

Surfacing Visualization Mirages

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ABSTRACT

Dirty data and deceptive design practices can undermine, invert, or invalidate the purported messages of charts and graphs. These failures can arise silently: a conclusion derived from a particular visualization may look plausible unless the analyst looks closer and discovers an issue with the backing data, visual specification, or their own assumptions. We term such silent but significant failures *visualization mirages*. We describe a conceptual model of mirages and show how they can be generated at every stage of the visual analytics process. We adapt a methodology from software testing, *metamorphic testing*, as a way of automatically surfacing potential mirages at the visual encoding stage of analysis through modifications to the underlying data and chart specification. We show that metamorphic testing can reliably identify mirages across a variety of chart types with relatively little prior knowledge of the data or the domain.

Author Keywords

Information visualization; deceptive visualization; visualization testing

CCS Concepts

•Human-centered computing → Visualization; Information visualization;

INTRODUCTION

Visualizations, like all forms of communication, can mislead or misrepresent information. Visualizations often hide important details, downplay or fail to represent uncertainty, or interplay with complexities in the human perceptual system. Viewers often encounter charts produced by analytical pipelines that may not be robust to dirty data or statistical malpractice. It is straightforward to generate charts that, through deceit, accident, or carelessness, appear to show something of interest in a dataset, but do not in fact reliably communicate anything significant or replicable. We refer to the charts that superficially convey a particular message that is undermined by further scrutiny as visualization *mirages*.

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In this paper, we present a conceptual model of these visualization mirages and show how users' choices can cause errors in all stages of the visual analytics (VA) process that can lead to untrue or unwarranted conclusions from data. Using our model we observe a gap in automatic techniques for validating visualizations, specifically in the relationship between data and chart specification. We address this gap by developing a theory of *metamorphic testing for visualization* which synthesizes prior work on metamorphic testing [92] and algebraic visualization errors [54]. Through this combination we seek to alert viewers to situations where minor changes to the visualization design or backing data have large (but illusory) effects on the resulting visualization, or where potentially important or disqualifying changes have no visual impact on the resulting visualization. We develop a proof of concept system that demonstrates the validity of this approach, and call for further study in mixed-initiative visualization verification.

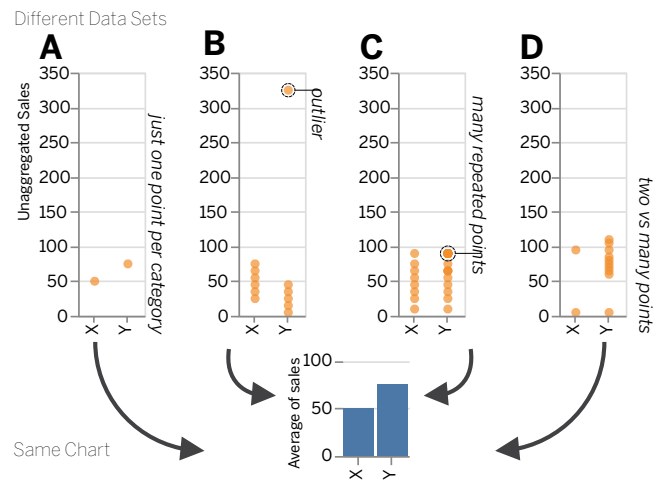


Figure 1. Visualizations that aggregate data can mask their underlying data distributions, which can create mirages, as in this bar chart over synthetic data. Not all distributions equally support the message that sales in Y are reliably higher than X. For instance, this difference could be driven by a single outlier (B), a possibly erroneously repeated value (C), or be an artifact of high variability caused by low sample size (D).

VISUALIZATION MIRAGES

We define a visualization mirage as follows:

A **visualization mirage** is any visualization where the cursory reading of the visualization would appear to support a particular message arising from the data, but where a closer re-examination of the visualization, backing data, or analytical process would invalidate or cast significant doubt on this support.

A long sequence of contexts and decisions, from the initial data curation and collection, to the eventual reader’s literacies and assumptions, determine the message that a visualization delivers. Mistakes, errors, or intentionally deceptive choices anywhere along this process can create visualization mirages, from dirty data [53] to cognitive biases [26]. Failures can occur at an early stage, but not result in a mirage until a later stage. For instance, missing data as a result of an error in data collection may be visible in a particular visualization, such as univariate data in a dot plot, and so be unlikely to lead to an error in judgment. Yet this data flaw may be invisible in a less robust visualization-design such as a histogram [22]. Whether the missing data results in a mirage is contingent on the choice of eventual visualization design.

Mirages also depend on the reader’s task. What may be misleading in the context of one task may not interfere with another. For instance, bias in estimating angle caused by a poorly selected aspect ratio [42] or improperly selected scales [16] could potentially produce a mirage for a viewer interested in correlation, but is unlikely to impact a viewer concerned with locating extrema. Figure 1 shows how mirages can arise for the task of comparing values in a bar chart: while the final bar chart is identical for all for cases A-D, some of these cases suggest statistical or data quality concerns that would cause a reader to doubt the reliability or robustness of any conclusions drawn from the direct comparison of values in the bar chart.

Not all errors in charting are mirages; for a viewer to be mistaken, the visualization must appear to credibly communicate *something*. Errors that fail to generate visualizations (such as software errors), or generate errors that are readily visible (e.g. “glitch-charts” [2]) do not function as mirages: either there is no illusory message to dispel, or the visualization has visible irregularities that cast its accuracy into immediate doubt. We also exclude charts which are intended to be consumed only as art, that Ziemkiewicz et al. [120] place outside of the traditional rhetorics of information visualization, although many artistic or ambient visualizations can and do persuade [73], and so have the potential to mislead. We instead focus on cases where the chart appears correct, but where tacit issues in the analysis and generation pipeline have produced a mismatch between the conclusions supported by the data and the message communicated by the chart.

Mirages pose an important design problem: tools in the VA process should help to augment [40] and enhance the reader’s understanding of their data in such a way that the reader either automatically avoids mirages or is alerted to them in a useful manner. Simply alerting the reader to potential issues in a given visualization may be sufficient to provoke skepticism or follow-up analysis that would dispel the mirage.

In the next section we provide a narrative exemplifying how mirages can arise in the course of an analysis session. We then provide an in-depth discussion of the ways that mirages can form and the problems they cause. We then consider prior systems for addressing these errors, and introduce the use of our *Metamorphic Testing for Visualization* technique for identifying visual encoding-based mirages. We substantiate our technique through a computational experiment.

