Towards a Skill-based Self-Regulated Learning Recommendation System

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Abstract

The ability for learners to self-regulate their learning, is considered as a key factor to achieve academic success. With the increasing popularity of digital learning environments, it has become critical to develop effective ways of supporting self-regulated learning in these contexts to ensure that learners are able to take advantage of the benefits of these platforms, and therefore, measuring self-regulated learning. This paper aims to describe a new approach for analyzing self-regulated learning strategies, while assessing learning skills being acquired by the learner. We propose a two-layer approach that combines an analysis of learners skill levels with the analysis of self-regulation strategies through data traces. This analysis of skills mastery and behaviours leads to qualify the relevance of self-regulated learning strategies. These assessments could serve as a basis to recommend behavioral strategies. This article mainly focus on the presentation of this two-layer system and its first implementation on the Quick-Pi platform dedicated to the learning of the python programming language.

Keywords

Self-Regulated Learning, Online Learning Environment, Learning Analytics, Process Mining, Skill Assessment, Bayesian Knowledge Tracing

1. Introduction

Self-regulated learning (SRL) is the ability for learners to control their own learning, and is considered to be a key factor in achieving academic success. Such ability involves setting goals, monitoring progress, and adapt to changing situations [1]. With the emergence of technologies, online learning is now a popular form of education. In Online Learning Environments (OLEs), the teacher or instructor's presence is often low. As such, learners require effective SRL skills to be efficient [2]. In spite of the significance of SRL, learners encounter obstacles that hinder their ability to regulate effectively, impeding their overall learning progress. Such setbacks can be portrayed as a lack of good strategy use, a lack of metacognitive knowledge or a lack of experience in learning environments. The application of metacognitive strategies necessitates the possession of specific metacognitive skills, which are not universally mastered by all learners. For this reason, it is of major importance to support SRL of each learner in OLEs through tailored guidance according to their skill level [3].

OLEs offer a significant advantage in their capacity to capture and store data, as learners generate a substantial amount of data through their interactions with the platforms. This yields to multiple data repositories such as interaction data (also known as trace data), personal data and academic information [4]. Such data contain valuable information highlighting learners initiated behaviors during their learning session, and can be exploited to build measures or indicators that support inferences about a learner usages of SRL strategies. Measurements of SRL in OLEs resorts in the generation of data analytics, and have been mainly studied in the context of Learning Analytics (LA) and Educational Data Mining (EDM) [4]. By leveraging these measures, learners can receive accurate feedback regarding their ability to self-regulate, enabling them to gain awareness of their own SRL process and take appropriate actions to enhance their self-regulation skills.

This thesis is part of a research project that aims at exploring effective support for self-regulated learning on a large scale. The project focuses on identifying and utilizing knowledge about learners' skill levels to provide tailored assistance and guidance. To the best of our knowledge, SRL support through performance at a skill level has not been explored, hence addressing the following research question: *How to support SRL based on skill level observations ?* In this paper, we present and position a system that includes a 2-layer measurement service in charge of collecting and analyzing OLE data, and a recommendation service aimed at providing support to learners. The dual-layer measurement service consists of two modules: the performance layer, which is primarily responsible for skill assessment, and the behavioral layer, which is responsible for tracing and analyzing SRL strategies. The main objective of the skill tracing module is to identify successful phases where learners show progression of

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their skill mastery level at specific time intervals. We conducted an experiment on the skill tracing module using the Quick-Pi programming platform to track learners' python programming skills. We hypothesize that during specific time intervals when progression of skill mastery is observed, effective SRL strategies are employed. To achieve this, an SRL strategy recognizer module is developed to transform raw trace data into identifiable SRL strategies. Subsequently, these strategies are analyzed using Process Mining (PM) methods to uncover successful transitions between different strategy uses and identify behaviors that predict success. These identified behaviors are then stored and utilized for future recommendations.
The structure of this paper is as follows: first, section 2.1 provides a background on SRL theory. Then, section 2.2 delves into the manifestation of SRL in OLEs. Finally, section 2.3 introduces the measurement methods utilized to capture SRL.

