Exploring Synergies between Visual Analytical Flow and Language Pragmatics

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Abstract

Interactive visual data analysis is most productive when users can focus on answering the questions they have about their data, rather than focusing on how to operate the interface to the analysis tool. One viable approach to engaging users in interactive conversations with their data is a natural language interface to visualizations. These interfaces have the potential to be both more expressive and more accessible than many other interaction paradigms. In this paper, we focus on supporting a natural flow in data conversations by considering pragmatics, or the ways in which context in a conversation influences meaning. We explore the requirements of a pragmatics component in a natural language system for visualizations and the research challenges that arise in understanding the context of data-related conversations.

Flow and Visual Analytics

'Flow' is a state of complete immersion in an activity. According to psychologist Mihàly Cskszentmihlyi, the mental state of flow is "being completely involved in an activity for its own sake. Every action, movement, and thought follows inevitably from the previous one. Your whole being is involved, and you're using your skills to the utmost (Csikszentmihalyi 1991)." A person in a state of flow is completely absorbed in their activity, to the exclusion of everything else. Activities in which people can use their creative abilities are especially likely to lead to a state of flow.

However, with the world inundated with mobile devices, social media and various forms of multi-tasking, much of our lives consist of endless interruptions, hindering productivity and reducing our ability to simply enjoy the moment. These interruptions have ramifications while using computer software, with the product or interface itself often getting in the way. In data analytics, these interruptions can often hinder a user from having a fluid conversation with her data and exploring answers to questions she may have along the way. The excitement and flow of finding insights in the data are often disrupted by endless wizards, dialog boxes or long wait times. Instead of engaging with her data to answer questions, the user spends her time thinking about how to operate elements of the interface.

Visual analytics tools help to engage a user in the flow of analysis. The human visual system is extremely adept at processing visual information such as color, shape, and size. By encoding data in these visual variables, visualization tools offload cognitive work to the perceptual system, enabling users to focus on answering questions about their data rather than reading and comparing data values.

A critical component of any visualization tool is interactivity. Rarely can a user's complex questions be answered by a single static chart. Most of the time, a user will need to interactively change the data display by filtering, navigating, and seeking details-on-demand, to focus on a small portion of the data relevant to the question at hand. Moreover, a user may create and explore a whole series of charts to answer new questions that arise. It is during these interactions that it is critical to keep users in the flow of conversation. Classic interaction techniques such as dynamic queries (Ahlberg, Williamson, and Shneiderman 1992) were designed precisely to keep the user's focus on the data display rather than on external interface widgets.

Nonetheless, interacting with powerful analytic tools can be challenging and often requires substantial user practice to become proficient. A critical requirement to facilitate analytical flow is for the system to answer a user's question intelligently without expecting the user to be a skilled statistician or database expert. It has long been known that inexperienced users have difficulty using native database query languages such as SQL to express their data needs (Li and Jagadish 2014). But, even with visual drag-and-drop interfaces, users can still struggle to express their data-oriented questions in terms of tool operations (Grammel, Tory, and Storey 2010). This can occur for a variety of reasons; for instance, the question may be vague rather than clearly formulated, the entry point for the question may not match that required by the tool (e.g., thinking about the data attributes involved when the tool requires you to first choose a chart type), there may be a mismatch between the terminology in the question versus naming of the tool's functions, or the user may simply not know what set of operations is needed to answer the question.

Our goal is to build intelligent analytical tools without barriers that get in the way of people asking and answering questions. In this way, we hope to help people do what they do best: think and create.

Natural Language Interfaces

Natural language interfaces to data have emerged as a promising new way of interacting with data and performing analytics. These interfaces take, as input, an utterance formulated in natural language and returning an appropriate answer. This approach is promising in maintaining flow, as users may be able to express their questions more easily in natural language rather than translating those questions to appropriate system commands.

There are several companies actively investing in this space. IBM has released Watson Analytics that features a natural language interface for starting an analysis. Microsoft released Q&A in Power BI to allow users to type in natural language queries of their data such as “sales per sq ft by store in NC”. ThoughtSpot provides a natural language search engine for data. Narrative Science has developed a product to generate natural language summaries of visualization. Each of these systems is interesting but has fundamental limitations. Most return minimally interactive visualization in response to queries meaning the answer needs to be exactly right rather than approximate. Many require experts to perform modeling before the systems are effective. None are richly integrated with a self-service analysis tool in a manner that allows natural language interactions to become part of a richer visual cycle of analysis. Creating robust natural language interfaces are often difficult to realize, as they have to handle difficult problems inherent in the task of automatically interpreting natural language. In addition, natural language expressions are often diverse and imprecise, requiring extensive knowledge and sophisticated reasoning for computers to interpret them.

