User-oriented Generation of Contextual Visualization Sequences

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Abstract
A visualization sequence is an effective representation of meaningful data stories.Existing visualization sequencing approaches use heuristics to arrange charts in a meaningful order. While they perform well in specific scenarios, they do not customize the generated sequences to individual users' preferences. In this work, we present VisGuide , an assistive data exploration system that helps a user create contextual visualization sequence trees by sequentially recommending meaningful charts tailoring to the user's preference on data exploration. Our results show that VisGuide can recommend chart sequences that interest users and are also considered meaningful by domain experts.

Author Keywords
Data-driven storytelling ; Visualization sequencing; User preference adaptation

Introduction
Data-driven storytelling with visualization combines narratives and interactive graphics [17, 10, 11, 20, 1]. This new class of visualizations helps users navigate a series of events to identify data trends, patterns, or causally related events, and form *data stories*. An important step toward assisting users to craft data stories is to generate meaningful and contextual visualization sequences. An ideal

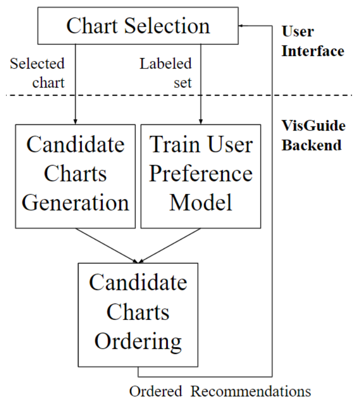

Figure 1: System overview of VisGuide. The chart selection module acquires users' preferences through their interaction with the interface. Clicking on a data point reveals user's interest for further exploration and is utilized as a filter information. All acquired information is used to train and update a user preference model, which generates candidates for recommending next charts. Finally, VisGuide lists the recommended charts in the order of the user's preference score predicted by the user preference model.

visualization sequence consists of (a) interesting charts to present insights [19, 13, 4, 5, 15, 16], (b) an understandable ordering of charts to show events [7, 8, 9], and (c) a personalized style adaptive to individual users [21, 6].

In various types of data stories, *drill-down story* is a common genre of storytelling [17, 12] to help users identify interesting data subsets by progressively adding filters. Previous studies recommend charts using features on data statistics to identify interesting charts [19, 13, 4, 5, 18, 2, 15, 12, 16]. However, without a contextual ordering strategy, these charts cannot present comprehensible data stories. To arrange charts in an understandable order, Hullman et al.[8] conducted user studies and identified two structure patterns that can improve the comprehensibility of sequences: *hierarchical structure* that groups subsets of charts with shared data properties, such as common measure, time period, or spatial region; and *parallel structure*, which repeats a pattern of transitions several times in a sequence.

In this work, we aim to help users create ideal drill-down visualization sequences. We present an assisting data exploration system that interactively recommends interesting *drill-down* charts based on the data statistic features and *comparison* charts that help users create sequences with structural patterns. The proposed *sequence tree* can help users explore the search space in breadth and depth. The recommended charts are ranked by our proposed utility function, which is a Stochastic Gradient Descent (SGD) regression model based on chart features that we designed, and can quickly adapt to users' preference during the exploration process. The user study reveals that VisGuide assisted users to generate data stories with better user satisfaction and higher expert rating than the state-of-the-art method, VisPilot [12].

Related Work

Data-driven storytelling with visualization attempts to combine narratives with interactive graphics to convey data stories effectively. Segel and Heer [17] analyzed examples from online journalism, blogs, and visualization research and proposed the design space of narrative visualization. They also brought up the idea of author-driven and reader-driven stories. The former has a strictly linear path through the visualization and includes no interactivity while the later is more flexible for users to create the story line. VisGuide balanced the author- and reader-driven approaches by letting users to choose their interested subsets and providing recommendations to help them form a structured story. Also, VisGuide adopt a tree view to present the story that can clearly show the search space in breadth and depth.

Visualization sequencing approaches [12, 9, 17, 7, 8, 1, 3] often used utility functions to measure the transitions between two charts and recommended sequences that maximize the overall utility score. GraphScape [9] proposed utility functions based on the interpretation difficulty of visual encoding changes between charts and rewarded sequences ordered in a parallel structure [8]. VisPilot [12] evaluated the "deviation" in the data statistic metric and gave high utility scores if two charts have different data distributions. In all of these works, the weights for the features in the model are fixed, and hence are not suitable to produce visualization sequences that are customized to difference user's preference. On the contrary, VisGuide adopts data statistic properties to define chart features and interactively trains a regression model using labels given by users while they explore a data set. The resulting model can therefore adjust feature weights for each user and provide user-oriented recommendation results.