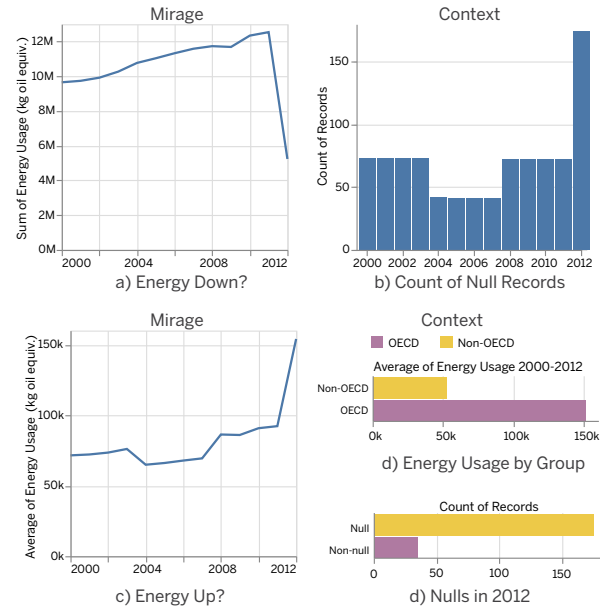


Figure 2. Do we always see what we get? Here we show energy usage by countries from the “World Indicators” dataset [36]. Even these simple charts contain subtleties that can cause a careless analyst to make errors that give way to mirages. For instance, the choice of aggregate can make the trend in global energy usage appear to be either dramatically increasing or decreasing in 2012. But neither line chart reveals the large number of missing values in 2012, or the biased nature of the values that remain.

Illustration: World Indicators

Mirages arise in the ordinary process of visual analytics, and can require significant effort or knowledge to detect and diagnose. We present a sample VA session and highlight mirages based on real situations encountered by the authors. Through this analysis we aim to answer a question: “What is the trend of global energy usage over time and what drives this trend?” We focus on the “World Indicators” dataset [36] which consists of per-country statistics from 2000-2012. We choose this dataset because of its prior use in showing the value of visualization to understand the trajectory of human development [88].

We begin our analysis by constructing a time series visualization of energy usage. Figure 2a appears to show a sharp decrease in energy usage in 2012, which may indicate a worldwide shift towards sustainability initiatives. However, this decrease is illusory, and is caused by a problem in curation: there are far fewer records for 2012 than in previous years, as shown in Figure 2b. To lessen the impact of these missing values, we change from aggregating by SUM to aggregating by MEAN. The resulting visualization, Figure 2c, now appears to show the *opposite* trend: energy usage sharply increased in 2012. However, the missing records combined with our choice of how to wrangle the data has created another mirage. The only non-null entries for 2012 are OECD (Organisation for Economic Co-operation and Development) countries. These countries have significantly higher energy usage than other countries across all years (Figure 2d).

Given these irregularities, we filter out 2012 and focus instead on the gradual upwards trend in energy usage for the remaining years. This upwards trend might indicate energy usage corresponds with a general increase in the length and quality

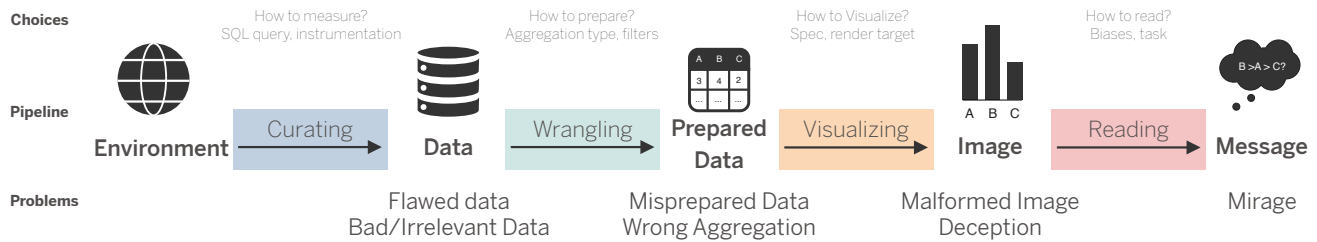


Figure 3. Each stage in the VA process offers users agency but also presents an opportunity for errors, which can give way to mirages. We see errors as occurring at the discrete stages of our pipeline (symbols), which are caused by the choices made by users (arrows). This framing allows us to identify the dependencies between actions, errors they create, and ways that those errors can propagate to deceive the reader.

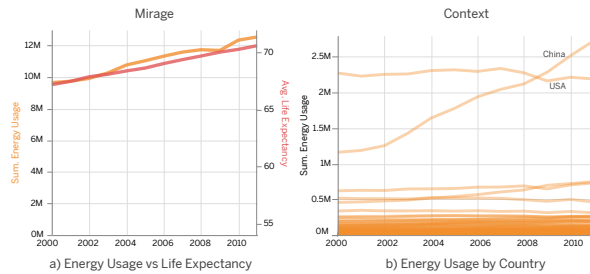


Figure 4. Energy usage compared to life expectancy in the “World Indicators” dataset [36] appear to be well correlated, but that inference is an illusion driven by two significant outliers (the US and China) and by a malicious manipulation of one of the y-axes (in particular starting the right y-axis from 55 instead of 0).

of life. Figure 4a appears to support this hypothesis: worldwide energy usage appears to be tightly correlated with life expectancy. This, too, is a mirage. The y-axis of the chart has been altered to make the rates of increase appear similar: while average life expectancy only increased 4% from 2000-2011, overall energy usage increased 30%. These y-axis manipulations can bias viewers of the chart [16, 78], as can plotting two potentially unrelated variables in the same chart [115]. We would categorize the latter mirage, arising from the Reading stage of our pipeline, as an *Assumption of Causality* (see Supplementary Materials for additional details).

Moreover, aggregating all countries together obscures considerable variability in the purported universal trend. When we disaggregate the data and remove the dual-axis, we see that much of the global growth in energy usage is attributed to China (whose usage more than doubled across the time period in question), moderated by a slight decrease in energy usage in the United States Figure 4b. These countries dominate the trend, with most of the remaining countries having relatively flat trends when plotted in the same visual space.

In the absence of automated or semi-automated tools to highlight potential concerns, it is up to the attention, skepticism, domain knowledge, and statistical sophistication of the consumer of the visualization to attempt to verify the accuracy of what they are seeing. The visualizations themselves fail to provide any indication of potential errors of interpretation, and indeed many appear to present a clear, reasonable, and final answer to the questions posed by the analyst.

WHERE DO MIRAGES COME FROM?

We show how choices can create errors and highlight the way that those errors can propagate to become mirages in Figure 3. Following Heer [41], we focus on moments of agency in the

visual analytic process (denoted in our diagram by arrows) that can introduce failures either by themselves, or in concert with other decisions, to generate visualization mirages. This perspective gives us clues to the causal relationship between choices and mirages, which is beneficial for automatically surfacing these issues to the chart creator.

Our model builds upon pipeline-based descriptions of problems in the VA process [14, 79, 102, 105]. Our work most notably expands upon Borland et al.’s [8] categorization of where threats to validity arise in VA, Sacha et al.’s [89] model of how visualization awareness and trust disseminate across the sensemaking loops of the process, and Heer’s [41] description of the points of failure across the analytics process. While we acknowledge that real-world analytics processes include many cycles and nested sub-processes [79], our simplified pipeline allows us to directly *attribute* errors to specific points, and *trace* those errors to the resulting mirage. Errors in some parts of this pipeline are more amenable to automation than others. For instance, errors in reading may require statistical education or critical reflection, whereas errors in data quality or statistical analysis could be automatically surfaced.

