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Detecting students' perception style by using games

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ABSTRACT

Knowing students' learning styles allows us to improve their experience in an educational environment. Particularly, the perception style is one of the most important dimensions of the learning styles since it describes the way students perceive the world as well as the kind of learning content they prefer. Several approaches to detect students' perception style according to Felder's model have been proposed. However, these approaches exhibit several limitations that make their implementation difficult. Thus, we propose a novel approach to detect the perception style of a student by analyzing his/her interaction with games, namely puzzle games. To carry out this detection, we track how students play a puzzle game and extract information about this interaction. Then, we train a Naive Bayes Classifier to infer the students' perception style by using the information extracted. We have evaluated our proposed approach with 47 Computer Engineering students. Experimental results showed that the perception style was successfully predicted through the use of games, with an accuracy of 85%. Finally, we conclude that games are a promising environment where the students' perception style can be detected.

1. Introduction

Students learn in many ways (Felder & Silverman, 1988); they acquire and process information on the basis of their learning styles. A learning style model classifies students according to where they fit into a number of scales related to the ways in which they receive and process information.

Identification of students' learning styles makes it possible to (a) personalize the way the information is presented to them (Alkhuraiji, Cheetham, & Bamasak, 2011; Li, Lau, & Dharmendran, 2010), (b) improve group performance (Alfonseca, Carro, Martín, Ortigosa, & Paredes, 2006), or (c) assist them during Web-based courses (Schiaffino, Garcia, & Amandi, 2008). A number of learning style models and frameworks have been proposed (Jung, 1971; Kolb, 1984; Myers & McCaulley, 1985). One of them is Felder's model, proposed by Felder and Silverman (Felder & Brent, 2005; Felder & Silverman, 1988). This model has been widely studied and applied, especially in engineering education. It is also most appropriate for Web-based courses and in research related to learning styles in advanced learning technologies (Carver, Howard, & Lane, 1999).

Felder's model comprises four dimensions: perception, input, processing and understanding, each defining two opposite learning styles. In this work, we focus on the detection of the students' perception learning style (perception style for short) from Felder's model (Felder & Silverman, 1988). The dimension of perception distinguishes between sensitive and intuitive students. Sensitive students like facts, data and experimentation and are patient with detail. In contrast, intuitive students prefer principles and theories and welcome complications. In summary, this dimension responds to the question: what type of information does the student preferably perceive: sensory (external) sights, sounds, physical sensations, or intuitive (internal) possibilities, insights, hunches?

We focus on the perception style for being the most important learning style dimension according to the literature (Felder, Felder, & Dietz, 2002; McCaulley, 1990). Particularly, this style is important because it is correlated with career preferences and aptitudes, management styles, learning styles, and various behavioral tendencies (Felder & Silverman, 1988). Thus, identification of students' perception style (a) allows professors to improve their teaching style, for instance, they can strike a balance between concrete information (facts, data, real or hypothetical experiments and their results) and abstract concepts (principles, theories, mathematical models) (Coffield, Moseley,

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Hall, & Ecclestone, 2004; Felder, 2010); (b) allows students to understand how their learning process works, thus, they may become more comfortable with this process, less critical of themselves for having it, and more positive about education in general (Felder & Silverman, 1988); and (c) allows educational environments to personalize the reading material and adapt course content to students' perception style (Alkhuraiji et al., 2011; Carver et al., 1999; Cha, Kim, Lee, & Yoon, 2006, pp. 513–524; Kolekar, Sanjeevi, & Bormane, 2010; Popescu, Badica, & Moraret, 2010).

Several approaches to detect the students' learning styles and, in particular, the perception style of the Felder's model, have been proposed. In general, these approaches track how the student interacts in an educational environment (Web-based courses, online courses, etc.) and extract some information about this interaction (Crockett, Latham, Mclean, Bandar, & O'Shea, 2011; García, Amandi, Schiaffino, & Campo, 2007; Graf & Kinshuk, 2010; Graf, Kinshuk, & Liu, 2009; Hj Ahmad & Shamsuddin, 2010; Özpolat & Akar, 2009; Villaverde, Godoy, & Amandi, 2006) such as type of reading material preferred (abstract or concrete), exam results, kind of participation in chats and forums, and time devoted to exam revision. Thus, these approaches categorize students on the basis of their perception style by considering the information extracted mentioned above. The automatic detection of learning styles has several advantages over traditional approaches (questionnaires). Since information is gathered from the students' interaction with the educational system, no supplementary amount of work - such as answering a questionnaire or providing explicit feedback about learning preferences – is required from the students. In addition, an automatic approach gathers information from a time span rather than from a specific point in time. Therefore, changes in the students' learning characteristics can be followed over time.

