A MODEL TO PERSONALIZE EDUCATIONAL AND PLAYFUL ASPECTS IN SERIOUS GAMES

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Abstract

Game-based learning like serious games is growing more and more, but to be effective, these games have to be personalised according to the learning progress while keeping their playful aspect. Learning analytics techniques are usually used to collect data about a significant portion of learner activities and analyse learning progress. However, the current works on learning analytics do not include playful aspects. In another side, video games analytics techniques are restricted to entertainment to keep the player connected to the game as long as possible. So, the paper aims to propose to personalise the content to be learned in an educational and playful manner for players-learners within a same model. Three software agents compose this model, they interact with the learner through the game interface and use several data structures. The most important data is of course domain data, for instance a set of exercises that could be used by the game and the learning paths. Learner data concerns all the activities that are relevant to analyse performance, like success/failure, response time, etc., as well as psychological profile of player. Some pedagogical rules are also stored to validate learning progression, specially success conditions and importance level of a given content. The first step of the personalisation consists of selecting the better game mechanics to be used for each learner, such as social function or scores table. These game mechanics can be used within any game phase. They are added to the game or else the game evolves whilst respecting player preferences. Messages will need to be predefined to interact according to these mechanics. This is the task of the telemetry agent, it also collects learner activities to analyse their performance. The personalisation agent evaluates the better content to be proposed to learner according the results obtained by the telemetry agent. Finally, the visualisation agent offers a help to all the users – learner, teacher, or parent – of the serious game, it can show the impact of the performed work with a graph and makes predictions on the remaining work. The model was validated by creating a prototype that verified its functionality on a breakout game to learn French grammar rules. Thus, with this model, the game can offer the most relevant content for learner, show their progress and interact according to the game mechanics that best suits each learner. Although playful personalisation is limited, the model is flexible enough to adapt to any form of educational content and any field of study. Tests involving learners will be made more later and would allow a more advanced validation.

Keywords: Serious game, learning analytics, serious game analytics, learner model.

1 INTRODUCTION

Learning analytics include all the models that aim at using learner data, measured or deduced, to improve digital devices in educational context [2]. A category of models groups applications of business intelligence to academic data in order to predict failed students and was used for the first time by Goldstein and Katz [4]. Educational data mining integrates data mining techniques to help stakeholders of education, by using supervised or non-supervised machine learning [9]. Personalised adaptive learning concerns the capability to personalise the content to be learned in function predefined rules, that is applied mainly in intelligent tutorial systems. As defined by Psotka et al. [8], the purpose of these systems is to offer feedback and personalised indications to learners according their performance. It should be noted that a good model of learning analytics requires to identify the data to be measured, the targeted actor (learner, teacher, institution, etc.), the objective of the measure and the techniques to use [2].

The majority of learning analytics models can be applied on serious games, however these techniques are often concerned on educational aspect of software. But, the link between learner and player is not there. In serious games, two mechanics are one: the pedagogical mechanic and the gameplay mechanic. The main design objective of serious game is not entertainment but well optimization of content learning [6]. In addition, a serious game is different of gamification, which consists of the application of gameplay mechanic on software that is not a game [13]. For instance, an educational software can use medals and scores system to motivate its users. However, in this case, gamification
is only an alternative to increase the user retention. This distinction has to be made because the thinking is different and this is not the same context [6]. Games run real time, so a good serious game should react at the same time as the player is playing and not only at the end of the game in an asynchronous way. A game generates telemetries as a classic software, moreover, giving one to measure the learner’s interactions. But whether it is video game analytics that enables entertainment development or learning analytics, we have to found new models able to exploit fully learner-player traces [6].

Section 2 describes the model that we propose to include educational and playful aspects together, and how it can interact with the serious game. Section 3 shows the experiment conducted with a prototype of this model. We conclude on the perspectives to give to this project.

2 A MODEL OF SERIOUS GAME ANALYTICS

Serious games use one or several gameplay mechanics and exploit the pedagogical content recorded in a base to offer the learner-player an experiment of game. We based our model on this principle, as illustrated by Figure 1.

We inspired on research works on intelligent tutorial systems, that divide system tasks by several modules. In our model, we dissociate data and agents to provide some flexibility and a separation of functions. To realize an effective personalisation, we need three types of data: domain data, learner data and pedagogical rules. Domain data and pedagogical rules are recorded during the design phase and adjusted after the deployment. Learner data are collected during the gameplay by the telemetry agent. The agents measure data on the learner’s progression and make personalisation activities, i.e. adapting pedagogical content and gameplay mechanics. We also define relevant data and inference heuristics on these data. As we wanted a generic model, we did the least possible assumptions. Some models are specific to board games or adventure games and they are powerful for their type of games, but lacks flexibility. Our model does not aim at a specific type of games and can be integrated in an existing game.
2.1 Data structures

The purpose of this section is to present the data needed by our model and their roles and how they are represented. It is important to well understand the elements required to make the personalisation.

