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Using Process Mining for Learning Resource Recommendation: A Moodle Case Study

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Abstract

Nowadays, Learning Management Systems (LMS) play an intrinsic role in education. They gather traces about the learner (course view, wiki view, quiz attempt, etc.) in event logs. These logs offer the opportunity to provide dashboards and analysis on learners. There are several techniques that analyze event logs for different purposes (adaptation, recommendation, performance detection, etc.). Within this framework, our central focus is upon Educational Process Mining technique which generates process models for improving learning resource recommendation.

We set forward an architecture leading to discover process models and recommend to the learner not only learning resource but also process models, each of which is relative to a specific learning resource. These models exert a certain influence on the result of learning resource recommendation. One of the reason that endows our work with an original aspect is that it automatically analyses event logs based on multi-features extracted from the learner's profiles. However, the state of the art works require a manual analysis step based on learning results uniquely. We evaluated the discovered process models grounded on the event logs of Moodle LMS. These event logs contain 42,438 traces of 100 students who learned a course over one semester. Results corroborate the good performance of our work.

Keywords: Process mining ; Learning Management System; Event logs ; Learning resources; Clustering; Recommendation.

1. Introduction

With the fast pace of modern life, E-learning is taking an increasingly important part from primary school to university. It stands for a teaching-learning process where teachers and learners are geographically distant and where the

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latter autonomously manage their activities (learning resources). It allows prevented public to continue their learning, as we have witnessed with the health crisis associated with the new Coronavirus.

The amount of data produced and traces left by users on Learning Management Systems (LMS) offer the opportunity to provide dashboards and analysis on learners.

These data illustrate: i) the learner's features that may be stored in his/her profiles (learning style, interests, learning results, etc.) and ii) the traces of the performed activities, namely event logs. There are currently multiple techniques for analyzing data from LMS such as Educational Data Mining [2], Process Mining [19] and Educational Process Mining [5]. In our work, we are basically interested in Educational Process Mining. It allows to discover, monitor, and improve real process models by extracting knowledge about the learner based on several steps [18]: process discovery, conformance checking, enhancement and evaluation.

Basically, several research works have been particularly oriented towards enhancing algorithms used for process discovery (fuzzy miner, inductive miner, etc.) rather than elaborating the quality of the input data. Most of the proposed works analyse event logs based on learning results uniquely [13, 3, 7]. We judge that event logs and learning results are insufficient as input data in process discovery. In fact, taking into account another source of data may be beneficial in order to find the adequate process models for the learner and enhance the learning scenario relative to learning resources. From this perspective, we propose to consider also the learner's features since they reflect the learner's needs.

In fact, the learner has several activities available to him/her in order to acquire the necessary skills for graduation in a specific learning resource. We aim to apply process mining techniques from event logs, learning results and learner's profiles in order to make useful recommendations to learners that would enable them to build up their own learning scenario. For this reason, we set forward an architecture to discover process models and recommend to the learner not only learning resources but also process models, each of which is relative to a specific learning resources.

The discovered process models were assessed based on the event logs of Moodle LMS. These event logs involve 42,438 traces of 100 students who learned a course over one semester. Results reveal that the generated process model can promote learning resource recommendation for a specific learner.

The rest of this paper is organized as follows. In section 2, we present certain state of art works addressing process mining and Educational Process Mining . In section 3, we provide an overview of the proposed architecture tackling process mining and recommendation. In section 4, we focus on describing the process mining layer. In section 5, experimental results are displayed. Section 6 wraps up the conclusion, exhibits some concluding remarks and offer new perspectives for future works.

2. State of the art

In our previous works, our central focus was upon the research area of recommendation systems. The latter aim to recommend learning resources such as tags [12], web services [10] and events [17] based on learner's interests (expressed by keywords). In this paper, we basically consider not only learner's interests but also his/her behavior, expressed by process models, in order to recommend learning resources.

For this reason, we are concerned more with another research area of process mining so as to recommend not only learning resources but also process models.

In this section, firstly, we discuss briefly process mining. Secondly, we report relevant research papers about Educational Process Mining. Finally, we compare these different works and we highlight their limitations.

2.1. Process mining

Process mining is used in several areas, including information retrieval in a digital library [16], healthcare [14], social media [11], etc. The purpose of process mining is to discover, monitor, and improve real processes by extracting knowledge from event logs which is readily available in current information systems [20].

