Remote Experimentation supported by Learning Analytics and Recommender Systems

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ABSTRACT

This paper proposes a process based on learning analytics and recommender systems targeted at making suggestions to students about their remote laboratories activities and providing insights to all stakeholders taking part in the learning process. To apply the process, a log with requests and responses of remote experiments from the VISIR project were analyzed. A request is the setup of the experiment including the assembled circuits and the configurations of the measuring equipment. In turn, a response is a message provided by the measurement server indicating measures or an error when it is not possible to execute the experiment. Along the two phases of analysis, the log was analyzed and summarized in order to provide insights about students' experiments. In addition, there is a recommendation service responsible for analyzing the requests thus returning, in case of error, precise information about the assembly of circuits or configurations. The evaluation of the process is consistent in what regards its ability to afford recommendations to the students as they carry out the experiments. Moreover, the summarized information intends to offer teachers means to better understand and develop strategies to scaffold students' learning.

CCS CONCEPTS

• **Social and professional topics** → Professional topics → Computing education → Student assessment • **Information systems** → Information systems applications → Decision support systems → Data analytics

KEYWORDS

Remote Experimentation, Learning Analytics, Recommender Systems

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1 Introduction

The evolution of technology has been promoting in recent decades new approaches to education, being supported mainly by the internet, remote learning, interactive learning and e-learning. All these possibilities give students a broader view of the fundamentals in a particular subject by increasing understanding and making knowledge more systematic [1]. In engineering education, many resources are available, among them, calculus classes, hands-on laboratories, simulations and remote laboratories, i.e. important resources in the training of students.

Traditionally, experimental work has been developed in laboratories. However, the increased number of higher education students in the last decades has put pressure on the physical structures and lab resources. To overcome this issue, researchers have developed computational simulations and remote laboratories, enabling the expansion of educational boundaries. According to [2], remote laboratories are nowadays an important tool for teaching and learning, mainly in engineering. In addition, the authors mentioned that such potential intends to leverage students' learning beyond hands-on classes.

In order to foster the students' learning process, this scenario opens new perspectives. Regarding e-learning systems, the data produced by students through the interaction with remote laboratories and simulations can be gathered and analyzed. Therefore, areas such as Learning Analytics (LA) and Recommender Systems (RS) have been promoting support.

Learning Analytics (LA) is a relevant tool to foster students' learning experiences, proving suggestions to leverage their performance on e-learning activities. It provides clues or insights to improve teachers' classes. LA is a knowledge discovery paradigm and as such can help all stakeholders taking part in the learning process to understand its potential and interconnections [3]. Applying LA techniques from data collected in e-learning environments creates opportunities to foster the educational context by providing recommendations to students and teachers. In this regard, Recommender Systems (RS) can provide suggestions to scaffold students' performance during their learning activities. Traditionally, RS analyze historical interactions to suggest items to users [4][5]. Despite their origin from e-commerce, the evolution of RS is impacting many other areas such as e-learning, supporting students in choosing courses, subjects, learning materials or activities [6]. Another possibility is to apply the RS principles thus offering means to scaffold students' performance in remote laboratory activities.

This paper proposes a process based on LA and RS to assist students in their remote lab activities with two main goals. The first one refers to collecting data from student interaction via remote experimentation environments and analyzing such data to offer clues and insights to stakeholders in the educational context. The second one refers to producing recommendations that can enhance students' performance in learning activities. Section 2 introduces the background of the study. Section 3 presents the proposed process. Section 4 shows the experimental design. Section 5 presents the results, the scenario analysis, as well as a general discussion about the process. Finally, section 6 draws conclusions.

2 Background

2.1 Remote Experimentation

Calculus classes and hands-on laboratories are still the main traditional educational resources in the students' learning process. Calculus classes in engineering education are generally more abstract and methodic when dealing with mathematics and knowledge about the class topics [7]. Hands-on laboratories enable students to acquire more complex competences and so strengthen the relation between theory and practice, leading to the achievement of haptic skills and instrumentation awareness [7][8][9]. Simulation is another important engineering education resource. As stated by [10], it is suitable to make clear to students that such a resource is a simulation of reality, avoiding any kind of problem between real and virtual worlds. However, some authors [11][12] state that simulations are complementary to calculus classes and hands-on laboratories.

