BOLT: A Natural Language Interface for Dashboard Authoring

Arjun Srinivasan and Vidya Setlur

Tableau Research, USA

Abstract

Authoring dashboards is often a complex process, requiring expertise in both data analysis and visualization design. With current tools, authors lack the means to express their objectives for creating a dashboard (e.g., summarizing data changes or comparing data categories), making it difficult to discover and assemble content relevant to the dashboard. Addressing this challenge, we propose the idea of employing natural language (NL) for dashboard authoring with a prototype interface, BOLT. In this paper, we detail BOLT's design and implementation, describing how the system maps NL utterances to prevalent dashboard objectives and generates dashboard recommendations. Utilizing BOLT as a design probe, we validate the proposed idea of NL-based dashboard authoring through a preliminary user study. Based on the study feedback, we highlight promising application scenarios and future directions to support richer dashboard authoring workflows.

CCS Concepts

• ***Human-centered computing*** → ***Visualization; Interaction techniques; Natural language interfaces;***

1. Introduction

Dashboards, often described as a "*visual display of the most important information needed to achieve one or more objectives*" [Few06] are ubiquitous across domains [SCB*18]. Despite their prevalence, the process of authoring dashboards remains challenging, requiring expertise in both data analysis and visualization design. Dashboard authors often need to explore and understand the data, author individual charts or views, and then combine the individual views into a coherent dashboard. Recent work has shown that going beyond individual view recommendations (e.g., [MHS07,WMA*15,SST*21]) and recommending collections of views and filtering widgets based on dashboard intents or objectives can effectively assist dashboard authoring [PSS23]. However, expressing *dashboard objectives* (e.g., creating a dashboard that summarizes data changes over time) and identifying content relevant to those objectives remains an open challenge.

Natural language interfaces (NLIs) have shown promise in helping users express their data-related goals as natural language (NL) utterances to generate visualizations [SSL*22]. NLIs can be particularly helpful in a scenario like dashboard authoring, where a set of complex, multi-step analytical inquiries can be simply expressed in plain language. An NLI for dashboard authoring could enable authors to express their high-level dashboard objectives as NL utterances (e.g., "*I want to show an overview of the company performance*," "*Display an analysis of highest grossing movies*") and recommend a relevant set of visualizations in response.

Building upon this premise, we explore the idea of using NL input for dashboard authoring with a prototype interface, BOLT. Specifically, we first formulate a list of design goals for supporting NL-based dashboard authoring by reviewing prior work on visualization recommendations and NLIs for visualization. We then describe the design and implementation of BOLT, an NLI for dashboard authoring that maps input utterances to popular dashboard objectives, generating a set of dashboard recommendations. Using BOLT as a design probe, we conducted a preliminary user study to validate the proposed idea of NL-based dashboard authoring. Participant feedback confirmed that NLIs like BOLT can support fast and flexible dashboard authoring and assist authors with varying levels of expertise with visualization tools.

2. Related Work

NLIs for visualization. Numerous research efforts have explored how NLIs can support analytical inquiry by producing visualizations [SLJL10, GDA*15, HSTD17, STD19, TS19, YS19, NSS20, SNL*21]; a detailed review of which can be found in survey manuscripts such as [SS17, SSL*22]. While these NLIs present different capabilities, they typically share the common approach of generating *individual* visualizations using a combination of data attributes and low-level analytic tasks [AES05] inferred from an input utterance. We extend this line of research on NLIs for visualization by investigating a novel use case of dashboard authoring. Specifically, we contribute a system that maps utterances to higher-level dashboard authoring objectives (e.g., change analysis, comparison) compared to low-level analytic tasks (e.g., sorting, finding correlation) in prior work [SLJL10, GDA*15, SBT*16, NSS20]. In this paper, we describe linguistic challenges and considerations for interpreting NL queries for these higher-level dashboard objectives. Additionally, by focusing on dashboards (as opposed to singleton charts in prior systems), we also illustrate how NLIs can present multiple view and widget recommendations in response to a single query and allow users to mix-and-match system recommendations to customize the output.

