Dissecting Visual Analytics: Comparing Frameworks for Interpreting and Modelling Observed Visual Analytics Behavior

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Abstract

This paper provides an empirical, comparative exploration of the role of analytic frameworks in interpreting and modelling visual analytics behavior through data gathered in observational studies. The crucial research on understanding the complex and multi-faceted interplay between visual analytics tools and their users is often done through controlled or naturalistic observations of analysts engaging in the visual analytic process, followed by the interpretation of the observation data. The researchers in Human Computer Interaction and Cognitive Sciences have long used structured analytic frameworks for such analyses, where a guiding set of principles and questions direct attention to relevant aspects of the studied behavior, eventually leading to more complete and consistent analyses. Such frameworks are rarely applied in the visualization domain however, and information about how to apply them and their benefits is scarce. With this paper, we contribute a comparative account, grounded in empirical data collected in a user study with 10 participants using Tableau to analyze domain-specific data, of the types of insights we can glean from interpreting observational data using three different frameworks: Joint Action Theory, Distributed Cognition, and Situated Cognition.

CCS Concepts

• ***Human-centered computing*** → ***Empirical studies in visualization;*** *Visualization theory, concepts and paradigms;*

1. Background

Empirically studying and understanding the analytical processes that arise from the interplay between humans and visual analytics tools is crucial for designing and evaluating visual analytics processes and techniques, as well as for advancing our understanding on how people reason with visual analytics. Despite this, research on this topic are still relatively scarce [PDH17]. To study the analytic process, visualization researchers commonly interview or observe domain experts as they use visualization to perform analyses, then interpret the observational data using thematic coding and analysis [Cha06,BC06]. Observation is typically done either in controlled or naturalistic settings, and is often combined with think aloud protocol [Cha06, BC06]. Thematic analysis is most often inductive, meaning that themes are expected to arise from the data itself. To date, such approaches have lead to insights regarding onboarding of visualization novices [LKH*15, cKFY11], the process of determining visualization-clients' needs [MRC*19], or aspects of industrial data analysis [KPHH12].

However, a drawback of thematic analysis is that it is dependent on the experience and particular expertise of the coders involved [FMC06]. Seasoned researchers are often significantly more attuned to relevant aspects in the user behaviors they've observed and are likely to produce more detailed and insightful codes [BC06]. The expertise and interests of coders are also likely to bias the types of observations they make. For example, a researcher with expertise in interaction design may focus on the interplay between the visualization and its user, while a visual analytics researcher might focus on the types of computations that can be offloaded to automatic algorithms. These factors can lead to variability in both the quality and focus of how observational data is interpreted. While triangulation in the form of multiple coding and reconciliation is often used to reduce these effects [BC06], it requires the time of multiple coders with diverse abilities.

These drawbacks are exacerbated by the fact that data analytics facilitated by visualization is highly complex and multifaceted. Many factors are at play at the same time such as the interplay between visual encodings and the perceptual system; aspects related to interaction and data manipulation; an analyst's goals and how these can be decomposed into tasks and data questions [AES05,LTM17,YaKS07]; sense- and decision-making models [PC05, KMH06a]; and users' cognitive resources [GRF09]. Such complexity can easily overload a coder's attention and makes the study of the analytic process challenging [KF14].

The difficulty of analyzing complex behavior, especially one ob-

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served in naturalistic settings (e.g., through ethnography), has been long recognized in domains such as Human Computer Interaction and Cognitive and Behavioral Sciences [BC06, BF05, HK96]. Researchers found that analyzing observation data using structured analytic frameworks, whereby a guiding set of principles and questions direct coders' attention to relevant aspects of the participants' behavior often leads to more complete and consistent analyses [BF05].

As examples of how structured frameworks help shape analysis, Robson suggests nine aspects to pay attention to while documenting behavior during ethnographic observation (e.g., space, actors, activities, events, goals, feelings) [RM16]. Hutchinson links the theory of Distributed Cognition (DCog) to ethnography as a means to study cognitive processes by observing the interchange of representations as they are passed between agents in the system [HK96]. To provide further guidance on applying DCog as an analysis framework in practice, Blandford and Furniss introduced Distributed Cognition for Teamwork (DiCoT) [BF05]. DiCoT consists of a set of three facets (physical layout, information transformation, and artefacts) grouping 18 principles (e.g., space and cognition; information movement, transformation; mediating and scaffolding artefacts) that provide detailed guidance on aspects that experimenters should watch out for while interpreting collaborative (team) behavior. Similarly, Suchman posits that the way people use interactive interfaces arise organically from the dialogue between the people and the interface, and suggest to study it by capturing the evolution of a number of factors over time [Suc87].

