Challenges of the adoption of MultiModal Learning Analytics in Smart Learning Environments

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1. Introduction

Smart learning Environments (SLEs) seek to provide personalized support to learners based on their individual needs and context. Such support is possible thanks to the adoption of Learning Analytics (LA) based on students' interaction with the different learning resources [1]. However, when such analytics consider only the interactions spanning with digital tools, the behavior and social interactions of learners taking place in the physical space are misrepresented, especially in collaborative activities. In this regard, the adoption of MultiModal Learning Analytics (MMLA) can compliment and provide a more concise perspective of the current situation through the learning processes, which potentially ends in a more meaningful support for learners [2]. Even so, the adoption of MMLA in SLEs raises different challenges.

This abstract explores such challenges in the context of the integration of MBOX (Multimodal Box), a lightweight toolbox for collecting human interactions for collaborative learning scenarios, and SCARLETT (Smart Context-Aware Recommendation of Learning Extensions in ubiquiTous seTtings), an SLE designed to facilitated the management and coordination of multiple learning environments across spaces to deploy personalized recommendations [3].

2. Supported scenario

The supported scenario consists on a project-based activity performed face to face in the laboratory, where students have to work in groups to develop a solution for the monitorization of the environment conditions of the center. Through the different activities, each group has to write down the decisions made in a shared document and submit the resulting artifacts in the learning management system (LMS) of the course.

While students work on the activities, SCARLETT can interact with the involved systems to gather learning traces of the actions of each group, such as the updates and changes performed in the shared documents or the number of submissions sent to the Learning Management System (LMS) for each of the stages of the activity. This set of logs helps SCARLETT to characterize

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how each groups is progressing through the whole activity and, consequently, to detect and notify underperforming groups for assistance according to the status of the shared document and the stage they are currently working on. However, this information reports only how learners interact in the virtual space and ignores the collaboration within each group. MBOX can compliment this information with audio and video analytics related to the recordings of the session. More specifically, MBOX can detect the ID of the speaker, the conversation flow and the overlap during the discussion through the activity. These analytics help to differentiate groups who are not progressing due to lack of participation from groups that are discussing constantly about the activity.

3. Challenges

Despite the opportunities raised with the integration of both systems, the inclusion of such analytics present different concerns and challenges to overcome. One of such challenges is related to the availability and readiness of the learning traces and analytics from the physical space. The processing required to extract the different analytics from the data collected from the students is not insignificant. Depending on the delay this information is available to be used by SCARLETT can affect the type of support and interventions provided to learners, specially for real-time support. Considering the previous scenario, the detection of struggling groups may result in a late response and notification to the group.

Another main issue to overcome refers to the identification of the shared analytics. The analytics provided by MBOX need to include a reference of the physical context they are related to, for a unique connection with the activities described in the learning design in SCARLETT. In a similar fashion, the identification of the students needs to be consistent or configurable for properly combining the reported traces from different sources for each student.

Additionally, the integration of MBOX and SCARLETT presents challenges in the interpretation and usage of the analytics. Although the combination of time-series data with event-logs from the virtual space facilitates a deeper analysis of students' behavior, its interpretation and usage by an autonomous system requires a deeper understanding of the supported scenario.

References

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