Supporting Collaborative Information Analysis: A Classroom Study

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ABSTRACT
Collaborative information analysis involves strategic analysis and representation of complex information space through synchronous and asynchronous team interactions over extended time periods. Chances are rare to observe how technology mediates team analysis over extended period of time because complex scenarios are difficult to model in lab studies, and professional analysts are limited to access in real world. Classroom study provides a testbed in which students are trained to become professional analysts and course projects are designed to simulate real world tasks. We developed a tool, CAnalytics, which aims to integrate data modeling and data analysis, and to support activity awareness amid demanding cognitive tasks. We deployed our tool in class and observed the usage of the tool by teams in their project. The paper reports the findings and discusses design implications.

Author Keywords
Collaborative information analysis; visualization; classroom study;

ACM Classification Keywords
H.5.3. Information Interfaces and Presentation (e.g. HCI): Computer-supported cooperative work

INTRODUCTION
Collaborative information analysis is a form of sensemaking wherein a team analyzes a complex information space of facts and relationships to identify and evaluate causal hypotheses. A common example of collaborative information analysis is crime investigation; a variety of putative facts are assembled, including financial records, witness observations and interviews, and social connections of various sorts among persons of interest, from which investigators collaboratively assess means, motives, and opportunities, articulate and investigate further hypotheses and deductions, and develop one or more theories of the crime. Other examples include intelligence analysis, business intelligence, scientific research, and social constructivist learning.

Every submission will be assigned their own unique DOI string to be included here.

A critical challenge for information analysts is building an adequate preliminary data model from textual documents, and insuring that the data model is employed effectively in hypothesis development and evaluation. This is an open challenge [1]. Standard methods often do not support it at all; for example, Analysis of Competing Hypotheses (ACH) assumes that data has been modeled, and that relevant evidence can be adduced appropriately to various hypotheses, but provides no structured support for either. Visual analytics systems, as Ware termed as "asymmetry in data rates" [21, p. 382], emphasized data flowing from visualization systems to users far more than from users to systems. Functionalities are mostly designed to adjust visual representation rather than remodel data underlying the representation, which is a critical aspect in information analysis. In contrast, other techniques, such as Information Extraction and Weighting (IEW), help structure modeling of evidence, but do not add analytic support or extend utilization of evidence to hypothesis generation. We therefore are motivated to develop an integrated workspace in which analysts can model and analyze data in one place, and investigate how that will affect analytic process.

Any work of information analysis at a non-trivial scale is fundamentally collaborative. A key enabler for effective collaboration is *activity awareness*, defined as team's awareness of its own sustained collaborative activity [6]. Derived from Activity Theory, activity awareness transcends synchronous awareness of who collaborators are, where a collaborator is looking, etc. It encompasses issues of many different kinds of information covering all aspects of an activity, such as events, tasks, goals, mediating artifacts, social interactions, and group values and norms, which becomes higher demanding as the activity becomes more complicated. Awareness support in such a complex activity of information analysis is perhaps also more challenging than many other situations (e.g. collaborative writing). Teammates could be working with much more complex data structure (e.g. spatial data, temporal data, and relational data, as opposed to only text), coordinating through multiple analytic artifacts (e.g. map, timeline, network, as opposed to only a document), and making sense of different levels of analysis, assumptions, and hypotheses, both synchronously and asynchronously throughout a long-term course of collaborative interaction. Hence we will investigate how technology can mediate team collaboration in a complex analytic task over extended period of time.

We situate our study in classroom learning of information analysis. Classroom study provides a natural environment in which participants engage in long term, complex class projects. Due to difficulty in accessing professional analysts or having them in long term design loops, analysts in training who are learning to be information analysts are a good compromise [16]. They already have some knowledge and experience with state-of-the-art analytic techniques and tools. In class projects students are graded on their ability to understand and enact professional practices of information analysis. This strong normative emphasis on problem solving practices is a great evaluation context for new interactive tools: Tools are only valuable to the students insofar as they actually support better practices and better outcomes.

We thus are motivated to investigate the feasibility, effectiveness and consequence of supporting integrated data modeling and analysis, as well as supporting activity awareness in complex information analysis, in the context of classroom study. We have developed a tool that includes annotation for data modeling, interactive visualization for data analysis, and a set of awareness features. For the balance of this paper, we describe the tool we have developed, the classroom settings, and our observations. We conclude with design implications derived from the study as well as future work.

RELATED WORK

Many studies have been reported to investigate specific design features to support collaborative information analysis. For example, Goyal and Fussell [11] studied the effect of hypotheses sharing on sensemaking. Mahyar and Tory [17] designed a visualization to connect collaborators' common findings and evaluated its support for team performance. Hajizadeh et al. [13] explored how sharing teammate's interactions affects awareness. These studies report interesting results of controlled lab studies to validate hypotheses of specific design features. However, they do not provide insight on how teams would collaborate with a complete tool as nexus of features in the real world over extended period of time.

Field studies were conducted aimed to understand design requirements of collaborative information analysis in more realistic settings. Chin et al. [7] observed and analyzed the analytic strategies, work practices, tools ad collaboration norms of professional intelligence analysts. Kang and Stasko [16] studied how student analysts, as in our study, completed in-class intelligence projects. Carroll et al. [5] attempted to model a complex analytic task scenario in a lab setting, and examined the development of team awareness in a four-hour-long task. These studies helped improve understanding of current work practice with state-of-the-art tools or no tools at all. We built our tool based upon their study findings, and pursue to further explore design implications by investigating tool usage in a similar naturalist environment.

