A Review of Multimodal Learning Analytics Architectures

Shashi Kant Shankar
Tallinn University
Tallinn, Estonia
shashik@tlu.ee

Luis P. Prieto
Tallinn University
Tallinn, Estonia
lprisan@tlu.ee

María Jesús Rodríguez-Triana
Tallinn University
Tallinn, Estonia
mjrt@tlu.ee

Adolfo Ruiz-Calleja
Tallinn University
Tallinn, Estonia
adolfo@tlu.ee

***Abstract*—There is an increasing interest in Multimodal Learning Analytics (MMLA), which involves complex technical issues in gathering, merging and analyzing different types of learning data from heterogeneous data sources. However, there is still no common reference architecture to face these technical challenges of MMLA. This paper summarizes the state of the art of MMLA software architectures through a systematic literature review. Our analysis of nine architecture proposals highlights the uneven support provided by existing architectures to the different activities of the analytics data value chain (DVC). We find out in those infrastructures that data organization and decision-making support have been under-explored so far. Based on the lessons learnt from the review, we also identify that design tensions like architecture distribution, flexibility and extensibility (and an increased focus on data organization and decision making) are some of the most promising issues to be addressed by the MMLA community in the near future.**

***Index Terms*—Multimodal Learning Analytics; MMLA; Software Architectures; Data Value Chain**

I. Introduction

Learning Analytics (LA) aims to collect and measure learning data, and analyze them to understand learning behavior and its contexts [1]. Most of the LA proposals so far study learning processes and contexts from a single data source (e.g. Learning Management System –LMS– logs or questionnaires) [2], which provides a partial view of learning [3]. Thanks to recent advancements in digital technologies, data can now be collected from complementary sources (e.g., audio, video, sensor data), enabling further analyses and reflection about the learning process [4]. Aware of the aforementioned need of a deeper understanding of learning situations, the Multimodal Learning Analytics (MMLA) research community aims to "collect, synchronize and analyze data from different communication modalities, to provide on-time feedback" [5].

MMLA solutions tend to be complex, since they often involve different stakeholders, multiple data sources, or data processing activities [6]. Software architecture becomes then a key aspect of their design, as it helps to analyze and structure the behavior of software systems before their development [7], and to better understand the data flow among different components [8]. A systematic review of MMLA architectures can thus be complementary to other general LA reviews (e.g. [1], [9]–[11]), which have helped to pave the way for current and future LA research. Although previous MMLA reviews do exist [6], [12], to the best of our knowledge no review has focused on architecture. As (MM)LA systems are by definition data-intensive, our review uses a well-known analytics data value chain (DVC) [13] as its main analytical lens.

II. Methodology

We followed the systematic review method by Kitchenham and Charters [14]. We set our database search query as: *("multimodal" OR "multimodal learning analytics" OR "MMLA") AND ("architecture")*. We searched in the proceedings of the Learning Analytics and Knowledge (LAK) conferences available in the ACM digital library[1], the CEUR proceedings of the MMLA and across-spaces workshops[2], and in the Journal of Learning Analytics[3]. We also queried the IEEE Xplore engine[4] and Google Scholar[5], to capture gray literature and other non-academic sources. The paper retrieval was carried out between November 27th and December 11th, 2017.

The query results returned a total of 122 potentially relevant papers. In order to ascertain whether these papers actually depicted an MMLA architecture, we read the abstract and keywords, and skimmed the full length of the articles, searching for architecture-related figures or tables. This filtering process led to a total of nine papers. Table I summarizes the results of this process (note that the same article may appear in more than one database). The resulting nine papers were then read in full, noting how they address the seven activities of the DVC [13] (see Figure 1).

TABLE I
Summary Table of Query Results

Source	Query Result	Selected
LAK proceedings	25	2
Journal of LA	31	1
MMLA and across-spaces Workshops proceedings	10	1
IEEE Xplore	26	2
Google Scholar	First 30 results	5
Total	**122**	**9**

[1] https://dl.acm.org/citation.cfm
[2] E.g., http://ceur-ws.org/Vol-1828/
[3] http://learning-analytics.info
[4] http://ieeexplore.ieee.org/Xplore/home.jsp
[5] https://scholar.google.com

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DOI 10.1109/ICALT.2018.00057

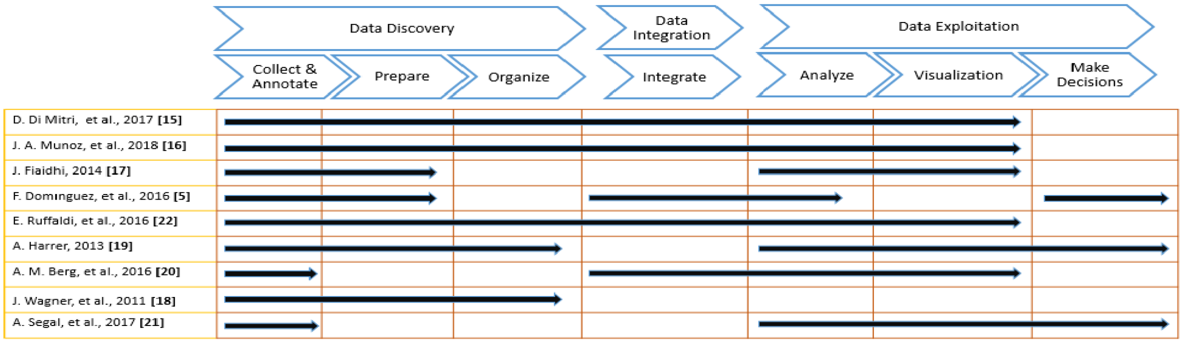

Fig. 1. Data Value Chain activities covered by each reviewed MMLA software architecture

III. Results

The following subsections and Figure 1 provide an overview of the nine reviewed MMLA architectures and the design decisions they represent, in terms of seven activities of DVC.