Although these approaches exhibit a certain degree of precision for detecting students' perception style, we observe some limitations in their application. Firstly, in order to address the different characteristics of the perception style, educational environments need to present a large amount of information available in multiple formats. For example, the content presented should balance concrete information, such as facts and data, with abstract concepts and theory. Moreover, educational environments should provide a large number of exercises so that students' may perform repetitive tasks and at the same time promote innovative thinking. As we will explain in Section 3.1, puzzle games incorporate, from their inception, most aspects of the perception style by supporting students with different preferences.

Secondly, students are not usually motivated to use educational environments because the information presented disregards their learning styles from the beginning of the interaction. Since personalization of the educational environment is a key factor to motivate students and improve their learning experience (Ley & Young, 2001; Papanikolaou, Grigoriadou, Kornilakis, & Magoulas, 2003; Popescu et al., 2010; Schiaffino et al., 2008; Verpoorten, Glahn, Kravcik, Ternier, & Specht, 2009), we consider it essential to identify students' perception style before they start to interact with the educational environment. In this context, games can help to solve this problem, avoiding students' initial frustration.

Finally, previous works have demonstrated that students' inexperience at work with Web-based courses modifies their behavior and makes learning style detection difficult (García et al., 2007). In this respect, we think that students are less likely to exhibit changes in behavior while playing games since games do not require previous experience: students learn to play the game by playing it (Prensky, 2001).

For this reason, the objective of this work is to present a new environment where students' perception style can be detected. We propose a novel approach to detect a student's perception style by analyzing how he/she interacts with games, namely puzzle games. We claim that the educational environment-based approaches present a number of limitations, which can be solved by using a game-based approach.

In the last years, games have been more and more used in education (Shih, Squire, & Lau, 2010; Sung, 2009). From an educational standpoint, games are engaging and adaptable to almost any subject. They can be particularly useful for teaching cause-and-effect relationships, and the lessons learned from games often tend to stay with students because of the interactive nature of the learning experience (Consortium, 2005). Also, because playing is not perceived as *working*, students may spend more time playing a game than they would reading related material or solving problems at the end of the chapter (Annetta, Minogue, Holmes, & Cheng, 2009). Furthermore, games improve students' motivation, since games are very popular among students nowadays (Prensky, 2003).

To carry out the detection of the perception style from games, we track how students play a puzzle game and extract information about this interaction (results obtained, time elapsed, total times played, level reached). Then, we define and train a Naive Bayes Classifier, which models different aspects of the student–game interaction in order for us to infer students' perception style. Notice that both the game- and educational environment-based approaches can coexist. Our approach focuses on the early detection of the perception style, that is, we focus on the detection when the student's perception style is completely unknown. In fact, it is in this early stage where the existing approaches show some limitations. However, after detecting the perception style, the educational environment can be personalized immediately, and the student's behavior can be monitored for style updating in case some change is detected.

The experimental results show that a high precision in the detection of the students' perception style can be obtained from little information. The experiments were carried out with 47 Computer Engineering students who played a puzzle game called *Equilibrium*. We obtained a precision of 85.1% in the detection of the students' perception style, which is higher than several approaches for perception style detection that track students in an educational environment.

The rest of the article is organized as follows. Section 2 introduces the background topics in the area of learning styles detection and also in games and education. Section 3 presents the approach to detect students' perception style by using games. In Section 4, the results extracted from the experiments are presented. Finally, in Section 5, we state our conclusions and suggest future work.

2. Background

In this section, we review two streams of research related to the learning style detection approach proposed in this paper. First, we present some current directions and related works in the area of learning style detection. Then, we analyze the benefits of using games in education, and we present a number of related works that support this idea.

2.1. Learning styles detection

Students acquire and process information in different ways depending on their learning styles. There are many learning style definitions, but one widely accepted by leading theorists is the one given in Keefe (1979, pp. 1–17) which states that: "[a learning style is] the composite of characteristic cognitive, affective, and psychological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment". Learning styles are described in learning style models, which are defined by theorists in the fields of psychology and cognitive science. A learning style model classifies students according to where they fit on a number of scales belonging to the ways in which they receive and process information.

