Context-aware Multimodal Learning Analytics Taxonomy

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ABSTRACT: Analysis of learning interactions can happen for different purposes. As educational practices increasingly take place in hybrid settings, data from both spaces are needed. At the same time, to analyse and make sense of machine aggregated data afforded by Technology-Enhanced Learning (TEL) environments, contextual information is needed. We posit that human labelled (classroom observations) and automated observations (multimodal learning data) can enrich each other. Researchers have suggested learning design (LD) for contextualisation, the availability of which is often limited in authentic settings. This paper proposes a Context-aware MMLA Taxonomy, where we categorize systematic documentation and data collection within different research designs and scenarios, paying special attention to authentic classroom contexts. Finally, we discuss further research directions and challenges.

Keywords: multimodal learning analytics, human-labelled observations, automated observations, classroom observations, technology-enhanced classrooms, learning design, context

1 INTRODUCTION AND BACKGROUND

As teaching and learning processes most often take place blended learning settings, to create a holistic picture of educational context and analyse these processes for different purposes, different data sources and collection methods are needed. Learning interaction (between people and/or with artefacts) has been an important part of educational research. While some decades ago, researchers focused on face-to-face interactions and used traditional data-collection techniques such as observations, technological advancements led attention to Technology-enhanced Learning (TEL) researchers towards digital interactions, as it is illustrated by the appearance of the Learning Analytics (LA) community. Thus, both research trends often cover only one part of the educational process due to the data available. The Multimodal Learning Analytics (MMLA) field emerged as a response to this need, combining different data-sources from different spaces, e.g., with the help of sensors, EEG devices etc. At the same time, to guide the data collection and analysis process, human inference and contextual information (such as learning designs where teachers report about their intentions, actors, roles, media use and other information about the learning context) are often needed (Hernández-Leo, Rodriguez Triana, Inventado, & Mor, 2017). To address this need, previous research proposes to benefit from the synergistic LD and LA relationship, where LD contextualizes data analysis and LA informs LD.

The Learning Analytics (LA) community emerged with the widespread adoption of digital learning platforms, mainly focusing on the analysis of digital interactions (Ochoa & Worsley, 2016). However, depending on the learning activity, meaningful interactions may also not be tracked in theses spaces, narrowing down the interaction analysis to the data available in the digital platforms that can lead to a street-light effect (Freedman, 2010). To respond to this limitation, a new wave of Multimodal Learning Analytics (MMLA) community promotes the collection and analysis of different data sources across spaces (Blikstein & Worsley, 2016). Typically, MMLA datasets include not only log data, but also data generated by sensors located in mobile and wearable devices (Ochoa & Worsley, 2016). To make sense of the MMLA data, input from humans is often used; human-mediated labelling is often used to relate raw data to more abstract constructs (Worsley et al., 2016)(Di Mitri, Schneider, Klemke, Specht, & Drachsler, 2019). At the same time, analytics approaches need theory (Joksimović, Kovanović, & Dawson, 2019) to create a hypothesis space (Di Mitri, Schneider, Specht, & Drachsler, 2018). Moreover, contextual information such as the learning design can guide the data collection and interpretation (Lockyer & Dawson, 2011)(Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2013). However, it is worth noting that in authentic settings LD may not be available due to different limitations and adoption problems (Dagnino, Dimitriadis, Pozzi, Asensio-Pérez, & Rubia-Avi, 2018)(Lockyer, Heathcote, & Dawson, 2013; Mangaroska & Giannakos, 2018).