Dashboard and Multi-View Visualization Recommendation Systems. Despite being an established topic of interest among visualization practitioners [WSC17, Few06], studies have highlighted a scarcity of research on dashboard design and systems [SCB*18, TBFGC21, BFAR*22]. In response, a recent surge of systems has explored the idea of content recommendations to aid dashboard authoring. For instance, MultiVision [WWZ*21] and Dashbot [DWQW22] recommend a group of views based on underlying data patterns and any user-selected data attributes. Medley [PSS23] recommends collections of views and widgets for a given combination of data attributes and/or dashboard intents (e.g., measure analysis, change analysis). Supporting rapid dashboard design, LADV [MMG*20] helps author dashboards by generating templates based on example images and roughly-drawn sketches. We contribute to this growing body of work on intelligent dashboard authoring tools by designing an interface that recommends dashboards based on NL input. Specifically, the proposed NL-based approach helps authors explore data during the dashboard authoring process by interpreting their high-level dashboard objectives expressed in plain language and returning relevant sets of views.

3. BOLT

3.1. Design Goals

We reviewed prior work on NLIs for visualization (e.g., [SLJL10, GDA*15, STD19, SNL*21]) and multi-view visualization systems and guidelines (e.g., [QH17, WBWK00, DWQW22, PSS23]) to compile a set of four goals that motivate BOLT's initial design.

DG1. Recommend multiple candidate dashboards and views. Dashboard authoring can be a subjective task where a predefined single collection of views and widgets may not always exactly map to the author's goals [PSS23]. Rather than recommending one single 'best' dashboard for an analytical inquiry, the interface should recommend a set of dashboard candidates and views for the author to choose from or further refine.

DG2. Support linguistic variations and ambiguity. Prior work has shown that people tend to use a variety of phrasings when expressing their intent in NL utterances and that these utterances are often ambiguous [GDA*15, STD19, SNL*21]. Hence, the interface should accommodate phrasing variations (e.g., "*Sales Overview*" vs. "*Generate a dashboard showing an overview of the company's sales*" should generate the same dashboard) and ambiguous utterances (e.g., an utterance like "*Company performance overview*" is ambiguous because the term 'performance' can map to multiple attributes such as `Sales`, `Profit`, etc.), showing the provenance of how these utterances are interpreted.

DG3. Provide reasonable defaults in the generated dashboards. Users of dashboard authoring tools, particularly novices, often lack knowledge about good dashboard design practices [BFAR*22, PSS23]. The interface should reduce friction in the dashboard authoring process by implicitly incorporating interaction and design guidelines for dashboards and multi-view displays [QH17, WBWK00, Rob98] (e.g., using consistent colors and scales across charts, optimizing the layout, enabling multi-view coordination).

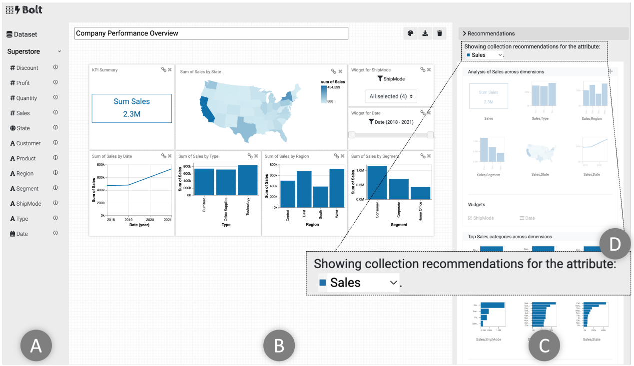

Figure 1: *BOLT's user interface. (A) Data panel, (B) the dashboard canvas, and (C) a collapsible recommendation panel. Views and widgets added to the canvas are implicitly organized in a grid layout and are faded out in the recommendation panel. A dropdown menu (D) is presented at the top of the recommendation panel to resolve erroneous attribute inferences.*

DG4. Enable multi-modal repair and refinement. Prior work on dashboard authoring tools has shown that authors appreciate the ability to fine-tune the dashboard design [WWZ*21, PSS23, DWQW22]. Studies with NLIs have also shown that making authors aware of the interpretation logic or errors and giving them the ability to rectify these errors through interactive widgets can improve system accuracy and user confidence [GDA*15, SBT*16]. In addition to recommending multiple candidate dashboards incorporating popular design guidelines, the interface should also provide direct manipulation affordances to update its default responses.