Each event in such a log refers to an activity (a well-defined step of a process) and is associated with a particular case (a process instance). Process mining techniques use additional information such as the resource (a person or device) that performs or initiates the activity, the timestamp of the event, or data items recorded with the event (e.g., the size of order) [20].

The process mining techniques are various (specific algorithms or using the notion of a region in graphs, genetic algorithms, etc.) [18]. They aim to extract knowledge about processes by discovering them, checking their conformance and improving current processes.

The first use of process mining is **process discovery**. A discovery algorithm takes an event log and generates a model without using any prior information. Among process discovery algorithms, we cite inductive miner, fuzzy miner, heuristic miner and alpha miner. These algorithms produce process models in various forms, such as Petri nets, BPMN models, EPCs, etc.

The second use of process mining is **conformance checking**. At this level, an existing process model is compared to an event log of the same process. The conformance checking can be used to check whether the reality, as recorded in the log, conforms to the model or not.

The third use of process mining is **enhancement**. The idea lies in extending or improving an existing process model, thereby using information about the actual process recorded in an event log.

In order to evaluate the results of process discovery algorithms, three main quality dimensions (metrics) are invested [6]: i) **Fitness** (F) which determines how well the model allow the behavior present in the event log, ii) **Precision** (P) that corresponds to the rate of activities in the event logs compared to the total of activities observed in the process model and iii) **Generalization** (G) measures the ability of the model to generalize the behavior present in the event log.

A suitable model has to find a balance between these metrics.

2.2. *Educational Process Mining*

Educational Process Mining works allow to discover learner process models from event logs for different purposes such as predicting student performance, adaptation and recommendation.

Authors in [3] explored the relationship between learning behavior and learning progress in MOOCs. They aimed to better understand how successful and unsuccessful students distribute their activities differently over the weeks' courses. To find the patterns in the learning behavior of students in the MOOC, an exploratory sequence analysis using process mining and hierarchical clustering is applied as an excavation method.

The objective of [7] resides in discovering the self-regulated learning (SRL) processes of students during an e-Learning course using the techniques of process mining. [7] applied the Inductive Miner algorithm to student interaction traces in a one-semester online course on the Moodle 2.0 platform. They divided the log file into two groups resting on the students' final grades: pass and fail. In addition to pass-fail files, they divided event files into subfiles by a unit to further analyze students' behavior and predict their academic performance [8].

In [15], a preprocessing task is performed to group users according to their type of course interactions. This study allowed to discover the most specific browsing behaviors using the clustered data only rather than the full data set by applying the Heuristic Miner.

Authors in [13] suggested applying process mining to understand learning processes based on student activity traces from MOOC platform logs. They divided the students into separate groups in order to improve their analysis. The grouping criteria are the type of certificate for which the students register and the level of success or the final grade which they aspire to achieve. They applied the fuzzy miner process mining algorithm in order to visualize and reproduce the real behavior of the students.

In [1], the authors attempted to identify the self-regulated learning patterns of students with the process mining technique using data and information extracted from an online learning environment. One of the most frequently cited self-regulated learning models is the Zimmerman. This model relies on the interaction between three phases of self-regulated learning, i.e. forethought, performance and reflection. This study reveals that the process mining technique offers new opportunities to better understand self-regulated learning behaviors in online learning. Using the Fuzzy model and animation, [1] managed to trace how students adopt self-regulated learning throughout the course.

2.3. *Synthesis*

Table 1 plots a comparative study about Educational Process Mining works. The comparison rests upon the method used for analysing event logs, features, the used process discovery algorithm, metrics of evaluation, the data proposed in the process models and the objectives of the research work.

We notice that despite the efforts provided in certain works in order to brush up the results of process discovery based on different algorithms, which are in turn evaluated based on the Fitness metric; these works exhibit certain deficiencies in terms of input data. In fact, most of the proposed works require a step of manual analysis (clustering) of event logs before process model discovery [15, 7]. Furthermore, the analysis of event logs rests only on learning results such as certificate [13] and grade [7]. Moreover, some works focus on a specific type of activity (practice [13, 3] or theoretical [15]). Thus, the discovered process may correspond to the learner's features.