Our study took place during the 10th week of the course. Before that students learned several analytic techniques, including IEW (a technique to extract and assess values of evidence), ACH (a technique to evaluate multiple hypotheses against evidence), timeline analysis and network analysis, as well as state-of-the-art tools to facilitate these techniques. Two weeks before our study, students practiced applying these techniques in a hands-on project. A typical workflow started with IEW to extract and model data from documents. Students then replicated key facts into analytic artifacts such as an ACH Matrix in PARC ACH, a timeline and a network graph in Analyst's Notebook. They had to repeat the process for each different tool because the data cannot be shared and carried over directly. Most tools they used lacked serious collaboration support (except that some teams used Google Doc to construct an IEW table). Analysts were unable to contribute simultaneously (also known as production blocking [9]). The analysis work was often divided by tools: each individual created and analyzed an artifact with a tool on their own. This had the consequence that findings and hypotheses be made without integrating collective efforts and diverse knowledge. Analysts must coordinate work by manually sharing notebooks or graphs, resulting in a scattered placement of results, requiring repeated manual resynchronizing to identify redundant or missing pieces of information, analysis of information, and analytic hypotheses. The instructor and students in our study were aware of the shortcomings of available tools with respect to support of collaboration.

CANALYTICS FEATURES

We developed a collaborative information analysis tool, CAnalytics (Figure), to support teams of analysts in identifying, visualizing, integrating and assessing facts from multiple sources. The design is informed by earlier paper prototype studies [5], where the researchers examined team's spontaneously created artifacts when teams were sovling a complex crime scenario. We also take into account findings from empirical studies conducted by Chin et al. [7] and Kang and Stasko [16] when making design decisions.

CAnalytics supports evidence modeling through annotation. In the document view users can select and highlight snippets of information and annotate them as a type of entity such as a person, location, events, etc., or as a relationship between entities. Unlike in other entity-based systems such as [3, 20], we use annotation to allow analysts to manually create evidence objects of interest. Manual annotation allows for greater user control, allows more integrated source data objects to be identified, and avoids the user problems associated with automatic identification of disaggregated people, locations and times [2]. Users can decide their own information of interest and granularity that best suits their ad-hoc analytic needs.

Users can add attributes to the annotated object, e.g. adding time attribute in an event, and placing coordinate in a location. Users can also make reference to other objects in the attribute; for example, users can add people objects to an event indicating that these people were involved in the event. In this case, a relationship between the people and the event is automatically created. Users can also explicitly create a relationship between two entities by selecting a source entity and a target entity and labeling the relation name.

When users are explicitly creating an annotation, they are also implicitly creating a provenance of the modeled entity— annotation records the source where a data object was created. As observed in Carroll et al.'s [5] empirical study, while integrating information in a visual artifact helps sharing and pooling information with teammates, the action also removes

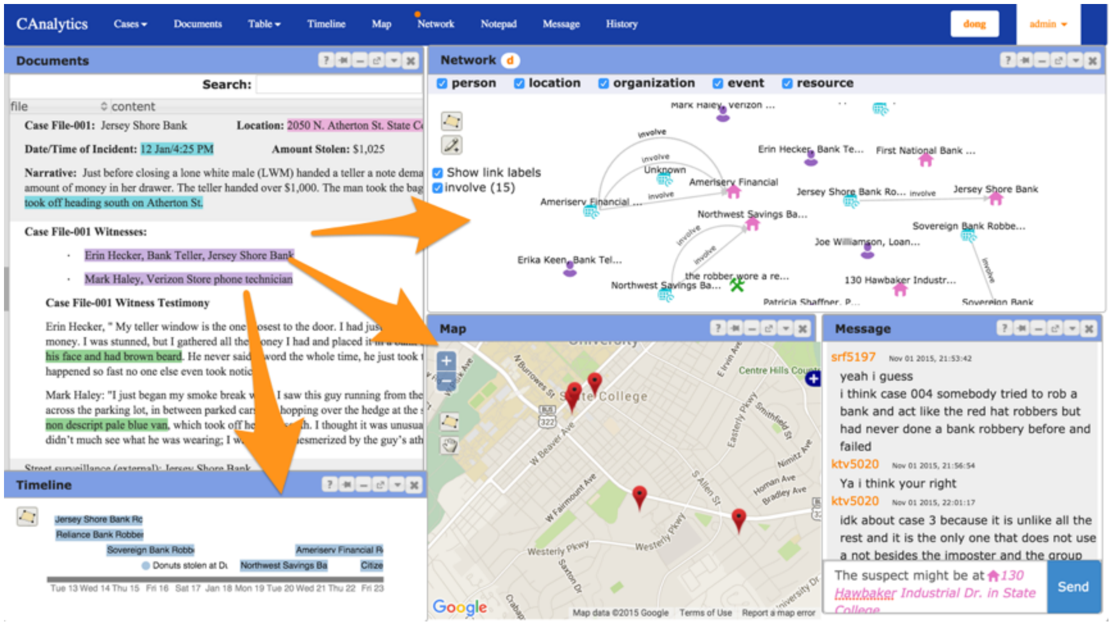

Figure 1. CAnalytics user interface

problem information from its original context. Participants often forget what an entity refers to and why it is such positioned in an artifact. Entities in CAnalytics are linked back to the location of documents where they were created through annotation. Users can always re-access the data objects for provenance, a critical requirement emphasized by Chin et al. [7].