Data-Driven Mirages

We use the term **Curating** to denote the entire process of collecting, measuring, organizing, and combining data. Once the datasets are created, the analyst must clean, filter, subset, model, and shape the data into a form that is usable by the visualization system. We refer to this step as **Wrangling**. The efficacy of a visualization is limited by the quality and characteristics of its backing data. Even the most well-designed chart will be fundamentally flawed if the data on which it relies is irrelevant, incomplete, or biased, or has been processed or combined carelessly. The resulting “dirty data” (see Kim et al. [53] for a taxonomic overview) can lead to mirages as in Figure 5 and Figure 6. Tang et al. [98] describe the challenge of automatically detecting and understanding the ways in which dirty data can create misleading trends as one of the most important open problems in visualization.

Design-Driven Mirages

Once the data are in a proper form, the next step is to render the data in some human-legible way. We refer to this step as **Visualizing**. The last step is then for a human to read, interpret, and comprehend the resulting design. This **Reading** involves the literal decoding of the visual variables in a chart to retrieve the values of interest, as well as reasoning about the importance of the patterns identified in the data and updating prior beliefs based on new information.

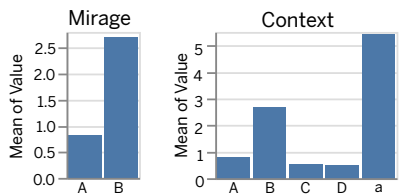


Figure 5. Data curation errors can cause mirages. The first chart uses a case-sensitive filter to directly compare ‘A’ and ‘B’, hiding that fact that many values were mistakenly entered as ‘a’ and producing the impression that sales for ‘B’ are significantly higher than ‘A’. If these ‘a’ values are merged with ‘A,’ this apparent difference would reverse.

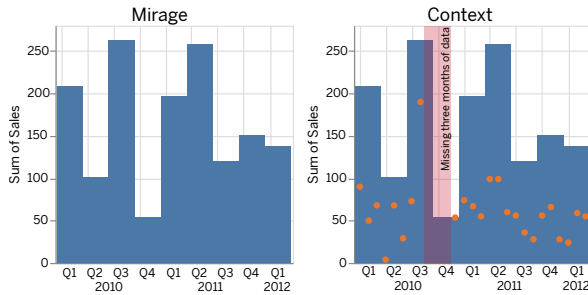


Figure 6. Wrangling and curation errors can cause mirages. In this synthetic example, the decision to aggregate hides three months of missing data, and gives the impression that sales were down in 2010Q4.

Many visualization designs are known to be deceptive or prone to misinterpretation, as in Figure 7 [10, 11, 12, 13, 21, 45, 96, 106]. Pandey et al. [78] find that commonly discussed errors such as truncated y-axes and size/area confounds impact subjectively assessed trends and differences in values. Kong et al. [57, 58] find that slanted and biased chart titles can impact how the data are later recalled. Cleveland et al. [16] find that scale alterations can bias the perception of correlation in scatterplots, and Newman & Scholl [76] find that bar charts create a bias when viewers estimate the likelihood of samples. These deceptive practices, and the biases they induce, can create mirages. In addition, prior knowledge or priming can result in viewers having different interpretations of the same data [116]. Inattention to accessibility may also create mirages. For instance, designers that are not mindful of color vision deficiencies can create visualizations that communicate markedly different messages to different audiences [80].

Mirages at the Intersection of Data and Design

The data and visualization may not have problems on their own, yet still create mirages when combined. For instance, Correll et al. [22] describe how data errors, including outliers and missing values, may fail to be detectable in univariate visualizations only for certain design parameters. Zraggen et al. [117] found that, in systems without visualizations of statistical uncertainty or control for robustness, many “insights” reported from a sample of a dataset failed to be true of the larger dataset. In Simpson’s paradox [3, 38] patterns can appear to reverse based on the level of aggregation. Lee et al. [61] describe the drill-down fallacy wherein ignoring explanatory variables during the process of filtering can result in erroneous claims of causality. There has been relatively little scholarship formalizing the problems that can occur in

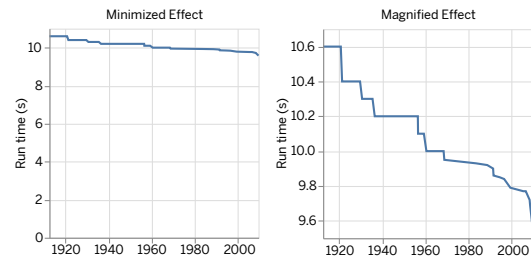
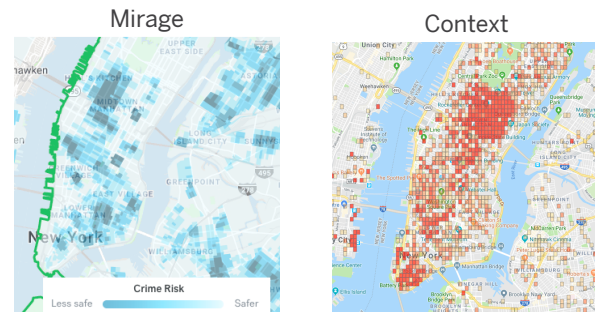


Figure 7. Visualizations can be grammatical yet deceptive. Changes to Men’s 100-meter dash world record over the last century. The left image suggests that there hasn’t been much change in that time, yet the image on the right shows a consistent pattern of improvement. The relevant effect size (is a 1 second improvement important or not?) can be exaggerated or hidden by the designer’s choice of axis.



(a) Trulia crime map [100] (b) White collar crime map [60]

Figure 8. Crime maps typically are generated by 911 calls and police reports, which capture only a subset of criminal activity. White collar and financial crimes are often excluded from these maps; their inclusion paints a different picture of locations in the city where the most crimes occur. The choice of which data to include or exclude, and biases in how these data are collected, can control the message of the chart.

the specific relationship between data and chart [43, 54, 55, 65], which entails a corresponding gap in testing strategies for automatically probing for problems.

Other Sources of Mirages

Reading errors can occur in conjunction with other parts of the pipeline, such as with Curation errors. For instance, biases and assumptions on the part of the chart creators and readers can skew the resulting messages gleaned from charts [26, 101]. Without appropriate context, readers often believe charts present an objective view-from-nowhere [39], as opposed to their inherently persuasive and subjective role. A visualization may address the right problem but be doing so using the wrong data set, or there may be a mismatch between assumptions about the data and the data itself, as in Figure 8. The people creating the dataset (or choosing what data are collected) can significantly impact the analytic process [18, 25, 77]. Even representations that present reliable data in a faithful manner are not free from potential mirages. A reader may have previously seen a chart which emphasized facets of the data, anchoring them to their earlier understanding and causing them to misunderstand the current chart. There are myriad additional ways that mirages can arise in the VA pipeline. In the Supplemental Materials we compile a list of errors that can create mirages, and describe the method by which we compiled those errors. We include a subset in Table 1.