A. Overview of Analyzed Papers

The first DVC activity (see Figure 1) focuses on the *data collection* from one or more data sources, and their *annotation* in form of metadata. All of the reviewed articles cover more than one source: from physiological data (such as heart rate, step count [15], body posture, or gaze position [5]); digital traces (e.g., logs from learning platforms [16]–[18], student records [19], [20], or learning artifacts [16], [21]); to multimedia data [18], [22].

Seven out of nine reviewed architectures include a *data preparation* activity [5], [15]–[19], [22]. Common strategies are data reduction [21], pre-transformation [15], extraction of basic features [22], data sharing [21], and pre-processing [17]. 2 proposals use the xAPI[6] specification (currently a *de-facto* standard) and store them in a Learning Record Store (LRS) [15]. Aside from this use of standards, we have not found any papers discussing best practices on dataset preparation for MMLA.

Five out of nine reviewed papers cover *data organization* [15], [16], [18], [19], [22]. Specifications for learning designs and learning activities (e.g., IMS-LD [23]) play a major role in this step, guiding the selection of relevant data sources and organizing the data according to the design decisions and the affordances of the learning context [16], [21].

Data integration (also known as data fusion, referring to the alignment of all the data sources which can reveal learning information [24]) is one of the most crucial activities in multimodal analytics. Six out of nine reviewed architectures cover such data integration [5], [15], [16], [18], [20], [22]. Different solutions are mentioned regarding the storage of integrated data, e.g., MySQL databases [22], Learning Record Stores (LRSs) [15], or more generic data warehouses [20].

Except for [18], all the reviewed papers tackle the *data analysis* activity. Various statistical analysis methods are used, such as descriptive, inferential and multivariate analyses [5], [22]. Machine learning techniques are mentioned in several reviewed works [19]–[21], and more concrete techniques like Linear Mixed Effect Models (LMEM) [15] or Random Forests [21] are mentioned when attempting predictive modeling. Interestingly, while most of the architectures mention the data analysis, several do not include any details about how such analysis is done [5], [16], [17], [20], [22].

Analytical results are provided to different stakeholders (e.g., teachers, students, educators, parents and policy makers) by means of *visualizations*. Six out of nine architectures use visualization techniques [16], [17], [19]–[22], such as dashboards, indicators using color coding, or warnings. In this sense, dashboards are by far the most frequently used visualization device [16], [17], [20], [21].

It is noticeable that only three out of nine papers [5], [19], [21] explicitly support *decision making*. These three architectures focus on teachers as decision makers, albeit two of them additionally target students as decision makers [5], [19]. In these two cases, the MMLA infrastructure offers students an awareness of their individual learning process, while teachers get information about the progress of the whole class/group.

B. Discussion and Design Decisions

We extracted and identified several design tensions, decisions and issues that may have a major impact on the support that MMLA architectures provide to stakeholders and data management:

1) *Role of learning-specific constructs in data organization:* Albeit MMLA software architectures are designed to handle learning and educational data, still not many of them consider learning-specific vocabularies, be them about the learning context [15] or the description of the learning activities [5], [16], [21]. The degree of embedding of learning-specific notions in an MMLA architecture is also an issue open for discussion.
2) *Flexibility and extensibility of architectures:* Architectures must be flexible and extensible enough to be adapted to different learning scenarios, and to future technologies. This includes their support for devices,

[6] https://experienceapi.com/overview

technologies and related methods with different communication and data format standards. In this regard, it is worth noting that many devices still often have their own proprietary data formats and/or do not support explicit configuration.

3) *Need of simpler interfaces:* The complexity of MMLA data, the analyses used and their visualization, may pose considerable challenges for stakeholders' current data literacy. Hence, the design of user interfaces (currently in its infancy) shall become a key aspect for MMLA adoption. While this is not strictly a software architecture issue, the design of future MMLA architectures should be flexible enough to serve such novel interfaces still to come, which represent meaningful analytical results, contextualized and pedagogically-grounded.

IV. Conclusions

MMLA systems are complex and data intensive due to the inclusion of multiple data sources and activities related to data processing. To extract design principles that may guide the creation of future MMLA software architectures, we have reviewed how existing solutions address the different activities involved in the data value chain [11].

Our analysis of nine architectural proposals portrays MMLA as a young community, where first systems/proposals are starting to be tested in authentic settings, and still none is widely adopted in practice. One major reason which hinders this adoption is the lack of support for data organization. The use of xAPI and LRSs, which have emerged as a *de-facto* standards (for data format and data storage, respectively) in LA, can be a first step in facilitating such data organization.

We hope the issues raised in this paper are useful for the growing community of MMLA researchers. We believe that the short- and medium-term MMLA agenda should encourage researchers to pay special attention to the design of flexible infrastructures that support the whole data value chain, enabling the scalable adoption of MMLA, in real scenarios, and in a sustainable way.

Acknowledgment

This research has been partially funded by the European Union via the European Regional Development Fund and in the context of CEITER and Next-Lab (Horizon 2020 Research and Innovation Programme, grant agreements no. 669074 and 731685).

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