The data modeled through annotation is then displayed in multiple coordinated views in the same workspace, including table, timeline, map, and network graph—artifacts frequently constructed to hold attribute data, temporal data, spatial data and relational data respectively [5]. Figure shows an example of the tool interface: when an annotation is created in the document view with information about time, location, participants, and their relationships, a new event is created in the timeline view, a new location is created in the map view, and new people are added to the network graph with a labeled edge representing the relationship (or new edges are added to existing nodes). Hovering mouse over an entity will activate an entity detail window that displays attributes in detail, and analysts can modify, or re-model the entity in situ.

The views are coordinated and afford brushing and linking interaction; that is, when users apply a graphic filter in one view, related information is displayed in other views. Thus the analyst can retrieve entities within a time range using timeline filter, make a spatial query with map filter, or select a cluster of entities by drawing a filter area in the network view.

CAnalytics supports real-time collaborative editing, similar to Google Docs. Users can open several concurrent editors and collaboratively edit multiple annotations. Annotations are immediately shared within a team and are automatically added to teammates' document views and other visualizations. Different from Google Docs, CAnalytics supports the editing of more complex data structures than text, including spatial data, temporal data, and object attribute data.

In addition to real-time data sharing, CAnalytics is built in with several other awareness features, including a notification system, a feature we named "tool coordinator", a message tool, and a history tool, and a collaborative editor. A notification system sends individual's actions to the team, in the form of a text box in the top right corner of the workspace. The tool coordinator is an iconic indicator on top of a tool window, suggesting who is working on the tool. The message tool is a real time chat window that enables team communication with persistent message history. The system also maintains a traceable log of time-stamped individual activities in a history tool. Users can learn team activity about who did what to which object at when. Entities and relationships mentioned in the message tool and history tool are hyperlinks that will trigger pop-up detail window when being moused over. With these awareness features, users who work synchronously can be informed of others' activity continuingly; users who work asynchronously will be able to use the history to reconstruct their work status and become aware of changes beyond the point of their last interaction.

We also included a simple notepad to support collaborative hypothesis development. We integrated Etherpad [1], an open-source collaborative editor similar to Google Doc, for teams to compose their hypotheses. Users can insert tables (e.g. an ACH matrix) and images (e.g. screenshots of the tool views).

CLASSROOM STUDY SETTINGS

The context for this study was an undergraduate course in an intelligence training program in a US university (Figure 2). The program was designed to train students to become professional intelligence analysts. A key requirement of the course

[1] http://etherpad.org

Figure 2. Classroom setting

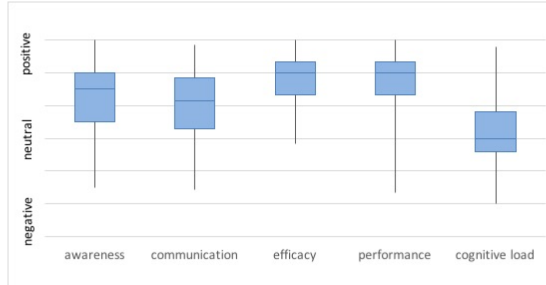

Figure 3. Survey responses (box shows Q1-Q3 and median; whiskers show maximum and minimum)

is to emphasize hands-on practice on team-based intelligence analysis. During the first nine weeks, students learned strategic knowledge (e.g. bottom-up analysis and top-down analysis) and structured analytic techniques, such as IEW, ACH and network analysis, and practiced to apply these techniques to solving two small projects with state-of-the-art tools including PARC ACH and IBM Analyst's Notebook.

Our study began from the 10th week of the course and lasted for one week. The task was to investigate a series of bank robberies fabricated by the course instructor. Teams were provided with a set of documents pertaining to seven robberies, including police reports, witnesses reports, video records, and news media. The task was designed open-ended, which meant that there was no single answer to the task. The instructor explained that the task was to simulate real world scenarios, in which analysts always reasoned in the circumstances of uncertainty, ambiguity, and complexity. The instructor told the students that 6 hours was expected to complete the project, including in-class and outside-class work. In the end of the project students were required to submit a team report, describing their hypotheses, assumptions, conclusions and supporting evidence.

Students were given a tutorial on CAnalytics a week before the project began. One of the authors walked through features of CAnalytics and then let students accomplish a small case analysis on their own pace. During the study week, one author was always available to help with any technical issues. Although students were encouraged to make full use of CAnalytics, to ensure a naturalist environment students were always free to employ any other tools that they believed useful.

Of the 98 students enrolled in the course (from two sections), 73 consented to participate in the study. Students were randomly assigned into 25 teams (23 three-person teams and 2 two-person teams). Research suggested that group size be an important factor in group collaboration, thus two-person teams might behave differently from three-person teams. We thus excluded data from the two-person teams in our analysis in this paper. Also, from the log (and confirmed by their questionnaire), we found that one team made little use of CAnalytics and opted for other tools (Google Doc). Hence their data was also excluded. Thus in this paper we reported the result from 22 teams.

All the students held major in the program of Security and Risk Analysis. Most (75%) of them were in the third academic year (3.05 years in average), indicating that participants had been exposed to knowledge and techniques in the domain of intelligence analysis. Participants' age ranged from 19 to 28 (20.3 in average). 77% of the participants were male.

We employed several data collection approaches. We administrated a post-study questionnaire, which included questions using a seven point likert scale that measure individual's self-reported awareness (adapted from [8]), team communication (adapted from [8]), collective efficacy (adapted from [8]), perceived performance (adapted from [12]), and cognitive load [14]. The questionnaire also included open-ended questions asking how the tool helped or impeded their work. We captured user interactions with system logs. Instead of simply logging low-level events like mouse click and keyboard strokes, we recorded actions such as making an annotation and deleting an entity. Finally, we reviewed team reports and graded them as an indicator of team performance. We designed an assessment rubric together with the course instructor. In analysis of the result, we utilized artifact analysis, log analysis, and qualitative analysis of the questionnaire.

