Multi-Criteria Optimization for Automatic Dashboard Design

Jiwon Choi and Jaemin Jo

1 Sungkyunkwan University, Suwon, South Korea

Abstract

We present Gleaner, an automatic dashboard design system that optimizes the design in terms of four design criteria, namely Specificity, Interestingness, Diversity, and Coverage. With these criteria, Gleaner not only optimizes for the expressiveness and interestingness of a single visualization but also improves the diversity and coverage of the dashboard as a whole. Users are able to express their intent for desired dashboard design to Gleaner, including specifying preferred or constrained attributes and adjusting the weight of each criterion. This flexibility in expressing intent enables Gleaner to design dashboards that are well-aligned with the user’s own analytic goals leading to more efficient data exploration.

1. Introduction

Exploratory visual analysis (EVA) is an iterative process of identifying questions, examining questions, and clarifying one’s hypothesis with visualizations [BH19]. Also, analytic dashboards are used to display and explore complex data using interactive visualizations [BFAR22]. However, designing analytic dashboards for EVA is not only tedious but also a mistaken-prone process that often produces false findings [ZZZK18, BH19].

Recently, several automated systems have been proposed to design analytic dashboards quickly and accurately. For example, MultiVision [WWZ’21] leverages data table and provenance data as a training set of LSTM-based models to design analytic dashboards automatically. Another recent example is Dashbot [DWQW22], which employs deep reinforcement learning to imitate exploratory analytic processes of humans. However, these systems lack the ability to incorporate the user’s analytic tasks such as understanding data, analyzing relationships, and hypothesis formulation [BH19] into the dashboard design process; indeed, these systems are fully automatic and the users are not able to control or adjust to express their intent.

In contrast, MEDLEY [PSS23] incorporates user intents into an automatic dashboard design system using a fixed collection that was derived from the user study. However, users are still unable to customize the recommendation algorithm to satisfy their more sophisticated intents; for example, users may want to include or exclude specific data transformations, and chart types. Also, users want to select which statistical features are in consideration.

We present Gleaner, a system that automatically designs analytic dashboards considering inter and intra-visualization dashboard design criteria. We first formulate the dashboard design process as the interaction between three main components: Generator, Oracle, and Explorer. Then, we elaborate on the four design criteria, namely Specificity, Interestingness, Diversity, and Coverage with each having its own scoring function that can evaluate a dashboard design. The user specifies their analytic goals as the weights between the criteria, and the three components search for a dashboard that maximizes the total score.

2. Automatic Dashboard Design Framework

Inspired by the evaluation-focused framework for single visualization recommendation by Zeng et al. [ZMD’21], we defined our automatic dashboard design framework as an interaction of the following three primary components: (1) Generator, which stochastically queries single or multiple charts from design space. (2) Oracle, which scores and ranks the candidate dashboard based on multiple criteria. Users can control the weight between scoring functions to make Oracle well-aligned with users’ analytic goals. (3) Explorer, which explores the search space of candidate dashboards that are combinations of single charts generated by Generator. Each component is implemented using Python, pandas, NumPy, and Altair [VGH’18].

3. Dashboard Design Criteria

In contrast to single visualization recommendation systems, dashboard design systems have to consider not only the usefulness of individual charts but also the interrelationships between them [WBBK00]. To address this challenge, we surveyed design guidelines or objectives for the analytic dashboard from prior studies and defined the four dashboard design criteria as follows:

Specificity quantifies the degree to which a dashboard fulfills the user’s analytical goals. Battle et al. argue that the spectrum of analytic goals in EVA ranges from having no specific goals to having clear prior goals and hypotheses. Furthermore, analysts can adjust their goals flexibly within this spectrum [BH19]. To accommodate
Figure 1: The interface of Gleaner. (A) Users can express their analytic goals by controlling the weight between criteria. (B) Also, users can specify the constraints and preferences to express their sophisticated intents. (C) Gleaner composes multiple charts as a dashboard and displays them for users. The interface of Gleaner is implemented using TypeScript, React, and Vega-Lite [SMWH16].

4. Conclusion and Ongoing Work

In this paper, we present Gleaner built upon four dashboard design criteria. We also present a user interface for Gleaner where users can control the weight of each criterion to reflect their requirements and preferences. We plan to extend our work by devising an efficient search algorithm that accelerates the automatic design process. Additionally, we plan to perform user studies to evaluate our system with data analysts and examine the ecological validity of Gleaner.
Acknowledgement

This work was partly supported by Institute of Information communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No. 2019-0-00421, AI Graduate School Support Program (Sungkyunkwan University)) and the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. NRF-2022R1F1A107310111).

References


