Field Experiment Methodology for Pair Analytics

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ABSTRACT
This paper describes a qualitative research methodology developed for experimental studies of collaborative visual analysis. In much of this work we build upon Herbert H. Clark’s Joint Activity Theory to infer cognitive processes from field experiments testing collaborative decision making over data. As is true of any methodology, it provides the underlying conceptual structure and analytic processes that can be adapted by other researchers to devise their own studies and analyze their results. Our focus is on collaborative use of visual information systems for aircraft safety analysis, however the methods can be have been extended to other tasks and analysts.

Categories and Subject Descriptors

General Terms
Performance, Design, Reliability, Experimentation, Human Factors, Theory.

Keywords
Pair Analytics, Ontology, Evaluation, Collaborative Visual Analytics, Observational Research, Cognitive Science, Joint Activity Theory

1. INTRODUCTION
It is generally understood that the goal of visualization is to enhance the performance of a cognitive task by human analysts and decision-makers. This was expressed in the title of Stuart Card’s keynote address “Information Visualization: Wings for the Mind” at the first Information Visualization Symposium in 1995. Fifteen years later a Dagstuhl Workshop on Scientific Visualization [21] echoed this call in their proposal that we move “From Visualization to Visual-enabled Reasoning”. It seems that this process is more of a challenge than one might have thought. While graphical representations of data can be driven primarily or even exclusively by data processing and computer graphics, evaluation of the impact of visualization methods on cognitive task performance must necessarily take into account the ways in which visualization supports human reasoning processes. In effect visualization must become a cognitive science. Metrics for evaluation of visualization must adapt and extend methods from the cognitive and social sciences in order to provide a sound scientific basis for the design and evaluation of interactive visual information systems and the methods by which they are used by individuals, in organizations and in the greater context of society.

Cognitive and social scientists place a great deal of emphasis on the development of structured research methodologies that are then documented and communicated in order to build a methodological “common ground” among researchers. Only through the use of these well-documented shared methods is it possible for studies to be replicated, general scientific theory to emerge, and the science to progress. We believe that this is just as true for the “science of analytical reasoning facilitated by interactive visual interfaces” as it is for other cognitive sciences. What we lack most are a shared set of empirical methods that have been designed (or at least adapted) for evaluation of visualization in use. These must be predictive enough that they can serve to test hypotheses and build general theories of visually enabled reasoning.

Our goals in this paper are first, to describe some methods that we have developed for this purpose, and secondarily to describe the overall methodological approach so that others can adapt and use it in their own empirical investigations. Where it is possible and appropriate we will give examples of ways in which the aerospace work has shaped the methods we use, but will not describe the results of those studies in any detail here. We conclude with a brief description of the ways in which the use of technology by participants in those studies have led us to adapt cognitive science research methods to deal with the special characteristics of visual analysis in our pair analytic field experiments.

2. BACKGROUND
In the natural and social sciences the relationship between a methodology and science is a familiar one. A methodology can be distinguished from a method or taxonomy of methods in that it is a conceptual approach, here for evaluation of how people collaborate on the use of visual information systems, in particular in the pair analysis situation but certainly generalizable to other collaborative situations. The methodology comprises the structure of the conceptual and methodological common ground shared by a cohort of researchers that they use when they address a broad class of phenomena in their separate studies. It is not limited to a specific method, rather the methodology includes a set of shared
assumptions that enable a population of researchers to conduct individual studies so that their results can be compared, contrasted, and argued and in so doing a general theory can emerge. If one group of researchers makes assumptions consistent with the Human Information Processing approach in psychology while another makes assumptions consistent with the distributed cognition approach their paradigms are incommensurable and they are unlikely to make progress together. Our goal in this paper is to relate the underlying research methodology that structures our approach to designing field experiments and their analysis in the hopes that it will benefit of the visualization and analytics community.

A six-year collaboration with a major aircraft manufacturer provided us with the opportunity to support the incorporation of visual analysis methods in a large engineering organization with a strong emphasis on safety and performance. Our collaboration has addressed a variety of application areas, and has resulted in changes in the design of several aircraft and a pilot training manual [22,27]. Initially our approach was to build an understanding of aircraft safety analysts, their tasks, datasets, and situations through ethnography methods. We would then use our knowledge of human perception and cognition to design visual information systems for those users, tasks, and situations of use. While these methods proved invaluable, we soon discovered that the depth of knowledge of aircraft safety engineers and the complexity of their tasks and organizational processes made it necessary to add an intermediate stage of translational field experiments to bridge our cognitive ethnography and design studies. We present this as an example of a way in which researchers can restructure the analysis task so as to better apply and advance theory and methods from cognitive science to visualization in the field.