RESULT

Over the week, teams created 1805 entities and 1529 relationships in total. The number of entities teams created ranged from 24 to 223 (M=82, SD=39.9), and the number of relationships ranged from 7 to 237 (M=69.5, SD=51.0). The large variety of modeled data was related to team strategy, which will be detailed later.

Overview of the survey items indicates that students rated positive on CAnalytics overall, as shown in Figure 3. CAnalytics were ranked favorably in all aspects except cognitive load, towards which they had a close to neutral feeling.

Benefits of activity awareness support

One recurring theme in the subject feedback we collected was that the collaboration features were helpful for solving the problem on a team basis. Participants appreciated that the tool added collaboration support to traditional analytic tools such as Analyst's Notebook, and added analytic support to common collaboration tools such as Google Doc. One user described CAnalytics as *"an analysts notebook that multiple people could work on at once. . . [and] an analysts version of a Google Doc."* (P65). Teammates can do individual work while not interfering others. To quote a user's comment:

"It was much easier to coordinate as a team with CAnalytics because we could all work on the same system at the same time. Without CAnalytics, we were forced to do the work separately and compile all the work onto one system after we had finished." (P156)

Students reported being able to see teammate's status made the task more motivating and enjoyable. The data displayed in the system was not static, but dynamically updated by teammates, along side with the notifications and other awareness features each time a collaborator made a change. As participants commented:

> During class I wasn't sure if my teammates were doing work for that class or another thing but then seeing their dot [tool indicator] switch between applications on the software and updates pop up on my screen I knew they were doing work for 231. (P141)

> The fact that you can see what other teammates are doing and they can see what you are doing creates a sense of accountability in terms of separating the work load. (P51)

The awareness features were received well. In the survey (Figure 3) 88% of the students rated positively on their team awareness. When asked what features helped them stay aware of team activities, 28 participants mentioned the tool coordinator, 24 mentioned the notification system, 19 mentioned the history tool, 14 mentioned the real-time update of user-generated data, 12 mentioned the collaborative editor, and 7 mentioned the message tool. While the number of mentions does not simply indicate tool usefulness, it suggests users appropriate these features and were explicitly aware of their support.

We categorized participants' feedback based on the element of awareness, or awareness of *what* as emphasized in [18], into social awareness, information awareness, action awareness, history awareness, and intention awareness, as shown in Table 1.

The positive support of awareness is further corroborated by the interaction log. For example, we measured the number of entities accessed by collaborators versus by the author only. While data generated by users is automatically shared, it is up to collaborators to choose to read the shared information or ignore information altogether. A high awareness team would keep updated with collaborators' generated information and read information soon after it is shared; whereas a low awareness team might experience a significant delay or even never access it. We found that most teams shared a high proportion of entities (mean=77.6%). We found that in average, 77.6% of the created entities were accessed by at least one teammate.

One major critique is the lack of sharing support of intermediate analytic result for close collaboration. When individuals gain an insight from a specific configuration of visualization (e.g. after a series of zooming, filtering, panning, and highlighting interactions), they did not have a simple channel to communicate that insight together with the associate views to the team. The team could "be looking at the same information but arranged in completely different ways" (P131). One had to explicitly ask the team to listen to his/her ideas while stopping their own work and turn their to his/her screen. This coordination cost, while seemingly trivial each time, could prohibit one from actively sharing their intermediate findings to withdraw from constant interrupting, which might later lead to team overlooking an important piece of evidence [4].

Another challenge participants faced was the sharing of the frame to model data. Three users mentioned that their team lacked a shared understanding of *what* to annotate. Individuals modeled different levels of details and evidence of various relevance. Four users mentioned that their team did not have a shared understanding of *how* to model data. The teams had inconsistent naming conventions for the same type of evidence. Or they could model the same evidence as different types of entities (e.g. modeling bank as location vs. organization). These misunderstandings can have a big impact on team analysis because such information serves as the foundation for analysis from which a team draws final conclusions.

Intertwined data modeling and analysis

We examined the pattern of data modeling and data analysis by looking at a visualization of the entire interaction log (e.g. Figure 4 shows the interaction log of one team). It was obvious to see teams started with data modeling since teams at first read documents and made annotations as they went through. However, teams did not wait to start analysis till they finished data modeling; instead, the activity of data modeling and data analysis were highly intertwined. After a certain point, participants frequently switched from one activity to the other activity . The state transition diagram (Figure 5) better demonstrates the frequent transitions between states, in which we encode the number of switches as width of the link.

To look at the consequence of intertwined data modeling and data analysis, we examined the analytic product teams created, the network graph in particular because social relationships played the most critical role in this specific scenario and teams spent most time on network analysis (as reflected from the log). We found the network views fell into one of two categories: the networks consisted of 1) separate clusters, or 2) connected clusters. For example, networks from 8 out of 22 teams consist of separate clusters (Figure 6b). Nodes within a cluster are connected, representing information space of a robbery case; Nodes between clusters are nonetheless not connected, indicating each robbery is a self-contained case. However, these teams still claimed connections between robberies in their report. Where did they externalize these connections? Or did the teams simply share orally and held them in mind? It turns out that these teams documented possible relationships between robberies in the notepad tool. They used free text to document similarities and common patterns between cases instead of modeled data in the visualization.