Although learning styles have been critically analyzed by some authors (Coffield et al., 2004; Pashler, McDaniel, Rohrer, & Bjork, 2008), these styles have been widely applied in educational technologies obtaining promising results (Alfonseca et al., 2006; García et al., 2007; Graf et al., 2009; Latham, Crockett, McLean, & Edmonds, 2012). It is worth noticing that the main criticism was directed to how the learning styles are applied once they have been manually or automatically obtained. For example, it is still controversial how to adapt learning content to learning styles in adaptive educational systems (Brusilovsky & Millán, 2007).

In this work, we use the model proposed by Felder and Silverman for engineering students (Felder & Silverman, 1988). The dimensions of the learning styles in this model are: perception (sensitive-intuitive), input (visual-verbal), processing (active-reflective), and understanding (sequential-global). Particularly, the perception dimension is considered as the most important learning style dimension (Felder et al., 2002; McCaulley, 1990). Next, we list a formal description of all dimensions, and all learning styles of Felder's model:

- *Perception*: this dimension relates to the type of information a student prefers to perceive. The learning styles of this dimension are:
  - *Sensitive*: sensors like facts, data, and experimentation. They like solving problems by standard methods and dislike "surprises". They are patient with detail but do not like complications. Sensors are good at memorizing facts and are careful but may be slow.
  - *Intuitive*: intuitors prefer principles and theories. They like innovation and dislike repetition. They are bored by detail and welcome complications. Intuitors are good at grasping new concepts and are quick but may be careless.
- *Processing*: this dimension describes the way perceived information is converted into knowledge. The learning styles of this dimension are:
  - *Active*: active students do not learn much in situations that require them to be passive. They work well in groups and tend to be experimentalists.
  - *Reflective*: reflective students do not learn much in situations that provide no opportunity to think about the information being presented. They work better by themselves or with at most one other person and tend to be theoreticians.
- *Input*: this dimension considers the way in which students prefer to receive external information. The learning styles of this dimension are:
  - *Visual*: visual students remember best what they see: pictures, diagrams, flow charts, time lines, films, demonstrations.
  - *Verbal*: verbal students remember much of what they hear and more of what they hear and then say.
- *Understanding*: this dimension describes the way students progress towards understanding. The learning styles of this dimension are:
  - *Sequential*: sequential students follow linear reasoning processes when solving problems and can work with material when they understand it partially or superficially.
  - *Global*: global students make intuitive leaps and may be unable to explain how they came up with solutions. They may also have great difficulty understanding partial information.

The traditional way by which Felder's learning styles are obtained is to apply the ILS questionnaire (Felder & Soloman, 1997). However, in recent work, several approaches for students' learning style detection have been proposed. In general, these approaches automatize this detection by tracking how the students interact with an educational environment. To do this in an automatic way, several machine learning techniques have been applied: neural networks (Kolekar et al., 2010; Villaverde et al., 2006), Bayesian networks (García et al., 2007; García, Schiaffino, & Amandi, 2008), decision trees (Cha et al., 2006, pp. 513–524; Crockett et al., 2011; Özpolat & Akar, 2009), genetic algorithms (Chang, Kao, Chu, & Chiu, 2009; Yannibelli, Godoy, & Amandi, 2006), and rule-based methods (Graf et al., 2009; Graf & Kinshuk, 2010). Most of these machine learning techniques are feed with the students' actions and, once the algorithm has been trained, it allows the educational environment to classify new students according to their learning styles. In this context, the general structure of a neural network consists of an input layer with one neuron for each student's action tracked, a number of hidden layers, and an output layer with one neuron for each learning style to infer. Similarly, the structure of a Bayesian network consists of leaves nodes for every student's action tracked and a root node for the learning styles. In turn, decision trees consist of leaves representing the learning styles to be inferred, and branches representing the actions tracked that lead to those learning styles. Regarding genetic algorithms, a group of chromosomes are defined where each gen is associated with a student's action, and new populations of chromosomes are generated that best describe the students' learning styles. In addition, rule-based methods calculate the number of matching hints between student's actions and the learning style model descriptions to predict learning styles preferences.