As we define it, Pair Analytics [2,3,4,8] takes from formal logic the distinction between analysis and analytics. Analysis takes place in a particular situation, by one or more analysts working on a particular dataset and problem. Analytics on the other hand is the underlying structure of (here visually-enabled) reasoning operations whose result can be shown to be reliably correct. The goal of a visual analytics by this definition should be to generate a set of methods by which interactive visualizations can be designed and used that will be effective and correct for a range of users, tasks, and situations of use. A “pair analytics” in this view should include communication between members of analytic dyads as they distribute the cognitive task between them using interface operations, language and gesture in addition to the design and evaluation of visualizations per se and the proper use of those visualizations to support human reasoning.

Pair analysis, then, is a field experiment protocol and companion data analysis method. It is akin to many protocol/analysis methods used in experimental social psychology [6] to elicit specific social interactions that will inform general theories of human social interaction — e.g. to support or disconfirm hypotheses. They contain an intermediate level of control, less than a laboratory experiment but more than an observational study. As with other field experiment protocols, a pair analytics experiment design must describe both the experimental approach and the data analysis method. It should be applicable to a variety of pair analysis situations, and its findings should speak to deeper theories of socially distributed cognition, enactive/embodied cognition, and human information processing.

Our first pair-analysis protocol socially distributed the analysis task by introducing the Visual Analytics Expert (VAE) into the process, giving her responsibility for control of the interface. At the task level this insures that any request by the Subject Matter Expert (SME) for information that is not currently visible on the screen must be verbalized with enough specificity that the VAE can retrieve that information. This greatly enhances the ability of researchers to understand why a given control action was done. At the cognitive level the VAE is given responsibility for understanding and communicating “visual analytic tradecraft”, the ways in which a given visualization or interaction might be incorrect or misleading for a given analysis question. Finally, at the collaborative level the VAE is tasked with maintaining clarity of communication, supporting the process of building and maintaining “common ground” as we discuss in depth below. This restructuring of the analysis task into two complementary roles creates a need for a discussion of the analysis that is captured on video and analyzed in our lab. The use of interactive visualization software for the analysis grounds the discussion in the visual representations of data and the interface actions e.g. the queries that are executed by the VAE.

Analysis of these sessions is done by our adaptation of Clark’s Joint Activity Theory (JAT) and cognitive discourse analysis methods. Our use of Clark is not limited to a description of how JAT theory ought to inform design of collaborative systems, nor do we limit our discussion to a description of how JAT concepts such as adjacency pairs, ladders of meaning, and grounding mechanisms might provide lenses for examination of observational data. Both of these are valuable, but we have chosen to implement a specific experimental design and tailored analysis method that together might enable us to build and validate extensions of Joint Activity Theory and methods that can shed light on how we integrate interactive visualization and human communication processes to distribute cognitive tasks across humans and technological artifacts. We believe that the combination of a specific experimental protocol and tailored analysis method is a novel approach that is not subsumed by current taxonomies of visualization evaluation.

### 2.1 Relation to visualization evaluation taxonomies

The call to increase the sophistication of empirical studies of visual analysis has grown over the last decade. In “Illuminating the Path”, Thomas and Cook called for the formulation of an infrastructure to support evaluation in VA [25]. Criteria for an evaluation infrastructure have been formulated in different ways [25,16]. One general overview examines the relations between artifacts, users, tasks, and data as key elements of an evaluation framework [16]. Other visualization design method taxonomies have been proposed. Sedlmair et al [23] and Shneiderman and Plaisant [24] discuss evaluation throughout the development cycle, including observational case studies and lab experiments (but not field experiments as we propose). Similarly [14] goes into some detail listing a variety of field studies and qualitative methods (e.g. open coding), but does not discuss field experiments (as opposed to field studies) as a method.

