Towards A Systematic Discussion of Missingness in Visual Analytics

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ABSTRACT
Data-driven decision-making has been a common task in today’s big data era, from simple choices such as finding a fast way for driving to work, to complex decisions on cancer treatment in healthcare, often supported by visual analytics. For various reasons (e.g., an ill-defined problem space, network failures or bias), visual analytics for sensemaking of data involves missingness (e.g., missing data and incomplete analysis), which can impact human decisions. For example, data, with missing records, can cost a business millions of dollars, and failing to recognize key evidence can put an innocent person into a sentence to death as a falsely convicted of murder. Being aware of missingness is critical to avoid such catastrophes.

To achieve this, as an initial step, we present a framework of catagorizing missingness in visual analytics from two perspectives: data-centric and human-centric. The former emphasizes missingness in three data-related categories: data composition, data relationship and data usage. The latter focuses on the human-perceived missingness at three levels: observed missingness, inferred missingness and ignored missingness. Based on the framework, we discuss possible roles of visualizations for handling missingness, and conclude our discussion with future research opportunities.

Index Terms: Human-centered computing—Human Computer Interaction; Human-centered computing—Visualization

1 INTRODUCTION
For various reasons (e.g., network problems, system design failures or bias), missingness often exists in a human sensemaking process. It (e.g., missing data and biased data selection [39]) impacts human decisions and can lead to severe consequences. For example, data with missing records cost millions of dollars per year in business [1]. Due to the failure to notice incomplete evidence, John Bunn was falsely convicted of murder [20], and Sunil Tripathi was wrongfully accused as a suspect in the Boston Marathon bombing on social media [26]. These tragedies lead us to question, “What are possible missingness in analytics?“ and “Can we design techniques to prevent people from falling into the traps of such missingness?”

While investigating missingness in analytics remains an elusive skill and an understudied task, much effort has been put in a narrow and focused direction: estimating missing data (e.g., imputation [12]). It aims to “fix” identified missingness by replacing it with some “best, reasonable inference” based on existing data [33]. However, such a replacement “breaks” missingness, especially when considering missingness as a type of data [33][36], so it may bring a false impression of completeness. In fact, using the imputation techniques for handling missingness implies that users must realize the existence of missingness. Thus, a successful awareness of missingness is an initial but critical step for handling missingness.

Visualization can help with missingness awareness for data analytics [3][11]. With proper visual encodings, the existence of missingness gets salient and perceptually attracts user attention. For example, given a dataset of connections between two sets of entities, showing it in a matrix with different cell colors (blue indicates the existence of a connection and white means no connection) may be easier for users to realize missing connections than listing all connections in an edge list. By marrying advanced computation with human cognition via interactive visualizations, visual analytics [18], in particular, is well suited to support handling missingness.

Nevertheless, the current understanding of missingness with visual analytics approaches seems scattered and primarily focusing on data value (e.g., missing data). However, missingness can be more complicated when analysts make sense of various data types and with different goals. In this work, we investigate missingness from a sensemaking perspective. The goal is to establish a systematic understanding of missingness and pave the road for future research using visual analytics to handle issues related to or caused by missingness.

As an initial step for better developing visual analytics techniques to address missingness, we present a framework to categorize missingness that may exist in a sensemaking process with visual analytics. This framework considers missingness from two perspectives: data and human. The former regards the information to be investigated by users and the latter highlights how users may perceive the information. Specifically, the data-centric perspective regards missingness in three data-related groups: missingness in data composition, missingness in data relation and missingness in data usage. The human-centric perspective separates missingness into three perceptual-oriented levels: observed missingness, inferred missingness and ignored missingness. The two perspectives consider the two key parties in visual analytics: computation and human cognition, which are glued together by interactive visualizations. Computation can help to identify certain data-related missingness [4] (e.g., missing relationship detection [10][41][42]). Moreover, how data is visualize can impact user awareness of missingness and their judgement on data quality [36].

This framework enables a systematic consideration of missingness in visual analytics. Relying on it, to handle missingness, the visualization design needs to reveal possible data-related missingness and aims to prevent users from simply ignoring missingness. We hope this work can draw attention to future exploration of the design space of visualizing missingness and studying insights from missingness in sensemaking.

