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Modeling layout design for multiple-view visualization via Bayesian inference

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Abstract Layout design for multiple-view visualization (MV) concerns primarily how to arrange views in layouts that are geometrically and topologically plausible. Guidelines for MV layout design suggest considerations on various design factors, including *view* (e.g., bar and line charts), *viewport* (e.g., mobile vs. desktop), and *coordination* (e.g., exploration vs. comparison), along with expertise and preference of the *designer*. Recent studies have revealed the diverse space of MV layout design via statistical analysis on empirical MVs, yet neglect the effects of those design factors. To address the gap, this work proposes to model the effects of design factors on MV layouts via Bayesian probabilistic inference. Specifically, we access three important properties of MV layout, i.e., maximum area ratio and weighted average aspect ratio as geometric metrics, and layout topology as a topological metric. We update the posterior probability of layout metrics given design factors by penetrating MVs from recent visualization publications. The analyses reveal many insightful MV layout design patterns, such as views in coordination type of comparison exhibit more balanced area ratio, while those for exploration are more scattered. This work makes a prominent starting point for a thorough understanding of MV layout design patterns. On the basis, we discuss how practitioners can use Bayesian inference approach for future research on finer-annotated visualization datasets and more comprehensive design factors and properties.

Keywords Multiple-view visualization · Layout design · Bayesian inference

1 Introduction

Multiple-view visualization (MV) is a specific technique that composites multiple views in a cohesive manner, to enable simultaneous data exploration from different perspectives (Roberts 2007). As data are becoming increasingly large, complex, and heterogeneous, MVs have been extensively used for exploratory data analysis and visual analytics. However, despite the ubiquity of MVs, it remains a challenging task to arrange multiple views in a geometrically and topologically plausible layout. Developers usually need to

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explore different possible layouts through trail and error. Experience and expertise are required to create visualizations that can effectively facilitate data analysis (Qin et al. 2020).

Many authoring tools have been developed to facilitate MV design, such as Tableau[1] and Power BI.[2] The tools provide a set of commonly used templates as prototypes for MV layouts, like sales dashboard templates in Tableau. These predefined templates however only cover a small portion of the diverse design space of MV layouts. Some recent studies aim to reveal the design space of MV layouts, using statistical analyses (e.g., Chen et al. 2021c; Al-maneea and Roberts 2019) or interactive dashboard (e.g., Zeng et al. 2021a; Chen et al. 2021a) on empirical MV layouts curated from visualization publications. Chen et al. (2021c) revealed some interesting design patterns regarding view composition. For example, it is found that designers tend to position *diagram* in the center of MVs, and they prefer to adopt simple and perceptually accurate view types.

Besides view type, a number of works examine the impacts of other design factors on MV layout design, such as *viewport* (e.g., Sadana and Stasko 2016; Brehmer et al. 2019; Kister et al. 2017; Langner et al. 2019, 2018; Horak et al. 2019), *coordination* type (e.g., North and Shneiderman 1997; Roberts 2007; L'Yi et al. 2021; Chen et al. 2021b), and expertise and preference of *designer* (e.g., Pretorius and van Wijk 2009; Grammel et al. 2010). Nevertheless, these studies typically consider MV design from a single perspective, while effective MVs require a comprehensive consideration of all these perspectives. As a result, there is a lack of concrete design guidelines specifying geometric (e.g., view size and position) and topological properties of MV layouts. Those existing guidelines (e.g., Wang Baldonado et al. 2000; Qu and Hullman 2018) have little to no relevance to the geometric and topological properties.

This work aims to fill the gap, by modeling the effects of various design factors, including *view*, *coordination*, and *designer*, on MV layout design via Bayes' rule. We focus on three important quantitative metrics for MV layouts, i.e., maximum area ratio (MAR) and weighted average aspect ratio (WAAR) as geometric metrics, and topology types as a typological metric (Sect. 3.2). To achieve the goal, we first complement a public MV dataset (Chen et al. 2021c) with fine annotations of designer and coordination information (Sect. 5). Viewport is omitted in the annotation and consequently the analysis, since MVs in the dataset are mostly designed for the desktop. We conduct an independence analysis using the Chi-squared independence test and confirm that the design factors are independent to each other (Sect. 6.2). Next, we construct Bayesian probabilistic inference by updating the posterior probability of layout metrics upon the design factors by penetrating MVs in the dataset and utilize Chi-squared significant difference test to further check whether the effects are significant (Sects. 6.3–6.5). Through the quantitative analyses, we reveal some insightful MV layout design patterns. For example, *coordination* factor has the greatest influence on MV layouts, wherein views of *comparison* coordination type exhibit more balanced area ratios, while those of *exploration* have more scattered area ratios.

The main contributions of this work are summarized below:

- We complement a public MV dataset with information of designer and coordination type. The dataset is available on https://lingdan33.github.io/bayesmvlayout for further research on MV layout design.
- We construct Bayesian inference models that describe the effects of various design factors on MV layout design based on empirical MVs in the dataset.
- We reveal some common MV layout design patterns, which can potentially lead to concrete MV design guidelines.

2 Related work

2.1 Multiple-view visualization (MV)

MV is a specific visual data exploration technique that presents two or more views to show different perspective of data (Wang Baldonado et al. 2000; Roberts 2007). To design MVs, one needs to consider how many *views* to be used, what kinds of *coordination* between views, and how to layout and position views in a constrained *viewport*. The process requires substantial expertise and experience of *designers* to manage MVs in plausible layouts (Pretorius and van Wijk 2009; Grammel et al. 2010; Heer et al. 2008).

[1] https://www.tableau.com/.

[2] https://powerbi.microsoft.com.

