CoALA: Contextualization Framework for Smart Learning Analytics

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***Abstract*—Learning Analytics (LA) has become a prominent paradigm in the context of education lately which adopts the recent advancements of technology such as cloud computing, big data processing, and Internet of Things. LA also requires an intensive amount of processing resources to generate relevant analytical results. However, the traditional approaches have been inefficient at tackling LA challenges such as real-time, high performance, and scalable processing of heterogeneous datasets and streaming data. An Internet of Things (IoT) scalable, distributed and high performance framework has the potential to address mentioned LA challenges by efficient contextualization of data. In this paper, CoALA, a Smart Learning Analytics conceptual model is proposed to improve the effectiveness of LA by utilizing an IoT-based contextualization framework in terms of performance, scalability, and efficiency.**

***Index Terms*—Learning Analytics, Internet of Things, Contextualization, Big Data**

I. Introduction

Given the recent advancements in technology and their widespread adoption in learning management systems (LMS), educational institutions have been collecting and possessing a great number of educational data repositories [1]. These arrays of data comprise students' historical and streaming data resulting from their interactions with LMS. Moreover, those institutions have traditionally been inefficient in analyzing those data and extracting proper knowledge from them [1]. Gaining useful insight from the educational data has become a key requirement for those institutions [1]. To address this need, Learning Analytics (LA) has emerged as a new paradigm in education [2]–[6]. It helps educational data organizations with their efficient decision making processes based on the insight which is extracted by utilizing advanced data mining techniques on the educational data.

LA has multiple definitions in the literature [2], [4], [5]. The most established definition for LA is "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and environments in which it occurs" [1]. Key LA requirements can be categorized as the following: (1) data collection, integration and student profiling, (2) insight extraction, extrapolation and projection, (3) decision making, and (4) personalization.

Given that the learning process spans through space, time and media, a large amount of educational data is generated when students interact with the LMS. This also includes students' corresponding social media activities. Gathering different data elements from these diverse sources is a critical task. Also, a set of advanced statistical analysis and data mining techniques is required to integrate the collected educational data. On the other hand, defining concrete and stable profiles for students assists the organizations to build a robust educational environment [7]. Moreover, by having the integrated data from the data collection and integration phase, one can start building effective user profiles and link their accounts to their digital footprints for further analysis [4], [5].

Proper educational insight can be extracted by applying diagnostic and descriptive analytics techniques on the integrated data. This phase is mainly focused on the summarization and reduction of the historical data which describes the meaning of the events happened thus far. Furthermore, applying advanced predictive analytics techniques gives educational institutions the ability to extrapolate likely future event given their past data [4], [8], [9]. One example is identifying students at the risk of being failed by utilizing certain predictive methods over the learners' historical education data [4], [5], [8].

The need for taking intelligent actions towards student cohorts given their previous performance is one critical task which can be addressed by utilizing sophisticated data-driven analytical techniques [5], [8], [9].

Adaptive and personalized educational systems have been the center of attention lately. Given students' different needs and aptitudes, educational institutions can dynamically generate or amend the learning materials for each student. This newly emerged requirement needs the utilization of strong optimization and recommendation techniques [7]–[9].

To address the above mentioned LA requirements, several analytical models (referred to as Learning Analytics Models) have been proposed [5], [6], [8], [10], [11]. Moreover, Learning Analytics approaches need to take into account some of the key issues such as: development of methods capable of processing heterogeneous and huge data (referred to as *Big Data*) [4], [8], personalization and focusing on the learner's objectives [4], ethical issues like students' privacy, deidentification of educational data and getting consented data [8], [12], performance, scalability, reliability and usability [8]. On the other hand, Internet of Things (IoT) as a new paradigm of connecting billions of devices to the Internet, shares the similar challenges with LA. Contextualization of

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the data in IoT has been discussed in cloud-based solutions for improving scalability, performance and knowledge deduction from massive amount of data in health [13], smart city parking management [14], and security [15]. In this paper we discuss how a cloud-based data contextualization techniques can potentially tackle the similar challenges in LA. We propose CoALA, a conceptual model for an IoT-based Learning Analytics platform followed by a use-case scenario.

The remainder of the paper is organized as follows. In Section II, we discuss the background related to this paper divided into two categories of IoT and Learning Analytics. In Section III, the *Smart Learning Analytics* framework is introduced that is elaborated in a use-case scenario in Section IV. Finally, Section V, concludes the paper.

II. Background

In this section we briefly discuss the background of this work categorized into two main sections: Internet of Things and Learning Analytics.