Figure 2: (A) **Sequence view** shows the generated visualization sequence tree. A chart with a blue border is the user-focused chart. If users add a chart from the recommendation view, the added chart will be placed at the next tree level of the focused chart. In each chart, a dark blue line/bar represents a subset of data points (filtered dataset) and a light blue line/bar represents overall data points (pre-filtered). The difference between these two distributions represents the Deviation information. The maximum and minimum data points are marked with dark blue border as point insight hints. The user-clicked data point is marked with red dot/bar. (B) **Recommendation view** shows the next Drill-down and Comparison charts. The leftmost chart of each expanded type is the highest ranked recommendation. Users can click on the "arrow" buttons to get lower-ranked recommendations. The chart will be added to the visualization sequence tree if users click on the "add" button next to the chart. (C) **Exploration view** shows a thumbnail of the sequence view. Users can toggle each node to display or hide its corresponding chart.

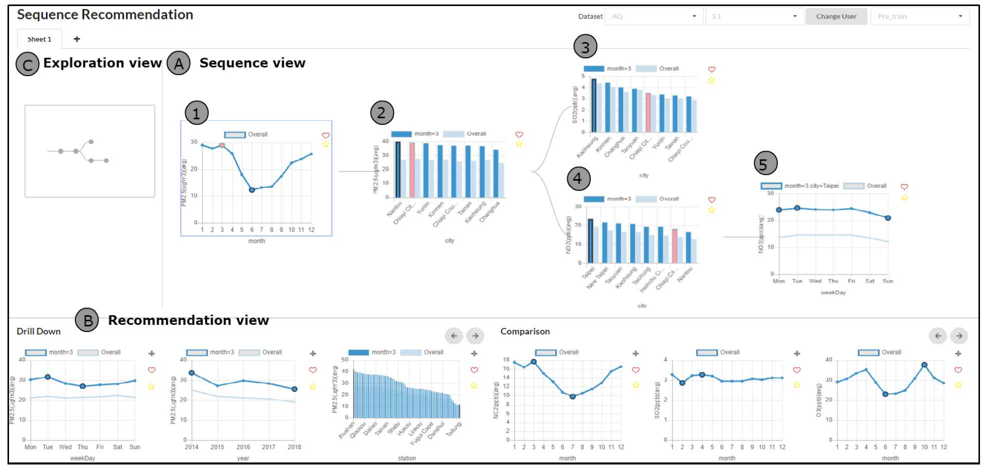

Figure 2: User interface.

Design Methodology

The sequence generation process in VisGuide is illustrated in Figure 1. We introduce each module below.

Chart Selection

Users can specify the *preference label* of a recommended chart through three actions: clicking on the ♥ button or ⋆ button on the chart, adding the chart to the sequence tree. We encode these actions to a 3-level numeric score, 1.0, 0.3, and 0.6. In this way, users can focus on their interested charts without having to rate all charts.

Candidate Charts Generation

When users click on a data point that they are interested in on a chart of the visualization sequence tree, the action triggers VisGuide to recommend next charts. The clicked point indicates users' interest on a particular data subset. To generate human comprehensible sequences that present interesting data subsets, VisGuide generates the next candidate charts by applying *Drill-down* and *Comparison* operations to the selected chart on the sequence tree. The design of VisGuide incorporates the findings from [8] regarding the *hierarchical structure* and the *parallel structure* which human uses in sequencing visualizations. By repeatedly adding a recommended chart to the sequence tree, users can easily create a structured drill-down story.

Drill-down operation zooms in to a user-interested data subset by applying the user-clicked data point as a filter condition. The output of the drill-down operation are candidate charts that share the same Y channel attribute (measure) but different X channel attribute from the user selected chart. For example, Chart 2 in Figure 2 is a drill-down chart of Chart 1.

Comparison operation facilitates users in comparing different measures of the same data subset. The operation generates *comparison charts* which share the same X channel and filter values, but different Y channel from the user selected chart. For example, Chart 3 in Figure 2 is a comparison chart of Chart 2.

