Analysis of Meaning Making in Online Learning

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Abstract: This paper reports on our efforts to deepen the analysis of online collaborative learning. Most studies of online learning use quantitative methods that assign meaning to contributions in isolation and aggregate over many sessions, obscuring the actual procedures by which participants accomplish learning through the affordances of online media. Methods for studying the interactional construction of meaning are available, but have largely been developed for brief episodes of face-to-face data, and do not scale well to online learning where media resources, time scale, and synchronicity all differ. In order to resolve this tradeoff, we are developing an analytic method that scales up sequential and interactional analysis to longer term distributed and asynchronous interactions. The paper describes applications to data derived from asynchronous interaction of dyads and small groups. Our long-term objective is to obtain a deep understanding of how learning is accomplished in technology-mediated interactions that take place at multiple time scales in different media.

Keywords: Collaborative learning, analysis methodology, interactional construction of meaning

1 Introduction

Recent developments have highlighted the ascendancy of online learning [1, 2]. Online collaborative learning brings together social processes of learning and representational aids for this learning, providing a fertile area for research and development while serving an important application. An understanding of how participants appropriate and are influenced by the affordances of the medium is needed to adequately inform the design of the learning experience and the resources that support it [3]. Because learning is largely social, it is also critical to understand the intertwinement of individual and intersubjective trajectories of meaning-making [4]. Yet we do not yet sufficiently understand these areas. Since most online learning has been mediated through text-based tools, we lack intensive study of how richer representations mediate online learning. Moreover, most studies of online learning use quantitative methods that disaggregate interaction into segments and assign meaning to these segments in isolation through coding, losing the interactionally constructed meaning. These methods aggregate over many sessions, obscuring the actual procedures by which participants accomplish learning through the affordances of online media [5]. Methods for studying the interactional construction of meaning are available [6, 7], but have largely been developed for brief episodes of face-to-face data, and do not scale well to online learning where media resources, time scale, and synchronicity all differ. This analytic tradeoff between scalability and fidelity must be resolved in order to inform the design of improved online learning environments and participation structures that engage participants more deeply in intersubjective meaning-making during collaborative inquiry. In this paper we report on our efforts to resolve this tradeoff by scaling up sequential and interactional analysis to longer term distributed and asynchronous interactions while remaining grounded in participants' use of media. The paper describes applications to data derived from asynchronous interaction of dyads and small groups. Our objective is to obtain a deep understanding of how learning is accomplished in technology-mediated settings when analyzing asynchronous computer-mediated interactions that take place over various durations of time, in different media, among large groups of people. We begin by briefly considering existing analysis paradigms and outlining our approach before providing examples of analysis.

2 Analysis of Online Learning

The experimental paradigm compares an intervention to a control condition in terms of one or more variables. Where process data is considered, it is most often analyzed in the "quantitative" paradigm, in which units such as actions and utterances are annotated under some coding system (e.g., [8]) and then statistical methods are used to compare counts across groups to draw conclusions concerning aggregate (average) group behavior. Such methods are suitable for testing proposed differences between groups. For example, our own work [3, 9] tested hypotheses concerning "representational guidance," e.g., that users of one version of evidence mapping software will talk more about evidence than users of another version. Yet, coding and counting cannot capture the actual practices of intersubjective meaning-making, and hence the most interesting part of collaborative learning is missed. There are two basic problems. First, the meaning of an act is assigned as an isolated unit, missing the sequential construction of this meaning. Second, when data is aggregated, one loses the actual methods by which individuals appropriated the medium to accomplish collaborative knowledge construction. Without observing how media affordances are used or how opportunities are lost, it may be more difficult to generate design recommendations.

Therefore we began explorations in analysis paradigms that better capture intersubjective meaning-making and the role of technology affordances in supporting these processes. Methods of analysis that find the meaning and significance of each act in the context of prior interaction include Conversation Analysis [10], Interaction Analysis [6], and the family of analysis methods loosely classified as "sequential analysis" [11]. Typically, video or transcripts of naturally occurring interactions are studied to uncover the methods by which participants make themselves accountable to each other and accomplish their objectives. For examples applied to the analysis of learning, see Baker [12], Roschelle [13], Koschmann et al. [14], and Koschmann, et al. [5]. This paradigm is becoming increasingly important in computer supported collaborative learning (CSCL) because an approach that focuses on accomplishment through action is necessary to truly understand the role of technology affordances [15].

