On Metavisualization and Properties of Visualization

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Abstract: Metavisualization is the "visualization of visualizations" which is the commonly used definition. However, there is a gap in the theoretical foundations of metavisualization. This gap has led to the under-utilization of metavisualization, which is much needed today, given the proliferation of the use of visualizations in data science. Two observations have inspired this work to build the theory of metavisualization: (i) the interdisciplinary differences in the understanding of metavisualization, and (ii) the inter-relationships between metavisualization, analysis of visualizations, and visual analytics. Hence, we conduct a systematic literature review on metavisualization, identify visualization properties that can be used for generating a metavisualization, and propose a design space for these properties. This work is a theoretical discourse on metavisualization of visualization and its properties, based on the visualization-based understanding and practice of metavisualization.

1 INTRODUCTION

With the advent of machine learning (ML), deep learning (DL), and artificial intelligence (AI), visualization has increasingly become a relatively *new* data format of interest (Wu et al., 2021). Visualization is observed to be a multimodal dataset that includes visual encodings, images, text, etc. AI and ML methods are used for *analysis of visualizations* (AV). This type of analysis is not new (Savva et al., 2011), but is different from *visual analytics* (Keim et al., 2008) (VA), which is also called *visual data mining* (Nocke and Schumann, 2002). VA is a data science workflow for any dataset, but with visualization methods and a feedback loop included. Both AV and VA are of interest to the visualization research community today.

We find a high degree of similarity between the hand-crafted features in these ML models in AV and the data used in *metavisualization* (Gilbert, 2005) (MV). Metavisualization is a *visualization of visualizations* that provides cues to the users to enhance the interactivity for knowledge discovery (Weaver, 2005). The *properties* of the visualization serve as input data to MV and are also used as features in learning models in AV. They are analogous to the information of the data, *i.e., metadata* (Nocke and Schumann, 2002).

Despite its established usefulness (Weaver, 2005; Sikachev et al., 2011), metavisualization in itself is not fully studied owing to its complexity of involving both visualization design, user interactions, and performance studies. This has led to the gap in extending metavisualization to the larger context of *study of visualizations* as a data format. Integrating MV with associated topics of AV and VA is bound to improve its usage. The reason why metavisualization is to be revived and studied further is primarily to cater to the growing popularity of visual analytics. This uptake may be attributed to publicly available third-party visualization libraries especially in Python and Javascript, and VA tools, *e.g.,* Tableau®.

VA provides the third actor in our analysis owing to its interconnected relationships with both MV and AV. We look at two ways in which VA is used as an input to the other two. Firstly, VA tools widely use composite visualizations (Javed and Elmqvist, 2012),

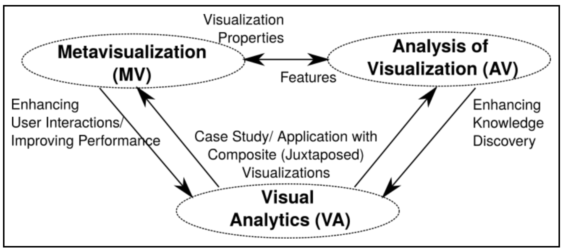

Figure 1: The interconnectedness between the three workflows (actors) pertaining to visualizations, namely, metavisualization (MV), analysis of visualizations (AV), and visual analytics (VA).

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especially the juxtaposed design. MV is used with coordinated and multiple views (Knudsen and Carpendale, 2016), which is the same as juxtaposed views. Secondly, the surge in popularity of VA tools has led to rapid growth in the volume of data visualizations, especially information visualizations. This has in turn led to its use as training and testing data for AI and ML for visualizations in AV (Wu et al., 2021). In return, MV enables improving user interactions in VA, by design, and AV improves knowledge discovery in VA. Thus, we observe the tight interconnections between the three different workflows used in the visualization research community (Figure 1).

The study of these interconnections leads to interlinking various practices in the visualization community. Amongst the three actors here, VA is the most studied and AV is an expanding topic. Hence, we focus on MV that has scope for reflection. The data used in MV is the set of properties of visualization, which needs to be explored in this specific context.

