THEORIES AND MODELS OF GROUP COGNITION

Statement of Work

This project brings a broad range of theoretical approaches, mixed-method analyses and computational models to bear on a rich data set of team interaction. The data provides a complete record of eight hours of intense synchronous problem solving by two virtual math teams. The data was collected in 2006 under IRB-approved protocols; the data is completely anonymous online chat data.

Within the project, the data will be analyzed in three primary ways: (i) through manual qualitative conversation analysis, (ii) through leading-edge techniques of natural language automated processing and (iii) through mixed methods of qualitative and quantitative analysis, data mining, cluster analysis, statistical analysis and network analysis.

The findings from the original analyses described above will be compared with a range of relevant previous literature. This includes the following sources: (i) previous work of the PIs themselves, (ii) related work by other researchers in the ONR CKI program, (iii) coding schemes developed in the field of computer-supported collaborative learning (CSCL), and (iv) seminal works on distributed cognition, situated cognition, activity theory, mediated cognition, situated learning, knowledge building, ethnomethodology, actor network theory, dialogics, small-group theory and social theory.

In addition to publishing project findings in white papers, conference papers and journal articles, the PIs will organize workshops to: (i) compare different coding schemes and analysis methods and to discuss potentials for synthesis and mixed methods combinations, (ii) analyze the data set for this project from different methodological perspectives from other CKI and CSCL projects, and (iii) consider different theories and models of macrocognition as applied to the data set for this project.

The goals of the project will be: (i) to identify the nature of group cognition processes (macrocognition) in ad hoc problem-solving teams, (ii) to clarify terminology, (iii) to distinguish related theories, (iv) to validate or expand theory, and (v) to contribute to computational models and other tools, coding schemes and metrics for analyzing macrocognition.

THEORIES AND MODELS OF GROUP COGNITION

This project brings a broad range of theoretical approaches, mixed-method analyses and computational models to bear on a rich data set of team interaction. The data provides a complete record of eight hours of intense synchronous problem solving by two virtual math teams. The data will be made available in a number of formats convenient for analysis. Within the project, the data will be analyzed in three primary ways:

- Using an adaptation of conversation analysis applied to text chat, the interactions will be analyzed to identify methods of group cognition or macrocognition, whereby the group constructs new knowledge that emerges through the group interaction and that none of the participants previously possessed.
- Using techniques of natural language processing, the interactions will be automatically coded using coding schemes that identify key moves and utterances that are associated with collaborative knowledge building or macrocognition.
- Using mixed methods of qualitative and quantitative analysis, data mining, cluster analysis, statistical analysis and network analysis, the two approaches above will be bridged, identifying measures that connect the qualitative manual conversation analysis results and the quantitative automated coding analysis results.

The findings from the original analyses described above will be compared with a range of relevant previous literature. This includes the following sources:

- The previous work of the PIs themselves, including the analyses in Stahl's *Group Cognition* and *Studying Virtual Math Teams*, and the past work by Rosé on language analysis and coding of knowledge building.
- Related work in the CKI program, including publications from projects funded by CKI, such as Cooke's and Warner's analyses of interaction data.
- Other coding schemes for collaborative knowledge building developed in the field of computer-supported collaborative learning (CSCL).
- Seminal works on distributed cognition, situated cognition, activity theory, mediated cognition, situated learning, knowledge building, ethnomethodology, actor network theory, dialogics, small-group theory and social theory.

The project leads (Stahl and Rosé) are both leaders in the international CSCL research community. The project will leverage their connections in the CSCL and CKI communities to involve other researchers in collaboratively pursuing the project investigations and in disseminating the emerging results. In addition to publishing project findings in white papers, conference papers and journal articles, the PIs will organize the following kinds of events:

- A workshop at which researchers with different methodological perspectives from other CKI and CSCL projects gather to compare different coding schemes and analysis methods and to discuss potentials for synthesis and mixed methods combinations.

- A workshop at which researchers with different methodological perspectives from other CKI and CSCL projects gather to analyze the data set for this project.
- A workshop at which researchers representing different theoretical perspectives gather to consider different theories and models of macrocognition as applied to the data set for this project.

The goal of the project will be to identify the nature of group cognition processes in ad hoc problem-solving teams, to clarify terminology, to distinguish related theories, to validate or expand theory and to contribute to computational models and other tools, coding schemes and metrics for analyzing macrocognition.

Impact of Proposed Work

The proposed project will result in the design, development and testing of analysis methods, automated tools, dynamic models and empirically grounded theory for the understanding of group processes of macrocognition (aka group cognition) in ad hoc teams confronted by non-standard problems.

ONR Mission Relevance

The proposed project is directly responsive to the ONR CKI Program focus on analyzing group processes involved in team decision making in tactical teams. The project develops tools for analyzing, theorizing and modeling group processes involved in team decision making in small ad hoc groups collaborating on complex problem exploration, analysis and solving.

Management Approach

Gerry Stahl will coordinate work at Drexel and Carolyn Rosé will coordinate work at CMU. They will stay in weekly contact to coordinate the overall project. Drexel will act as lead on the grant and 50% of the grant is subcontracted by Drexel to CMU.

All human data to be used is strictly anonymous online chat data recovered from Math Forum server logs. The data was created in Spring 2006 under protocol approved by the Drexel IRB, which is certified under Human Subject Assurance Number FWA0001852. CMU's IRB is also certified.

