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SmartLET: Learning analytics to enhance the design and orchestration in scalable, IoT-enriched, and ubiquitous Smart Learning Environments

Smartlet

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ABSTRACT

This paper presents the SmartLET project, a coordinated research project funded by the Spanish Ministry of Science, Innovation and Universities, which just started in 2018. The main aim of this project is to provide support for the design and orchestration of Smart Learning Environments (SLEs) with the support of learning analytics and the Internet of Things. This paper gives an overview of our conception of SLEs based on previous works, provides some ideas about the connection of learning design and orchestration with SLEs, and analyses different ethical and privacy issues for SLEs. In addition, an initial hypothesis and some specific objectives for a support environment for SLEs are proposed.

CCS CONCEPTS

• **Applied Computing** → Education → Interactive Learning Environments **Applied Computing** → Education → E-learning • **Information Systems** → Information Systems Applications → Data mining

KEYWORDS

learning analytics, Internet of Things, smart learning, learning design, orchestration

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1 Introduction

The concept of Smart Learning Environment (SLE) [1] has recently emerged with the aim of transforming current technology enhanced learning environments so that they can provide learners with adequate support at the right time and place based on their needs, which are determined by analyzing their learning behaviors, performance and contexts. SLEs are promising but also challenging especially in the case of physically-situated scenarios where participants interact with multiple devices, such as those proposed in Ubiquitous Learning environments based on the Internet of Things, or in the case of scenarios with a massive number of participants which are usual, for example, in Massive Open Online Courses.

There are two problems that hamper the success of SLEs in both types of scenarios. First, the design and redesign of increasingly effective learning situations are currently not informed by indicators of the impact in learning of previous design realizations [2]. Second, the orchestration of learning situations is a daunting task for teachers and learners, that involves the monitoring, awareness, (self-)regulation and assessment of learning activities [3]. Both problems stem from the fact that obtaining the adequate information required to make decisions about the (re)design and orchestration of non-trivial learning situations is out of reach for teachers and learners, given the high number of participants or the diversity of devices that can be involved in the scenarios.

Learning analytics can be considered a suitable approach to tackle both problems as they deal with the analysis of data about learning with the aim of understanding and optimizing learning and the environments in which it occurs. In fact, the potential of learning analytics to improve the support of teachers and students in different settings has already been shown. However, according to a recent report of the European Commission's JRC, much research still needs to be done to tailor learning analytics for specific needs and contexts such as the aforementioned problems in SLEs.

This paper presents SmartLET, a coordinated research project that aims at improving the support of (re)design and orchestration of physically-situated scenarios based on different devices and massive scenarios within the context of SLEs by means of learning analytics. To do so, the project will propose (1) a set of learning analytics services that will provide indicators furnishing actionable information about the (re)design and orchestration, adequate visualizations of the indicators that will help participants make informed decisions that improve the (re)design or orchestration, and interventions that can be automatically triggered based on the indicators also to ameliorate them; (2) a framework for the integration of the proposed services in different SLEs; and (3) a set of pilot experiences showing how such services enhance the (re)design and orchestration.

The rest of the paper is structured as follows. Section 2 examines the need to improve the support of design and orchestration in SLEs in order to support the fruitful realization of pedagogically relevant scenarios that may involve ubiquitous learning, large amounts of participants or the use of IoT. Next section discusses how learning analytics can be used to improve both design and orchestration in such scenarios. This requires addressing two important practical challenges that are highlighted in section 4. Section 5 presents the initial hypothesis and objectives that have been defined in order to guide the research that is being carried out in the project. Finally, section 6 draws the main conclusions.

2 Scalable, IOT-Enriched and Ubiquitous SLEs

The concept of **Smart Learning Environments (SLEs)** has emerged as technology-supported learning environments that make adaptations and provide appropriate support to learners based on an analysis of their behaviors, performance and their contexts [1]. The concept of SLE is promising, as it envisages a modernization of education towards better teaching support, enhanced learning outcomes and improved quality processes in educational centers, such as schools, campuses or professional training settings [4,5]. Yet, the requirements of SLEs are challenging. Key requirements stress that applications in a SLE should be sensible, ubiquitous and scalable [6]. Sensible environments are associated to Internet of the Things (IoT) scenarios, in which there is "an omnipresent network, consisting of physical or virtual objects/resources, equipped with sensing, computing, communication and actuating capabilities" [7]. Networked devices can then transfer the sensing information or mediate ubiquitous and contextualized access to information (e.g., in mobile devices, ambient displays, etc.). Moreover, SLEs should be scalable, capable of accommodating learning scenarios of different and growing sizes (e.g., large classrooms, massive open online courses - MOOCs) [4,8]. These requirements shape the desired characteristics of the technological infrastructure that might support relevant and effective SLE scenarios.

