test, while 4 corresponds to deception test.

In the second study, we wanted to understand whether an artificially generated scenario and data can lead to a similar deceptive effect under the same distortion techniques. Similar to the first pilot study, the participants were deceived, however, we did not find any noticeable difference between the responses when real or artificial scenario/data were used. The final user study was designed based on the findings of these two pilot studies.

In the final study, we conducted two types of experiments targeted to assess each of the two deception types - Message Exaggeration/Understatement, and Message Reversal. In the first type of experiment, we conducted tests on three deceptive visualization cases, one for each of the three distortion techniques - "truncated axis", "aspect ratio", and "area", individually. For the second type of experiment, we conducted tests on the "inverted axis" type of distortion technique. All the experiments were performed in a crowd-based setting with the primary goal to find an effect of distortion on users' responses, and additionally capture other interesting trends. The following section describes the experiments in detail.

Experiment Setup

The experiment consisting of four individual visual distortions (three for message exaggeration/understatement type of deception; the other for message reversal type of deception) was conducted using Amazon Mechanical Turk (MT). We chose MT as our primary experimental platform because it allowed us to conduct parallel studies on a diverse subject pool in an iterative fashion, allowing us to quickly test and refine our hypotheses. While conducting behavioral research based on self-reported measures on a crowdsourced platform may be considered problematic, several researchers have demonstrated the viability of MT as a reliable data collection platform [18, 26]. For instance, Paolacci et al. [28] compared results of classic experiments in judgment and decision-making using traditional and crowdsourcing methods and found that participants behave consistently.

For our final user study, we recruited 330 unique participants from MT who self-reported a United States location and whose previous task approval rate was equal to or exceeded 99%. Each experiment took 5-10 minutes and the participants were paid US $0.30 for participation.

Procedure

To take part in the study, the participants clicked on the link provided in the description of our task on MT. The link redirected the participants to a webpage hosted on our internal servers, where they undertook various stages of the experiment, as shown in Figure 6. Participants were provided a consent form with the description of the study, the data we would collect, and the tasks they would need to perform. Upon agreeing to the terms, we presented a personal information form (stage 1) to collect the basic demographic information about the participants, such as age, gender and education level. The next page presented a visual ability test (stage 2). The test was designed to include visual processing tasks [23, 20]. Next, the participants were presented a chart familiarity test (stage 3) where we asked how familiar they were with the specific types of charts: bar-charts, line-charts, and area-charts. We added a simple chart example to each of the familiarity questions. The participants provided their answer on a 5 point Likert scale, ranging from 1 (not familiar at all) to 5 (very familiar). Once the participants clicked "Proceed", one of the 6 treatments was assigned to them - control or deceptive from one of the 3 distortion types - in the message exaggeration/understatement focused experiment, or one of the 2 treatments - control or deceptive from the inverted axis distortion type - in the message reversal focused experiment.

On the treatment page (stage 4), we presented a brief **overview** about the chart, the actual **chart**, a message level **deception test** question, and an **attention check** question. The question to detect message level deception was designed to ensure that the participant did not have to perform any estimation tasks, avoiding the graph comprehension problem. For the bar-charts and bubble-charts, we asked the participants to **compare** the quantities presented, by asking "*how much better do you think is [quantity A] as compared to [quantity B] in terms of [the context]*". Similarly, for the line-charts, we asked the participants to detect **improvement** of a quantity over time, by asking "*how much do you think [quantity A] has improved in terms of [the context] between [time period]*". For the line-area-charts of the message reversal type of deception, we asked "*what can you say about the effect of [quantity A] over [quantity B]?*". It is important to note that in each of the presented treatments, the actual numbers/data were presented on the chart as we were interested in detecting deception due to visual representation even in the presence of accurate data. Based on the information presented in the chart, we asked an attention check question to filter out random clickers. Finally, at stage 5, the participants responded to a simplified need for cognition scale. Once the study was successfully complete, the participants were paid through Amazon Payments. We later used the responses collected at stages 1, 2, 3 and 5 to determine individual differences, and those collected at stage 4 to detect deception.