Another challenge is handling the disconnect between the user’s model and how the system interprets the user’s intent. One of the most important aspects of maintaining flow, is how the natural language interface handles this ambiguity and allows for the user to correct the system if the interpretation wrong. One way to deal with ambiguity is to make a ‘best guess’ at the user’s intent so that a chart can be shown right away. With the Articulate system, Sun *et al.* (Sun et al. 2010) accomplished this by extracting syntactic and semantic information from a user’s query, applying a supervised learning algorithm to translate that into an understanding of their intention, and then generating an appropriate visualization. However, Articulate focused primarily on *generating* a visualization; it enabled very little interaction with the visualization and therefore fell short of supporting cycles of conversation with one’s data.

DataTone (Gao et al. 2015) improved the analysis flow by making a best guess at the user’s intent, producing a chart according to that best guess, and then providing ambiguity widgets through which the user could change their chart if the system’s guess was incorrect. More recently, another system called Eviza (Setlur et al. 2016) provided a natural language interface for interacting with an existing visualization rather than starting from a blank sheet and simply asking questions of an entire data set. This reduces the scope of the problem and makes a more useful answer more likely. The system also built in rich domain awareness of time, space, and quantitative reasoning as well as linking into existing knowledge bases like Wolfram. This reduces the need for end users to do sophisticated modeling prior to using the system while supporting more expressive queries.

However, there are other aspects of natural language interfaces that could further help with flow. Conversation frequently consists of a series of related utterances, often referring to past references and context (Allen 1982). As part of this conversational flow, the semantics of a particular query can be influenced by each other, a concept known as language pragmatics.

Language Pragmatics

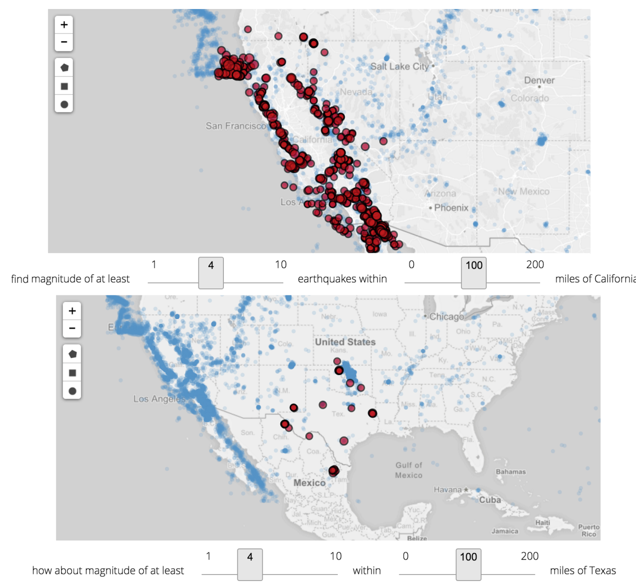

Figure 1: Example of contextual inference in pragmatics for visual analysis. Top: An initial result for the query “Large earthquakes in California”, shows earthquakes within a 100-mile radius of California of magnitude 4 and greater. Bottom: A subsequent query “how about Texas?” resolves to finding earthquakes around Texas with ‘large earthquakes’ associated with this state.

Incomplete utterances are prevalent in communication among humans, ranging from sentences without sufficient semantic information to syntactically incomplete sentence fragments. often, these utterances cannot be understood in isolation, but rather in a known, established context (Allen 1982). Determining the semantics of these utterances is a difficult problem for natural language systems. Pragmatics is particularly important for visual analysis flow, where questions and insights often emerge from previous questions and patterns of data that a person sees.

Studies show that systems where users are expected to employ syntactically and semantically complete utterances, can often be frustrating (Carbonell 1983). Constraining human-system communication to only a subset of utterances, would force users to give less attention to analytical goals in order to concentrate on the preciseness of the utterances.