Remote laboratories represent an evolution in the learning process affording real experiments with real experimental apparatuses. Even without the students' presence, remote laboratories demand space and devices. Notwithstanding, such a feature leverages ways to carry out experiments by increasing frequency and places [9]. The last-mentioned authors also state that in this modality experiments are shared thus extending the functionalities of hands-on laboratories. Therefore, remote laboratories are complementary tools that impact the students' learning process by sharing some advantages of hands-on and computer simulations. Through remote laboratories, students can deal with real apparatuses and have the possibility to acquire learning experience beyond the classroom [13]. However, as remote labs are linked to real equipment in specific situations, availability may bring about some problems. In this way, remote labs and also simulation labs are useful tools commonly used to complement other teaching resources [9][14].

2.2 Learning Analytics

Learning is a topic with a wide impact on peoples' lives, and nowadays there is an attempt to accommodate ways mainly based on technology to boost students' performance. In addition, as stated by [15], learning is highly distributed taking into account space, time and media. Such a fact generates a high volume of data about students' interactions as well as about the learning process. In this context, regarding students' behavior, learning analytics (LA) has become a valuable learning tool by attempting to impact their performance positively.

Among the many definitions of Learning Analytics, one of the most cited is "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" [16]. LA has its basis from business intelligence (BI) concepts, which have been appropriated by education institutions [17]. Other fields supporting LA, according to [18], include web analytics, educational data mining, and recommender systems.

Primarily focused on the capture and report of data by educational administrators and the performance enhancement of educational institutions, learning analytics also achieved an operational perspective aiming to provide tools targeted at a better understanding of students' experiences.

2.3 Recommender Systems

Since mid-1990s, Recommender Systems (RS) have become a relevant research field [4][5][19]. RS intend to provide suggestions mainly in situations where there is a great volume of options once such situations may pose difficulties for the user [20]. RS start through the collaborative filtering approach and currently promote support for a wide range of research areas and applications.

This kind of system is suitable for both the user and the service provider once it has the ability to assist in choosing items, making the task more enjoyable and tending to deliver results that are more appropriate. Based on these arguments, [21] state that "the purpose of RS is to generate valid recommendations for items that may be of interest to a set of users". As mentioned by [22], an "item" refers to something tangible or a digital object, such as a product, a service, or a process within the scope of recommendation of an RS to the user considering their interaction with some media. According to [23], "item" is the general term that designates what the system recommends to users. In the literature, there are several RS approaches, among the most common: content-based filtering (CBF), collaborative filtering (CF), and hybrid filtering [24][25]. More recently, RS have taken advantage of semantic web technologies and knowledge representation to properly deal with the overload of information, heterogeneous data sources and knowledge domain [26] [27].

Many are the applications and areas in which RS promote support. In the educational context, for instance, e-learning recommender systems have evolved since the 2000s based on the development of traditional e-learning systems [6]. These systems intend to support students in their choices about courses, subjects or learning activities, helping them to achieve better performance.

3 The Proposed Process

This section describes the proposed process considering the context of learning analytics and recommender systems. It aims to analyze the data generated from the interaction of students with a remote experimentation environment and produce suggestions that can help them carry out the experiments. It intends to provide ways to scaffold students' performance on remote experimentation. Figure 1 shows the process flow in which a student performs experiments and, depending on the configurations, receives further information. Section 4 details the elements that compose an experiment.

