A Methodology and Formalism for Eclectic Analysis of Collaborative Interaction

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Abstract: The interactional structure of learning practices is a central focus of study for CSCL. Different approaches produce complementary insights, but rely on incompatible notations for their results, creating challenges in comparing and contrasting different analyses. Building on recent analytic work within our laboratory, we propose an analysis methodology consisting of a unifying theoretical foundation and abstract representation, the "uptake graph," that is suitable for use by multiple analytical traditions.

Introduction

Learning in collaboration with others is the foundation of Computer Supported Collaborative Learning (CSCL). An overview of the historical development of the field (Stahl, Koschmann, & Suthers, 2006) reveals the presence of several research traditions, including an analytic tradition that began with a conception of collaboration as a "continued attempt to construct and maintain a shared conception of a problem" (Roschelle & Teasley, 1995, p. 70). More recently, there have been calls to define the field's agenda as the study of "the practices of meaning making in the context of joint activity" (Koschmann, 2002) or "intersubjective meaning making" (Suthers, 2006b), from which "group cognition" (Stahl, 2006) emerges. Analysis of interactional processes must be sensitive to the specifics of interaction and its environment. The different environments under examination have spawned multiple environment- and medium-specific analytical notations. Ethnography relies to a large extent on freeform notes taken by observers. Work on conversation has used simple transcripts of utterances (Roschelle, 1992) and more detailed transcripts using Jeffersonian notation (Sacks, Schegloff, & Jefferson, 1974). Video has become the standard recording medium and the basis for Ethnomethodological studies of practice (Koschmann & LeBaron, 2002) and Interaction Analysis (Jordan & Henderson, 1995). Video analysis tools (Pea; Woods, 2006) provide support for exploring and annotating video records, but the annotations are tied to the tool in which they were created. The shift to online interaction has simplified the creation of transcriptions: software tools can record a detailed and comprehensive log of an interaction, but online media introduce asynchronicity and hide the production of contributions (Clark & Brennan, 1991), introducing different demands on analytic notations. Analysis of the simultaneous use of many communication media and channels has relied on ad hoc, eclectic representations (see, for example, Goodwin, 2000; Hmelo-Silver, 2003; Hutchins, 1995).

In order to enable the cross-pollination of these different lines of work, there is a need for shared definitions and a common notation. Notations and tools for analysis must be applicable to multiple media because interaction relies on many different semiotic resources. This paper offers a common theoretical foundation and formal representation for the field's diverse analytical methodologies. The methodology—*Uptake Analysis*—and notation—*Uptake Graphs*—are based on several years of our own analytic work. This work began with an analysis of synchronous computer-mediated communication (CMC) involving chat and evidence mapping tools, in order to understand how knowledge building is accomplished via these media (Suthers, 2006a). Subsequently, we began analyzing asynchronous CMC involving threaded discussion and evidence mapping tools (Suthers, Dwyer, Vatrapu, & Medina, 2007). The asynchronicity and multiple workspaces of this data exposed various issues that motivated the methodology described in this paper. The objective of this paper is to document these motivations, the theoretical foundations, and the practical aspects of the methodology that have resulted from intensive work over the past year. Brief examples are provided, but we refer the reader to the two papers just cited for detailed examples that are not possible to include here due to space constraints.

Motivations

Analytical methodologies in CSCL can be roughly divided into two approaches: statistical aggregation and analysis of interaction. An effective hybrid methodology must provide the same abilities as existing methodologies while also addressing the unique issues and needs of computer media.

Statistical Aggregation

Many approaches to the study of learning follow a quantitative paradigm in which contributions (or elements of contributions) are annotated according to a well-specified coding scheme (De Wever, Schellens, Valcke, & Van Keer, 2006; Rourke, Anderson, Garrison, & Archer, 2000). Statistical methods are then used to extract characteristic aggregate behaviors that may then be compared across experimental conditions. This approach has three significant strengths. First, a coding scheme is a concrete classification of behaviors that is less susceptible to subjective interpretation—at the very least, statistical methods exist for estimating the consistency (reliability) between multiple analysts. Second, the approach has well defined mathematical basis for comparing results from multiple sources of data such as alternate experimental conditions and replications of studies. Third, this approach provides tools for scaling up the analysis by quantifying data across large groups. The trade-off is that "coding and counting" loses the sequential structure and situated methods of the interaction. "Coding" assigns the meaning of an act as an isolated unit, before the sequential construction of this meaning has been taken into account. "Counting" or statistical aggregation loses the methods by which media affordances are used in particular learning accomplishments, making it more difficult to identify important design elements at the same temporal and spatial grain as the actual interaction itself.

Analysis of Interaction

A contrasting approach finds the meaning and significance of each act in the context of the unfolding interaction. This approach includes Conversation Analysis (Goodwin & Heritage, 1990; Sacks, Schegloff, & Jefferson, 1974) and Interaction Analysis (Jordan & Henderson, 1995) (a special case of the broader category of "analysis of interaction" being discussed here). Typically, these methods repeatedly examine the micro-structure of short interaction segments to uncover the methods by which participants make their actions accountable to each other (Garfinkel, 1967). This approach is a complement to statistical aggregation methods and has the opposite strengths and weaknesses. These methods document the actual practices of learning by attending to the sequential structure of the interaction. The detailed descriptions this produces are deeply situated in their medium, and this provides insight into the medium's effects. Analyses of interaction are, however, difficult to generalize to different media or groups (Flyvbjerg, 2004), and are time consuming to produce. The family of methods loosely classified as "sequential data analysis" (Sanderson & Fisher, 1994) address some of these concerns with computational support for statistical and grammatical analysis (Olson, Herbsleb, & Rueter, 1994).

