A Prototype Framework for a Distributed Lifelong Learner Model

Patrick OCHEJA [a*], Brendan FLANAGAN [b], Solomon Sunday OYELERE [c], Louis LECAILLIEZ [a] & Hiroaki OGATA [b]
[a] *Graduate School of Informatics, Kyoto University, Japan*
[b] *Academic Center for Media and Computing Studies, Kyoto University, Japan*
[c] *School of Computing, University of Eastern Finland, Finland*
* ocheja.ileanwa.65s@st.kyoto-u.ac.jp

Abstract: Learning is ubiquitous and as learners change environment, it becomes necessary to collect their learning footprints across multiple systems. However, as these learning footprints are collected as logs on different systems, protected by varying privacy definitions, there exist of problem of not being able to process these logs together in a useful manner. In this work, we build on a blockchain of learning logs platform (BOLL) to construct a learner's user model based on logs from multiple systems in a distributed method using a decentralized network. We propose a framework that can also connect a learner's user model from multiple systems into one representative model that can answer questions about the learner's lifelong learning. Finally, we show typical scenarios of how such lifelong learner models can be used to support teaching and learning.

Keywords: lifelong learning, learning logs, user model, learner model, blockchain, BOLL.

1. Introduction

The use of learning systems has become prevalent in schools and continues to result in more data being logged from students' interactions. By analyzing these learning logs, it has also become possible to support a more data-driven and personalized education (MacMillan & Schumacher, 2010). This include supporting at-risk students (Akçapınar et al., 2019), learning content design (Demchenko, Gruengard & Klous, 2014), facilitating group activities (Messina et al., 2013), recommending useful learning contents (Tarus, Niu & Yousif, 2017) and sharing successful learning habits (Zhu, 2012). Although students may attend more than one institution, current learning analytics processes rely heavily on data from students' current institution regardless of their past learning experiences or learning logs. Thus, the following problems arise:

- It is difficult to fully assess and understand the learner's knowledge or lifelong learning.
- Inability to personalize learning with minimal effort (the *cold-start problem*).
- Unable to diagnose and provide concrete answers to a learning difficulty.
- Limitations with sharing successful learning habits at scale.

These problems could be caused by factors such as: the difference in learning tools and data standards, lack of interoperability, the difficulty in facilitating communication between systems due to privacy limitations as well as other ethical concerns.

To solve these problems, we propose a framework that can connect a learner's lifelong learning across different institutes and learning platforms in to a learner model. We acknowledge that different learning systems may store their learners' data in varying formats. In this work, we focus on exploiting how logs from multiple learning systems with similar data formats can be unified. We demonstrate how learners can also manage their privacy, reflect on their lifelong learning, share and access successful learning habits of other students at different schools in a privacy preserving manner. We also show how teachers and content designers can use the resulting lifelong learning user model to diagnose and solve learning difficulties, and design personalized learning contents.

2. Related Work

There are previous researches on ontology mapping as reviewed by Choi, Song and Han (2006) as well as the use of knowledge or concept maps in learning design (Baker & Inventado, 2014). However, the use of isolated data storage sites and the lack of decentralized technologies (before now) to manage distributed access has made it difficult to connect and construct concept maps from students' lifelong learning. To solve the limitations of disconnected lifelong learning such as the cold-start problem and lack of transferability of learning logs, Ocheja, Flanagan & Ogata (2018) and Ocheja, Flanagan, Ueda & Ogata (2019) proposed and implemented a Blockchain of Learning Logs (BOLL). BOLL is a platform that allows the transfer of learning records through the blockchain and provides a means to manage privacy permissions using smart contracts. However, using these records to realize a user model that can answer some useful questions about a student's lifelong learning is yet to be considered.

Kay & Kummerfeld (2019) proposed a conceptual model for evaluating how learning applications and data repositories can be used to realize Personal User Model for Lifelong, Life-wide Learners (PUMLs). Our work takes the discussion further by presenting a concrete framework with an existing privacy-first (Conoscenti, Vetro & De Martin, 2017), decentralized application that truly connects lifelong, life-wide learning: a limitation acknowledged by Kay & Kummerfeld (2019). We extend the BOLL platform to enable computing of user model from distributed records and provide a query enabled interface for supporting and personalizing learning.

Platforms like ALEKS, a web-based intelligent tutoring system (Canfield, 2001), have been found useful in diagnosing learning difficulties and supporting learning as demonstrated by Hagerty & Smith (2005). However, the ALEKS platform provides learning assistance by using information within the learners current learning environment. In contrast, our proposed framework diagnoses learning using a learner's records from various learning environments. It is important to be able to use data from multiple learning environments as such data may provide adequate information to achieve personalized learning.