Yet we also encountered limitations in these methods, mostly due to the assumptions the methods make about the *interactional properties* of the media they study. Both Conversation Analysis (using audio recordings with Jeffersonian transcripts) and Interaction Analysis (which relies on video recordings) are concerned with face-to-face interaction. The temporality and ephemerality of spoken interactions requires *turns* [10] and *adjacency pairs* [16] as the units of analysis. These units of analysis are not as appropriate for computer-mediated communication (CMC) since most online media support parallel production and persistence of contributions. Online media allows multiple participants to produce contributions simultaneously, eliminating the need for turn taking. Furthermore, 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 an inscription that was created much earlier. Online, conceptual coherence is decoupled from temporal adjacency. We cannot simply focus analysis on the relationships between adjacent events. Nor can we treat CMC as a degenerate form of face-to-face interaction since people adapt to these media attributes and use them to create new forms of interaction [17].

The properties of asynchronous online media require an alternative basic unit for analysis of interaction that accommodates noncontiguous contributions and allows for tracking of availability as a prerequisite to awareness and access. Additionally, this unit of analysis must be applicable to the wide variety of temporal, spatial, and social scales of online activities. Since collaboration is only possible when something is shared and transformed between participants, we began to work with the concept of "uptake": the event of a participant doing something with previously expressed information, attitudes and attentional orientation. Uptake can incorporate a participant's own prior contribution as well as those of others: by identifying both, we can characterize the mixture of intrasubjective and intersubjective knowledge construction. Uptake is similar to the "thematic connections" of Resnick, et al. [18], but allows for media as well as linguistic relationships.

These ideas were originally developed using data from synchronous interaction of dyads [19]. Over the past year we further developed these ideas by analyzing data from an experimental study of pseudo-asynchronous, dyadic collaboration [20]. We found it necessary to separate participants' media actions from the analysts' inference of an uptake event. This led to a three-level analysis method:

1. Identification of "Fixed Points." The first level identifies points where the existence of a conception is empirically grounded in intentional acts of coordination between conceptions and representations [21] (such as editing a shared workspace). We call them "fixed points" because they provide empirically grounded points of departure for further analysis.

2. Identification of Dependencies (Potential Uptake). The second level of the analysis builds a dependency graph of how these acts refer to, manipulate, or otherwise take up previous conceptions. Evidence for dependencies can be roughly divided into media dependencies (e.g., sequences of actions on a representational element) and conceptual dependencies (e.g., reuse of words and phrases). Dependencies are candidates for uptake events.

3. Analysis of Intersubjective Meaning-making. The third level of analysis identifies uptake events, assigning interpretations to sequences of dependencies based on the theoretical phenomena of interest, such as argumentation or collaborative knowledge construction. The dependency graph can serve as a basis for comparison and integration of multiple theoretical interpretations, i.e., a *boundary object* [22] for the study of collaboration. Our own approach seeks to understand the meaning of an uptake act in terms of how it brings forth and actualizes some aspect of the prior interacction as being significant for this moment and subsequent interaction.

3 Examples

In this section we provide two examples from our exploratory analyses. The first example, based on data from dyads interacting in a laboratory setting, is offered to illustrate intersubjective meaning-making in a highly instrumented asynchronous context. The second example, based on server logs of asynchronous threaded discussions in an online course, is offered to illustrate how our method can be adopted to conventional online learning settings.

3.1 *Asynchronous Meaning-Making between Dyads in a Laboratory Setting*

The data for this example comes from a study in which participants interacted via a shared “evidence mapping” workspace to identify the cause of a disease on Guam (ALS-PD). The update protocol simulated asynchronous interaction [20]. In this setting, rich data including server logs and video capture of the screens are available to us, so we are able to examine the interaction in great detail. Information was distributed across participants such that information sharing was necessary to refute weak hypotheses and construct a more complex hypothesis. At the end, participants wrote individual essays. Our analysis sought to identify whether and how the contents of the essays were accountable to the interactive session, and especially whether intersubjective meaning-making influenced the essays. In brief, how does collaboration lead to learning? We began by tracing back dependencies from the essays of participant 1 (P1) and participant 2 (P2) into the session to identify uptake trajectories that may have led to the essays. In their individual essays, both P1 and P2 mentioned “duration of exposure” as a factor. The example focuses on this convergence.