Much of the foundational work in the analysis of interaction has addressed face-to-face interaction. Production blocking and the ephemerality of spoken interactions constrain communication in such a manner that turns (Sacks, Schegloff, & Jefferson, 1974) and adjacency pairs (Schegloff & Sacks, 1973) are appropriate units of analysis for face-to-face data. These units of analysis are not as appropriate for CMC since most online media support simultaneous production and persistence of contributions. Contributions may become available to other participants in unpredictable orders, may not be immediately available, and because of the medium's persistence participants may at any time address earlier contributions (Garcia & Jacobs, 1999; Herring, 1999). Conceptual coherence is decoupled from temporal adjacency. We cannot simply focus analysis on the relationships between adjacent events. Nor is it appropriate to treat CMC as a degenerate form of face-to-face interaction (e.g., by seeking an analog to adjacency pairs) since people use these media attributes to create new forms of interaction (Herring, 1999).

Further Requirements

In the introduction we noted that analysis of interactional processes must be sensitive to the semiotic resources of the specific medium being analyzed, yet also be applicable across multiple media in order to support unification of the CSCL agenda. This introduces a pair of related challenges to the creation of a generalizable methodology: it must be media agnostic but simultaneously media aware. A workable methodology needs to be independent of the form of the data under analysis. It should be equally applicable to conversation transcripts, video recordings, and chat logs as well as more complex, heterogeneous software environments that incorporate multiple representations and new forms of deixis and expression. This is necessary to accommodate the new media that invariably lies over the horizon. At the same time, the methodology needs to maintain a record of how people make use of the specific capabilities and affordances of media. This is required to allow the analysis to speak to design and empirically drive the creation of new, more effective media. We seek an alternative representation of the data that abstracts from the particular media of interaction while retaining links to the original data format, supporting analysis of and comparisons across heterogeneous media.

Based on considerations discussed in this section, we sought an analytic approach that (1) maintains the sequential and situational context of activity so that an account of the interactional construction of meaning is possible, (2) does not assume that the medium of interaction has any particular interactional properties (e.g., synchronicity, availability of contributions, or persistence), but (3) records these properties where they exist. Additionally, it should (4) be sufficiently formalized to enable computational support for analysis, and most importantly (5) capture aspects of interaction that are critical to learning. The methodology we developed draws heavily on other interaction analysis methods, but it uses generalized concepts of interaction elements and structures that are independent of any particular medium. The remainder of the paper describes the theoretical framework and associated notational structure, and how it is constructed and used.

Theoretical Foundations

Although we believe that the methodology we offer in this paper can support analyses under a variety of views of learning, it is worth noting how the methodology is motivated by our own views of how learning takes place in social settings. We conceive of learning as not merely the transfer of information but also as an interactional process of change. This conception is compatible with theories of learning that identify socially embedded individuals (Doise & Mugny, 1984; Vygotsky, 1978), social systems (Engestrom, 2001), or communities (Wenger, 1998) as the locus of change. This change need not be deliberately sought: it is a result of participants' attempts to make sense of a situation (Dervin, 2003). *Meaning-making*, as we call it in this paper, takes place at multiple levels: solving a problem, maintaining interpersonal relationships, and/or affirming identity in a community (Bronckart, 1995). To study learning in social settings we must necessarily study the *practices* of *intersubjective meaning-making*: how people in groups make sense of situations and of each other (Suthers, 2006b). Meaning is interactionally constructed and situated: the meaning of a given contribution is best understood as a function of its relationships to prior interactions and indexically with respect to the physical and social context. Meaning-making is mediated by the physical and social environment in diverse ways (Engestrom, 2001; Hutchins, 1995; Wenger, 1998). As designers of media for online learning, this mediation gives us an avenue for influencing meaning-making and possibly learning through the socio-technical affordances of the tools that we design (P. Resnick, 2002).

We have reviewed the need for a unit for analysis of interaction that abstracts from media-specific concepts such as adjacency, is applicable to the wide variety of temporal, spatial, and social scales of online activities, allows for tracking of availability as a prerequisite to awareness and access, and is capable of addressing intersubjective meaning-making. Since collaborative learning is only possible when something is shared and transformed between participants, we chose the concept of uptake for this unit of analysis. *Uptake* is the event of a participant doing something with reifications of prior participation, such as previously expressed information, attitudes and attentional orientation (Suthers, 2006a). Uptake acknowledges and transforms the taken-up by interpreting it as having certain relevance for further participation. A participant can take up one's own prior reifications as well as those of others: by identifying both, analysts can characterize the mixture of intrasubjective and intersubjective knowledge construction. Uptake is similar to the "thematic connections" of Resnick, et al. (1993) but allows for media as well as linguistic relationships. Uptake must sometimes be inferred, suggesting that the relatively objective evidence of participants' media actions be separated from the analysts' identification of uptake. We also wanted a formal structure amenable to computation. These considerations led to the development of the "uptake graph".