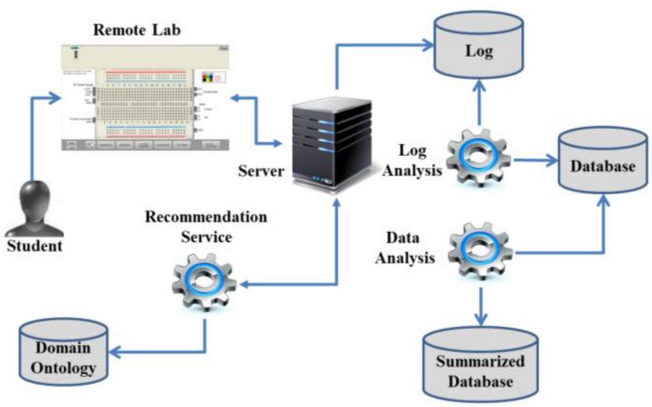

Figure 1: Overview of the proposed process.

The process comprises four phases consisting of logging, recommendation service, log analysis, and data analysis. It starts by students configuring and performing the experiments. All settings about the experiment are sent to the server, which stores them in a log file as a request. In addition, the server invokes a recommendation service. The service, then, using a domain ontology, creates an instance with the parameters of the experiment and initiates an inference verifying whether the request is correct or not. In the negative case, the service suggests a more detailed list of errors. Such errors represent a response that is sent back to the remote lab interface, enabling students to check their settings and carry out necessary changes. Responses, whether correct or not, are logged by the server.

The other two phases occur in the backend. The log analysis phases focus on monitoring the log file composed of requests and responses by performing the inspection from time to time. The request and response structures will be detailed in Section 4. Each log entry is analyzed and persisted in the database in order to facilitate future analysis about the students' achievements. Similarly, the data analysis phase intends to synthesize the log information from the database in a new summarized database. The database keeps the statistics that describe the experiments, such as the amount of experiments, the frequency of use of components and instruments, the most common errors as well as information relating students and experiments. All the information is distributed by periods of time. The summarized database aims to provide clues and insights for teachers about difficulties faced by the students. Furthermore, it allows highlighting the possible causes of deficiency in specific subjects, guiding teachers toward improvements in both theoretical and hands-on classes.

3.1 Support Structures

A given experiment is characterized by a set of components and settings being evaluated by the server that provides a response. Both request and response are stored in a log file. From this, a log analysis is carried out by collecting each entry and persisting it into a database in order to evaluate students' performance and to provide stakeholders with information about the learning process. To clarify this matter, a database model was developed, as illustrated in
Figure 2.

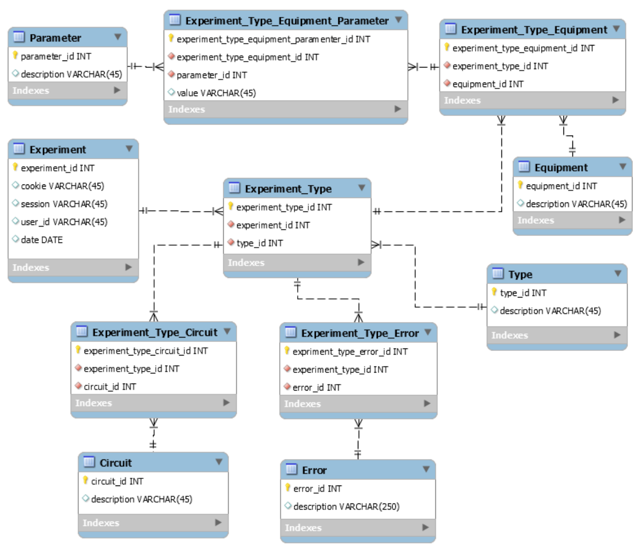

Figure 2: Database model to support analysis in the remote experimentation context.

The main table represents the experiment and is called **Experiment**. Each experiment is an arrangement of circuits and equipment settings regarding one or more of the following equipment: Multimeter, Function Generator, Oscilloscope, and DC Power. In addition, there are two basic types registered into **Type** table, request and response. After experiment configurations, the student can perform an experiment being characterized as a request. From that, the remote experimentation server analyzes the request to determine if all settings were correctly entered. In the affirmative case, all the measurements carried out are returned, thus enabling results to be presented through the interface.

