Learning Analytics of and in Meditational Processes of Collaborative Learning

Dan Suthers, University of Hawai‘i, suthers@hawaii.edu
Alyssa Friend Wise, Simon Fraser University, alyssa_wise@sfu.ca
Bertrand Schneider, Stanford University, schneibe@stanford.edu
David Williamson Shaffer, University of Wisconsin-Madison, dws@education.wisc.edu
H. Ulrich Hoppe, University of Duisburg-Essen, hoppe@collide.info
George Siemens, University of Texas at Arlington, gsiemens@uta.edu

Abstract: This panel will illustrate and discuss the potential of Learning Analytics, viz. computationally supported collection and analysis of data about learners and their settings, to analytically uncover mediational processes in CSCL and possibly participate itself as a mediator. The focus on meditational processes takes the conference theme of the "material conditions" of learning broadly to include cultural, digital and physical "material". The panel illustrates the relevance of Learning Analytics for CSCL with applications ranging from dyads and small group interaction to meditational processes in communities.

Keywords: learning analytics, meditational means, network analysis, epistemic, computational, multimedia, multimodal

Introduction

Learning Analytics (LA) has been defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Learning Analytics and Knowledge 2011 web site). There has been an emphasis on organizational needs, particularly in higher education; on "big data", particularly in conjunction with the recent popularity of xMOOCs; and on how to leverage the explosion of social and Web 2.0 media for learning objectives. Thus, learning analytics is motivated in part by "rapidly expanding forms of social, cognitive and technical mediation" (CSCL 2014 conference theme). However, learning analytics also includes work that deals with "small data" and looks closely at interaction in other settings. The third conference called for a "productive multivocality" between the various strands in the LA community (Learning Analytics and Knowledge 2013 chairs' introduction).

This panel does not attempt to be representative of LA as a field, but rather brings to our attention specific work of interest to CSCL. Inspired by the conference theme of the "material conditions of learning", and taking "material" broadly to include conceptual and digital artifacts as well as physical ones, this panel focuses on *learning analytics of the mediational means of learning in social settings* (i.e., CSCL broadly construed). Examples of mediational means from the panelists' work include discussion messages as conceptual and interactional resources; gestures and gaze in relation to one's physical setting; discourse elements evidencing the skills, knowledge, identities, values, and epistemologies of a community of practice; how digital media participate in forming communities in a large online network; and the evolution of ideas and domain concepts over time in communities. When we ask how actors and mediational means factor into learning in interaction, networks (particularly multimodal networks) provide natural models; hence we see several networked based approaches on this panel. However, when analyzing the mediated interaction of dyads and small groups, other methods tracing interaction over time, space, modalities and media are also useful, and are represented on the panel. Panelists are asked to use their work to address the questions: What potential does learning analytics have to either *uncover* or *participate in* mediational processes in CSCL? What are its limitations?

Our discussant is George Siemens, a founder of the Learning Analytics and Knowledge conference series and its associated Society for Learning Analytics, and hence the world's foremost promoter of learning analytics, but also a person who is experientially grounded in the challenges of applying learning analytics in his online courses. Siemens is the originator of connectivism, a theory of learning as the formation of networks of connections at levels ranging from the brain to the socio-cultural. He also originated MOOCs as connectivist or "cMOOCs", based on his strongly social vision of learning, to be distinguished from the current trend in which large numbers of individuals work through courseware in "xMOOCs". He has indicated that he will ask panelists to address the gap between learning analytics theory and practice. Brief statements from the panelists are below.

Alyssa Wise, Simon Fraser University

While advances in the availability of data and methods for processing it present exciting opportunities to provide real-time feedback to students on their collaborative processes, translating a CSCL research program into learning analytics is far from trivial. An additional knowledge base is needed to leverage CSCL methods and models to be useful and effective in this context. Specifically, there are four core issues to address: (1) reconciliation of the inherent group orientation of CSCL with the fundamentally individual orientation of Learning Analytics; (2) how to interpret data traces of collaborative learning processes that are in progress rather than completed and may be part of a larger trajectory of learning to collaborate; (3) recognition of students and teachers (rather than researchers) as the active agents who will receive, interpret and make decisions based on the results of the analyses; and (4) the existence of the analytics themselves as a change in the material conditions of learning that mediate interactions between learners and their learning environment, their instructor and their peers. This perspective emerged out a CSCL research program investigating how students attend to the messages of others in asynchronous online discussions (The E-Listening Project). One of the material conditions of an online discussion is the products of others: messages mediate learner interactions with both the conceptual content of the discussion and each other. Thus how students engage with existing posts is an important, though often overlooked, element of participation in a discussion. Our research tracks how students attend to others' posts and presents analytics that students and instructors use to reflect on their discussion participation. Some analytics were embedded in the learning environment to provide students with real-time information on their activity in-progress; and others were presented to students in a separate digital space for reflection. In both cases the creation of the analytics represents a change in the material conditions of learning that mediates how learners interact with the discussions, each other, and in some cases, the instructor.