The *uptake graph* is rooted in principles taken from Hutchins' theory of Distributed Cognition and also draws on elements from the Ethnomethodological and Activity Theoretic traditions. Hutchins' theory of Distributed Cognition (Hutchins, 1995) is founded on the concept that information is transformed as it propagates via coordinations of representations through a distributed social-technical system. According to Hutchins, the coordinated representations include individuals' internal conceptions in addition to external, perceptible representations. We draw on the idea of coordination, noting that that coordination between personal and shared realms can be accepted apart from whether one accepts the existence of cognitive representations. From a computational standpoint, a distributed cognition analysis starts by identifying the system's function (e.g., steering a ship) and involves tracing the propagation of information through the system and identifying transformations that take place at points of coordination between the participants and external representations. We argue that because meaning-making is fundamentally concerned with the creation of new knowledge, the "enactment of functional relationships" implies too static an interaction structure. Uptake Analysis, in contrast, starts with the identification of points of coordination and uses these to derive the transformations (uptake) and functioning of the interactional processes—the intersubjective meaning-making. Practices of intersubjective meaning-making are akin to the enactment of a type of social order. Although participants are primarily concerned with their interactions with each other rather than with media, all interaction is mediated by external tools and representations (Cole & Engeström, 1993), whether ephemeral media such as speech and gesture, or persistent media such as writing, diagrams, or electronic representations. Our purpose in studying representations is not only to understand the functioning of an existing social-technical system, but also to determine how external representations and intersubjective meaning-making practices mutually influence each other. We draw on the ethnomethodological idea that actions are indexical (their meaning is deeply tied to the time and place of their enactment, and the consequence that the sequential structure of activity is, therefore, of fundamental importance.

The uptake analysis methodology tries to be equally applicable to the different theoretical and analytic paradigms, but is based on three theoretical assumptions about the nature of artifact-mediated interactions:

- Media actions (both expressions and perceptions) are intentional efforts to coordinate between the personal and social realms (e.g., Hutchin's conceptual and external representations, although this assertion may also be understood in a non-cognitivist sense).
- The meaning of any of these actions is indexical with respect to the ongoing interaction and contingent on both prior and subsequent interaction elements.
- The sequential structure of these co-ordinations is significant in understanding how intersubjective meaning-making is accomplished.

A schema for the basic analytical elements is shown in Figure 1. Observable media coordinations (e.g. mc1 and mc2) imply the existence of conceptions (e.g. c1 and c2). These can be understood as existing in the cognitive and/or social realms, depending on the analyst's theoretical orientation. We refer to the media coordination/conception pairs as "fixed points" (e.g. fp1 and fp2) of analytical stability that provide "points of departure" for the analysis. Fixed points are analytic entities that index to the data, and are not to be understood as substituting for the data itself. A fixed point (e.g., fp1 or fp2) constitutes a claim that some conception (e.g., cx or cy) exists as evidenced by the indexed media coordination (e.g., mc1 or mc2). Fixed points are not necessarily single points in the data: they may index to a range or region of the data. Dependencies between media coordinations are then offered as evidence that an uptake relation exists. Further analysis may identify the conceptions involved (e.g., c1 and c2) and the uptake relation. This theoretical framework enables the construction of a formal transcription of the interactional structure of collaborative processes. This representation takes the form of a directed acyclic graph consisting of fixed points and the dependencies between them. (See Suthers, 2006a for a formal definition.) This representation has two primary purposes. First, the uptake graph is specified formally so it can support algorithmic and automated analyses. Second, the uptake graph is meant as a boundary object that enables discussion and collaboration across different analytical traditions.

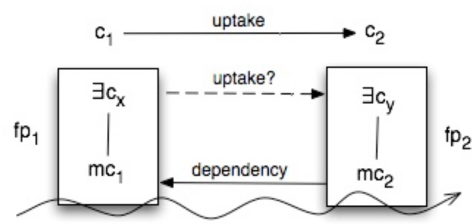

Figure 1. Schema for a dependency

Uptake Analysis

The practical steps of producing an uptake graph are reasonably simple to state, although we have identified a number of subtle issues. Creating the uptake graph is an iterative process of identifying fixed points and dependencies. As the uptake graph is independent of the interaction medium under examination, the steps are presented here as generalizations. These are accompanied by concrete examples from our analysis work over the last year.

Step 1: Identifying Fixed Points

Uptake analysis begins with identifying fixed points in the data. Fixed points represent observed media coordinations for which conceptual significance is claimed. The fixed point is anchored in the media record and provides evidence to justify its existence. Fixed points are a generalization of elements from other analytical methods. Content analysis methods that work with text highlight and code elements in the text record. Conversation analysis and video-based micro-analysis identify points of interest in the media recording or transcript, and the media or transcript may be similarly coded or annotated. Fixed points fulfill the same function as these, but are defined independently of the medium.

Fixed points are anchored in specific media actions. Fixed points can vary in granularity—the can refer to a period of time as well as a time point. Fixed points are anchored in the source data, but they are not a replacement or proxy for it. The uptake graph representation functions as an abstract transcript of an interaction. The fixed point stands in for the media action in the analysis, but, as in most interaction analysis methodologies, the source data is always the final authority. The fixed point's anchor should be specific enough to allow the analyst to return to the media action.