TECHNICAL APPROACH

Outline of Proposed Work

In each of the project's three years, there will be six types of tasks, including (1) corpus definition, (2) manual analysis, (3) coding scheme design, (4) automated coding, (5) data analysis and (6) theory building:

1. *Corpus Definition*: In each year of the proposed work, we will work with a different existing corpus of interaction data so that by the end of the project, we will be able to engage in theory building that generalizes across multiple tasks under multiple configurations. By the end of the project, we will be in a good position to derive generalizations that have substance and generalizability. We will apply both the transactivity-based coding scheme and coding schemes from the CKI and CSCL communities to the same data.
2. *Hand Analysis*: For each of our corpora we will analyze up to half of the data by hand and then use automatic coding technology to code the rest. This hand analysis will be based upon interaction analysis of the corpus. Although the hand analysis will attempt to uncover structures to guide the design of the coding scheme, it will more generally seek to discover the full range of macrocognitive processes that take place in the data at the group unit of analysis.
3. *Coding Scheme Design*: Our work will be focused on a transactivity-style analysis, however we expect to have to make adjustments to the category definitions for each corpus we work with in order to be true to the nuances of the discussions going on there while maintaining high reliability and without changing the spirit of the codes. Additionally, we will be working with coding schemes from the CSCL and CKI communities, beginning with Cooke and Gorman's (2009) work on interaction-based measures of cognitive systems, especially measures of communication flow, which allow for analyses of influence and stability within group discussions.
4. *Automated Coding*: As in our prior work, we will make heavy use of automated coding technology in this proposed work. In our experience, the technology is still new enough that each corpus we work with raises new challenges for this technology. However, as we address those challenges, we produce new knowledge in the area of text mining and text classification, which generates additional insights and publications.
5. *Data Analysis*: One major goal of our data analysis across all three corpora is to validate the transactivity framework by correlating occurrences of subsets of codes with important outcome measures. But we'll also be exploring correlations between occurrences of transactivity-related events with those of the types of analysis schemes explored previously in the CKI and CSCL communities. In general, the data analysis will explore diverse methods and mixed-method combinations to specify data points and group interaction methods (macrocognitive processes) as discovered in the data by both hand analysis and automated coding, in order to test and refine theories and models of team decision making in ad hoc groups.

6. *Theory Building*: The ultimate goal of our theory building will be to stimulate exchange of ideas and findings between the CKI community and the CSCL community through workshops, symposia and publications at the International Conference of the Learning Sciences, the Computer-Supported Collaborative Learning conference and the *International Journal of Computer-Supported Collaborative Learning*.

Detailed Description of Project

1. Corpus Definition

Data that captures interesting examples of collaborative knowledge building is hard to find. The Group Cognition Lab worked for six years to generate good data for analysis (Stahl, 2006). It defined an online environment in which groups can meet and everything that group participants share interactionally is captured by the computer logs. We defined tasks and facilitated sessions to realize ad hoc, complex, one-of-a-kind team problem-solving scenarios. We led the groups to focus on building and processing new knowledge for their problem solving. Moreover, we recruited students at a stage where they were just learning the fundamentals of abstract thinking, so that we could observe the emergence of new individual and group skills in concert with each other. The lab developed technologies for instrumenting the online environment and for replaying the interactions in ways that support detailed analysis by researchers. In addition, we explored alternative analysis methods and developed our own approach to interaction analysis.

The core data set selected for this project was generated as part of the Math Forum's VMT Spring Fest 2006 in May of 2006. The student participants were normal users of the Math Forum online services; their identities were completely anonymous, signified only by a self-selected login chat handle. The best examples of group cognition can be found in the logs of Team B and Team C. These logs reveal rich examples of cognitive processes accomplished interactively by the groups. Each Team engaged in four hour-long sessions during a two-week period. There are dramatic signs of longitudinal development at both the individual and group level as they learned new communication and problem-solving skills and methods appropriate to their socio-technical and goal-oriented situation.

The log for the two teams together consists of about 3,000 chat postings and 3,000 other actions. This is a sizable corpus for manual and automated analysis. We already have considerable experience analyzing brief excerpts from this corpus. These excerpts form the core of two exceptional PhD dissertations that have already been completed (Çakir, 2009a; Sarmiento-Klapper, 2009a). Other excerpts have been analyzed by colleagues from other labs internationally, as reflected in chapters of *Studying Virtual Math Teams* (Stahl, 2009b) and in symposia on VMT data at the CSCL 2007 and 2009 conferences (Koschmann & Stahl, 2009; Stahl, 2007).

The core data set is being made available as open source through an international CSCL data archive. This will not only make it globally available to researchers for making comparisons, but it will format it in a common XML-based scheme, making it susceptible to being displayed in various templates. This is part of an on-going effort within the CSCL community to enhance comparability of different methodological approaches. The proposed project will be part of this international effort in a number of ways.

The selected data corpus will be analyzed in detail within the proposed project through three phases:

- Year I: Session 4 of Team B. This is probably the session with the most examples of collaborative knowledge building. Therefore it will provide a rich source for initial development of a coding scheme that identifies and classifies instances of effective macrocognition.
- Year II: Team C Sessions 1 and 4. This is data involving the same web-based technology and the same problem-solving task as in Year I, but conducted by a different group of participants. The inclusion of the team's first and last session offers data with a longitudinal contrast, as well as some comparison with the year I data. It therefore provides a solid basis for testing and generalizing the year I coding.
- Year III: The complete combined corpus of Team B and C data (all sessions). This provides an extensive data corpus of over 6,000 events. It includes many group interactions. It provides a rich source for statistical comparisons among interactions.

2. Hand Analysis

The VMT Project at the Group Cognition Lab at Drexel University has developed an ethnomethodologically-informed approach to interaction analysis of synchronous online interaction data (Zemel, Xhafa & Çakir, 2009). This approach is defined and described in Chapter 28 of *Studying Virtual Math Teams* (Stahl, 2009c). It is illustrated especially in Chapters 6, 7, 8 and 9 of that volume (Çakir, 2009b; Sarmiento-Klapper, 2009b; Toledo, 2009; Zhou, 2009). The method involves data sessions using the VMT Replayer to engage a group of experienced researchers in the conversation analysis of an excerpt from an online session to define the linguistic, visual and indexical work being carried out by the group and the group cognition thereby accomplished. The method is rigorous, generalizable and reliable, as discussed in Chapter 28.