While the field experiment and its tailored analysis method have not received much attention in the visualization evaluation literature, we can see how our work might fit within these larger frameworks. For example the comprehensive analysis in [23] would place our methods under Core: Deploy: Release & Gather Feedback. Lam et al [20] propose Collaborative Data Analysis evaluation as a category, and our methods would fit well in that category. Finally, since our situated conversational analysis
includes the communicative as well as the practical aspects of the use of the interface (e.g. transcripts of conversations between analysts) it bears some resemblance to protocol analysis [7]. As described by Ericsson and Simon protocol analysis has some aspects of a field experiment, i.e. the requirement that subjects vocalize their thought processes. For the original protocol analysis method it must be argued that this does not substantially alter the analysis process. Indeed, a good part of the discussion in Ericsson and Simon’s book [7] is devoted to defence of this proposition. For pair analysis, on the other hand, we do not argue that our method does not impact normal patterns of use of the interface. Instead we strategically restructure the analysis process and include the fundamental mechanisms of coordination that it requires in our analysis of those data. This enables us to build a cognitive task model based on the fundamental mechanisms of coordination in paired analyses that will serve as an infrastructure for evaluation of the value of the technology for cognitive task performance. We describe this model as an ontology in that it proposes a structure of events and relations that, while they may take different form in different applications, should be found in many pair analysis tasks.

2.1.1 Relation to qualitative analysis methods

Pair analysis video sessions are analyzed by skilled qualitative researchers using cognitive discourse analysis methods based on Clark’s JAT. Analysis is supported by a number of familiar qualitative analysis tools such as ATLAS.ti, HyperRESEARCH, and NVivo. More recently we have begun using ChronoViz, an analysis package from the Distributed Cognition and Human-Computer Interaction Laboratory at the University of California at San Diego [9]. This application was built to support cognitive ethnography, a method of analysis that focuses on how cognitive processes are distributed across multiple human (and possibly non-human) actors.

In most cases these applications are used for qualitative analysis of observational data using methods such as grounded theory that refrain from a-priori assumptions about the underlying structure of the information [6]. The approach described as Cognitive Ethnography [12] is of particular interest for our purposes in that it focuses on how meaning is socially constructed and cognitive processes take place through the coordinated activities of multiple actors using artifacts specialized for their tasks. Recent work by this group [13, 28] using ChronoViz included temporal analysis of the coordination of control actions and even eye position with discourse among commercial airline pilots as they accomplish their tasks using a number of artifacts (i.e. controls) that make up a high-fidelity flight simulator. The specific nature of the tasks that their subjects perform (e.g. re-routing the aircraft) provides a reliable task structure for analysis—where there may be multiple ways in which the task might be accomplished, they are limited in number and are generally known to the researchers. The analysis then focuses on the mechanisms by which actions are coordinated and by implication cognition is distributed in the cockpit.

Applying cognitive ethnographic methods to visual analytics practice has been quite challenging. Under normal circumstances there is a single analyst whose tasks are not specified in advance (e.g. “to detect the expected and discover the unexpected”[25]). The key artifact is an interactive visual information system with a large number of possible states and interface actions. We address the first of these challenges through our pair analysis field experiment protocol where SME and VAE analysts must coordinate analysis as a joint activity. The second challenge is addressed by building an ontology of coordination that is consistent with and adapted from Herbert H. Clark’s joint activity theory [5]. The conceptual framework of joint activity theory allows us to identify the unit and level of analysis suitable for integrating various aspects of the artifacts, users, data, analysis, context, and process as appropriate for a particular focus question. In effect we use Clark’s general model of human coordination as a structure for analysis rather than to rely on knowledge of a pre-existing task structure as Hutchins et al do in their studies.

Following Clark [5], we examine the fundamental mechanisms that underlie joint activities. We use concepts that allow us to take contextual and procedural knowledge into account when evaluating a paired analysis project. The goal is to be able to identify aspects of the underlying social and cognitive structure of a paired analysis that may occur in across a range of users, tasks, datasets and situations.

3. IMPLEMENTING PAIR ANALYTICS

Pair Analysis is most effective after technology has been introduced, as a way of surfacing the structure of cognitive task performance as it is shaped by the use of interactive visual information systems. Typically, a pair analytics project will study how a visual analytic expert (VAE) works with a subject matter expert (SME) to pose and solve analytical problems using interactive data visualizations. Situated pair analytics is a translational approach to evaluation in visual analytics [11] in that it builds a reciprocal connection between real-world analysis and theories of human cognition. As is the case with many translational research approaches, it begins with an organizational immersion using interviews and ethnographic methods that examines cognitive work practices and seeks to identify appropriate analysts, to determine suitable analytical problems, and to evaluate and/or propose suitable visual analytic tools.