Most fixed points are easy to identify. When analyzing spoken conversation or chat, utterances and messages are obvious candidates for fixed points. In our work with shared argumentation visualizations (Suthers, 2006a; Suthers, Dwyer, Vatrapu, & Medina, 2007) the creation of a node or link in the shared representation is similarly easy to identify as a fixed point, as are e-mail messages or postings in a threaded discussion. Other fixed points are less obvious. For example, if two items are placed near each other in a workspace this may be an expression of relatedness. This illustrates the more general issue of not confusing the representational vocabulary of a medium with the actions supported by the medium. For example, a medium that supports spatial positioning may be used to create groups even if no explicit grouping tool is provided.

Perceptions (e.g. hearing or reading another's expression) are another form of coordination between representation and conception. Explicit indications of perceptions are frequently absent from other analysis methods—most assume that each participant perceives every contribution, and at the time that it is produced or displayed. With asynchronous data showed this assumption is clearly untenable, but we also question the assumption for synchronous interaction. Therefore the notation allows for explicit specification of evidence for perceptions as another form of media coordination. While it is difficult to identify the conception that results from a perception, it is sufficient to assume that *some* conception results and mark the perception event as a fixed point.

A fixed point is incomplete without a description of the evidence on which the analyst based its identification. Requiring an explicit statement of the evidence forces the analyst to explicitly ground the fixed point in the data. This addresses several issues. First, this practice limits the degree to which analysts can make assumptions about media coordinations. For example, in our work with evidence maps and threaded discussions, we can determine when a participant acts to make contributions visible on the screen, but we have no way of knowing whether or not they have actually read the contents. Maintaining this distinction explicitly has forced us to question our assumptions about which contributions are available to others. Second, specifying the evidence helps distinguish the descriptive "what" of the interaction from the explanatory "why" of the analyst's interpretation. The requirement to specify this evidence requires the analyst to closely examine their justifications for the fixed point, and allows multiple analysts to collaboratively review their observations and interpretations. Communicating observations between analysts can be difficult because expressions are composite actions. Even a reasonably unitary action such as posting a reply to a threaded discussion has multiple components. An analyst may identify fixed points anchored in the author, time, or content of the reply, or even the act itself. Providing this specification facilitates trans-disciplinary discussions. For example, social network analysis might be more interested in the author identities of the message posts, whereas argumentation analysis might focus more on the message content. The analysts' evidence disambiguates the fixed points by making clear the specific details that were seen as significant.

Step 2: Identifying Dependencies

The second major step in uptake analysis is to identify and document the dependencies between the fixed points. Dependencies are identified at the media level—posting a discussion message enables a reply and creating an element in an evidence map enables it being read or modified. A dependency represents a grounded assertion that the media coordination identified by one fixed point enables the media coordination identified by another fixed point. (For brevity we sometimes refer to dependencies as existing between fixed points.) Dependencies map out the sequential unfolding of the interaction in the external representation and are candidates for uptake relations. They are defined in terms of a set of participating fixed points and grounded evidence for their interdependencies.

Two or more fixed points can participate in a dependency relationship. Dependencies are directional and point backwards in time. A dependency expresses how a single media coordination depends on one or more prior media coordinations. If multiple coordinations are dependent on a single coordination, then multiple dependencies are specified. Dependencies do not imply causality. If fp2 depends on fp1 then the simplest assertion is that fp1 enabled fp2, but there is no assertion that fp1 caused fp2. We might say fp1 is necessary but not sufficient for fp2, but the reality of identifying dependencies is that we as analysts are not always able to determine the level of necessity. In our work we have frequently had to assert the existence of “potential dependencies” and work with the ambiguity of multiple possible interpretations of the data. Dependencies are a generalization of relationship types from other sequential data analysis methodologies, such as CA “adjacency pairs,” and indicate candidates for uptake.

As with fixed points, the specification of a dependency must include supporting evidence. Specifying the evidence for the dependencies serves the same purpose as for the fixed points. In particular, explicit examination of the evidence makes it easier to distinguish the assertion of the dependency from its interpretation; in contrast to many coding methods in which the analyst simply asserts an interpretation. With dependencies the evidence must support the assertion that one or more media coordinations played a role in enabling another media coordination. There are a number of types of evidence, some of which are more easily identified than others. We have used three types of evidence for dependencies in our work. Starting with the most concrete they are media-level dependency, representational similarity, and semantic dependency. These are discussed below along with examples.

The most concrete evidence is in the form of *media-level dependencies*—one action on the representation could not have taken place in the absence of a previous action. In a shared artifact such as an evidence map, modifying an element of the graph depends on the previous act of creating the element. Similarly, a reply in a threaded discussion depends on the prior existence of the message being replied to. These sorts of media-level dependencies can fall into the trap of conflating the representational vocabulary with the steps in the interaction. Consider a reply in a threaded discussion. The reply message is “physically” dependent on the message being replied to, but it is more accurate to say that the creation of the reply message is dependent on the author's perception of the message being replied to. Figure 2 (adapted from Suthers, Dwyer, Vatrapu, & Medina, 2007) contrasts the reply structure of a short discussion (inset figure) with the fixed point dependency structure from which we inferred uptake (main figure). Nodes with letters such as 8a, 7b, etc represent perceptual fixed points evidenced by message read events). Including the perception-related fixed points tells a much different story about the creation of the discussion. In particular, the penultimate posting (labeled “2”) is not only related to the single message being replied to but is the result of a series of reads that encompasses two subthreads of the discussion.