From an extensive literature review on the usage of the term "metavisualization" (Dyer, 2021; Bertini et al., 2011; Gilbert, 2005; Peck et al., 2019), we observe that there exists a gap in the understanding of the term, "metavisualization." This is attributed to two key reasons, namely, (i) differences in the conceptualization of metavisualization as used in the research communities, and (ii) the lack of a systematic study on which properties of visualization can be used in its metavisualization. In this work, we study the definition of metavisualization as the "visualization of visualizations." This definition is analogous to *metadata* being the "data about data." Here, we build the theory of metavisualization based on the properties of the visualizations that are usable in generating it.

In an in-depth study of metavisualization and properties of visualizations, our contributions are:

- We conduct an extensive systematic literature review on the usage of the term "metavisualization" across different disciplines.
- We study the visualization properties currently used as input to metavisualization, the handcrafted features in ML algorithms, the extractable properties using AI/ML, and the indirect properties stemming from the user.
- We propose a high-level design space providing three types of the visualization properties usable in its metavisualization.

2 LITERATURE REVIEW

The etymology of the word is such that the prefix *meta* refers to "transcending" (Merriam-Webster, 2022). Thus, words such as "metadata," "metaphysics," and "metapsychology" belong to the set of terms that depict a scope transcending the object or topic of interest, *i.e.,* data, physics, and psychology, respectively. We explore how the term "metavisualization" is perceived in different communities in this section. To the best of our knowledge, metavisualization is discussed widely in the research communities of STEM (Science, Technology, Engineering, and Mathematics) learning and data visualization.

In STEM Learning: Visualization is a process of determining and filtering out useful insights into data through visual representation. In that train of thought, metavisualization relates to the effectiveness of narration in learning, thus taking the learning outcomes as an aspect of metavisualization (Dyer, 2021).

Metavisualization involves metacognition as perceived in the domain of science education, where it is a quality or property of the teacher and the student (Chang, 2022). Since the focus of this definition is the relationship between the human-in-the-loop and the visualization, there are four key aspects governing metavisualization (Chang, 2022). Metavisualization of the user means his/her: (i) epistemic knowledge of visualization, *i.e.,* the knowledge of its scope, purposes, and limitations, (ii) demonstration of metacognitive capability in visualization, where "metacognition" means "thinking of thinking" (Flavell, 1979), (iii) capability to critique visualizations using judgment criteria, and (iv) application of metavisual strategies such as resourcing, focusing, inducting, deducing, perfecting, intuitive modeling, and recall. The use of visualization in education also has been further studied through the lens of accessibility for different subpopulations with respect to several components of education (Peck et al., 2019), including metavisualization.

Metavisualization gained significant attention through Gilbert's works which defined it as an important constituent of visualization competence, thus upgrading metavisualization as an essential quality of the teacher or the student (Gilbert, 2005; Gilbert, 2008). In all such studies, visualization plays an indispensable role in STEM learning and education. For instance, the role of visualization in learning chemistry has been studied (Locatelli et al., 2010), which serves as a case study in STEM education. Provenance-enabled visualization systems are useful for improving the learning experience of the users (Davidson and Freire, 2008).

In Data Visualization: In the visualization community, metavisualization is seen as a "visualization of visualizations," which is a sufficiently general term used for the structure and operation of nested visualization (Weaver, 2005). This perspective has led to work in metavisualization predominantly around structure, *e.g.,* layout of views (Bertini et al., 2011) in a juxtaposed composite visualization (Javed and Elmqvist, 2012). In the evaluation of high-dimensional data visualization, metavisualization strategies refer to the *list* and *matrix* layouts of views, where the scatter plot matrix is an example of the latter. Metavisualization is then referred to as the analysis and display of the inter-relationships between the different views (or simpler visualizations) in the layout, including their perceptual similarities (Peltonen and Lin, 2013). The layout can be further optimized by rearranging the plots in a scatter plot matrix and other layouts by using a machine learning approach (Peltonen and Lin, 2013).