3.2. System Overview and Examples

Figure 1 shows BOLT's interface comprising of a data panel on the left, the main canvas, and the recommendation panel on the right. Typing an NL utterance in the text box at the top of the canvas (Figure 1B-top) and pressing the "enter" key invokes the system's interpretation of the utterance. The recommendation panel (Figure 1C) shows previews of the system recommendations, and a dashboard author can add content from the recommendation panel to the canvas (**DG1**). Once items are on the canvas, authors can refine the dashboard by dragging, resizing, or removing objects (**DG4**) and also export (⬇) the dashboard as an interactive web page.

BOLT is implemented as a web application that accepts any tabular CSV dataset as input. Visualizations in the tool are created using Vega-Lite [SMWH16]. Below we briefly describe how BOLT generates dashboards based on NL utterances.

Dashboard Objectives and Collection Templates. BOLT currently supports five dashboard objectives derived from Pandey et al.'s dashboard intent framework [PSS23]. These include:

- *Overview of Measure(s).* This dashboard objective typically involves 1–3 quantitative attributes (measures) and displays a set of views summarizing those measures across other categorical, temporal, and geographic attributes in the dataset. Figure 1A illustrates a dashboard focusing on this objective.
- *Change Summary.* Dashboards corresponding to this objective contain a set of views and widgets that highlight changes in a

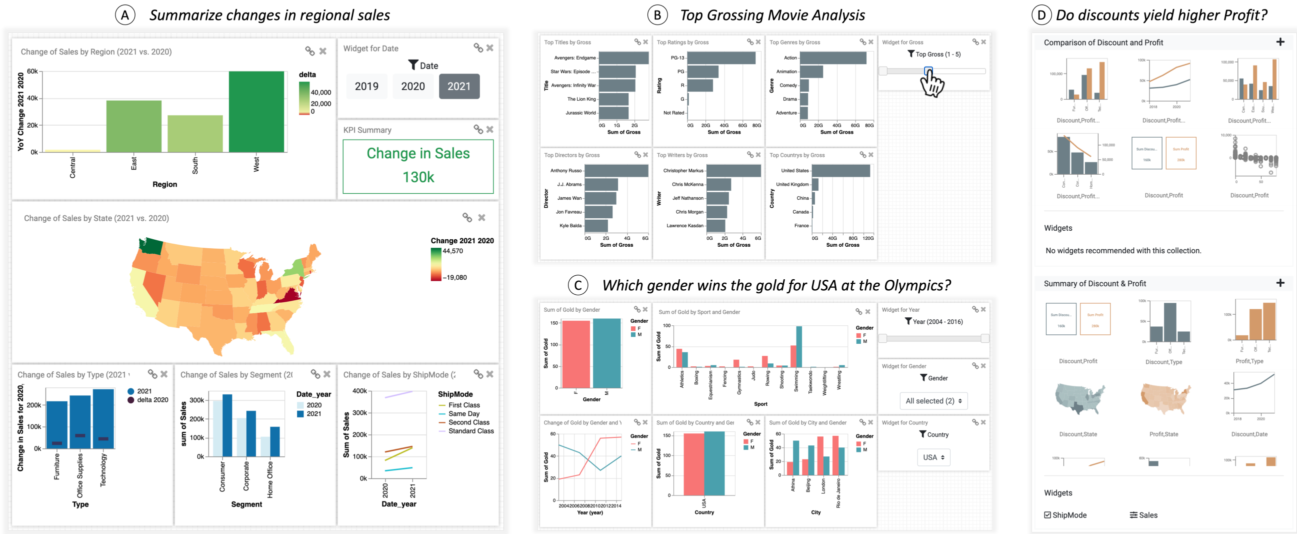

Figure 2: BOLT*'s responses for utterances in the context of different datasets, including sales (A, D), movies (B), and Olympics medal winners (C). Utterances in (A)-(C) convey both attributes and objectives, whereas the utterance in (D) only references attributes and does not clearly state the dashboard objective.*

measure's value over time across other attributes in a dataset. Figure 2A shows an example of such a dashboard that displays the year-over-year change in the measure `Sales`.