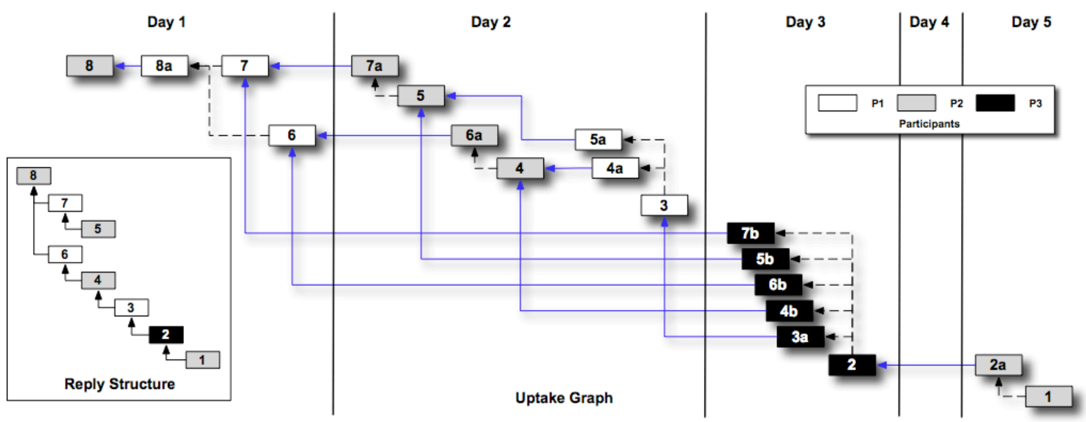

Figure 2. Comparison of threaded discussion reply structure (inset) and uptake graph (main graph). Fixed points without letters are evidenced by message postings and with letters are evidenced by message reads. Dashed lines represent intrasubjective uptake.

The second type of dependency evidence is *representational similarity*. The use of similar representational attributes is often used to indicate relatedness (Dwyer & Suthers, 2005). The representations can have similar visual attributes (e.g. color or type face) or they can be grouped together or aligned spatially. Temporal proximity can also indicate relatedness—expressions that follow each other closely are often part of the same exchange. Each of these indications of relatedness can imply a dependency—the second item is dependent on the first for its representational attributes. In Figure 2, temporal proximity is part of our evidence for the dependency of 2 on 7b, 5b, 6b, 4b, and 3a. Representational similarity can also consist of repeated words and phrases. Their re-use can indicate a dependency on the fixed point representing their initial introduction. This can be fairly easy to identify. In experiments with evidence maps (Suthers, Medina, Vatrapu, & Dwyer, submitted; Suthers, Vatrapu, Medina, Joseph, & Dwyer, submitted), participants were given source materials written in a much more formal tone than they used themselves. In this case, phrases from the materials usually stood out from the text created by the participants. However, in less constrained environments it may be much more difficult to identify the original source of any content or to determine whether or not its re-use is actually dependent on the original use.

The final type of evidence is *semantic dependency*: the semantic content of a media action can be traced to the semantic content of another media action. This can be difficult to identify and is often open to debate. In one case we looked at (to be reported elsewhere), one participant added three related nodes to an evidence map. The other participant, after reading them, added a forth node that seemed to summarize the first three. Other instances were not as clear. In these cases, the evidence for the dependency facilitated their review.

Documenting other media elements

An uptake graph is a partial transcription of an interaction. It is frequently necessary to record additional information to contextualize the interaction elements. This additional information can annotate or augment the formalism for representing fixed points and dependencies. For example, the reply structure of a threaded discussion is an important resource for understanding the participants' view of the medium, and so is included in uptake graph representations. In another study (Suthers, Vatrapu, Medina, Joseph, & Dwyer, in press) we used an asynchronous protocol. In order to understand what representational elements each participant had available at any point in time, we incorporated indications of workspace updates by which participants received new data from their partner (the vertical bars in Figure 3). The ability to incorporate additional media elements highlights one other benefit of the formalism.

Iteration

Analysis of interaction, and hence production of the uptake graph, is an iterative processes. Multiple passes through the data identify additional elements and provide new insights into the interactional process. The formalism of the uptake graph provides support for this process. New fixed points and dependencies can be continually added to the graph. This has the following three ramifications. First, the graph can grow in complexity to reflect a deepening knowledge of the data. The trade off is that the graph can only be considered "complete" with regard to particular representational elements. For example, while it is possible to claim that every discussion posting or e-mail message has been recorded as a fixed point, it is more difficult to definitively assert that a practice or pattern never occurs. Second, the quality of the analysis is proportional to the density of the data. In our work with threaded discussions we only had log entries for when a message was created and when a user caused the message to be displayed on the screen. Our experimental software, on the other hand, provided a complete record of every mouse and keyboard event, every action on the shared representation, and a video capture of the computer screen from each client. The density of the latter data has allowed us to examine interaction at a much finer grain. Nonetheless, the threaded discussion data is sufficient for coarser grained analysis. Finally, repeated iterations may identify new *types* of representational elements, fixed points, and dependencies. Work with the different media has suggested two other constructions: interactionally defined representational elements, which do not correspond to any explicit representational notation, and composite fixed points, in which two or more media events seem to share a conception.