As described in Chapter 28 on "*Toward a Science of Group Cognition*" (Stahl, 2009c), the analysis of group cognition explores how small groups engage as a group (i.e., at the group unit of analysis) in the accomplishment of cognitive tasks. These include such tasks as: intersubjective meaning making, interpersonal trains of thought, shared understandings of diagrams, joint problem conceptualizations, common references, coordination of problem-solving efforts, planning, deducing, designing, describing, problem solving, explaining, defining, generalizing, representing, remembering and reflecting. Groups develop general methods of doing these things, always adapted to the situations in which they are engaged and the media and other resources that are at their disposal (Stahl, 2009a).

3. Coding Scheme Design

Machine-learning algorithms can learn mappings between a set of input features and a set of output categories. They do this by using statistical techniques to find characteristics of hand-coded "training examples" that exemplify each of the output categories. The goal of the algorithm is to learn rules by generalizing from these examples in such a way that the rules can be applied effectively to new examples. In order for this to work well, the set of input features provided must be sufficiently expressive, and the training examples must be representative. Typically, machine-learning researchers design a set of input features that they suspect will be expressive enough (Strijbos, 2009). At the most superficial level, these input features are simply the words in a document. But many other features are routinely used in a wide range of text-processing applications, such as word collocations and simple patterns involving part of speech tags and low-level lexical features; we will draw from this prior work.

Once candidate input features have been identified, analysts typically hand code a large number of training examples. The previously developed TagHelper tool set (Rosé et al., 2008) has the capability of allowing users to define how texts will be represented and processed by making selections on the GUI interface. In addition to basic text-processing tools such as part-of-speech taggers and stemmers that are used to construct a representation of the text that machine-learning algorithms can work with, a variety of algorithms from toolkits such as Weka (Witten & Frank, 2005) are included in order to provide many alternative machine-learning algorithms to map between the input features and the output categories. Based on their understanding of the classification problem, machine-learning practitioners typically pick an algorithm that they expect to perform well. Often this is an iterative process of applying an algorithm, seeing where the trained classifier makes mistakes, and then adding additional input features, removing extraneous input features, or experimenting with algorithms.

Applying this iterative process requires insight and skill in the areas of linguistics and machine learning that the social scientists conducting corpus analysis are unlikely to possess. TagHelper tools support this interactive processes by making it easy to define different processing configurations through the GUI and then providing reports about how the configuration worked and where the process may have broken down. The goal of our tool development is to make this process easier for social scientists. In particular, the process of identifying where the process has broken down and how the configuration can be tuned in order to improve the performance requires more expertise than typical social scientists would possess. Thus, the bulk of our development work will be in developing the machinery to bridge the gap between the natural structure of the input texts and the behaviors that social scientists are interested in cataloguing and coding, using bootstrapping approaches.

In our recent corpus-based experiments (Josh & Rosé, 2009; Arora, Joshi, & Rosé, 2009) we have explored the usage of alternative types of syntactically motivated features on text classification performance. Our methodology is extensively discussed in our recent journal article in the *International Journal of Computer-Supported Collaborative Learning*, investigating the use of text classification technology for automatic collaborative learning process analysis (Rosé et al., 2008).

Advancing Beyond the Capabilities of Keyword-Based Approaches. Linguistic Inquiry and Word Count (Pennebaker, 2003) is a paradigm case of keyword-based approaches to analysis of verbal data, that is very commonly used in social psychology, especially but not solely in work related to health communication. LIWC indicators that are designed to measure latent characteristics of authors such as emotional or psychological state based on vocabulary usage have been successfully calibrated with a wide range of behaviors over multiple types of studies. Nevertheless, they have limitations that must be taken into account methodologically. LIWC indicators have typically been used in studies where the external variables of interest are health outcomes or health related behavior. In studies where consistent stories based on calibrations of LIWC indicators with external variables are reported, the corpora used were created under very controlled circumstances, always only within the experimental condition of a study in which the genre and topic of the writing were determined by the experimental manipulation. When these tight constraints are removed, the story becomes much less clear. For example, Pennebaker and Francis (1996) present results from a study with two different conditions. The experimental variation lay in the change of the topic participants wrote about. In this study, the LIWC indicators made opposite predictions about behavioral outcomes and emotional states in the experimental condition in comparison to the control condition. Discrepancies like this occur because there are many linguistic factors besides the emotional state of the author or speaker that affect the frequencies of word usage. For example, many words have multiple meanings and only convey negative emotion in some contexts and not in others. For example, the words "bake" and "roast" used while talking about the weather convey a feeling of discomfort, whereas in the context of a discussion about cooking, they do not. Base frequencies of terms also vary between topics. Thus, a difference in frequency of a term may either indicate a difference in the emotional state of the author or simply a difference in topic. If LIWC predictors were truly indicative of emotional state independent of topic, and fluctuations in emotional state predict corresponding fluctuations in health and behavior outcomes, it is difficult to reconcile the difference in the direction of predictions between conditions reported in that paper. Nevertheless, if one accepts that LIWC indicators are merely proxies that can be used for estimating measurement of psychological state within very narrowly constrained contexts, then the pattern makes sense. However, this limitation has strong negative implications for the applicability of LIWC indicators within naturalistic communication settings in which there is a wide variation in the communicative goals motivating individual contributions, such as in naturalistic on-line learning environments where students may interact about a wide range of topics in connection with a variety of activities over time.