3. Research Method

The design of the proposed framework is based on participatory design (Simonsen & Robertson, 2012). Participatory design is a co-design approach which involves the active engagement of all stakeholders in the design process in order to ensure the outcome fulfill the needs of the stakeholders. To solve the problems with enabling a connected lifelong learner model, we identified three main stakeholders: *students*, *teachers* and *administrators*. We carried out the co-design process with 4 students, 3 teachers and 3 administrators. Specifically, we discussed with the stakeholders on the current challenges of constructing lifelong learner models from learning logs, identified key factors to solving the problem and tested various solutions.

4. Proposed Framework

We propose a privacy-first framework for connecting lifelong learning of students across multiple institutes and improve personalized learning by constructing and providing reusable/extendable user models. Our proposed framework focuses on constructing ontologies that represents a learner's knowledge from their learning logs on learning platforms. This work solves the challenge with making sense of learning logs previously generated in a different learning platform. In figure 1, we show our proposed framework and how we solve this problem by: (A) designing processes for data collection, (B) model generation and unification and, (C) integration of a query-enabled interface to support learning. In the following subsections, we will discuss each of the components of the proposed framework.

4.1 Data Input and Collection

We first discuss the method for data input and collection from multiple sources. Because students may have engaged in learning on different platforms, it becomes necessary to define how their learning logs from these systems may be securely collected and held privately. Ocheja et al. (2018) already proposed

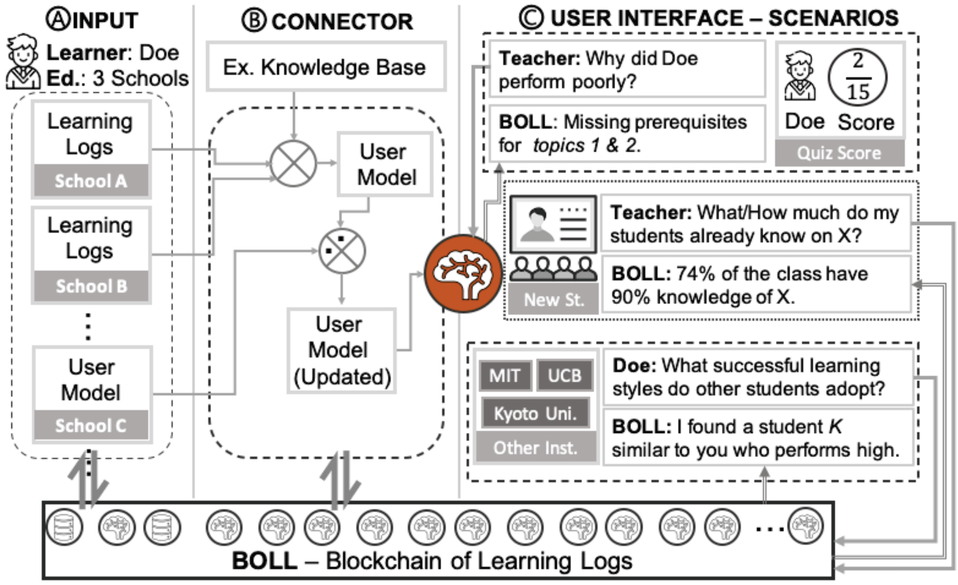

Figure 1. Connected lifelong learning framework.

a framework for connecting distributed learning records and implemented as BOLL (Ocheja et al., 2019). We use this as a basis for our data input phase. In figure 2 we show how the BOLL system can transfer data from one learning providers learning infrastructure to another. The onboarding processes are steps 0 – 5 in figure 2. Steps 0 – 5 are carried out if the learner is using the BOLL system for the first time otherwise, the learner can provide their BOLL unique ID (hexadecimal string) to their school's node and only step 5 will be performed.

