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Towards a Learning Ecosystem for Linemen Training

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Abstract. In this paper I present our ongoing work on developing a Learning Ecosystem for Training Linemen in Maintenance Maneuvers. First, challenges involved in training Linemen are introduced. Then, I discuss opportunities for creating a Learning Ecosystem for Linemen training using the Experience API standard and Learning Analytics. Although presented experimental results are reduced, these already show the value of Learning Analytics in exploiting data from already adopted technologies and new educational data sources for enhancing Linemen training.

Keywords: experience API, learning analytics, Learning ecosystem, learning manangement systems, self reports.

1 Introduction

Electric utilities are companies in charge of electricity generation, distribution, and power infrastructure maintenance. The latter is carried out by highly skilled workers called *Linemen*. Due to safety, technical, and business reasons the Linemen Maintenance Training (lMT) is mandatory [14]. The former involves physical preparation, knowledge on physics and electricity theory, theoretical and physical knowledge of maintenance maneuvers execution, and hygiene and industrial rules [3]. The adoption of cutting-edge technologies for the lMT is necessary to increase its effectiveness while avoiding risks.

The objective of this proposal is to pose a Learning Ecosystem (LE) for lMT to improve trainees' maintenance maneuvers apprenticeship. Loosely speaking, this will combine multiple educational technologies to exploit data generated by these to enhance learning within the environment systems [8]. For such endeavor I propose to employ systems based on the Experience API (xAPI) standard. The latter will allow formal and informal distributed learning experiences to be standarized and collected into a single repository [9]. Then, learners' traces collections will be wrangled, analyzed, and modelled using Learning Analytics (LA) to enhance the lMT [11]. In this work we detail how LA will be used for building visualization tools that enable educational stakeholders, specially tutors and course designers, to obtain valuable information of the overall educational process.

In section 2, I present the related work around lMT using intelligent learning environments and new perspectives. In section 3, the proposed Learning Ecosystem is shown. Section 4, discusses the experimental results for LMS and xAPI data using LA. Finally, conclusions, and future research is discussed.

2 Related Work

The lMT has used several technologies, the most used have been non-immersive Virtual Reality Training Systems (VRTS). VRTS have shown to be sucessful in lMT by reducing linemen accidents [13]. Another technological venue in utilities staff training is the usage of LMS along with Shareble Content Objects Repositories [1]. Moreover, ITS have been proposed to support and improve the learning processes within the electric domain by employing blended learning, affective estimation, and open learner models [6]. In these cases, data logs generated from users activities and its exploitation in favor of personalized education has been oversighted.

The xAPI standard allows users learning experience data be collected from heterogeneous learning systems by traducing these into *Activity Statements* (AS). AS are validated and stored in a Learning Record Store (LRS) database to exploit data for increasing training effectiveness [9, 8]. Data integration from educational systems under the xAPI umbrella, and its exploitation for tailoring personalized instruction conforms a Learning Ecosystem [8]. Some recent LE examples are a generic framework based on xAPI and GIFT [8], a Live Fire Training LE proposed by the U.S. Army [4], Transmedia Learning [12], and a xAPI-based framework for collecting and monitoring Self Regulated Learning [10]. In particular, the last two references rely on the usage of Self Reports (SR) for self monitoring, tutor monitoring, measure participants attitudes towards training, and so on. An un explored venue, is the usage of SR altogether with the xAPI standard for gather and exploit emotional self reports such as the Positive And Negative Affect Schedule (PANAS) or the Discrete Emotions Questionnaire [5].

Learning Analytics is consider a multidisciplinary paradigm for manipulating, modelling, and visualizing data from different educational sources to address: learners behaviors and performance, measuring social impact in learning, students' performance prediction, emotional states assessing, identifying student's learning strategies, provide decision making tools for educational stakeholders, and so on [11, 10]. Fig. 1 shows the general data science process, the same framework employed by LA. It starts with a real-world problem, data is then collected and manipulated to conform a data set suitable for Machine Learning (ML) modelling. In parallel, an Exploratory Data Analysis (EDA) is performed for visualizing data beyond formal modelling or hypothesis testing. Afterwards, findings are communicated and validated by educational stakeholders. This part is critical in LA since it allows stakeholders ponder ML models usage in decision making. In accordance to the former, data-based products are built (e.g. model for predicting students performance) and launched, then, the process iterates into new products or into refinement of previous ones.