Analysis of collaborative learning interactions have demonstrated that what happens on the process level is important for predicting what cognitive benefits participants in a conversation take away from it (e.g., King 2007). More complex learning is supposed to occur in "spirals of reciprocity," where learners are intensely engaged with one another (Salomon and Perkins 1998). In particular, learners can attain new levels of understanding during interactions where more complex cognitive activities occur, such as analytical thinking, integration of ideas and reasoning. These include activities such as elaborating on content (e.g., Webb 1989), explaining ideas and concepts (e.g., Chi et al. 1994), asking thought-provoking questions (e.g., King 1998, 1999), argumentation (e.g., Kuhn 1991), resolving conceptual discrepancies (e.g., Piaget 1985) and modeling one another's cognitive states. These activities may not be adequately represented by patterns of individual turns taken out of context. Modeling these processes instead requires categorical coding schemes building on precise definitions of categories (see Chi et al. 1994). Trained human coders are able to consistently apply well-defined coding schemes across multiple contexts. However, we acknowledge that applying coding schemes like this by hand is extremely tedious. And effectively writing rules by hand to reliably match against complex patterns, which is an option provided by some corpus analysis environments, is difficult as well.

When human coders apply categorical coding schemes, they bring insights with them from their human intellect. Human language is highly complex, encoding meaning on multiple levels, and carrying very subtle nuances that are difficult to formally capture with a rule based model. Interpretation of language involves using cultural sensitivity to style and lexical choice, applying world knowledge, integrating meaning across spans of text, and often making inferences about what is implied in addition to what is literally stated. In contrast, regardless of approach, machine coding will always be based on rigid rules that are necessarily an over-simplification of the reasoning processes that humans rely on for their interpretation. Note that word counting approaches such as LIWC, which were discussed earlier, are an extreme case of this over-simplification. This simplification threatens the face validity of the coding that can be accomplished automatically because this word based approach may not be measuring what it is purported to be measuring. Using an example from our own work, we have used LIWC to examine the language behavior of five different tutors who participated in a series of calculus problem solving studies (Gweon et al. 2006). We evaluated tutor effectiveness by comparing them with respect to the average learning gains of the students they tutored. Based on this analysis, we determined that the more effective tutors scored higher on LIWC's confidence scale. When we examined which words from the tutors' contributions the associated LIWC word list was matching against, the most frequent word was "factor", which came up inside discussions about algebra. Thus, the LIWC confidence scale was not ranking tutors based on their confidence at all, but rather their tendency to supplement their calculus tutoring with basic algebra concepts such as factoring. Thus, word-counting approaches like LIWC that make their assessment based on individual words taken out of context should be used with caution. We see from our calculus example that they are not guaranteed to reflect accurately the mental states they were designed to assess.

Machine learning based approaches can transcend the limitations of keyword-based approaches because they allow for more complex representations of text beyond simply keywords. In our recent work, for example, using more complex grammar and context oriented features in addition to word level features, we have demonstrated significant improvements in analysis accuracy over simple word based representations of text for tasks such as collaborative learning process analysis (Rosé et al., 2008), sentiment analysis (Joshi & Rosé, 2009; Arora, Joshi, & Rosé, 2009), and text compression (Chaudhuri, Gupta, Smith, & Rosé, 2009; Gupta, Chaudhuri, & Rosé, 2009).

Advancing Beyond the Capabilities of LSA. Latent semantic analysis (LSA) is well known as a practical method for representing words in terms of classes of words that share a similar distribution in terms of the "neighborhoods" or words they occur with. One can think of it as a way of identifying groups of semantically related words (Landauer et al., 1998). We would expect that methods that offer a way of generalizing over alternative phrasings of the same or similar ideas would be useful in tracking initiation-reply links that form the elementary units of knowledge building processes in conversation.

In the typical method for applying LSA, we first construct a term-by-document matrix. Next, LSA applies singular value decomposition to the matrix, and reduces the dimension of the feature space of terms to a 300-dimensional concept space. We can then represent a term vector, whether it is a simple term vector or an expanded term vector, in terms of this LSA space by averaging across the LSA representation for each word in the text within that 300 dimensional space. Text vectors that have been transformed in this way can then be compared using cosine similarity.

However, for the purpose of tracing the knowledge-building process of students, there is a major limitation of LSA as it is typically applied that must be taken into account. Note that not all words carry equal weight within the vector that results from the averaging process in constructing an LSA vector for a text. Words that are closer to the "semantic prototypes" represented by each of the 300 dimensions of the reduced vector space will have vectors with longer lengths than words that are less close to any single one of those prototypes within that space. Thus, those words that are closer to those prototypes will have more of an effect on the direction that the resulting vector will have within the space. Thus, they will have more of an effect on the comparison with other texts. However, one should note that in a running discussion, it is the unusual content, the noteworthy ideas, that often form the links between initiation and responses, rather than the common concepts that form the background for the ongoing discussion. And thus, one major limitation of LSA as it is typically applied is that it de-emphasizes the contribution of precisely those words that are most important for making the textual links in the discussions that we would like to identify.

Recently we have developed a new approach to applying LSA that overcomes this limitation. For the task of identifying initiation-reply links in a conversational thread recovery task, it significantly outperformed the typical method for applying LSA as well as other baseline approaches making use of lexical resources such as Wordnet. Further work along these lines will be a major focus of the technical component of this proposed research.