2.1.1 Domain data

These data correspond to the learning path and content, which is going be used by the serious game. The learning path is represented by a graph of topics, each one containing 1 to n items. This graph can have several depth levels depending on the complexity of the domain. So, the schedule is the sequence that the teacher wants to follow with the learners. The learning content is composed of sets of elements that the serious game uses as educational support, for instance exercises, questions, etc. These sets of elements are part of the leaf nodes of the graph.

2.1.2 Learner data

To record learner data, our model makes a copy of the graph of the domain data in order to note the learning evolution for each node during game sessions. The history of measured and inferred learning data is retained in learner data. By using telemetry technique, our model collects the learner’s activities when using the serious game, and obtains the logging of usage information. These data are different according the gameplay mechanics used. However, it is possible to enumerate the relevant data: success, failure, response time, timestamp of all data and obtained scores.

But these data allow only the personalisation the pedagogical content. To personalise the playful aspect, our model identifies the player profile based on psychological features. Indeed, the designers of games call psychologists to understand the player behaviour. The Hexad model [7] seems to be the most relevant for the moment, it is validated by Tondello et al. [11] for gamification. This model defines six categories of player profiles: Disruptor, Free Spirit, Achiever, Player, Socialiser, Philanthropist. Each category is related to possible motivation and gamification elements. To obtain the profile of a given learner, a questionnaire [12] can be used. Four questions by each category, with a simple vocabulary dedicated for persons that do not know the video game vocabulary, have to be scored out of seven (0: negative, 7: positive). The affinities of the learner for each category is obtained by adding the four scores. A research study [5] tried to obtain the player profile without the questionnaire on the basis instead on interaction elements in an open world game, but this yielded mixed results with few correlations between world elements and psychological aspects.

2.1.3 Pedagogical rules

These rules are all information that are going to prescribe the speed of the learner’s progression, specially the conditions of success and the importance degree of each learning topic or subtopic. These degrees enable to add weights on the edges of the graph domain. A success rule is attached to the leaf nodes as a condition for determining the learning level (ongoing to acquired). For instance, let us assume the success rule is “succeed three exercises in less than three minutes”. If the learner succeed three exercises in five minutes, the learning level for this step is near acquired.

2.2 Agents

Three agents – telemetry, personalisation, and visualisation – are defined to manage the data described in the previous section, and apply them to personalise educational and playful aspects.

2.2.1 Telemetry agent

The first step of personalisation is to select the good gameplay mechanics to be used with a given learner. These mechanics can be used in any phase of the game, they can be added to the game or evolve to respect the learner preferences. The learner data contains the scores of the questionnaire for the six profiles, so with six gameplay mechanics. But, developing six different mechanics is very expensive. To address this problem, we inspired the solution proposed by Lavoué et al. [3]. We compute an affinity matrix to determine the best mechanic to be used with the following equation:

\[ R = A \cdot F \]

with A the affinity matrix of a given learner obtained with the questionnaire, and F the matrix that contains the correlations (values from 0 to 1) between gameplay mechanics and Hexad profiles. Then, the telemetry agent chooses the mechanic that obtained the greatest value in the matrix R to interact
with the learner. Table 1 presents an example of this matrix R. The matrix A corresponds to the values obtained with the questionnaire. The matrix F has three game mechanics M1, M2 and M3, the values of preferences are from research works on psychology. The matrix R gives M2 as the best game mechanic to exploit.

Table 1. Example of game mechanics choice

<table>
<thead>
<tr>
<th>Matrix A</th>
<th>Philanthropist</th>
<th>Socialiser</th>
<th>Free Spirit</th>
<th>Achiever</th>
<th>Disruptor</th>
<th>Player</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3</td>
<td>14</td>
<td>7</td>
<td>20</td>
<td>12</td>
<td>25</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Matrix F</th>
<th>Philanthropist</th>
<th>Socialiser</th>
<th>Free Spirit</th>
<th>Achiever</th>
<th>Disruptor</th>
<th>Player</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>0.5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>M2</td>
<td>0</td>
<td>0.75</td>
<td>0</td>
<td>0.25</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>M3</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.25</td>
</tr>
</tbody>
</table>

| Matrix R | M1   | 5    | M2   | 15   | M3   | 13 |

The telemetry agent evaluates the performance of the learner while playing, by collecting relevant data. For that, the agent uses the pedagogical rules and determines the rating to be assigned to the corresponding leaf node. A rating scale is needed ranging from 0 (not yet seen topic) to X (achieved level). It is important to work out a compromise between granularity and complexity, because statistical calculations are going to be done by using this scale. More the number of values is great, more the number of probabilities increases. A good compromise would be to choose three intermediary values for this scale. Each value of the scale has to have an interval of scores in order to enable the transformation of a calculated value in a rating easier to manipulate and understand. These ratings assigned to the leaf nodes of the graph are going to be used to personalised the playful aspect of the serious game.