2. Background and related work

2.1. SRL Theory

SRL encompasses various dimensions, namely cognitive, metacognitive, behavioral, motivational, and emotional/affective aspects, representing a well-established concept [1]. Zimmerman is credited as one of the pioneering researchers who initially formulated the theory of SRL [1]. His work emphasizes the fundamental perspective that self-regulation empowers students to be autonomous and assume responsibility for their own learning. This autonomy is realized through the regulation of the aforementioned aspects of SRL. Ultimately, the primary objective of adopting SRL is to facilitate the achievement of personal goals.
Following Zimmerman's groundbreaking contributions to SRL theory, there has been a notable surge in publications within the field and the introduction of various SRL models [5].
SRL models offer a comprehensive framework that delineates the processes and sub-processes employed by learners. While some models offer a broad perspective on SRL [6], others concentrate on specific SRL aspects, such as emotion/affect [7], or metacognition [8].
In order to engage in self-regulated learning, learners need to employ strategies that enhance their learning experience.
Self-regulation strategies become evident through the behaviors exhibited by learners. Consequently, these SRL strategies can be observed by examining how students employ them in their learning.
Various assessment instruments have been developed and proposed for evaluating SRL. Traditional methods of SRL assessment involved the utilization of questionnaires and self-reports [9].
Although questionnaires remain a reliable way to measure SRL, scholars in learning analytics pointed out potential limitations [10]. One limitation is their inability to capture the dynamic changes in learners' adaptation and modification of learning tactics and strategies during the learning process[11]. As a result, there has been a shift towards exploring more tailored approaches for assessing SRL in OLEs, which will be further discussed in the upcoming section.

2.2. SRL in OLEs

The increasing popularity and effectiveness of exercise-based platforms have led to the widespread adoption of large-scale OLEs [12]. The effectiveness of these OLEs hinges significantly on the learner's capacity to assume responsibility for their own learning [13]. While previous research on SRL has primarily concentrated on traditional physical settings such as classrooms, there is a growing body of scholarship investigating SRL in online contexts (eg. [14]).
OLEs offer the benefit of collecting and storing learner data for analysis and measurement objectives. According to Winne [4], trace data provides observable indicators that support valid inferences about metacognitive monitoring and metacognitive control, which are essential and fundamental aspects to SRL. In OLEs, trace data are favored due to their ability to provide precise observations of learners' interactions with an online platform [15].
Collecting and analyzing such data enables the provision of feedback on learners' SRL and promotes their awareness of the learning process. Trace data refers to the data produced through learners' interactions with the online platform. Log files are regarded as the most feasible data source due to the level of information they provide and the coding effort and time required for analysis [16].
Log files encompass a diverse range of information, including details about learning activity sessions, login and logout events, resource views and downloads, uploaded assignments, attempted quiz items, and forum posts addressed to both general and specific peers [4].
Approaches that have been proposed to assess SRL in OLEs, includes mainly the usage of LA and EDM. LA is "the measurement, collection, analysis, and reporting of data and their contexts for the purposes of understanding and optimising learning and the environments in which it occurs"[17], while EDM places its emphasis on exploring and analyzing educational data to acquire a deeper understanding of students' learning. In the context of SRL, LA is applied within online settings where users interact with an online platform. Data is captured through various inputs, such as devices (e.g. mouse focus and keyboard typing) and platform events (e.g. opening doc-

uments, highlighting text), and is aggregated for analysis purposes, including usage flow analysis, knowledge tracing, and social network analysis. By processing this data, behavioral analysis can be conducted. LA can provide students with information regarding their behaviors and the use of SRL strategies, serving as cues for monitoring and controlling their learning processes.

Viberg et al. [18] demonstrated that the majority (70%) of empirical research in LA focuses on higher education and primarily centers around measuring SRL in OLEs.

2.3. SRL measurement

In order to support SRL, it is crucial to gain an understanding of learners' self-regulatory abilities. To observe these abilities, the measurement of SRL becomes essential. This involves constructing indicators that gather data and offer learners, instructors, and the system valuable information about learners' interactions and their utilization of strategies during their performance phase. Empirical research, including the study conducted by Pekrun et al. [19], provides support for the utilization of frequency measures. In their study, they investigated the interplay between achievement goals, achievement emotions, and self-regulation strategies. The findings suggest that the relationship between achievement goals and achievement emotions is partly influenced by the frequency of self-regulation strategy usage.