In our study design, *distortion type* is the main independent variable, whereas *user response* to the deception test question is the only dependent variable we take into account for the statistical analysis purposes. For the individual differences test, we consider three factors - *chart familiarity, visual ability, and need for cognition*, which may play a confounding role in modulating the *user response*. Other variables derived from *user response* are *response accuracy* - the percentage of correct responses - used to detect message reversal type of deception, and *mean/average user response* - the average of *user response* for the given condition.

RESULTS

We conducted a series of crowdsourced user studies to explore deceptive visualizations, and to determine how severe different distortion techniques are in terms of deceiving the user. We studied two types of deception: Message Exaggeration/Understatement and Message Reversal by applying relevant distortion techniques on commonly used visualizations and asking "How much" and "What" types of questions to detect the two types of deception, respectively. As the two studies are dissimilar on various aspects, we analyzed the data separately. In this section, we first present findings on the message exaggeration/understatement type of deception, and later on the message reversal type of deception.

Message Exaggeration/Understatement

We chose three distortion techniques - Truncated Axis (bar chart), Area as Quantity (bubble chart), and Aspect Ratio (line chart) - to study this type of deception. For each distortion technique, we created two treatments: control and deceptive. The deceptive visualization examples from the actual study are shown in Figure 7[a,b,c].

We recruited 250 unique participants for this study and assigned one of the six treatments to each of them. As a step to filter out the noise and retain the data quality, we filtered out those participants who did not provide a response to the attention check question or incorrectly answered it. The final distribution of the participants by distortion technique and treatment is shown in Table 1.

Treatment	Truncated Axis	Area as Quantity	Aspect Ratio
Control	37	40	38
Deceptive	43	40	42

Table 1. Distribution of participants (*who answered all the attention check questions correctly*) by treatment (Control, Deceptive) and distortion technique (Truncated Axis, Area as Quantity, Aspect Ratio).

Effect of Distortion on Response

Across all chart types, we found a significant effect of distortion on participants' responses. We found that participants who saw the deceptive visualization perceived the underlying message in its exaggerated form, and responded higher on the 5-Likert scale when asked the "**How much**" question. Table 2 shows the average participant response when exposed to one of the 6 treatments, and Figure 8 shows the distribution with 95% confidence interval.

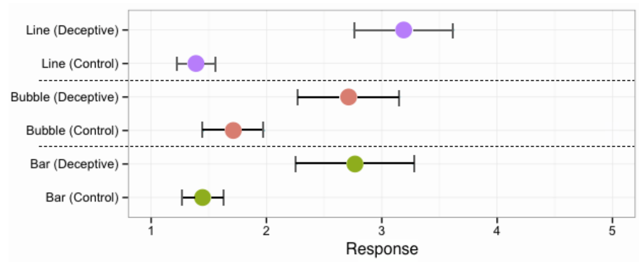


Figure 8. Average participant response with 95% confidence interval, when exposed to a treatment.

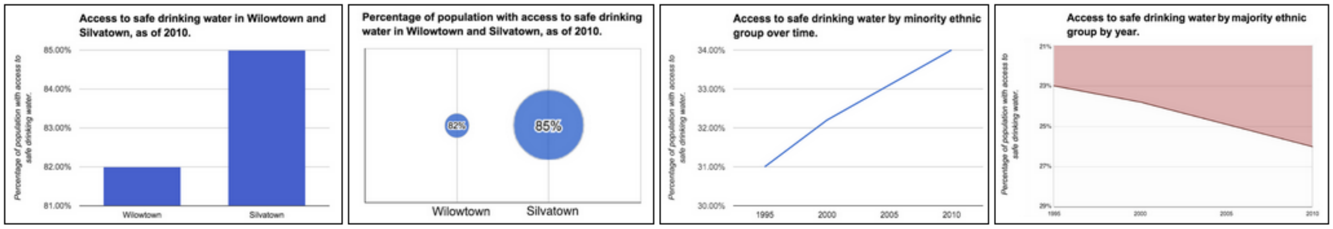
Treatment	Distortion Technique	Average Response
Line (Deceptive)	Aspect Ratio	3.19, 95% CI [2.76, 3.62]
Line (Control)	Aspect Ratio	1.39, 95% CI [1.23, 1.55]
Bubble (Deceptive)	Area as Quantity	2.71, 95% CI [2.27, 3.15]
Bubble (Control)	Area as Quantity	1.71, 95% CI [1.45, 1.98]
Bar (Deceptive)	Truncated Axis	2.77, 95% CI [2.26, 3.28]
Bar (Control)	Truncated Axis	1.45, 95% CI [1.27, 1.62]