In the visualization domain, the application of models and frameworks as a means to inform a more structured thematic analysis of observation data is relatively limited to date. A few models of cognition or sense-making, most notably DCog [HK96], Klein's frames [KMH06a, KMH06b], or Piroli and Card's sense-making process [PC05], have indeed been cited as appropriate for explaining the visual analytic process [PSM12, PDH17, LNS08, Mac15]. A number of more specific frameworks have also been developed to understand cognitive activity supported by interactive visualisations [SP13], visual analytic insight generation [SND05,GGZL14], and Analysis Goals Framework [LTM17]. However, we found limited empirical work using them to analyze the visual analytic process. Exceptions include work by Jolaoso et al. who use the sense-making and frame models to guide their analysis [JBE15], and Pohl and Heider who use Yi et al.'s task taxonomy [YaKS07] to study interaction logs, and Klein's frames to study think aloud protocols [PDH17]. Perhaps more relevant to our work is research by Aria-Hernandez et al., Kwon et al., and Kaastra and Fisher who introduced Pair Analytics, an experimental methodology relying on the observation of diads of Domain Experts and Visual Analysts as they work together to analyze data, and the interpretation of their behavior using Joint Action Theory (JAT) [KF14, AHKGF11, cKFY11]. Broadly however, there seems to be little work on the use of structured frameworks to model visual analytics behavior in the visualization domain, let alone a comparative and empirical investigation on the application of these frameworks.

Motivated by these, this paper explores the role of analytic frameworks by reporting on an empirical pair analytics study in which we observed 6 pairs of domain experts and visual analysis experts working together in sessions of about approximately one hour to explore data from the expert's domain. We identified pair analytics as a study case where interaction takes place at several levels (e.g., people-people, people-computer) and through several modalities (e.g., visual, verbal, gestures, touch), and thus requiring a comprehensive thinking during the interpretation and modelling of the study data. We analyzed the collected data (audio, screen recordings, and video) using three different analytic frameworks: join action theory (JAT); distributed cognition (DCog); and situated cognition (SC).

We contribute a comparative, empirical account of the types of information that these different analytic frameworks can yield when used to analyze observational data of this sort. We find that for pair analytics, JAT provides an effective mechanism for segmenting the analysis into high level stages of analysis and for capturing synchronization mechanisms between participants. However, it cannot explain the way visualization supports or drives the analysis, and it lacks the tools to explain how high level stages of analysis translate into lower level goals and tasks. DCog overlaps with JAT in its ability to capture synchronization mechanisms between participants, but adds the ability to explain how visualization and interaction extend perception and cognition. However it lacks guidance on how to make sense of the analytic process itself. Finally, SC seems particularly useful in studying exploratory analysis processes as it is able to capture how points of action and constraints within the data and the analysis tool modulate user goals.

2. Study & Methodology

We used Pair Analytics [AHKGF11, KF14] to observe and record six pairs of participants - one visual analytic expert (VAE) and one domain area expert (DAE) - analyzing data together for about one hour using a laptop running Tableau Software[†], a leading visualization and business analytics solution. We then interpreted recorded data using JAT, DCog, and SC, and compared the three frameworks in terms of their ability to describe the visual analytics process.

Participants: The DAEs, three from social science and three from human computer interaction, brought their own datasets to be used in the experiment. The datasets varied in scope from survey data describing gaming to a sensor dataset capturing gardening conditions (e.g., seed growth). All DAEs were invested in understanding these datasets but had not done so before the experiment. We recruited four distinct VAEs, two MSc graduates and two academics from our university's data science program. The two MSc graduates participated in one session each, while the two academics participated in two sessions each. While initially we intended to use distinct VAEs for each session by recruiting more MSc students, we found that the higher expertise of the two academics lead to richer analyses; we thus re-recruited them in the last two sessions.

Procedure: In advance of each experimental session we asked DAEs to send their datasets along with a short description to VAEs, and VAEs to spend about 30 minutes to load the data and ready it for analysis in Tableau on their own computers. The pair then met, were seated next to each other in front of Tableau, and were

† https://www.tableau.com/

instructed to freely explore the data for about an hour. The VAE operated the computer and interacted directly with data and Tableau, while the DAE provided input with respect to analysis goals. At the end participants were debriefed separately in semi-structured interviews for about 10-15 minutes.

Collected data: We recorded the participants' dialog; video of their faces, their upper bodies, and some of the screen; and a screen recording. We transcribed the audio using a combination of an automated tool (otter.ai) and manual correction, and examined the video and screen recordings in parallel to identify high level interactions between participants, the visual analytics system, and the environment, and mark them on the transcription.

Analysis and results: We analyzed the data by following principles from Joint Action Theory, Distributed Cognition in combination with Distributed Cognition for Teamwork, and Situated Cognition. A detailed description of these frameworks and a rationale for their choice is provided in Section 3. During analysis we referred to transcribed and annotated data but also used raw video data to identify events and aspects that were particular to each analytic framework but the previous high level annotation did not capture. We then compared the frameworks in terms of their strengths and weaknesses in aiding the empirical data analysis process and in describing the visual analytics process.