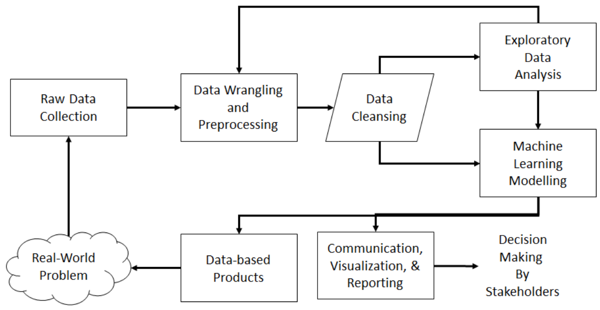


Fig. 1. The Data Science Processed used for performing Learning Analytics.

3 Proposed Learning Ecosystem

The LE proposed for lMT is conformed by an LMS, Traditional Training, a VRTS, and SR. In particular, affective trainees' assessment is done through SR. For each case, students learning experiences are mapped into AS, and collected into a LRS. LA is used for performing knowledge discovery on trainees' trace data, build ITS-inspired components, and provide insight to educational stakeholders. The proposed LE is shown in Fig. 2a.

3.1 xAPI Activity Statements

Any xAPI AS is syntactical similar to English. In its simplest form, AS are composed by an **Actor**, a **Verb**, and a **Object**. The *Actor*, corresponds to a unique id associated to a specific subject (e.g. Lola the trainee). The *Verb*, such as in any language, classifies an actor's activity using a unique internationalized resource identifier (IRI). *Objects* can be of several types and must contain an unique id property for unambiguous identification [9]. For example, a trainee assigned to execute step 1 from maneuver 1 in her lMT may have the following statement generated:

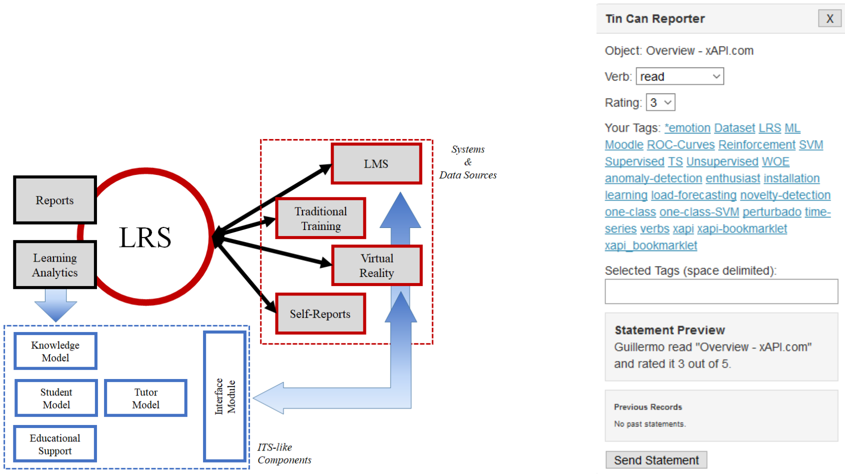
Lola the trainee (*actor*) **executed** (*verb*) **step 1-maneuver 1** (*object*).

3.2 Data Sources and Technological Requirements

VRTS and Traditional Training are already used by utilities to carry out lMT and other staff training [13]. Traditional training is stored from text documents to adhoc computational systems. Maintenance maneuvers execution are practiced and evaluated using a VRTS, data generated by the former is stored in a local relational database. Consequently, first data from these sources needs to be gathered and mapped into its xAPI AS form, for its latter ingestion into an LRS. On the other side, LMS are currently not been employed for lMT, thus, an LMS is required. LMS is a type of technology vastly explored for educational purposes, thus, we do not detail it. However, it is worth mentioning that, a great advantage of LMS is that several platforms already generate their internal logs using the xAPI AS format. Thus, data from such systems can be immediately reported into an LRS.