Table 2. Average participant response (with 95% CI) to the "how much" question, by treatment (Control, Deceptive) and distortion technique (Truncated Axis, Area as Quantity, Aspect Ratio). ***(minimum = 1, maximum = 5)***

We ran a Mann-Whitney's U test (one-tailed) to evaluate the difference in the responses of our 5-item Likert scale question, for each of the treatment categories (Line, Bubble, Bar). We found a significant effect of distortion for all three treatment categories. For the treatments with bar-charts, the "truncated axis" distortion led to difference in the responses between the control condition and the deceptive visualization condition. We found the difference in participants' responses highly significant ($p < 0.001$) for control/deceptive conditions across all the distortion types. For the "aspect ratio" distortion type, the mean ranks of Line (Control) and Line (Deceptive) were 24.42 and 55.04, respectively; $U = 1409$, $Z = 5.88$, $p < 0.0001$, $r = 0.66$. Similarly, for the treatments with bubble-charts where the "area as quantity" distortion plays a role, the mean ranks of Bubble (Control) and Bubble (Deceptive) were 32.47 and 48.52, respectively; $U = 1121$, $Z = 3.08$, $p = 0.0007$, $r = 0.34$. The treatments that involved bar-charts (affected by the "truncated axis" distortion), the mean ranks of Bar (Control) and Bar (Deceptive) were 31.08 and 48.60, respectively; $U = 1144$, $Z = 3.36$, $p = 0.0003$, $r = 0.37$.

Message Reversal

We chose a single yet common distortion technique - Inverted Axis - to study this type of deception. We applied this distortion technique on a line-area-chart where the representation distorted the underlying message. This led the participants to interpret the fact ("**what**" type of question)



a. Truncated Axis **b.** Area as Quantity **c.** Aspect Ratio **d.** Inverted Axis

Figure 7. Deceptive visualization examples with corresponding distortion technique used in the study. Examples (a), (b) and (c) are used for message exaggeration/understatement technique, and (d) for message reversal.

presented in the message wrong, unlike the previous deception type where participants would misinterpret only the extent ("**how much**" type of question) of the presented fact. In other words, this distortion technique facilitates an estimation of accuracy in participants' responses, hence it can be tested in a between-subject design. We created only 2 treatments (control/deceptive) to study this distortion. Each treatment accompanies a deception test question to calculate response accuracy - the variable which we later used for all analysis purposes. The deceptive visualization example from the actual study is shown in Figure 7[d].

We recruited 80 unique participants for this study and randomly assigned one of the two treatments (control/deceptive) to them. We applied the same filtration mechanism to eliminate noise from the data. Out of the 80 participants, 78 passed our filtration criteria and were included in the dataset for further analysis. 38 of those participants were shown the deceptive visualization and 40 were shown the control condition.

Effect of Distortion on Response

Based on the information presented in Figure 7[d], we asked the participants "***what** can you say about the condition of access to safe drinking water by majority ethnic group over time?*", and provided a correct interpretation ("improved"), an incorrect interpretation ("declined") and an uncertain ("I do not know") answer choice.

Out of the 38 selected participants who saw the deceptive visualization, 30 responded incorrectly, 7 correctly and one chose the uncertain response. For the 40 participants who saw the control condition, 39 responded correctly, 1 responded incorrectly and no participant reported uncertainty. The response distribution by treatment type is shown in Table .

Treatment	Selected	Correct	Incorrect	Uncertain
Control	**40**	39 (97.50%)	1 (2.5%)	0
Deceptive	**38**	7 (18.42%)	30 (78.95%)	1 (0.02%)

Table 3. Response distribution (Correct, Incorrect, Uncertain) by treatment type for the *Inverted Axis* distortion.

To test for statistical significance of the differences in response we use the Freeman-Halton extension of Fisher's Exact Test, testing the null hypothesis that distortion has no effect on the participants' response. The findings were statistically highly significant ($p < 0.0001$), showing the effect of distortion on participants' response, hence, rejecting the null hypothesis.