A. Internet of Things

The Internet of Things [16] is a revolution of connecting billions of Internet-connected devices that are interacting intelligently to provide products and services. It is expected to have more than 50 billion IoT devices on the Internet by 2020, that is 7 times more than the population of the world on the same year [17], [18]. Given the widespread usage of Smart devices (referred to as *things*) such as smart phones, tablets, smart home appliances and so forth that are capable of connecting to the Internet, the amount of generated data has increased exponentially. IoT is transforming major cities to Smart Cities by enabling the introduction of smart services that help improve services in cities such as transportation, health, security, agriculture, energy, and so forth [19]–[23].

IoT large-scale services are replacing with several traditional services due to the advantages in using IoT such as cost, efficiency, accessibility and so forth [16]. For example, Smart Learning is one potential large-scale substitution for the current educational systems. In such systems, sensors can provide data for Learning Analytics. As an instance, a sensor can detect presence of the students (e.g., students solving problems in a lab). Furthermore, Smart Learning gets the advantage of using human sensors [24] as a source of data. For example, students can act as a sensor to provide information related to their studies which in turn can be used for decision makings towards more efficient and effective learning. IoT has been surveyed in several studies such as [16], [20], [25] and there are already several platforms and frameworks to provide large-scale and scalable IoT applications and services [26]–[28]. In [13], ConTaaS has been introduced as a platform to perform contextualization on Internet-scale data. Contextualization is a method to effectively mitigate the complexity of data processing by reducing the data from several aspects including volume, velocity, and variety in IoT applications [13]. Contextualization in IoT is a process of identifying the data relevant to an entity based on the entity's contextual information [13]. Context or contextual information is information about all entities (i.e., persons, places, or things) that are relevant to a given IoT service, and it can be used to contextualize IoT data [14].

B. Learning Analytics

Analytics in general is considered as a comprehensive data-driven decision-making concept which collects and processes data to understand its patterns and disseminates the results to proper targets [2], [4], [5]. It also reflects the significance of data-related problems to be investigated and their impact on academic and industrial environments [29], [30]. Given the heterogeneous data generated from different sources and analyses associated with them, enterprises have increasingly become interested in data-driven approaches to help them discover future opportunities. Furthermore, they take advantage of those opportunities by following recommended decisions resulted by the proper analytical methods [31]. Educational institutions have been keen to utilizing analytical approaches because they need to take benefit of their educational data in improving their learning environments and make effective decisions [1]. Given that pedagogical applications and learning management systems are capable of producing data according to students' explicit and implicit activities, educational institutions demand for coherent analytical techniques to extract insight act based on the generated results[1]. Learning Analytics is a new paradigm in the context of education to address the requirements [2], [3], [5], [9]. With regard to the Learning Analytics requirements, the body of research can be categorized as the following: (1) [1], [4], [5], [8], [9] are concerned with the processes of gathering data from diverse educational sources and unifying them into one standard format which can be used by other analytical approaches. (2) The research in [1], [7] is focused on developing sound user modeling and profiling techniques to enable more efficient information storage and extraction. (3) The [1], [7]–[9] propose interesting analytical techniques in extracting insight from the educational data and provide the processed results to the stakeholders in terms of effective, comprehensible and yet clear visualizations. (4) The [1], [5], [8], [9] are focused on proposing accurate predictive models to extract proper trends on the likely future scenarios and at the same time, providing coherent recommendations to prescribe intelligent actions to be taken. (5) The [1], [7]–[9] introduce particular methods to establish an adaptive learning systems. They also address certain aspects of a given learning environment to satisfy the personalization requirement of LA.

Furthermore, LA aims at producing and disseminating intelligent actions based on educational institutions' objectives to improve their learning environment and to assist them with their decision-making processes. Prescriptive analytics is a new frontier in business intelligence capable of providing optimal, adaptive and near real-time sequences of actions to enterprises dealing with big data based on their objectives

[1]http://www.nmc.org/pdf/2011-Horizon-Report-K12.pdf

[32]. It also helps educational institutions improve the student experience and elevate the learning environment [32]–[34].

It is essential to mention two other prominent analytical paradigms in the context of higher education which are related to but different from LA to get a more clear understanding of LA: educational data mining (EDM) and academic analytics (AA). A quick comparison of these two analytical perspectives shows that [1], [4], [35], [36]:

- Educational data mining is a specialized area of data mining for higher education which deals with educational data and develops methods to extract insight and value from them. EDM is mostly concerned with the technical issues.
- Academic analytics is a particular type of analytics concerning on the economic and policy issues of higher education. AA is mostly focused on the administrative units of the educational institutions where admission policies, funding directions and other relevant processes are taking place. Its goal is to improve educational institutions' effectiveness by using their data and enhancing their and processes, resource allocation approaches.