Going further beyond view layouts, metavisualization has been referred to as the visualization of view relations in coordinated and multiple views (CMVs) (Knudsen and Carpendale, 2016). These view relations are categorized into thirteen concepts, namely, (i) tasks, (ii) interactions, (iii) brushing and linking, (iv) axis relations, (v) legend relations, (vi) visual components, (vii) grouping views, (viii) overlay/show more information, (ix) direction, flow, and order, (x) line arrows, (xi) strength of relations, (xii) clutter and scalability, and (xiii) interference with views. The findings of these concepts are grouped as tasks, representations, interactions, and challenges.

The integration of multiple views requires a system implementation that uses several embeddings to characterize the dynamic nature of the linkages (Weaver, 2005). The view relations can also be part of a system that facilitates multiple users to interact simultaneously and collaborate, and such a system has been referred to as meta-visualization (Tobiasz et al., 2009).

In the context of CMVs, different from view layouts, metavisualization has been referred to as visualization of elements of data that can be categorized as metadata (Roberts, 2007). Similarly, the interactive exploration of the algorithm used in the visualization has also been referred to as metavisualization (Sikachev et al., 2011). The history of data and workflows are part of a larger set of terms referred to as *visualization provenance* (Callahan et al., 2006; Ragan et al., 2015). Metadata is well-studied including its classification (Nocke and Schumann, 2002). The visualizations of the metadata itself provide inputs related to the filtering of data, which is done by the user. Also, the metadata is considered a property of the visualization. Thus, by design, visualization of metadata is indeed a metavisualization.

Finally, different from being a visualization itself, metavisualization has also been used as a framework for interacting with the elements in the visualization parameter space (Sikachev et al., 2011). These elements are mapping of data to parameters used in visualization algorithms, such as isosurface value in isosurface extraction.

Procedure for Systematic Literature Review (SLR): We performed a systematic literature review, adopting the method used in health sciences (Lame, 2019). We followed these steps:

1. Review question: We framed our review question on the definition of metavisualization. This review is necessary to find a widely accepted definition(s) needed for identifying usable visualization properties.
2. Inclusion-Exclusion Criteria: We included all publications using the word "metavisualization," "meta-visualization," and "meta visualization." We did not use any specific explicit exclusion criteria.
3. Locating Studies: We used Google Scholar and its optimized search engine to identify the papers of interest. The choice of database is important to expand the search to the largest extent.
4. Study Selection: We selected all studies which were not specifically case studies. This is because a generalized understanding of metavisualization is needed here.
5. Data Extraction: The author has exclusively collected the selection of papers over a period of three years along with the research on chart analysis. Given the relatively smaller set of appropriate papers, a single reviewer was sufficient. The author reviewed 8 papers in the visualization domain and 10 papers in the education domain.
6. Result Presentation: The results have been presented in this paper in the form of reporting and inter-domain comparisons.

Hereafter, we retain the focus on the definition of metavisualization as perceived in the visualization community, without delving deeper into the perspective of the education community.

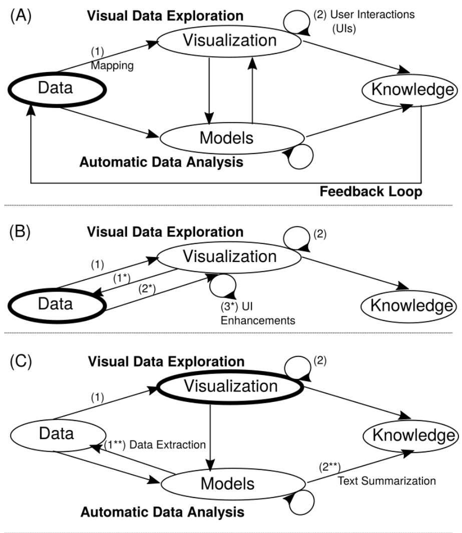

Figure 2: Comparing the workflows in (A) visual analytics (VA) (Keim et al., 2008), (B) metavisualization (MV), and (C) analysis of visualizations (AV) using machine learning models. (1) and (2) are present in all. (1*) and (2*) correspond to data extraction and mapping exclusively for MV, respectively. The bold ellipse indicates the input to the workflow, and in (C), the input is a static visualization, and (2) is applicable only for redesigned visualizations.

