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Towards Multimodal Data Analytics: Integrating Natural Language into Visual Analytics

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Abstract

The continuous interaction between users and the system in visual analytics can be considered a dialogue. We propose the use of multiple two-way channels facilitated by a multimodal interface as a central aspect of interactive visualization design, in particular, the use of natural language with interactive visualization. We discuss key related concepts, potential benefits, challenges and opportunities that emerge as a research agenda for multimodal data analysis.

ACM Classification Keywords

Human-centered computing [Interaction design]:
Interaction design theory, concepts and paradigms

Introduction

The continuous interaction between users and systems in visual analytics can be considered a *dialogue* [10]. From the user side, the dialogue often happens through multiple one-way channels – selecting items with direct manipulation or modifying parameters with menus. The feedback that the system then returns, however, is mostly restricted to a one-way channel in the form of implemented visual encodings. This limits the quality and quantity of feedback that can be given to the user regarding the effects of his/her actions. Extending multimodal interaction to both sides is the challenge that

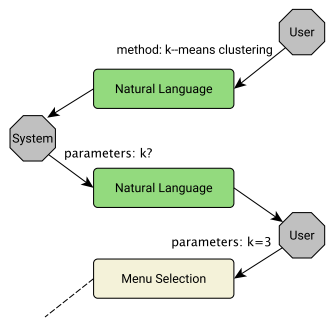


Figure 1: Example of multi-channel dialogue.

we address in this ongoing work; our focus at this stage is on the use of natural language in interactive visualization.

By envisioning the use of multiple two-way channels facilitated by a multimodal interface, we argue that there are benefits to systems and users; maximizing these benefits requires design choices that depend on the context of the exchange of information, such as the type of information, user tasks and roles and the stages of analysis.

We discuss potential benefits and underlying challenges related to this context, setting up a research agenda for the integration of natural language into visual data analysis.

Concepts for multimodality in analytical processes

Regarding natural language and multimodality, natural language has seen a recent surge of interest in interactive visualization, with researchers focused on the implementation of common visualization interactions in natural language interfaces [2, 8]. To move beyond replication of interactions from the information visualization literature, we suggest that it is essential to identify the *role of users* at different stages of analysis.

On this topic, Meignan et al. [5] described five user roles for intelligent systems in operations research, which are based on various aspects of interacting with algorithms, but primarily, the target of the user interaction. In visual analytics, equivalent roles can be defined for the targets that match the stages and elements of analytical workflows, as follows:

Adjust/enrich: when the user modifies the *inputs* used by algorithm, such as the data items or classes used in

classification problems;

Assist: when the user mimics the algorithm by correcting *outputs*, which can be fed back to the system for improvement;

Guiding: when the user modifies the *features* used by algorithms, such as including or excluding attributes that are used for a clustering method, or *steers* algorithms;

Tuning: when the user modifies supporting *parameters* of algorithms, such as the number of clusters;

Depending on the tasks and expertise, users can take on one or more of these roles at any stage of the analysis. With this in mind, the different channels through which information is sent can be assigned or limited to different roles: a system can enable the user to *tune* algorithms only using menus and *assist* it using natural language. At the same time, the system might show the outputs only through visual encodings, reporting back its current state with natural language. Figure 1 shows an example of a multi-channel dialogue based on this design.

On the potential of multimodal analytics

This new paradigm of multimodal analytics has several potential benefits for both users and algorithmic approaches. This section describes these two categories of benefits, as well as the underlying challenges that must be addressed to maximize them.

For the algorithm

Learning more than outputs

Active learning is an established technique through which users can provide examples of correct results to algorithms. Stumpf et al. [9], however, found that users, if given the chance, are keen to provide more than correct results. Natural language can increase the expressiveness

in this type of interaction.

Quality of results

Although algorithm-specific solutions to improve results by learning from users have been investigated [3], the challenge in multimodality is maximizing the improvements by considering not only the appropriate channels but *what* feedback is passed on to users. Amershi et al. [1] demonstrated that users can train better models when presented with *high-value* inputs.

Targeting inputs and features

High-value inputs can also help users to *steer* algorithms by targeting these inputs in the data, in a mixed role of enriching and guiding the system. A key aspect for this is presenting users with incomplete results and enabling the algorithm to be steered [10].

For the user

Comprehension

User interaction can lead to better algorithm results when they improve their understanding of the methods with the appropriate feedback [6] and new generated knowledge [7]. For this, the methods must be adapted for *extracting* the new knowledge and converting them into explanations.

Transparency

Systems can also communicate decisions to users without necessarily bringing new knowledge. Greater transparency was shown to lead to increased satisfaction with results [4], also leading to an increased trust.

Challenges and opportunities

Based on these benefits, we see the following challenges and opportunities as the way forward to achieve them:

Empirically-evidenced multimodal analytics workflows and vocabularies:

Designing workflows, such as the one in figure 2, enables systematic design of studies based on different user roles and stages of analysis, leading to structured vocabularies for improved active learning. At the same time, state-of-the-art AI methods facilitate extending the vocabulary with new utterances after deployment. These can then be used in explanations for increased user comprehension and transparency.

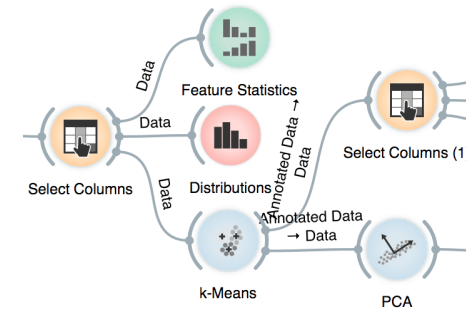


Figure 2: Example of a clustering workflow using Orange ¹

Establishing & evaluating user behaviour in different roles:

User interaction and system feedback must match the different user roles and aims. If users intend to tweak parameters of algorithms, they must sufficiently informed by *how* the parameters will change the results. This requires the development of new evaluation approaches that are targeted to elicit the role of the user and the algorithm in each step of an analytical workflow.

Visualization designs for multimodal analytics:

Although auto-completion and suggestions are commonly used to instruct users about available interactions, speech

¹<https://orange.biolab.si>

needs an altogether different approach – visual cues might be used as hints for interaction targets. The same principle applies to conveying feedback when the visualization does not radically change after an interaction.

Conclusion

With the increasing adoption of complex algorithmic approaches in data analysis, methods to enable analysts to effectively utilise algorithms and action on their results are of critical importance. With this paper, we argue that multimodal analytics offers novel opportunities to specifically enhance the experience and the value at this intersection of humans and algorithms. With this paper, we present an initial position to approach multimodal analytics with a discussion on open challenges and opportunities to motivate further work in this emerging area.

Acknowledgements

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