4. Automated Coding

Many of the fundamental activities in on-line organizations, such as brainstorming, decision-making and training, require communication. This underlying conversation both furthers the goals of a team and reflects the underlying structure of interactions and relationships within social institutions (Zimmerman & Boden, 1991). Several decades of research in Computer Mediated Communication (CMC) have examined how the use of media affect team communication processes (e.g., Hall, 1976; Li, 1999; Setlock & Fussell, 2007). However, progress in this research community is hampered by how time consuming it is to do this analysis by hand. For example, one recently published study of the effects of culture on negotiation processes required over a year to collect the data, refine the coding scheme, and code and analyze the data. The outcome of this work is a better understanding of one of many communication processes in virtual teams performing one of many different tasks. To extend such work to the full domain of teams, tasks and communicative activities would take decades. As a basic part of our approach, we propose to use a traditional approach to using analysis of corpora by hand in order to increase understanding of virtual teams on a small to medium scale and then use the automatic analysis to expand to a dramatically larger scale.

In our prior work, we have made substantial progress towards detecting properties of conversation that are specifically associated with quality of collaboration. We have focused on a property known as *transactivity* (Rosé et al., 2008; Wang, Rosé, & Joshi, 2007; Joshi & Rosé, 2007), an important property of collaborative discourse. Participants in a collaborative setting are said to have transactive discussions when they elaborate, build upon, question or argue against the ideas presented by their partners in the process of working towards a common understanding of the task and reaching a shared solution. This process of understanding the partners' ideas, comparing them to one's own understanding, arguing and forming a common ground upon which a solution can be built collaboratively has been shown as important for learning (Teasley, 1997; Azmitia & Montgomery, 1993).

The idea of transactivity has its roots in educational psychology with Piaget's model of assimilation/accommodation and Vygotsky's socio-cultural theory of learning. Piaget's model is a particularly key component of the theoretical underpinnings of our proposed work since it provides a framework for characterizing the difference between simply managing existing pieces of knowledge, as one might characterize work so far on macrocognition in the CKI community, and more major cognitive restructuring that can occur at certain points within an assimilation/accommodation cycle.

Digging into the details a little more deeply, at the heart of Piaget's theory of learning is the assimilation-accommodation cycle in which students encounter stimuli in the world that provide data either in support of or in conflict with their own internal model of the world. During assimilation, a student imposes his own model on the stimuli he sees, interpreting everything in that light, and rejecting what does not fit. During accommodation, a student is open to considering a model of the world that may be imposed from the outside. When these processes are in balance, the conditions are most favorable for a student to notice a gap or deeper flaw in his own mental model. When a student becomes aware that stimuli from the world reveal a gap, that student may then choose to search for a revised model of the world that accounts for the new data, which may even require a dramatic paradigm shift or major reorganization of knowledge.

It is important to note that an important ingredient in Piaget's theory is the equality of power or partnership between students working together that is important for creating an environment in which assimilation and accommodation are in balance. Note that equal power does not imply equality in knowledge. Based on Piaget's foundational work (Piaget 1985), one can argue that a major cognitive benefit of collaborative learning is that when students bring differing perspectives to a problem-solving situation, the interaction causes the participants to consider questions that might not have occurred to them otherwise. This stimulus could cause them to identify gaps in their understanding, which they would then be in a position to address. This type of cognitive conflict has the potential to lead to productive shifts in student understanding. Examining the discourse between students in a collaborative-learning setting can reveal evidence of the power relationship between students, the exchange of views and evidence of the opportunity for cognitive conflict in the socio-cognitive conflict that is manifested in the argumentation that occurs between students. The impact of socio-cognitive conflict on learning has been noted especially in connection with difficult-to-learn content (Azimitia & Montgomery, 2005; Russell, 2005). And the important connection between relationship development and socio-cognitive conflict has also been documented (Azimitia & Montgomery, 1993). Examining the discourse between students can also reveal where an imbalance in a power relationship can hinder participation and learning. For example, Elbers & de Hann (2004) provide a qualitative analysis from a socio-cultural perspective on how racial stereotypes affect the power/authoring relationship between students, which may hinder collaborative discussion.

Vygotsky's theory argues for similar patterns of discussion from another angle. While Piaget's theory focuses on equal power but difference in knowledge, Vygotsky focuses more directly on differences in knowledge, but also argues in favor of relationship development and the social nature of knowledge construction. Based on Vygotsky's seminal work (Vygotsky 1978), we know that when students who have different strengths and weaknesses work together, they can provide support for each other that allows them to solve problems that would be just beyond their reach if they were working alone. This makes it possible for them to participate in a wider range of hands-on learning experiences. In our own work, we have observed evidence of helping behavior as a socio-cognitive variable that mediates learning (Gweon et al., 2006; Gweon et al., 2007). Social aspects of group functioning as they relate to and result from patterns of interaction are unquestionably key consideration for groups that will interact with one another over a long period of time. However, one could argue that they are even more essential in ad hoc teams with a critical purpose since any subtle incident that might harm trust or hinder the flow of information might interfere with the success of the encounter.

Surveying the field of computer-supported collaborative learning for frameworks for analyzing group conversations, one might conclude that there are a plethora of different approaches. Nevertheless, one might also consider it not a giant leap to consider that the topic of what makes group discussions productive for learning and community building has been explored with very similar findings, perhaps with subtle distinctions, and under different names such as *transactivity* (Berkowitz & Gibbs, 1983; Teasley, 1997; Weinberger & Fischer, 2006) in the cognitive learning community and *uptake* (Suthers, 2006), *group cognition* (Stahl, 2006) or *productive agency* (Schwartz, 1998) in the socio-cultural learning community. Despite differences in orientation between the cognitive and socio-cultural learning communities, the conversational behaviors that have been identified as valuable are very similar. Building on these common findings, the field of Computer-Supported Collaborative Learning has emerged where support for collaborative learning has been developed that addresses observed weaknesses in conversational behavior related to this phenomenon.