An illustration of frequency measures can be observed in the tool NoteMyProgress developed by Pérez-Alvarez et al. [20]. This tool analyzes data and incorporates a dashboard equipped with visualizations that enable students to monitor their activity and develop an understanding of their self-regulated learning strategies within a selected MOOC course [20].

Vazquez and Nistal [21] introduced a monitoring system that encompassed various learning strategies such as time management, goal setting, and monitoring. They identified and integrated specific indicators (e.g., resource usage time, project engagement time, strategy frequency) for each strategy, along with potential approaches for analyzing and interpreting the obtained results. Subsequently, Manso-Vazquez et al. [22] further explored the significance of relevant data for monitoring SRL.

While numerous tools and technologies have been suggested for measuring and assisting students' SRL, there remains a gap in our understanding of how these tools actively promote the enhancement of students' SRL for domain skill improvement. Hence, addressing our aforementioned research question: How to support SRL based on skill level observations ?

3. Skill-based SRL Recommendation System Architecture

To address our research question, an architecture for a behavioral recommendation system designed to assist learners during their performance is proposed. This section introduces the Skill-based SRL Recommendation System (S-SRL-RS) architecture designed to support learners during their performance in OLEs. The system utilizes learning data collected from the platform, including exercise outcomes and learner interactions. This data is then used to assess the learner's skill mastery levels and identify successful competence phases. Additionally, trace analysis is conducted to detect SRL strategies employed by the learner. The appropriateness of these strategies is examined considering the learners' skill levels and individual learning context. The identified strategies are stored for future reference to provide recommendations to learners. The subsequent sections will provide detailed descriptions of each component of the system, and it's implementation within the Quick-Pi OLE.

3.1. Quick-Pi Learning Environment

Quick-Pi is an online platform designed to provide high-school students with educational content and interactive activities focused on programming connected objects. These activities are presented as exercises that allow students to work with IoT devices while learning the fundamentals of Python programming. The platform offers courses in three different programming languages: Blockly, Scratch, and Python. For our experiment, we specifically selected the Python course, which consists of eight activities. In total, we conducted our experiment using sixteen exercises from the initial course. To establish a connection between behaviors and existing skills, it is crucial to develop a skill taxonomy of reference that outlines the available skills on the platform and their dependencies. The construction of this taxonomy will be elaborated upon in the following paragraph.

Skill Taxonomy of reference To create our skill taxonomy of reference, we manually extracted concepts in the Python programming language by completing each exercise on the platform. These concepts include variables, functions, and others. Then we extract from each concept the specific doable operations. As shown in figure 2 for instance, a function can be defined or called. Then, a description of the expected achievements for each concept and its operations is formulated in table 1, outlining what learners are expected to accomplish through their learning (eg. be able to define a variable). Twelve skills related to python programming are poten-

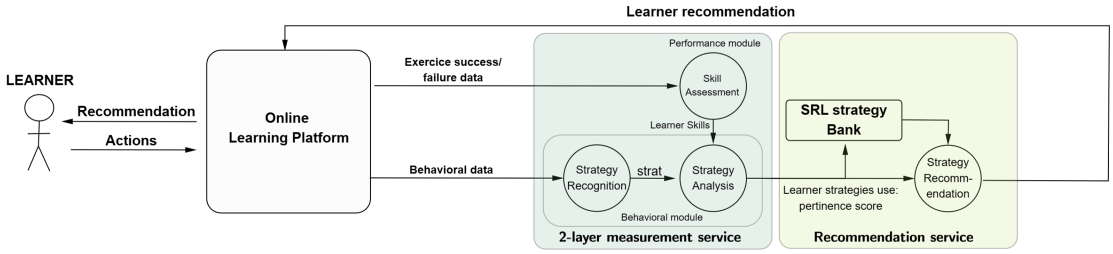

Figure 1: Functional diagram of our Skill-based SRL Recommendation System (S-SRL-RS)