Attribute	Level	Line chart	Bubble chart	Bar chart
Education	Low	3.93, [3,29, 4.56]	3.07, [2.42, 3.72]	2.73, [1.91, 3.54]
	High	2.85, [2.36, 3.33]	2.50, [1.93, 3.05]	2.73, [2.20, 3.24]
Chart Familiarity	Low	2.72, [1.91, 3.53]	2.60, [1.73, 4.49]	4.34, [3.98, 4.69]
	High	3.41, [2.96, 3.89]	2.71, [2.22, 3.21]	2.42, [1.93, 2.94]
Visual Ability	Low	2.88, [1.95, 3.79]	2.72, [1.75, 3.69]	4.07, [3.36, 4.79]
	High	3.33, [2.86, 3.79]	2.68, [2.21, 3.18]	2.23, [1.73, 2.74]
Need for Cognition	Low	3.40, [2.63, 4.20]	3.10, [2.08, 4.15]	3.22, [2.10, 4.32]
	High	3.18, [2.71, 3.68]	2.56, [2.10, 3.03]	2.67, [2.12, 3.20]

Table 4. Average participant response (with 95% CI) across various individual differences attributes, grouped by the deceptive chart type.

Analyzing Individual Differences

As explained in Section , we collected relevant participant data (stages 1,2,3 and 5 in Figure 6) to identify individual differences. Our main goal was to see whether some of these personal attributes have an impact on how susceptible a person is to the deceptive effect. Here we provide the results of our analysis on the four main individual difference proxies we used: *education level* (collected as part of the demographic data), *chart familiarity*, *visual ability*, and *need for cognition*.

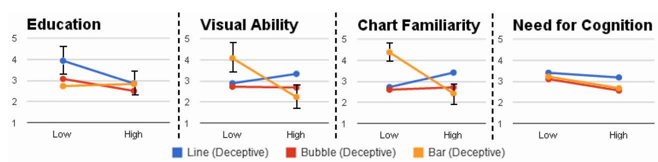


Figure 9. Comparison of average user response across deceptive charts, by the low/high level of individual differences factors.

Individual differences are studied largely in behavioral research where personal attributes of the user have an effect on his response [25]. Following this line of research, we conducted a quantitative analysis on the effect of individual differences on participants' responses, and also correlation between each of these factors to test for their independence. To facilitate our analysis and the communication of the main results, we binned the values obtained from individual differences into "high" and "low" values. For example, out of the 5 education levels (primary, secondary, undergraduate, graduate, doctorate), we regarded "primary" and "secondary" as "low education", and the rest as "high education". Participants who correctly responded to more than three questions on the visual ability test were tagged as "high visual ability", and the remaining ones as "low visual ability" participants. Similarly, those who self-reported a chart familiarity of 4 or 5 were tagged as "high chart familiarity", and those with 3 or below as "low chart familiarity" participants. Participants with overall "Need for Cognition" (range = [18, 90]) less than

54 were tagged as "low need for cognition", and greater or equal to 54 were tagged as "high need for cognition".

The results are presented in Figure 9. Table 4 presents all the effect sizes for individual differences with confidence intervals. Each chart in Figure 9 represents the effect of one individual difference factor (*education*, *visual ability*, *chart familiarity* and *need for cognition* from left to right). Within each chart, a line represents the effect size (that is the deceptive effect) obtained when the individual difference factor is low (left side) and high (right side). Line color represents the distortion effects we tested: *line*, *bubble*, *bar*.

As one can see from the figure, no clear trends exist between individual differences and participants' responses, across all chart types. The only major trend we observed was the effect of *visual ability* and *chart familiarity* on deception when a bar chart is shown (yellow line). *Education* also seemed to have an effect when a line chart was used, although the confidence intervals overlap. For the other charts, the effect was not clear as the confidence intervals are wide and overlap substantially, and hence are not shown in the figure. As the two charts provide very similar results, we also performed a correlation analysis between *visual ability* and *chart familiarity*, which revealed low correlation ($p = 0.171$) between the two factors. While *education* and *need for cognition* seem to follow a similar trend across chart type, the confidence intervals overlap substantially, making it hard to provide strong conclusions on these effects. We also performed a correlation analysis between all the individual difference factors and none of them showed strong correlation. Despite our expectations the analysis on individual differences did not provide definite conclusions.

DISCUSSION

The main goal of this study was to investigate whether and to what extent people are deceived by a number of well-known distortion techniques employed in graphical presentation of data and statistics. We also set out to see whether this effect is modulated by a set of individual differences we selected for the study.