2 A DATA-CENTRIC VIEW OF MISSINGNESS
A data-centric view categorizes missingness in three data-related groups: data composition, data relationship and data usage. In this section, we first introduce our notion of data composition and data relationship and then discuss the data-centric view of missingness.

2.1 Data Composition and Data Relationship
The composition of data can include three major components [6][8]: entity, attribute and value. An entity is a data item, which is a basic unit encoding a piece of information. An attribute is a specification that describes an entity, and an entity can have multiple attributes. A value reveals how an entity performs on an attribute. Thus, a dataset can be considered as a collection of entities, described by one or multiple attributes with specified values. For example, in an image dataset, each picture is a data entity. Attributes that describe each picture include width and height, with values such as 1080px and

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gives an example of them.

960px. These three components have also been used for database
management, specifically as a relational model \[8\], which organizes
data in tables. Each row is an entity, each column corresponds to an
attribute, and each cell includes a value.

The relationship between data entities can be described using the
concept of entity set. An entity set refers to a set of unique data enti-
ties that share the same attribute(s) (e.g., a collection of photos or a
list of locations). For two entity sets X and Y, a relationship between
them, \( R(X, Y) \), is a subset of their Cartesian product \( X \times Y \). When
\( R(X, Y) \) is not empty, we say \( X \) is related to \( Y \). Otherwise, we say
that \( X \) is independent from \( Y \). The relationship \( R \) can be determined
by using data values of selected data attributes. Moreover, for differ-
ent usage scenarios, the relationship \( R \) can be determined differently.
For example, in cyber security, \( R \) may be defined as communication
between computers and web URLs; while in bioinformatics, \( R \) may
determined based on expressed genes under conditions.

2.2 Missingness in Data Composition

Based on the data composition discussed in Section 2.1, there are
three possible types of missingness, including: 1) missing data enti-
ties, 2) missing data attributes, and 3) missing data values. Figure 1

gives an example of them.

Missing data entities highlights the absence of data entities, which
is also called as missing observations \[32\]. It often comes
from errors in the process of data collection \[2\]. For example, in
fitness tracking devices, some sensor data might not be successfully
recorded due to network connection failures.

Missing data attributes reveals the incompleteness of data at-
tributes. This may come from a careless design of the data collection
mechanism \[28\]. For example, when designing a logging system of a
cloud application, some user behaviors could be overlooked \[37\],
when creating a survey, researchers might fail to include all the rele-
vant. Due to such careless designs, even a data collection process
runs successfully, certain data attributes can still be missing.

Missing data values (often named as missing data) are the loss of
data values. Compared to the other two, it has drawn the most
attention and been heavily studied \[13, 14, 36\]. Specifically, when
considering the distribution of data values, missing data values can
be further categorized into the following three groups \[31\]:

* Missing completely at random (MCAR): missing data is as-
sumed to not have any underlying mechanism and therefore
should exhibit no relationships with either existing data or
other missing data.
* Missing at random (MAR): assumes dependencies on observed
values, but assumes no underlying relationships between the
missing values themselves.
* Missing not at random (MNAR): is the most restrictive and
requires dependencies between missing values.

Besides real absent values, missing data values also involves a
special case, named as disguised missing \[27\], in which the value is
present but not accurate. For example, a user fills out a questionnaire
and leaves a default value, such as January 1st for a birthday for
privacy reasons. In this case, the data value is not actually absent
but a selected default value that may not reflect the truth. Thus, in
the case of disguised missing, even data values are present, the true
information that data collectors need remains missing and unclear.

2.3 Missingness in Data Relationship

Missing data relationships refers to the absence of relations among
data entities. As is shown in Figure 2 from a graph perspective, it
highlights the lack of links among nodes in a graph. This means that
for a given set of data entities, some connections between data
entities are not present. An absence of relationships among data
entities may either result from errors in a data collection process or
be a reflection of algorithmic results of data relationship discovery.
For example, there is no link between two bank accounts due to the
loss of an intelligence report; or the connection between two persons
cannot be computationally identified based on word cooccurrence.

Missing data relationships can be formalized as the problem of
missing links in graphs. Similar to using the imputation techniques
for missing value inferences, based on existing links, missing links
can be computationally identified \[41, 42\]. A common goal of such
to find potentially useful missing links (e.g., serving as a bridge that connects two communities in a social network),
and further fix and verify them by adding back the lost ones \[42\].