Table 1. Examples of errors resulting in mirages along different stages of our analytics pipeline, sorted by the analytical step we believe is responsible for the resulting failure in the final visualization, and colored following Figure 3. This list is not exhaustive, but presents examples of how decision-making at various stages of analysis can damage the credibility or reliability of the messages in charts. A longer version of this table with additional mirages is included in our supplemental materials.

	Error	Mirage
Curating	Missing or Repeated Records	We often assume that we have one and only one entry for each datum. However, errors in data entry or integration can result in missing or repeated values that may result in inaccurate aggregates or groupings (see Figure 6). [53]
	Outliers	Many forms of analysis assume data have similar magnitudes and were generated by similar processes. Outliers, whether in the form of erroneous or unexpectedly extreme values, can greatly impact aggregation and discredit the assumptions behind many statistical tests and summaries. [53]
	Spelling Mistakes	Columns of strings are often interpreted as categorical data for the purposes of aggregation. If interpreted in this way, typos or inconsistent spelling and capitalization can create spurious categories, or remove important data from aggregate queries. (See Figure 5) [109]
Wrangling	Drill-down Bias	We assume that the order in which we investigate our data should not impact our conclusions. However, by filtering on less relevant variables first the impact of later variables can be hidden. This results in insights that address only small parts of the data, when they might be true of the larger whole. [61]
	Differing Number of Records by Group	Certain summary statistics, including aggregates, are sensitive to sample size. However, the number of records aggregated into a single mark can vary dramatically. This mismatch can mask this sensitivity and problematize per-mark comparisons; when combined with differing levels of aggregation, it can result in counter-intuitive results such as Simpson’s Paradox. [38]
	Cherry Picking	Filtering and subsetting are meant to be tools to remove irrelevant data, or allow the analyst to focus on a particular area of interest. If this filtering is too aggressive or if the analyst focuses on individual examples rather than the general trend, this cherry-picking can promote erroneous conclusions or biased views of the variables. Neglecting the broader data context can result in the Texas Sharpshooter Fallacy or other forms of HARKing [17]. [31]
Visualizing	Analyst Degrees of Freedom	Analysts have a tremendous flexibility in how they analyze data. These “researcher degrees of freedom” [34] can create conclusions that are highly idiosyncratic to the choices made by the analyst, or in a malicious sense promote “p-hacking” where the analyst searches through the parameter space in order to find the best support for a pre-ordained conclusion. A related issue is the “multiple comparisons problem” where the analyst makes <i>so many</i> choices that at least one configuration, just by happenstance, is likely to appear significant, even if there is no strong signal in the data. [34, 81, 117]
	Confusing Imputation	There are many strategies for dealing with missing or incomplete data, including the imputation of new values. How values are imputed, and then how these imputed values are visualized in the context of the rest of the data, can impact how the data are perceived, in the worst case creating spurious trends or group differences that are merely artifacts of how missing values are handled prior to visualization. [93]
	Non-sequitur Visualizations	Readers expect graphics that appear to be charts to be a mapping between data and image. Visualizations being used as decoration (in which the marks are not related to data) present non-information that might be mistaken for real information. Even if the data are accurate, additional unjustified annotations could produce misleading impressions, such as decorating uncorrelated data with a spurious line of best fit. [21]
	Overplotting	We typically expect to be able to clearly identify individual marks, and expect that one visual mark corresponds to a single value or aggregated value. Yet overlapping marks can hide internal structures in the distribution or disguise potential data quality issues, as in Figure 11. [22, 68, 72]
	Concealed Uncertainty	Charts that do not indicate that they contain uncertainty risk giving a false impression and may cause mistrust of the data if the reader realizes the information has not been presented clearly. Readers may incorrectly assume that data is high quality or complete, even without evidence of this veracity. [31, 69, 89, 93]
Reading	Manipulation of Scales	The axes and scales of a chart are presumed to straightforwardly represent quantitative information. However, manipulation of these scales (for instance, by flipping them from their commonly assumed directions, truncating or expanding them with respect to the range of the data [16, 19, 21, 78, 85], using non-linear transforms, or employing dual axes [55, 12]) can cause viewers to misinterpret the data in a chart, for instance by exaggerating correlation [16], exaggerating effect size [19, 78], or misinterpreting the direction of effects [78]. [12, 16, 19, 21, 55, 78, 85]
	Base Rate Bias	Readers assume unexpected values in a visualization are emblematic of reliable differences. However, readers may be unaware of relevant base rates: either the relative likelihood of what is seen as a surprising value or the false discovery rate of the entire analytic process. [20, 81, 117]
	Inaccessible Charts	Charts makers often assume that their readers are homogeneous groups. Yet, the way that people read charts is heterogeneous and dependent on perceptual abilities and cognitive backgrounds that can be overlooked by the designer. Insufficient mindfulness of these differences can result in miscommunication. For instance, a viewer with color vision deficiency may interpret two colors as identical when the designer intended them to be separate. [62, 80, 114]
	Anchoring Effect	Initial framings of information tend to guide subsequent judgements. This can cause readers to place undue rhetorical weight on early observations, which may cause them to undervalue or distrust later observations. [46, 85]
	Biases in Interpretation	Each viewer comes to a visualization with their own preconceptions, biases, and epistemic frameworks. If these biases are not carefully considered cognitive biases, such as the backfire effect or confirmation bias, can cause viewers to anchor on only the data (or the reading of the data) that supports their preconceived notions, reject data that does not accord with their views, and generally ignore a more holistic picture of the strength of the evidence. [24, 25, 31, 101, 107]

EXISTING VISUAL ANALYTICS TESTING TOOLS

Mirages are dangerous because the reader is unaware of them. Automated or semi-automated systems could alleviate this danger by surfacing potential mirages as a way of encouraging data skepticism and re-analysis of the elements underlying a particular chart. An essential focus of our work is developing methods for automatically detecting mirages that occur in the relationship between data and design. In the following section we locate this work within prior techniques for verifying the correctness of analyses at different points in the pipeline.

Data Verification

There are a variety of approaches for automatically detecting data quality issues. Many systems employ combinations of statistical algorithms, visualizations, and manual inspection to detect and correct data quality issues [51]. Most relevant to our approach, Muşlu et al. [75] employ the metaphor of continuous testing to detect potential data quality concerns, the Vizier system [9] surfaces data “caveats” that might indicate data quality concerns., and Hynes et al. [47] propose a data linter and find that many common datasets for use in training and evaluating machine learning models contain elementary data quality issues. Wang & He [109] propose an automated

error detection system for tables based on statistical analyses. Salimi et al. [90] describe a system for automatically detecting bias in analytical queries. Barowy et al. [4, 5] present systems for debugging data in spreadsheets. A mixed-initiative data wrangling metaphor is present in a variety of systems [52, 83, 95] as well as in commercial solutions [97, 99].