Learning Analytics, on the other hand, is mostly concerned with the educational issues and learner success. LA utilizes methods in collecting data from learners, analyzing data and extracting valuable information from them, and reporting the results to the learner, educator and the institute. The ultimate goal of LA is to develop new ways to analyze educational data and constantly improve the learning and teaching processes [37]. It aims at transforming the educational data into useful actions to enhance the quality of learning [10].

TABLE I
INTERNET OF THINGS VS. LEARNING ANALYTICS

	Internet of Things	**Learning Analytics**
Observation	Collecting data from sensors or Internet-connected devices	Collecting educational data from heterogeneous sources
Orientation	Deducing knowledge from raw sensory data with data processing techniques and integration of the data by using semantics	Analysis and extrapolation of data based on three analytical paradigms comprising descriptive, predictive and prescriptive analytics
Decision	Decisions to control Smart Objects (*things*) such as automated door, air conditioner, alarm, and so forth	Pedagogical decisions such as recommending courses or learning materials, suggestions in taking particular quizzes and tests, and learning path recommendations
Action	Performing the decisions made, (e.g., turn off/on a Smart light)	Performing the decisions made (e.g., taking recommended tests, enrolling in certain courses)

III. Smart Learning Analytics

In [14], IoT large-scale services/applications have been described in an OODA loop that involves Observation - collecting data, Orientation - processing and integration of the data, Decision - making appropriate decisions, and Action - act based on the decisions made. In this section we describe how LA components can be integrated with an IoT large-scale framework by mapping its components to an IoT OODA loop represented in Table I.

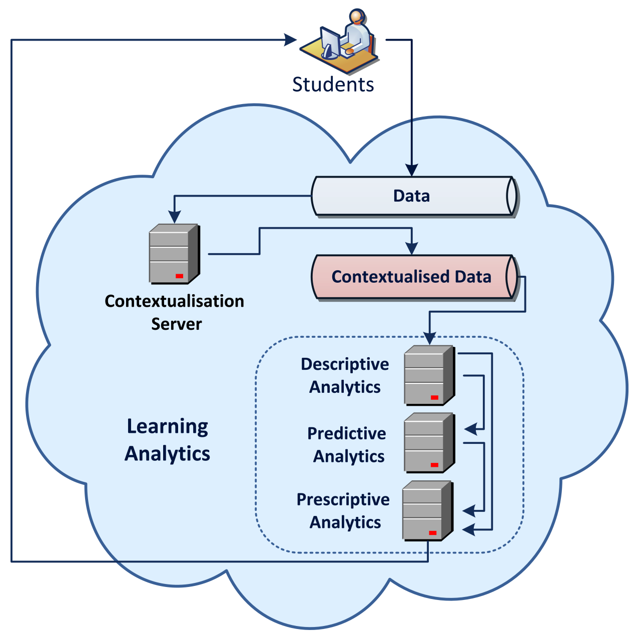

Fig. 1. CoALA Architecture

Observation: The input component is focused on collecting different types of educational data from diverse sources. The data elements comprised of static and streaming educational data. The static data refers to students' historical data of interacting with the learning management system in the past (e.g., previous tests, assignments and grades in the LMS, preferences and objectives). The streaming data refers to the data gathered from students' social media activities, their interactions with the LMS, and live data collected from sensors (e.g., posting and replying to comments in the LMS discussion board, tagging course related subjects in their social media, and presence in a lab).

Orientation: The process component is concerned with the analytical tasks. This phase is divided into two sub-components: analysis and extrapolation, and advice and personalization. The analysis and extrapolation sub-component is focused on applying proper descriptive and predictive analytics methods. The descriptive analytics collects and unifies the contextualized data. Descriptive analytics then extracts useful patterns from the data and generates comprehensible reports about the past. The predictive analytics, on the other hand, utilizes accurate predictive techniques on the historical data unified by the descriptive analytics to extrapolate likely future outcomes. Predictive analytics delivers different trends with associated probabilities. The advice and personalization sub-component provides intelligent feedback to the student cohorts and in some cases to each student. Its main element is prescriptive analytics which gets the system's predefined objectives, the wealth of information unified by the descriptive analytics, and the extrapolated scenarios from the predictive analytics as input. It then generates proper courses of actions in terms of intelligent feedback to be disseminated to the students [38].