3 VISUALIZATION PROPERTIES FOR METAVISUALIZATION

With the advent of modern methods of image processing using learning models, *i.e.,* ML and DL, we observe that some of the properties of the visualization can be extracted using automated systems. At the same time, a few properties are already being used in feature engineering in ML (Wu et al., 2021). We compare the handcrafted features in ML methods and the attributes used for metavisualization. Further, we discuss the key image processing methods for extracting these features. We then separate the visualization-based and user-centric properties of MV, where the latter has not been used in MV to the best of our knowledge. We refer to them as *direct* and *indirect* visualization properties, respectively. Finally, we propose a high-level design space of visualization properties usable in MV, and the implications of such a design space.

3.1 ML Model Features and Visualization Properties in MV

To establish the inter-relationships between input data to MV and features extracted in AV, we first compare MV and AV, respectively. We start with the familiar VA workflow (Keim et al., 2008), based on the interconnectedness of the trio (Figure 1). In Figure 2, (A) is the simplified state diagram that shows the VA workflow with the feedback loop and presence of data science workflow. We mark the recurring features in the trio, namely, (1) mappings and (2) user interactions (UIs). In (B), we see that the source visualization is used to retrieve data in (1*), and then the target visualization, *i.e.,* metavisualization is generated in (2*). We separate the UIs in metavisualization as (3*) from th UIs of the original visualization. In (C), the static visualization is the input to the workflow, and it can be redesigned to an interactive one using the extracted data using the learning models (1**). These learning models are required to extract information from the image and text data of the visualization (Dadhich et al., 2021a; Dadhich et al., 2021b). The extracted data and concerned learning models for natural language generation (NLG) are further used for *text summarization* (Al-Zaidy and Giles, 2017). Thus, a comparative study of these workflow diagrams conveys the similarities and differences in these three known processes, and explains their tight interconnectedness, as seen in Figure 1.

Narrowing down our focus to Figure 2 (B) and (C), we now look at the similarities between visualization properties (Weaver, 2005) and engineered features (Wu et al., 2021). The data used in a metavisualization tool, Improvise (Weaver, 2005) includes relationships between windows (views), interactions, and visualizations. Thus, these relationships are used as visualization properties. Additionally, the layout of the visualizations and their elements, in the form of a list or matrix (Bertini et al., 2011), is a visualization property. We also find the mappings from data to visualization parameter space (Sikachev et al., 2011) can be considered as properties. The data and its metadata itself are also inputs (Nocke and Schumann, 2002). Given the disparate use-cases of metavisualization, there is no systematic study on the specific visualization properties that are used as its inputs.

At the same time, we observe that these properties recur in feature engineering in ML models. These features are classified as graphics, program, text, and underlying data (Wu et al., 2021). Amongst these, graphics features include image descriptors, element positions or localized regions, and element styles. The program features include parameters, communicative signals, and design rules. The text includes largely statistical model features, and data includes both statistics and the one-hot vectors.

Narrowing down our scope to VA tools, the similarities between these features and properties include the structure of visualizations and interactions/communicative signals. The features that have the potential to be considered as inputs to MV in the future are image descriptors and statistical models in text. This is because the image and text properties of the visualization can enhance user interactions.

3.2 Visualization Properties Extracted from Images

With the advent of ML/DL practices and methods (Alom et al., 2018), *e.g.,* ImageNet benchmark database (Deng et al., 2009) and AlexNet (Krizhevsky et al., 2017), tasks such as classification and segmentation using artificial perception are automated (Beyer et al., 2020). Applying modern image processing to the images of visualizations may appear as a conflict with metavisualization, as “processing of visualization” is different from “visualization of visualizations.” We argue that image processing can be seen as an alternative to manually curating information about the visualization, thus automating processes in generating metavisualization. At the same time, this opens up questions on which outcomes of image analysis are conventionally used in MV.