Self Reports

For this endeavor a bookmarklet, a small software stored as a bookmark in a web browser, can be employed. If the SR bookmarklet complies with the xAPI activity reporting standard, it will allow to capture basic learning experiences, and even personalized AS using non-basic fields provided by the xAPI standard. Since these already comply with the xAPI activity report format, learning experience can be immediately stored into the LRS. An example of a SR bookmarklet is shown in Fig. 2b.



(a) **(b)**

Fig. 2. Proposed Learning Ecosystem. On (a) a diagram of the LE, on (b) an example of a SR software.

Emotional SR requires the usage of the *Extension* xAPI field. In short, this field allows to define new attributes using a combination of a key (or property) and a value using the URI scheme. This is used within other xAPI fields such as the *Object*. Thus, using the extension field, we can employ the Discrete Emotions Questionnaire (DEQ) [5] for SR. DEQ distinguishes eight state emotions, i.e. anger, disgust, fear, anxiety, sadness, happiness, relaxation, and desire. Thus, once the DEQ is manipulated to fit into xAPI statements, any student may report its emotional state using the SR bookmarklet. For instance, using the previous xAPI example, if *Lola the trainee* felt *happiness* while executing step 1 from maneuver 1 in her lMT, may report her affective state generating a statement such as:

Lola executed step 1-maneuver 1 $feeling$ **happiness**.

Learning Record Store
In accordance to its core specification, an LRS is a cloud-based system which is in charge of storing and retrieving learning data exclusively formatted as xAPI statements [2]. In its most basic setup it only provides functions for store and retrieve xAPI statements. However, several LRS providers may also include tools and dashboards to visualize, combine, and manipulate AS data.

3.3 Learning Analytics

LA is a multidisciplinary paradigm, among the disciplines employed by it stands Text Mining (TM), Natural Language Processing (NLP), Web Data Mining, Exploratory Data Analysis, Machine Learning, among others [11]. In particular, for EDA we can employ *Word Clouds* (WC). This are visual text data representations which depict words importance (e.g. frequency) within a document(s) using several schemas e.g. larger words represents most frequent words whereas less important words have smaller font sizes. WC are used to quickly perceive the most (relative) important terms. Thus, by using EDA methods, we expect educational stakeholders can distill valuable information for adapting systems, course design, or identify profile characteristics of students at-risk [13].

Machine Learning can be used to build unsupervised and supervised models for the purpose of personalized education. On one hand, employing utilities documents along TDM and clustering algorithms we can build a knowledge structure that can be used as a coarse domain model [7]. On the other hand, we can relate the proficiency scores of each trainee to the errors committed using a Bag of Errors scheme [13].

4 Preliminary Experimentation

In the following I present the initial experiments towards a LE for lMT. The experimental configuration and software used are detailed in the following. Then, LMS and xAPI SR data are visualized. The corresponding LA experimentations for domain and student modelling have already been carried in [7] and in [13], respectively.

4.1 Experimental Setup

Due to a lack of an LMS and SR for lMT a proxy is used. Data from students enrolled in a *Machine Learning course*[1], is used. The course was carried out from 01-29-2018 to 06-01-2018 with 9 posgraduate students (master and PhD) which generated 2527 activity records. Activities and emotional SR were generated for the same course. To incentive students to SR, activities and emotional reporting

[1] https://www2.ineel.mx/posgrado/maestrias/mce.html

accounted for 10% each of the final course grade. SR were generated using the following instructions:

– *Activity:* during a learning session related to the course, if a student found a material which she considered important, useless, clear or confusing, that *object* would be reported using the SR tool.
– *Emotion:* at the start of a learning session related to the course, a student reported her emotional state by employing one of the emotions defined by the DEQ. Table 6 of [5] was used to clarify each emotional state.

SR were generated by Rustici Software LLC bookmarklet [2]. This allows to capture 4 basic learning experiences (i.e. experience, read, bookmark, and tweet), rate an Object, and personalized AS using tags (e.g. extension field). It is shown on Fig. 2b. Using it 420 AS were collected: 208 correspond to activities whereas 212 correspond to emotional SR. For the LMS Moodle™ was used whereas the Watershed™ LRS was selected. All LA experimentation was carried out using R and RStudio™.