Decision: The system's deliverables are categorized in this particular component. These decisions are results of prescriptive analytics to be disseminated to proper students. One example is providing a list of particular learning materials/resources to a student right after the student has answered a quiz or test incorrectly. We could then recommend them relevant resources for further study based on the misunderstood concept(s). Another example is suggesting the student to take particular tests/quizzes covering those concepts.

Action: The actions component is the feedback collected from students when they interact with the LMS. The fact that whether they have followed the prescribed recommendation could be monitored and measured by analyzing their activities in the LMS afterwards. These feedback elements can be fed into our system as new input items which are monitored and collected by the input component and the analytical sub-components can assess their impact on student's learning. Furthermore, if the student has not followed the recommended instructions, the prescriptive analytics can re-prescribe generated decisions or analyze the new circumstances and generate new courses of actions to be recommended to the student. Our approach can be flexible to changes in near real-time.

The architecture of the proposed model is depicted in Fig. 1. Collected educational data elements from students' interaction with the LMS are stored in the *Data* storage. The *Contextualization Server* will reduce the data by applying Contextual Filter and Contextual Aggregate operations [13]. The result of this phase is stored in the *Contextualized Data* storage to be fed into the *Learning Analytics*. The descriptive analytics gets the reduced data and unifies it to be utilized by the predictive and prescriptive analytics. The generated courses of actions of the prescriptive analytics will also disseminated to the target student(s) in terms of intelligent feedback lines.

IV. Scenario

In one particular example, one may consider the enrolled students in different universities in a city as dynamic sources for generating educational data when they interact with their LMSs or with one another. This way, we can assume the entire city as one particular digital university with their students as sensors that generate data. Also, those sensors are capable of generating huge amounts of educational data of different types and with various speeds. Therefore, we can consider these data elements *Big educational Data* satisfying the main three attributes of big data including volume, variety and velocity. The mapping of each OODA loop element with our use-case scenario is described in the following:

Observation: Suppose that we are collecting data from students studying computer science in Australia. These students have various skill levels, have passed certain courses, have variant upcoming courses to enroll and so forth (considered as *contextual information*). This information can be used in LA to process students' status and make proper educational decisions. The representation of the data in our system is in triples of the form:

$$< subject, predicate, object >$$

where the $object$ is the data describing $subject$ with regard to the $predicate$. For example, an input such as:

$$< student1, hasPassed, "Java" >$$

describes that the $student1$ has passed the course Java.

Orientation: As we discussed earlier, two levels of orientation including contextualization and analytical processes of the data are considered. In this scenario, contextualization helps to reduce the amount of educational data by applying Contextual Filter and Contextual Aggregate operations defined in [13] and [14]. For example, Fig. 3 represents a contextualized graph of

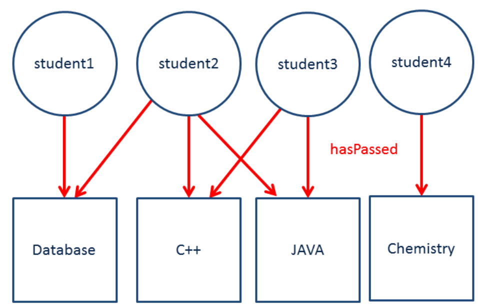

Fig. 2. Sample Graph

the sample graph illustrated in Fig. 2. By applying the two contextual operations described in [13], we have a reduced graph that will decrease the amount of required processing for LA. Next, Learning Analytics gets its preprocessed, reduced,

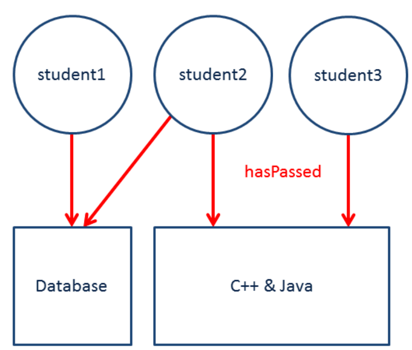

Fig. 3. Contextualized Graph

and contextualized educational data from the *Contextualization Server* to be analyzed. As mentioned earlier, LA comprises three analytical paradigms: descriptive, predictive and prescriptive analytics. These three are interconnected with each other and exchange different data items. We proceed with one particular example to elaborate their functions.

Consider querying all students who have a certain level of Java programming language skill. Given students' marks in the range from 0 to 100, they should be categorized in one of the five grade scales to satisfy our objective. The five grade scales can be defined as HD for high distinction in the range from 80 to 100, DI for distinction from 70 to 79, CR for credit from 60 to 69, PA for pass from 50 to 59, and NN for fail from 0 to 49. Our goal is to identify students at the risk of being failed in the Java programming course and provide them with intelligent feedback to bring them back on track and lead them to pass the course.