For this reason, we opt for analysing automatically event logs based on a clustering algorithm. The latter takes into account not only learning results but also learner's features that are stored in the learner's profiles distributed in different LMS.

Table 1. Comparison of related works

work	Analysing Event Logs		Process Discovery Algorithm	Metrics of evaluation	Data proposed in the process models	Objectives
	Method	Features				
[3]	Hierarchical clustering	-Certificate -Quiz scores -Mean scores of watching videos per week	Inductive Miner	No evaluation	Watch videos Submit quizzes	Describe and explain the sequences of learning behaviors
[1]	No clustering	No features	Fuzzy miner	No evaluation	21 activities (view the course, view the link, view the quiz, etc.)	Identify Student SRL Models
[7]	Manual clustering	Students' final marks: Pass/Fail Unit	Inductive Miner	Fitness	16 activities (quiz attempt, page view, etc.)	Evaluate the skills of students in SRL during an e-learning course
[15]	Manual clustering Automatic clustering	Students' marks Interactions in Moodle	Heuristic Miner	Fitness	20 activities (view the course, view the file, etc.)	Discover the browsing behavior of students
[13]	Manual clustering	Type of certificate Final grade or achievement level	Fuzzy miner	Fitness	Watch videos and submit quizzes	Model and profile student behavior throughout the course

3. Overview of the proposed architecture for recommendation based process mining

This section introduces the architecture of applying process mining for recommendation. This architecture is based on our previous architecture [9] for learner's profiles interoperability. This architecture is confined to allowing: i) the data exchange between heterogeneous learner's profiles based on an interoperability layer and ii) adapting the navigation over learning resources to learners based on adaptation layer. However, in this research study, the proposed architecture is extended by two other layers allowing to apply process mining for recommendation. As depicted in figure 1, only four layers are illustrated, namely client, recommendation, process mining and source. Additional details about the interoperability and adaptation layers are recorded in [9].

Within this framework, the client layer allows the interaction between the learner and e-learning systems (LMS). Thus, the learner can send a request by clicking on the provided links through different types of devices (PC, mobile,...).

The source layer involves distributed databases of learning results, event logs,process models, global profiles and learning resources.

The learning results include the knowledge or skills learners should acquire by the end of a particular course, activity, etc. The event logs are files that contain a large amount of raw data about the interaction of learners with LMS. As data in event logs are often noisy, this database necessitates a preprocessing step before applying the process mining steps.

The global profile database provides a profile for each learner containg a global view about his/her data that is distributed in different e-learning systems. Building up the global profile is a preliminary step in the interoperability layer, which is detailed in [9]. It is represented by the FOAF[1] language and involves several features: personal data, demographic data and social data that characterize the known persons (friends) and interests (the learner's interests