Traditional human-mediated data collection methods, such as observations can also respond to the aforementioned need for contextual information, as they are inherently highly contextual. Through observational methods, quantitative and qualitative data can be systematically collected and analysed (Cohen, Manion, & Morrison, 2018)(Eradze, Rodríguez Triana, & Laanpere, 2017). However, despite the richness of observational data, several constraints prevent researchers and practitioners from applying them (e.g., time-consuming data collection and analysis, intrusive approach, difficulties registering fine-grain events or multiple events at the same time, etc). Therefore, educational research and practice may benefit from aligning traditional (human-labelled) and modern (automated) classroom observations; thanks to the evidence collected from the physical space, they can support the triangulation, contextualization and sensemaking of MMLA data. On the one hand, observations could aid the MMLA contextual and methodological needs, and on the other MMLA could alleviate the complexity and workload of human-driven observations: enrich the data, speed up the observation process by automatization or gather evidence on indicators unobservable to the human eye, as already indicated by previous authors (Anguera, Portell, Chacón-Moscoso, & Sanduvete-Chaves, 2018)(Bryant et al., 2017). Furthermore, technological solutions may further reinforce the use of specific coding schemas, contributing to the quality and availability of the data; speed up the process of observations (Kahng & Iwata, 1998), and enhance validity and reliability of data (Ocumpaugh et al., 2015).

Based on the overviewed community challenges and concerns rooted in previous research, to provide a holistic picture on teaching and learning processes and with a systematic picture on the use of MMLA in different scenarios, this research has connected two research paradigms (traditional and modern) based on systematic, human-labelled and automated observations. More concretely, we explore synergies between these two approaches in authentic, blended, TEL classroom settings. Also, to reinforce the contextualization, whenever available, we propose to use the LD, reflecting the pedagogical grounding and the teacher intentions leading to that activity. Connecting these three factors: human-mediated, automated observations and LD contextualization is not a trivial task, and special attention needs to be paid to the specificities, meaning, affordances, constraints and quality of the data sources, as well as LD availability challenges.

To envision the data collection and documentation process, we propose a *Context-Aware MMLA Taxonomy*. The presented taxonomy classifies different research designs depending on how systematic the documentation of the learning design and the data collection have been. The following section will overview the taxonomy and the final chapter of the paper will close with a discussion detailing further research directions and challenges.

2 CONTEXT-AWARE MULTIMODAL LEARNING ANALYTICS TAXONOMY

To provide a contextualized and holistic view of the teaching and learning activities taking place in TEL classrooms, connecting two research paradigms (Daniel, 2019), this paper proposes a *Context-aware MMLA Taxonomy* to support the alignment of LD, human and automated observations (MMLA). In this taxonomy, in line with previous research indicating to LA adoption challenges (Buckingham Shum, Ferguson, & Martinez-Maldonaldo, 2019), we regard authentic learning contexts as a baseline, anchoring scenario. The taxonomy (Figure 1) classifies human-labelled and automated data collection on two axes: systematic documentation and data-collection, viewing authentic cases as a baseline for data collection and analysis. These two axes represent context-awareness (systematic documentation) and rigorous quantitative classroom observation data collection (systematic data collection) to enable alignment of data sources and rich MMLA analysis.

Ideal - Systematic documentation and data collection: In the most desirable case, the learning design (including actors, roles, resources, activities, timeline, and learning objectives) is set up-front and documented in an authoring tool. Then, during the enactment, logs are collected automatically from the digital space and systematic observations from the physical one. During the enactment, the additional layer of enactment lesson structure is inferred through unstructured observations. To ensure the interoperability, actors and objects should be identifiable (across the learning design, logs and observations) and timestamps for each event should be registered. Once the data is aggregated in a multimodal dataset, further analysis can be executed.