3.1 Ontology of Collaborative VA

It is well understood in the Computer Supported Collaborative Work community that technology can be used to structure cognition and collaboration around common goals. In the context of an organization analysts use a visual analytics package not only to solve a problem or to answer a question but to make an argument. It makes sense that evaluation would take into account how well those aims are met. However, detecting errors or inefficiencies can only be done in retrospect from this kind of summative analysis. And, as many researchers have already pointed out, visual analytics has such a broad range of applications that generalization is difficult, and insight elusive [17].

3.1.1 Developing an Event Structure

When we initiate our work with an application stakeholder we begin with placement of students or postdocs as interns in positions that we have identified as strategic in our preliminary discussions. These interns use ethnographic methods to understand how information flows, analysis is conducted, and decisions are made, with a particular focus on the use of coordinating artifacts such as visual information systems.

One pattern is that a project often begins when a VA expert (VAE) meets with a stakeholder to identify a potential project, setting in motion a series of negotiations. The analyst and stakeholder identify a project, translate it into a VA problem (if necessary), outline an analysis process and set of deliverables, carry out the project, and when it is complete, move on to something new. Generally speaking, organizations will have a
culture of practice that determines how these activities are carried out. One pattern we have observed is:

1) The VAE meets with Subject Matter Expert (SME) to build a shared understanding (i.e. common ground) about the business problem

2) An initial exploratory analysis is conducted and communicated using interactive visualization. The choice of tool and visualization is made by the VAE in consultation with SME

3) This initial analysis leads to a focusing and sometimes a redefinition of analytic objectives.

4) One or more cycles of increasingly focused analysis are conducted using refined objectives and methods. This is the phase that is most likely to be captured on video and analyzed using the procedures discussed here.

5) In parallel with #4, SME and VAE manage data and tools to optimize their analysis practices.

6) The “best practice” approach that emerges is documented as a business process for reuse.

When researchers in our lab examine this process, we use it to help outline and explain coordination in paired analysis. Rather than discuss it a theory of practice, we examine how the process structures coordination at a more fundamental level. We reach for the fundamental mechanism that takes into account the role of the process in collaborative VA. This fundamental mechanism is represented by the idea of Event Structure. Put simply, phases of activity have negotiated beginnings and endings, phases of activity can be nested, and phases of activity can have qualitatively different characteristics (e.g. rhythm, pacing, density, and balance).

3.1.2 Joint Projects, Joint Activities, Joint Actions

The basic unit of analysis is the joint activity [5, 2, 3, 4]. For the purposes of this discussion, we can describe three categories of joint activity: Joint Projects, Joint Activities, and Joint Actions (see Table 1). A joint project refers to an overall endeavor, a problem that needs solving, or an opportunity to cultivate data and perform operations with novel technologies. A joint activity is an exchange between two or more participants that advances a project, for example, a meeting, phone call, or email exchange between the stakeholder and the analyst. A joint action is a coordinated exchange that manages joint attention, for example pointing (with hand or mouse) to a spot on a screen, leaning or tilting the head to demonstrate gaze for another person, or using intonation to specify the meaning or role of an utterance [2, 3, 4].

For all of these terms, layers of coordinated responses hinge on the analysts’ understanding and operational awareness of their roles, personal and shared goals, and their ongoing efforts to advance, repair, and ground their interactions (see Section 2.2).

Table 1. Ontological Terms and Examples

<table>
<thead>
<tr>
<th>Joint Projects</th>
<th>Joint Activities</th>
<th>Joint Actions</th>
<th>Individual Acts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Research contract</td>
<td>Email exchange</td>
<td>Attending together</td>
<td>Preparing materials</td>
</tr>
<tr>
<td>Shared goal</td>
<td>Phone call or</td>
<td>Analyzing together</td>
<td>Taking notes</td>
</tr>
</tbody>
</table>

Individually actions: differ from joint actions only in the way the actions are managed with respect to the overall exchange. For example, an analyst might look at a series of numbers on screen and write them down on a piece of paper. The analyst might have decided to use those numbers for the next Lotto 649. This would be considered an individual action. If the analyst draws the attention of others to those numbers and uses them to advance, repair, and/or ground the analytic activity, those individual acts become part of the mutual awareness, mutual beliefs, mutual knowledge, and mutual assumptions [3] that drive the collaborative analysis. We look for markers to determine when an activity begins, how the activity is carried out, and when it ends.