- *View* A view is formed after data transformation, visual mapping, and view transformation (Card et al. 1999). To cope with various input data and analytical tasks, many views types have been designed, e.g., bar chart, line chart, etc. Views of different types can have distinct geometric properties, including aspect ratio and view size, as unveiled by a recent study (Chen et al. 2021c). When composing multiple views into one MV, there can be potential conflicts between preferable aspect ratio and size for individual view, and the overall geometric plausibility of an entire MV layout. Hence, this work examines the effects of *view* factor on MV layouts.
- *Coordination* Views in MVs are mostly coordinated, i.e., a view updates its content in response to users' interactions in other views (North and Shneiderman 1997; Scherr 2008). The visualization community has identified various coordination types. A basic coordination type is to present the data in various forms and offer linked interactions across multiple views, which helps users perceive insightful relationship and facts from different perspectives. For example, VitalVizor (Zeng and Ye 2018) integrates a spatial map and a metrics view to present spatial and attributive information of urban vitality simultaneously. Besides, multiple views can be arranged side-by-side to facilitate comparison (Gleicher et al. 2011; L'Yi et al. 2021). Roberts (2007) presented a taxonomy of coordination types and provided design guidelines for MV design based on coordination among views. Yet the guidelines are rather implicit. This work aims to provide more concrete MV layout design suggestions based on coordination types.
- *Viewport* Many MVs (e.g., Zeng et al. 2021b; Pan et al. 2021; Xia et al. 2020b) have been developed for exploratory data analysis and visual analytics in different application fields. However, most of the MVs are designed for the desktop. With the extensive popularity of mobile devices, VR/AR, and display walls, more research has been shifted toward designing visualizations beyond the desktop, e.g., mobile devices (e.g., Sadana and Stasko 2016; Brehmer et al. 2019), multiple viewport setups (e.g., Horak et al. 2019; Langner et al. 2018, 2019), or even distributed servers (e.g., Xia et al. 2020a). These works have a common basis of MV layout design shall be in line with the viewport.
- *Designer* Designers may rely on their experience and expertise to design effective visualizations. Grammel et al. (2010) showed that visualization novices only used simple heuristics and preferred familiar view types (e.g., bar chart and pie chart) when constructing visualizations. Pretorius and van Wijk (2009) further reminded designers to think from the user perspective in addition to their experience. Nevertheless, no direct evidence has shown how designers, as a factor in the designing process, affect MV layout design.

This work aims to provide evidence-based guidelines for MV layout design, by exploiting the effects of the above-mentioned design factors (except *viewport*) on empirical MV layouts. We opt for Bayes' rule that has been successfully applied in many other design problems.

2.2 Layout design

Layout design focuses on finding feasible spatial configuration for a set of interrelated objects. The quality of layout design can be evaluated from two perspectives: *geometry* that specifies the position and size of each object, and *topology* that specifies logical relationships between objects (Michalek et al. 2002). Research on layout design spreads in a wide range of applications, including interface design (e.g., Swearngin et al. 2018; Lee et al. 2020), and architecture (e.g., Yang et al. 2013; Wu et al. 2018). In this work, we focus on MV layout that concerns view arrangement in a viewport.

The visualization community has proposed guidelines and revealed practices for MV layout design. For example, Qu and Hullman (2018) suggested various constraints, validations, and exceptions for consistency in MVs, while Chen et al. (2021c) conducted an in-depth analysis of composition and configuration patterns of layouts in empirical MVs. It is a general consensus that the design space for MV layout is huge. Many studies adopt simplified heuristics for MV layout design. Sadana and Stasko (2016) used vertical stacking or grid-based layouts when design MVs on mobile devices, while Horak et al. (2019) arranged multiple views across viewports by positioning similar views side-by-side. As such, there is an emerging need for modeling the effects of various considerations on MV layout design. This work makes a contribution in this direction using Bayesian probabilistic inference.

2.3 Bayes for design

Bayes' theorem is used to describe the probability of an event, given some prior knowledge of conditions that could be related to this event. Compared with classical statistics, an unknown fixed parameter value can be represented as a random variable in Bayes' theorem. In other words, Bayesian statistics deals exclusively with probabilities, so one can use it to determine the optimum decision to take in the face of the uncertainties.

Many works in assisting design rely on Bayesian models learned from existing design dataset. For example, Talton et al. (2012) employed Bayes' rule to learn grammar production rules to parse web-pages. Deka et al. (2016) presented a method that can automatically generate mobile UI by Bayesian model merging learning from UI data captured by interaction mining. Dudley et al. (2019) demonstrated the effectiveness of Bayesian optimization in assisting interface design. Following in line with these studies, this work also employs Bayes' rule to infer the effects of design factors on MV layouts, by updating the posterior probability distribution of layout properties based on empirical MVs.

3 Overview

This section summarizes design factors for MV layout (Sect. 3.1) and layout metrics considered in the work (Sect. 3.2).

3.1 Design factors

Figure 1 presents a typical design process for MV layouts. Given a set of views and predefined coordinations among the views, a designer carefully arranges the views in the target viewport, yielding MVs of various layout design patterns. We formulate the relevant design factors in the following categories.

- *View* There have been several view type taxonomies in the history of data visualization (e.g., Lohse et al. 1994; Shneiderman 1996). In this work, we adopt the taxonomy by Chen et al. (2021c) that categorizes views into 14 types including 12 chart types of information visualization adopted from Borkin et al. (2013), along with *SciVis* and *panel*. Studies (e.g., Chen et al. 2021c; Al-maneea and Roberts 2019) have shown that different view types typically have distinct layout design patterns, to maximize space usage and optimize view expressiveness. This work extends these studies with a probabilistic model that unveils the effects of view types on layout design.

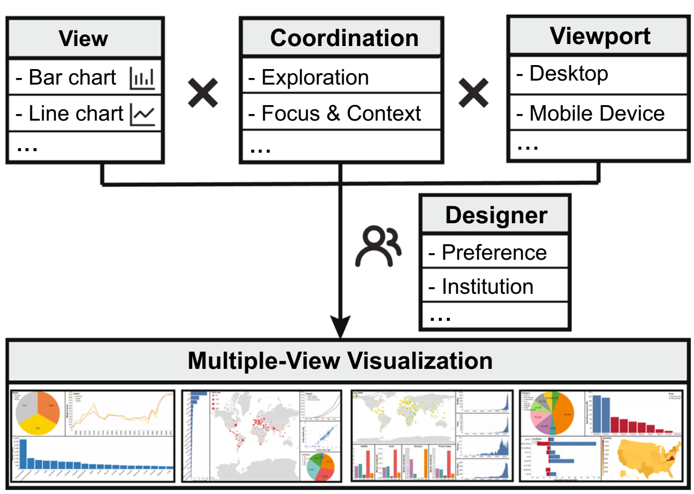

Fig. 1 Illustration of the design process for MV layouts: given the inputs of multiple *views* (e.g., bar, line chart), *coordination* (e.g., exploration, focus + context), and *viewport* (e.g., desktop, mobile device), the *designer* arranges the views in proper layout to achieve effective MVs

- *Coordination* Chen et al. (2021b) recently developed a coordination framework that generalizes coordination structures in terms of composition of interactions and data transformations. The framework was built upon a systematic review of coordinations from existing theories and applications. Nevertheless, it is not feasible to derive detailed coordination structures from static MV images collected in papers. As such, we adopt a simplified classification by Roberts (2007) that suggests six categories of coordination types: (1) overview+detail, (2) focus+context, (3) difference, (4) master/slave, (5) miniature views (often used in virtual reality), and (6) small multiples. Some coordination types are not exclusive when annotating, while some other coordination types are not available in the dataset. In the end, we formulate categories of coordination types as follows:

  1. *Exploration* For MVs in *exploration* coordination type, each view encodes a different aspect (or dimension) of data. Selection of an object in one view results in other views highlighting the same object. From the statistic analysis (see Fig. 4), we find that *exploration* is the most common coordination type.
  2. *Focus +context* For MVs in *focus +context* coordination type, there is a focused main view that allows for closer inspection, and the other views are usually used for showing context of the entire dataset.
  3. *Comparison* Views of *comparison* coordination type can be used for presenting different datasets, or the same dataset in a different context (e.g., different years), or the exact same dataset and context but from different angles for comparison and comprehensive presentation of the data.