[1] http://www.foaf-project.org/

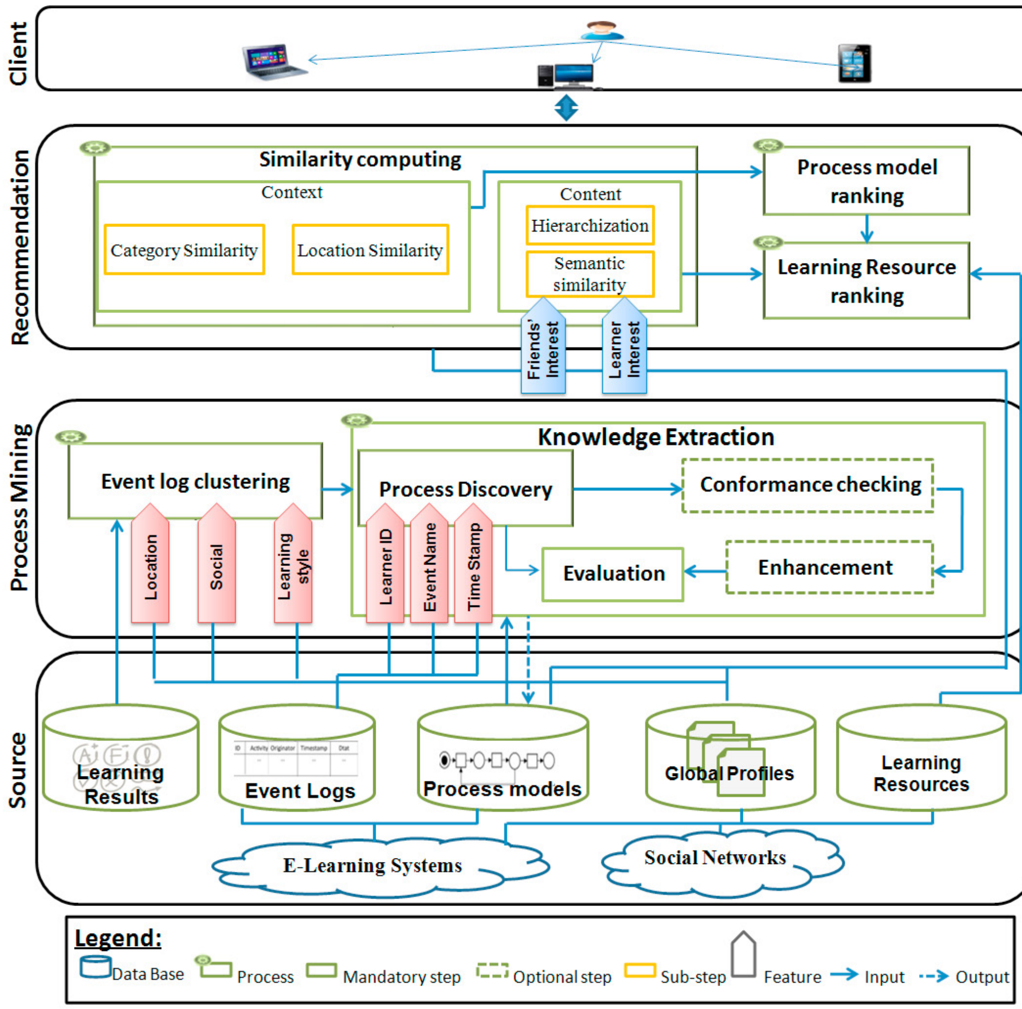

Fig. 1. The architecture of applying process mining for recommendation

and those of his/her friends). The interest corresponds to the topic of the learning resources which the learner finds pleasure in spending time learning about. In this paper, we extend the global profile by new features in order to further improve the result of process mining and recommend pertinent learning resources. These features describe the location of the learner (distant, face-to-face or hybrid), the social aspect (individual or collaborative work) and the learning style (theoretical or practice aspect).

The learning resources database encompasses any element involved in the learning process such as course, quiz, web pages, images, videos, etc. These elements can be represented by different standards such as Learning Object Metadata[2] (LOM) , Information Message Service Simple Sequencing[3] (IMS SS) and IMS Learning Design[4](IMS LD).

The process mining layer allows the discovery of process models based on event logs and learning results. Each process model demonstrates the most common usage behavior by learners in an LMS. It consists of the number of occurring activities and their frequencies. The analysis of process model allows to visualize and reproduce the real

[2]https://standards.ieee.org/findstds/standard/1484.12.1-2002.html
[3]https://www.imsglobal.org/simplesequencing/index.html
[4]https://www.imsglobal.org/learningdesign/index.html

behavior of the learner, so as to find the patterns in the learning behavior of learners, and even to recommend learning resources that seem to play an intrinsic role in learning.

For this reason, we propose in the recommendation layer recommending not only learning resources but also process models based on a process for similarity computing between the process models and the global profile features.

4. Process mining layer

In order to generate process models relative to a specific learner, we propose to cluster event log based on learning results and learner's features. From this perspective, the process mining layer branches out into two processes: clustering and knowledge extraction.

4.1. Clustering of event logs

Clustering is applied in order to group learners with similar learning results and features. Learners are grouped using the k-means clustering algorithm.
First, event logs are split into two clusters based on learners' learning results: Pass (containing only events of learners who passed the learning resource) and Fail (containing only events of learners who failed the learning resource). Second, from the Pass-Fail clusters, we increase the granularity by dividing the event clusters into sub-clusters based on learner's features that are stored in the global profile (cf. section 3). The sub-clusters allow to analyze learner's behavior more thoroughly.