- *Top N.* This objective is facilitated through dashboards that showcase the top data categories for a specific measure. An example is shown in Figure 2B, where the dashboard displays top categories for the `Gross` measure.
- *Dimension Comparison.* Dashboards focusing on this objective typically contain a set of views and widgets that facilitate comparison between values for a categorical attribute (dimension). Figure 2C presents an example dashboard for this objective comparing the values for the dimension `Gender`.
- *Measure Comparison.* Dashboards that map to this objective often present a set of views that enable comparison between two measures to understand their relationship and underlying data trends. Figure 2D-top illustrates an example of this type of dashboard comparing the measures `Discount` and `Profit`.

Each objective is mapped to collection templates comprising a set of views and filtering widgets. We defined the templates based on an existing survey of popular dashboards created with mainstream visualization tools like Tableau and Microsoft Power BI [PSS23]. For instance, as shown in Figure 1B, the template for the *Overview of a single measure* objective contains a data summary view, a map, one line chart, three bar charts, and two filter widgets.

Interpreting NL Utterances. BOLT's parser removes stopwords (e.g., 'a,' 'the') and conjunctions/disjunctions (e.g., 'and,' 'or') from the utterance and extracts a list of N-grams (e.g., "*Company Performance Overview*" → [Company], [Performance], [Company Performance], etc.). To detect attribute tokens in the utterance, the system compares the N-grams to available data attributes looking for both syntactic (e.g., misspellings) and semantic similarities (e.g., synonyms) using the Levenshtein distance [YB07] and the Wu-Palmer similarity score [WP94], respectively.

The parser uses a combination of a grammar- and lexicon-based approach to infer dashboard objectives. Specifically, BOLT performs parts-of-speech tagging and generates a dependency tree to understand relationships between words in the input utterance. The extracted tags and dependencies are then matched against a predefined set of grammar patterns (e.g., "*summary of changes in <measure>*," "*<measure> versus <measure> analysis*") and keywords (e.g., 'change,' 'compare,' 'top') corresponding to the five objectives listed above.

BOLT can thus interpret a wide range of dashboard specification utterances spanning different phrasings (**DG2**) and accommodate misspellings and synonyms for data attributes, as highlighted through utterances in Figure 2A-C. For instance, the phrase 'Summarize changes' in the utterance in Figure 2A matches the lexicon for the *Change Summary* objective, resulting in the system recommending a yearly change analysis dashboard for the measure `Sales` (also referenced in the utterance). Similarly, the word 'Top' in Figure 2B helps BOLT infer a *Top N* objective, resulting in the displayed dashboard containing a series of sorted bar charts. Lastly, the grammar of the utterance in Figure 2C matches a phrasing template for the *Dimension Comparison* objective, and the dependencies between terms enable the system to infer `Gender` as the focus dimension and `Gold` as the focus measure.

There may, however, be cases where the input utterance does not contain terms matching data attributes or is phrased such that they do not map to predefined objectives. BOLT also includes safeguards for such scenarios and "guesses" attributes or objectives based on ambiguous utterances (**DG2**). For instance, when an objective is detected from an utterance but there is no reference to attributes, the system guesses the primary attribute type that a dashboard for the inferred objective focuses on. Consider the utterance "*Company Performance Overview*." Here, the term 'overview' suggests the *Overview of measure(s)* objective but there is no attribute mentioned in the utterance as the words 'company' and 'performance' do not match any attributes listed in Figure 1A. In such cases, similar to prior data- and insight-based recommendation systems [DWQW22, PSS23], BOLT computes a series of statistical metrics (e.g., the standard deviation to characterize value distributions, z-scores to detect trends) for all possible measures (e.g., `Profit`, `Sales`, `Discount`) that can fit the objective's collection template and selects the attribute yielding the highest score (in this case, `Sales`). However, since the system's interpretation may not match the user's mental model, BOLT also provides a direct manipulation widget for authors to update the default attributes and get an updated set of recommendations (**DG4**, Figure 1D).