However, regardless of the Machine Learning technique applied, all these works need to process a large amount of information extracted from the interaction between the students and the educational environment. Graf et al. (Graf et al., 2009), analyze 27 behavioral patterns obtained from 6 system features. These features include: content objects, outlines, examples, self-assessment test, exercises, and discussion forums. In particular, 13 behavioral patterns related to the perception dimension were identified, such as: performance on questions about facts as well as question about theories and concepts; number of self-assessment test and exercises; traditional or new ways in which problems are solved; time students take for self-assessment tests; number of revisions performed before submitting a test or exercise. Graf et al. reported using Moodle, an open source educational environment, with 75 Computer Science students. They developed a tool for automatically identifying learning styles named DeLeS, which allows teachers to specify which data persisted by the educational environment are related to the analyzed patterns mentioned above. The evaluation method consisted of a comparison between the results obtained through their approach and Felder's ILS questionnaire. The results showed a precision of 77% in the detection of the perception style.

In Hj Ahmad and Shamsuddin (2010), the information of interaction is stored as attributes in a student profile. In all, 20 attributes and values (much/few) are stored. These attributes include: number of exercises visited, number of viewing/reading forum, access to example, exam revision, and PowerPoint slide access. The authors used Moodle as the educational environment in a Data Structure course. However, the data were not collected from the educational environment, but were simulated. In all, 1184 simulated records were analyzed with different mining techniques such as Bayesian Networks, Decision Trees and Association Rules. From the results, the authors concluded that Decision Tree algorithms have better precision than the other analyzed mining techniques. A serious weakness of this work is that the information analyzed was not collected through the educational environment. Instead, the data were simulated and no information is given about which technique was used for the generation.

Similarly, in Özpolat and Akar (2009) the authors applied Decision Trees to detect student's learning styles according to Felder's model. Their approach consisted in an examination of the queries submitted by students in a web search engine such as Google. Keywords of the queries were mapped to Felder's learning styles. For instance, words such as *theoretically* and *in principal* were mapped to intuitive learning style; whereas words like *practically*, *experimental data* and *real world* were mapped to sensitive learning style. The experimentation was carried out with 30 graduate students, and the results were compared with Felder's ILS questionnaire. The precision of the proposed approach for the perception style was 73%. One major limitation of this work is that the learned model always predicted the same result (neutral) for all the students. In other words, the model was over fitted to the data, and it is very likely that it will not be able to successfully predict new sensitive or intuitive students.

Finally, in García et al. (2007) the authors used an e-learning system named SAVER. Their proposed approach was evaluated with 27 Computer Science students during an Artificial Intelligence course. The information of the interaction used to build the user profile included 10 actions carried out by the students in the educational environment, where each action is represented by a variable such as reading material, access to examples, answer changes, exam delivery time, and forum usage. A Bayesian network was used as the mining technique to analyze the information gathered. At the end of the experiments, the proposed approach obtained a precision of 77% in the detection of the perception style, the same result as Graf et al. (2009).

In summary, although these approaches exhibit certain precision to detect students' perception style, some limitations can be found. These limitations take place especially in the early detection of the students' perception style, that is, in the detection when the student's perception style is completely unknown. The limitations are as follows:

- Time and effort required by the students and teachers: students must interact substantially and during a long period of time with the educational environment so that the information relevant to the detection is generated. For this reason, teachers must provide a large amount of information available in multiple formats in order to address the different characteristics of the perception style.
- Non-personalized start: if we use the educational environment as a means to detect the student's perception style, it is not possible, at least during the first course the student takes, to personalize the environment from the start. This fact can lead to lack of motivation and a frustrating learning experience (Ley & Young, 2001; Papanikolaou et al., 2003; Popescu et al., 2010; Verpoorten et al., 2009).
- Students inexperience: previous works have demonstrated that students tend to change their behavior when working with Web-based courses because of lack of experience, which makes the learning style harder to detect (García et al., 2007).

Finally, it is worth noting that approaches using games for the detection of learning styles have not been proposed in the current literature.

2.2. Games and education

Although the digital game proposed to detect the perception style is not necessarily an educational game, we present in this section some points of interest that relate games and education. In particular, in this section we remark how games improve student's motivation and how they support various learning styles.

Several advantages of using games in education have been described. Games attract and encourage students to apply subject matters to the real world (Shih et al., 2010), by presenting abstract concepts in the context of familiar real-world applications (Sung, 2009). Moreover, games are very popular among students nowadays (Prensky, 2003). Consequently, students' motivation is improved when they play games (Prensky, 2003). In the context of automatic detection of learning styles, we claim that the student will be more motivated to play a game (Prensky, 2007, p. 144) than to use an educational system that has not been personalized yet.

