

Learning Analytics for a Puzzle Game to Discover the Puzzle-Solving Tactics of Players

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Abstract. Games can be used as effective learning tools, proved to enhance players' performance in a wide variety of cognitive tasks. In this context, Learning Analytics (LA) can be used to improve game quality and to support the achievement of learning goals. In this paper, we investigate the use of LA in digital puzzle games, which are commonly used for educational purposes. We describe our approach to explore the way players learn game skills and solve problems in an open-source puzzle game called *Lix*. We performed an initial study with 15 participants, in which we applied Process Mining and cluster analysis in a three-step analysis approach. This approach can be used as a basis for recommending interventions so as to facilitate the puzzle-solving process of players.

Keywords: Learning Analytics · Educational Data Mining · Serious games · Puzzle games · Technology enhanced learning · Cluster analysis · Process mining

1 Introduction

There is a growing field of investigation on the application of games as technology-enhanced learning tools, used to complement or enhance traditional education [1]. Learning Analytics (LA) and Educational Data Mining (EDM) can be applied in combination with game analytics to improve game quality and to support the achievement of learning goals [2, 3]. Various methods of analytics in e-learning and game analytics help researchers make sense of data collected from user behavior, particularly through the use of modeling techniques [4] such as Process Mining (PM) [5, 6] and cluster analysis [7].

In this paper, we propose the use of LA methods in one specific class of games: digital puzzle games. This type of game is commonly used for educational purposes [8], possibly given its typical reliance on problem-solving and on logical and mathematical intelligence [9]. We describe our approach to explore

the way players learn game skills and solve problems in the game, automatically extracting players' tactics and creating reference models for further analysis of other players' behavior.

We developed and tested our proposed approach in a puzzle game that offered an adequate development and testing environment, given its constrained interaction, deterministic game engine, clear success criteria, and limited dependence on external knowledge. Our goal is to define an analytics approach that can be extended to different types of learning games. Additionally, we aim to use this approach in the future to support the implementation of automatic adaptive features for educational games, such as targeted interventions, appropriate feedback, and timely hints for the player/learner.

2 Game Description and Data Collection

We extended an existing open-source puzzle game called *Lix* [10], which is inspired by *Lemmings*, a 1991 game by DMA Design. In *Lix*, the objective is to guide a group of simple characters to a designated exit (Fig. 1).



Fig. 1. *Lix* game interface.

To collect game data, we altered the game following a Service-Oriented Architecture approach [11]. The game performs network calls to a web service that listens to relevant game events, and records them in a database. The events recorded are of two types: *game* traces and *meaningful variable* traces [3]. The *game* traces indicate timestamps of when the player started the game, started or restarted a puzzle, paused the game and returned to the menu. The *meaningful variable* traces consist of a simple record of a timestamp, a short code describing the skill assigned to a character, an internal identifier of the character to which the skill was assigned and an internal measure of game time.

We collected preliminary game data in a study with 15 adult participants. Participants were given a brief explanation of the study and of the goal of the game. No explanations about the game user interface were given. Participants were given a pre-test questionnaire to collect demographic data and gaming

experience. They were asked to play one intermediate level puzzle of the game as many times as they wanted. They were asked to think aloud for us to take notes on their reactions, tactics, persistence, etc. The data was used to develop our analytics approach, explained in the next section.

3 Analytics Approach

We developed a data-driven analytics approach that combines PM and cluster analysis to discover the way players learn skills, solve problems, and succeed in a specific puzzle game. In particular, our objective was to discover the clusters of the tactics applied by the players and identify a reference sequence for each cluster. We obtained the reference sequences by building the process models of tactics. These process models identify the most significant activities and transitions through PM. The reference sequences play a central role in validation of the results. By comparing a player’s process to previously established successful references, we aim to detect whether the player behaves closely to them.

Our analytics approach comprises of three main steps. A preliminary step is collecting the data from the game (‘A’ in Fig. 2), as explained in Sect. 2. The first step is to identify the tactics adopted in the game by players through cluster analysis (‘B’). In the second step, we aim to obtain the process models of the identified tactics through PM. These models represent the most significant components of the tactics which yield references that are central in validation of our results (‘C’). Finally, we validate the results of cluster analysis and PM by measuring how the elements of a tactic cluster converge to their reference (‘D’).

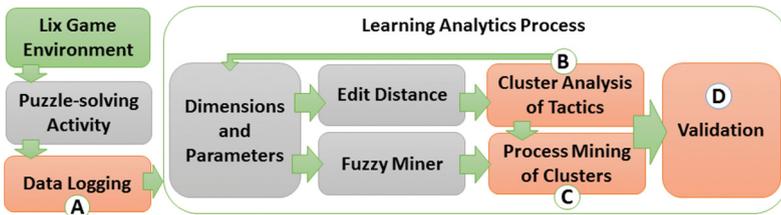


Fig. 2. Learning Analytics approach

4 Conclusions

In this study, we present a novel approach to apply LA methods on interaction data collected from an open-source puzzle game called *Lix*. This game is used in our study because of the value of puzzle games for educational purposes [8, 9], and, as such, developing ways to automatically analyze players’ problem-solving processes can be a valuable tool for educators and game designers alike.

We presented a three-step analytics approach that uses clustering, process mining, and validation to extract the puzzle-solving tactics from data, even without previous knowledge about the nature of the puzzle. The advantages of this approach can be explained as follows: we can identify previously unknown tactics, and not only the ones assumed by the game designer. We can avoid manually defining optimal strategies for every level of a game. Also, this approach can raise awareness of the educators about the learning progress by visualizing how close or far away from the optimal tactic any player is.

The results confirms that our LA approach was successful: two main successful tactics were discovered through cluster analysis, the process models of these tactics were successfully obtained, and yielded references for validation. Finally, the validation results indicate that we obtained meaningful clusters of different tactics, as the members of each cluster converged to their reference.

In the future, we will verify our approach by reporting the results and applying the same methodology to more data, in order to cross-validate the obtained process models. Additionally, we aim to extend our approach to other skill-based puzzle games, using it as input to automatically recognize the different stages of puzzle solving and to detect which players are most likely to quit the game. Finally, we plan to use this approach as the basis for recommending interventions that could allow the game to provide the player/learner with help on time, for instance by automatically comparing a given player's tactic to the successful tactics identified by this approach.

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