Now consider an alternative utterance "*Do discounts yield higher profits?*" that explicitly references data attributes (`Discount`, `Profit`) but does not map to a predefined objective. Detecting the two measures, BOLT infers *Measure Comparison* and *Overview of Two Measures* as potential objectives the author is interested in, recommending relevant collections (Figure 2D). In cases where BOLT is unable to detect both attributes and objectives (e.g., "*Show a dashboard for this dataset*"), the interface responds with a message noting that it could not interpret the utterance and asks authors to try a different utterance.

Generating Dashboards. When BOLT infers attributes and objectives from an utterance, the interface automatically adds the first recommended collection to the canvas. In cases like Figure 2C where the utterance includes value references such as 'USA,' as with the `Country` dropdown menu at the bottom-right, BOLT also filters the dashboard by the specified value if a corresponding widget is available in the collection. For ambiguous utterances, the interface only populates the recommendation panel, allowing authors to first assess the recommendations and then choose the content they want to add to the canvas (**DG1**, **DG4**).

When content is added to the canvas, BOLT computes a grid layout that shows views most relevant to the input utterance first (e.g., difference bar chart in Figure 2A), maximizes space for maps and charts with a large number of categories (e.g., map and grouped bar chart in Figures 2A, 2C, respectively), and attempts to group filtering widgets in one location to the right of the views. The interface also implicitly configures interactive links between the views to facilitate actions like brushing and linking. While BOLT applies these design rules as smart defaults, authors can manually override both the layout and the links between views (**DG4**).

4. User Feedback and Future Work

Using BOLT as a design probe, we conducted a preliminary user study with six participants (*P1-P6*) having varying levels of experience with dashboard authoring (three novices, one intermediate, and two experts). We had two goals for the study: 1) elicit feedback on the idea of NL-based dashboard authoring and 2) assess BOLT's current design and identify areas for improvement. Sessions were conducted remotely and lasted approximately 30 minutes. Participation in the study was voluntary and participants were recruited via Slack channels at a data analytics software company.

To avoid biasing participants and understand how they might naturally interact with an NLI, we only gave a brief introduction to the tool and asked participants to use NL to author dashboards in the context of three datasets (attached in supplementary material), discussing their reactions to system responses. After the trial phase, we demonstrated any unexplored system capabilities using additional utterances and concluded with a semi-structured interview focusing on the two study goals.

Participants issued a total of 14 utterances (2-3 per session), with 10 utterances being phrased as dashboard titles or keyword-style queries, three questions, and one command. All but two utterances that did not yield a response ("*Generate an interesting dashboard*" and "*GBR Metrics*") were successfully interpreted by BOLT. Among the 12 interpreted utterances, *Measure comparison* was the most frequently referenced objective (5), followed by *change summary* (4), *measure overview* (2), and *top N* (1). For feedback on the overall idea, participants were unanimously positive about the idea of using NL for dashboard authoring for: 1) bootstrapping users new to a dataset or visualization tools and 2) rapid ideation and prototyping as the key use cases. For instance, *P*5 said, "*When you're given a new dataset and you're not sure exactly about the direction you want to go, being able to ask simple questions or give it a dashboard title and do some of that quick ad-hoc analysis is great and is even faster than drag-and-drop.*" Alluding to the potential for fostering ideation and rapid prototyping, *P*2 compared BOLT to language generation models like GPT [BMR*20] and said, "*This is a great ideation tool for the analyst. They already know how to make individual views, but which are the interesting ones? What are interesting points that I can jump off of for a dashboard? This is a great way to play with options.*" Similarly, *P*3, a dashboard expert, commented, "*I could see myself using this to quickly generate a canvas to see what the data looks like and which views might go well together and I might also use this as an inspiration tool when I don't know much about the data.*"