3. Frameworks

Joint Action Theory (JAT) posits that participants in a task coordinate individual thoughts and actions into joint actions to deliver outcomes [Cla05], and that this happens seamlessly through language and gestures which participants deliver and monitor.

According to Arias-Hernandez et al., using JAT to analyse the visual analytics process involves segmenting the behavior into joint actions [KF14]; once the structure of joint actions identified, "the different lines of reasoning pursued by participants" becomes apparent [AHKGF11]. Concretely, experimenters should first identify joint actions by focusing on the markers that delineate them. In practice these are typically utterances and gestures. Vertical markers indicate transitions between joint activities (e.g., analyst says "all right!" while leaning towards the computer to indicate a new analysis phase) while horizontal ones mark a continuation within one activity (e.g., analyst says "hmm" and nods to signal engagement). Second, they should describe joint action activities and goals and identify their role within the analytic process. Third, describe the coordination of joint attention by noting utterances and gestures that are used to advance analysis while ensuring that participants remain 'on the same page' about their course of action or data and tasks they refer to [AHKGF11, KF14].

Distributed Cognition (DCog) sees cognition as distributed across both the mind of the user and the external environment (e.g., in physical and computational artefacts) [Hal02]. The concept of 'external cognition' is often linked to or subsumed into DCog [PSM12]: we offload information and computation onto external artefacts (e.g., physical artefacts such as dials, knobs, maps; computational ones such as computers) to scaffold our cognition.

DCog supports ethnographic observation well because in a cognitive system that is distributed, the flow of information between people and artefacts is observable [HK96]. This has lead researchers to refine and extend DCog as a tool for interpreting ethnography data. For example, Distributed Cognition for Teamwork (DiCoT) asks researchers to watch out for three facets (physical layout, information transformation, and artefacts) grouping 18 principles (e.g., space and cognition, arrangement of equipment; information movement, transformation, and hubs; mediating artefacts, goal representing artefacts) when interpreting collaborative behavior [BF05]. While visualization researchers recognize the potential of DCog to serve as an explanatory framework for visual analytics [Mac15, LNS08, PSM12, SP13] we were unable to locate empirical studies using DCog as a means to interpret observations of visual analytics.

Situated cognition (SC) posits that cognition arises from an interplay between a person and their environment [Gre98]. Specifically, once a person adopts a goal, they become attuned to affordances, constraints, and invariants in the environment that can support or block their path towards the goal. Affordances refer to elements which suggest possibilities of action (e.g., a button); constraints to those that block them (e.g., a grayed out button); and invariants to environment aspects unlikely to change despite action. To understand how decision making occurs researchers should focus on (i) a person's goals and subgoals and how they evolve during decision making; (ii) what the person perceives as affordances, constraints, and invariants (these may depend on element properties; a person's considered goals, their past exposure to similar environments, and their mental models); (iii) and the plans and decisions that arise as a consequence. Connected to SC are Suchman's situated plans and actions. In Suchman's view the way people interact with devices does not follow predefined plans envisioned by system designers, but rather emerges from the affordances and constraints that are built into the system, and from the (often limited) information available to both the user and system [Suc87].

Selection rationale: Arias-Hernandez et al. advocates for the use of JAT in Pair Analytics studies [AHKGF11]. DCog is well established in Human Computer Interaction and recognized within the visualization community as useful in explaining visual analytics [Mac15, LNS08, PSM12, SP13], yet we were unable to locate empirical studies using it in practice. We thus thought its exploration would be valuable to our community. We included SC in a second stage of our data analysis when noticing that most analyses in our study were exploratory and driven by salient features within the data and easily accessible options in Tableau. We thought SC would be powerful in explaining this process. It could have been interesting to explore other frameworks as well, such as Klein's frames [KMH06a, KMH06b], or Piroli and Cards sense-making model [PC05]. As also noted in Section 4, we think Lam et al's Analysis Goals Framework [LTM17] could augment the frameworks studied here. However, including a fourth framework was beyond the scope of this account.

4. Results

Our results are the three frameworks' strengths and weakness in capturing the visual analytics process, as they emerged from our use of the frameworks to interpret the empirical data (see section 2).

JAT strengths: First, focusing on vertical and horizontal markers helped us identify distinct analysis phases. Horizontal markers such as soft utterances (e.g., “mhmm, “yeah”) and small body movements (e.g., head nods) indicated engagement within the current phase. Vertical markers such as assertive utterances (e.g., “okay”, “right”) and changes in body position (e.g., sudden leaning towards or from the screen) suggested changes in analytic phases. Second, a focus on how participants maintain joint attention (e.g., via horizontal markers) and mutual situation awareness (e.g., by pointing to data with their hands or cursor; through explicit verbal explanations) can reveal the social mechanisms of pair analytics and potentially inform the design of collaborative systems.