The lines between individual and joint actions, or between joint actions may not be easy to distinguish. For example, the activity, “define analytic objectives” may be interrupted by various excursions into the data. The activity may be resumed, or the excursion into the data may lead to an entirely new problem. In addition, joint activities are often nested. For example, in a larger activity such as, “apply analytical methods,” there will be several phases of joint activity toward that broader aim.

One of the main advantages of using this ontology is that it reveals tacit and explicit negotiations. For example, analysts might use words to indicate that they are settling down to work (e.g. “here we go”). Other times, analysts use a nonverbal cue (e.g. backing away, turning to face a new screen) or even an onscreen gesture (e.g. activating the History feature in Tableau [4]) to move from one activity to another. Tacit, or explicit, the fundamental mechanism of event structure holds.

By having an idea that nested joint activities have negotiated entrances, bodies, and exits, we can begin to divide observational data into meaningful units for analysis, and from there broaden our understanding of collaborative visual analytics in a way that is based in a more fundamental mechanism. When joint activities are labeled, it becomes possible to observe how social roles are negotiated (e.g. who leads the activity), how analytical processes unfold (i.e. through rhythmic speech, overlapping speech, and silences), and how multimodal communicative practices can function as markers in collaborative analysis [3, 4, 8]. For research purposes, the step of labeling communicative actions and joint actions is a key component of understanding the observational data. You cannot interpret a head nod without an understanding of the context of that nod with respect to the joint activities of which it is a part. In sum, the terms we use to organize and explain our observational data are based in the fundamental mechanisms of event structure (joint projects, joint activities, joint actions, and layering).

3.2 Relations

Researchers in our lab use a number of specific terms to show how an action or activity progresses. From the discussion in section 2.1 we already have an idea that joint actions can be layered. That is to say, within a larger joint project, activities and actions take place that demonstrate some relation to the way the project unfolds. Joint activities have a negotiated entrance, body, and exit, they can be interrupted and resumed, they can occur simultaneously, and they often can be characterized in terms of balanced effort (e.g. leader/follower) and periodicity (e.g. rhythmic or overlapping speech). Calling them joint activities...
gives us the structure to examine how the activities are operationalized in paired analysis.

VA experts in our study tell us that the following non-trivial processes occur every time a new project gets underway:

- Identifying goals and priorities
- Validating assumptions
- Clarifying roles
- Clarifying terms
- Identifying strategies for using available data to address analytical objectives.

These are such ubiquitous components of the analysis process as a whole, that analysts seek to offload them onto the analysis tools that they use as much as possible. To the degree that this can be accomplished, these components need to be consciously and actively managed, reducing effort on the analysts’ part and increasing the robustness of the analysis process as a whole.

In order to build support for these processes into the tools, we must first aim to characterize not only those processes mentioned above, but also the fundamental mechanisms that govern the multimodal communicative practices that give them an observable form. We aim to show how aspects of the multimodal communicative practices are operationalized in collaborative analysis.

3.2.1 Advancing

A joint project can be understood as we have described it above, that is, an overall endeavor, a problem that needs solving, or an opportunity to cultivate data and perform operations with novel technologies. But a joint project can also be conceptualized as an operational term governing collaborative activity. In Clark (1996), “A joint project is a joint action projected by one of its participants and taken up by the others” ([5] p. 191). In order to understand the operationalization of joint projects, we need a way of showing how joint projects are proposed, taken up, and advanced on the fly. The advancing relation blurs the categories outlined above on purpose to demonstrate the complexity and multimodality of coordination.