Visualization Verification

Visualization research has not solved the problem of visualization designs responding correctly and clearly to important changes in the underlying data, while not exaggerating trivial changes. While there has been some work from the scientific visualization community on verifying the correctness of images [56], there has been little work [35, 48] on analyzing correctness in basic charts. Rogowitz [86, 87] explore how minor alterations to color maps can result in different perceptions of patterns in visualizations. Wickham et al.’s [111] “line-up” protocol in which viewers look at a collection of charts with randomized data and one with the actual data, and are tasked with identifying the chart containing the real data. Hofmann et al. [44] use reliability at performing this task as a proxy for the statistical power of a visualization [44]. Visualizations where graphical inference is unreliable suggest that either the

statistical pattern of interest is not robust or that the visualization design employed is insensitive to such patterns. Proposed mixed-initiative solutions to issues of robustness involve supplementing visualizations with additional metrics that indicate their reliability [7, 104, 118], or performing pre-analyses to automatically detect potential concerns in a dataset [38]. Lunzer et al. [63] explore the robustness of a visualization by superimposing alternative chart configurations.

Other Techniques for Visualization Skepticism

Avoiding known deceptive practices is often instantiated through carefully selected defaults [31] in visualization authoring or through recommendation systems (such as in Tableau’s “Show Me” [66] or Moritz et al.’s Draco [74]). To our knowledge, no system exists that automatically detects or surfaces deceptive elements of a visualization design itself.

Even if visualization designs are not deceptive, our cognitive biases can still cause us to make incorrect or unjustified assumptions about the data [26]. Similar to our work, Wall et al. [107] propose a system that automatically augments a visual analytics system with warnings about cognitive biases that may be present in the current course of analysis. In a later work Wall et al. [108] describe a design space of strategies for mitigating bias in visual analytics systems.

Mirages can occur in ways that are difficult or perhaps even impossible to detect in an automatic way, relying as they do on potentially idiosyncratic misreadings or omissions in chart interpretation. To that end, automatic methods such as ours could be augmented by tools for introspection that can help identify biases and perceptual problems. Dörk et al. [28] construct a four point system for critically analyzing infographics. Lupi [64] prompts chart makers to reconsider their relationship with their data and rendered image. Wood et al. [112] ask visualization designers to engage with potential problems originating at different stages in the design process through linted design-schemas, which ask designers to answer questions from a variety of sources including D’Ignazio & Klein’s [24] *Feminist Data Visualization*, such as “How do I communicate the limits of my categories in the final representation?”

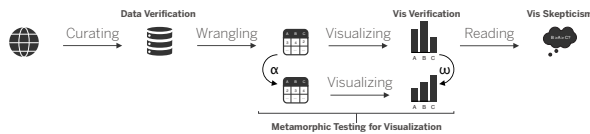


Figure 9. *Metamorphic Testing For Visualization* connects directly to our pipeline in Figure 3 by combining algebraic visualization design [54] and metamorphic testing [92]. Our tests alter either the way that the data are manipulated, or the design of the final visualization, with the expectation that (in-)significant changes to the design or data will result in corresponding (in-)significant changes to the final visualization. Failures indicate sensitive or unanticipated choices that can result in mirages.

METAMORPHIC TESTING FOR VISUALIZATION

Our review of the visual analytics testing literature suggests that there has been comparatively less consideration towards detecting errors that occur in the relationship between data and chart, as in Figure 9. Prior work principally focuses on embedding best practices through automatic chart recommendation rather than validating existing charts. To address this gap we

combine a concept from the software engineering community, *metamorphic testing*, which focuses on detecting errors in contexts that lack a truth oracle, with work from Kindlmann & Scheidegger’s Algebraic Visualization Design (AVD) [54], to form a notion of metamorphic testing for visualization.

Algebraic Visualization Design

Under the AVD framework, trivial changes to the data (such as shuffling the row order of input data) should result in trivial changes in the resulting visualization, and important changes in the visual appearance of the visualization should only occur as a result of correspondingly important changes in the backing data. These assertions are formalized in a commutativity relation, which describes the properties of an effective visualization across potential data transformations:

$$v \circ r_2 \circ \alpha = \omega \circ v \circ r_1 \quad \begin{array}{ccc} D_1 & \xrightarrow{r_1} & R_1 & \xrightarrow{v} & V_1 \\ \alpha \downarrow & & & & \downarrow \omega \\ D_2 & \xrightarrow{r_2} & R_2 & \xrightarrow{v} & V_2 \end{array} \quad (1)$$

Where D_i is the original data, r_i a change in representation, R_i a representation of data, v the visualization process, and V_i the resulting image. α is a change to the data which should commute with the corresponding change to the visualization, denoted ω . Failures of these assertions can result in “hallucinators” (visualizations that look dramatically different despite being backed by similar or identical data, such as in Figure 10) and “confusers” (visualizations that look identical despite being backed by dramatically different data). In the worst case, visualizations can be completely non-responsive to their backing data, functioning as mere number decorations and creating what Correll & Heer [21] refer to as visualization “non-sequiturs.” These AVD failures directly tie to our notion of mirages (as they can result in visualizations that are fragile, non-robust, or non-responsive), but, by providing a language of manipulations of data and visualization specification, lend themselves to mixed-initiative or automatic testing. AVD provides a useful framework for designing tests that detect failures that require little domain knowledge. We can simply induce trivial or non-trivial data change, and check for corresponding changes in the resulting visualization.

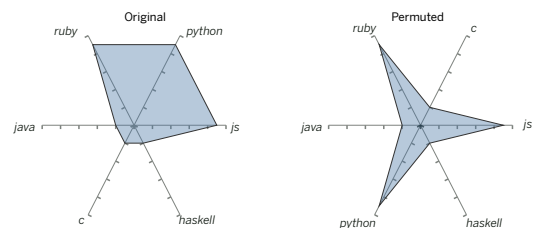


Figure 10. Radar charts are often used to compare the skills of job candidates [32]. Here we show two radars of the programming language skills for a hypothetical job candidate. One axis ordering seems to suggest that the candidate is skilled in one area, while the other suggests that their skills are varied. The change in meaning based on an arbitrary design parameter is an AVD *hallucinator* [54].

Metamorphic Testing

In complex software systems it can be difficult or prohibitively expensive to verify whether or not the software is producing

correct results. In the field of software testing distinguishing between correct and incorrect behaviour is known as the “test oracle problem” [6]. The metamorphic testing (MT) ideology attempts to address this challenge by verifying properties of system outputs across input changes [92]. Rather than checking that particular inputs give correct outputs, MT asserts that properties called *metamorphic relations* should remain invariant across all appropriate metamorphoses of a particular data set. MT has been successfully applied to a wide variety of system domains including computer graphics [27], deep learning [92], and self-driving cars [119].