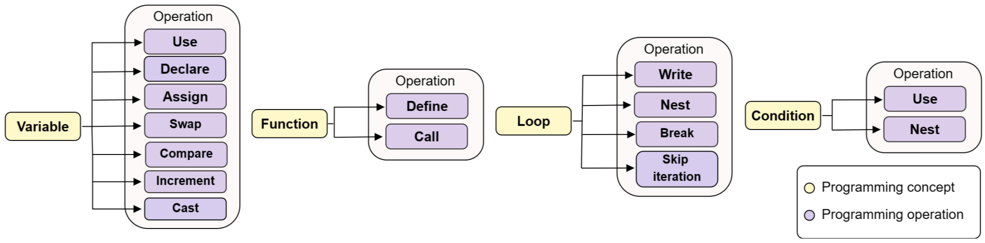

Figure 2: Illustration of programming concepts related to their operations.

	Be able to
C_1	Call a function without argument
C_2	Call a function with argument
C_3	Write a for loop
C_4	Write a while loop
C_5	Nest two loops
C_6	Use an if statement
C_7	Use an *if-else* statement
C_8	Use arithmetic operators
C_9	Use comparison operators
C_{10}	Use logical operators
C_{11}	use a variable
C_{12}	increment a variable

Table 1
Table of 12 skills mobilized on Quick-Pi platform

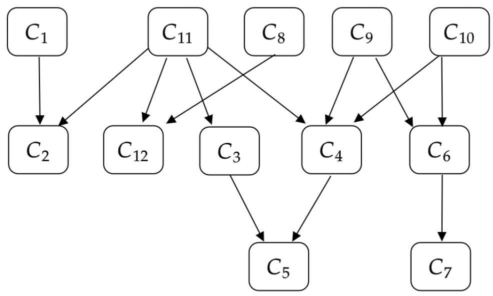

Figure 3: Graph of skill dependencies illustrating the prerequisite relationships between skills

tially mobilized in the exercises proposed on this platform. Finally, a skill dependency graph is created to establish relationships between each skill, where the notation $C_i \rightarrow C_j$ indicates that skill C_i is a prerequisite for skill C_j. Figure 3 depicts the prerequisite relationship among different skills.

3.2. Skill Assessment

Skill modeling serves as the foundation of our system, enabling the exploration of behavioral patterns that contribute to the advancement of learners' skill mastery level.

In the field of skill modeling and assessment, the primary proposals can be categorized into three main groups: Item Response Theory (IRT), Knowledge Space Theory (KST), and Bayesian Knowledge Tracing (BKT) [23]. In this thesis, the de-facto standard for student modeling method BKT was opted for. By utilizing a BKT model, learner performance at a granular skill level can be observed, revealing instances where a progression of their skill mastery level is demonstrated. This allows us to investigate the SRL strategies employed by learners during their learning process.

Outside the scope of this work, we propose a BKT model that integrates a structure of skill dependencies, and external factors such as exercise difficulty [24]. We established a specific skill taxonomy of reference, show in figure 1 and 3 for the exercises offered on the Quick-Pi

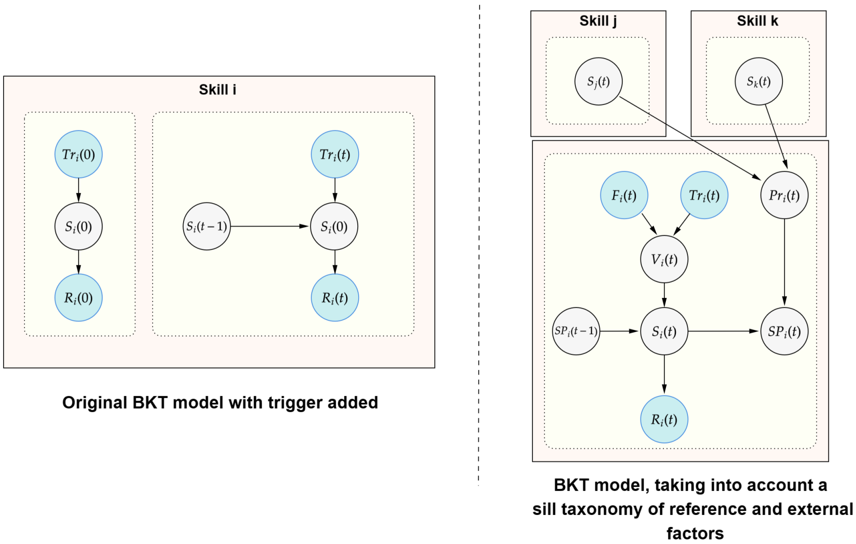

Figure 4: Comparison of BKT models: The figure showcases the original BKT model with an added trigger on the left side, while the BKT model on the right side incorporates external factors and a skill taxonomy of reference [24].

platform, focusing on the python programming domain, and implemented the BKT model accordingly using our taxonomy.