2.4 Missingness in Data Usage

The utility of data for sensemaking activities involve two key types:
1) data selection and 2) analytical method selection. The former
refers to which parts of a given dataset will be selected for analysis.
The latter means which analytical methods will be picked and ap-
plied to the selected data. Missingness in data usage can happen in
both activities due to uncertainties and selection biases \[15\]
\[40\].

Missingness in data selection reveals that not the whole dataset is
selected for analysis. For example, to find similar cars, 4 out of
100 attributes are selected and the rest remains unused; or instead of
using all data entities, a dataset is sampled and then analyzed. When
selected attributes or samples of data entities are not representative
(e.g., stratified sampling \[38\]), missingness exists in data selections.

Missingness in analytical method selection reveals that not a full
set of analysis methods is selected. For real-world problems, it is
not easy or sometimes even impossible to identify a complete set of
analytical methods, this missingness highlights that the performed
analyses are not sufficient. For example, to explore similar cars,
just one centroid-based clustering method (i.e., k-means clustering)
is used but other clustering techniques that might reveal additional
insights are not applied.
Figure 4: Compared to listing connections between individual entities (left), it is easier for users to see missing connections when showing the same data in a matrix with different cell colors (right).

3 A HUMAN-CENTRIC VIEW OF MISSINGNESS

A human-centric view categorizes missingness at three levels: 1) observed missingness, 2) inferred missingness and 3) ignored missingness. They reveal how the data-centric missingness discussed in Section 2 is perceived by people.

3.1 Observed Missingness

Observed missingness means that users can directly perceive missingness. It indicates that the visibility of missingness is high, and users can easily notice it. For example, a user quickly realizes that a data value is missing, after she sees an empty cell in a table; or by checking and following ribbons in a parallel set [21], a user finds that there is no connection between two categorical data entities [9].

Because the visibility of missingness is affected by the way that data is represented, observed missingness relies on the visual context, in which data is encoded by certain visualizations. Different visual encodings impact how easily users can observe missingness. For example, as is shown in Figure 4, it is easier for users to see missing links by looking at a matrix than checking the same data displayed lists of node-pairs. Thus, for observed missingness, users can verify their perceived missingness by referring to the given visual context (e.g., pointing to an empty cell).

3.2 Inferred Missingness

Inferred missingness refers to that the visibility of missingness goes low or missingness even gets invisible, so it is impossible for users to directly observe missingness. However, via an investigation with given data, users can infer the possible existence of missingness. For example, by reading the following four intelligence reports that are modified based on the Sign of the Crescent dataset [16]:

“Report on 04/24/2003. Phone calls on 22 April, 2003 made from 703-659-2317 to the numbers: 804-759-6302 and 804-774-8920. A translation of this message reads: ‘I will be in my office on April 30 at 9:00AM. Try to be on time’.

Report on 01/11/2003. Abdul Ramazi is the owner of the Select Gourmet Foods shop in Springfield Mall, Springfield, VA., with a phone number 703-659-2317.

Report on 03/18/2003. A check with mobile phone providers shows that a Sprint cell phone 804-774-8920 is registered in the name Mukhtar Galab.

Report on 04/14/2003. The contact given by Faysal Goba was: 1631 Capitol Ave., Richmond VA; phone number: 804-759-6302. From an interrogation of a cooperative detainee in Guantanamo. Detainee says he trained daily with a man named Faysal Goba at an Al Qaeda explosives training facility in the Sudan in 1994.”

One may infer that the three persons, Abdul Ramazi, Mukhtar Galab and Faysal Goba may collude suspicious activities together. However, this seems missing in the given reports as it was not explicitly reported. Compared to observed missingness, inferred missingness may not be easily verified. Thus, observed missingness is more confirmative, while inferred missingness is more hypothetical.

3.3 Ignored Missingness

Ignored missingness indicates no observation nor awareness of missingness, or the presence of possible missingness is not considered. It may appear for two reasons. First, the visibility of missingness is too low to raise user awareness. For example, in Figure 4, a user may never realize that missing edges exist after looking at lists of edges. Second, due to some biases or the impact of cognitive capture (or tunneling) [35], users turn a blind eye to possible missingness. For example, to explore possible treatment for a disease, all effort has been put on the group of people who have been infected by the disease, while the uninfected group never gets any attention.