In the current literature, we can find many works that relate games and education. In Hamalainen, Manninen, Jarvela, and Hakkinen (2006), multiplayer online games are used as a platform to collaborative learning. Moreover, in Becker (2005), the authors examine how modern games support learning styles in their design and gameplay. In this work, it is remarked that one of the qualities of the games that makes them distinct from other learning technologies is that they are highly interactive. In the same way, Castell and Jenson (2006) describes and analyzes the ways in which video games capture and hold the attention of the students.

In Gros (2007), video games are defined as useful instruments for learning specific strategies and for acquiring knowledge. Similarly, in Rosas et al. (2003) the goal of the study was to evaluate the effects of the introduction of educational video games into the classroom, on learning, motivation, and classroom dynamics. In accordance with that work, games have several characteristics that make them attractive in education such as clear goals, appropriate level of complexity, high speed, incorporated instructions and holding power. These characteristics can be helpful to solve some of the limitations of current approaches used to detect learning styles. For instance, instructions and clear goals allow players to understand the game while playing, with no need of previous experience. Additionally, students are soon engaged and motivated since games introduce problems hard to master, promote high speed interactions and continually challenge students' abilities.

In short, digital games have proved useful in education. For this reason, and taking into account the limitations of the current approaches described in the previous section, we propose using digital games as an alternative environment in which the students' learning styles can be detected.

3. Detecting perception style by using games

Taking into account the limitations of the approaches described above and the advantages of using games in education, we present a novel approach to detect the student's perception style by tracking how he/she interacts with a puzzle game. To do this, we build a profile to model the behavior the student exhibits when he/she plays the game. Then, we train a Naive Bayes Classifier (NBC) that represents the students' perception style taking into account the information stored in the profiles. Once the NBC is trained, we can infer the perception style of new students.

3.1. Building the student profile from a puzzle game

To build the student profile, we track how he/she plays a puzzle game. We decided on a puzzle game because this kind of games tends to exercise some characteristics related to perception (Becker, 2005). Specifically, puzzle games introduce abstract concepts, raise complex problems, and require players to think out of the box to solve them. The puzzle game used in this work was *Equilibrium*. Fig. 1 shows a snapshot of the game. Equilibrium is a game in which some figures (balloons and weights) should be placed on a balance so that the torque of the forces associated with these figures is zero. To reach this goal, the player must conform to the following rules:

- There cannot be more than one figure on a balance's cell.
- The figure of the man weighs 1 kg.
- Each cell of the balance measures 1 m.
- The torque is given by multiplying the weight of the figure by the distance from the balance's center to the cell in which the figure is placed.

For example, in Fig. 1, we can see the following information:

- The force applied by the balloon is 20 kg/m (5 kg*4 m) counterclockwise.
- The force applied by the figure of the man is 1 kg/m (1 kg * 1 m) clockwise.
- The total torque is 20 kg/m^{-1} kg/m $=$ 19 kg/m counterclockwise.

In this game, players start playing at the initial level (Level 1) and move on to the next level when the proposed solution is correct. Intuitively, complexity of level i is greater than level $i-1$. The game has 10 levels, and if the proposed solution is wrong, the player must start at the initial level again. Moreover, the player has 120 s by level to determine a solution. To sum up, Equilibrium has some characteristics strongly related to perception. Firstly, it introduces abstract concepts, namely force and torque. Secondly, it presents problems hard to solve. Finally, it requires students to think in innovative ways to find a solution.

In order to build the student profile, the following information is extracted from the interaction between the students and the game:

- Result: represents the results obtained by the student in each level played.
- Total: is the number of times that the student plays a level in the game.
- Time: represents the average time elapsed to finish a level.
- Level: is the maximum level reached by the student.

This information is stored in a database that the game updates every time the student completes a level. Also, it is worth noticing that these variables are calculated by taking into account all the participations of the student in the game.

The reasons for choosing these variables are as follows: we expect that students who think in innovative ways will be able to reach the last levels of the game (Level) in less time (Time) and will get better results (Result) than students who prefer to solve problems using standard methods. Furthermore, we predict that students who prefer to solve complex problems and feel comfortable with abstract concepts will play more and longer (Total) than students who do not like complications and prefer concrete information.