Discussing areas for improvement, all participants noted that they would benefit from example utterances to help understand the system's capabilities. One direction for future work is to explore the design and generation of utterance recommendations [SS21] to enhance the discoverability and learnability of NL input during dashboard authoring. Five participants noted that they see BOLT's recommendations as a starting point and wanted the ability to specify or fine-tune individual views (e.g., adjust encodings, swap axis orientation). We intentionally did not support manual view specification in BOLT to specifically solicit feedback on NL input; integrating the NL experience with a manual view specification environment would enable more multimodal utility of the interface. We employed a heuristics- and template-based logic for NL interpretation and dashboard recommendation in the context of five dashboard objectives (Section 3.2), as this afforded a deterministic set of output for testing and feedback. However, future work is needed to generalize the system to a wider array of dashboard objectives and designs. Such generalization would entail updating the system heuristics (e.g., adding utterance templates, updating objective-to-collection mappings) and/or exploring machine- and deep learning-based techniques for NL interpretation [LTL*21, MS23] and dashboard design [LLW*22].

In conclusion, through the implementation and evaluation of BOLT, we illustrate the feasibility and potential of an NLI for dashboard authoring. We hope the work can guide future research on designing more expressive and intelligent dashboard authoring tools.

References

[AES05] AMAR R., EAGAN J., STASKO J.: Low-level components of analytic activity in information visualization. In *IEEE Symposium on Information Visualization.* (2005), IEEE, pp. 111–117. 1

[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. 2

[BMR*20] BROWN T., MANN B., RYDER N., SUBBIAH M., KAPLAN J. D., DHARIWAL P., NEELAKANTAN A., SHYAM P., SASTRY G., ASKELL A., ET AL.: Language models are few-shot learners. *Advances in neural information processing systems 33* (2020), 1877–1901. 4

[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. 2, 4

[Few06] FEW S.: *Information dashboard design: The effective visual communication of data*, vol. 2. O'reilly Sebastopol, CA, 2006. 1, 2

[GDA*15] GAO T., DONTCHEVA M., ADAR E., LIU Z., KARAHALIOS K. G.: Datatone: Managing ambiguity in natural language interfaces for data visualization. In *Proceedings of the 28th Annual ACM Symposium on Yser Interface Software & Technology* (2015), pp. 489–500. 1, 2

[HSTD17] HOQUE E., SETLUR V., TORY M., DYKEMAN I.: Applying pragmatics principles for interaction with visual analytics. *IEEE transactions on visualization and computer graphics 24*, 1 (2017), 309–318. 1

[LLW*22] LIN Y., LI H., WU A., WANG Y., QU H.: DMiner: Dashboard design mining and recommendation. *arXiv preprint arXiv:2209.01599* (2022). 4

[LTL*21] LUO Y., TANG N., LI G., TANG J., CHAI C., QIN X.: Natural language to visualization by neural machine translation. *IEEE Transactions on Visualization and Computer Graphics 28*, 1 (2021), 217–226. 4

[MHS07] MACKINLAY J., HANRAHAN P., STOLTE C.: Show me: Automatic presentation for visual analysis. *IEEE Transactions on Visualization and Computer Graphics 13*, 6 (2007), 1137–1144. 1

[MMG*20] MA R., MEI H., GUAN H., HUANG W., ZHANG F., XIN C., DAI W., WEN X., CHEN W.: Ladv: Deep learning assisted authoring of dashboard visualizations from images and sketches. *IEEE Transactions on Visualization and Computer Graphics 27*, 9 (2020), 3717–3732. 2

[MS23] MADDIGAN P., SUSNJAK T.: Chat2vis: Generating data visualisations via natural language using ChatGPT, Codex and GPT-3 large language models. *arXiv preprint arXiv:2302.02094* (2023). 4

[NSS20] NARECHANIA A., SRINIVASAN A., STASKO J.: NL4DV: A toolkit for generating analytic specifications for data visualization from natural language queries. *IEEE Transactions on Visualization and Computer Graphics 27*, 2 (2020), 369–379. 1

[PSS23] PANDEY A., SRINIVASAN A., SETLUR V.: MEDLEY: Intent-based recommendations to support dashboard composition. *IEEE Transactions on Visualization & Computer Graphics 29*, 01 (2023), 1135–1145. 1, 2, 3, 4

[QH17] QU Z., HULLMAN J.: Keeping multiple views consistent: Constraints, validations, and exceptions in visualization authoring. *IEEE Transactions on Visualization and Computer Graphics 24*, 1 (2017), 468–477. 2