While ignored missingness cannot be completely avoided in the analysis, the ignored missingness, if identified, can bring critical values for sensemaking activities [29]. Based on this, we consider that ignored missingness is similar to the concept of white space (sometimes also named as opportunity space) discussed in the business domain [17]. The white space suggests new leads for possible growths of a business. For example, the customers of a credit card product fall into two primary age groups 25-35 and 50-70. The gap between 35 and 50 reveals a white space. It indicates that the current product seems not attractive for the age group 35-50, given the lack of users of that age group. Thus, this white space implies an opportunity to design a different credit card product with new awarding features for competing in the market of the missing age group. While a white space can bring useful values to business, it is usually difficult to discover and may easily slips one’s attention (e.g., the missing age group catches no attention at all).

In summary, observed missingness takes the least amount of user effort to perceive possible missingness; while for ignored missingness, users are not aware of the existence of missingness in the whole sensemaking process. For inferred missingness, users can realize missingness but it takes more effort.

4 HANDLING MISSINGNESS: THE ROLE OF VISUALIZATION

Based on the data-centric and human-centric perspectives of missingness mentioned before, in this section, we discuss four possible roles of visualizations for supporting missingness handling. The first and second roles highlight supporting the detection of data-centric missingness. The other two roles aim to improve user awareness of data-related missingness. In summary, visualizations can assist to uncover the data-centric missingness and improve their expressiveness, so they become more visible and accessible to users.

4.1 Bridging Existing Data and Missing Data

Visualizations play a key role of bridging the gap between existing data and missing data. If we consider existing data as a visible land and missing data as an invisible world, a usable bridge connecting them is critical to enable users to explore and walk into the invisible part from the visible one. This is because users need existing data as a landing point before digging into the data-centric missingness. However, to enable the analytical transition from the existing data to the missing part, users need the support of necessary information hints or leads, which can be provided by visualizations [7].

To establish such a bridge, a commonly used strategy is space-filling that reveals missingness as empty (e.g., an empty space in a bar chart [36], gap (e.g., broken lines in a line chart [36], or different-looking space (e.g., a matrix with different colored cells [13][41]). The focus of such visualization techniques are on the existing data. As the present data is mapped to certain visual encodings, possible missingness gets visible. By looking at the visually salient space, users can be aware of data-centric missingness. Thus, the visualized existing data serves critical visual context that enables users to identify data-related missingness.

4.2 Supporting the Analysis of Analytic Provenance

Visualizations can serve a usable solution to understand and audit analytical provenance [22][20], which is helpful to address missingness in data usage. It is challenging for users to keep tracking the process of their analyses. In a sensemaking process, some parts of data may not receive enough attention and users may miss one or
several possibly applicable methods unintentionally. To help avoid such data usage related missingness, visualizations can be used to support tracking analytical provenance and further analyze it.

To help identify missingness in data usage, two key aspects need to be considered: 1) the selected, investigated, derived and newly generated data, and 2) the method or process applied to such data. They, respectively, correspond to the provenance of data and process [24]. Visualizing them offers a way of analyzing analytic provenance. By checking such visualizations, users may notice missingness in data usage and further realize the limitation of their analyses.

4.3 Improving Awareness: from Ignoring to Observing

From a perceptual-oriented perspective, a key role of visualization is to prevent users from falling in the trap of ignoring data-centric missingness. The presence of missingness can get more visible to users via the usage of visualizations than without them, so it is more likely for users to be aware of missingness. This implies that using visualizations can improve the expressiveness of data-centric missingness. The higher such expressiveness goes, the easier it is for users to observe possible missingness. Thus, using visualizations to handle data-centric missingness attempts to move forward from ignoring missingness to being able to observe it.

Proper visual encodings can direct user attention to data-centric missingness (e.g., missing data values) [19], which may otherwise be ignored by users. The data-centric missingness is often unknown to users at the initial analysis stage, unless they are informed. Thus, a sensemaking process with data-centric missingness is exploratory in nature and the original analysis goal may not consider missingness at all. However, by referring to visualizations used in a sensemaking process, users may realize the existence of missingness, which could happen at an “aha” moment [23]. This matches both the spontaneous insight [5] of visual analytics and one of the key characteristics of visualization insight – unexpected [25].