User Preference Model Training

To learn a customized recommendation model for a user, VisGuide utilizes the preference labels given by the user during the chart selection process, and trains a linear regression model of chart features. This model is used to predict the user preference score on candidate charts and sort them in a user-oriented order. We first introduce the regression model and then chart features below.

Stochastic Gradient Descent Regression Model

VisGuide trains a linear regression model using the stochastic gradient descent (SGD) method [21]. The resulting model is used as the utility function to predict a user's preference score on each candidate chart. We define the utility function of a visualization as follows:

$$U(V) = w_0 + \sum_{i=1}^{n} w_i F_i^V + \epsilon, \tag{1}$$

where V denotes a visualization chart and w_i is the weight of the ith chart feature F_i^V of V. w_0 is the intercept and ϵ is the error term. The SGD algorithm updates the weights to minimize the loss function, which is the least square error with L2 regularization.

Chart Features

We design five chart features to describe a chart. The first two are data statistic features that measure the informativeness of each single chart, and the other features consider the context of a sequence. The following are the descriptions of the features.

(F1) Insight Significance measures the magnitude of *insights* in a chart. The insights of a chart may be point insights, each of which represents a data subset that is remarkably different from others (e.g., extreme or anomaly points), or trend insights such as ascending or descending. In this work, we only consider the point insights proposed in previous works [19, 21, 5, 4].

(F2) Deviation measures the difference between the probability distribution of a recommended candidate chart and that of the reference chart [12, 15, 21]. A recommended candidate chart shows stats of a filtered data subset, while its reference chart shows the stats of pre-filtered data. We use Jensen-Shannon divergence (JSD) to measure the difference of two distributions. Among the candidate charts, the one with larger JSD value is considered more interesting.

(F3) Granularity. A visualization sequence is more understandable if the charts in the sequence present the data from general to specific or reversely [7, 8, 9]. The granularity feature quantifies the degree of such transitions (e.g., general-to-specific or specific-to-general) from one chart to its following recommended candidate charts.

(F4) Consistence of generation operations. A visualization sequence is considered more contextual if the generation operation (i.e., drill-down or comparison) of more transitions in the sequence are the same [7, 8, 9]. This feature calculates the proportion of transitions in the sequence having the same generation operation.

(F5) Encoding Transitions. The relationship of dataset attributes between two consecutive charts is also impor-

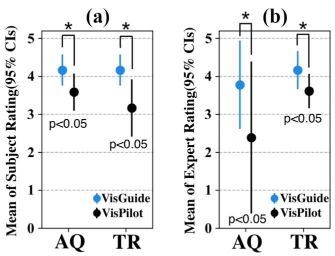

Figure 3: (a) Mean of subjects' self-ratings on the meaningfulness of data stories. (b) Mean of experts' ratings on the meaningfulness of data stories.

tant for recommending next charts. We record the channel encoding transition between two charts to capture a user's preference on the transition of the attributes. For example, if the X channel attribute of the parent chart is *City* and that of its children chart is *Station*, the value of the feature *X-Encoding-Change* will be $City2Station$.

Visual Encoding and Generalization
After finding the interesting data subsets, we need good visualization to present the data insights. VisGuide adopted the rules for meaningful visualizations proposed by [14] to decide the visual encoding of each chart. VisGuide can be applied to various datasets with nominal, quantitative, and temporal attributes since the design of chart features and visual encoding are based on the attribute types rather than designing for specific types of datasets.

Evaluation Study

We compare the quality of visualization sequences generated by VisGuide (VG) with those by VisPilot (VP) [12] as VP also aims to help users find a meaningful drill-down sequence. The main differences are the design principles between these two works: VP provides automatic recommendations at once while VG offers customized repeated recommendations via user interactions. To achieve a fair comparison, we use the same web interface and visual encoding (e.g., chart type and aggregation method) to display the recommendations by the two systems. We want to evaluate whether the participants' satisfaction and quality of the visualization sequences are better on customizedly generated sequences (by VG) than those on automatically generated ones (by VP). We used participants' self-ratings and domain experts' ratings to evaluate visualization sequences. We recruited 12 participants (6 males and 6 females), who are graduate students majoring in engineering, science, or management.