Example

Figure 3 presents an uptake analysis graph of data from a study of collaborative argumentation with evidence maps (Suthers, Vatrapu, Medina, Joseph, & Dwyer, submitted). This analysis was done to understand how two participants converged on a conclusion (Suthers, Medina, Vatrapu, & Dwyer, submitted). Construction of the uptake graph and the subsequent uptake analysis of the example presented above allowed us to discover an interesting interactional pattern. In fixed points 27, 27a, 20, 19 and 20a the information countering aluminum as a factor of the disease ("aluminum is the third most abundant element") has been successfully shared in the evidence map. From an information sharing perspective, this sequence is sufficient to explain the fact that both the participants mentioned the abundance of aluminum (the successfully shared information) in rejecting aluminum as a disease factor. But participants did another round trip for social confirmation in 7-7a-8-8a. Notice how the uptake analysis example presented in Figure 3 demonstrates how a fixed point (essay outcomes in this case; e18 and e13) might have multiple dependencies (e18-8a, e18-20a; e13-8, e13-20) to multiple fixed points (e18 to 8a, 20a and e13 to 8, 20) with different media anchors (evidence map, threaded discussion) and different types of evidence (media manipulation, semantic dependency)

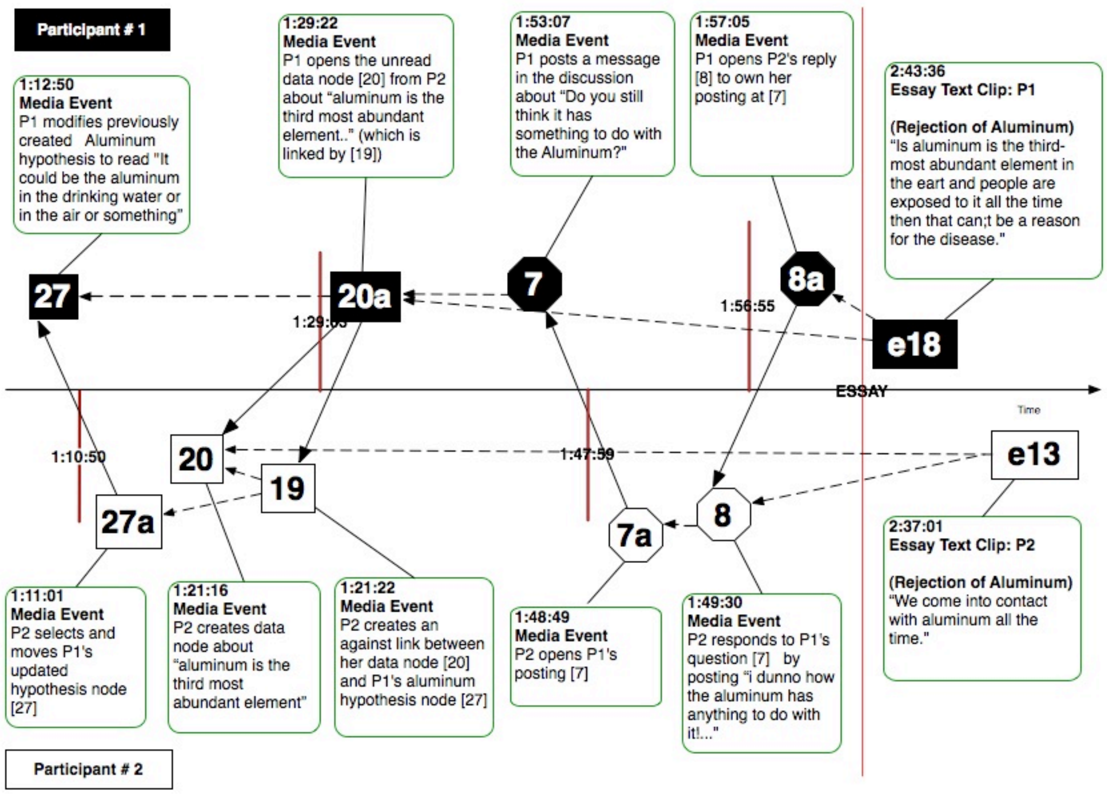

Figure 3. Uptake graph of a segment of collaborative argumentation data

Not only did our uptake analysis uncover this additional interactional round-trip of but it also helped us discover that participants accomplished this additional social conformation round-trip by moving to a different interactional medium, the threaded discussion. As a result of the uptake analysis we uncovered that the participants' individual essay learning outcomes (as a product of collaborative argumentation) in e18 and e13 are thus dependent on both the social conformational round-trip in 7-7a-8-8a enacted by their appropriation of the media affordances of threaded discussion and the information sharing round-trip in 27-27a-20-19-20a accomplished by their appropriation of the media affordances of evidence map.

Discussion

The initial motivation for developing the uptake graph formalism was to support our analysis of how participants accomplish collaborative knowledge construction through computer media (Suthers, 2006a). As our work progressed, we realized that we could use the uptake graph as a boundary object between our different analysis methods. We used the uptake graph both to create aggregate statistics of interactions and their relationship to the media (Suthers, Vatrapu, Medina, Joseph, & Dwyer, submitted), and to examine the sequential structure of interaction (Suthers, Dwyer, Vatrapu, & Medina, 2007). The sequential structure of the interaction preserved in the uptake graph allowed us to trace the asynchronous interaction between the pairs of participants back from results in the final essays that we wanted to explain. Our most recent analysis of the data (Suthers, Medina, Vatrapu, & Dwyer, submitted) bridged the two approaches by algorithmically identifying instances of an interaction pattern we refer to as a "round trip" and then applying statistical tests on their frequency across the experimental conditions.

