CrossMMLA in practice: Collecting, annotating and analyzing multimodal data across spaces

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ABSTRACT: Learning is a complex process that is associated with many aspects of interaction and cognition (e.g., hard mental operations, cognitive friction etc.) and that can take across diverse contexts (online, classrooms, labs, maker spaces, etc.). The complexity of this process and its environments means that it is likely that no single data modality can paint a complete picture of the learning experience, requiring multiple data streams from different sources and times to complement each other. The need to understand and improve learning that occurs in ever increasingly open, distributed, subject-specific and ubiquitous scenarios, require the development of multimodal and multisystem learning analytics. Following the tradition of CrossMMLA workshop series, the proposed workshop aims to serve as a place to learn about the latest advances in the design, implementation and adoption of systems that take into account the different modalities of human learning and the diverse settings in which it takes place. Apart from the necessary interchange of ideas, it is also the objective of this workshop to develop critical discussion, debate and co-development of ideas for advancing the state-of-the-art in CrossMMLA.

Keywords: multimodal learning analytics, learning spaces, sensor data

1 BACKGROUND

The field of multimodal learning analytics (MMLA) is an emerging domain of Learning Analytics and plays an important role in expanding Learning Analytics goal of understanding and improving learning in all the different environments where it occurs. The challenge for research and practice in this field is how to develop theories about the analysis of human behaviors during diverse learning processes and to create useful tools that could that augment the capabilities of learners and instructors in a way that is ethical and sustainable. CrossMMLA workshop will serve as a forum to exchange ideas on how we can analyze evidence from multimodal and multisystem data and how we can extract meaning from these increasingly fluid and complex data coming from different kinds of transformative learning situations and how to best feedback the results of these analyses to achieve positive transformative actions of those learning processes. CrossMMLA aims at helping learning analytics to capture students' learning experiences across diverse learning spaces. The challenge is to capture those interactions in a meaningful way that can be translated into actionable insights (e.g., real-time formative assessment, post reflective reviews; Di Mitri et al., 2018, Echeverria et al., 2019) .

MMLA uses the advances in machine learning and affordable sensor technologies (Ochoa, 2017) to act as a virtual observer/analyst of learning activities. Additionally, this virtual nature allows MMLA to provide new insights into learning processes that happen across multiple contexts between stakeholders, devices and resources (both physical and digital), which often are hard to model and orchestrate (Scherer et al., 2012; Prieto et al., 2018). Using such technologies in combination with machine learning, LA researchers can now perform text, speech, handwriting, sketches, gesture, affective, or eye-gaze analysis (Donnelly et al., 2016; Blikstein & Worsley, 2016, Spikol et al., 2018), improve the accuracy of their predictions and learned models (Giannakos et al., 2019) and provide automated feedback to enable learner self-reflection (Ochoa et al, 2018). However, with this increased complexity in data, new challenges also arise. Conducting the data gathering, pre-processing, analysis, annotation and sense-making, in a way that is meaningful for learning scientists and other stakeholders (e.g., students or teachers), still pose challenges in this emergent field (Di Mitri et al., 2018; Sharma et al., 2019).

CrossMMLA provides participants with hands-on experience in gathering data from learning situations using wearable apparatuses (e.g., eye-tracking glasses, wristbands), non-invasive devices (e.g., cameras) and other technologies (in the morning half of the workshop). In addition, we will demonstrate how to analyze/annotate such data, and how machine learning algorithms can help us to obtain insights about the learning experience (in the afternoon half). CrossMMLA provides opportunities, not only to learn about exciting new technologies and methods, but also to share participants' own practices for MMLA, and meet and collaborate with other researchers in this area.

2 CROSSMMLA HISTORY AND DEVELOPMENTS

CrossMMLA continues a recently-established, but already very consistent tradition of workshops on MMLA and CrossLAK, organized at both EC-TEL and LAK conferences. These past events have leveraged a variety of formats, from hands-on learning experiences and tutorials, based on participant contributions/papers, as well as conceptual and community-building activities (which have eventually led to the creation of a Special Interest Group within Society of Learning Analytics Research - SOLAR CrossMMLA SIG[1]).

The CrossMMLA community aims to become the focal point of contributions coming from a variety of fields (e.g., learning, HCI, data science, ubiquitous computing). Prior to the CrossMMLA event, we launch a call for submissions that shapes the hands-on activities to be performed. The contributions normally belong in one or more of the following categories:

1. Data gathering setups and prototypes (e.g., the use of the Multimodal Learning Hub and EEGlass).
2. Data analysis/annotation methods and tools (e.g., Visual Inspection Tool, coding schemas and "grey-box" analyses).
3. Learning activities/Pedagogical designs that could benefit from CrossMMLA techniques.
4. Examples of CrossMMLA research designs or case studies.

[1] Multimodal Learning Analytics Across Spaces Special Interest Group (SOLAR CrossMMLA SIG): https://www.solaresearch.org/community/sigs/crossmmla-sig/

During the CrossMMLA events, there is a formation of teams that then engage in different CrossMMLA projects. These teams use the aforementioned contributions to define learning scenarios or learning activities to be performed, the research questions to be investigated through the use of CrossMMLA, and the data gathering, annotation and analysis to be undertaken during the workshop.

Announcements and future CrossMMLA calls are available here: http://crossmmla.org/

3 OBJECTIVES AND INTENDED OUTCOMES

It is expected that at the end of the CrossMMLA workshop, participants engage with:

- The state-of-the-art ideas, designs and implementations of CrossMMLA systems.
- Capture, analyze and report multimodal data on-the-spot.
- Contribute and shape the research agenda and future of CrossMMLA community.

Aside from the (intangible, but very important) learning of participants about CrossMMLA, and the strengthening of the SoLAR Special Interest Group on CrossMMLA, the workshop also has targeted the following two tangible outcomes:

1. Based on the contributions of the participants we provide a catalogue of shared community knowledge.
2. Based on the learning activities tested in the workshop, and the rest of the hands-on activities, an open “CrossMMLA dataset” will be made available to the community (through the SIG/Workshop website or other European open science repositories)

All contributions and materials are made available on “LAK Companion Proceedings”. Organisers are planning to create a collaborative contribution describing the consensus reached during the workshop. Based on the outcomes of the workshop and participants interest, similarly with previous versions of Cross-MMLA, we will consider proposing a special issue in an international journal (e.g., JLA, CHB, BIT or else).

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