2.2.2 Personalisation agent

The role of the personalisation agent is to select the best pedagogical content according the learner data observed. At the first session of game, there are not any data on learner performance. If there is not any rules, the agent chooses randomly a topic to begin the learning session. After the learner data are collected, the agent can choose the new content to be proposed by using the ratings noted in the learner graph.

On a game time, the learner can pass on a limited number of content and topics. For more efficiency, the model proposes to sort the nodes of the graph to make a selection of the most relevant topics to be practised. As previously mentioned, the telemetry agent assigns a rating only to the leaf nodes of the graph. These ratings have to be propagated all over the graph. To calculate the new rating of a parent node, the model includes an equation that groups the ratings of all child nodes and adds the current rating of this parent node. This equation takes also into account the weights of the edges of the graph as well as the importance assigned to the rating of the parent node vs the importance of the ones of child nodes. These two values of importance is represented by a percentage (for instance 20% vs 80%). In the equation, the ratings have to be transformed in scores as described previously:

\[ Sp = Spc + Ip \times \sum_{i=0}^{n} \left( \frac{Sc_i \times Wc_i}{\sum_{j=0}^{n} Wc_j} \right) \]

with:
- \( Sp \): the new score of the parent node \( p \) to be calculated,
- \( Spc \): the score value of the current rating of the parent node \( p \),
- \( Ip \): the importance assigned to the score of the parent node \( p \),
- $Ic$: the importance assigned to the score of the child nodes,
- $Sci$: the score of the child node $i$,
- $Wci$: the weight of the edge linking the child node $i$ to the parent node $p$,
- $Wcj$: the weight of the edge linking the child node $j$ to the parent node $p$.

Finally, the new score $Sp$ has to be transformed with the rating scale to obtain the new rating of this node.

When all the ratings are updated, the personalisation agent ranks the topics to be studied for the next game sessions. A breadth-first search explores the graph to choose the future topic to be proposed to the learner, and in order that the content of the graph is studied in a consistent way. The topics with the lowest rating are going to be priority. So and according to research works on spaced repetition (for instance [10]), the topics on which the learner performs less are repeated and seen through time. However, it is important to provide some balance between repetition and discovery. The learner has not to stay on the same topic on a too long period of time. This flexibility can be defined as a pedagogical rule. The joint work of the classification according to ratings and the use of the pedagogical rules allows the personalisation agent to propose a learning session as close to the learner’s needs.

2.2.3 Visualisation agent

The role of the visualisation agent is to help all stakeholders that interact with the serious game. This agent can show the impact of work done by the learner and on the future work. For that, it displays the graph of data learner, which gives an overview of the done work, her/his strengths and weaknesses. The agent also shows how the graph would be after one or several learning sessions. The learner can choose a node as future work and the agent computes the impact on the ratings of the whole graph. The agent is going to create a Bayesian network from the domain and learner graphs and a probabilities table.

For a given topic, the agent computes the probabilities of all the possible ratings of each child node, i.e. by determining the score of the vector of the ratings of the child nodes with the same equation used by the telemetry agent. The probabilities of ratings are obtained by using intervals in the distribution, as the same way than the rating scale. This distribution has to be reproduced for all the combinations for the whole graph, to the agent can answer the learner’s questions. For instance, if the learner asks: “If I am working on the topic A and I obtain the rating 3, what is the probability that I know well the topic B (rating 4)?”, the visualisation agent generates the Bayesian network and indicates the most likely rating for the topic B.

Such predictions allow the learner to manage her/his work to improve her/himself. The learner, but also teacher or parent, can see the possible impact to study a specific topic. Specially, when the learner decides to work on this topic out of the serious game, it is important to show the possible impact on her/his work [1].

The set of these structures and agents makes up a coherent model that observes the learner and adapt the serious game according her/his progress. To validate the model, we built a prototype presented in the next section.