After the request or response registration, the **Experiment_Type** relationship table is fulfilled, allowing storing the information on which circuits were used and configured, which equipment was configured for the experiment and which parameters were defined. The **Experiment_Type_Circuit** table keeps circuits defined in the experiment taking into account the set of circuits available in the **Circuit** table.

Another part of the model represents all possible equipment configured in the experiment. The **Experiment_Type_Equipment** has the function to store such equipment. Also, this table is related with the **Experiment_Type_Equipment_Parameter**, which stores all settings associated with a particular equipment and experiment. **Equipment** and **Parameter** tables represent the list of equipment and parameters, respectively.

In addition, during an experiment, the Server may identify errors. In this case, the relation between a specific error and a response is stored in the **Experiment_Type_Error** table. Table **Error** stores the list of errors that the experiments can produce.

To support the process as a whole, a domain ontology is used. The ontology represents the knowledge base with the rules that make it possible to determine whether a given experiment has an error, as well as what type of error. Figure 3 displays the ontology that represents a multimeter.

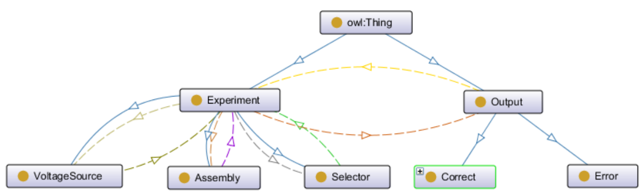

Figure 3: Domain ontology used in the analysis of the experiments and suggestion of possible errors.

The ontology is composed of a set of classes in which the **Experiment** and **Output** classes are the principal ones. The **Experiment** class allows defining an instance through a set of properties. The instance represents a request made by the student relating it with instances already defined in the **VoltageSource**, **Assembly**, and **Selector** classes. Using this information and through a reasoning process, it is possible to determine whether the output represents an error or not. In case of error, the Server gets a more detailed message and thus can send it to the remote lab interface as a suggestion, enabling student evaluation.

4 Experimental Design

The evaluation of the proposed process was carried out using data from the VISIR project. In order to better describe the experimental design, both the VISIR project and the log are detailed.

4.1 Remote Experimentation

The Virtual Instruments Systems In Reality (VISIR) project focuses on the subject of circuit theory and practice, providing support to the area of Electrical and Electronics Engineering.

Remote experimentation as a complementary approach to other educational strategies, such as calculus classes, hands-on labs, and simulations, provides an additional means to foster students' skills.

A VISIR remote lab installation from the Polytechnic of Porto - School of Engineering (ISEP) is used to interact with the physical panels and components. Using the remote experimentation environment, the student is able to assemble the circuits and set up all measurement parameters for a particular experiment. Figure 4 shows an example of configuration and measurement.

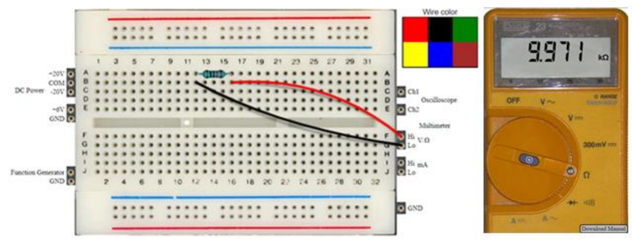

Figure 4: Example of a VISIR remote experimentation environment.

4.2 Data

After assembling the circuits and settings of the measurement parameters for a particular experiment, the student is supposed execute it. When doing so, the server receives the request and performs all the checks and calculations, providing a response with the measurements. If any problem is identified, an error message is provided; however, without informing the specific type of error. Both the request and the response generated by the server are then logged.

For the present work, a copy of the VISIR logs from the ISEP we used. The log has 545.152 records (requests or responses) from 2010-07 to 2018-03. Responses can indicate errors as well.