Human interactions rarely take place on a single level. This is because there are many functions that an utterance or gesture can serve. Consider the levels of activity:

1) Executing behavior (e.g. utterance, gesture)
2) Presenting signal (e.g. utterance, gesture)
3) Signaling that state for actor (e.g. utterance, gesture)
4) Proposing joint project (e.g. utterance, gesture)

These levels are not distinct levels of knowledge or information. Rather, they form the basis for participation in joint activity. An utterance or gesture may simultaneously serve each of the four levels above [8]. Clark’s principles of “upward completion” and “downward evidence” apply ([5], p. 222). It is the way something is uttered or the way a gesture is carried out that determines how an activity is advanced. Joint projects are continuously proposed and taken up. Participation is a way of managing the mutual knowledge, mutual assumptions, mutual expectations and mutual awareness [5] of the participants toward a common goal. In joint activity theory, we call this “advancing common ground”. This conceptualization allows us to reveal the tacit processes in coordinated analytic activity, i.e. the relation between utterance and the joint activity of which it is a part. For example, how an onscreen gesture can propose that the analysts move to a new phase of analytical activity [3, 4].

3.2.2 Repairing

One of the more interesting areas of investigation in the ontology of collaborative visual analytics is the idea of repair as a relation between aspects of collaborative activity. The SCIENCE Lab has been advocating an ecological view of visual analytics that includes human-human-computer interaction. As mentioned earlier, we aim to identify the unit and level of analysis suitable for integrating various aspects of the artifacts, users, data, analysis, context, and process as appropriate for a particular focus question.

It seems like common sense to say that repair is an ongoing relation in collaborative visual analytics. There is always an impulse to check that analysts view the problem the same way, that the tool is capable of solving the problem, that the data is complete enough to use for solving the problem, and so on. Again, stating it this way, repair operates at a surface level. Rather than simply being a way to make up for errors or mistakes, we view the repair mechanism as a fundamental aspect of our ability to maintain an operational awareness of our joint activity over all levels of communication, from the pragmatic to the conceptual.

We want to go deeper in order to learn how to build a repair relation into novel VA technologies. To do this, we need to conceptualize aspects of the fundamental mechanism of which repair is a part. We need to re-conceptualize visual analytics as a participant coordination problem, rather than a third party coordination problem ([5], p. 73). In order for a VA tool to really be considered part of the system, it must meet the criteria for inclusion in the participant coordination problem.

Put simply, the repair relation is the ongoing monitoring of evidence that the things we are doing are correct in terms of the content (track 1) and the process (track 2) of a joint activity. At the most basic level, participants are looking for evidence that the utterances and gestures they are using are being taken up by others. For interpersonal communication, this means drawing on self-evidence and other-evidence ([5], p. 282). At level 1, Executing behavior, participants monitor their own utterances and gestures for evidence that their own actions meet the requirements for participation in tracks 1 and 2. Participants also monitor others’ utterances and gestures for evidence of such “completion” [5]. At Level 1 this evidence is always available. However, at subsequent levels, evidence is only available periodically (see Figure 1).

If there is evidence “sufficient for current purposes” ([5], p. 223) for closure in a joint activity, there is no need for repair. However, many times utterances, gestures, artifacts, and processes appear incomplete. When this occurs in conversation, participants fail to arrive at closure, and the joint activity breaks down. The idea
behind the repair relation as it is presented here is that participants are continually seeking self- and other-evidence and continually monitoring their performance for new signs of completion at the four levels. But closure at level 4 depends on successful completion at levels 1-3.

What follows from this conceptualization is the idea that a repair relation is relative not just to the phase of an activity, but to the level for which there is enough evidence for completion of a joint activity. Once enough of the joint activity is conceptualized in this way, the repair mechanism can be operationalized across participants possibly including some automation at certain stages of analytic joint actions.

3.2.3 Grounding
Analysts are always working to ground their action in the context of the paired analysis. We have previously discussed grounding in terms of performance [8, 15]. Participants are not only participating, they are demonstrating their participation through various multimodal means. As mentioned above this grounding takes place on two separate tracks: the content on track 1, and the process on track 2. The content of an analysis includes an ongoing awareness of the business problem, analytic objectives, the state of the data, and the desired outcomes. The process of an analysis includes conventions of conversation as well as conventions of analytic activity. Grounding, like advancing, and repairing, is a basis for participation in joint activity. It is the effort that an analyst spends selecting the utterance that demonstrates not only how they understand what another is doing, but how they are contributing to that activity. Analysts ground their actions in different ways. We have identified a few areas that are common in our observational data [3, 4].