Contextual inferencing in dialog is a common technique for supporting pragmatics, wherein context established by the preceding dialog is used to create a complete utterance (Reinhart 1982). For example, in Figure 1 consider the utterance, "Large earthquakes in California." For a following query state "how about Texas?", attributes in the previous query state such as 'large' and 'earthquakes' , as well as user settings where large is set to 4 and above, are all augmented to the utterance, and the map shows large earthquakes of magnitude 4 and higher in Texas (Setlur et al. 2016).

While the usage of pragmatics helps with analytical flow, there is room for improvement. Based on some preliminary studies conducted with Eviza, reactions to system memory of previous queries were mixed, with some users finding this behavior very helpful and others finding it unexpected. We need to explore better criteria for deciding when to remember information from prior queries, and support flexibility for users to correct poor system choices. In addition, there are several opportunities for inferring context to better understand user's intent during her analytical reasoning.

Research Challenges

In this paper, we believe that a pragmatics-based approach has strong potential for supporting the flow of visual analysis. A robust system needs to explore ways to further develop pragmatic support to understand the wide variety of utterances employed in human communication. In particular, we propose the following research challenges to further enable users to ask questions in the same way they think.

Machine Intelligence: We have seen how pragmatics in natural language interface involve some way of preserving the context of utterances to disambiguate and guide the interpretation of analytical flow. An area worth exploring in this space, is the development of an 'expert system' that creates a behavioral model of a user or a community of users. Such a system could conceivably observe historical interactions by the user and exhibit user-adaptive pragmatics capabilities. Rather than second-guessing the syntactic form of an utterance using just a general language based approach, inferences can be made from the user's unique flow behavior while performing data analytics. Personalized pragmatics could boost intelligence in other analytical functions of the system such as smarter visual encoding defaults. Domain knowledge could also be used to further the intelligence of the system. Such ontologies may help facilitate the semantic interpretation of these utterances.

Modalities and Device Environments: Touch and gesture interactions offer some rich opportunities to explore multimodal input for visualizations. Multimodal input would be useful to examine how context influences other forms of interaction as well. Trying to infer the analytical task is itself a challenge; one could try to do so by examining past actions the system has performed, and interactions through other input modalities, including navigation and highlighting. While gaining a deep understanding of the user's intent could be very difficult, it may be sufficient to classify whether or not an action belongs to the same group of actions that has just occurred.

With the prevalence of analytical tools on mobile devices such as tablets, spoken dialog is a preferred modality to free other channels of communication, particularly in an intensely graphical visual analytics environment. Further with large public displays and augmented reality, hands, gestures and eye movement could be used as additional context for supporting pragmatics.

User experience: One interesting research challenge around pragmatics is identifying the natural breaks in a data-related conversation and reacting appropriately. For example, a user who has just examined data about malaria infection rates in Thailand, and who then asks for rates of yellow fever, may or may not intend to continue focusing on Thailand. Both keeping the existing data context when the user intended to start over, and starting over when the user wished to continue where they left off, require the user to make repair utterances to correct the system. While a few repair utterances are tolerable, a frequent need for them breaks the flow of analysis and forces the user to think about communication with the system rather than answering her questions about her data. Identifying and modeling the characteristic behaviors that identify acts of drilling in on an existing question versus starting a new line of inquiry are therefore valuable future work.

Another important aspect of this problem may be individual differences, as different people may have varying preferences around pragmatics behavior and different levels of tolerance for misinterpretation. Some people may prefer to have precise control over the system behavior, even if it requires longer input statements, whereas others may prefer a more rapid conversational exchange even if it involves frequently correcting the system. While it may be impossible to predict a user's preferences a priori, ideally a pragmatics system should be able to learn them based on past repair utterances.

Conclusion

Natural language interfaces are a promising approach to interacting with data and making analytics accessible to a broad audience. By enabling users to ask questions in the same way they think, natural language has strong potential to support the flow of visual analysis. Language pragmatics is an integral piece in supporting this conversational flow. Understanding human utterances necessitates identifying richer forms of context through better machine intelligence, user history and the different modalities of interaction. The goal of data analytics is empowering people to do their best work by taking care of the grunt work that machines do so well. These programs should give people the chance to experience the creativity found in a flow state. When a well-designed system enables flow, people unlock their ideas and contribute in ways they consider to be the highest use of their skills, intellect, and capabilities. When this happens, they improve their lives, their organizations, and the world.

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