We now consider an example from computer graphics for motivation. Donaldson et al. [27] make use of MT to identify bugs in graphics shader compilers. They do so by selecting a shader, making changes to the code that should not affect the rendered image (such as introducing code paths that will never be reached), and checking if the resulting images are the equal after execution. They formalize this technique by asserting that the following equation should be invariant:

$$\forall x : p(f_I(x)) = f_O(p(x)) \quad (2)$$

where x is a given shader program, p a shader compiler, f_I perturbations to the input, and f_O changes to the output (usually the identity under their framework). The definition of equality in MT plays a significant role in the effectiveness of its analysis. Donaldson et al. use χ^2 distance between image-histograms as a proxy for image equality. Using this approach they found over 60 bugs in commercial GPU systems.

Applying Metamorphic Testing

We now introduce the idea of use metamorphic testing as a mechanism to verify individual visualizations. Tang et al. [98] describe visualization as the function $vis(Data, Spec)$. This suggests two key aspects across which we can execute metamorphic manipulations: alterations to the data and alterations to the design specification. This perspective has the advantage that we can test a wide variety of types of visualization without knowing much about the chart being rendered. For instance, in Figure 11, introducing a trivial *morphism* (in this case a reduction in mark opacity) with the expectation that it should have relatively little change on the resulting graph reveals a chart error. We observe that Equation 2 is isomorphic to AVD’s commutativity relation, Equation 1. MT is a concrete way to test the invariants of systems in general, whereas AVD describes the types of invariance-failures that occur with visualizations specifically. Observing this overlap we define a **Metamorphic Test for Visualization (MTV)** as a function parameterized by an equality measure (Eq), an input perturbation (α), a visual perturbation (ω), which evaluates a tuple of data and chart specification (denoted as a pair as x), and returns a Boolean. We describe this function in pseudo-Haskell:

$$\begin{aligned} MTV :: (Eq, \alpha, \omega) \Rightarrow (spec, data) \Rightarrow Boolean \\ MTV(Eq, \alpha, \omega)x = Eq(v(\alpha(x)), \omega(v(x))) \end{aligned} \quad (3)$$

We leave v , the visualization system, out of the parameterization because we are interested in testing for problems in the relationship between data and chart specification, as opposed to validating the system mapping chart specification to data

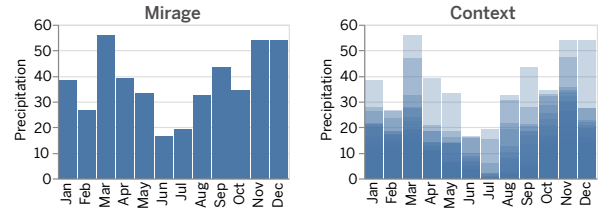


Figure 11. The lack of a set aggregation for the precipitation axis results in many bars being overplotted in the same visual space (and so causing a potential misinterpretation as only the maximum value for each category is visible). While we could test for this error by directly consulting the visual specification of the chart, not all charts (or even bar charts) are inherently invalid simply because they fail to include an aggregate. A morphism could detect this issue without this constraint. For instance, we would assume that reducing the opacity of marks in a chart would result in a visually similar chart to the full opacity version. A violation of this assumption indicates overplotting.

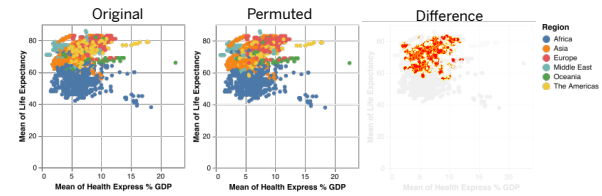


Figure 12. Shuffling the input data can reveal potential mirages. Here we consider a scatterplot drawn from the “World Indicators” dataset [36] (left), we permute the input data (center), and construct a the pixel difference (right). This reveals a property of this spec and data combination that it is not resilient to order permutation. In the language of AVD, this chart has a hallucinator. The difference here is due to overdraw: interior regions of the central cluster may or may not be visible among the dominant classes depending on the order in which the data are rendered.

space (which we assume to be error free). This formulation clearly describes the relationship between expectation and permutation in a manner that we believe allows for concise and unambiguous descriptions of invariance tests.

To our knowledge MT has not previously been used in visualization contexts, though there has been prior work that uses implicitly related techniques. Guo et al. [38] use a metamorphic-like strategy to detect instances of Simpson’s paradox in a visual analytics system. McNutt et al.’s [70] visualization linting system touches on MT-adjacent techniques as a way to identify some AVD failures. Chiw et al. [15] use MT to validate the correctness of a compiler for a scientific visualization DSL. Our approach is closely related to techniques that use bootstrapping, randomization, or other statistical procedures to reveal various properties [1, 4, 5, 67], such as Gotz et al.’s [35] “Inline Replication” analysis of the visual impact of “alternative” analyses and tests for the reliability of a given chart, or Dragicevic et al.’s [29] “Multiverse Analysis.”

Proof Of Concept

We implemented a proof of concept system for inducing morphisms on static Vega-Lite [91] specs and their backing data in order to identify potential mirages or unreliable signals in charts. Our primary goal in this system is to demonstrate the validity of our metamorphic testing concept. Our proof of concept focuses on Vega-Lite because of its advantageous API, although our techniques are applicable in principle to

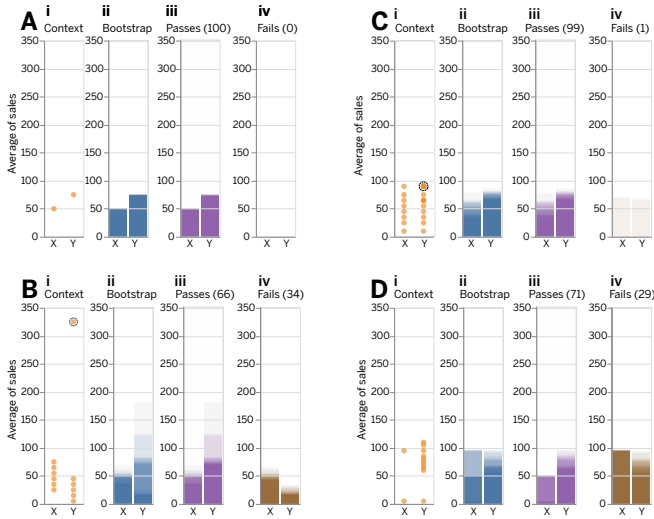


Figure 13. We apply our *MTV: Bootstrap* test to the quartet of distributions shown in Figure 1, shown here in (i). In each case we execute our test $N = 100$ times. We create 100 new potential bar charts by re-sampling from all the data that are aggregated into each bar. We show the results of this test in (ii-iv) by overlaying each low opacity “potential” bar chart on top of each other. Large “fuzzy” bands indicate that the specific values in the chart are not robust to resampling. We sort our bar charts into two categories: “passes” (iii) where the original insight that $\text{AVG } X > Y$ is preserved, and “fails” where this insight is not preserved (iv). A high number of passes indicate a robust insight.

any charting system. In the following subsections we present a set of metamorphic tests for visualization (MTVs). Each test should have predictable impacts on the resulting image. Failing to adhere to a prediction (and hence violate an MT relation) can indicate an error in the backing data or visual specification of the chart, pointing to a potential mirage. We include a visual explanation of each of the transformations involved in the following tests in the Supplemental Materials.

