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It's About Time: 4th International Workshop on Temporal Analyses of Learning Data

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ABSTRACT
Interest in analyses that probe the temporal aspects of learning continues to grow. The study of common and consequential sequences of events (such as learners accessing resources, interacting with other learners and engaging in self-regulatory activities) and how these are associated with learning outcomes, as well as the ways in which knowledge and skills grow or evolve over time are both core areas of interest. Learning analytics datasets are replete with fine-grained temporal data: click streams; chat logs; document edit histories (e.g. wikis, etherpads); motion tracking (e.g. eye-tracking, Microsoft Kinect), and so on. However, the emerging area of temporal analysis presents both technical and theoretical challenges in appropriating suitable techniques and interpreting results in the context of learning. The learning analytics community offers a productive focal ground for exploring and furthering efforts to address these challenges. This workshop, the fourth in a series on temporal analysis of learning, provides a focal point for analytics researchers to consider issues around and approaches to temporality in learning analytics.

Categories and Subject Descriptors
K.3.1 [**Computers and Education**]: Computer Uses in Education – *collaborative learning.*

General Terms
Measurement, Design, Human Factors,

Keywords
Learning analytics, temporality, discourse analytics, knowledge building, sequence mining, CSCL

1. WORKSHOP BACKGROUND
The temporal component of learning has typically been underexplored in both applied and research contexts [15, 18, 19]. This is a complex issue; temporality involves consideration of duration, sequence, pace, and salience of target events [21, 27], in addition to consideration of accretion over time [10, 15, 18]. For example, while many discussions around MOOCs emphasize student retention rates by simply counting students' online actions, the analysis of temporal patterns in the clickstream data tracking student actions has the potential to uncover deeper insights and provide greater predictive power [4, 13].

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Measures and methods for characterizing and analyzing the temporal evolution of dynamics of group interactions are needed and emerging [1, 3, 7, 24]. Despite the relative ease of access learning analytics researchers have to process data (through log files for example), relatively little research has made use of this temporal information [24], with most research opting for a "coding and count" strategy [as discussed in 25, 28]. With the rise of online learning and available trace data, the availability of data for analysis is growing [9], but we should be mindful that 'bigger' is not necessarily 'richer'; methodological and conceptual work is needed to develop analytic approaches that leverage the temporal features of these data sets to make increasingly sophisticated knowledge claims and diagnostic assessments about learning [23]. In addition new approaches are needed to integrate analysis of data streams, thereby revealing how phenomena (e.g., mouse clicks, utterances, gazes, gestures, persistent representations such as diagrams) co-occur, interact, and facilitate learning, and furthermore, show how they dynamically affect one another over time. Such analyses can help reveal dynamic relationships and support the development of theory and design principles [2].

We are not only interested in how sequences of click-stream data are related to learning outcomes, but why. Moreover, the separation of data within clickstreams – which clicks are associated, how they are chunked into meaningful sequences, and what objects are available to click – are related to a theorized account of data representation and segmentation. Greater understanding of temporality is key here; the very understanding of an 'episode' or 'event' is tied to temporal notions around the demarcation of meaningful segments. Issues are more complex yet, in addition to temporal analyses which consider the arrangement of events within sequences and the organization of multiple events over time, there are those which explore time as a continuous flow of events, examining their positioning, rates, and duration [20]. Both approaches raise complex questions around operationalization and data collection [26].

Much recent work (for example the use of use of 'lag sequential analysis' [8, 22] in [used in 5], t-patterns [16, 17] in [14], pattern-analyses [e.g. used in 12], and Markov models [see recent inclusion in the analytic techniques of, 6]) has focused on analysis of recurring sequences and their association with learning. While t-pattern analysis can be used to explore longer, more temporally separated sequences than LSA and Markov models, all these techniques are best suited to relatively short recurring sequences and analysis of event transitions [24]. Therefore, other approaches will be needed for temporal analysis of accretion and 'flow' or development over time. For example, in analysis of the unstable and evolving nature of topics in dialogue, Introne and Dreschler take as their unit of analysis "a sequence of replies, seek[ing] to understand how clusters of words in these reply sequences change, merge, and split" [11]. Here their interest is in modelling the statistical properties of the co-occurrence of words over time, as opposed to modelling probabilities based on dictionary entries or other corpora. Regardless of focus, fundamental to these examples is the bringing together of both analytic and theoretical accounts. The learning analytics community offers a productive focal ground for exploring and furthering such efforts through its positioning at the nexus of learning and analytic concerns.

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