A grounding relation draws on some basic principles related to what we discuss above: closure, evidence, economy, and immediacy [5]. Grounding is a function that is carried out in joint activity – it is the basis for arriving at a successful coordination. Grounding is often carried out through “coordination keys”, or aspects of the context, process, and joint activity that offer completion one of the levels mentioned above. A coordination key can be the quality of an utterance or gesture, the timing of an utterance or gesture, an aspect of the environment that is jointly salient and relevant, an artifact that contains important information (such as the internal document “Lifecyle of a VA project”), a color that represents something important in the data, or, literally anything that is drawn into the joint activity upon which aspects of the activity are held. The idea of building a grounding relation into a VA tool is a powerful one that is sure to play a significant role in the success of future VA tools. Doing this will require highly advanced theories of perception in virtual environments, and a deep understanding of the fundamental mechanisms that drive coordination in paired analyses.

In sum, we have chosen to discuss the relations, advancing, repairing, and grounding as a way of situating criteria for evaluation in the context of pair analytics.

4. PAIR ANALYTICS AND VISUAL ANALYTICS
Our conceptual framework is based in the fundamental mechanisms, or bases, participants have for advancing, repairing, and grounding the analytical work. Our primary goal in this paper is to introduce an integrated empirical approach, the field experiment, and its companion analysis method, discourse analysis based on Joint Activity Theory. We will conclude with some examples of how this approach has been used in our investigations and how it might lead to new approaches in the design of visual information systems. Interested readers should refer to our earlier work [2, 3, 4] for more detail.

The visual information systems used in our studies with industry include quantitative data packages such as Tableau and text-mining applications such as IN-SPiRE. Their ability to display data in ways that are commonly understood by all participants in the analysis process gives them a role in maintaining common ground.

Our earlier work [3] has documented ways in which gestures to objects on the screen support shared understanding of data and their implications. This finding links to a larger body of literature in cognitive science and CSCW on joint attention, (e.g. [3, 10, 26]). This body of literature has not been well explored in the visualization community. For our purpose this use of shared space by participants is a valuable, but largely passive role that is played by visual analysis tools in joint activities. Analysis of on-screen gesturing is a fruitful area for investigation of collaborative use of visual information systems. It also holds the possibility of extending Clark’s model more clearly into the realm of collaborative use of technology. We anticipate more focus on this as it interacts with joint attention through our attempts to integrate eye movement analysis into our pair protocol studies [18].

Our analysis points the way towards a new perspective on the design of visualization environments—they should be designed to facilitate the range of signaling and repair mechanisms that we discuss above. By understanding the mechanisms that humans use throughout the process of creating, executing and concluding joint projects we will be able to provide specific support not only for understanding data but also for human coordination mechanisms that enable the joint activity to progress to a satisfactory conclusion without complication. This capability will support pair analysis and enable visualization environments that can be used by groups as well as pairs of analysts. In collaboration with the BC Child Injury Prevention and Research Network, we have conducted preliminary studies of group analysis in decision support for multi-stakeholder public health analysis that apply these methods to understand this more complex social cognitive analysis process [1].

One observation we have made is to our knowledge unique to visual analysis in a social context, the use of “self talk” in analysis [3]. These incidents happen when one analyst needs time to think about the analysis and wants to keep the current state of the visualization. In these situations the social context would normally require them to advance to the next stage of analysis. Rather than to simply ask that the VAPE pause (or if they are the VAPE, to pause themselves) the analyst may spontaneously engage in a “thinking aloud” protocol as they would in conventional protocol analysis. They do this to maintain common ground with their partner as well as to provide an inducement and a reason for keeping the visualization as it is.

5. DISCUSSION AND FUTURE WORK
Our analysis points the way towards a new perspective on the design of visualization environments—they should be designed to facilitate the range of signaling and repair mechanisms that we discuss above. We have earlier proposed a “cognitive prosthetic” approach to building and maintaining common ground in computer supported collaborative learning systems [19] based on Clark’s framework. This support for human coordination mechanisms will enable visualization environments to be used by
groups as well as pairs of analysts. For example, our conceptual framework points to the need to include robust repair functionality in visual analysis environments. This can work two ways: 1) a system of checks on data extracts and analysis provenance, where work flows are well understood; and 2) an iterative process around collaboration and version control to keep the system self-sustaining.