The algorithm of event log clustering is portrayed in Figure 2. It takes as input the event log, the number of

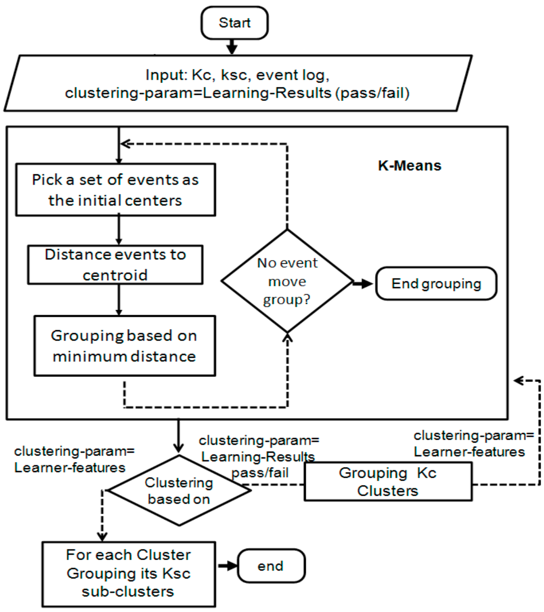

Fig. 2. Event log clustering

clusters "kc", the number of sub-clusters "ksc" and the "clustering-param" which is initialized by "Learning-Results (pass/fail)". It applies k-means to generate, for each event log, "kc" clusters according to the parameter "Learning-Results (pass/fail)". Afterwards, it applies the k-means algorithm to generate, for each cluster, "ksc" sub-clusters according to the learners' features (learning style, location and social behaviour).

Each sub-cluster contains a set of events performed by learners who are very close in their location (face-to-face study, online learning or hybrid learning), learning style (theoretical or practice activities), social behaviour (individual or collaborative learning).

4.2. Knowledge extraction

The knowledge extraction process allows the extraction of learning scenarios that are commonly used by users designed in process models. The originality of this process refers to the fact that it rests on the result of event log clustering. The knowledge extraction takes place according to four steps. The first step stands for a process discovery by applying a set of process discovery algorithms (cf. section 2.1). This step is mandatory for knowledge discovery resting on event logs provided by an LMS. Event logs contain all of learners' events recorded during their interactions characterized by attributes such as timestamp, learner full name (ID), event context (the course and activities to which the user have accessed), event name and Description.
As far as this research is concerned, only three attributes are invested corresponding to the most required by process discovery algorithms: Learner ID, Event name and timestamp. Each student identified in LMS left a trace of an event(s). Each event represents an activity that was performed. An activity may be initiated to specific learners depending on their learning style, location and their social behaviour. Timestamp is the time at which the event was performed. It is used to identify the order of activities, delay, and bottleneck.

The second step is conformance checking, which is performed in order to check whether the data recorded in the event log correspond really to the process model or not. The third step is enhancement. It allows to improve an existing process model. The fourth step allows the assessment of the process model based on evaluation metrics. This step gives much importance to all metrics by assigning weights. Depending on the evaluation result, the third step may be re-executed.

The extracted process models are ranked in the recommendation layer in order to recommend to the learner learning resources with the closest process model (relative to his/her features).

5. Experimental results

In this paper, the experimental results are basically grounded upon the evaluation of the process mining layer (discovered process models). This section reveals, at a first stage, the methodology undertaken for event log preprocessing in order to prepare for Knowledge extraction. At the second stage, it exhibits the results.

5.1. Data set

In order to assess the discovered process models, we extracted the event logs of learners who studied the course "Introduction to human-machine interfaces (HMI)" created on the Moodle platform of the University of La Rochelle (France). A pedagogical scenario has been established allowing the learner to achieve the final goal. These event logs include 42,438 traces of 100 students that learned a course over one semester. Each trace corresponds to an activity performed by a learner.

The log file provided by Moodle involves each learner's events recorded during his/her interactions with Moodle summarized in nine attributes: Time, User full name, Affected user, Event context, Component, Event name, Description, Origin, and IP address. We used only three attributes relative to the process discovery algorithm requirement (cf. table 2).

Table 2. Data set description

Data requirement	Moodle Attribute
CaseID	User full name
Activity	Event name
Timestamp	Time

It was necessary to preprocess and filter the log file. This stands for an essential step when we are using real event logs and the data is often noisy. For this reason, we convert the time into a format that matches the process discovery algorithm and filter the activities that are not useful.