For the purpose of skill assessment, performance data is collected from the platform. The performance data relates to skill assessment and indicates the success or failure of learners in exercises. Subsequently, the collected data is inputted into the BKT model to estimate the learner's current level of skill mastery. The model updates the probability of skill mastery at each timestep, where a timestep corresponds to the moment when a learner submits their exercise. As a result, the model's output provides the probability that a skill is mastered at a specific level of mastery. To demonstrate this, an initial experiment was conducted on a learning platform to track the skills of learners and identify specific time intervals where they successfully achieve mastery in a particular set of skills.

Model construction The classical BKT model (left model of figure 4) is a random process that uses Boolean variables to represent the skill level of a learner over time, denoted as $S_i(t)$ in figure 4. The model simplifies the skill level to either "not acquired" ($S_i(t) = 0$) or "acquired" ($S_i(t) = 1$), while there are more complex scales that can be considered [24]. In our case, we define a scale of 4 level of mastery, described in the mastery level scale legend of figure 5.
At each timestep, the variable $R_i(t)$ represents the assessment of an exercise. In a basic BKT model, a learner's assessment can be categorized as either passing ($R_i(t) = 1$) or failing ($R_i(t) = 0$) the exercise. In our case, we have defined four levels of assessment, which are described in the assessment result legend shown in figure 5.
In a traditional BKT model, it is assumed that a skill is utilized at each timestep (exercise). However, in our case, this assumption is not valid as the exercises performed involve distinct subsets of the defined skills. Consequently, we add a trigger variable to the original BKT model, called $Tr_i(t)$ to condition the evolution of the skill on whether it was actually mobilized during the exercise ($Tr_i(t) = 0$ for skill "unused", and $Tr_i(t) = 1$ for skill "mobilized") [24].
To incorporate the prerequisites outlined in our skill taxonomy of reference, we aggregate the prerequisite skills into the variable $Pr_i(t)$ as shown in figure 4 on the right model, which represents the level of skill attainment for a given set of prerequisite skills. Therefore, the skill level $S_i(t)$ depends not only on the previous skill level $S_i(t-1)$, but also on the mastery of the prerequisite skills at the previous timestep, $Pr_i(t-1)$. We incorporate this result by aggregating $S_i(t)$ and $Pr_i(t)$ into $SP_i(t)$.
Finally, to incorporate external factors $F_i(t)$ that influences on the skill acquisition, such as exercice difficulties, we add a latent variable $V_i(t)$ which describes the learning speed of $S_i(t)$, and integrate external factors $F_i(t)$ and the trigger $Tr_i(t)$ in $V_i(t)$ [24].

BKT Application Figure 5 presents the initial findings of estimating the mastery level of the 12 skills over time for a specific learner as they progress through their activity. Throughout the experiment, the learner engages