The research done in the field of Technology Enhanced Learning (TEL) has brought important innovations during the last years. These innovations enable learning scenarios with large numbers of participants or IoT or/and ubiquitous learning situations where learners interact in the real-world context and with physical resources. State-of-the-art examples in the area of **IoT** include the introduction of NFC, RFID and QR codes in the physical space, e.g. [9] or [10], the introduction of wearables in the classroom, e.g. [11], or physical sensors to track students [12]. However, despite the illustrated potential of IoT in education there are still many challenges related to the realization of pedagogically relevant scenarios that achieve effective active learning in a way that is affordable for their implementation by educators and use by learners [13].

Hwang et al. [14] offer a good review of context aware **ubiquitous** applications, impacts and trends. The report shows the potential of mobile devices to improve learning gains, motivation and interest in formal and informal learning scenarios. Besides, other technologies can help extend teaching and learning beyond the walls of the classrooms in additional ways. For instance, Virtual Learning Environments may bridge classrooms and online activities [3], while Augmented Reality and IoT can help connect virtual and physical spaces [15].

Relevant state-of-the-art on **scalable** technologies for learning includes approaches to support large classrooms and MOOC platforms. MOOC platforms are management systems devised to handle massive numbers of learners [16]. As studied by the members of the research teams, such platforms provide features to support long conversation flows in different sized groups [17], enable peer review [18] and can be used in combination with external applications, such as social media tools [19]. Emerging visual analytics tools such as ANALYSE for Open edX [20] show the potential of enabling tracking students' progress in videos or exercises with a large number of students, but also that there is a need of providing solutions for more meaningful visualizations to support educators and learners.

Overall, previous research in these areas of massive, IoT and ubiquitous learning [8,21,22] show that a fruitful pedagogical realization of these scenarios does not necessarily happen if the scenarios are not carefully planned (designed) by educators to create the most favorable conditions (activities, physical and digital settings, and social groupings) for their students to learn, or if the scenarios are not properly managed by the educators and the learners in real time (orchestrated) through monitoring, assessment and a flexible regulation or adaptation of the activities.

3 Learning Analytics for the Design and Orchestration in SLEs

Learning Design (LD) is a field of educational technology research and practice focused on understanding and supporting the processes undertaken by teachers when devising the educational activities to be proposed to their students to learn [23]. Most of the work in LD (by the scientific community and by the teams in collaboration with international researchers, i.e. see the METIS project) has focused on tools and representations to support it, as well as on mechanisms for sharing its outputs between practitioners. Existing approaches emphasize the need to scaffold practitioners in the phases of the design process and to offer them templates to base their designs on sound pedagogical principles. If the designs are properly documented, they can also be used to support reflection processes leading to the potential improvement (**redesign**) of educators' practices.

Orchestration of learning refers to the "the process of productively coordinating supportive interventions across multiple learning activities occurring at multiple social levels" [24]. The conceptualization and scope of orchestration have been profusely discussed: while Dillenbourg restricts orchestration to the enactment of learning situations [25], other authors extend the orchestration scope, covering the whole process from the creation of a learning situation (the learning design, as described above) to its enactment [26]. We take the perspective of [25], which focused on the real-time management of (an already designed) learning situation. The role of the teacher in the orchestration process is also not unanimously established: while some authors consider the orchestration as strongly teacher-centered [3], others emphasize the importance of sharing the orchestration load with students, especially in complex scenarios such as ubiquitous ones [27].

In spite of their importance, the design, and (re)design, of these types of non-trivial learning scenarios are currently not informed by indicators of the learning setting and previous design realizations [2], and their orchestration is still a daunting task for teachers and learners [3], in both cases given the potential high numbers of participants or the diversity of ubiquitous spaces and devices involved. (Re)design and orchestration are unresolved pivotal problems that condition the success of SLEs. SmartLET aims to tackle these problems by means of using learning analytics.

In a context of a SLE, analysis of data about learners and their contexts (**learning analytics**) can be very helpful to support teachers and students. Learning Analytics (LA) refer to "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [28]. LA typically employs large datasets to provide insights about the quality of the learning experiences. LA are rooted in data science, artificial intelligence, and practices of recommender systems, online marketing and business intelligence and its intersection with learning sciences. Tools and techniques developed in these domains make it possible to identify trends and patterns, and then benchmark individuals or groups against these trends. Indicators have been proposed and implemented using data mining in education such as students' skills, engagement, affective states or different meta-cognitive skills [29]. Adaptation of existing indicators to new scenarios is required, e.g. for skill modelling [30] or help-seeking behavior [31]. Existing advances in LA, however, do not consider the particular requirements of SLEs with massive number of participants or offering ubiquitous learning opportunities based on IoT or the new requirements that these scenarios pose to interoperability.