- *Viewport* Various types of viewports, such as desktop and mobile device, have become the primary means of accessing information. It is, therefore, becoming increasingly important to develop multiple-view visualization that adapt to any viewport (Roberts et al. 2014). However, we find that most MVs (e.g., Zeng et al. 2021b; Pan et al. 2021) in the MV dataset are designed for the desktop. As such, this work considers the desktop as the sole condition of viewport. We leave it to the future work to consider other viewport conditions like mobile devices and large displays.
- *Designer* MV layout design is a creative process that depends on expertise and preferences of designers (Pretorius and van Wijk 2009; Grammel et al. 2010; Heer et al. 2008). Different designers may have diverse preferences about choices of view types, and positions and sizes of views, yielding different layouts. Nevertheless, it is nearly impossible to quantify the expertise levels and preferences of designers. Alternatively, this work analyzes primary institute of designers of a MV, which can be retrieved from the publications, as the condition for *designer* factor.

3.2 Layout metrics

Given a MV of n views, i.e., $MV := \{v_i\}_{i=1}^{n}$ where v_i denotes a view, we measure the following geometric and topological metrics:

- *Geometry* Visualization conveys data and information in a limited display space. As such, space utility is a primary consideration for MV layout design. In this work, we access the following two metrics that reflect area and aspect ratio of space utility.

  1. *Maximum area ratio (MAR)* For visualization design, space allocation shall depend on the importance of data and information. We hypothesize that view areas are affected by the above-mentioned design factors. For example, in MVs of *focus +context* coordination type, the *focus* view is typically allocated a large space, while the *context* view is small, leading to a large MAR value. In comparison, views of *comparison* coordination type typically have the same size; thus, the value of MAR will be relatively small. We measure area ratio of the largest view to areas of all views as:

$$\mathrm{MAR} = \frac{\max(w(v_i) \times h(v_i))}{\sum_{i=1}^{n} w(v_i) \times h(v_i)}, \quad \forall v_i \in MV, \tag{1}$$

where $w(\cdot)$ and $h(\cdot)$ represent width and height of a view, respectively. MAR ranges in (0,1), where values toward 1 indicate that MVs have a view in dominant size.

  2. *Weighted average aspect ratio (WAAR)* Proper aspect ratio looks visual aesthetic and can effectively clarify a presentation. For instance, artists and architects typically proportion their work to approximate the golden ratio of approximately 1.6180 (or 13:8). Aspect ratio has also been adopted

for evaluating visualizations, e.g., treemap design (Bederson et al. 2002). Chen et al. (2021c) revealed that views of different types are usually arranged in different aspect ratios. For example, aspect ratio of bar charts usually ranges from 1/7 to 7, while that of line charts usually ranges from 1/5 to 5. As such, this work further examines how aspect ratios are affected by view type and other design factors. Specifically, we use WAAR to emphasize views of larger sizes, in comparison with unweighted aspect ratio used in treemap (Bederson et al. 2002). The metric is measured as:

$$\mathrm{WAAR} = \sum_{i=1}^{n} \left\{ \frac{w(v_i)}{h(v_i)} \times \frac{w(v_i) \times h(v_i)}{\sum_{i=1}^{n} w(v_i) \times h(v_i)} \right\}. \tag{2}$$

We figure out that WAAR ranges in [1, 8.5] in the dataset, where close to 1 values indicate that the views are in balanced aspect ratios like matrix arrangement.

- *Topology* Topological structure of MV layout reflects visual information flow among views (Lu et al. 2020). Chen et al. (2021c) figured out about 100 layouts in existing MVs. Yet most of the layouts have only one sample, which is not enough for Bayesian analysis. To overcome the deficiency, we summarize the topology of MV layouts into *horizontal*, *vertical*, and *hybrid*, as illustrated in Fig. 2. Horizontal topology arranges all views side-by-side horizontally. There are three horizontal layouts identified in the dataset. Similarly, vertical topology arranges all views side-by-side vertically, and only three vertical layouts are identified. Hybrid topology divides the display via slicing-and-dicing, and most layouts are in hybrid topology. We would like to examine whether the topology of view layout is affected by the designer, similar to reading where most Western languages go from left to right, while Arabic and Hebrew are read from right to left, and some Asian languages are read vertically. We count the frequency of topology types on conditions of different design factors and construct Bayesian models to examine the impacts of design factors on the choices of layout topology.

4 Bayesian inference for MV layout design

The ultimate goal of this work is to detect and model the effects of design factors on MV layouts. We opt for Bayes' rule to model the design patterns, by inferring the posterior probability of layout metrics given design factors observed in empirical MVs.

4.1 Definitions

To facilitate the discussion, Table 1 introduces common notations adopted in the work. Here, we define the d-dimensional *design space* of all possible design factors, $\mathscr{C} = \{C_1 \times C_2 \times \ldots \times C_d\}$, where C_i is the domain of ith design factor. As described in Sect. 3.1, this work considers three-dimensional factors, i.e., *view* (C_1), *coordination* (C_2), and *designer* (C_3). We learn design patterns from a *MV dataset*, $\mathscr{M} = \{MV_1, MV_2, \cdots, MV_m\}$, and correspondingly the set of layouts $\mathscr{L}$ derived from $\mathscr{M}$. This work considers three-perspective layout metrics of *MAR*, *WAAR*, and *topology*, which are denoted as $\mathscr{L}_{mar}$, $\mathscr{L}_{waar}$, and $\mathscr{L}_{topo}$, respectively. Each MV can be encoded as a tuple in the form of (*view*, *coordination*, *designer*). For example, the MV in Fig. 3 is originally encoded as

$$([table, map, map, grid, bar, point], [comparison, exploration], HKUST),$$

indicating that the MV comprises one table (Fig. 3a), two maps (Fig. 3b1, b2), one gird (Fig. 3c), one bar chart (Fig. 3d), and one point chart (Fig. 3e); the MV has both comparison and exploration coordination types; and its primary institute is HKUST.