Here, we are interested only in those automated tasks that provide such properties of the visualization. Examples of such properties include its chart/visualization type and the dataset used, including its metadata. We also find that textual summarization (Demir et al., 2008) is yet another task that is descriptive in nature pertaining to the important aspects of the data, and textual content is generated using these findings from the chart visualization. Last but not the least, the provenance of the visualization is one of its key properties (Callahan et al., 2006).

There is also active research on the analysis of visualizations that automate activities involving both human perception and cognition systems, *e.g.,* answering a question on the data using the visualization as an aid to understanding the data. In our visualization-based MV, we refer to such information gleaned from a visualization as *indirect properties*, and they are further explained in Section 3.3.

Chart Classification: Chart classification is considered an important step in automated chart interpretation (Savva et al., 2011; Battle et al., 2018; Choi et al., 2019; Dadhich et al., 2021a; Dadhich et al., 2021b). This is because the consequent analysis of data extraction and chart redesign are chart type-dependent. For type classification, low-level features are computed on the images of charts and run on a supervised learning model (Savva et al., 2011; Battle et al., 2018). Recently, convolutional neural networks are directly used for the classification of such images, *e.g.,* using the ResNet (Choi et al., 2019) and VGG-16 (Dadhich et al., 2021a; Dadhich et al., 2021b) architectures.

Data Extraction: Automated extraction of data from images of charts has been a challenging problem of interest in the last two decades. With a mix of ML/DL models and geometry-based image processing, there have been several works that extract data from simpler charts, *e.g.,* scatter plots (Cliche et al., 2017; Dadhich et al., 2021b; Daggubati and Sreevalsan-Nair, 2022), bar charts (Al-Zaidy and Giles, 2015; Dadhich et al., 2021a; Daggubati et al., 2022), and a mix of charts (Choi et al., 2019; Sreevalsan-Nair et al., 2021). Such systems include object detection, text detection and recognition using Optical Character Recognition (OCR) and appropriate Natural Language Processor (NLP) CNNs, and pixel-to-data conversion in their workflows (Al-Zaidy and Giles, 2015; Choi et al., 2019; Dadhich et al., 2021a; Dadhich et al., 2021b).

The problem statement of data extraction from visualizations has spurned an important area of research in making visualizations accessible to the visually impaired (Choi et al., 2019; Dadhich et al., 2021a). Given there are several images available on the web, automated extraction and interpretation of those visualizations enable improving the usage of the content.

Textual Summarization: There are several existing works that focus on generating textual summaries of the charts. Such summaries have been widely implemented for bar charts (Demir et al., 2008; Al-Zaidy et al., 2016; Dadhich et al., 2021a; Daggubati et al., 2022). These summaries are generated using a *protoform* (Al-Zaidy et al., 2016), *i.e.,* a template. One such system identifies the sign of the trends in the data represented by the bar chart (Demir et al., 2008). Apart from data of *salient* bars, information is extracted using a semantic graph that connects the structural features of the graph, namely, the axis labels, the legend information, etc. Further, design study methodology (Sedlmair et al., 2012) has been used to improve the content used in textual summaries (Daggubati et al., 2022). Natural Language Generator (NLG) neural networks are instrumental here.

Provenance of a Visualization: Vistrails is one of the earliest frameworks to allow the user to explore the provenance of a visualization (Callahan et al., 2006). It is an important milestone as it reinforced the importance of the data and algorithm used in a visualization. Also, while several discussions so far in our work have examples of information visualization, Vistrails is a framework that was primarily designed for scientific visualization. Thus, discussing Vistrails here makes our work inclusive of both scientific and information visualization.

In an organizational framework for different perspectives surrounding provenance, two such categorizations have been proposed, namely, types of provenance information and the purposes of provenance (Ragan et al., 2015). In our work, we are interested in the former which includes five types, namely, of (i) data, (ii) visualization, (iii) interaction, (iv) insight, and (v) rationale. Even with these types, our study of visualization-based metavisualization will be limited to the provenance types of data and visualization alone, as the remaining types interface with the users. Data provenance itself is given significant attention in the visualization community, as seen in several works (Xu et al., 2020). Data provenance includes both prospective and retrospective types (Davidson and Freire, 2008), as well as process provenance (Ragan et al., 2015). Provenance analytics and visualization are useful to improve the concerned visualization itself (Davidson and Freire, 2008), thus cementing the place of data and visualization provenance as input data in MV.