Some new areas that we are investigating are:

5.1 Collaborative analysis at a distance
The pair analysts we have studied to date are co-located, however we have been asked to examine situations where pair or group analysis takes place at a distance. In situations such as these coordination mechanisms are challenged in ways that are familiar to many in the computer-supported collaborative work community. An understanding of JAT might well enable us to coordination of joint activities is conducted might be useful in the design and evaluation of these systems.

5.2 Mixed initiative analysis
Ingesting data extracts can be a painful and time-consuming process, and problems can arise around collaboration and version control. In addition, a VA project frequently relies on what the analysts call, “tribal knowledge” of the subject domain. Many aspects of the content and procedural knowledge have not been captured in an artifact. Sometimes, only a subject matter expert (SME) can provide information on the meaning or interpretation of key metrics or variables, or information on how to properly integrate or reconcile different data sources, or information on where to simply find the right data.

Included in this picture is the idea that the VA tool and analysts are working as a system, and it remains to be seen where the limits can be drawn in terms of including the VA tool as a full participant – capable of posing and or structuring problems, structuring and reconciling data, and perhaps monitoring the mutual knowledge, mutual awareness, mutual expectations, and mutual beliefs of the system on the fly.

In many cases there is a need for more sophisticated processing of data through the application of mathematical and computational models and machine learning methods. In situations such as these we may ask whether the VA tool should be capable to whatever extent is possible to act as a cognitive agent and to utilize similar signaling and repair mechanisms.

5.3 Analytic Provenance
As described in “illuminating the path [25] visual analytics is a highly iterative activity characterized by fluent “human-information discourse”. Tracking the process by which a decision was made or conclusion drawn is challenging. The current generation of tools does not lend itself to the convenient capture and maintenance of clear and easy to grasp analysis provenance. Iteration can sometimes happen on a high level, with analytical insights altering the motivation and strategy of a project as whole, and always on a low level, involving the description, verification and transformation of data, and also the synthesis of new data and information as a product of the analysis itself. Visual analytics enables faster iteration of these low level operations in near real-time chains of question/answer operations. One drawback to this fluent interaction with information is that the compounded results of successive iterations can accrue faster than the analysts’ ability to internalize and understand them. Eventually, analysts find themselves looking at a visualization that is potentially very valuable, but no longer anchored to the concepts that motivated the analysis. Computational or statistical methods will often require code or scripts to drive them, in which case the code can act as a default artifact of the analysis provenance. Visual analytics lacks this, so analysts are often required to keep detailed notes, apart from the natural workflow enabled by the visual analytics tool itself. This is problematic in that it a) relies on the diligence of the analyst to be an effective strategy and b) slows down the workflow and can limit the gains in speed affected by visual analytics in the first place. We believe that visual information systems that can document the use of coordination actions such as we describe here can substantially disambiguate documentation of analysis processes. If we can apply these conceptualizations and operationalize them within the context of visual analysis environments, we ought to be able to reconcile problems that arise during analyses. A key effort will involve JAT-based design of visual information systems to the point where they have analytic agency – where it becomes a more equal participant in the coordination problems posed by the paired analysis setting.

6. CONCLUSION
The pair analytics methodology is a framework for evaluation that takes an ecological perspective on collaborative visual analytics. The terms and relations presented in this paper can be used as an infrastructure for evaluation that takes into account the system of collaboration in fundamental units of analysis. This approach adds two key areas of insight: 1) tacit processes of coordination, and 2) context-specific interpretation. The ontology of collaborative visual analytics is aimed at operationalizing some of the tacit and context-specific aspects of collaborative decision making over data. If these aspects of analytic practice can be conceptualized with greater clarity, they can be built into existing VA frameworks for evaluation, and incorporated in the ongoing design of novel VA packages. For example, this framework can be used to pin point areas where additional functionality may improve quality assurance, particularly in the areas of repairing and grounding. When human-human-computer coordination problems are understood from these fundamental mechanisms, checks and balances can be introduced to strengthen the system. For example, principles like, “upward completion” and “downward evidence” [5] bind a system together from lower level, tacit, processes to higher-level products and negotiations. Our lab’s current and future work builds on this framework to connect perception studies with observational studies using this pair analytics methodology.

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