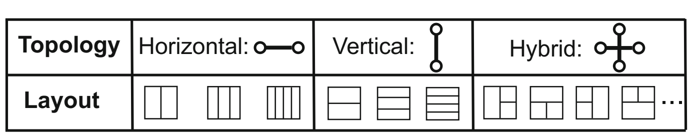

Fig. 2 This work categorizes MV layouts into three topology types: horizontal, vertical, and hybrid

Table 1 Notations and their descriptions

Notation	Description
$\mathscr{C}$	The space of possible design factors
C_i	One-dimensional design factor
$\mathscr{M}$	The set of all MVs collected
$\mathscr{L}$	The set of all MV layouts derived from $\mathscr{M}$

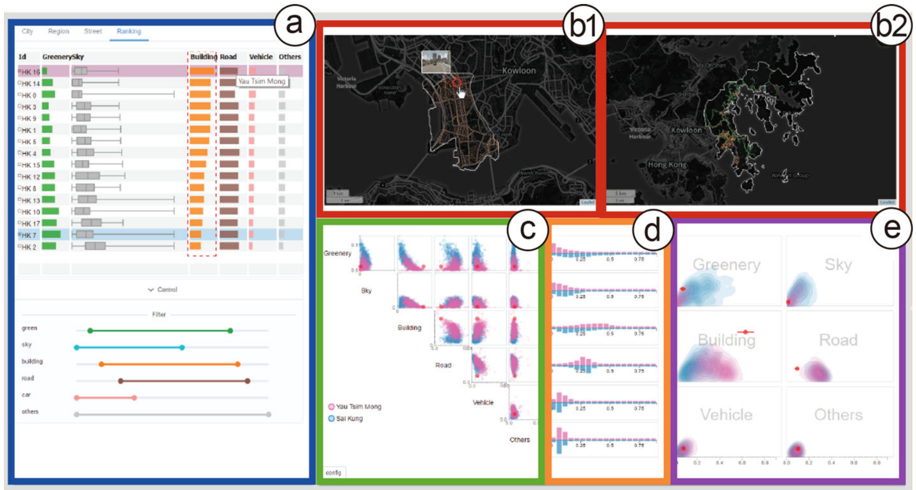

Fig. 3 Annotating coordination types for StreetVizor (Shen et al. 2018). Views *b1 and b2* are side-by-side maps for comparison, thus being labeled as *comparison*. Views *a, b1, b2, c, d, and e* explore street views from different perspectives, thus being labeled as *exploration*

Note that each dimensional design factor involves various discrete data values. For example, we identify 128 primary institutions in the MV dataset (see Sect. 5.2), i.e., $|C_3| = 128$ if we consider each individual institute. Nevertheless, this will yield excessive discrete data values, hindering Bayesian inference. We overcome the deficiency by clustering institutes into groups based on continent (see Sect. 6.2). Similarly, we categorize all possible data values of *view* dimension (C_1) by considering if the MV contains a specific view type or not, e.g., bar chart. We keep coordination dimension (C_2) as origin since the number of coordination data values is small. In this way, the above tuple can be simplified as

$$(with\ bar, [comparison, exploration], Asia).$$

4.2 Modeling

The model is used to explain the probability of events occurring. Given a set of design considerations $\mathscr{C}$, we need to formulate a *predictive* probability distribution over the design space of possible MV layouts. But before we formulate a *predictive* probability distribution, we need to formulate the *posterior* distribution,

$$P(\vec{\mu}|\mathscr{C}) \propto P(\mathscr{C}|\vec{\mu})P(\vec{\mu}), \tag{3}$$

where $\vec{\mu}$ is a K-dimensional vector which describes the probability of each layout, $P(\mathscr{C}|\vec{\mu})$ is the likelihood of the set of design considerations $\mathscr{C}$ given a particular $\vec{\mu}$, and $P(\vec{\mu})$ is the prior of MV layouts.

- *Prior*. In our work, the three variables of design factors (i.e., view, designer, and coordination) are all categorical. Their observed values conform to a polynomial distribution, so we set the prior to the Dirichlet distribution. For the domain of $\mathscr{L}$ with K possible categories, we define a K-dimensional vector $\vec{\mu}$ to describe the probability of observing each of the K categories. And we assume that the prior distribution over all values of $\vec{\mu}$ is the Dirichlet distribution with parameter $\vec{\alpha}$

$$P(\vec{\mu}) = \text{Dirichlet}(\vec{\mu}|\vec{\alpha}) \\ = \frac{\Gamma\left(\sum_{k=1}^{K}\alpha_k\right)}{\prod_{k=1}^{K}\Gamma(\alpha_k)}\prod_{k=1}^{K}\mu_k^{\alpha_k-1}. \tag{4}$$

- *Likelihood* After we label the dataset and make statistics, we know the observation counts for each of the K possible categories. We denote the observation count for the category i with m_i and denote the total count of the dataset with N. Given a particular $\vec{\mu}$, the likelihood can be calculated as follows

$$P(\mathscr{C}|\vec{\mu}) = \begin{pmatrix} N \\ m_i m_2 \ldots m_k \end{pmatrix}\prod_{k=1}^{K}\mu_k^{m_k}. \tag{5}$$

We define a K-dimensional vector $\vec{m}$ to describe the observation count m_i. By combining Eqs. 3–5, we can calculate posterior probability

$$P(\vec{\mu}|\mathscr{C}) \propto P(\mathscr{C}|\vec{\mu})P(\vec{\mu}) \\ = \text{Dirichlet}(\vec{\mu}|\vec{\alpha}+\vec{m}) \\ = \frac{\Gamma\left(N+\sum_{k=1}^{K}\alpha_k\right)}{\prod_{k=1}^{K}\Gamma(\alpha_k+m_k)}\prod_{k=1}^{K}\mu_k^{\alpha_k+m_k-1}. \tag{6}$$