In contrast, 6 other teams created networks composed of connected clusters. While a cluster is still a representation of a robbery, some of them are connected through an evidence node. An example is Figure 6c, in which we mark four *connectors* that link the clusters. These connectors were key evidence that led the teams to hypothesize that those robberies

Table 1. Subject feedback of awareness aspects

Element	Example
Social awareness *who is present?*	CAnalytics helped me stay aware,of my teammates activities because I could see who was logged on in the top,right corner (P123)
History awareness *Who has done what?*	The way you are able to view when and where your teammate made or updated annotations/information was the key to staying aware of what your team has done. It is a great tool in respects to that. For example, I was able to view the changes my team made while I was not using the CAnalytics tool at the same time they were using the history tab. (P171)
Information awareness *What is being changed?*	CAnalyitics was very helpful in keeping us updated on what was being changed/noted/amended by whom and when. This was very beneficial for staying on the same page and knowing what changes were being made so no one individual was out of the loop. (P157)
Action awareness *Who is doing what?*	I liked how you could always see what your teammate were viewing on the website. For example I was working on the bluf when my teammates were working on the network part of the program. If I were to come across a piece of information that I thought might be helpful to them I would just tell them. My teammates did the same thing in return. (P51)
Intention awareness *Who is going to do what?*	CAnalytics showed what tab [tool] my teammates were working on which helped me be aware of what they were working on. For example, if I saw that one of my teammates was on the network tab, I knew that they were attempting to connect the information that was relevant to one another.,I would then be able to mention any new findings I had that could influence their work (P160)

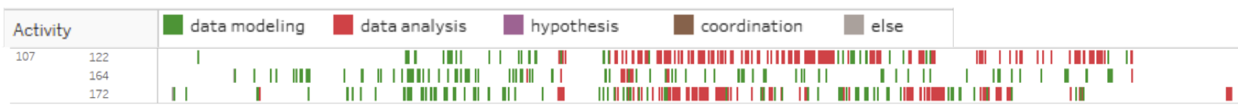

Figure 4. Visualization of interaction logs of Team 107. Each row of colored marks indicates the sequence of top level activities a participant performed.

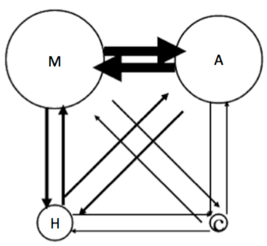

Figure 5. State transition diagram of interaction logs of Team 107. Each node is an activity, whose size represents the time spent on the it; a link represents a switch from one activity to another, whose width encodes the number of switches.

were related and might be committed by the same criminal group.

While many causes might account for the different network views, we attempt to interpret the difference from a perspective of uncertainty. For instance, links within a cluster are factual relationships literally modeled from raw documents (e.g. a white van was witnessed at a location), but links between clusters are often inferences beyond literally documented (e.g. a white van at location A is the same van witnessed at location B). Teams creating separate clusters only represented facts in the network and held evidence with uncertainty in a separate artifact. One advantage of distinguishing facts and inferences is that teams can be aware of assumptions made when making a hypothesis. And since all inferences are held in one place, teams are forced to confront them and review their uncertainty iteratively in the process. However, the strategy also adds difficulty to analysis as analysts may overlook or fail to combine evidence scattered in different artifacts.

On the contrary, some other teams overlaid facts and inferences in the same artifact. Both facts and inferences drove the layout of the network, thus influencing team's framing of the problem. Most teams made evaluation of the uncertainty of inferences when adding them to the network. This strategy was relatively more interactive among teammates: they needed to negotiate, evaluate, and reach consensus on the value and validity of every inference. To some extent teams might forget whether a relationship is factual or inferred, and ask whether conclusion derived from the visualization can be trusted under uncertainty.

From granularity of entities, We noted a distinction between accretion and filtering strategies in data modeling, similar to findings in a paper prototype study where participants constructed information artifacts on paper [5]. Filtering is selectively modeling of data and adding to an artifact. Users must decide what information is relevant, and thus what is to be excluded, as well as what granularity of information is to model. Filtering requires more team coordination, because teammates must reach a common ground of the current problem as well as information needed to answer the problem. Figure 6a is an example of filtering, highlighting only the key information of each robbery and how robberies are connected.

Accretion is an attempt to comprehensively represent the problem by adding all information to an artifact. Users extract every fact from the document, regardless of its immediate relevance to the problem. Accretion costs less coordination as it is relatively mechanical note taking. A disadvantage of accretion is that it could be time consuming to model all details and the produced artifact could be fairly complex. An example is Team 108, who modeled every step the suspects took, which resulted in many more entities than the average and much more cluttered network view (Figure 6d). Users reported that they spent too much time in details that they lost the bigger picture:

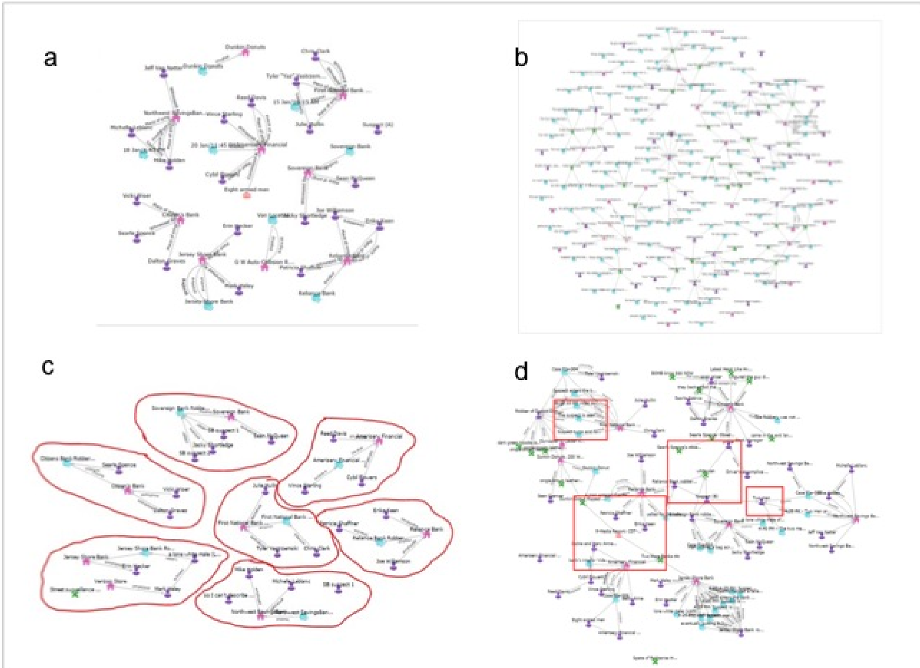

Figure 6. User created network graphs. a) Exemplar network with filtering strategy; b) network with accretion strategy; c) network consisting of separate clusters; d) network consisting of connected clusters

> We would find ourselves glued to our computer screens, and spent too much time on intelligence gathering rather than analysis (P135)

Different from the result in paper prototype study, however, participants seemed to be more tempted to accretively add information with CAnalytics. Students reflected that many annotations did not help them solve the problem at all because those entities were unrelated to their problem.

> I felt that after we were done annotating, we hadn't really accomplished anything and that we were no closer to solving the case than when we had started. In the end it didn't really help that we had annotated the data,

Why did this happen? We guess both the context of classroom study and the system design contributed. Unlike in the lab study where teams were temporarily assembled, teams in a class evaluated peers either consciously or unconsciously. Such social pressure motivated individuals to make contributions, and to make *visible* contributions more than valuable contributions. The awareness features in our system unfortunately made some contributions more *visible* than others. For example, creating an annotation would be immediately broadcast to the team, whereas writing a hypotheses on a notepad produced no notification, although the text was also shared. The selective awareness seemed to also exert bias to recognition of contribution.

DISCUSSION

Reflections on method

The goal of the study is to explore design opportunities to support collaborative information analysis by evaluating tool usage in a natural environment over extended period of time. This is to complement research that only tests tools in short term lab studies (e.g. [8, 11]). Due to the constraint of time (usually about one hour), these studies had to employ a simplified task with significantly reduced content and complexity. Teams would then not create complex information artifacts and had less difficulty balancing limited cognition between problem solving and team coordination. More complex information artifacts and higher cost of coordination would have provided more insights into team process of combining information and tool usage for integrating efforts.

Besides, the limited time may prevent teams from developing sufficient awareness to work properly. Participants in lab studies face a fresh new setting: a new formed team, a new collaborative tool, a new task, and a new environment. It takes time for teams to establish common ground, and to learn to appropriate the tool to best serve their team. Allowing teams for more time to explore and make trials would have provided an opportunity to observe how team awareness have developed and how teams have appropriated the tool to best solve the problem.

Our classroom study attempts to gain deeper insights on collaborative information analysis behavior by better simulating real world settings in two aspects:

1. The study was one-week long. Teams were able to explore multiple strategies to solve the problem, and to change a strategy if they encountered a problem. For example, two teams decided to change the use of the tool halfway in their analysis. One team started with dividing work by case documents, but later decided members should annotate different entity types. Another team started with an accretion strategy by annotating all entities. Later they discovered

that this strategy brought too much noise instead of useful information, and decided to clean out irrelevant entities (filtering strategy). Such change occurs as a consequence of increased awareness of team functions and tool capabilities, which takes time to develop.

2. Participants in this study are being trained to be professional analysts. Since they had already been introduced to the information analysis techniques and to the state-of-the-art tools that support this task, they had a basedline against which to compare CAnalytics. Therefore their feedback is likely to provide deeper insight into strength and weakness of CAnalytics.

Yet classroom study also has limits. For example, many factors and variables could exist that affect team performance. The fact that these factors are often impossible to model or control adds to the difficulty in data analysis (e.g. identifying performance correlated factors with linear regression). Also, data collection is challenging because team interactions are not always accessible. Teams can choose to work synchronously or asynchronously, and it is difficult to predict when or where the interaction of most interest is to occur. Due to these limits, result of classroom study is more likely to identify problems and generate hypotheses, while lab studies and case studies can be conducted to evaluate solutions and validate hypotheses with greater control and deeper access.

Reflections on result

A misconception about information analysis is that data modeling and data analysis are two staged activities. Most analytic tools assume data has already been modeled and ready to be visualized and analyzed. This is akin to the waterfall software development model, which features a sequential process that flows downwards through the phases of requirement conception, software design, software implementation, testing and maintenance. Critics have pointed out that the staged approach may not work properly, because clients may not know exactly what their requirements are before they see the working software and designers may not be fully aware of future difficulties in a new software product. Instead, an iterative design process is often required that leads to reframe user requirements, redesign, redevelopment, and retesting.