The relevant subgraph is in Figure 1; many fixed points and dependencies are omitted for simplicity. P1’s actions are on the top and P2’s actions on the bottom. In general, time flows left to right, but this being an asynchronous setting we cannot assume that a contribution is available as soon as it is created. The vertical lines in each participant’s half demarcate when that participant’s workspace was updated to display new work by the partner. Numbered nodes represent fixed points, which may include contributions (editing the evidence map) or perception of the partner’s contribution (evidence map objects must be opened to be read). Arrows between the nodes represent dependencies (potential uptake relations). Dotted arrows are intrasubjective and solid arrows intersubjective uptake (always by a perception event).

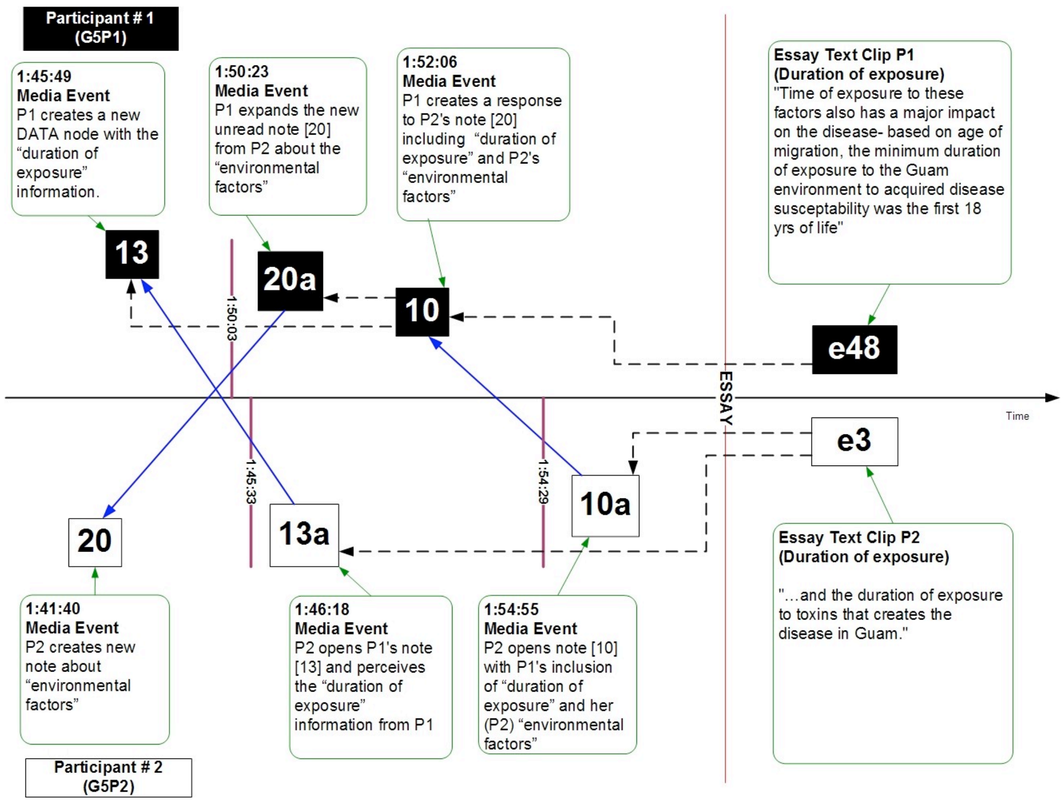

Figure 1: Intersubjective meaning-making analysis of asynchronous dyads

Node 20 represents a summation of the disease causes expressed by P2 in a note posted to her workspace (but not yet visible to P1). Shortly after that in clock time but asynchronously from the participants' perspectives, P1 creates a data object derived from an article; node 13 represents the conception expressed by this object. Subsequently, a workspace refresh makes the note expressing conception 20 available to P1: node 20a represents the conception that results from P1's reading of this note, and the corresponding arrow represents the first example of intersubjective uptake. Sometime later, P1 creates a note indicated by node 10. This node is an uptake of both 20a and 13, as evidenced by the following media-level facts. First, in the interface this note follows that for 20a in a sequential note object: uptake is evidenced by direct media-manipulation. Second, 10 incorporates the concept of "duration of exposure" from 13, expressed as "… time has a factor, the longer you're exposed…." Here, uptake is evidenced by conceptual similarity. Clearly, 10 is an integrative contribution.