5. Data Analysis

To complement the ethnomethodologically informed interaction analysis and the machine-learning algorithms for automated coding (Strijbos, 2009), we will also analyze the three corpora using content analysis (Krippendorf, 2004) and network analysis (Wasserman and Faust, 1994). The content analysis will be performed on the 3,000 chat postings and the network analysis will be performed on the 6,000 chat and drawing actions.

The content analysis will be executed using two rubrics (Goggins & Laffey, forthcoming). The unit of analysis for this work will be a complete unit of conversation (Krippendorf, 2004). The first rubric will evaluate the development of group identity within the small groups, using Tajfel's (1978, 1979, 1982) description of group communication as inter-group, inter-personal, intra-group and inter-individual. Inter-group communication is communication across groups, and only rarely occurs in this data set. Inter-personal communication takes place between two individuals. Intra-group communication is within the group, where all members participate in the dialogue. An utterance addressing individual members in the presence of the whole group as an aside is coded as inter-individual communication.

The second rubric will evaluate the corpus of data for knowledge co-construction using a rubric developed by Gunawardena et al (1997). Two raters will score the conversations on these rubrics and measure inter-rater reliability using Krippendorf's alpha (2004). This type of analysis is performed by Goggins, Laffey & Gaylen (forthcoming) on asynchronous communication records, and the contrast with the results from synchronous chat data will provide a helpful contrast of synchronous and asynchronous knowledge co-construction in small groups.

Social network analysis will be performed on the 3,000 chat postings and 3,000 other actions in order to determine if there are patterns of networked interaction that correspond with the development of group identity or the co-construction of knowledge. The resulting networks will be bi-partite (users and objects) and regular. Since the networks in our corpora are closed and small, we will focus our analysis on small network evolution and elaborating semantically meaningful measures of tie strength.

Tracking longitudinal evolution will involve developing a time-series set of network views, possibly addressing the state of the network as a feature that contributes to other forms of analysis. We will also explore the advantages of deriving measures of tie strength from the results of machine-learning algorithms, response-time lag and length of sustained interaction between pairs of group members.

These quantitative analyses will not be performed in isolation from the interaction analysis or the automated coding. Decisions about the granularity in both network analysis and content analysis will take the findings and approaches from these other two methods into consideration. The findings of all these mixed-method analyses will inform the design of computational models (Wee & Looi, 2009) and supply a basis for calibrating the models of macrocognition.

6. Theory Building

The findings of the analyses described above will be synthesized into a theoretical framework of group cognition / macrocognition. This theory will be compared to competing theories in current research literature, such as: distributed cognition (Hutchins), situated cognition (Suchman), activity theory (Engeström), mediated cognition (Vygotsky), situated learning (Lave), knowledge building (Scardamalia & Bereiter), ethnomethodology (Garfinkel), actor network theory (Latour), dialogics (Wegerif), small-group theory (Weick, 2005) and social theory (Giddens, 1984). The comparison will aim to determine areas of overlap, respective limitations, potential conflicts and possibilities for synthesis.

DELIVERABLES

As detailed above, in each of the three years, there will be six types of tasks, including (1) corpus definition, (2) coding scheme design, (3) hand analysis, (4) automated coding, (5) data analysis, and (6) theory building. These six types of activities are broken down into tasks associated with target dates within the three years of the proposed work in the table below. Target publications appear in bold.

Type of Activity	Year 1	Year 2	Year 3
1. Corpus Definition	Drexel: Prepare Team B session 4 data by Dec 2009	Drexel: Prepare Team C session 1 & 4 data by Dec 2010	Drexel: Prepare all Team B and Team C data by Dec 2011
2. Hand Annotation	Drexel: Annotate half of the Year 1 corpus by hand by the end of February 2010, present hand analysis at annual CKI workshop in early Spring	Drexel: Annotate half of the year 2 corpus by hand by the end of February 2011, present hand analysis in progress at annual CKI workshop in early Spring along with findings from theory building from year	Drexel: Annotate half of the year 3 corpus by hand by the end of February 2012, present hand analysis at annual CKI workshop in early Spring along with findings from theory building from year 2.

		1.	
3. Coding Scheme Design	CMU: Develop coding manual for applying the transactivity coding scheme to acquired corpus by the end of December 2009	CMU: Adapt coding manual for applying the transactivity coding scheme as well as Nancy Cooke's coding scheme to new corpus by the end of December 2010	CMU: Adapt coding manual for applying the transactivity coding scheme as well as Nancy Cooke's to new corpus by the end of December 2011
4. Automatic Analysis Work	CMU: Extending recent research in automatic language analysis using the coded data, working towards a paper **submission for the Association for Computational Linguistics or the Intelligent Tutoring Systems conference in Spring of 2010 or CHI 2011 in Fall of 2010,** continue work on automatic analysis continues through summer of 2010. Result will be a fully coded corpus and new automatic analysis technology by the end of Summer 2010.	CMU: Test generality of automatic analysis from year 1 on the new corpus and coding scheme. Complete full coding of corpus by the end of Spring 2011. **Possible extension to automatic coding technology to be submitted to the Association for Computational Linguistics or Artificial Intelligence in Education.**	CMU: Test generality of automatic analysis from year 1 with possible extensions from year 2 on the new corpus and coding schemes. Complete full coding of corpus by the end of Spring 2012.
5. Post hoc Analysis of study data	Drexel: Conduct a post hoc analysis of corpus 1 study data using multiple methods, revisiting findings from initial analysis using the new transactivity-based coding.	Drexel: Conduct a complete analysis of this year's data using multiple methods, and **prepare a submission for GROUP 2011**.	Drexel: Conduct a complete analysis of this year's data using multiple methods, and **prepare a submission for CHI 2012**.
6. Theory Building	Jointly: Integrating insights from	Jointly: Rethinking the CKI framework,	Jointly: Final integrated

	transactivity with the CKI framework, resulting in a **submission to the Computer-Supported Collaborative Learning conference in Fall of 2010**	challenging the notion that all of the information needed to solve the task was known to at least one group member prior to the task. **Submit revised theoretical framework paper for the International Conference of the Learning Sciences in Fall of 2011.**	framework resulting in a **submitted journal article for the *International Journal of Computer-Supported Collaborative Learning***