As the research teams, in collaboration with international researchers, have been very recently discussed in scientific workshops (e.g., at LAK2017, LAK2018, ECTEL2017), ubiquitous SLE situations can generate diverse type of data coming from different tools, due to the fact that learning activities may take place in different physical and virtual spaces either at different moments or simultaneously, thus deriving the need to advance research in across-spaces and multimodal learning analytics [32]. Besides, massive SLE situations may produce huge amounts of data. However, current LA techniques are based on algorithms that were not designed to deal with big data sets. It is therefore necessary to explore the use of alternative algorithms that are highly scalable.

Connecting different services and tools in SLEs requires that interoperability issues should be overcome, at the data level, but also at the systems level. A recent review about interoperability in learning analytics [33] helps to point out the challenges. The learning analytics community established specifications such as Contextualized Attention Metadata (CAM) [34], xAPI or IMS Calliper that solve the data format interoperability issue. However, semantic interoperability among different educational systems is in its infancy. The problem is also present in other domains, such as eHealth or transportation [7]. In addition, distributed architectures should be evaluated and analyzed to address the system interoperability issue and e.g. solutions for the interoperability of rules for adaptation [35], should be explored for the extension to SLEs.

Moreover, the research community [26,31] and a recent report by the European Commission claim that important *research still needs to be done to tailor data analytics towards supporting more meaningful learning design in SLEs as well as a more effective orchestration using data collected and processed during runtime*. Some authors state that a **tandem between LD and LA** offers the opportunity to better interpret the resulting data against the original pedagogical intent and the local context, to evaluate the success of a particular learning activity. LA can provide evidences of the impact of a design in one or several learning situations in aspects such as engagement patterns in the activities proposed by the learning design, learning paths followed by the learners, time consumed to complete the activities, etc. These data can support reflection about the effects of the learning designs as well as (re)design processes, by facilitating the identification of design elements that need to be revised before reuse. In the context of massive, IoT-enriched and ubiquitous learning, promising applications of analytics to support educators during the learning design process include, for example, the planning of groups for a massive collaborative learning activity considering learners' profiles, planning the configuration of an IoT-enriched classroom depending on the outcomes of previous activities run in that classroom or offering awareness of learners' performance regarding a set of interrelated activities happening in diverse spaces (e.g., city, museum, classroom) [36]. Prospective **LA supporting orchestration** include, for example, predicting the level of engagement of students [37], monitoring of the learning situations involving the use of multiple tools [38], or providing formative assessment feedback to learners based on multimodal LA, making sense of their experiential performance while interacting with physical objects [39]. However, *the required* *collection of data to overcome the aforementioned (re)design and orchestration limitations of SLEs impose additional requirements to the technological infrastructure of the SLEs themselves. Also the analysis and visual reporting should be aligned with design and orchestration needs.*

4 Important Practical Challenges

Ethical and privacy issues and data protection are among the most challenging areas of LA [29]. In the last years, a lot of effort has been devoted to identifying potential risks derived from the use of LA and how to comply with European and national-wide regulations (e.g., SHEILA project, with participation of the members of the teams).

Another challenge for successful adoption of LA is the **need of building capacity** to interpret results and act on them. Depending on the specific use of LA and data in the educational context, learning designers, teachers and other educational staff will need training to better understand how to interpret data and in particular how to use the data obtained from LA to enrich their current teaching and learning practice. Also, researchers and developers need to increase their understanding of end-users needs and restrictions. Research methods that foster co-design approaches that integrate the users in the design cycle will contribute to proposals that are easier to understand and to adopt by learners and teachers. Team members in SmartLET project will pay attention to empower stakeholders to use and understand how to employ the information derived from the analytics obtained.

Therefore, this project shall address learning design and orchestration challenges in IoT/sensible, ubiquitous and/or scalable SLEs by providing and evaluating in pilot experiences *a set of learning analytics services* (providing indicators, visualizations and interventions) that advance the state of the art overcoming the aforementioned explained limitations as well as offering *guidelines* on how to use the proposed services by educators and learners, considering their needs, and privacy and ethical aspects (see also Fig. 1. for a graphical representation).