The results confirm that these techniques do lead to major misinterpretation from the reader's side and that the effects are also rather large. When asked to compare two entities or variables by answering on a scale between 1 and 5, the distorted charts lead to responses between 58.5% and 129.5% bigger than the control condition. Out of the three charts that use a *message exaggeration/understatement* technique, the line chart is the one with the biggest effect, followed by the bars and then bubble, suggesting that these type of charts may have a more pronounced effect. The same is true for the conditions covering *message reversal* in which the deceptive condition led to 97.5% incorrect responses whereas the control condition led to only 18.4% incorrect responses.

Our analysis of the individual differences did not provide any conclusive information. However, some of the individual differences attributes seemed to have en effect for a particular type of chart. Further research is needed to disentangle the relationship between deception technique, chart type and individual differences. More precisely, it is necessary to understand if the effects depend on the chart type or only on distortion technique used. Another interesting direction is to take into account the general graphical literacy of the participants, and see whether it correlates with the response. The visualization literacy test developed by Boy et al. [11], can be employed for this purpose. While our study includes an elements that can be considered a proxy for literacy, e.g., *chart familiarity*, an objective measure of literacy may lead to more interesting results.

It is also important to discuss the main implications of this study. While deception through visualization has been known and discussed for a long time, our study allows a solid foundation for such discussions. It is important to advance the science of visualization and to help visualization practitioners with visualization principles and guidelines. It is also necessary to devise strategies to cope with the problem we identified and discussed in this study. It is necessary to educate readers and increase their ability to spot problematic and potentially deceiving information.

At last, we put forth a series of questions regarding real world visualizations. Are they designed intentionally to deceive? How can we distinguish between the intentionally and unintentionally created misrepresentations? Analyzing the root causes that lead to the publication of this kind of charts would lead to a better understanding of the phenomenon and hopefully to better solutions to the problem.

CONCLUSION

We presented in this study a first step in empirical analysis of deceptive visualizations. We started with a formal definition of deceptive visualization, outlining what deception means in the context of data visualization, what its types are, and what kind of distortion techniques are used to induce certain types of deception. We conducted a series of user studies to propose, test and establish the hypothesis that visual distortion indeed has an effect on participants' responses. Finally, we examined the effect of individual differences on participants' responses, followed by a discussion of how severe various distortion techniques are based on the quantitative analysis of the collected responses. We believe that future research will benefit from our work as it provides a foundation for further exploration of the space of deceptive visualizations.

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REFERENCES

1. Business Insider. `http://read.bi/1esYzVd/`, 2014.
2. Flickr. `https://www.flickr.com/photos/oversight/8475012926/in/photostream/`, 2014.
3. Media Matters. `http://mediamatters.org/research/2012/10/01/a-history-of-dishonest-fox-charts/190225/`, 2014.
4. Visualising Advocacy. `https://visualisingadvocacy.org/blog/`

disinformation-visualization-how-lie-datavis/, 2014.