JAT limitations: While we could identify broad analytic phases (e.g., identifying analysis goals; dataset clarification; visual analysis; discussions about future analyses), we found it difficult to segment these further, as markers between more granular phases became subtle. More importantly, we had trouble linking identified phases to analytic goals or task formalized in the visualization community (e.g., Brehmer and Munzner’s [BM13]) and ultimately our descriptions of joint actions felt rather vague. Retroactively, we thought that our segmentation would have benefited from the application of Lam et al.’s Analysis Goals Framework [LTM17] as a means to formalize the description of analytic phases and suggest this as future work. Also, JAT captured little of the interplay between our analysts and the visual analytics tool, in particular of how the tool supported and participated in the analysis process. This seemed like a significant limitation given the focus of the visualization domain.

DCog strengths: Additional guidance from the DiCoT framework was effective. "Physical layout" principles overlapped with JAT in their ability to capture how our two participants coordinated. For instance, the principle of "subtle bodily support" drew our attention to gestures used similarly to JAT markers, while that of "situation awareness" could capture how participants maintained awareness. However, "artefacts" principles provided what JAT was lacking: an analysis of how Tableau supported analysis. Since DCog and DiCoT where somewhat vague about the types of external support to look out for, we relied mostly on types of support mentioned in the external cognition domain: memory support; cognition support; computation support; process support; and perception and motor support. For example, Tableau’s sheet feature, whereby multiple analyses can be saved and explored in parallel, extended our analysts’ memory by allowing them to refer back to them, supported cognitive and perceptual tasks such as comparisons, and supported process by providing a savable account of the analysis. As such, we argue that a better grounding of external cognition into visual analytics could benefit observational studies.

DCog limitations: DCog proved somewhat limited in its ability to capture the overall analytic process. Focusing on DiCoT’s ‘information flow’ facet can in principle reveal how information changes throughout the analysis, possibly from raw data into hypotheses and models. However, we found that more guidance or an additional framework would be needed to structure that process.

SC strengths: We were able to capture how perceived affordances and constraints within the tool modulated the plans and goals of our participants. This was particularly relevant as most analyses in our study were exploratory and seemed to be driven primarily by salient features in the data and easily accessible options within Tableau. Departing from typical uses of SC to understand user interfaces, we found it useful to distinguish between affordances/constraints within Tableau and those in the data.

Affordances within Tableau included available views, marks, and filters. Visualizations our analysts created were rarely planned in advance but rather emerged by combining these options. Constraints in Tableau manifested as unavailable or difficult to access options. For example, in multiple cases the DAEs were interested in looking at unstructured text data or asked for statistical data to back visual observations. VAEs dismissed such requests on grounds that Tableau lacked the features necessary. We also noticed that focusing on what DAEs perceived as affordances within the tool could reveal clashes between user mental models and the rationale behind the tool design. For example, on occasion DAEs asked VAEs to combine dimensions explored in different bar charts. The DAEs expectation seemed to be that bars from different charts could simply be merged together, and seemed surprised by the complexity of having to define additional dimensions as formulas.

Focusing on affordances and constraints within the data can help characterize and explain the analysis process, especially during incipient, exploratory stages. We observed a common analysis pattern where DAEs asked to quickly inspect a series of dimensions, stopped once they found one with an interesting pattern, then asked to see other dimensions which related to the interesting one. We would call this an affordance within the data, a door to a potentially interesting data partition. Conversely, sometimes looking within such a data partition yielded nothing interesting and lead to an analysis dead-end. We would call that a data constraint.

SC limitations: The framework cannot capture some of the aspects where JAT and DCog excel, such as the ability to model shared awareness or to help segment the analysis process.

5. Concluding observations

We found that combining DCog, with guidance from DiCoT and an emphasis on principles of external cognition, and also SC can explain visual analytics most effectively as this combination can capture interactions between participants, the system’s support, and analysis drivers (affordances and constraints). As future work, complementing these with task frameworks such as those by Lam et al. [LTM17] or Brehmer and Munzner [BM13] may provide guidance for identifying and describing analytic phases formally.

We also note that while pair analytics can capture how data analysis emerges through interactions between VAEs and DAEs, it may be less suited for studying single-user analytics. Our experience was that this setup lead to VAEs driving the process to an overwhelming extent and reduced the DAEs to spectators with little initiative. An approach such as that of Chul Kwon et al. [cKFY11] whereby the DAE drives the process while a researcher or a VAE asks probing questions and provides targeted suggestions, may be better suited to study single-user visual analytics as it preserves the advantages of pair analytics while avoiding some of the drawbacks we experienced.

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