Design Considerations of Insight-Driven Dashboard Generation

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Abstract—Analytical dashboards are popular in business intelligence to facilitate insight discovery with multiple charts. However, creating an effective dashboard is highly demanding, which requires users to have adequate data analysis background and be familiar with professional tools, such as Power BI. To create a dashboard, users have to configure charts by selecting data columns and exploring different chart combinations to optimize the communication of insights, which is trial-and-error. Recent research has started to use deep learning methods for dashboard generation to lower the burden of visualization creation. However, such efforts are greatly hindered by the lack of large-scale and high-quality datasets of dashboards. In this work, we propose using deep reinforcement learning to generate analytical dashboards that can use well-established visualization knowledge and the estimation capacity of reinforcement learning. Specifically, we use visualization knowledge to construct a training environment and rewards for agents to explore and imitate human exploration behavior with a well-designed agent network. The usefulness of the deep reinforcement learning model is demonstrated through ablation studies and user studies. In conclusion, our work opens up new opportunities to develop effective ML-based visualization recommenders without beforehand training datasets.

Index Terms—Reinforcement Learning, Visualization Recommendation, Multiple-View Visualization

1 INTRODUCTION

Analytical dashboards have been broadly used in business intelligence to help data analysts explore and discover data insights with multiple-view visualizations (MVs) [29]. Even with the help of professional authoring tools, such as Tableau and Power BI, creating an effective dashboard is still a highly demanding task, requiring expertise in data analysis and visualization. Specifically, the analyst needs to explore the dataset, select appropriate data columns and visual encodings to configure charts, and investigate whether the charts are insightful. In addition, the analyst has to consider the relationship between charts to exhibit different perspectives of the dataset [44]. Such a process of exploratory data analysis for dashboard generation is trial-and-error [7].

To reduce the burden, many studies have investigated rule-based and machine learning-based (ML-based) methods for visualization recommendation. Rule-based methods, such as APT [20], CompassQL [48], and Voyager [47,49], translate well-established visualization design rules (e.g., expressiveness and effectiveness criteria [29]) to be programmable constraints for the recommendation. Differently, ML-based methods employ state-of-the-art models, such as decision trees [19] and deep neural networks [12,13,17], to learn common patterns of visual encodings from large-scale chart datasets [11,15]. Though useful in generating effective charts, these methods focus on single visualizations instead of MVs, where the relations between charts are important.

Towards the generation of MVs, a series of studies investigate the use of hand-crafted rules. For example, to tell data stories, Datashot [43] and Calliope [35] adopt statistics metrics (e.g., Pearson correlation coefficient) to extract facts from datasets and then generate charts according to the facts. These successful cases prove the usefulness of hand-crafted rules. Recently, deep learning-based methods have also been used to improve the efficiency of generating MVs. For example, MultiVision [33] trains deep neural networks to score the goodness of single charts. Then the single chart scoring is combined with customized metrics to generate multiple charts. In this method, the generation of MVs is conducted indirectly due to the lack of high-quality MVs datasets, which could harm the training process and results.

In this paper, we propose to use deep reinforcement learning to generate analytical dashboards, taking advantage of established visualization knowledge and efficient machine intelligence. We argue that applying reinforcement learning to such a scenario has several advantages. 1) Intuitive modeling. Reinforcement learning agents learn from environments through exploration, which is similar to the mechanism of exploratory visual analysis. Therefore, modeling the exploratory visual analysis process with reinforcement learning is natural. 2) Self-play training. With carefully designed environments, action spaces, and reward functions, agents can be constantly trained with different datasets and obtain a shared experience of dashboard generation, with no need for beforehand training data with labels. 3) Online recommendation. Due to a similar mechanism, a reinforcement learning-based recommendation system supports a swift switching between human steering and automation. When users update the dashboards by preference, the agents can generate subsequent recommendations promptly.

However, designing a reinforcement learning model for analytical dashboards is challenging. First, it lacks a well-established environment for “visualization agents” to explore and train. Different from training agents to play games (e.g., AlphaGo [37]), in which the winning and losing can explicitly measure the goodness of agent actions, there is no deterministic rule to evaluate the generated dashboards. Second, it is difficult to design an agent to imitate complex human behavior in generating dashboards, including configuring charts by multiple parameters (e.g., mark types, encoding types, data fields, and data transformations) and exploring the large space of chart combinations.

To address the above challenges, we developed System, a deep reinforcement learning-based recommendation system for analytical dashboards. For the first challenge, we investigated state-of-the-art design guidelines for MVs [27,44] and conducted a preliminary study with a collection of dashboard designs of Tableau and Power BI. From the study, we investigated how to use design guidelines for assessing dashboards. Built upon the guidelines and knowledge gained, we designed a dashboard playground, which scores the generated dashboards and provides an interface for the agents to explore the dashboard design space. For the second challenge, we formulated the exploratory dashboard generation to be a sequence prediction problem. Specifically, at each state, agents can decide the actions to take (e.g., adding or removing a chart) and configure chart parameters (e.g., chart types and encoding types). We designed a novel deep neural network to achieve the prediction. To improve training efficiency, we proposed a constrained sampling strategy to ensure the validity of generated charts while preserving the exploration uncertainty of the agents. To validate the usefulness of the proposed method, we conducted an ablation study for the model design and comparative experiments with a state-of-the-art dashboard generation system. We also analyzed the user feedback and reflected on designing automatic agents to generate analytical dashboards. In summary, we have four major contributions.