To summarize, with this game we want to evaluate whether the students respond well to abstract concepts, like complex problems, and are able to solve them creatively. Considering intuitive and sensitive students features, we expect that intuitive players will perform better than sensitive players in this game. In fact, the traditional approaches of automatic detection of learning style apply this idea to select the variables that will be part of the student model. For example, several works (García et al., 2007; Graf et al., 2009; Hj Ahmad & Shamsuddin,

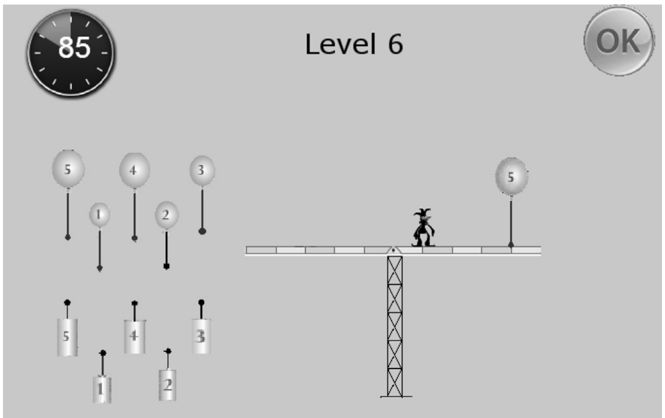

Fig. 1. Snapshot of equilibrium.

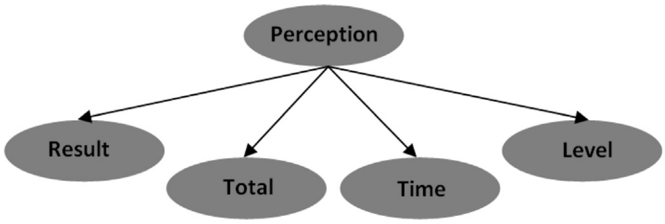

Fig. 2. Naive Bayes model to classify the student's perception style.

2010) track if the student revises the exam after finishing it, because it is known that sensitive students tend to do this task, but intuitive ones do not.

3.2. *Modeling students' perception style with a Naive Bayes Classifier*

Our approach uses a Naive Bayes Classifier (NBC) to model the students' perception style. An NBC is a compact, expressive representation of uncertain relationships among parameters in a domain. An NBC is modeled as a directed acyclic graph that represents a probability distribution, where nodes represent random variables and arcs represent probabilistic correlation or dependency between variables (Charniak, 1991). The strengths of the dependencies are given by probability values. For each node, a probability table specifies the probability of each possible state of the node given each possible combination of states of its parent. These tables are known as conditional probability tables (CPT). Table for root node (or independent node) just contain unconditional probabilities. The Naive Bayes model is a popular model due to its high representational and computational simplicity while maintaining an impressive performance on classification tasks, despite its strong assumption of conditionally independence of the attributes given the class (Kjærulff & Madsen, 2008). The two steps needed to build a student model based on Bayesian paradigm are to define (a) the structure of the network (qualitative model) and (b) the network's parameters (quantitative model) (Brusilovsky & Millán, 2007).

In our approach, random variables represent the student's perception style and the information gathered from the game. In short, we assume that it is possible to detect whether the student is sensitive (likes facts, data and experimentation), intuitive (prefers principles and theories) or neutral (does not have a defined preference), by tracking his/her average results (Result), the number of times that he/she plays the game (Total), the time played (Time) and the maximum level reached (Level). Fig. 2 shows the NBC model which consist of 5 nodes: Perception, Result, Total, Time and Level. The Perception node has 3 possible states according to the result of the ILS questionnaire: Intuitive (from −11 to −5), Neutral (from −3 to 3) and Sensitive (from 5 to 11). The discretization of these states was suggested by Felder and Spurlin in Felder and Spurlin (2005). The Result node has 3 possible states, which are calculated as the total levels won minus the total levels lost: Lost (less than 0), Intermediate (between 0 and 18) and Won (19 or more). This variable was discretized using uniform width intervals. The Total node has 2 possible states: Few (between 0 and 5 times) and Many (6 times or more). The Time node has 2 possible states: Low (between 0 and 32 s) and High (more than 32 s). The limit of the intervals for nodes Total and Time were calculated from their mean value. Finally, the Level node has 3 possible states according to the complexity of the game: Low (level 4 or lower), Medium (between level 5 and level 7) and High (level 8 or higher). The states of the nodes Result, Total, Time and Level were set based on our knowledge of the game internals and expertise.