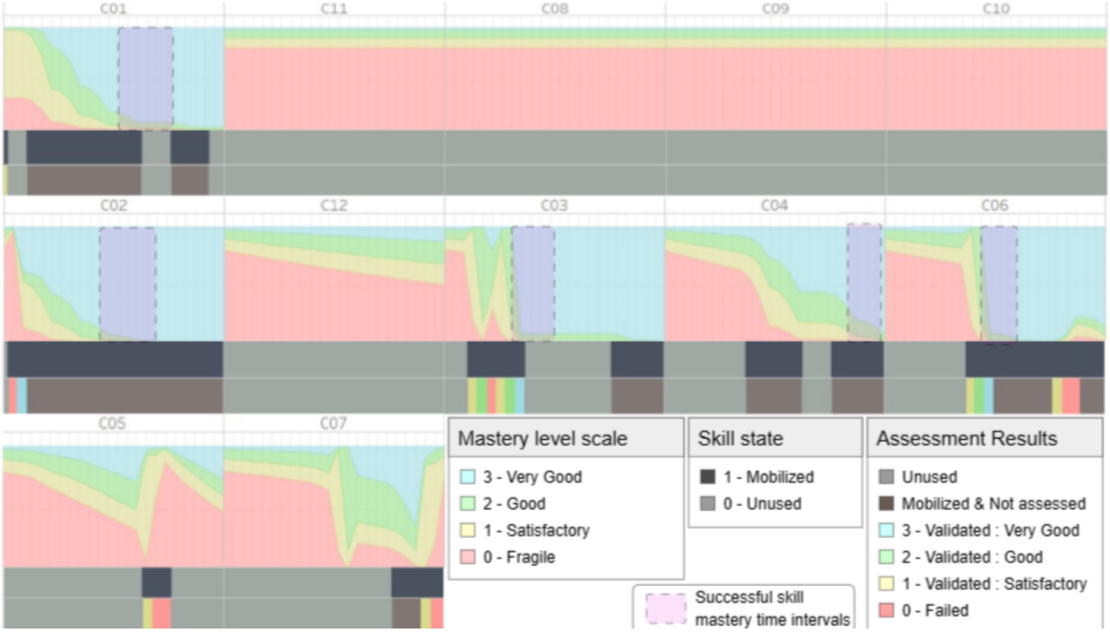

Figure 5: Estimation of the mastery level of the 12 skills over time for one of the learners, based on their activity. For each skill, the periods in black show the moments when the skill is mobilized, and the eventual assessment result [24].

in exercises that primarily involve skills $C01$ and $C02$. During the initial iterations, skill $C03$ is mobilized and assessed, while skills $C04$ to $C06$ come into play in the later iterations. In terms of assessment, except for the first iteration, direct evaluation of skill $C01$ is not conducted. However, its continuous utilization over time contributes to an increase in mastery level. Skill $C02$ initially receives a negative evaluation but later shows significant improvement, accompanied by ongoing utilization, resulting in a faster growth in mastery level. The performance on skill $C03$ demonstrates variability initially but gradually improves over time. Other skills that are not directly assessed, such as $C05$ or $C07$, also show an upward trend in mastery level with practice but may experience a decline when they are subsequently assessed negatively.

Throughout the activity, various time intervals arise where successful skill mastery becomes apparent. Notably, skills $C01$, $C02$, $C03$, $C04$, and $C06$ exhibit intriguing time intervals characterized by a significant increase in their mastery level. These findings lead us to hypothesize the presence of effective SRL strategies. To explore this further, delving into the analysis of SRL strategies is conducted within the behavioral layer of our system, which comprises two modules: the strategy recognition module and the strategy analysis module. The details of these modules are discussed in section 3.3.

3.3. Behavioral Module

The behavioral module constitutes the second layer of our system and has the role of identifying and examining SRL strategies initiated by learners during their performance phase. Initially, we will introduce the strategy recognition module, which plays a central role in identifying SRL strategies from raw trace data. Subsequently, we will delve into the strategy analysis module, where the detected strategies are thoroughly examined and analyzed using process mining.

Strategy Recognition Concurrently with skill assessment, behavioral data is collected and analyzed to uncover SRL strategies employed by learners during their learning phase. This process is carried out using the strategy recognition module. This module is designed to process raw trace data that captures the various behavioral actions initiated by learners. Its primary function is to encode and interpret this data to identify the SRL strategies employed by learners.

A trace-based SRL protocol is a methodological approach that involves utilizing raw trace data obtained from a digital environment, which comprises patterns or sequences of events for measurement purposes [25]. These data are then translated into indicators that provide insights into learners' utilization of SRL tactics and strategies [26].