- A preliminary study that reviews practical dashboard designs and summarizes the design considerations for the recommendation.
- A reinforcement learning formulation for dashboard generation that features the definition of reward functions for evaluating the expressiveness and insightfulness of the dashboards.
- A novel deep neural network for agents to explore the actions and
parameters for generating dashboards.
• A series of quantitative and qualitative studies that validate the usefulness of the proposed approach and lessons learned in designing automatic agents for visualizations.

2 RELATED WORK

In this section, we introduce related studies from the perspectives of visualization recommendation, multiple-view visualization generation, and reinforcement learning for visualization.

2.1 Visualization Recommendation

Existing visualization recommendation approaches can be categorized into rule-based methods and ML-based methods [28, 52]. Rule-based methods utilize the principles in visualization theories to construct visual mapping. For example, APT [20] incorporates expressiveness and effectiveness criteria [8] into graphical languages to formulate visualizations. Show Me [21] and CompassQL [48] employ query techniques to enumerate visual encodings. Furthermore, Voyager [47, 49] adopts statistics and perceptual measures to rank the generated visualizations and supports interactive exploration.

ML-based methods incorporate machine learning models to predict the visual mapping. A number of methods formulate the visual mapping as a non-linear regression from hand-crafted data features to charts, such as VizML [14, 44], NL4DV [25], and wide-and-deep recommendation network [26]. Other methods formulate the recommendation as different problems, such as sequence-to-sequence translation [12, 55], learning-to-rank [19, 24, 39, 54], and knowledge graph [17, 27]. However, these recommendation methods mainly focus on generating a single chart, which might be insufficient for solving the visual analysis problems with high-dimensional data.

2.2 Multiple-View Visualization Generation

Multiple-view visualizations (MVs) are useful in visual analysis for their capability in representing different perspectives of data simultaneously. Numerous MVs, which refer to visual analytics (VA) systems, have been created to discover patterns and insights [4, 50]. Existing studies of visualization recommendation for VA systems focus on layout problems regarding organizing multiple views [53]. For example, Al-manee and Roberts [6] proposed a series of criteria to decompose the VA systems in the publications and quantify their layouts. Chen et al. [10] investigated view composition and configuration of the systems.

Existing studies of MV generation target to creating MVs from tabular data for insight discovery [16] or storytelling [13, 32]. For example, Voder [38] and QRec-NLI [22] adopts natural language processing models to extract data facts or recommending next-step queries for dashboard exploration. Zhao et al. [55] proposed ChartStory, a system that composes charts into comic-style visualizations. DataShot [43] generates data fact sheets with a template-based method for visual storytelling. Similarly, Calliope [35] obtains data insights with customized metrics and identifies the best ones using a Monte Carlo tree search. These rule-based methods can well integrate visualization domain knowledge into the design of metrics. Recent research also explores the generation of dashboards with deep learning. MultiVision [53] employs bidirectional long-term memory models to score and rank single charts for MV generation. In this work, we integrate deep learning methods and visualization knowledge to generate analytical dashboards. Specifically, we utilize the capability of deep neural networks in simulating complex environments and take advantage of well-established visualization design rules to score the generated visualizations.

2.3 Reinforcement Learning and Visualization

Reinforcement learning aims to train agents to take actions in specific environments so that the agents can gain the highest accumulated rewards. Given a current observation, Q-learning [45] is designed to predict the rewards that can be gained and choose the actions with the highest rewards. However, Q-learning can only handle a small number of observations and actions. To cope with the problems with complex situations, more variants based on deep learning have been proposed. For example, to handle the large observation space of game screens during playing Atari video games, Mnih et al. [23] proposed deep Q-learning. Though useful, deep Q-learning fails when there is a high-dimensional action space. The problem of instability during training also arises. A series of policy gradient methods [18, 22, 30, 31] have been proposed to address these problems. In this work, we choose to use asynchronous advantage actor-critic algorithm (A3C) [22], a state-of-the-art reinforcement learning framework, to handle the problem of dashboard generation, in which both observation space (i.e., dashboards with different chart combinations and variant chart numbers) and action space (i.e., generating chart configurations) are high-dimensional.

A few studies have used reinforcement learning models for visualization generation. For example, MobileVisFixer [51] adopts an explainable Markov decision model to optimize the layouts of visualizations on mobile devices. Bako et al. [6] also adopted a Markov decision process model to recommend potential D3 syntax for authoring visualizations. Tang et al. [40] adopted reinforcement learning to create storyline layouts. Shi et al. [34] and Wei et al. [46] used reinforcement learning to predict next-step operations of chart editing. In this work, we target the dashboard, a multiple-view visualization with larger design space, and formulate the problem of dashboard generation to be a reinforcement learning problem.

