Multi-Criteria Optimization for Automatic Dashboard Design

Jiwon Choi [1] and Jaemin Jo [1]

[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 [BFAR*22]. 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 [WBWK00]. 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

© 2023 The Authors.
Proceedings published by Eurographics - The European Association for Computer Graphics.
This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

DOI: 10.2312/evp.20231064

delivered by EUROGRAPHICS DIGITAL LIBRARY www.eg.org diglib.eg.org

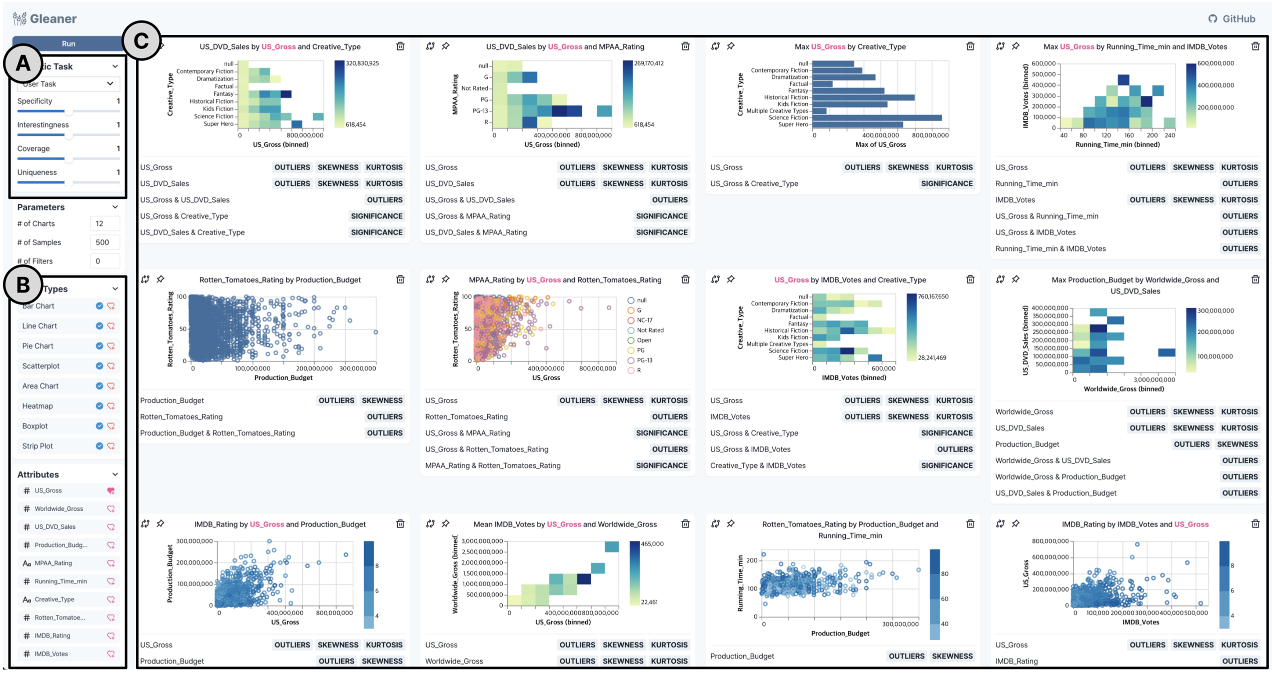

Figure 1: *The interface of Gleaner. (A) Users can express their analytic goals by controlling the weight between criteria. (B) Also, users can specify the constraints and preferences to express their sophisticated intents. (C) Gleaner composes multiple charts as a dashboard and displays them for users. The interface of Gleaner is implemented using TypeScript, React, and Vega-Lite [SMWH16].*

this characteristic of EVA, *Gleaner* allows users to specify their intent with constraints and preferences. User-specified constraints are used to distinguish which charts should or should not be included in a dashboard by including or excluding constraints from *Generator*'s generation process. Also, *Oracle* considers the user's preferred chart specifications, such as attributes, aggregation types, and filters by assigning higher scores to candidate dashboards that include the user's preferred chart specifications. For example, if the user specifies constraints and preferences as **Constraint**: {Exclude *Bar Chart* } and **Preference**: { *IMDB Votes* , *Mean* }, *Generator* exclude *Bar Chart* while generating candidate dashboards and *Oracle* scores higher if each chart contains *IMDB Votes* and *Mean* .

Interestingness measures the number of statistically significant insights each chart shows. Discovering intriguing insights from data is a key objective of the EVA. However, it is common for users to come across false insights during the EVA process [ZZZK18]. To mitigate false insights and facilitate insight discovery, we utilize statistical metrics inspired by prior insight-based visualization recommendation systems [DHPP17, HRM*21]. *Oracle* performs a predetermined set of statistical tests on the data that each visualization of a dashboard shows and gives a score proportional to the number of statistically significant findings. For instance, if there is a significant difference in the average of *US Gross* by *MPAA Rating* , *Oracle* assigns a high *interestingness* score to this chart.