Procedure
Each participant used VG and VP to explore two different real-world datasets, the Air Quality (AQ) dataset and the Transactions of a Department Store dataset (TR), in two different trials. The ordering of the methods (VG, VP) and the datasets (AQ, TR) in the two trials are counterbalanced and randomized to avoid the bias from the ordering effect. In each trial, a participant had 20 minutes to freely explore a dataset. After each trial of exploration, participants were asked to report their findings and self-rate their findings' meaningfulness on a 5-point Likert scale. The self-ratings measured the participants' satisfaction. After the experiment, each participant was interviewed and asked to fill a post-study questionnaire to compare the performance of two systems, Participants would not know which system is VisGuide or VisPilot as they can only select an answer from three options: "the first system you used," "the second system you used," and "tie". We also invited two domain experts: an air quality expert, who is a graduate student majoring in Environmental Engineering, and a data analyst familiar with the transaction data of department stores, to evaluate the rationality of participants' findings on a 5-point Likert scale.

Results
Participants' self-ratings and Experts' ratings on findings. We performed Kruskal-Wallis test on the rating result due to the small sample size in each group (18 data points, consisting of the top 3 stories from each participant's self-rating result). Figure 3(a) shows the participants' self-rating scores on their findings. VG received significantly higher rating than VP in both datasets ($p = 0.0002$, $p < 10^{-6}$). This indicates that the participants were more satisfied with the visualization sequences generated by VG. Figure 3(b) shows the expert's ratings on the meaningfulness of the data stories.

	VG	VP	Tie
Q1	75%	8%	17%
Q2	83%	17%	0%
Q3	91%	0%	9%
Q4	58%	33%	9%
Q5	83%	17%	0%

Table 1: Preference of the participants' choices in the comparison questionnaire. VisGuide was preferred by the participants in all aspects.
Q1: Interestingness;
Q2: Reasonableness;
Q3: Comprehensiveness;
Q4: Less time spending;
Q5: Overall preference.

VG received significantly higher ratings than VP in both datasets ($p = 0.03$, $p = 0.014$). It suggests that with VG, users can find more reasonable data stories than VP.

Post-study questionnaire and interview. Table 1 lists the results from the questionnaire. VG was preferred in all aspects and the overall preference shows that over 80% of the participants like the data stories found in VG more than in VP. In the interview, 10 of 12 participants mentioned that they preferred exploring charts that interested them by manually choosing filters. Although VisPilot can provide charts with the most different distributions, there are still many charts in its sequence trees that are not interesting to users because the filter values sometimes make no sense to them.

Expert Interview

To evaluate whether our system could help domain experts explore data stories, we also invited the two experts to explore AQ and TR datasets with VisGuide respectively. After the exploration sessions, we conducted an interview with the experts. These experts reported that our system efficiently helps them organize the charts to construct visualization sequences, mainly because that VisGuide directly showed them the comparison and drill down charts. They could quickly scan through these recommended charts to identify meaningful charts and select charts to the sequence tree. Besides, the expert users mentioned that they could find interesting charts among the first few recommended charts. These interesting charts guide the expert users to discover interesting and/or surprising findings that are different from their previous knowledge. Both experts said that the tree view is useful when they needed to present the results to other people because it can clearly show the breadth and depth of the stories to make the events more understandable.

Discussion

Taking a balance between the author- and reader-driven storytelling approaches. VisGuide attempts to take the advantages from both the author- and reader-driven storytelling approaches, by designing an interactively-grown, trees-based display of the charts users selected from the recommendation list. Our *visualization tree* is more flexible and efficient because it is formed by the charts that interest users. As the tree grows with the user's exploration process, it automatically records their data exploration process. A drawback of the interactive exploration like VisGuide is that it takes more time to explore data at first. We plan to adopt collaborative filtering methods based on previous users' preferences to improve the initial recommendation result.

Diversity of the recommendations. In this work, we only consider the drill-down and comparison story types. We'll extend VisGuide to other sequencing types based on the design strategies proposed in [17] and increase the diversity of recommendation results to prevent users from being trapped in a converged preference result.

Conclusion

We present an assistive data exploration tool that guides users to generate meaningful visualization sequences. VisGuide implements an interactive learning model to learn a user's preference and is able to recommend suitable charts tailoring to the user's interest. VisGuide also provides a tree-structured view for a user to organize the multiple paths of visualization sequences that a user would typically encounter during the exploration process. The personalized model for the next chart recommendation and the tree-structured view have been shown useful in our user studies.

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