Time format conversion: Departing from the collected data, there was a problem with the Time attribute whose value could not be used as a timestamp. The format of the value did not match any timestamp pattern. Therefore, in the preprocessing phase, we implemented an algorithm in order to change the format of the Time attribute to conform to the predefined timestamp.
Filter by instances: The total activities for the students on Moodle before filtering by instances were 42,438. This filter let us reduce the log file from 42,438 to 36,816 records. The reduction in the number of events led to the reduction of the number of activities from 64 activities to 28 activities.

5.2. Results

In order to implement our approach, we attempted to explore software and libraries that support process mining. We found several commercial software and open-source libraries such as Disco[5], ProM[6] and PM4Py[7]. We chose the library PM4Py [4] founded by process mining group of Fraunhofer FIT headed by W.M.P. Aalst. This library displays a relatively wide range of functionalities. It contains basic algorithms for process discovery as Alpha miner, Inductive miner and Heuristic miner.

As previously mentioned, the process mining layer of the proposed architecture rests on event log clustering and process discovery. Firstly, we fixed the number of clusters after successive experiments. We divided the event log into two clusters of learners based on learners' results (pass and fail). Afterwards, each cluster was divided into 3 clusters based on the learners' features (cf. section 4.1). For example, for the pass learners we detected in the first cluster 32% of learners who preferred face-to-face study, collaborative learning and theoretical activities. The second cluster contains 32% of learners who opted for online learning, collaborative and practice activities. The third cluster contains 34% of learners who would prefer rather Hybrid Learning , collaborative learning and practice activities.

Secondly, we evaluated process mining algorithms resting on the result of event log clustering. In fact, we used three process discovery algorithms to obtain the models representing the event log's behavior. These algorithms are: alpha miner, inductive miner and heuristic miner. Subsequently, the Fitness (F), Precision (P) and Generalisation (G) of discovered models were measured (cf. Table 3). These metrics are foregrounded in section 2.1.

Table 3. Evaluation metrics obtained on graphs mined from the used data set

	Inductive Miner			Heuristic Miner			Alpha Miner		
	F	P	G	F	P	G	F	P	G
All learners	1	0.0367	0.7760	0.9861	0.2284	0.8661	0.7655	0.1052	0.7892
ClusterP0	1	0.0504	0.7928	0.9917	0.1587	0.7717	0.7721	0.1031	0.8067
ClusterP1	1	0.0439	0.7145	0.9874	0.1410	0.7513	0.5552	0.0923	0.7482
ClusterP2	1	0.0505	0.8191	0.9928	0.1520	0.7784	0.5847	0.1183	0.8333
ClusterF0	1	0.0424	0.7508	0.9926	0.1665	0.7825	0.4553	0.1236	0.7873
ClusterF1	1	0.0533	0.8135	0.9889	0.1786	0.7330	0.4539	0.1245	0.8237
ClusterF2	1	0.0391	0.6802	0.9886	0.1613	0.7498	0.4677	0.0998	0.6880

Table 3 displays the obtained values of metrics for the application of each algorithm on the event log of : i) all learners and ii) each generated cluster (clusters of pass learner: clusterP0, clusterP1 and clusterP2, clusters of fail learner: clusterF0, clusterF1 and clusterF2). As plotted in the table, the inductive miner proves its high performance in the fitness value (1) and generalisation values that vary between 0.6802 and 0.8191. The alpha miner confirms its efficiency in generalisation values (between 0.6880 and 0.8333). However, the heuristic miner generates the best values of fitness (between 0.9861 and 0.9928), precision (between 0.1410 and 0.2284) and generalisation (between 0.7330 and 0.8661). Consequently, the heuristic miner proves to be the best algorithm as it sets a balance between the three metrics. Indeed, the discovered process models are indicative of the actual process occurring in Moodle for each

[5]https://fluxicon.com/disco/
[6]https://www.promtools.org/doku.php
[7]https://pm4py.fit.fraunhofer.de/

cluster of learners. Figure 3 presents an extract of the process model generated from Heuristic Miner algorithm. The output of this algorithm is a Heuristics Net that can be then converted into a Petri net.