4.4 Scaffolding Missingness Inference

Visualizations offer a usable mean to scaffold missingness inference. Different from the other two perceptual levels of missingness (i.e., observing and ignoring missingness), inferring missingness requires more user effort, as possible missingness is not directly revealed but somehow can be inferred with enough cognitive effort. This can be supported by using visualizations. In this case, instead of merely encoding missing parts of data or existing parts for the purpose of indicating the “hole” in data, visualizations may focus on displaying either the connections across different parts of data or the provenance of a sensemaking process. These help users to infer possible existence of data-centric missingness.

Since inference is a reasoning process, instead of a static stage, to scaffold missingness inference, multiple types of visualizations may be used and fusing information across them can be helpful. For example, by examining connections in a social network graph, checking related organizations, and reading relevant reports, users may infer that two suspects colluded some threats together, which has never been reported in a given dataset. Thus, visualizations can play an important role in scaffolding missingness inference, but it has more complex needs for the design of visualizations.

5 Discussion and Conclusion

While handling missingness remains a challenging problem in sense-making, as an initial exploration, we present a framework that helps to systematically view and categorize missingness in visual analytics. It highlights considering missingness from two key perspectives: data-centric and human-centric. The former regards missingness in three data-related categories: data composition, data relationship and data usage. The latter focuses on the human-perceived missingness at three levels: observed missingness, inferred missingness and ignored missingness.

Based on the framework, we discuss four possible roles of visualizations for helping to handle missingness in a sensemaking process. While this framework lays a preliminary theoretical foundation that aims to systematically consider missingness in visual analytics, to handle missingness in practice, there are three research themes that are worthy of future studies: 1) missingness detection, 2) missingness visualization and 3) missingness insight.

5.1 Detecting Missingness

Missingness detection lays the foundation for effective data analysis. Detecting missingness is not as simple as it looks like. Unless there is a clear detection goal or some evidence that reveals something is missing (e.g., data value), detecting missingness is fundamentally attempting to address an unknown unknown problem [24]. This brings a deeper question: how can we help users know which types of data-centric missingness (e.g., missing data attributes, missing data relationships, or missing data selections in the usage) exist? This is essential as it sets the detection goal. If users were not clear about this, it would be hard for them to further explore and work on detection methods. Also, a sensemaking process can have multiple types of data-centric missingness. For example, a vulnerable system with an interrupted network connection and an inaccurately designed logging mechanism can lead to missing both data values and attributes. For such cases, detecting missingness is even challenging. The framework presented in this work may help to clarify the detection goals.

5.2 Visualizing Missingness

The design of missingness-oriented visualizations remains an under-explored direction. Prior work has investigated visual encodings for missing values [13, 14, 36] and missing links [41]. However, the design space of visualizing missingness can be broader, especially considering that there are different categories of data-centric missingness and they may need different visual encodings. As studied in [36], even for the same type of missingness, different visual encodings can be designed, which further impacts user-perceived data quality. How to formalize the design space of missingness visualizations still needs further explorations. Furthermore, considering the evaluation of missingness visualization, how and if possible can we measure the expressiveness of visual encodings for data-centric missingness? It enables comparing different designs for visualizing missingness, which can be helpful to support making design decisions. The perceptual-perspective discussed in our framework may help to derive usable measures.

5.3 Discovering Insights from Missingness

Studying possible insights that users gain from missingness in sense-making is a highly sought-after research challenge. Missingness can be considered as a type of “data” [36] from which users can gain useful insights. This turns missingness from being considered as dirty [19] to usable. For example, in an intelligence analysis, a missing link between two key suspects may drive the subsequent analysis towards an investigation of any possible connections between them. While this is a simple example, it shows that missingness can be used in a sensemaking process. The insights derived from missingness may depend on an application domain and different types of data-centric missingness may bring different insights. Moreover, insights discovered from missingness, if possible, via using visual analytics, may enlarge the set of characteristics of visualization insight [25]. This may further broaden our understanding of evaluating visualizations by considering the value of missingness.

In summary, we present a framework that provides a systematic view of missingness in visual analytics. We hope this work can draw attention to future studies on visual sensemaking with missingness.