As already mentioned, an entry in the log consists of a request or a response. The request contains all the settings stablished by the student through the interface, and the response contains all the measurements calculated by the server. If the settings are misconfigured or put the physical lab equipment at risk, a general error is produced and sent back to the remote lab interface. Figure 5 shows a fragment of the log considering a request.

```
<protocol version="1.3">
  <request sessionkey="d689237e8da24d93c406c6be22945d39">
    <circuit>
      <circuitlist>
          W_X DMM_VHI A9
          W_X DMM_VLO A6
          R_X A6 A10 1k
    </circuitlist>
    </circuit>
    <multimeter>
      <dmm_function value="resistance"/>
      <dmm_resolution value="3.5"/>
      <dmm_range value="10"/>
    </multimeter>
    .... Other configurations ...
  </request>
</protocol>
```

Figure 5: Fragment of the log file taking into account a request message.

The log entry representing a request stores all the components with the positions in the breadboard being identified by the <circuitlist> element.

Furthermore, when the student selects and configures a measurement instrument, for instance a Multimeter, the values used for that are kept by the <multimeter> element. In the remote lab interface, other instruments are also available, such as Function Generator, an Oscilloscope, and a DC Power, being these resources available for simultaneous use.

5 Results and Analysis

This section summarizes the main results achieved regarding the data analysis and recommendation phases, as shown in the process described in Section 3.

5.1 Data Analysis

The data in the log is composed of 545,152 entries, being 50% requests and 50% responses. Each entry represents an interaction carried out by students (requests) or the messages provided by the server (responses). Considering the 272,576 requests made by students from the interface of the remote laboratory, 238,949 (87.66%) had a correct answer, that is, after the evaluation, the server sent back a response with the result of the measurements. The remaining responses provided by the server, 33,627 (12.34%), represent measurement errors. Of these, 22,970 (68.71%) refer to previous requests also with error. In the current version of VISIR, the response error is generic and is only reported when the equipment is put at risk.

Each request belongs to the context of a remote lab session in which the student sets up a given experiment and sends it to the server. During the session, components and parameters can be adjusted, enabling multiple experiment submissions. A total of 37,645 distinct sessions were identified, averaging 7.24 requests.

Finally, a distribution analysis of the types of instruments used in the remote experiments is shown in Figure 6. Multimeter is the most used instrument with 79.46%, followed by DC Power, Function Generator and Oscilloscope with 78.64%, 48.83, and 47.52%, respectively.

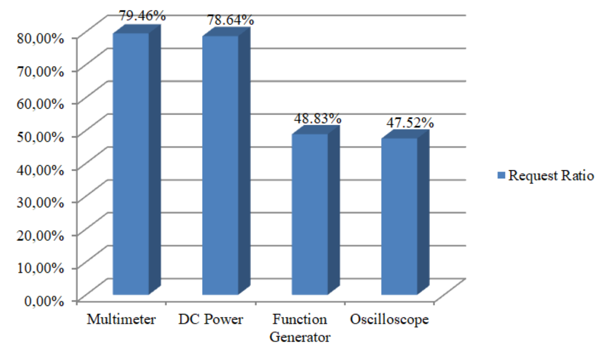

Figure 6: Distribution of the instruments used in the experimentation requests.

5.2 Recommendation Approach

In this phase, the requests are analyzed in order to provide suggestions about the remote experimentation. Once the server receives the request, it accesses the recommendation service.

The recommendation service receives the request parameters containing information on the configuration of the circuits and the measurement equipment. After that, it fulfills an instance of the **Experiment** class in the domain ontology using object properties. Figure 7 shows an instance of an experiment named **Experiment_1**.

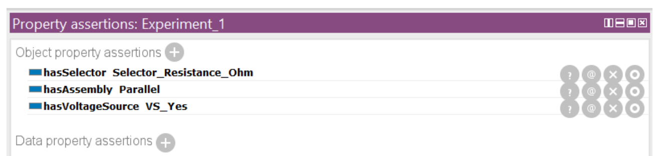

Figure 7: Instance of an experiment named Experiment_1.