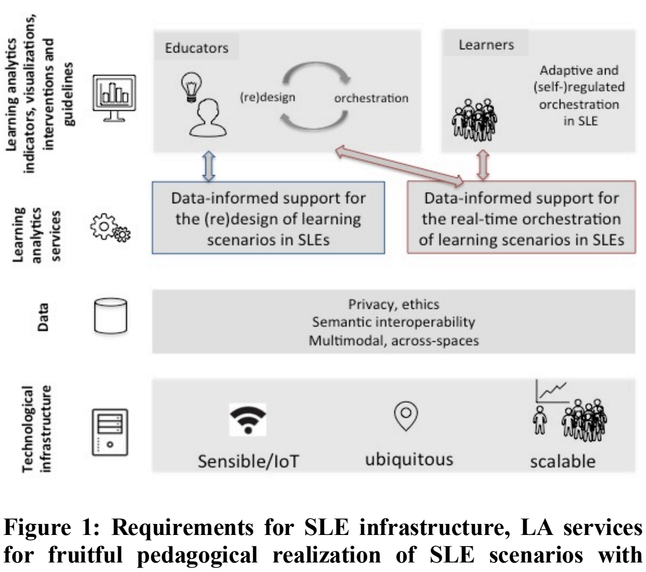

Figure 1: Requirements for SLE infrastructure, LA services for fruitful pedagogical realization of SLE scenarios with indicators, visualizations, interventions and guidelines for educators and learners.

5 Initial Hypothesis and General Objectives

The initial hypothesis is that the (re)design and orchestration of non-trivial learning activities need to be informed by the appropriate information, and that this information can be collected, processed and visualized based on context specific learning analytics indicators and, as a result, appropriate support and interventions can be tailored to individual teacher's' and learner's needs.

The main objective of SmartLET is to improve the support of (re)design and orchestration of physically-situated scenarios based on different devices and massive scenarios within the context of SLEs by means of LA. This main objective is decomposed in the following sub-objectives:

- O1: To define a **research framework**, consisting of four core parts: the identification of *opportunities* in the leading state-of-the-art on the use of LA for (re)design and orchestration in SLEs; the definition of physically-situated with multiple devices and massive *scenarios* in SLEs to extract indicators, provide visualizations, and make interventions; the selection of *technologies* (i.e. platforms, tools and devices) that allow supporting these scenarios; and the definition of an *evaluation framework* that allows measuring the impact and results achieved in applying these technologies to these scenarios.
- O2: To design and develop **learning analytics services for the (re)design** of physically-situated with multiple devices and massive scenarios in SLEs, including the definition of context specific *indicators*, *visualizations* and automatic *interventions* aimed to support teachers' decision making in the planning and (re)design of active learning activities. These LA services shall be integrated with existing learning design tools to support the (re)design of the scenarios.
- O3: To design and develop **learning analytics services for the orchestration** of physically-situated with multiple devices and massive scenarios in SLEs, including the definition of context specific *indicators*, *visualizations*, and automatic *interventions* aimed to enhance monitoring, awareness, self-regulation and assessment of learning activities. These LA services shall be integrated with existing platforms, tools and devices to support the orchestration of the scenarios.
- O4: To enable an **interoperability framework for SLEs** and to deploy and implement it in different pilots. The proposed solution will be able to *integrate the different LA services* for the (re)design and orchestration being interoperable with existing platforms and tools. The proposal will include the selection and adaptation of existing data interoperability standards of data collected from different sources (e.g., sensors, tools and platforms) but also the semantic interoperability to analyze data from multiple sources. The proposal will also include the global interoperable architecture.
- O5: To design, implement and evaluate **pilot experiences** of physically-situated with multiple devices and massive scenarios with SLEs and related **teachers' capacity building workshops**. These pilot experiences will be done in the areas of *engineering, science, health and teachers' training*; will be developed in some of the following contexts: *secondary education, higher education, lifelong learning and learning*

at the workplace; and will be (re)designed and orchestrated taking advantage of the learning analytics services previously developed.

6 Conclusions

There are different views of the concept of SLEs. We consider SLEs as a distributed set of learning resources and services in a ubiquitous way for which educational data can be collected and monitored to provide adaptive and appropriate support for learners, and that can be used by a massive number of users.

SLEs bring new possibilities of scenarios for education in which data from different sources is combined to provide an intelligent support. Specific scenarios covered by SLEs are based on MOOCs and/or educational IoT ones.

Learning design and orchestration is a key challenge in SLEs. The proposal of learning analytics indicators and visualizations can be used to guide the design and orchestration in SLEs.

There are different associated challenges for the approach of using learning analytics for the re(design) and orchestration. The most important are: interoperability issues (not only at the format level but also at the semantic level), ethical and data privacy implications, or the need of building capacity for the relevant stakeholders.

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