Once the NBC structure is defined, we must assign the probability distribution to each node in the graph in order to indicate the strength of the relationships previously modeled. To do this, we used the NBC module of the Weka[1] tool. This module allows us to determine the probability values of the CPTs from the experimental data tracked. Finally, the students profile is feed into the NBC in order to infer the perception style of the students.

Once we classify each student, the inferred perception style can be used to update the student profile in an educational environment that uses a machine learning algorithm for modeling the perception style, such as García et al. (2007, 2008); Alkhuraiji et al. (2011) and Hj Ahmad and Shamsuddin (2010). Thus, the educational environment can take advantage of the perception style learned through games and adapt the learning material accordingly.

4. Experimental results

4.1. *Method*

We evaluated our proposed approach with 63 junior Computing Science students in the context of three different courses, namely: Exploratory Programming, Artificial Intelligence and Software Engineering. In one class, the students were asked to play any of 10 games published on-line.[2] One of these games was Equilibrium. Data were gathered for all the published games. The students were not given any further information about the objectives of the experiment, nor were forced to use any particular game. In a word, students were free to choose which game to play and whether to play it or not. Before start playing, students were asked to log in and complete the ILS questionnaire.

The experiment took two weeks. At the end of this period, 47 of 63 students had played Equilibrium or at least had opened the game one time without playing, and had completed the ILS (Index of Learning Styles) questionnaire. Second column of Table 1 shows students' perception distribution according to the ILS instrument. As we can see, the proportion of perception styles was: 12 intuitive students (26%), 17 neutral students (36%) and 18 sensitive students (38%). In all, the students played 449 levels with an average played time of 3.43 min. Notice that the fact that a student decides not to play the game is captured in the dataset. This is the case of students 25, 28, 35, 37, 42 and 44,

[1] http://www.cs.waikato.ac.nz/ml/weka/.
[2] http://www.games2d.com.ar/.

Table 1
Population of students.

Student	Perception (ILS)	Result	Total	Time	Level	Perception detected
1	Intuitive	Lost	Few	High	Low	Neutral*
2	Intuitive	Won	Many	Low	High	Intuitive
3	Intuitive	Won	Many	Low	High	Intuitive
4	Intuitive	Tie	Many	Low	High	Intuitive
5	Intuitive	Lost	Few	High	Low	Neutral*
6	Intuitive	Lost	Few	High	Low	Neutral*
7	Intuitive	Lost	Few	High	Low	Neutral*
8	Intuitive	Won	Many	Low	High	Intuitive
9	Intuitive	Tie	Many	Low	High	Intuitive
10	Intuitive	Tie	Many	Low	High	Intuitive
11	Intuitive	Lost	Few	High	Low	Neutral*
12	Intuitive	Tie	Many	Low	High	Intuitive
13	Neutral	Lost	Few	High	Low	Neutral
14	Neutral	Lost	Few	High	Low	Neutral
15	Neutral	Lost	Few	High	Low	Neutral
16	Neutral	Won	Many	Low	High	Intuitive*
17	Neutral	Lost	Many	High	Low	Neutral
18	Neutral	Lost	Few	High	Low	Neutral
19	Neutral	Tie	Few	Low	Low	Sensitive*
20	Neutral	Tie	Many	Low	Medium	Sensitive*
21	Neutral	Won	Many	Low	High	Intuitive*
22	Neutral	Lost	Few	High	Low	Neutral
23	Neutral	Tie	Many	Low	Medium	Sensitive*
24	Neutral	Tie	Many	Low	Medium	Sensitive*
25	Neutral	Lost	Few	Low	Low	Sensitive*
26	Neutral	Lost	Few	High	Low	Neutral
27	Neutral	Lost	Few	High	Low	Neutral
28	Neutral	Lost	Few	Low	Low	Sensitive*
29	Neutral	Lost	Few	High	Low	Neutral
30	Sensitive	Tie	Many	Low	Medium	Sensitive
31	Sensitive	Lost	Few	Low	Low	Sensitive
32	Sensitive	Lost	Few	High	Low	Neutral*
33	Sensitive	Tie	Many	Low	Medium	Sensitive
34	Sensitive	Tie	Few	Low	Low	Sensitive
35	Sensitive	Lost	Few	Low	Low	Sensitive
36	Sensitive	Lost	Few	Low	Low	Sensitive
37	Sensitive	Lost	Few	Low	Low	Sensitive
38	Sensitive	Lost	Few	Low	Low	Sensitive
39	Sensitive	Lost	Few	Low	Low	Sensitive
40	Sensitive	Tie	Few	Low	Low	Sensitive
41	Sensitive	Tie	Many	Low	Medium	Sensitive
42	Sensitive	Lost	Few	Low	Low	Sensitive
43	Sensitive	Lost	Few	Low	Low	Sensitive
44	Sensitive	Lost	Few	Low	Low	Sensitive
45	Sensitive	Lost	Few	Low	Low	Sensitive
46	Sensitive	Tie	Many	Low	Medium	Sensitive
47	Sensitive	Tie	Many	Low	Medium	Sensitive