Similar to continuous cases, our prior and posterior in the discrete scenario are also conjugate distributions. The Dirichlet prior for discrete attributes has only one parameter: $\vec{\alpha}$. Since the number of MV designs in the dataset is limited, we use Laplace smoothing to avoid the condition when *predictive* probability is calculated to be 0. We set $\vec{\alpha}$ to be a vector of K equal numbers (1.0), which constitutes a uniform distribution across all possible MV layouts. Finally, we integrate our updated belief over all possible values of $\vec{\mu}$ to get the predictive probability for a given layout $\mathscr{L}_i$

$$P(\mathscr{L}_i|\mathscr{C}) = \int P(\mathscr{L}_i|\vec{\mu})P(\vec{\mu}|\mathscr{C}) \\ = \frac{\alpha_i+m_i}{\sum_{k=1}^{K}(\alpha_k+m_k)}. \tag{7}$$

5 Data processing

This work is built upon the MV dataset collected by Chen et al. (2021c). The dataset consists of 360 MV images collected from publications in IEEE VIS, EuroVis, and IEEE PacificVis conferences 2011–2019. Each MV image comprises two or more views. Type (e.g., bar chart, line chart, etc.) and bounding box (including center position and size) of each view have been marked by the authors. With the information, one can feasibly analyze view type compositions and layout configuration patterns of MV design (Chen et al. 2021c). The work requires additional information of coordination types and designers. We make up the information by labeling coordination types and designers (Sect. 5.1). Next, we conduct a preliminary analysis to reveal characteristics of the dataset (Sect. 5.2).

5.1 Dataset construction

In the MV dataset (Chen et al. 2021c), a view is classified into one of 14 view types, including 12 chart types of information visualizations (Borkin et al. 2013) + SciVis + panel. However, panels are usually used for controlling visualization parameters or displaying legends and colormaps. It is infeasible to classify the coordination type of panels with other views. Thus we omit MVs comprising only one view of information visualization or SciVis, along with one or more panels. This process yields 303 MVs for further analysis. Next, we adopt the following annotating strategies for labeling coordination and designer.

- ***Annotating coordination*** Coordination is a mutual relationship among two or more views. A MV consists of multiple views, and these views can form several coordination relationships. As shown in Fig. 3, the StreetVizor system (Shen et al. 2018) employs two map views (*b1* and *b2*) to compare spatial distribution of street views in two different cities. Hence, we annotate the coordination type for views *b1* and *b2* as *comparison*. Besides the map views, StreetVizor also employs a table view (Fig. 3a) for multi-scale navigation and feature filtering, along with three statistic views (Fig. 3c–e) for presenting quantitative measurements. As such, we also annotate the coordination type for views *a, b1, b2, c, d, and e* as *exploration*. In this way, coordination types for the MV are labeled as [*comparison*, *exploration*]. To annotate coordination types, we add a component to the labeling tool developed by Chen et al. (2021c). With the component, users can indicate which views are coordinated, and what is the type of coordination. For most MVs, one can directly identify the coordination type among views by looking at the visualization images. Nevertheless, there are cases that are hard to justify. In such scenarios, we refer to the corresponding publication and identify the coordination type by carefully examining the visualization image's caption and description in the main text.

- *Annotating designer* There are two perspective informations of designer in a MV. First, we can create a bipartite graph with set of *MV* as one part and set of *author* as another part. An edge between a MV and an author indicates the author is a designer of the MV. However, a MV can be connected to several authors, being unsuitable for Bayesian analysis. As such, we opt to generate a bijection graph that maps one-to-one correspondence between *MV* and *primary institute* of the first author, i.e., a MV has one and only one primary institute. In this way, we can feasibly access the impacts of designers on MV design. We can further cluster primary institutes by properties like continent, to check whether MV design is dependent on geographic location.

We add the newly annotated coordination and designer information to the JSON file by Chen et al. (2021c). Together with view type and layout information recorded in the original file, we can conduct Bayesian inferences on layout design for MVs.

5.2 Dataset characteristics

We analyze characteristics of MVs in the dataset prior to Bayesian modeling. Figure 4 presents the analysis results. On the left, the top 10 primary institutions are presented. From the figure, HKUST published the most number of 20 articles using MVs, showing its productivity in the field. Besides, Georgia Tech., Purdue University, Zhejiang University, University of Stuttgart, and TU/e have over 10 publications. Together with Peking University, institutes from China are remarkably active in developing MV systems. There are in total 128 primary institutions that have at least one MV publication in the dataset. Average number of MVs by an institute is 2.37 or so, and median value is 1. All the institutes are located in three continents, i.e., *Asia*, *Europe*, and *America* (both North and South America). On the right, the figure shows percentages of coordination types. Here we can see that *exploration* is the most popular coordination type in the MVs, indicating that the technique is mainly used for data exploration from different perspectives. *Comparison* is the second most popular objective for MVs, followed by *focus +context*. Notice that a MV can have multiple coordination types. We count all coordination types in these cases.

Other than primary institutions and coordination types, we also analyze frequency of view types and layout topology. The results are similar to those in Chen et al. (2021c). For instance, we found that (1) bar and line charts are the most frequently used chart types, while SciVis and circle chart have the least usage, and (2) simple layouts are more frequently used. Interested readers are referred to Chen et al. (2021c) for detailed analysis.

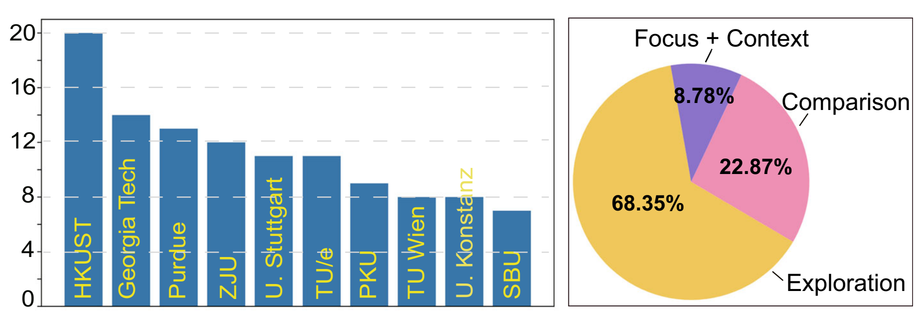

Fig. 4 Top 10 primary institutions (left) and percentages of coordination types (right) of MVs in the dataset

6 Analysis results

This section first introduces Chi-squared test (Sect. 6.1), followed by an independence analysis on the design factors (Sect. 6.2). In the end, we present in-depth analyses for effects of design factors on layout metrics (Sect. 6.3–6.5).

6.1 Chi-squared test

This work uses the Chi-squared test to check (1) whether the design factors are related, denoted as *independence* test; and (2) whether there is a statistically significant difference between the expected and the observed frequencies, denoted as *difference* test. The formula is:

$$\mathcal{X}^2 = \sum \frac{(O_i - E_i)^2}{E_i}, \tag{8}$$

where O_i denotes the ith observed frequency, and E_i denotes the ith expected frequency in theory. The calculated $\mathcal{X}^2$ value is then compared to the critical value from the $\mathcal{X}^2$ distribution table with degrees of freedom and chosen confidence level. Specifically, we conduct the following analyses when testing independence and difference.