There are multiple benefits to the uptake graph as a transcript notation. First, it addresses the tradeoff between statistical aggregation and interaction analysis described at the beginning of this paper. The dependency structure documents the sequential structure of the interaction and the formal graph can be analyzed or coded to provide raw data that can be aggregated statistically. Second, the notation is independent of the interaction medium and can be applied to face-to-face and online interactions as well as interactions that take place in multiple media. Third, the quality of analytical results scales with the quality of the source data. High-fidelity data can be used to produce a dense graph that can be subject to detailed analysis. On the other hand, sparse data will produce a sparse graph but will still support limited analysis. Finally, the graph data structure is open-ended—additional data can always be added, although this does imply that skepticism of the completeness of the graph should be maintained. The formalism of the graph structure supports building tools to manage its complexity and is amenable to algorithmic analysis and data mining techniques. Finally, the grounding of the fixed points in explicit media coordinations will allow analysis of correlations between interaction patterns and the media affordances the shape them. The fixed point and dependency representations formally extend the CA concepts of utterance and adjacency pair to online and asynchronous media. The use of generic media coordinations as the basis for fixed-points allows the inclusion of a whole range of communicative actions, including perceptions and interactionally constructed representational elements. The "dependency" extends the concept of adjacency across much longer time frames and accounts for cases where media coordination is the result of multiple, previous fixed points.

While the foundations of this methodology are sound, there are still many theoretical and practical issues to work out. The most pressing theoretical task is to extend the uptake graph formalism to better incorporate composite fixed point structures and the possible ambiguity of dependencies. A complete explication of these two items is necessary to extend the potential algorithmic support provided by the uptake graph structure. The greatest practical need is to develop software tools to help construct and use the uptake graph. The need for improved analysis tools is a recurring theme (Sanderson & Fisher, 1994), and the size and density of the potential data sets exacerbates this need. Elaborations on the visual representation should be explored, including embedding uptake graphs in a CORDTRA-style representation (Hmelo-Silver, 2003) to relate interaction to both media and episodes of activity. An important aspect of evaluating this methodology will be to determine how well it scales to the types of interactions and media that are of most interest. Specifically, we are interested in how the methodology can be applied to larger groups and across longer time scales. For example, it would be extremely useful to apply the methodology to a typical undergraduate course of 20-30 students over the course of a 16 week semester. The manual identification of fixed points and dependencies is time-consuming, but with improved automation it might be possible to generate uptake graphs for larger online communities over the course of months or even years.

References

Bronckart, J. P. (1995). Theories of action, speech, natural language, and discourse. In J. V. Wertsch, P. D. Rio & A. Alvarez (Eds.), *Sociocultural Studies of Mind* (pp. 75-91). New York: Cambridge University Press.

Clark, H. H., & Brennan, S. E. (1991). Grounding in communication. In L. B. Resnick, J. M. Levine & S. D. Teasley (Eds.), *Perspectives on Socially Shared Cognition* (pp. 127-149): American Psychological Association.

Cole, M., & Engeström, Y. (1993). A cultural-historical approach to distributed cognition. In G. Salomon (Ed.), *Distributed Cognitions: Psychological and Educational Considerations* (pp. 1-46). Cambridge: Cambridge University Press.

De Wever, B., Schellens, T., Valcke, M., & Van Keer, H. (2006). Content analysis schemes to analyze transcripts of online asynchronous discussion groups: A review. *Computers & Education, 46*(1), 6-28.

Dervin, B. (2003). Sense-Making's Journey from Metatheory to Methodology to Method: An Example Using Information Seeking and Use as Research Focus. In B. Dervin & L. Foreman-Wenet (Eds.), *Sense-Making Methodology Reader: Selected Writings of Brenda Dervin* (pp. 133-163). Cresskill, New Jersey: Hampton Press, Inc.

Doise, W., & Mugny, G. (1984). *The Social Development of the Intellect, International Series in Experimental Scoial Pscychology* (Vol. 10): Pergamon Press.

Dwyer, N., & Suthers, D. (2005). A Study of the Foundations of Artifact-Mediated Collaboration. In T. Koschmann, T.-W. Chan & D. D. Suthers (Eds.), *Computer Supported Collaborative Learning 2005: The Next 10 Years!* Taipei, Taiwan: Lawrence Erlbaum Associates.

Engestrom, Y. (2001). Expansive Learning at Work: toward an activity theoretical reconceptualization. *Journal of Education and Work, 14*(1).

Flyvbjerg, B. (2004). Five misunderstandings about case-study research. In C. Seale, G. Gobo, J. F. Gubrium & D. Silverman (Eds.), *Qualitative Research Practice* (pp. 420-434). London and Thousand Oaks, CA: Sage.

Garcia, A. C., & Jacobs, J. B. (1999). The Eyes of the Beholder: Understanding the Turn-Taking System in Quasi-Synchronous Computer-Mediated Communication. *Research on Language and Social Interaction, 32*(4), 337-367.