Similarly, relying only on information that has already been modeled and delivered to analysts will probably not solve all analytical problems [15]. It will probably be necessary to look elsewhere, re-model the data, and dig for more information. We therefore implemented functionality for manual annotation instead of presenting analysts with algorithm-extracted entities. Developers of the entity-based systems (e.g. [10]) admitted that the accuracy of automatic entity extraction is not sufficient to support human analysis. Relationships identified by algorithms are mostly limited to entity co-occurrence in the same document, but those that are semantically meaningful still requires human judgment. And algorithm treats all pieces of information equally with no regard to the problem analysts have at hand. Our findings show that analysts place varying priority on evidence depending on how they frame the problem [15], and that framing of the problem could change as their analysis proceeds, thus leading to change of evidence weight as well. Perhaps a better solution is to have human in the loop while leveraging algorithm computing power. The algorithm could suggest entities of interest and the analyst decides whether they are of relevance and how entities are related.

We noted the importance of representing uncertainty. We observed teams in our study spontaneously employed two different approaches to deal with team uncertainty given that the tool did not include specific support: to hold facts and inferences in separate artifacts, and place facts and inferences of high certainty in an artifact. This demonstrates both challenge and opportunity to design for uncertainty support. We propose that a richer graphic language be designed so that analysts can encode uncertainty into the network view. Links and entities with different uncertainty are visualized in different colors. Users can *filter by uncertainty* so that users can choose to have only facts to take into account or confront all inferences to make a review.

We found that participants tended to make more visible contributions than valuable contributions, and collaborative technology only made some activities more visible, thus unintentionally encouraged participants to do more these activities, although they might not be useful at all. This is especially true when team practice has not been established and thus can be easily shaped by outside incentives, such as the awareness features in our system. We should be cautious to distinguish between awareness system and contribution system. A contribution system should only include factors that bear value to the task, such as hypotheses created and validated in the context of information analysis, and should be explicitly displayed to users to highlight the value of these factors. Awareness system, on the other hand, should share all relevant activities (and perhaps highlight information most relevant to the current user, for example, when teammates edit your entity). The information, while valuable to the task goal, can motivate teammates to contribute in the same direction, and can remind teammates to pull you back when it deviates from the team goal (e.g. when one user created too many low-level entities in Team 108)

A possible design solution to a cluttered display when the number of entities increases is to enable collapsible data views. Indeed we found analysts often engaged in multi-level analysis in parallel, frequently coordinating between, say, confirmation of a location, to associating sequence of actions, to comparing two groups of evidence, to overviewing robberies as a whole. A collapsible view can help analysts focus attention on a certain level of details, and when in collaboration, draw teammate's attention to the specific item in your intention.

One major critic was the lack of view sharing support in the tool. In addition to data sharing, we find that views of data should become shareable resources as well. With the identical data pool, analysts often have different views of data. For example, analysts can apply a filter to have a reduced data view, highlight an area to sharpen analytic focus, and re-layout the node-link graph to cluster relevant entities. While the data pool represents the information the team have available, individual views of the data reflect analyst's *interpretation* toward the information. The views together with the underlying data embody user's intermediate analytic status. Therefore we propose that just like data, views, which embodies interpretation of data, should be shareable.

Views as resources should also be extensible and reusable. For example, several participants reflected that there were situations when they found a collaborator's view useful and wanted to build their own work upon that view without manually reproducing the view. With views as resources, individuals can take the views to their need. They can also deliberatively share their own view when they feel other collaborators will be interested. Shared views are interactive rather than static images, so that analysts can still perform full functions including filtering and highlighting, and are able to evolve the view with collective team efforts, a critical requirement emphasized in [5]

Our study suggests that the instrument plays an important role in shaping students' behavior towards more collaborative learning. With traditional single-user tools, students often employ a divide-and-conquer strategy; they divide their job responsibility, work individually on their own part, and put the results together in the end for report submission. In our study, we observed that students spontaneously conducted closer collaboration and enjoyed being able to contribute simultaneously.

Anecdotal reflections from the instructor suggested that the system can include support for instructor intervention. During the study, the instructor would go over to students and check their computer screen about how they were doing, and provide guidance if necessary. The instructor commented that he valued students' thinking and reasoning process, and believed that monitoring and guiding students' ongoing performance would be a valuable supplement to classroom instruction. As claimed by Heuer [15], training will be more effective if supplemented with ongoing advice and assistance. CAnalytics could do more in supporting the instructor. CAnalytics already provides an integrated workspace for data modeling, information analysis and hypothesis generation, and thus makes it easier to monitor the whole analytic process. Besides, students' interaction logs are already captured (for team awareness and research purpose only now), and could be streamed to the instructor for performance monitoring. The process data provides the instructor a new window to assess students' performance and to provide intervention when necessary, as suggested by learning analytics techniques [19].

CONCLUSION

In this paper, we present findings from a classroom study in which teams of information analysts in training collaboratively completed a complex intelligence project mediated by our tool. As collaborative information analysis is increasingly a typical and chronic task, it is important for research to examine, understand, and provide effective tools and environments for these long-term, real-world CSCW interactions. This requires situating research in more complex work activity contexts, and directly investigating interactions, experiences, and outcomes in those contexts. Our classroom study provides initial results on team interactions mediated by advanced technology over extended time periods. The encouraging results motivate us to continue refining and reevaluating the tool.

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To be added

References

[1] Richard V Badalamente and Frank L Greitzer. "Top Ten Needs for Intelligence Analysis Tool Development". In: *First Annual Conference on Intelligence Analysis Methods and Tools* May (2005).

[2] Eric a. Bier, Stuart K. Card, and John W. Bodnar. "Entity-based collaboration tools for intelligence analysis". In: *2008 IEEE Symposium on Visual Analytics Science and Technology*. Ieee, Oct. 2008, pp. 99–106. ISBN: 978-1-4244-2935-6. DOI: 10.1109/VAST.2008.4677362. URL: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4677362.