The *descriptive analytics* will summarize the educational data of all students enrolled in the computer science courses and filters those who have passed the Java programming language course or have currently taken the course. As descriptive analytics is focused on the historical data in the past, it generates reports on the number of students who have passed the course with HD mark. This information will be given to the descriptive analytics by the *Contextualization Server*. At the end of the descriptive phase, a list of students categorized in one of the five grade scales is produced.

The *predictive analytics*, on the other hand, takes into consideration students who have already taken the Java programming course. It utilizes accurate machine learning techniques to extrapolate the likelihood of those students being categorized in one of the five grade scales at the end of the semester based on their past performance in tests/assignments. The result of the predictive analytics phase is extrapolation trends through which students' performance are illustrated followed by their probability scores. Specifically, the trends will generate each student's likely future outcomes in terms of their final marks with the likelihood of each mark. For example, the predictive phase calculates five different grade scale likely scenarios for $student01$ along with their probability scores. This information can be utilized to identify at risk of being failed students. Figure 4 illustrates one sample result of the predictive phase in projecting $student01$ and $student02$ final marks categorized in five grade scales with their corresponding probability scores. According to Figure 4, $student01$ is unlikely to fail the course given that with 80% probability they will pass. However, $student02$ falls in the category of at risk of failing the course with the projected probability of failing at 60%.

Decision: The *prescriptive analytics* will take into account the currently enrolled students. Moreover, it gets the predictive analytics results in terms of extrapolated trends through which students' performance in the course has been projected. The prescriptive analytics also takes into consideration the predefined objective as the list of at risk of failing students in the Java programming course. It then applies particular recommendation and simulation techniques to generate certain courses of actions for the target students to help them pass the course. These actions can be of different kinds such as suggesting further learning materials/resources to be studied, recommending particular tests covering misunderstood concepts to be taken, and prescribing special tutoring labs or consultation sessions to attend. For example, given the students' projected performance in Figure 4, $student02$ is targeted as at risk of failing and is provided with particular sequences of actions to cope with the issue.

Action: The whole system keeps track the effectiveness of recommendations and monitors whether the students have followed feedback. If not, the prescriptive analytics re-prescribes the new courses of actions and disseminates them to the target students.

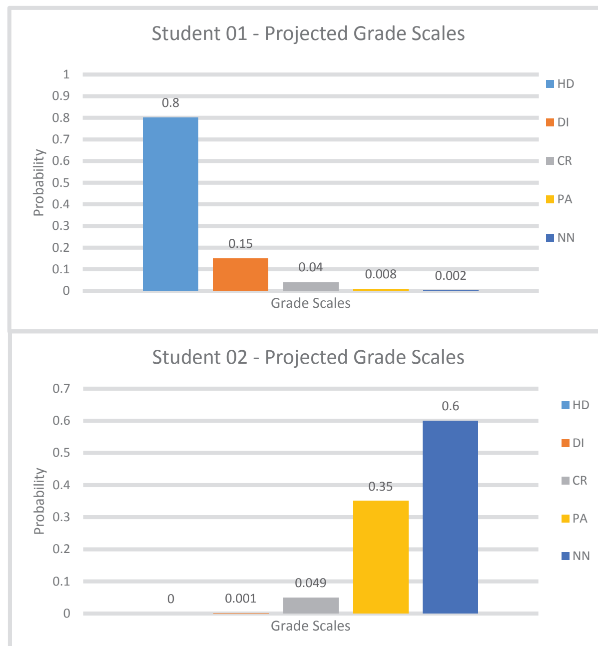

Fig. 4. Predictive Analytics Projected Grade Scales for Students 01, 02

V. Conclusion

In this paper, Smart Learning Analytics conceptual architecture is proposed to improve the effectiveness of LA by utilizing an IoT-based contextualization framework (CoALA) in terms of performance, scalability, and efficiency. Towards this, key requirements of LA are mapped onto IoT OODA loop components (Observation, Orientation, Decision, and Action). Observation in this context corresponds to the educational data collection and learner profiling, Orientation matches to the analytical paradigms of LA (Descriptive, Predictive, and Prescriptive Analytics), Decision relates to recommended intelligent feedback to students, and Action corresponds to the performed decisions by students (such as taking particular tests/quizzes, attending recommended tute/lab/consultation session, and so forth). We elaborated the impact of adopting our model in improving the learning process in one application scenario.

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