The protocol proposed by [26] establishes the relationships between trace data, learning sessions, learning tac-

Learning Actions	Description
READ_TASK	Learner reads the task set by the exercise
READ_HELP	Learner seeks help through documentation reading
NAVIGATION	Learner navigates through platform modules
PROGRAMMING	Learner is programming, therefore attempting to solve the exercise
SUBMISSION_FAIL	Learner submits exercise but solution is invalid
SUBMISSION_SUCCESS	Learner submits exercise and passes
CODE_DEBUG	Learner debug their program
CODE_TEST	Learner experiment their program before submission

Table 2
Learning actions captured in the platform

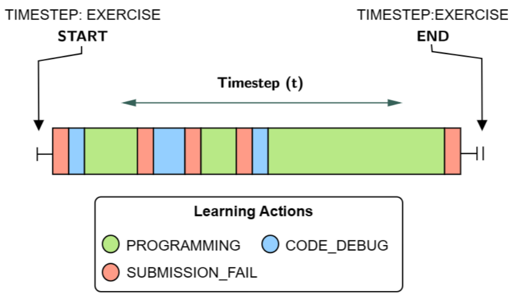

Figure 6: Action sequence of a learner

tics, and learning strategies. Subsequently, the protocol was further developed to incorporate a process-oriented approach for examining SRL strategies [27]. This protocol have been further illustrated in [28].
In our study, we investigate the protocol proposed by [26] to identify the learning strategy employed by learners throughout their learning sessions.
The captured behavioral data for this aspect includes diverse learner interactions within the Quick-PI platform during their learning phase. These interactions comprise timestamped navigational data and clickstream data, aggregated to form indicators that reflect the actions performed by learners. A total of 8 learning actions have been identified and are listed in table 2. For every timestep (i.e. at the end of each submitted exercise), a new learning sequence of learner actions is generated. For instance, figure 6 shows a learning sequence where learner undergoes several exercise submission failures.

Strategy Analysis The strategy analysis module constitutes the third component of our system. As mentioned earlier, timesteps correspond to the moments when learners submit their exercises, and these moments trigger the update of probabilities in the BKT model. At the end of each timestep, we examine specific time intervals where learners demonstrated improvement by observing the progression of their skill mastery levels. We also identify time intervals where learners did not progress, characterized by stagnant or significantly decreasing skill mastery levels. Based on this, we categorize the behaviors into two sets according to the evolution of skill mastery levels: one set (B^+) includes behavioral sequences that contributed to skill mastery level progression, while the other set (B^-) includes behavioral sequences that did not lead to skill mastery level improvement. Each of these sequences is linked to a learning context that encompasses the user who performed the sequence, the exercises involved, and the targeted skills. After extracting the B^+ and B^- sets, we utilize the α-miner algorithm to generate Petri nets. In these nets, nodes represent the action initiated by learners, while transitions indicate shifts between actions. Considering that each behavioral set is associated with a learning context, which can be related to the user, exercise, or skill, we generate two Petri nets per user, exercise and skill: one for cases of success, and one for cases of failure. Considering a given user for instance, their success and failure nets are compared to test the hypothesis that specific behaviors related to success have a positive impact on skill acquisition. The same analysis will be conducted for each exercise and skill. Consequently, we will be able to answer the following question: "Can the behaviors initiated by learners be characterized as a measure of overall success, either for a specific exercise or skill?" The next step in addressing our question involves the definition of comparison measures between positive and negative Petri nets. Based on this comparison, recommendations can then be generated.

4. Conclusion and perspectives

We introduced a system that consists of a two-layer measurement service responsible for gathering and analyzing data from online learning OLEs. The system includes a skill assessment module that enables instructors to understand the underlying factors contributing to learners' challenges in acquiring specific target skills.

This understanding is facilitated by the behavioral module, which provides valuable insights into learners' behaviors and strategies during their learning process. This service is complemented by a recommendation service that aims to provide support and guidance to learners.

To provide recommendations, we will suggest behaviors that have been successful for other learners and are beneficial for the specific skill or exercise being addressed. The recommendation system will primarily utilize collaborative filtering, which leverages the experiences of other users with similar profiles who have achieved a high level of skill mastery in a specific skill. Its objective is to support and assist learners facing challenges by suggesting behaviors similar to those of successful learners. Collaborative filtering generates recommendations by considering the relationships between users and items [29]. In our use-case, it can recommend that a learner adopt certain behaviors for a target skill based on the behaviors of similar learners who have successfully mastered that skill. The main question we ask here is: "What methods can be employed to assess the similarities among learners in order to offer them suitable behavioral recommendations ?"

Acknowledgments

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