MTV: Shuffle

We assert that changes to the order of the input data should not change the rendered image. Our detection technique is a pixel differencing algorithm for which we select a tunable threshold in order to reduce the number of false-positives. More formally, in this test we take Eq to be a maximum number of pixels differing between the rendered images, α to be a permutation of the order of the input rows, and ω to be the identity. This test allows us to detect over plotting, as exemplified in Figure 12, as drawing overplotted groups in different orders will result in visually different charts. Not all overplotting is necessarily indicative of a mirage, but alerting the user to its presence can be useful across many chart types.

MTV: Bootstrap

We assert that the apparent patterns in visualizations should be robust: that is, a particular relationship should continue to be present across minor changes [22, 63]. In this test we focus on bar charts as it allows us a greater degree of nuance in constructing our detector. We take Eq to be the same order of heights in the bar chart, α to be a bootstrap sample [30] of all the rows within each of the bars in the chart, and ω to be the identity. Bootstrapping allows us to test for

variability in a relatively parameter-free way across a wide variety of data distributions and complexities. We identify which input rows to modify through a backward provenance algorithm [113] that links each mark to the input tuples that describe it. Because bootstrapping relies on random sampling, we adapt our metamorphic testing to statistical view, in which we execute Equation 3 a large N number of times and define a pass as a sufficiently large ϵ fraction of passing sub-tests. To our knowledge this approach of using aggregated randomized metamorphisms is novel within metamorphic testing, though it bares a close resemblance to Guderlei et al.’s [37] statistical metamorphic testing, which tests functions containing randomness as opposed to using randomness to test functions as we do. This application of the bootstrap to visualization validation also bares a close resemblance to Gotz et al.’s [35] Inline Replication technique, but focuses less on the variability of a particular measure but more on the fragility of the actual visualization itself. Through this technique we are able to identify when visualizations are liable to be dependent on outliers or small number of divergent records are driving differences between aggregates, as in Figure 13. The specific tuning of N and ϵ is task, application, and encoding dependent and warrants further investigation.

MTV: Contract Records

Figure 1 demonstrates how aggregates can usefully summarize information but they can also mask data problems, such as differing number of records, sampling issues, and repeated records. In this test we examine the robustness of measures in the context of potentially dirty data. Just as in the previous test, we focus on categorical bar charts and take ω to be the identity, and Eq to be bar height order. Our new α identifies the minimum number of records that make up a bar, and contracts the number of records constituting all other marks down to that minimum through sampling without replacement. Just as in the previous test we also deploy a randomization procedure to probe the central tendency of this measure. If all bars have similar samples sizes, and this sample size is sufficiently large, and the aggregation method sufficiently robust to extreme values, this procedure ought to result in reasonably similar charts. This test therefore allows us to detect variability caused by sampling issues and other problems relating to differing number of records. Additionally, through this morphism we are able to detect some additional AVD confusers, such as Correll et al.’s [21] non-sequitur visualizations and some sorts of overdraw, such as the one described in Figure 11, as non-responsiveness to removing substantial amounts of data indicates a chart’s insensitivity to its backing data.

MTV: Randomize

Parameterized tests may not capture subtle relationships between variables. Anand et al. [1] use randomized non-parametric permutation tests to assess the relative likelihood of different visual patterns in scatterplots. We adopt this test by randomizing the relationship between two variables. As with the prior two tests, we focus on categorical bar charts, taking ω to be the identity, and Eq to be bar height order. Our α is then a random permutation of the value and category assignments. Unlike with the previous tests, we expect that

if the signal is not particularly robust, the charts will be relatively *similar*: destroying the relationship between variables would not change the chart much. A high proportion of highly dissimilar charts indicates significant relationships between category and value. This test can reveal mirages related to sampling error and signal-to-noise ratios. The test described in Figure 11 might also be achieved through randomization.

Simulation Results

We conducted a set of simulations to see whether mirages caused by data errors could be reliably detected by our metamorphic tests. To that end, we generated a series of synthetic data sets. Similar to Zraggen et al.’s [117] test on the reliability of insights from visual analytics, each data set consisted of two subsets sampled from two Gaussian distributions, X and Y , with $n = 50$, $\mu = 50$, $\sigma = 10$. These points were visualized as a categorical bar chart of means, as in Figure 1. We would expect any difference in the height of the bars to be non-robust and unreliable; any significant differences between the two categories would be a mirage. To assess the utility of our metamorphic tests we then varied the parameters of the generating Gaussian for Y to induce more or less robust group differences.

- (i) *mean*: We vary μ for Y ’s Gaussian. We expect this to produce more “reliable” differences and that *MTV: Randomize* will excel at identifying this change.
- (ii) *sample size*: We vary n of Y ’s Gaussian. We expect *MTV: Contract Records* to excel at identifying large differences in sample size.
- (iii) *outlying values*: We add k outliers to Y , generated by sampling uniformly from $[1.5 \times IQR + Q_3, 3 \times IQR + Q_3]$. We expect *MTV: Bootstrap* to excel at this task.
- (iv) *variance*: We vary σ of Y ’s Gaussian. We expect *MTV: Bootstrap* to excel at identifying the increased variability.

We generated 30 datasets for each of the 4 alterations across 5 effect sizes, for a total of $30 \times 4 \times 5 = 600$ datasets. We then tested the resulting charts with each of the MTVs described above, excluding *MTV: Shuffle*, which did not yield any variability in the output. Our datasets, as well as a prototype tool for exploring our tests, are available at <https://osf.io/je3x9>.

Figure 14 shows the results of our simulation. Each column is a different parameter we varied when generating the data, and each row is a different MTV. Boxes around the cells indicate tests we expected to be especially relevant for detecting the relevant manipulation. The y-axis for each chart is the variance in bar height. High variance indicates that the bar values are highly unstable or unreliable.