An experiment instance must be associated with some instance of **VoltageSource**, **Assembly**, and **Selector** classes. It occurs through **hasVoltageSource**, **hasAssembly**, and **hasSelector** properties, respectively. The example in Figure 7 shows an experiment instance related to instances **VS_Yes** (values can be "VS_Yes" or "VS_No"), **Parallel** (values can be "Series" or "Parallel") and **Selector_Resistance_Ohm** (values can be V- "Selector_Resistance_V-", V~ "Selector_Resistance_V~", A- "Selector_Resistance_A-", A ~ "Selector_Resistance_A~", Ω "Selector_Resistance_Ohm" or OFF).

After relating **VoltageSource**, **Assembly**, and **Selector** classes, it is possible to start the inference process in order to determine whether errors are present or not in the configuration. Taking into account the relationships between instances of classes, there are 24 output possibilities. Figure 8 presents two rules based on first-order logic promoting support to inference.

Rules:
hasVoltageSource(?x, VS_Yes), hasAssembly(?x, Parallel), hasSelector(?x, Selector_Resistance_Ohm) -> hasOutput(?x, Type_AD)
hasVoltageSource(?x, VS_Yes), hasAssembly(?x, Parallel), hasSelector(?x, Selector_Voltage_V-) -> hasOutput(?x, Type_AB)

Figure 8: Examples of rules analyzed during inference process.

According the above figure, the first rule evaluates the conditions and returns a Type_AD output. The output instance shows an error and has an associated message, i.e. "Resistance reading with the circuit in tension". On the other hand, the second rule returns a Type_AB output instance that represents a possible and correct configuration.

At last, based on the recommendation service returns, the server composes the final message representing an error or not by returning it to the remote lab interface. Figure 9 shows an example considering the first rule. The server also records the response in the log file for analysis.

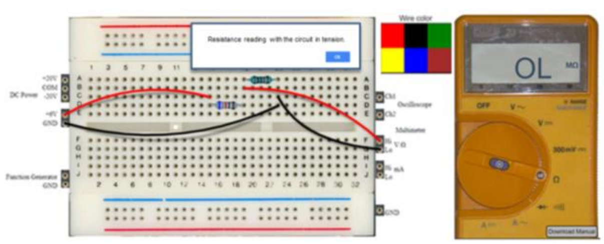

Figure 9: Example of a VISIR remote experimentation environment with response message.

6 Conclusion

Increasingly, education have been bringing new challenges that require the combination of strategies, approaches and tools toward a sustainable vision. Thus, the implementation of remote laboratories promotes ways to overcome some limitations faced by hands-on laboratories and simulations. This paper proposed a process based on learning analytics and recommender systems in the context of remote experimentation. The evaluation of the proposal considered an experiment log of student interactions in a remote lab made available by the VISIR project.

Experiment log analyses can reveal relevant information about the difficulties faced by students and, based on that, offer ways for teachers to enhance their classes in an attempt to scaffold students' learning. Regarding the total requests, 12.34% have responses with error associated. This indicates acceptable figures since, at first, in addition to the theoretical and practical classes, there is a learning curve about the remote experimentation environment. However, 68.71% of the total errors are due previously committed errors. This indicates that a correct definition of errors and presentation to students, rather than generic messages may improve their performance. Additionally, correlating students' errors to the course module being taken could provide additional information to understand the students' learning process in the remote experimentation context.

In the current version of the log, when the server evaluates a request as an error, just a general message is recorded, without reporting a specific type. In this sense, the proposed process uses a domain ontology to provide a knowledge base in order to clearly typify the response error. The ontology is still a fragment of the required knowledge to map all the possible errors. However, it allows an initial overview on how to offer a better response to the students, keeping detailed information in the database for future analysis.

These results are initial but consistent regarding the proposed process. Knowing the main errors occurred during the experiments and allowing them to be returned to students are key to leverage students' performance and help teachers improve their classes.

The development of this paper resulted in a process toward a better understanding of the difficulties faced by students in remote experimentation environments. Moreover, it provides a clear identification of errors and their correlation with remote experimentation activities, so teachers and other stakeholders in the learning process are offered valuable information.

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