



# Towards an automated Framework for benchmarking Learning Record Stores: Performance Requirements and Scalability

Chahrazed Labba, Azim Roussanaly, Anne Boyer

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## **Towards an automated Framework for benchmarking Learning Record Stores:**

### **Performance Requirements and Scalability**

*Chahrazed Labba, Azim Roussanaly, Anne Boyer*

*KIWI team, LORIA laboratory*

*University of Lorraine*

*{chahrazed.labba, azim.roussanaly, anne.boyer}@loria.fr*

### **Track**

Academic research: comprehensive evaluations of recent innovations in learning and student analytics approaches.

### **Context and Purpose**

Nowadays, with the high spreading speed of the standard xAPI or Tin Can, learning Record Stores (LRS) are increasingly used within digital learning systems.

Indeed, an LRS is defined by the Advanced Distributed Learning (ADL) [1] as follows:

“A server (i.e. system capable of receiving and processing web requests) that is responsible for receiving, storing, and providing access to Learning Records.”

In other words, the LRS is a storage warehouse whose role is to store digital learning traces generated by Learning Record Providers (LRP) in order to make them accessible and usable by third-party applications called Learning Record Consumers (LRC).

Multiple LRS products have made their appearance in the market. The competition is high. Indeed, most of these systems provide the same basic functionalities (recording and retrieving xAPI statements), however, they offer many varying features (i.e. Interfacing with various external

systems and visualization functions). Thus, for a specific organization, choosing the appropriate LRS is of high importance, since adopting a non-optimized one may lead to a loss of money, time and effort.

Therefore, the purpose of this work is to provide to those involved in the process of selecting an LRS, a benchmarking Framework. Indeed, according to a set of performance requirements, our Framework will allow recommending an LRS that fulfills the user 'needs.

### **Related work and discussion**

There are few reliable published works on the setting up of LRS. Some vendors, for example, Learning Locker [2], watershed LRS [3] and waxLRS [4] provide on their websites case studies and demos concerning the adoption of their systems. In [5], the author provided a range of considerations for choosing the LRS. However, the paper does not provide in anyway a comparative rating or evaluation of existing LRS products. Further, in [6], the authors proposed a web-based learning environment dedicated for training how to command and control unmanned autonomous vehicles. One of the main issues revealed in the work is the scalability and performance requirements of the integrated LRS for storing stream data. The authors found that the existing LRS may not perform well under certain circumstances. So, they proposed a storage system based on the use of an adhoc server over SQLite3. A comparative study has been performed to determine the efficiency of the proposed solution compared to an existing LRS (learning locker). Even though the proposed solution presents an efficient storage system, however it leaves out many facilities provided by the LRS. In [9], the authors presented an extended LRS called METALRS. It is intended to be used in the French lower secondary education system. The developed LRS is dedicated for a specific organization and was not compared to any existing LRS product.

To summarize, to the best of our knowledge, we are the first to focus on evaluating and rating

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existing LRS products. The aim is to recommend the optimized LRS for specific requirements such as scalability.

### **Work in progress**

For the time being, we are interested in studying and analyzing the performances of the open source LRS products including Learning Locker [2] and Trax [7]. As a first step, we focus on comparing both LRS in terms of scalability and their ability to support huge number of requests either to store or to retrieve learning records. To this end, we defined a set of performance indicators such as the supported concurrent users, the size of the request (measured in terms of the number of xAPI statements), the response time, the response latency, the average time of processing a request and the error rate. The performance indicators are collected under different load test scenarios performed on both LRS installed on machines having the same characteristics in terms of RAM and CPU. The scenarios are inspired from the mining of a real Moodle dataset [8]. In addition to choosing the right LRS, we would like to recommend the suitable strategy of sending PUT requests to reduce the LRS load and optimize the statements storage. To accomplish this goal, we distinguish two types of scenarios:

- Chunk the PUT requests by time interval. e.g. At each time interval (second, minute, hour, day), a request is sent with the generated number of statements.
- Chunk the PUT requests by number of statements. e.g. At each time, a number of statements (e.g. 1000) is generated, a request is sent.

To conclude, our aim is to automate the testing process and provide an automated benchmarking framework that can be used either by 1) the LRS providers to test the efficiency of their products under different load test scenarios; or by 2) the organizations that aim at setting up an LRS.

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