[Rob98] ROBERTS J. C.: On encouraging multiple views for visualization. In *Proceedings of the IEEE Conference on Information Visualization.* (1998), pp. 8–14. 2

[SBT*16] SETLUR V., BATTERSBY S. E., TORY M., GOSSWEILER R., CHANG A. X.: Eviza: A natural language interface for visual analysis. In *Proceedings of the 29th annual symposium on user interface software and technology* (2016), pp. 365–377. 1, 2

[SCB*18] SARIKAYA A., CORRELL M., BARTRAM L., TORY M., FISHER D.: What do we talk about when we talk about dashboards? *IEEE Transactions on Visualization and Computer Graphics 25*, 1 (2018), 682–692. 1, 2

[SLJL10] SUN Y., LEIGH J., JOHNSON A., LEE S.: Articulate: A semi-automated model for translating natural language queries into meaningful visualizations. In *Smart Graphics: 10th International Symposium on Smart Graphics* (2010), Springer, pp. 184–195. 1, 2

[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

[SNL*21] SRINIVASAN A., NYAPATHY N., LEE B., DRUCKER S. M., STASKO J.: Collecting and characterizing natural language utterances for specifying data visualizations. In *Proceedings of the Conference on Human Factors in Computing Systems* (2021), pp. 1–10. 1, 2

[SS17] SRINIVASAN A., STASKO J.: Natural language interfaces for data analysis with visualization: Considering what has and could be asked. In *Proceedings of the Eurographics/IEEE VGTC conference on visualization: Short papers* (2017), pp. 55–59. 1

[SS21] SRINIVASAN A., SETLUR V.: Snowy: Recommending utterances for conversational visual analysis. In *The 34th Annual ACM Symposium on User Interface Software and Technology* (2021), pp. 864–880. 4

[SSL*22] SHEN L., SHEN E., LUO Y., YANG X., HU X., ZHANG X., TAI Z., WANG J.: Towards natural language interfaces for data visualization: A survey. *IEEE Transactions on Visualization and Computer Graphics* (2022). 1

[SST*21] SHEN L., SHEN E., TAI Z., SONG Y., WANG J.: TaskVis: Task-oriented visualization recommendation. In *Proceedings of EuroVis (Short Papers)* (2021), vol. 21, pp. 1–5. 1

[STD19] SETLUR V., TORY M., DJALALI A.: Inferencing underspecified natural language utterances in visual analysis. In *Proceedings of the 24th International Conference on Intelligent User Interfaces* (2019), pp. 40–51. 1, 2

[TBFGC21] TORY M., BARTRAM L., FIORE-GARTLAND B., CRISAN A.: Finding their data voice: Practices and challenges of dashboard users. *IEEE Computer Graphics and Applications* (2021). 2

[TS19] TORY M., SETLUR V.: Do what I mean, not what I say! design considerations for supporting intent and context in analytical conversation. In *IEEE conference on visual analytics science and technology (VAST)* (2019), pp. 93–103. 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. 2

[WMA*15] WONGSUPHASAWAT K., MORITZ D., ANAND A., MACKINLAY J., HOWE B., HEER J.: Voyager: Exploratory analysis via faceted browsing of visualization recommendations. *IEEE Transactions on Visualization and Computer Graphics 22*, 1 (2015), 649–658. 1

[WP94] WU Z., PALMER M.: Verbs semantics and lexical selection. In *Proceedings of ACL* (1994), pp. 133–138. 3

[WSC17] WEXLER S., SHAFFER J., COTGREAVE A.: *The big book of dashboards: visualizing your data using real-world business scenarios.* John Wiley & Sons, 2017. 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. 2

[YB07] YUJIAN L., BO L.: A normalized Levenshtein distance metric. *IEEE transactions on pattern analysis and machine intelligence 29*, 6 (2007), 1091–1095. 3

[YS19] YU B., SILVA C. T.: FlowSense: A natural language interface for visual data exploration within a dataflow system. *IEEE transactions on visualization and computer graphics 26*, 1 (2019), 1–11. 1