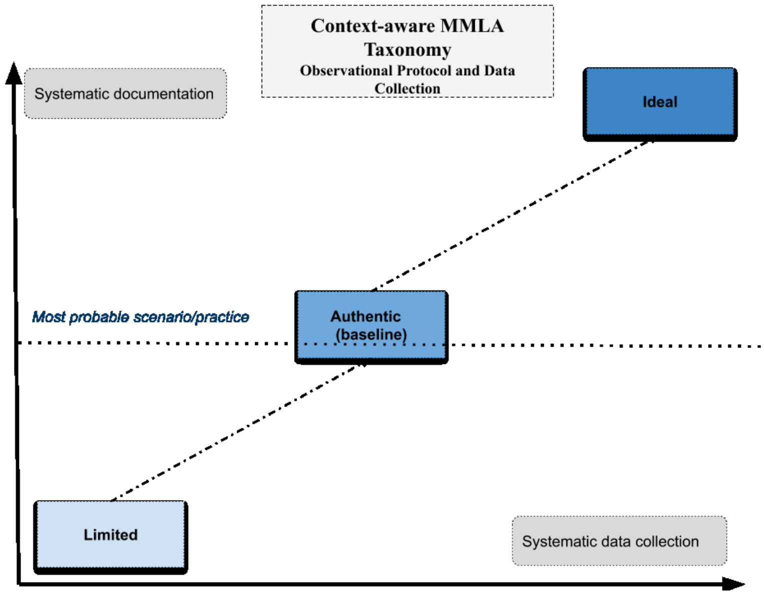

Figure 1: Context-Aware MMLA Taxonomy

Authentic (baseline) - Non-systematic documentation but systematic data collection: We regard this level as a compromise between the limitations of authentic settings but still rich in terms of data. Here, the predefined learning design cannot be automatically used to guide the analysis (either because of its format or because it is not available). However, the timestamped lesson structure is inferred by the observer. Therefore, the actors are not identifiable across observations and digital traces. Nevertheless, both structured observations and logs are systematically gathered and collected in the Learning Record Store using a common format (e.g., xAPI). These conditions will enable the application contextualized analysis on a more baseline level, using multimodal analytics.

Limited - Non-systematic documentation or data collection: Data collection happens non-systematically. As in the previous case, no information about the learning design is available (i.e., actors are not known). In terms of the design of the data collection, the protocol with corresponding codes may not be predefined, and semi-structured (non-systematic) observations are used. Thus, even if logs are systematically gathered, the lack of systematization of the observations hinder the application of multimodal data analysis. Although this is not an advisable scenario, logs and observations can be analysed independently and still provide an overview of what happened in the physical and digital planes. Besides, even if observations are done systematically, if the vocabulary (actors, objects and actions) are not agreed across datasets, then the potential of the multimodal analysis could be limited.

3 DISCUSSION, CHALLENGES AND FUTURE RESEARCH

This paper overviewed modern challenges in MMLA community underlying data contextualization and sense-making needs, especially in authentic learning scenarios. Based on these challenges and problems we suggested aligning modern and traditional data collection methods (human-labelled and automated) and LD. As researchers and practitioners need to take into account authentic learning settings in MMLA data collection, we proposed the *Context-aware Multimodal Taxonomy* to classify different levels of data collection and documentation, for different research designs. It is worth noting that we also created specific conceptual and technological tools (Eradze & Laanpere, 2017; Eradze, Rodríguez-Triana, & Laanpere, 2017). Both, the taxonomy and tools have been evaluated in authentic settings (corresponding to the *baseline scenario*) through an iterative analysis of multimodal data (human-labelled and automated observations) involving different qualitative sources such as teacher reflections and qualitative observations. Preliminary results show that, in authentic settings, the baseline scenario was useful for two-level contextualization: observed lesson structure, human-labelled observations. At the same time, in this specific case, systematic human-labelled observations introduced additional semantics, pedagogical constructs, and indicate to the potential of using theoretical constructs in the automated observation data-sets through (validated) coding schemas. This factor further contributes to the creation of hypothesis space.

However, to enable alignment of MMLA observations and LD, in *ideal scenarios* (see Figure 1) and to facilitate the adoption of MMLA in the context of classroom observations by final users, there is a need for further reinforcement for sense-making and analysis to enable actionable insights based on MMLA data. To reach that goal, it would be necessary to create MMLA architectures and pipelines to integrate MMLA data and visualize it in a dashboard. In this regard, the on-going MMLA research efforts (Schneider, Di Mitri, Limbu, & Drachsler, 2018; Shankar et al., 2019) look very promising. At the same time, further research is needed for the pedagogically-grounded and theory-driven analysis of data and understanding how the *Context-aware MMLA taxonomy* and the related solutions can inform the teaching practice.

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