[3] Eric a Bier, Stuart K Card, and John W Bodnar. "Principles and tools for collaborative entity-based intelligence analysis." In: *IEEE transactions on visualization and computer graphics* 16.2 (2010), pp. 178–91. ISSN: 1077-2626. DOI: 10.1109/TVCG.2009.104. URL: http://www.ncbi.nlm.nih.gov/pubmed/20075480.

[4] Marcela Borge et al. "Patterns of team processes and breakdowns in information analysis tasks". In: *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work - CSCW '12*. New York, New York, USA: ACM Press, 2012, pp. 1105–1114. ISBN: 9781450310864. DOI: 10.1145/2145204.2145369. URL: http://dl.acm.org/citation.cfm?doid=2145204.2145369.

[5] John M. Carroll, Marcela Borge, and SI Shih. "Cognitive artifacts as a window on design". In: *Journal of Visual Languages & Computing* 24.4 (2013), pp. 248–261. URL: http://www.sciencedirect.com/science/article/pii/S1045926X13000207.

[6] John M. Carroll et al. "Awareness and teamwork in computer-supported collaborations". In: *Interacting with Computers* 18.1 (Jan. 2006), pp. 21–46. ISSN: 09535438. DOI: 10.1016/j.intcom.2005.05.005. URL: http://iwc.oxfordjournals.org/cgi/doi/10.1016/j.intcom.2005.05.005.

[7] George Chin Jr, Olga A. Kuchar, and Katherine E. Wolf. "Exploring the analytical processes of intelligence analysts". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2009, pp. 11–20. ISBN: 9781605582467. URL: http://dl.acm.org/citation.cfm?id=1518704.

[8] Gregorio Convertino et al. “Supporting common ground and awareness in emergency management planning”. In: *ACM Transactions on Computer-Human Interaction* 18.4 (Dec. 2011), pp. 1–34. ISSN: 10730516. DOI: 10.1145/2063231.2063236. URL: http://dl.acm.org/citation.cfm?doid=2063231.2063236.

[9] Michael Diehl and Wolfgang Strpebe. “Productivity Loss In Brainstorming Groups : Toward the Solution of a Riddle”. In: *Journal of personality and social psychology* 53.3 (1987), pp. 497–509. DOI: 10.1037/0022-3514.53.3.497.

[10] C. Gorg, Z. Liu, and J. Stasko. “Reflections on the evolution of the Jigsaw visual analytics system”. In: *Information Visualization* 13.4 (July 2014), pp. 336–345. ISSN: 1473-8716. DOI: 10.1177/1473871613495674. URL: http://ivi.sagepub.com/lookup/doi/10.1177/1473871613495674.

[11] Nitesh Goyal and Susan R Fussell. “Effects of Sensemaking Translucence on Distributed Collaborative Analysis”. In: *CSCW ’16 Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*. 2016.

[12] Nitesh Goyal et al. “Effects of Implicit Sharing in Collaborative Analysis”. In: *Proceedings of the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2014, pp. 129–138. ISBN: 9781450324731. URL: http://www.cs.cornell.edu/%7B~%7Dngoyal/1470%7B%5C_%7DChi2014.pdf.

[13] Amir Hossein Hajizadeh, Melanie Tory, and Rock Leung. “Supporting awareness through collaborative brushing and linking of tabular data.” In: *IEEE transactions on visualization and computer graphics* 19.12 (Dec. 2013), pp. 2189–97. ISSN: 1941-0506. DOI: 10.1109/TVCG.2013.197. URL: http://www.ncbi.nlm.nih.gov/pubmed/24051785.

[14] Sandra G. Hart and Lowell E. Staveland. “Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research”. In: *Advances in Psychology* 52.C (1988), pp. 139–183. ISSN: 01664115. DOI: 10.1016/S0166-4115(08)62386-9. arXiv: arXiv:1011.1669v3.

[15] Richards J Heuer. *Psychology of intelligence analysis*. Lulu.com, 1999.

[16] Youn-ah Kang and John Stasko. “Characterizing the intelligence analysis process: Informing visual analytics design through a longitudinal field study”. In: *2011 IEEE Conference on Visual Analytics Science and Technology (VAST)*. Ieee, Oct. 2011, pp. 21–30. ISBN: 978-1-4673-0014-8. DOI: 10.1109/VAST.2011.6102438. URL: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6102438.

[17] Narges Mahyar and Melanie Tory. “Supporting Communication and Coordination in Collaborative Sensemaking”. In: *Visualization and Computer Graphics, IEEE Transactions on* 20.12 (2013), pp. 1633–1642.

[18] Kjeld Schmidt. “The Problem with ‘ Awareness ’”. In: *Computer Supported Cooperative Work (CSCW)*. 2002, pp. 285–298.

[19] George Siemens and Phil Long. “Penetrating the fog: Analytics in learning and education.” In: *EDUCAUSE review* 46.5 (2011), p. 30.

[20] John Stasko, Carsten Görg, and Robert Spence. “Jigsaw: supporting investigative analysis through interactive visualization”. In: *Information Visualization* 7.2 (2008), pp. 118–132. ISSN: 1473-8716. DOI: 10.1057/palgrave.ivs.9500180. URL: http://ivi.sagepub.com/lookup/doi/10.1057/palgrave.ivs.9500180.

[21] Colin Ware. *Information visualization: perception for design*. Elsevier, 2012.