3 DESIGN OF SYSTEM

To design an effective recommendation system, we conducted a preliminary study to understand the current practices of analytical dashboards and derive the design considerations of recommendation systems.

3.1 Preliminary Study

Existing studies for visualization designs mainly focus on visualization genres such as infographics [9], storylines [41], and data stories [36, 43]. There are few studies that investigate the design patterns for analytical dashboards [5, 29]. Therefore, we start with a preliminary study to gain an overview of the design practices.

We first collected dashboards with the most number of “likes” from the official galleries of Tableau [2] and Microsoft Power BI [1], which contain hundreds of high-quality examples. Not all examples in the galleries are dashboards and some of them are posters (telling stories mainly with text and charts only for assistance) or infographics (with only one well-designed view). Therefore, we carefully filtered the dashboards from the galleries. Finally, we obtained 40 Tableau dashboards and 50 Power BI dashboards.

Second, we analyzed the dashboards from visual and data presentation perspectives. Based on the design guidelines of multiple-view visualizations [44], a good design should follow the rules of diversity, complementarity, decomposition, and parsimony. We opted to understand the collected designs concerning these rules.

Diversity. We analyzed how diverse chart types are used to represent the data columns. A dashboard usually contains multiple views, and each comprises one or multiple charts or components (e.g., text and table). Therefore, for each dashboard, we annotated the types of charts and components, as shown in Fig. 1A. From the results, we discovered
that the bar chart is the most commonly used chart type, followed by line charts, maps, and donut charts. Text components are the second most common, used to summarize the insights in the charts or show key indicators independently. The table components are usually used to show raw data directly.

Parsimony. The rule of parsimony refers to minimizing the number of views while preserving effectiveness and expressiveness. Therefore, we counted the view numbers of the collected dashboards (Fig. 1(C)). We discovered that most dashboards are composed of 3-6 views. Only a small number of dashboards contain more than 8 views.

Complementarity & Decomposition. Complementarity refers to how charts complement each other to exhibit different perspectives of the datasets. Based on the definition in the prior study [53], we regard two views to be complementary to each other when they visualize different data columns. For example, a view encodes columns A and B and another view encodes columns C and D. On the contrary, decomposition refers to analyzing complex data with multiple charts, such as chunking the data or applying different aggregation methods to a data column. These charts will share the same data column. When investigating the examples in-depth, we discovered that few dashboards include views complementary to each other, because the dashboards usually concern specific “key columns”. In fact, in most dashboards (96.7%), all their views are related to one or two data columns.

From the analysis above, we understood that to design an effective dashboard, it is encouraged to identify a topic (i.e., a key column) and configure composed charts to discover insights surrounding the topic [43]. Besides, it is necessary to introduce adequate chart diversity to enhance the expressiveness but avoid a large chart number.

3.2 Design Considerations

Based on previous empirical studies [27][44], recommendation systems [35][53], and our preliminary study on current practices, we derive design considerations of a recommendation system for dashboards.

DC1 Generate valid dashboards automatically. The dashboards should be automatically generated with specific characteristics. Based on the preliminary study, an analytical dashboard commonly features multiple charts with diverse types and components of text and table. The charts should also follow effectiveness rules [20]. For example, bar charts are suitable to visualize the data of a nominal column and a quantitative column.

DC2 Facilitate self-steering data insight discovery. In addition to merely visualizing the data with appropriate visual encodings, an effective dashboard is supposed to convey data insights. When generating the dashboard, the system should recognize data insights, such as high correlations and temporal distributions, and prioritize selecting charts with insights into the dashboard.

DC3 Enable direct manipulation on the recommendations. It is unlikely to generate dashboards that fulfill the requirements of all users. Therefore, users should be allowed to modify the dashboards directly. The system should provide an interface for users to customize the dashboards according to their preferences and add new charts in an exploratory manner.

DC4 Support online recommendation during exploration. Editions on the dashboard inherently exhibit user preferences, which provide additional conditions for the recommendation. Therefore, the system should be able to start from current dashboard configurations and explore the best dashboards accordingly. Furthermore, the system should promptly generate new recommendations after the modifications to ensure interaction efficiency.

Guided by these design considerations, we develop a recommendation system empowered by a deep reinforcement learning-based computation module. The computation module is built with a deep neural network that can generate valid charts (DC2) and discover data insights (DC2) automatically. To ensure the validity of the generated charts, we propose a novel constrained sampling method to apply rules to the sampling state (DC1). Besides, we carefully design insight rewards to encourage the discovery of insights during the exploration (DC2). On top of the computation module, we develop an interactive interface that allows users to edit the recommended dashboards (DC3). The user editions are then fed back to the computation module, and the module generates new recommendations based on the editions (DC4).

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