Misclassified students are marked with an asterisk (*).

who entered the game and immediately closed it. Thus, in these cases, the values of the variables *Result* is *Lost* and *Level* is *Low*, since the student did not pass the first level; *Total* is *Few*, since the student did not play any level; and *Time* is *Low*, since the student left immediately the game after had entered.

4.2. Procedure

Data collected through the game were persisted and used to build the students profiles. Once we built the profiles, we trained and tested the NBC described in Section 3.2. To perform the NBC training and testing, we used the Naive Bayes module of the Weka tool. We used leave-one-out cross validation for assessing the results.

For measuring the precision of the proposed approach, the following formula proposed by García et al. (2007) was applied:

$$Precision = \frac{\sum_{i=1}^{n} Sim(LS_{BN}, LS_{ILS})}{n}, \tag{1}$$

where n is the number of students. In the equation (1), the function *Sim* is 1 when the learning style obtained with the NBC and ILS are equal, 0 if they are opposite, and 0.5 if one is neutral and the other an extreme value.

4.3. Results

Our approach obtained a precision of 85.1% in the detection of the students' perception style. We compared this value with the precision of two trivial baselines. These baselines were a classifier that always predicts the majority class (Sensitive) and a classifier that always predicts the class with the lowest error (Neutral). The first baseline obtained a precision of 56.4%, and the second one, 68.1%. Both baselines showed a precision lower than the precision obtained by our approach.

In Table 1, we compared the perception style detected (column *Perception detected*) and the ILS questionnaire result of the same student (column *Perception ILS*). We analyzed the cases in which the perception style detected by our approach did not match the ILS result (marked with an asterisk). In the case of the intuitive students classified as neutral (students 1, 5, 6, 7 and 11), we observe that the five students played few times. We claim that these students tried to solve the puzzle (the time played was high), but when they failed, they lost their interest in the game. Then, the interaction registered was insufficient to predict their perception style. As regards the neutral students who were misclassified as intuitives or sensitives, we think that one of the reasons for this misclassification is that neutral students are the most difficult to predict, because they do not have a strong perception preference. In fact, Felder and Spurlin (Felder & Spurlin, 2005) stated that neutral students would be expected to shift between categories readily rather than consistently exhibit behavior associated with a single category. On the other hand, only one sensitive student was misclassified.

In summary, a high precision in the students' perception style detection was obtained from little information. Furthermore, the interaction required by students to obtain this information took little time and previous experience was not necessary to reach this precision.

5. Conclusion and future work

In this paper, we have presented a novel approach to detect students' perception style, which is one of the main dimensions of Felder's model. Our approach detects the perception style of a student by analyzing how he/she interacts with games, namely puzzle games. Experimental results have demonstrated that it is possible to obtain a high precision in the detection of the students' perception style by using games. The extent of the study means that, whilst the findings are not generalizable, they do offer insights into the detection of learning styles using games.

As the main contribution, games have been presented as a promising environment in which students' perception style can be detected. In the context of learning style detection, we conclude that games have several advantages over educational environments. Using games, students do not need to have previous experience as in educational environments. Also, the information needed to predict the perception style using games is less than using educational environments. In addition, it is worth noticing that the time elapsed to gather the information needed to detect the perception style by using games is considerably littler than by using educational environments. Moreover, as several works have proved (Prensky, 2003; Rosas et al., 2003; Shih et al., 2010), students' motivation is improved since games are very popular among students.

As a limitation, our approach is sensitive to students who play few times, due to the fact that we have little information about them. Also, it might misclassify neutral students as they do not have a strong perception preference. For this reason, future work will concentrate on the analysis of other games and other variables that can influence the learning style detection, especially in such cases. For example, we will focus on detecting the reasons for which the students do not play the game or when the students start to change their behavior due to the fact that they have learned how to play. Finally, we wish to extend our approach to detect other dimensions of the Felder's model by using other types of games and by adding new variables to the student profiles.

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