Deliverables for this project include 5 coding manuals, 3 coded corpora (all of which are coded with two different frameworks, one transactivity based and one based on Nancy Cooke's work), and publications (at least 2 submissions per year, which include both conference papers and a journal article and include technological innovation as well as theory building). Extensions to automatic coding technology will be integrated with the already publically available text mining toolkits, TagHelper tools and SIDE, which have been developed in PI Rosé's prior work and are already in broad distributions (for example, TagHelper has over 1000 users in 57 countries).

FY2010

- Chapter on linguistic analysis of collaboration for the *International Handbook of Collaborative Learning* (already in progress)
- Workshop at Alpine Rendezvous on coding schemes for collaborative knowledge building
- Workshop at International Conference on the Learning Sciences on coding schemes for collaborative knowledge building
- Coding manual for Corpus 1
- Coded corpus 1
- Conference paper with automatic analysis results on coded corpus 1
- Quarterly and annual reports

FY2011

- Coding manuals for corpus 2
- Coded Corpus 2
- Workshop at GROUP on mixed methods for analyzing collaborative knowledge building

- Workshop at CSCL on theories related to macrocognition
- White paper on theories related to macrocognition
- Possible conference paper (ACL or AIED) related to automatic analysis
- CSCL 2011 paper introducing the CKI framework to the CSCL community, with theory building analysis from year 1 on corpus 1
- Quarterly and annual reports

FY2010

- Coding manuals for corpus 3
- Coded Corpus 3
- Publication of book on interaction analysis of Corpus 3 by MIT Press
- ICLS paper submission on results from study 1/Corpus 2
- CHI paper submission for study 2/Corpus 3
- Journal article submission synthesizing findings across all corpus analysis projects for this grant
- Quarterly and final reports

Qualifications of the Principal Investigators

The Group Cognition Lab at Drexel

The Group Cognition Lab conducts basic research on phenomena of distributed cognition that take place distinctively at the small-group level of description, such as collaborative knowledge building, joint decision making, group problem solving, shared meaning making, co-construction of knowledge representations. It is located at Drexel University in Philadelphia and is a joint project of the iSchool (College of Information Science and Technology) and the Math Forum. It is directed by Gerry Stahl, Sean Goggins and Stephen Weimar.

The Lab specializes in studies that make visible the development of group cognitive processes by generating, capturing and analyzing naturalistic episodes of computer-mediated interaction by novices, such as teams of students just learning to problem solve together online. The microanalysis of these episodes reveals characteristics of group process that contribute to an empirically grounded theory of group cognition, which is emerging from the lab.

The Lab is a flexible collaboration of researchers who bring complementary skills and interests to the multidisciplinary mission of the Lab. This includes information scientists interested in small-group cognitive processes, educators interested in how to promote learning of group-cognitive skills, qualitative and quantitative analysts interested in adapting social science research tools to the analysis of group cognition, software designers interested in developing online environments to support effective collaboration, and theorists interested in elaborating the theory of group cognition.

The following major activities are integrated within the Lab:

- Developing the Virtual Math Teams (VMT) service at the Math Forum for generating real-world data on small groups of students learning to engage in online problem solving of open-ended ill-structured and wicked math problems.
- Working with schools of education and math-teacher-training programs to involve teachers and students in exploring the potentials of the VMT service.
- Conducting collaborative data sessions of researchers to analyze the group interactions taking place in logs of online group work.
- Developing case studies and quantitative analyses of the data from logs of online group work to describe characteristics of group cognition.
- Designing new features for the VMT environment to support group-cognitive accomplishments, based on the microanalysis of interesting cases of usage.
- Extending the theory of group cognition, including building graphical and computational models, clarifying terminology, defining specific concepts, and relating to cognate theories.

The Lab has been recognized as a leading center for research on group cognition based on its work from September 2003 to August 2009. It has gone through many cycles of design-based research using a prototype VMT environment at the Math Forum, including Spring Fests in 2005, 2006 and 2007, in which student groups from around the world met for sequences of four hour-long sessions. This produced 2,000 student-hours of data, which was reported in about 200 academic publications. In addition, two major books were published: *Group Cognition* (Stahl, 2006, MIT Press) assembled studies of online collaboration that motivated the work of the Lab and the VMT service; *Studying Virtual Math Teams* (Stahl, 2009, Springer Press) includes the most important reports from the Lab and from collaborating researchers.

Potential directions for the coming years include the following:

- Design and implement additional functionality for the VMT collaboration environment, including dynamic geometric representations and intelligent tutoring support. (Research question: How do visual representations and automated guidance contribute to establishing common ground and scaffolding problem solving?)
- Explore web interfaces to support the spontaneous formation of ad hoc virtual teams within a large distributed community, including participants from different cultures and different time zones. (Research question: How to stimulate and support ad hoc teams and how to overcome geographic or cultural differences?)
- Further integrate synchronous and asynchronous media to coordinate group accomplishments at different time scales and different social scales, from intense interaction of small groups to community knowledge building over years. (Research question: What differences do temporal and social scales introduce into group cognition? How to archive synchronous interaction content as useful knowledge and data for the community to reuse asynchronously?)
- Scale up the VMT service to be a regular, year-round service of the Math Forum, used by a large number of groups in creative ways. (Research questions: How to foster and support an

online community with minimal staffing, and to manage large numbers of interactions within a safe and productive context?)