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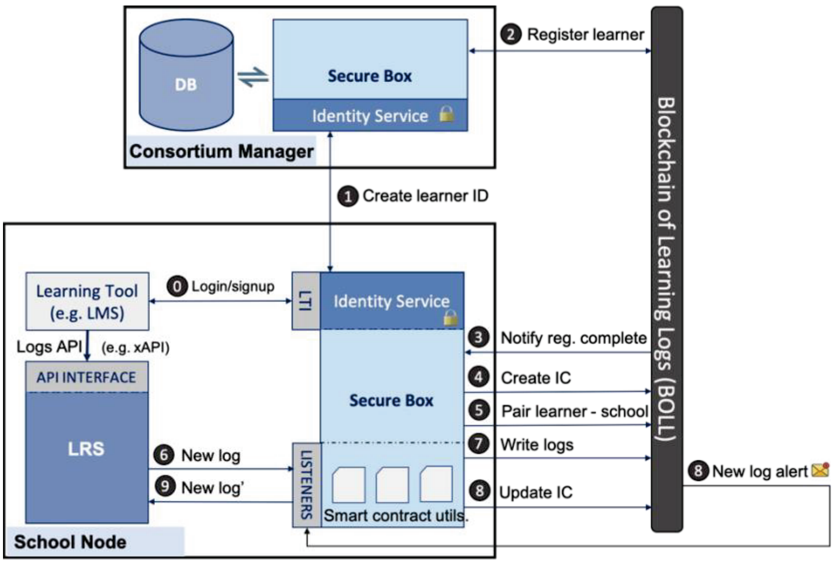

Figure 2. Blockchain of learning logs (BOLL) data transfer processes.

4.2 The Connector

This stage involves processing learning logs from multiple learning systems and using the resulting data to construct a user model such as a knowledge graph. For example, a learner who attended School A may enroll in School B. The learner can ask for their records to be transferred from School A through the blockchain to School B. School B could then use these records to create a new model or insights to onboard the newly enrolled learner. The data from the different learning environment enables the realization of a single knowledge graph representing the learner's knowledge (Lecailliez, Flanagan & Ogata, 2019). One major relevance of the resulting knowledge map is to help students reflect on past learning activities that are useful to current/future learning tasks. In figure 3, we show a hypothetical knowledge map representing a learner's lifelong learning from K-12 through to High Education over time that goes from the past on the left to the present on the right. At each level on the map and on each node (left to right), a learner can look back to reflect on their learning journey and possibly re-evaluate their preparedness for succeeding learning tasks (nodes) using various interactive objects on these nodes such as quizzes, and available associated learning contents.

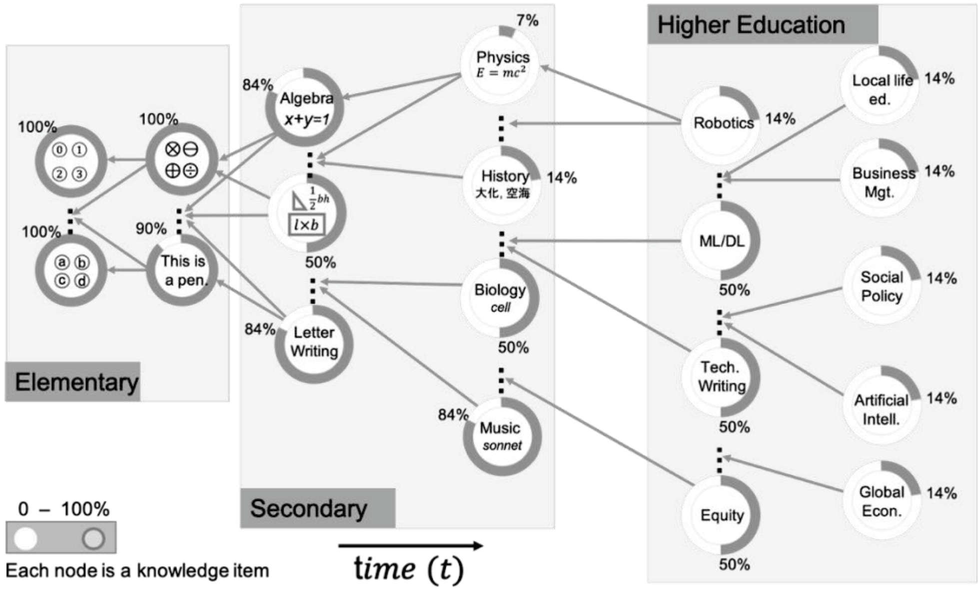

Figure 3. A sample learner's lifelong learning knowledge map.

The user model is expected to give an automatically exploitable representation of the learner's knowledge. This involve the ability to answer some key questions about the learner's learning history, assess a learner's readiness for a learning activity, and provide a base template for personalization in a new or existing learning environment. Also, the ability to update the model as the user progresses is important as learning is a continuous process.

4.3 Learner Model Interface with Scenarios

This phase mainly provides an interface to interact with and use the user model to support a learner's learning journey. It requires the development of a query-enabled interface for learners and teachers to access and assess a learner's knowledge and consequently provide learning support. For example, a teacher may be faced with the task of diagnosing why a student has performed poorly in a given quiz. The lifelong learner model becomes useful in providing answers to these questions in a faster and more comprehensive manner.