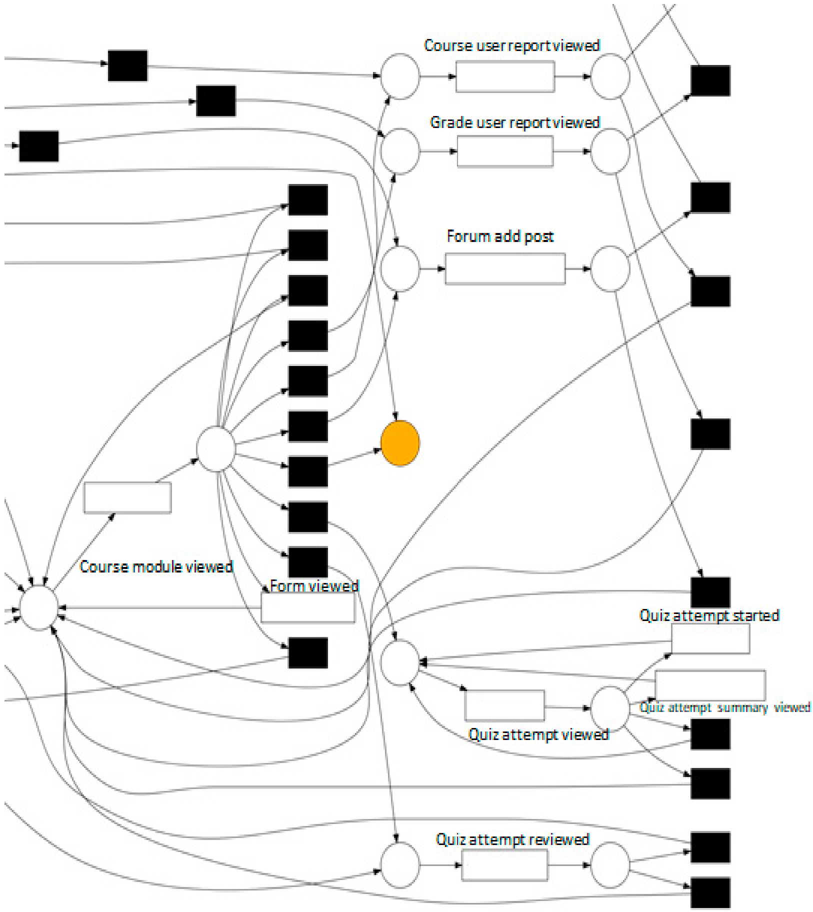

Fig. 3. Extract of the process model generated from Heuristic Miner algorithm

This figure illustrates a Petri Net example of the process model discoverd for clusterP1 representing learners who opted for online learning, collaborative and practice activities. As depicted in the Petri net, the most frequently adopted activities are performed online, collaborative (Forum add post) and practice ("quiz attempt started", "quiz attempt viewed", "quiz attempt reviewed", etc.). From this perspective, the type of activity reflects the learner's features for this cluster and each new learner belonging to clusterP1, will be guided with these activities.

6. Conclusion

The central objective of this paper is to enhance learning resource recommendation based not only on learner's interests [12, 10, 17] but also on learner's behaviour described by process models. The latter are generated by Educational Process Mining techniques. As a matter of fact, we have extended our previously elaborated architecture proposed in [9] through the addition of a process mining layer. This layer allows to extract process models resting on event log clustering and knowledge extraction based on multi-features of the learner which are related to his/her learning results, location, learning style and social behavior. The resulting process models are invested in the recommendation layer in order to suggest to the learner pertinent learning resources. Each learning resource follows the most adequate process model compared to the learner's features.

We experimented the proposed architecture, particularly, the process mining layer based on a data set extracted from the Moodle LMS. The generated results corroborate the effectiveness of the extracted process models and prove that they can enhance the result of recommendations as they depend mainly on the learner's features.

The most prominent implications of the research findings reside in identifying learners at risk of dropping out and potential failing students at an early stage as well as increasing significantly learners' academic outcomes. These implications are suggestive that we need to improve the proposed approach. Indeed, we can consider other learners' features in order to enhance the result of the process mining and recommendation layer.

At this stage of analysis, we would assert that our research is a step that may be built upon and taken further as it offers fruitful lines of investigation and opens promising research directions. Indeed, in future works, we aspire to improve the event log clustering by adding other learner's features in order to extract model processes that simulate more the learner. Moreover, we shall address the evaluation of the recommendation layer.

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