- *Independence* test proposes a null hypothesis H_0': *the two variables A, B are independent to each other*. The test firstly assumes that H_0' is true, i.e., $P(A, B) = P(A) * P(B)$. According to this condition, the expected frequency for every combination of variable A and B is calculated. For example, in Table 2, the expected frequency of $\{C_{21}, Asia\}$ is: $f_{\{C_{21},Asia\}} = P(C_{21}, Asia) \times total = P(C_{21}) \times P(Asia) \times total = 191/303 \times 74/303 \times 303 = 46.65$, while the observed frequency is 40. With all the observed and expected frequencies, the $\mathcal{X}^2 = 17.81$ is derived. The degree of freedom here is $df = (|A| - 1) \times (|B| - 1) = (3 - 1) \times (6 - 1) = 10$. In this way, we can conclude that the *designer* and *coordination* variables are independent for MV layout design at the significance level 0.05.
- *Difference* test proposes a null hypothesis H_0: *there is no significant difference in variable A among N groups of data*. The degree of freedom is denoted as $(|A| - 1) \times (N - 1)$, where $|A|$ is the number of categories or bins of the variable A. This test firstly postulates that H_0 is true, and calculates the $\mathcal{X}^2$ that represents deviation degree among N groups of data. With the calculated $\mathcal{X}^2$ and the degree of freedom, one can get the probability $\mathcal{P}$ supporting H_0 from the Chi-squared distribution table. Given a user-defined alpha level of significance, the hypothesis H_0 is accepted or rejected by comparing $\mathcal{P}$ with the alpha level. In this work, since the size of our dataset is relatively small, we set the alpha level to 0.05. Moreover, we assume that the expected frequency is uniform, while the observed frequency is the posterior probability of Bayesian model.

6.2 Independence analysis

To use Bayes' rule to model effects of design factors on MV layouts, we need to first verify the design factors are independent from each other. As described above, there are too many raw values of *view* and *designer* factors observed from the data, hindering Bayes inference. To overcome the deficiency, this work groups *designer* values into three categories, i.e., *Asia*, *Europe*, and *America*, and groups *view* values into two categories based on the existence of a specific view type, e.g., with and without bar chart. There are in total six *coordination* conditions observed in the dataset, i.e., $C_2 = \{[exploration], [comparison], [focus + context], [exploration, comparison], [exploration, focus + context], [comparison, focus + context]\}$. Note

Table 2 Contingency table of *designer* by continent of the primary institute and *coordination* factors

	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	Sum
Asia	49	3	1	0	17	4	74
Europe	53	11	6	3	16	0	89
America	89	7	11	2	28	3	140
Sum	191	21	18	5	61	7	303

that the observed coordination conditions indicate that a MV contains at most two types of coordination at the same time. As such, we keep *coordination* factor in its raw format.

After converting all the design factors into categorical variables, we use the independence test verify the Chi-squared independence among the design factors. Table 2 presents a contingency table between *designer* and *coordination* factors, where $C_{21} - C_{26}$ denote the six conditions under *coordination* type. Here, we form a null hypothesis that the two design factors (i.e., *coordination* and *designer*) are independent, and to get the expected frequency for each combination. The *independence test* gives a value of 17.81, with $\mathscr{P} > 0.05$ given $df = 10$. As such, the null hypothesis is accepted. In the same way, we calculate the $\mathscr{X}^2$ values between *designer* and *view* and between *coordination* and *view*. The maximum $\mathscr{X}^2$ value between *designer* and *view* is 5.31 with $\mathscr{P} = 0.07$, and $\mathscr{X}^2$ value between *coordination* and *view* is 10.554 with $\mathscr{P} = 0.61$. Thus, all the three design factors are independent to each other.

6.3 Modeling effects of design factors on MAR

In this section, we analyze the effects of different design factors on MAR. MARs of all MV layouts in the annotated dataset are within the range [0, 0.9]. As such, we first divide the value range of MAR into nine equal intervals of length 0.1. Next, we use the Bayesian inference model as described in Sect. 4 to calculate the posterior probability distribution of MAR under different conditions. Finally, we form a null hypothesis that the expected distribution of posterior probability distribution is uniform, and use Chi-squared difference test to verify whether the design factor influence is significant or not.

Through the analysis, we find design patterns as follows.

- *View* We first calculate the probability distributions of MAR upon the condition *view* type. As described above, we categorize MVs based on the existence of a specific view type. We first examine which view type has the most significant effects on MAR for each of the 13 view types (*panel* is omitted), by measuring probability distributions of MAR for MVs with and without the view type. We find that line chart has the greatest effect on MV layout among the 13 view types. Its $\mathscr{X}^2$ value is 18.187 and $\mathscr{P} = 0.020$.
  Figure 5 (right-1) presents the posterior probability distributions of MARs for MVs with and without line chart. The expected value for MAR is 0.357 when MVs have line chart, while the value increases to 0.436 when there is no line chart. Specifically, MARs for MVs with line chart are concentrated in the range [0.1–0.5], while those without line chart are more concentrated in the range [0.2–0.6]. Taking *a1 and a2* and *d1 and d2* in Fig. 5(left) for example, their coordinations are all *comparison*. The difference is that line charts exist in *a1 and d1*, but not *d1 and d2*. Figure 5 (right-1) shows that MARs for *a1 and a2* are within [0.1–0.2], while those for *d1 and d2* are within [0.3–0.4]. This is probably because line charts typically have a wide aspect ratio, which shrinks the display space for other views.
- *Coordination* In the same way, we calculate the probability distributions of MAR upon different *coordination* types. The $\mathscr{X}^2$ value is 128.104 and $\mathscr{P}$ = 3.72E–11, which means that *coordination* has a bigger effect on MARs than *view*. Figure 5 (right-2) presents the posterior probability distributions of MARs for MVs of coordination-type *exploration*, *comparison*, and *focus+context*. MARs of MV layouts of *exploration* coordination type are concentrated in the interval [0.3–0.6], those of *comparison* are