3.3 Indirect Visualization Properties

There are properties of visualization that are not conventionally used as data in MV. They stem indirectly from visualization, and hence, have not been used in MV until now. We discuss them here to indicate their potential usability in the future.

We categorize such properties into the *cognitive insights to the visualization* and the *metavisual skills of the user*. The former involves processes culminating in human cognition and the latter involves the user himself/herself. Thus, these properties are heavily dependent on the interpretation and usage of visualization by the human-in-the-loop. Overall, how they can be represented as a tangible input to MV requires an in-depth study. As discussed in Section 3.2, there is new interest in cognitive outcomes owing to the recent trend of them being automated using ML/DL methods, *e.g.,* reasoning over charts, which may promote the future use-cases.

Cognitive Insights to Visualization: The evaluation of visualization is conventionally done using user studies to accommodate the human-in-the-loop and the generative nature of the visualization process (Ellis and Dix, 2006). User study-based evaluation is an important aspect of the design study methodology in its *implement* and *deploy* stages in the *Core Phase*, as given in the nine-stage framework (Sedlmair et al., 2012). Thus, the evaluation provides more insight into the visualization and its purpose for a specific user in a specific context. The evaluation involves the analysis *of* the visualization based on the capability of the user, and hence, it directly does not provide information *about* the visualization. This may explain why the evaluation of visualization has not been considered in MV as yet.

Reasoning over charts is another activity that provides insight into visualization using human cognition. This activity is the outcome of a *question-answering (QA) system* based on charts. Such a system is designed to automatically answer the question posed to it concerning a plot. QA systems are characterized by the answer types. The answers can be binary (Kahou et al., 2017), from a fixed vocabulary (Kafle et al., 2018), or from open vocabulary (Methani et al., 2020). The core of such systems is a neural network model.

The process involved in the tasks of data extraction and reasoning over charts follow similar workflows, and these tasks have been implemented for simpler and more popular charts, namely, bar, line, and scatter plots. However, the outcome of the former can be seen as a direct visualization property, but not the latter. This may be attributed to the characteristic of the latter being user-centric and not visualization-based, as it mimics and automates the responses from the user. QA systems do not have to extract the data in its entirety, as the models are trained to extract relevant data to answer the questions alone. This is done in practice to reduce the cost of training a model for the entire dataset.

Metavisual Skills of the User: As discussed in Section 2, in the context of science education, MV is described as a *metacognitive* quality of the user of the visualization to "acquire, monitor, integrate, and extend" from a visual representation of a scientific concept for learning purposes (Gilbert, 2005). STEM education routinely suffers from *representation dilemma* as content learning requires that students need the competency to understand visual representations (Rau, 2017). For instance, in the chemistry laboratory, the students are expected to holistically understand and navigate through the transformations between macroscopic, sub-microscopic, and symbolic visual representations in the experiment design and implementation, *i.e.,* representations of equipments/chemicals, molecular models, and chemical equations, respectively (Chittleborough and Treagust, 2008). Thus, in the parlance of science education, MV represents the perspective of *representational competency* of the learner, *i.e.,* the competency of the user in effectively using text and multiple visual representations (Rau, 2017). Such a conceptualization of MV is essential in pedagogy.

Similarly, the data and visualization provenance types have been used in MV (Section 3.2), but there are certain provenance types that have not been. These include the provenance of interface with respect to the user, *i.e.,* of interactions, insight, and rationale (Ragan et al., 2015).

In the domain of computer science, analogous to the usage of the term *metadata*, the focus on metavisualization has been on the visualization structure and user interactions, as opposed to the quality of the user. The user-centric definition is a paradigm shift from the focus on the visualization or its image representation. We currently do not have a framework to study them both together or a user-centric study exclusively, which may be considered for future study.