- Collaborate with teachers and with math-teacher training programs to enhance the pedagogy, to support teacher involvement and to extend the user base of the VMT service. (Research questions: How to build a distributed community with different levels of expertise and to build teacher's reflective practice through participation in VMT?)
- Continue to hold data sessions of researchers to analyze data from new usage and to explore phenomena of interest in more depth. (Research question: What are the characteristics of group-cognitive problem-solving processes?)
- Apply new qualitative and quantitative social-science methods to the analysis of group-cognitive phenomena. (Research question: How to combine, e.g., conversation analysis and social network analysis or automated coding?)
- Develop quantitative measures of social presence, task performance, cooperative practices, longitudinal social relations and collaborative information behavior in self-assembling synchronous/asynchronous teams. (Research question: How can we measure processes on online group cognition?)
- Conduct a longitudinal microanalysis of the entire transcript from two four-hour Spring Fest sessions. This would be a ground-breading analysis approach and an innovative style of monograph, to be published by MIT Press. (Research question: What are the methodological issues in moving from diachronic snapshots of group cognition in brief excerpts to longitudinal changes in collaboration and shared understanding?)
- Continue to publish analyses and to share data with international collaborators. Further refine the theory of group cognition, including building graphical and computational models. (Research question: How can aspects of the theory be summarized in models?)

It is important to note that these aspects of future work are not separable, but need to be conducted as parts of the integrated work of the Lab. The foundational theoretical work of the lab builds upon empirical microanalysis of situated practical activities and aims to contribute to the improved design of tools, concepts and principles to support practical activities.

Gerry Stahl is a leading researcher and theoretician in computer-supported collaborative learning (CSCL). He has presented at every CSCL conference and founded the *International Journal of CSCL*. Trained in computer science, human-computer interaction, artificial intelligence, cognitive science and philosophy, he is a tenured Associate Professor at the College of Information Science & Technology, Drexel University.

Sean Goggins specializes in mixed-methods research on virtual teams. He is an experienced software developer and is now Assistant Professor at the College of Information Science & Technology, Drexel University.

Stephen Weimar has been the Director of the Math Forum at Drexel University for 15 years. The Math Forum is the premier online resource for mathematics, receiving more than three million visits monthly.

The **Group Cognition Lab** includes other faculty, graduate students and staff at Drexel and elsewhere, including specialists in anthropology, conversation analysis, educational psychology, math education, teacher training and computer science. The Lab has on-going collaborations at

Carnegie Mellon University, Rutgers, Hawaii, Missouri, Wisconsin, Singapore, Germany, Brazil and Romania.

The Language Technologies/HCI Institutes at CMU

Carolyn Rosé holds a joint appointment between the Language Technologies Institute and the Human-Computer Interaction Institute at Carnegie Mellon University (CMU). Locally at CMU, between her two departments she supervises or co-supervises a group of 10 graduate students, a post-doc, and a small number of undergraduates. As a tenure track professor at Carnegie Mellon University, she teaches courses related to collaborative learning, linguistic analysis, machine learning & text mining, and summarization.

The School of Computer Science at Carnegie Mellon University consists of 6 departments, including the Computer Science Department, the Machine Learning Department, the Language Technologies Institute, the Software Engineering Institute, the Human-Computer Interaction Institute, the Robotics Institute. The Language Technologies Institute is the only department of its kind in the nation that is completely dedicated to research in language technologies, and includes researchers from the full gamut of areas within that field. Similarly, the Human-Computer Interaction Institute was the first department of its kind and one of only two universities in the US with such a large and diverse faculty spanning all areas of the field of Human-Computer Interaction and containing the largest number of faculty named as CHI Fellows of any institution in the nation.

Carolyn Rosé is the Co-leader of the Social and Communicative Factors in Learning thrust of the Pittsburgh Science of Learning Center, which includes over 40 faculty from a variety of departments including Psychology, Education, Language Technologies, Robotics, and Human-Computer Interaction, both at Carnegie Mellon University and the University of Pittsburgh who are doing learning sciences research. The confluence of Rosé's two departments and the Pittsburgh Science of Learning Center provide a unique combination of human and technological resources that make her imminently well situated to successfully carry out innovative research.

Building on a foundation of research in speech translation, dialogue systems, intelligent tutoring, robust language understanding, and machine learning, Rosé has been working in the area of automatic discourse analysis for the past 15 years and has produced 25 peer reviewed publications related specifically to this topic (in addition to over 60 other peer reviewed publications on other topics) in prestigious venues such as the *International Journal of Computer-Supported Collaborative Learning*, the *Proceedings of Computer Supported Cooperative Work*, the *Proceedings of the Association for Computational Linguistics*, the *Proceedings of Artificial Intelligence in Education*. She was recently invited to write a chapter on linguistic analysis of collaborative learning for the *International Handbook of Collaborative Learning*. As the Secretary/Treasurer of the International Society of the Learning Sciences, Rosé has great visibility in the computer-supported collaborative learning community, and has co-organized workshops related to analyses of collaborative learning discussions yearly for the past four years. She is leading a number of research efforts, including a project bringing together research from the computer-supported collaborative learning community with that of the classroom-discourse community in collaboration with Lauren Resnick at the University of Pittsburgh, a project related to analysis of intercultural communication with Susan Fussell at

Cornell University, and a project related to dynamic support for virtual math teams with Gerry Stahl at Drexel University. As a product of an earlier ONR funded effort, Rosé produced the TagHelper tools package for text mining that currently has over 1100 users in 58 countries.

THEORIES AND MODELS OF GROUP COGNITION

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