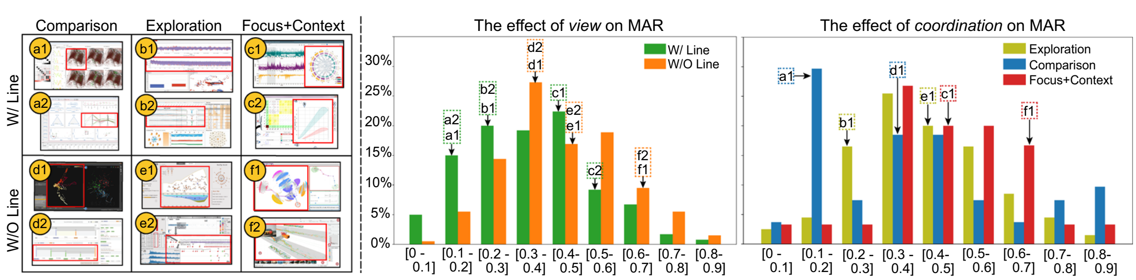

Fig. 5 The effects of *view* and *coordination* design factors on MAR: exemplar MVs from the dataset organized by their *view* and *coordination* attributes (left), and posterior probabilities of MAR distribution upon the condition of *view* (right-1) and *coordination* (right-2), derived from Bayesian inferences using the observed MVs

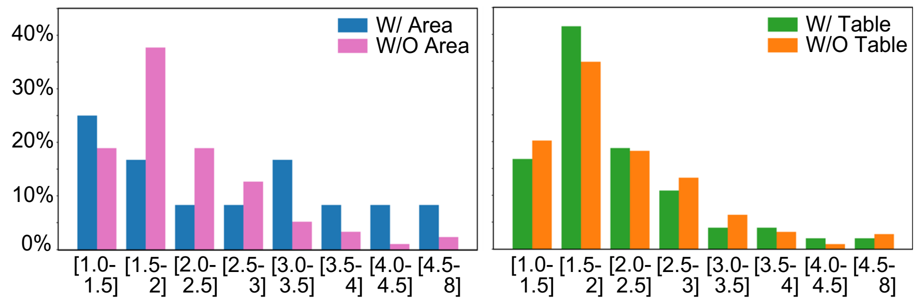

Fig. 6 Posterior probability distributions of WAAR when MVs are categorized by having *area* chart on the left, and having *table* on the right

prominent within [0.1–0.2], while those of *focus+context* have higher probabilities falling in [0.5–0.7]. Overall the observations coincide with our expectations. When the main purpose is for *comparison*, MVs typically adopt multiple views of the same size; see examples in column 1 of Fig. 5(left). In such cases, all views share a small area ratio, and MARs of the MVs are limited. Yet, it is surprisingly to notice that the MARs of comparative MVs are concentrated in [0.1–0.2]. We find that many cases are SciVis interfaces that arrange multiple views side-by-side, as shown in Fig. 5a1. In contrast, MVs of *focus+context* coordination type typically have a focus view that dominates the display space; see examples in column 3 of Fig. 5(left). MVs of *exploration* coordination type are relatively more balanced, in comparison with the other two types.

- *Designer* Last, we calculate the probability distributions of MAR of MV layouts upon conditions of *Europe*, *Asia*, and *America* designers. The $\mathscr{X}^2$ value is 8.713 with $\mathscr{P} = 0.925$. As such, the effect of *designer* on MAR is regarded to be insignificant. We skip further analysis for the effects of *designer* on MV layouts.

Summary Coordination type of views in MVs is the dominant design factor for determining the maximum view size in MVs. From the Bayesian analyses, MVs of *comparison* coordination type tend to use multiple and balanced view sizes, while MVs of *focus+context* coordination type tend to make the focus view dominant. View composition also has an effect on MARs, but not as significant as coordination. There is no obvious difference between MARs of MVs by designers in different continents.

6.4 Modeling effects of design factors on WAAR

WAAR that reflects the average aspect ratio of all views weighted by view sizes, is another geometric metric used in this work. We derive the range of WAARs is 1.0–8.5, for all MVs in the dataset. Notice that WAAR is always larger than 1, as the MVs are designed for desktops of wide screen sizes. Specifically, we notice that WAARs are concentrated in the interval [1.0–3.0], and those above 4.5 are rare. As such, we decide to divide the values into seven intervals with the step size of 0.5 for WAARs in the range 1.0–4.5, and the remaining WAARs above 4.5 are grouped into a separate interval. Next, we construct Bayesian inference models that derive posterior probability distribution of WAARs under different conditions. We use Chi-squared difference test to measure the significance of the design factors on WAAR. Similarly to MAR, we also find that both *coordination* factor has significant effects on WAAR, while *designer* factor has no

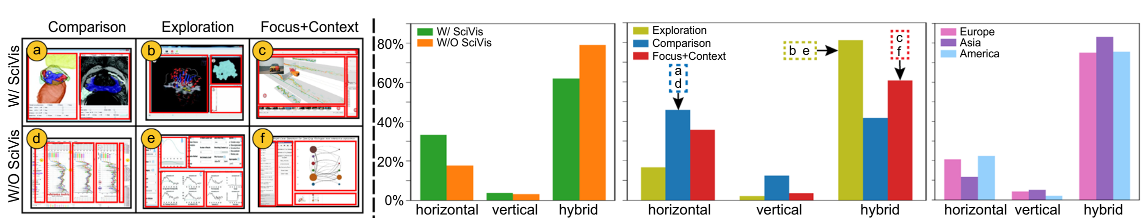

Fig. 7 The effects of *view*, *coordination*, and *designer* design factors on layout topology: exemplar MVs from the dataset organized by their *view* and *coordination* attributes (left), and posterior probability distributions of layout topology upon the condition of *view* (right-1), *coordination* (right-2), and *designer* (right-3), derived from Bayesian inferences using the observed MVs

significant effect. $\mathscr{X}^2$ value for *designer* factor is 13.052, with a $\mathscr{P}$ value of 0.522. Interestingly, we find that categorization by different view type has dynamic effects. Here, we examine the probability distribution of WAAR under MV categorization based on the existence of a specific view type. We find that only categorization by *area* chart has a significant effect on WAAR. Specifically, the $\mathscr{X}^2$ value is 18.733, and $\mathscr{P} = 0.009$. Categorization by all other view type has $\mathscr{P} > 0.05$.

Figure 6 presents a comparison between the posterior probability distributions based on categorization by *area* (left) and by *table* (right). We can find that:

- *Categorization by Area Chart* The probability distribution of WAAR is concentrated in [1.0 - 2.0], regardless of MVs with or without *area* chart. This indicates that most views tend to have average aspect ratios, and that their areas are relatively balanced. The most likely interval distribution for WAAR containing *area* chart is between 1 and 1.5, while those without *area* chart is most likely in 1.5 to 2. This means that the MVs with *area* chart have more balanced aspect ratios, probably because most *area* charts have similar widths and heights.
- *Categorization by Table* In contrast, we can find that the posterior probability distribution of WAARs is more similar for MVs with and without *table* chart, in all intervals. As such, categorization by *table* has no significant impacts on WAARs.