Bertrand Schneider, Stanford University

Nowadays, virtually all of educational outcomes in schools are measured by a unique product (a test, a portfolio or a project), while measuring the process of learning is mostly neglected. New sensing devices are now affordable and scalable, allowing us to 1) capture fine-grained information to perform formative assessment, and 2) feed this data back to students to support small group learning. In my own research, I have been using multi-modal learning analytics (MMLA) techniques to study and support collaborative learning. More specifically, I have been designing computational measures of group synchronization by applying Natural Language Processing techniques to students' transcripts, unsupervised machine learning algorithms to students' gestures (collected from a Kinect sensor) and cross-recurrence quantification to students' gaze (collected from a dual eye-tracking setup). I have found joint visual attention and discourse synchronization to be strong predictors of collaborative learning, while physical synchronization did not seem to be associated with productive interactions among dyads of students. Additionally, a promise of MMLA is the ability to design awareness tools to redirect this multi-modal stream of data back to learners, so that they can make better and more informed meta-cognitive choices when discovering new concepts. Following this line of work, I have found real time mutual gaze perception (i.e., students' ability to see the gaze of their partner in real time) to positively influence students' collaborative learning; additional findings suggest that visualizing collaborative eye-tracking data as networks (where the nodes of the graph represent joint fixations and edges represent saccades of a group) can provide researchers with strong predictors for different facets of a productive collaboration.

David Shaffer, University of Wisconsin-Madison

Epistemic network analysis (ENA) looks at computer supported collaborative learning as an occasion to assess performance in context by modeling the uptake and use of mediational means during collaborative problem solving. Three characteristics of ENA exemplify critical issues to this panel and to modeling the uptake and use of mediational means in collaborative learning. First, ENA is theory based. Mediational means do not exist in isolation. Epistemic frame theory, on which ENA is based, suggests that becoming part of a community of practice can be modeled by exploring the cognitive connections that individuals make among meditational means of a particular practice: the collection of skills, knowledge, values, identity, and epistemology that forms the epistemic frame of the community. This leads to a second characteristic of ENA: it is network based. ENA extends network science to develop tools for analysis and visualization that are specifically designed to investigate how connections among mediational means are formed and leveraged during collaborative learning. ENA collects longitudinal data in situ that document the development of and linkages among mediational means. These data are represented in a dynamic network model that quantifies changes in the strength and composition of an individual's epistemic frame over time. Specifically, ENA looks at the things an individual says or does for evidence of one or more mediational means from a community of practice. The association structure of the discourse is modeled by creating an adjacency matrix of mediational means based on their co-occurrence in discourse over time. Finally, while ENA is a computational technique and well-suited to the kind of data generated in computer-supported learning environments, it is equally suited to analysis of a wide range of qualitative data on collaboration.

Dan Suthers, University of Hawaiʻi

Work at the University of Hawaiʻi addresses the meditational means of learning at multiple granularities, and includes a line of work explicitly intended to bridge levels. Here we focus on our study of mediated communities in Tapped In, a formerly large and active online network of educators cultivated by Mark Schlager, Judith Fusco and Patricia Schank. Participants and organizers could choose between various digital media, including synchronous chats and asynchronous discussions and file sharing. Inspired by Licoppe & Smoreda's observation that the nature of interpersonal relationships is reflected and reaffirmed in the choice of media through which people interact, we ask how the nature of communities are reflected in their choice of media. Inspired by Latour, we treat media objects as "actants" that participate along with human actors in assembling social entities. The Tapped In network is modeled as a bipartite (actors and media) multimodal (chats, discussions and files) directed (read, write) weighted (number of events) graph. Then, a "community detection" algorithm is applied to the graph to find cohesive subgraphs that evidence collections of people and the media through which they interact. Inspecting the attributes of the actors and the nature of the media included in each cohesive subgraph, we can identify meaningful social entities (e.g., an asynchronous communities of practice mentoring program run by a large school district, or a sheepherder in Australia running a small English as Second Language chat group). The fact that graph clusters found through automated means were interpretable as meaningful by Tapped In developers illustrates the potential of network modeling methods to identify social phenomena that are the settings of learning interactions. Other techniques being refined in our laboratory are then applied to understand the nature of interaction in particular sessions and the roles of community members in these sessions.

Ulrich Hoppe, University of Duisburg-Essen

Learning Analytics features an inherent interest in computational methods of analysis and algorithms. This is not necessarily related to big data and corresponding algorithms and architectures. The "analytic" aspect is not just about empirical analyses in technology-rich settings, it actually also calls for non-trivial computational approaches as part of the analysis. This makes Learning Analytics a rewarding area for computer scientists and mathematically inspired researchers. Algorithmic approaches used in Learning Analytics include analytics of (1) content using text mining or other techniques of artefact analysis, (2) network structures including actor-actor (social) networks and also actor-artefact networks, and (3) processes using methods of sequence analysis. Of these, only actor networks directly address the social aspect of CSCL. However, sequential pattern analysis can be extended to include user-ids representing ownership and transactional patterns homogeneously without actually changing the underlying methods. As an extension of social networks, actor-artefact networks have been studied, e.g. to identify the evolution of ideas in knowledge building communities (e.g. Halatchliyski, Hecking, Göhnert & Hoppe, LAK 2013). Focusing on artefacts, the computational analysis of learner-generated content can reveal learners' understanding of domain concepts and especially misconceptions using text-mining methods (Daems, Erkens, Malzahn & Hoppe, J. Computers in Education 2014). Regarding temporal patterns in learners' action logs, Bannert, Reimann, & Sonnenberg (Metacognition and Learning, 2014) have used Process Mining, a computational technique with roots in theoretical computer science. It is both a challenge and an opportunity for CSCL to give more importance to such computational methods of analysis.