Diversity measures how different the charts in a dashboard are from each other. The diversity of dashboards is one of the primary reasons for using dashboards instead of single-view complex visualization [WBWK00]. Compared with a previous system [DWQW22] where only the types of charts are considered, our system takes a more comprehensive approach by also considering attributes, aggregation types, and filters applied on a visualization. *Oracle* measures the diversity of the dashboard using Jaccard distance between every single chart.

Coverage quantifies how exhaustive a dashboard represents the underlying data. Analysts often strive for completeness of coverage in their analysis and use a systematic approach to measure their progress [PS08]. Furthermore, Sarvghad et al. proposed that coverage information can assist analysts in exploring additional analytic questions and findings [STM16]. *Oracle* takes into account the coverage of the data by assessing the ratio of items appearing in the dashboard.

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*.

© 2023 The Authors.
Proceedings published by Eurographics - The European Association for Computer Graphics.

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

[BFAR*22] BACH B., FREEMAN E., ABDUL-RAHMAN A., TURKAY C., KHAN S., FAN Y., CHEN M.: Dashboard design patterns. *IEEE Transactions on Visualization and Computer Graphics 29*, 1 (2022), 342–352. 1

[BH19] BATTLE L., HEER J.: Characterizing exploratory visual analysis: A literature review and evaluation of analytic provenance in tableau. In *Computer Graphics Forum* (2019), vol. 38, Wiley Online Library, pp. 145–159. 1

[DHPP17] DEMIRALP C., HAAS P. J., PARTHASARATHY S., PEDAPATI T.: Foresight: Recommending visual insights. *Proceedings of the VLDB Endowment 10*, 12 (2017). 2

[DWQW22] DENG D., WU A., QU H., WU Y.: Dashbot: Insight-driven dashboard generation based on deep reinforcement learning. *IEEE Transactions on Visualization and Computer Graphics 29*, 1 (2022), 690–700. 1, 2

[HRM*21] HARRIS C., ROSSI R. A., MALIK S., HOFFSWELL J., DU F., LEE T. Y., KOH E., ZHAO H.: Insight-centric visualization recommendation. *arXiv preprint arXiv:2103.11297* (2021). 2

[PS08] PERER A., SHNEIDERMAN B.: Systematic yet flexible discovery: guiding domain experts through exploratory data analysis. In *Proceedings of the 13th International Conference on Intelligent User Interfaces* (2008), pp. 109–118. 2

[PSS23] PANDEY A., SRINIVASAN A., SETLUR V.: Medley: Intent-based recommendations to support dashboard composition. *IEEE Transactions on Visualization and Computer Graphics 29*, 1 (2023), 1135–1145. doi:10.1109/TVCG.2022.3209421. 1

[SMWH16] SATYANARAYAN A., MORITZ D., WONGSUPHASAWAT K., HEER J.: Vega-lite: A grammar of interactive graphics. *IEEE Transactions on Visualization and Computer Graphics 23*, 1 (2016), 341–350. 2

[STM16] SARVGHAD A., TORY M., MAHYAR N.: Visualizing dimension coverage to support exploratory analysis. *IEEE Transactions on Visualization and Computer Graphics 23*, 1 (2016), 21–30. 2

[VGH*18] VANDERPLAS J., GRANGER B., HEER J., MORITZ D., WONGSUPHASAWAT K., SATYANARAYAN A., LEES E., TIMOFEEV I., WELSH B., SIEVERT S.: Altair: interactive statistical visualizations for python. *Journal of Open Source Software 3*, 32 (2018), 1057. 1

[WBWK00] WANG BALDONADO M. Q., WOODRUFF A., KUCHINSKY A.: Guidelines for using multiple views in information visualization. In *Proceedings of the Working Conference on Advanced Visual Interfaces* (2000), pp. 110–119. 1, 2

[WWZ*21] WU A., WANG Y., ZHOU M., HE X., ZHANG H., QU H., ZHANG D.: Multivision: Designing analytical dashboards with deep learning based recommendation. *IEEE Transactions on Visualization and Computer Graphics 28*, 1 (2021), 162–172. 1

[ZMD*21] ZENG Z., MOH P., DU F., HOFFSWELL J., LEE T. Y., MALIK S., KOH E., BATTLE L.: An evaluation-focused framework for visualization recommendation algorithms. *IEEE Transactions on Visualization and Computer Graphics 28*, 1 (2021), 346–356. 1

[ZZZK18] ZGRAGGEN E., ZHAO Z., ZELEZNIK R., KRASKA T.: Investigating the effect of the multiple comparisons problem in visual analysis. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (2018), pp. 1–12. 1, 2

© 2023 The Authors.
Proceedings published by Eurographics - The European Association for Computer Graphics.