5. Webster's Dictionary. http://www.merriam-webster.com/dictionary/deception/, 2014.
6. Adar, E., Tan, D. S., and Teevan, J. Benevolent deception in human computer interaction. In *Proceedings of CHI*, ACM (2013), 1863–1872.
7. Bateman, S., Mandryk, R. L., Gutwin, C., Genest, A., McDine, D., and Brooks, C. Useful junk?: the effects of visual embellishment on comprehension and memorability of charts. In *Proceedings of CHI*, ACM (2010), 2573–2582.
8. Bertin, J. *Semiology of graphics: diagrams, networks, maps*. esri press, 1983.
9. Borkin, M. A., Vo, A. A., Bylinskii, Z., Isola, P., Sunkavalli, S., Oliva, A., and Pfister, H. What makes a visualization memorable? *IEEE Transactions on Visualization and Computer Graphics (Proceedings of InfoVis 2013)* (2013).
10. Borland, D., and Taylor II, R. M. Rainbow color map (still) considered harmful. *IEEE computer graphics and applications 27*, 2 (2007), 14–17.
11. Boy, J., Rensink, R., Bertini, E., and Fekete, J. A principled way of assessing visualization literacy.
12. Brewer, C. A. Spectral schemes: Controversial color use on maps. *Cartography and Geographic Information Systems 24*, 4 (1997), 203–220.
13. Cleveland, W. S., and McGill, R. Graphical perception: Theory, experimentation, and application to the development of graphical methods. *Journal of the American Statistical Association 79*, 387 (1984), 531–554.
14. Emerson, J. *Visualizing information for advocacy*. Tactical Technology Collective, 2013.
15. Huff, D. *How to lie with statistics*. WW Norton & Company, 1954.
16. Hullman, J., Adar, E., and Shah, P. The impact of social information on visual judgments. In *Proceedings of CHI*, ACM (2011), 1461–1470.
17. Jones, G. E. *How to lie with charts*. LaPuerta Books and Media, 2011.
18. Kittur, A., Chi, E. H., and Suh, B. Crowdsourcing user studies with mechanical turk. In *Proceedings of CHI*, ACM (2008), 453–456.
19. Kong, N., Heer, J., and Agrawala, M. Perceptual guidelines for creating rectangular treemaps. *Visualization and Computer Graphics, IEEE Transactions on 16*, 6 (2010), 990–998.
20. Lengler, R. Identifying the competencies of'visual literacy'-a prerequisite for knowledge visualization. In *IV* (2006), 232–236.
21. Levkowitz, H., and Herman, G. T. Color scales for image data. *IEEE Computer Graphics and Applications 12*, 1 (1992), 72–80.
22. Li, J., Martens, J.-B., and Van Wijk, J. J. Judging correlation from scatterplots and parallel coordinate plots. *Information Visualization 9*, 1 (2010), 13–30.
23. Micallef, L., Dragicevic, P., and Fekete, J. Assessing the effect of visualizations on bayesian reasoning through crowdsourcing. *Visualization and Computer Graphics, IEEE Transactions on 18*, 12 (2012), 2536–2545.
24. Monmonier, M. How to lie with maps.
25. Nov, O., and Arazy, O. Personality-targeted design: theory, experimental procedure, and preliminary results. In *Proceedings of the 2013 conference on Computer supported cooperative work*, ACM (2013), 977–984.
26. Nov, O., Arazy, O., López, C., and Brusilovsky, P. Exploring personality-targeted ui design in online social participation systems. In *Proceedings of CHI*, ACM (2013), 361–370.
27. Pandey, A., Manivannan, A., Nov, O., Satterthwaite, M., and Bertini, E. The persuasive power of data visualization. *Visualization and Computer Graphics, IEEE Transactions on 20*, 12 (Dec 2014), 2211–2220.
28. Paolacci, G., Chandler, J., and Ipeirotis, P. G. Running experiments on amazon mechanical turk. *Judgment and Decision making 5*, 5 (2010), 411–419.
29. Petty, R. E., and Cacioppo, J. T. *Communication and persuasion: Central and peripheral routes to attitude change*. Springer-Verlag New York, 1986.
30. Pinker, S. A theory of graph comprehension. *Artificial intelligence and the future of testing* (1990), 73–126.
31. Rensink, R. A., and Baldridge, G. The perception of correlation in scatterplots. In *Computer Graphics Forum*, vol. 29, Wiley Online Library (2010), 1203–1210.
32. Richards, J. *Deceptive advertising: Behavioral study of a legal concept*. Routledge, 2013.
33. Rogowitz, B. E., Treinish, L. A., Bryson, S., et al. How not to lie with visualization. *Computers in Physics 10*, 3 (1996), 268–273.
34. Rubinstein, R., and Hersh, H. *The human factor: Designing computer systems for people*. Morgan Kaufmann Publishers Inc., 1987.
35. Segel, E., and Heer, J. Narrative visualization: Telling stories with data. *IEEE Transactions on Visualization and Computer Graphics 16*, 6 (2010), 1139–1148.
36. Shah, P., and Hoeffner, J. Review of graph comprehension research: Implications for instruction. *Educational Psychology Review 14*, 1 (2002), 47–69.
37. Tal, A., and Wansink, B. Blinded with science: Trivial graphs and formulas increase ad persuasiveness and belief in product efficacy. *Public Understanding of Science* (2014), 0963662514549688.
38. Tufte, E. R., and Graves-Morris, P. *The visual display of quantitative information*, vol. 2. Graphics press Cheshire, CT, 1983.