Let us now examine how information originally available only to P1 (13) and P1's integration of it (10) become available to P2. Sometime after 13, a refresh makes the corresponding data object available to P2, who accesses it as indicated by fixed point 13a. Subsequently, another refresh makes the response note of 10 available to P2, taken up at 10a. Since P2 has accessed both the data object reporting the "duration of exposure" (13a) and P1's endorsement of the relevance of duration of exposure (rephrased) (10a), we view P2's inclusion of this concept in her essay (e3) to be an uptake of both of these conceptions. P1's essay portion (e48) also evidences uptake of the environmental factors originally expressed by P2 (20). The "round trip" from 20 through 20a, 10 and back to 10a and e3 represents intersubjective meaning-making on a small scale. We cannot rule out that e3 is uptake of only 13a and hence a one-way transfer of information, but nor can we rule out that P1's endorsement of the importance of the idea in 10, accessed at 10a, also influenced P2's inclusion of this idea in the essay. It is plausible that both were a factor.

In this and other examples, the analysis method enabled us to make sense of the rich data available, examine the meaning-making trajectories of individual learners as evidenced by their manipulations of the media, and identify entwinements of these trajectories in ways that sometimes led to conceptions that could only be understood as a product of intersubjective meaning-making.

3.2 *Multiple Participants in an Asynchronous Online Discussion*

The laboratory setting provided far richer instrumentation than might be expected in typical online learning applications. In order to explore how our method can be adopted to conventional online learning settings and what kinds of analyses are possible with lower resolution data, we analyzed server logs of asynchronous threaded discussions in an online graduate course. The discussion software records message-opening events as well as message postings, but recordings of participants' manipulations of the screen are not available. In each of the analyses we conducted, we were able to identify a sampling of interaction episodes showing the potential for the method in producing a feature-rich analytical artifact for interpretation. Figure 2 illustrates one example of convergence of two topics across two related online discussion forums involving multiple participants over a seven-day period. One is a subgroup discussion and the other is a large group forum. Students in each subgroup address a set of discussion questions (e.g., q15, q14, q10, q9 in Figure 2). Each group then posts a summary to the class discussion group, and the whole class then has the opportunity to discuss these summaries. The analysis for this episode unfolded by backtracking from a convergent idea in the group forum, represented by node 1 on the far right of Figure 2, through a series of postings that led through two parallel threads and across two discussion forums. The identification of these trajectories relies heavily on a complementary strategy that includes content analysis and access to server logs. The logs are used to determine and generate media-level fixed points: access to and posting of messages. Content analysis provides the means of transcending the media structure (access logs and reply structure), uncovering trajectories of meaning-making across fragments of discussion threads located in different forums. This ability to identify trajectories that are independent of yet influenced by media structures is an important strength of the method.