In general, the impact of our morphisms became larger as the severity of our data manipulations increased: the fragility of the values in a given bar chart increases as the means become closer together, the sample size shrinks, outliers are added, or the variability increases. The exception is the randomize test, where we would expect less variability as the two distributions become more similar: high variability in this case is an indication that there is a true signal that is being disrupted by our morphism. As with AVD, we expect significant changes to

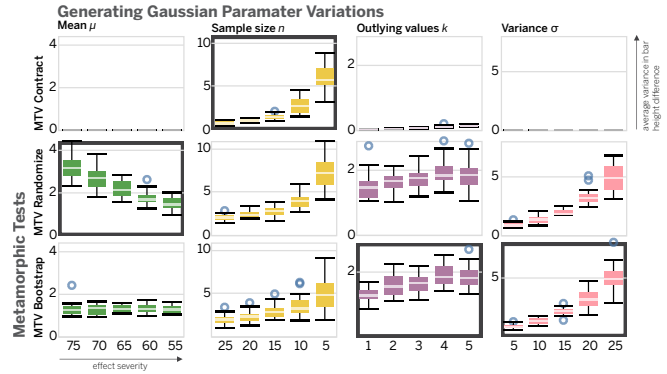


Figure 14. The results of our metamorphic tests on 600 simulated two-column bar charts (bar charts not-shown). We ran each test following our randomized MT approach with $N = 100$, and measured the variance in difference in bar height. A metamorphic visualization linter would flag charts with high variance flag for further examination. Note that in the sample size variation higher effect size means a lower number of points, this emulates under-sampled data.

our data to result in correspondingly significant changes in our charts: failures to do so should invite skepticism in the viewer.

While we recognize that our simulation does not fully capture the utility of our proposed metamorphic tests, we present these initial results as evidence that our tests can be used as measures for the robustness of signals in visualizations.

DISCUSSION

We believe that MT offers a useful complement to directly testing data or chart specifications, as it requires a smaller set of assumptions and parameters than statistical tests, and is portable across visualization toolkits. We see the types of visualization tests described here as being analogous to testing methods from software engineering. Direct tests, like unit tests, verify isolated properties (for instance, that quantitative axes begin at ‘0’ in bar charts); while metamorphic tests, like integration tests, look to see that the whole image is working as desired. We believe that, in tandem, these validation approaches offer an effective way to target a wide variety of charting errors arising in the Wrangling and Visualizing steps of visual analytics. This work is a first foray into an investigation into mixed-initiative verification of visualizations. There are a number of interesting challenges in this space including effective presentation of automated results, development of faster and more effective analysis techniques, and capturing additional domains and tasks. Even so, our testing regime can be extended to new instances of known visualization biases: there are many morphisms we can induce to test for areas of concern. For instance, many choropleth maps are not particularly informative [20]: by replacing the data with base rates, we can test for the strength of geospatial trends. As with graphical inference [44, 111], by replacing the data in a given chart with data generated under a null hypothesis, we can test for the detectability of important patterns.

UX/UI Challenges

Software analysis systems are only effective if they catch errors in a manner that improves the quality of the work being performed, which is contingent on being trusted by their users.

Our proof-of-concept system follows the interface pattern of a software linter. Linters are a type of software analysis tool that usually employ static analysis to catch semantic and stylistic programming bugs, like a spell-checker for code [50] (although some lint systems have moved into non-programming domains [4, 33, 47, 59, 70, 82, 112]). Like McNutt & Kindlmann [70], we find linters to be a useful paradigm for describing correctness in visual analytics. They are typically designed with the perspective that it is better for the user to be alerted to a non-existent bug (false-positives) than to miss a real one (false-negative), and allow the user to opt out of particular checks when they know better. Jannah [49] explores a linting metaphor for alerting users to data quality issues preceding data exploration. We believe that this type of granular and polite [110] control over analysis is a good fit for the level of detail and accuracy that our system can provide.

The optimal UI paradigm for expressing these computationally measured notions of correctness requires future research. While we believe that linters are a strong first foray into this topic, they are not without flaws. Srinivasan et al. [94] construct a system which presents statistical facts relevant to individual charts across the data exploration process. Users tend to interpret the presence or absence of these facts as endorsement or criticism. Future systems will need to carefully mitigate false-positives (so users do not ignore advice when it is valuable) and to clearly articulate false-negatives (so users know when to act on system output). As Sacha et al. [89] point out, striking the right balance is critical for maintaining user trust in the system. An important challenge is designing analytic rules that detect problems that meaningfully change the message of the visualization (mirages), and verifying that those rules work in practice. This is in contrast to rules derived from aesthetic preference, which are common in collections of guidelines, such as rules disallowing pie charts [23, 70, 71] regardless of their effectiveness for some tasks [84].

Limitations & Future Work

An appealing component of lint systems is that they are typically very fast. Our current methodology relies on bootstrapping and other statistical techniques which can cause a significant delay in the user receiving feedback (sometimes up to tens of seconds for very large data). Constructing a visualization linting system that addresses these performance challenges (perhaps in the vein of Muşlu et al.'s [75] continuous data integration system) is an intriguing systems problem. Some types of mirages do not make sense to metaphorically test. For instance, Pandey et al. [78] describe that flipped axes can lead to flipped understandings of the real message. While it is possible to design a metamorphic test to identify this type of mirage, it is simpler to query the chart specification directly, rather than induce a morphism and test for difference. Some of our tests address errors that are already well known and well studied, such as overplotting [72]. Some of our tests involve image diffing or other burdensome computations, which will likely be slower and more prone to error than an equivalent system for directly testing for overplotting.

In future work we would like to more fully develop our tool to validate a wider range of chart designs and types. We believe

it would be most useful to apply our system to ad hoc charting systems, such as Altair [103] or LitVis [112], which both consume vega-lite as charting engine. Following Donaldson et al. [27], our examples focused on tests where ω is set to be the identity for simplicity. In future work we intend to explore the class of α s that have predictable and computationally measurable ω s that are not equal to the identity. Visualization linters could be deployed as a continuous integration step that would verify that publicly displayed charts are mirage free.

The full space of visualization mirages is vast, and covers complex ground like critical reasoning, cognitive biases, and inequality. There are some mirages that may never be amenable to testing or verification, especially not in as straightforward a way as issues driven by outliers or sampling error. Even for the subset of mirages for which testing is appropriate, extending MT to other parts of our pipeline model may require new assessment techniques. For instance, Kong et al. [57] explore how differing titles affect comprehension of data, and Xiong et al. [116] explore how different primings about the data domain can bias how the data are interpreted. These sorts of morphisms can directly influence the creation of mirages but may be hard to algorithmically detect. We suggest handling this with a mixed initiative process of visualization certification, in which users answer questions about visualizations that have had various morphisms automatically applied to their data or chart specifications.

Conclusion

In this paper we introduce the idea of a *visualization mirage*: a visualization that provides an inference which, upon more detailed examination, disappears or is cast into doubt. To understand the origin of mirages we construct a conceptual model for identifying causal links between choices made in the visual analytics process and the downstream effects on reader comprehension. We improve on prior work on deceptive visualizations by describing errors that propagate across the visual analytic process and that are not encapsulated in a single aspect or part. Through this collection of ideas we describe a landscape of issues in the visual analytics process, the problems to user understandings they cause, and how they might be resolved. To address this final point, we introduce the idea of using *Metamorphic Testing* as a mechanism for automatically detecting mirages arising from the relationship between data and visual encoding. We provide evidence of the validity of this idea by constructing a prototype system that is able to discern an intriguing class of errors. We believe our model and testing approach provide ample starting ground for future work on automated detection of subtle errors in visualization, as well as validating the design of visualizations based on the relationship between their data and design.

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