Garfinkel, H. (1967). *Studies in Ethnomethodology*. Englewood Cliffs, New Jersey: Prentice-Hall.

Goodwin, C. (2000). Action and embodiment within situated human interaction. *Journal of Pragmatics, 32*, 1489-1522.

Goodwin, C., & Heritage, J. (1990). Conversation Analysis. *Annual Review of Anthropology, 19*, 283-307.
Herring, S. C. (1999). Interactional coherence in CMC. *Journal of Computer Mediated Communication, 4*(4).
Hmelo-Silver, C. E. (2003). Analyzing collaborative knowledge construction: Multiple methods for integrated understanding. *Computers & Education, 41*, 397-420.
Hutchins, E. (1995). *Cognition in the Wild*. Cambridge, Massachusets: The MIT Press.
Jordan, B., & Henderson, A. (1995). Interaction analysis: Foundations and practice. *Journal of the Learning Sciences, 4*(1), 39-103.
Koschmann, T. (2002). Dewey's Contribution to the Foundations of CSCL Research. In G. Stahl (Ed.), *Computer support for collaborative learning: Foundations for a CSCL community: Proceedings of CSCL 2002* (pp. 17-22). Boulder, CO: Lawrence Erlbaum Associates.
Koschmann, T., & LeBaron, C. (2002). Learner Articulation as Interactional Achievement: Studying the Conversation of Gesture. *Cognition and Instruction, 20*(2), 249-282.
Olson, G. M., Herbsleb, J. D., & Rueter, H. H. (1994). Characterizing the sequential structure of interactive behaviors through statistical and grammatical techniques. *Human-Computer Interaction, 9*, 427-472.
Pea, R. Diver. Retrieved Nov. 26, 2006, from http://diver.stanford.edu
Resnick, L. B., Salmon, M., Zeitz, C. M., Wathen, S. H., & Holowchak, M. (1993). Reasoning in conversation. *Cognition and Instruction, 11*(3&4), 347-364.
Resnick, P. (2002). Beyond Bowling Together: SocioTechnical Capital. In J. M. Carroll (Ed.), *Human-Computer Interaction in the New Millennium* (pp. 647-672). Upper Saddle River, NJ: ACM Press.
Roschelle, J. (1992). Learning by Collaborating: Convergent Conceptual Change. *The Journal of the Learning Sciences, 2*(3), 235-276.
Roschelle, J., & Teasley, S. D. (1995). The construction of shared knowledge in collaborative problem solving. In C. E. O'Malley (Ed.), *Computer-Supported Collaborative Learning* (pp. 69-197). Berlin: Springer-Verlag.
Rourke, L., Anderson, T., Garrison, D. R., & Archer, W. (2000). Methodological Issues in the Content Analysis of Computer Conference Transcripts. *International Journal of the Learning Sciences, 11*.
Sacks, H., Schegloff, E. A., & Jefferson, G. (1974). A Simplest Systematics for the Organization of Turn-Taking for Conversation. *Language, 50*(4), 696-735.
Sanderson, P., & Fisher, C. (1994). Exploratory Sequential Data Analysis: Foundations. *Human-Computer Interaction, 9*, 251-317.
Schegloff, E. A., & Sacks, H. (1973). Opening up closings. *Semiotica, 8*, 289-327.
Stahl, G. (2006). *Group cognition: computer support for collaborative knowledge building*. Cambridge, MA: MIT Press.
Stahl, G., Koschmann, T., & Suthers, D. (2006). Computer-supported collaborative learning: An historical perspective. In R. K. Sawyer (Ed.), *Cambridge handbook of the learning sciences* (pp. 409-426). Cambridge, UK: Cambridge University Press.
Suthers, D. (2006a). A qualitative analysis of collaborative knowledge construction through shared representations. *Research and Practice in Technology Enhanced Learning (RPTEL), 1*(2), 1-28.
Suthers, D. (2006b). Technology affordances for intersubjective meaning-making: A research agenda for CSCL. *International Journal of Computers Supported Collaborative Learning, 1*(3), 315-337.
Suthers, D., Dwyer, N., Vatrapu, R., & Medina, R. (2007). An abstract transcript notation for analyzing interactional construction of meaning in online learning. In *Proceedings of the 40th Hawai`i International Conference on the System Sciences (HICSS-34), January 3-6, 2007, Waikoloa, Hawai`i (CD-ROM)*: Institute of Electrical and Electronics Engineers, Inc. (IEEE).
Suthers, D., Medina, R., Vatrapu, R., & Dwyer, N. (submitted). *Information Sharing is Incongruous with Collaborative Convergence: The Case for Interaction*.
Suthers, D., Vatrapu, R., Medina, R., Joseph, S., & Dwyer, N. (in press). Beyond threaded discussion: Representational guidance in asynchronous collaborative learning environments. *Computers & Education*.
Suthers, D., Vatrapu, R., Medina, R., Joseph, S., & Dwyer, N. (submitted). *Conceptual representations enhance knowledge construction in asynchronous collaboration*.
Vygotsky, L. S. (1978). *Mind in society*. Cambridge, MA: Harvard University Press.
Wenger, E. (1998). *Communities of Practice: Learning, Meaning and Identity*. Cambridge: Cambridge University Press.
Woods, D. (2006). Transana. Retrieved Nov. 26, 2006, from http://www.transana.org