The user model may also be useful for learning content designers who want to deliver a well-tailored and personalized learning contents. This is made possible by the model's ability to provide a broad representation of the learner's readiness for new learning contents or activities. This can be measured by evaluating the extent to which a learner has covered prerequisite topics.

Another scenario where a lifelong learner model may be useful is in helping students to adjust their learning habits by learning from other students. This particular feature can be enabled through the decentralized architecture of the BOLL system when learners on the blockchain can anonymously probe the system for useful information. For example, a student at a university may be interested in knowing what learning patterns are being adopted by high achievers in their class or at other schools.

5. Discussion

In the beginning, this work set out to solve some problems with realizing distributed lifelong learner models. Here, we will address each problem and evaluate how the proposed framework solves it.

The ubiquitous nature of learning makes it difficult but necessary to connect all learning activities in order to realize a lifelong learning. Our proposed framework solves the challenge with assessing a learner's knowledge by processing learning records of a learner from various systems and using such data to construct a model that represents the learner's knowledge. Thus, the resulting model can be queried to understand what a learner knows. Because the constructed model relies on the learner's lifelong learning, this model also becomes useful in assessing a learner's lifelong learning.

The cold-start problem is usually faced by learning systems when such systems attempt to provide personalization to the user without prior information about the user. Our proposed framework solves the cold-start problem by enabling learning systems to integrate with the input arm (see A in figure 1) of the proposed framework so as to gain access to a learner's previous learning records at other institutes. The learning system could then use such information to determine what kind of personalization to provide.

Effectively tracing learning difficulties provide potentials to solving such difficulties. The framework proposed in this paper enables diagnosis of learning difficulties by providing a mechanism to measure students' knowledge on prerequisites topic. When a user's knowledge in a prerequisite topic is below requirement, it becomes possible for their teacher to know what areas to places emphasis on during teaching/learning.

Our proposed framework enables students to share successful learning habits by allowing students to anonymous share their learning habits with other learners on the blockchain of learning logs. Students could in turn query the blockchain to gain access to useful information on their learning journey. The importance of using the blockchain to facilitate this is to ensure that students' privacy rules are not violated and that only authorized entities can access protected information.

6. Limitations

We have shown how lifelong learning logs can be connected in a meaningful way across multiple systems with minimal information loss. Our proposal is made possible by the presence of a decentralized platform for connecting learning logs: the BOLL platform. However, some challenges exist.

The differences in learning logs format makes it difficult to process logs from different systems. While this work does not set out to solve problems with unifying logs defined in different standards, we acknowledge the existence of such a problem. It is therefore necessary for institutes to adopt standards that facilitate interoperability across different learning systems such as the xAPI standard.

Scalability of the blockchain is one of the main limitations to adopting the blockchain as extensively discussed by Vukolić (2015). The BOLL platform also suffers from the limitations of the proof of authority consensus algorithm upon which it runs. For instance, to add a learning log to the BOLL network will take from 15 seconds to 2 minutes (Ocheja et al., 2019). The problem with this is that learning logs are generated at a much faster rate than 15 seconds. Therefore, it is necessary to determine the best approach to write these logs on the BOLL network. One way we have identified to solve this problem, is to mine only representative learning logs to the blockchain and also to batch multiple learning logs in a single transaction. Initial experiments with this approach showed significant improvement. For example, over 1 million records which would take more than a year to write to the blockchain were transferred over a two weeks period using mining of representative learning logs.

7. Conclusion

In this work, we presented the current limitations with learning systems in connecting, and making sense of logs from multiple learning environments. To solve this problem, we proposed a framework that builds on the BOLL platform to construct models that can represent a learner's knowledge. This work also presented some practical scenarios where such models can be used to support learning and we also discussed the implications.

8. Future Work

Future work will be focused on making a concrete implementation of the proposed framework and validating its effectiveness in a typical learning environment. We will continue with the participatory co-design process at every stage of the implementation to ensure that the outcome remains consistent with the needs of the stakeholders. At the core of the proposed framework is the BOLL platform which we have been actively involved in its development. This makes it possible for us to be able to provide answers to the limitations of the BOLL platform identified in section 6. We also acknowledge that some aspects of the proposed framework may be revised during the course of the implementation to meet some system dynamics not initially anticipated. Consequently, we will provide an updated version (if any) of the framework in subsequent publications.

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