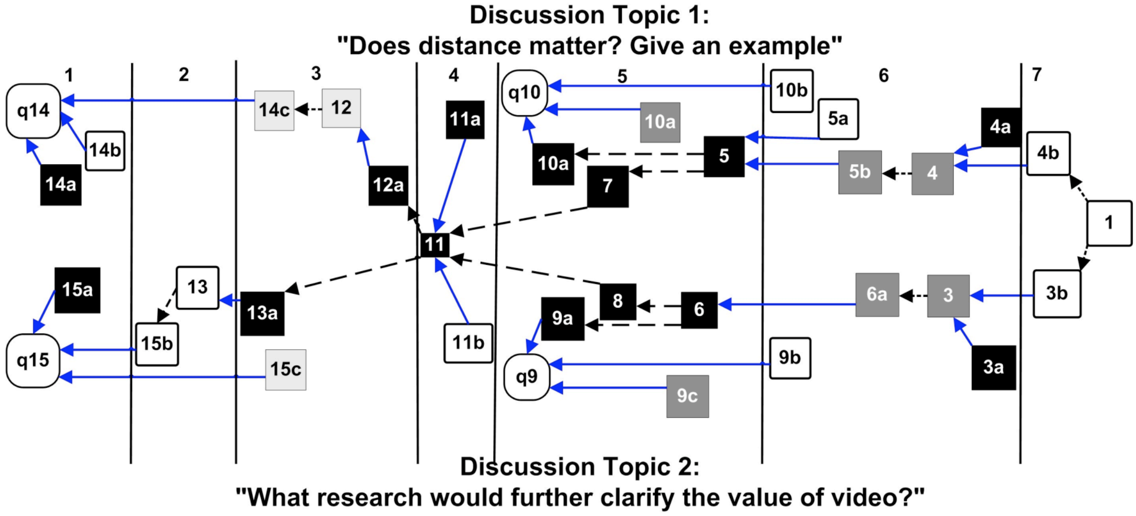

Figure 2. Fixed point graph on online interaction episode. Vertical lines represent days, colors represent participants, and arrows represent dependencies.

4 Advantages and Disadvantages of the Method

The dependency graph avoids premature theoretical commitment, so is able to function as a boundary object [22] for multiple theoretical analyses. This representation supports quantitative coding and counting, statistical approaches to sequential analysis, cognitive analysis and ethnographic analysis. If we started with one of these methods, the resulting representations would not support the other analyses. With the dependency graph the opportunity exists to determine how different theories explain the technology affordances for collaborative learning. The dependency graph is media-agnostic, and makes very few theoretical commitments to the nature of cognition or collaboration. It is a record of the multiple personal transformations that took place in an interaction and maps out their interdependencies. However, it is not media ignorant; it can bring in information about the medium. Intersubjective meaning-making can be identified independently of the media but is linked to media by the fixed points, so the relationship between meaning-making and the media can be examined. The analysis can function at multiple levels of detail, although any analytical results will be at the same level of details as the data under analysis. It will also scale according to the quality of the data: incomplete data allows incomplete analysis but does not obstruct analysis completely. Finally, the analysis of entangled personal trajectories does not require a solution to the individual/collective dichotomy. We can separate out individual trajectories and identify when contributions are available to and accessed by each individual, or we can step back and analyze the composite web of interpretations. Collective behavior such as "group cognition" [23] is observable as the result of multiple individuals allowing their individual actions to be influenced by the perception and interpretation of other's behavior.

There are presently a few disadvantages of the methodology. The major disadvantage is that it is time consuming to construct a dependency graph. Customized software support can help address this problem by partially automating data collection and the construction of the graph. The present work develops the specifications for such a tool. A related problem is the difficulty of retrieving information from and obtaining selective views of the dependency graph. Software support will also address this problem by through visualization technologies. In using the graphs for analysis, we have found that one must be careful not to make inferences based on the absence of fixed points and dependencies in the graph. Any graph is partial and can be extended indefinitely due to the continuous nature of human action. Also one must not conduct an analysis entirely by using the dependency graph. In addition to being a structure of interest in its own right, the graph should be used as an index to the original media records.

5 Conclusions

Current methods for analysis of the interactional construction of meaning have largely been developed from brief episodes of face-to-face data, and do not scale well to online learning where media resources, time scale, and synchronicity all differ. While quantitative methods scale well to online learning, they do so by segmenting interaction into units that can be coded and aggregated over many sessions. Consequently, these methods fail to capture the procedures by which participants accomplish learning through the affordances of online media. We are developing an analytical approach that scales up the advantages of sequential and interactional analysis to longer term distributed and asynchronous interactions. The approach has been prototyped on data derived from synchronous and asynchronous interaction of dyads and small groups. Ongoing work is refining the methodology and evaluating its relevance to design. Software support will also be required for this work, for example to view the uptake graph at multiple granularities and through filters, compressing it in time and/or scanning for patterns, and accessing the original data at will until we find an interactionally promising subgraph.

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