3 EXPERIMENT AND RESULTS

The model that we proposed to personalise the educational and playful aspects of a serious game needs to be validated. For now, the validation is limited to a verification of the functionality of the processes described by the model as explained in the next sections.

3.1 Presentation of the prototype developed

We built a prototype by using Neo4J for data structures, because this technology allows us to easily represent a graph in a language similar to the well-known SQL language. We also developed the agents with the Python language but another generalist language could be used. Figure 2 shows the technologies used and how the different parts interact.

This prototype was built independently any serious games, because unfortunately the development of the serious game that we could use was not completed. We then added a user interface to simulate
input/output data of a breakout game to learn French grammar. We were able to access a set of exercises generously to loan by a pedagogical expert. We verified if the model proposed well adapts the learning progress for each learner and in a same time adapts the game responses with the mechanics corresponding to this learner.

When running for the first time, the prototype asks to the learner to register and answer to the psychological questionnaire. A new graph based on the domain graph and related to this new learner is created. Two options are next proposed to the learner: practise or visualise. The practise option selects the best content adapted to the learner profile. The visualised option allows the learner to see her/his progress on the graph. The prototype collects the learner’s interactions during the practise sessions, analyses them and takes action if necessary, for instance on case of several consecutive failures, and according to the learner profile. At the end of a practise session, the graph is updated under the learning progress.

<table>
<thead>
<tr>
<th>Rating</th>
<th>Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>[ 0, 0.4 ]</td>
</tr>
<tr>
<td>2</td>
<td>[ 0.4, 0.6 ]</td>
</tr>
<tr>
<td>3</td>
<td>[ 0.6, 0.8 ]</td>
</tr>
<tr>
<td>4</td>
<td>[ 0.8, 1 ]</td>
</tr>
</tbody>
</table>

The prototype uses a scale of five ratings (Table 1) and three game mechanics to interact with the learner. These game mechanics are: chat session (social function), high scores table, and interaction with fantasy agents. We think these three mechanics cover a significant portion of the six Hexad profiles. The prediction of ratings by the personalisation agent is done by a Bayesian network as explained. We exploited the Python Library for Probabilistic Graphical Models. This library is easy to pick up for programmers and allowed us to reproduce the structure proposed for representing the
domain data. At each node of this structure, we could input the probabilities tables. The learner can asks the probabilities distribution for a given node knowing the ratings of the child nodes.

3.2 Results

We validated the functionality of the proposed model by implementing this prototype and operating with a real pedagogical content intended to a serious game. The agents and data structures work in tandem and allow to personalise the choice of the exercises to be presented to the learner according the learning progress. The main advantage of this analytics model is that it can be adapted to any pedagogical content. The structure of domain data is generic and flexible unlike the structures proposed generally in literature that are specific to an application domain.

Regarding the playful aspect, the proposed model allows only to guide the game on the way of interacting with the learner by choosing the most relevant game mechanics for a given learner. We think it should be interesting to include the type of game to this personalisation. There are different types of games, like shooting game, brick breaker, memory game, etc., that are more or less motivating according the learners’ preferences.

We plan to validate the model when the development of the serious game will be completed and other games should be planned to compose a platform designed to young people. An experiment should be conducted with a control group and a test group. The results should allow the validation of the proposed model beyond the functionality verification that we conducted.

4 CONCLUSIONS

Research works on learning analytics and gamification give relevant results to personalise the user’s experience and increase her/his engagement. However, the link between learner and player seems to be missing. We decided to propose a personalisation model as close as possible to the learner-player’s challenges. This model proposes data structures and heuristics that enable to personalise the pedagogical content and game mechanics. We verified the functionality of this model by developing a prototype with a set of exercises on French grammar. The results obtained by tests performed show that the pedagogical content and game interactions are personalised take the learning progress and the psychological profile into account, but the validation with learners remains to be done.

Future works are necessary to take the personalisation of the playful aspect further to increase the learner's engagement. For instance, one knows that for a competitive person, it is relevant to display a high scores table. But, this does not explain if racing game is more engaging than shooting game.

To conclude and as defined by Chatti et al. [2], when we presented our model of serious game analytics, we described the four elements to be considered to a good model. The first element is data to be measured, i.e. the learning progress compared to the domain data and the psychological profile of player. The second element corresponds to the aimed actor and in our model this is the learner, but teacher and parent might be interested. The third element concerns the purpose of the model, which corresponds to the personalisation of both educational aspect and playful aspect. Finally, to describe the fourth element, we explained the different techniques that we applied, these techniques are based on the principles used in intelligent tutoring systems and relied on the notion of spaced repetition and psychological profiles of players.

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REFERENCES