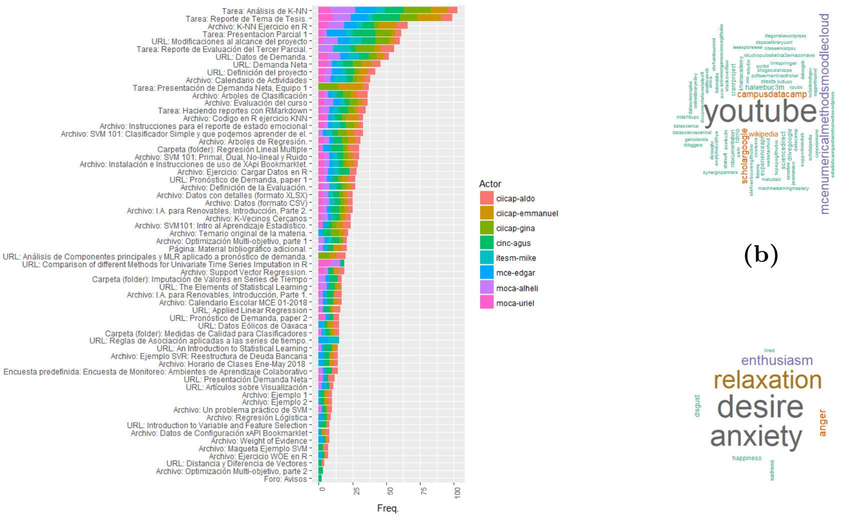
4.2 Results

In the first instance, data from the LMS is visually explored using a standard bar plot shown in Fig. 3a. This presents on the x-axis the frequency of items visited by the students in the LMS. On the y-axis the different items in the course ordered by the total frequency of visits. Colors depict *Actors*. We can appreciate in the figure that most students have the same distribution of visits per item. Also, the top visited items corresponds to *homework* and *course project* tasks, whereas the least visited items corresponds to the *announcements* forum and *archives* used as examples for several course topics.

In the second instance we analyze SR using word clouds. Activities and DEQ SR are shown in Fig. 3b and Fig. 3c, respectively. Results are thrilling, for instance, observe on of Fig. 3b the word cloud generated by websites reported by students in the aforementioned course. As expected, the most visited website is youtube which offers a vast amount of ML courses and related content. This is followed by the course LMS, and the MOOC *DataCamp*. Other appreciable websites are *Google Scholar* and *Wikipedia*. Among the other least visited sites are machine learning blogs (e.g. *Data Science Central*), and scientific search engines such as *ScienceDirect, Springer* and *IEEE Xplore Digital Library.* In regard to the word cloud generated for DEQ SR, we can observe that the most frequent emotions reported were *desire* and *anxiety*. In accordance to [5], *desire* is a pregoal, positive affect which presumably promotes reward acquisition. On the other side, *anxiety* is regarded as a negative, high arousal emotion associated which *fear*, which is evoked by vague, potential threats [5]. Other important emotions reported were *relaxation* and *enthusiasm*, both considered positive affect which presumably assists in promoting reward enjoyment. The least popular emotions were *anger* and *disgust*. These results seems that, students were eager

[2] https://xapi.com/bookmarklet/

to learn the concepts of the course, and, although were anxious about the results they felt fulfilled after accomplishing tasks.



(a) (c)

Fig. 3. Self-Reporting using the xAPI Bookmarklet. On (a) the Rustici xAPI bookmarklet is presented. Word clouds correspond to (b) Objects reported and (c) DEQ Emotions.

5 Conclusions and Future Work

In this work I presented a proposal for building a LE for lMT. This goes towards generating a standardized system for storing lMT learning experiences data from lMT systems, and its exploitation for adaptive learning. To date I have focused upon the tools for building the LE and some LA applications. Results for SR and LA are encouraging, thus, the next steps involve establishing a better experiment design for SR and emotional SR, establish contact with utilities managers to construct lMT courses within the proposed LE infrastructure, and use LA to exploit trainees trace and AS data for personalized instruction.

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