3.4 Design Space of Visualization Properties in MV

Inspired by the types of metadata (Nocke and Schumann, 2002; Riley, 2017), we propose types of visualization properties used in MV. The reason to establish this novel classification is two-fold. Firstly, it provides a design space, which is different from taxonomy, for identifying data required for generating MV. Thus, it provides a set of visualization properties rendered in MV. Secondly, as any design space (Javed and Elmqvist, 2012), it opens up potential directions for research in the future.

The four classes of metadata are namely descriptive, structural, administrative, and markup languages (Riley, 2017). Descriptive metadata is information on the source of the data or a resource. The structural metadata describes the inter-relationships of parts of resources. The administrative metadata has three subtypes, namely, technical, preservation, and rights. These pertain to the legal and management aspects of the data. Finally, markup languages are which integrate metadata with specific parts of the data itself.

For visualization properties rendered in MV, we propose three types, namely, "descriptive," "structural," and "provenantial." We list specific properties as examples of each type, and suggest their corresponding representative visualizations. These visualizations can then be added to MV.

Descriptive Metavisualization: Similar to that of metadata, this type pertains to the type of visualization, its creator, title, source, file format, and textual summary. These can be provided as annotations to an existing MV, as has been done for other forms of content (Knudsen and Carpendale, 2016). The type could also be visualized in the form of an icon or glyph. The textual summary can be visualized using a tag or word cloud. We propose the addition of image and text descriptors in the descriptive category.

Structural Metavisualization: This type pertains to the relations between the views and their layout in the visualization (Knudsen and Carpendale, 2016) and the mapping of data to its marks and channels (Munzner, 2014). View relations can be annotated, thus adding to MV (Knudsen and Carpendale, 2016). The mapping between the set of visual variables, *i.e.,* marks and channels, and that of the data variables can be visualized using a node-link diagram of the bipartite graph to study redundant encoding, as an example.

Provenantial Metavisualization: This type pertains to the provenance of the visualization. The provenance of the visualization itself depends on the data and the algorithm used to generate it (Weaver, 2005; Callahan et al., 2006; Roberts, 2007; Sikachev et al., 2011). The different examples of provenance studies have also shown the visualizations used as MV. These visualizations show the transformations to data and states of the algorithm being executed.

3.5 Discussion

In summary, we define metavisualization as follows:

Definition 1 (Metavisualization)**.** *The visualization of properties of a source visualization that are attributed to its description, structure, and provenance is defined as metavisualization of the source.*

The design space of visualization properties in MV (Section 3.4) now also provides the much-needed *scaffold* to include any property that fits the type description. We also observe that this also opens up the possibilities of different visualizations as MV.

We also use this work to provide interdisciplinary perspectives in two ways. Firstly, we connect the areas of computer vision and image processing with visualization where the results from the chart image analysis can be used in metavisualization. This specific relationship can be studied further in future work. Secondly, we compare and discern the differences in perspectives of the word "metavisualization." While this is not an exhaustive study in its current form, our work seeds a systematic investigation of metavisualization in these directions in the future.

4 CONCLUSIONS

In this work, we have theoretically determined the types of visualization properties that can be visualized, thus providing metavisualization. We perform a systematic study of existing literature to identify the different understandings of the term "metavisualization." We have further identified appropriate properties to be used, and also created a design space for them. This has been possible by bringing in interrelationships between metavisualization, the burgeoning area of AI/ML methods of analysis of visualization, and the widely used visual analytics.

Given the limited literature on metavisualization despite its value as a visualization practice, there is a need to formalize its implementation to improve its usage. Hence, as a first step, we identify visualization properties based on more recent and relevant practices, namely, AI/ML analysis of visualization and visual analytics. These properties are currently or have the potential to be input data to metavisualization.

Also, there is a bias towards information visualization systems and workflows in the literature on metavisualization. At the same time, scientific visualization has been studied at length in terms of provenance. Hence, building more metavisualization has the scope to expand the current state-of-the-art using elements from both scientific and information visualization practices. Such an expansion may prove beneficial in reviving the use of metavisualization.

As a concluding remark, the use of metavisualization is essential for enhancing usability and interactivity of increasingly complex visualization workflows; and this paper connects the theoretical aspects of metavisualization to the current practices.

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