Summary Designer factor has no obvious impacts on WAAR of MV layouts. The most significant factor influencing the distribution of WAAR is *coordination* design factor. Categorizing MVs based on *area* chart has a significant impact on WAAR. MVs having *area* chart are more likely to have balanced aspect ratios.

6.5 Modeling effects of design factors on topology

Layout topology determines the arrangement of views in MVs. Here, we divide the topology of MV layouts into *horizontal*, *vertical*, *hybrid*. In the similar way, we conduct Bayesian inference analysis to examine the effects of design factors on layout topology.

- *View* For each of the 13 view types, we conduct a comparative analysis, which shows that *SciVis* have the biggest influence on layout topology, with $\mathscr{X}^2 = 10.082$ and $\mathscr{P} = 0.006$. As shown in Fig. 7(right-1), we can find that MVs with SciVis have a higher probability to be in horizontal layout, than those MVs without SciVis. An example is Fig. 7a, which arranges two *SciVis* views side-by-side for comparison.
- *Coordination* We find that coordination is the most significant influencing factor with a $\mathscr{X}^2$ value of 121.297 and a $\mathscr{P}$ value of 2.7592e–21. We calculate the posterior probability distributions of layout topology for different coordination types. The results are shown in Fig. 7(right-2). Here, when *coordination* is *exploration* and *focus+context*, the probability distribution is focused on *hybrid*. This is probably because layout of *exploration* requires different views to display different data. In contrast, the layout topology of *comparison* is more focused on the *horizontal*.
  We show some examples in Fig. 7(left). We divide the examples into groups based on coordination and the existence of SciVis views. Here, both Fig. 7a with *SciVis* and Fig. 7d without *SciVis* tend to have a horizontal layout topology when *coordination* is *comparison*, while Fig. 7b, c containing *SciVis* and coordination of *exploration* or *focus+context* has a hybrid layout topology.
- *Designer* The $\mathscr{X}^2$ value and $\mathscr{P}$ value of *designer* are 5.846 and 0.211, i.e., *designer* factor has no significant impact on layout topology. Figure 7 (right-3) shows the posterior probability distribution of layout topology upon *designer*. No significant difference is observed among designers from *Europe*, *Asia*, and *America*.

Summary View and *coordination* design factors have a certain influence on layout topology, and the impact by *coordination* is the most significant. Given *exploration* and *focus+context* coordination types, hybrid layouts are more likely to be used. In contrast, MVs of *comparison* coordination type tend to adopt horizontal layouts. Similar patterns are observed for MVs with and without *SciVis* views.

7 Conclusion, discussion, and future work

This work constructs a Bayesian probabilistic inference framework that reveals MV layout design patterns on the conditions of three design factors, i.e., *view*, *coordination*, and *designer*. Specifically, we focus on three metrics that describe the geometric (MAR and WAAR) and topological (layout topology) properties of MV layouts and derive posterior probability distribution of the metrics derived from MVs in a new dataset. Based on this framework, we conduct in-depth analyses that reveal the effects of design factors on MV layouts. We summarize some valuable MV layout design patterns as follows.

- Coordination is the dominant design factor that has the most significant effects on MV layout design. Specifically, MVs of *comparison* coordination type are more likely to have balanced area ratios and be in horizontal layout, while those of *focus+context* are more likely to have a focus view with big size and be in hybrid layout.
- MVs with *line* chart are more likely to have lower MARs and be in vertical layout topology. *Area* chart has a significant effect on WAAR − MVs with *area* chart tend to have smaller aspect ratios. MVs with *SciVis* tend to be in horizontal layout.
- Designers categorized by continent have little to no significant impacts on MAR, WAAR, and layout topology.

This work makes a prominent starting point for a thorough understanding of MV layout design patterns. Currently we only analyze the impacts of a single design factor. Nevertheless, the proposed Bayesian probabilistic inference framework is flexible enough to be extended to other design factors. For example, in the annotation stage, we also noticed that MV layouts seem to be very different over time. MVs in early days seem to be more regular and in grid layout, while latest MVs seem to be more diverse. A possible reason is that new libraries and tools, which allow easy creation of diverse MV layouts, have emerged. The framework can also support further analyses like design factor combinations, since the framework can operate regardless of MV layout properties or dataset. Nevertheless, certain conditions such as independence analysis shall be conducted before using naive Bayesian.

Limitations Nevertheless, there are certain limitations in our work. First, the MV practices in the dataset are mostly deployed for the desktop usage; thus, we ignore *viewport* design factor in this work. A more comprehensive factor set would certainly provide more valuable insights. Second, we regard primary institute of the first author as design factor for *designer*. Nevertheless, this is not a good indicator for *designer* who really chooses the MV layout, and international collaboration among designers from different countries is becoming more popular. This may also be the main reason why *designer* has no significant impact on MV layout design. Third, our current analysis on layout topology is based on three categories (i.e., horizontal, vertical, and hybrid) of MV layouts. *Hybrid* layouts dominate the MVs in the dataset, which potentially affect the analysis results. A more reason categorization is to use the visual information flow (Lu et al. 2020) among views.

Future work There are several promising directions for future work. First, we plan to expand the MV dataset by including MVs from other sources like the Internet and Tableau Public. Doing this can enrich the diversity of MV layouts. However, layout design of these MVs may not be in the same quality with those collected from visualization publications. We shall come up with some selection strategy to ensure the quality. Second, we would also like to enrich information of the MV dataset, such as to include more design factors like viewport. There is a recent trend in developing visualizations for viewports beyond the desktop, such as on mobile devices (e.g., Wu et al. 2020; Kim et al. 2021) and in virtual reality (e.g., Zhang et al. 2021; Perhac et al. 2017). We call for close collaborations in the visualization community for constructing such a comprehensive dataset. In addition, our current models are based on naive Bayesian analysis that can only give probability distributions for model inference. We would like to explore the possibility of developed a recommendation system using the Bayesian analysis results for automating the design process of MV layouts. This again requires a new dataset with fine annotations. Last but not least, we look forward to integrating the results into existing visualization authoring tools, such that the tools can warn users of abnormal MV layout design, e.g., the MAR value of a MV is out of range given certain design factors. We envision that such a tool will help users design effective MV layouts.

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