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Exploring the use of online video games to detect personality dichotomies

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Abstract

Purpose

Personality trait detection is a problem that has been gaining much attention in the computer science field recently. By leveraging users' personality knowledge software applications are able to adapt their behaviour accordingly. To detect personality traits automatically users must substantially interact with software applications to gather enough information that describe their behaviour. For addressing this limitation, we explore the use of online video games as an alternative approach to detect personality dichotomies.

Design/methodology/approach

We analyse the use of several online video games that exhibit features related with Myers-Briggs Sensitive-Intuitive personality dichotomy. Then, we build a user profile that describes users' behaviour when interacting with online video games. Finally, we identify users' personality by analysing their profile with different classification algorithms.

Findings

The results show that games that obtained better results in the personality dichotomy detection exhibit features that better match with the Sensitive-Intuitive dichotomy preferences. Moreover, the results show that the classification algorithms should satisfactorily deal with unbalanced datasets, since it is natural that the frequencies of the dichotomies types are unbalanced. In addition, in the context of personality trait detection, online video games posses several advantages over other type of software applications. By using games, users do not need to have previous experience, since they learn how to play during gameplay. Furthermore, the information and time needed to predict the Sensitive-Intuitive dichotomy using games is little.

Originality/value

This study shows that online video games are a promising environment in which the users' personality dichotomies can be detected.

Keywords: Online Video Games, Myers-Briggs Type Indicator, User Profiles, Classification.

1. Introduction

The Myers-Briggs Type Indicator (MBTI) is a well-known psychological theory of human personality (Tieger and Barron-Tieger, 1993; Briggs Myers and McCaulley, 1992; Gulliver and Ghinea, 2010). In the MBTI model, four axes are defined to explain how humans perceive their environment, how they interact with others and how they make decisions based on these traits. Particularly, we focus on detecting the Sensing/Intuition (S/N) dichotomy. The S/N dichotomy reflects our preference for taking in knowledge through our five senses or through the filter of intuition (Briggs Myers and McCaulley, 1992). In this paper, we propose to detect certain personality traits (dichotomies) of the MBTI model building a user profile by using information extracted from the interaction between the user and online video games.

User profiles are vital in many areas in which it is essential to obtain knowledge about users of software applications automatically (Schiaffino and Amandi, 2009). A profile is a description of a user containing the most important or interesting facts about him or her. These facts can represent interests, goals, skills, behaviour, interaction preference, or individual characteristics. To build a profile, the user is observed while using a software application. Then, the observed information is stored in the profile. In this context, to gather the information needed for the profile, users must substantially interact with the software application. However, sometimes it is not possible to guide the users to interact thoroughly with the software application in order to gather enough information to build their profiles. Moreover, previous works have demonstrated that the inexperience of the users at working with a software application modifies their behaviour and makes the profile building difficult (García et al., 2007).

To avoid these limitations, we present an alternative environment in which the personality traits can be detected. We propose an approach to detect the personality traits of a user by analysing how he/she interacts with online video games.

In recent years, games have been used more and more frequently in diverse areas, such as education (Song, 2008; Turner, 2014), training (Rosser et al., 2007), health (Kato, 2010) and management (Tan et al., 2010), among others. Games attract and encourage users to apply subject matters to the real world (Shih et al., 2010), presenting abstract concepts in the context of familiar real-world applications (Sung, 2009). Furthermore, games improve the users' motivation, due to the fact that people nowadays are very familiarised with games (Prensky, 2001).

In this work, we focus on the detection of the users' S/N dichotomy of the Myers-Briggs model (Briggs Myers and McCaulley, 1992). This dichotomy reflects two different modes of perceiving: sensitive (S) and intuitive (N). Sensitive people prefer perception of the observable directly through the senses. In contrast, intuitive people prefer to go beyond the information given by the senses and look for meanings and potentialities. Thus, sensitive is reflected in practical and realistic characteristics whereas intuitive is the preference of creative and imaginative professions.

Since several works have shown that there is a relation between video games behaviour and personality traits (Worth and Book, 2015; Becker, 2005), to carry out this detection, we observe how the users play online games and store the information about this interaction in a user profile. Then, we define and train a classifier, which models different aspects of the interaction with the game, to infer the user's S/N dichotomy.

The experimental results showed that a high precision in the user's S/N dichotomy detection can be obtained from little information. The experiments were carried out with 82 Computer Engineering students who played 9 online video games. Moreover, we explored and compared the use of different classification algorithms, namely: Naive Bayes Classifier, Bayesian Networks, Decision Trees (J48 algorithm) and Support Vector Machines. We obtained the highest accuracy in the detection of the S/N dichotomy by using a Naive Bayes Classifier with a value of 76.74%.

The rest of the article is organised as follows. Section 2 introduces some concepts about the MBTI model and presents current work in the personality trait detection. Section 2.3 describes the approach to detect users' S/N dichotomy using online video games and presents the research questions that guided our work. In Section 3, the results extracted from the experiments are presented and the research questions are answered. Finally, in Section 5, we state our conclusions and suggest future work.

2. Literature Review

2.1. Myers-Briggs Type Indicator

The Myers-Briggs Type Indicator (MBTI) is a well-known psychological theory of human personality (Tieger and Barron-Tieger, 1993; Briggs Myers and McCaulley, 1992; Gulliver and Ghinea, 2010). It is based on the theory of Jung (Jung, 1971) that human behaviour is predictable and classifiable. Although MBTI view for measuring personality types has been questioned (McCrae and Costa, 1989; Barbuto Jr, 1997), many articles have proved MBTI validity and reliability (Carlyn, 1977; Tzeng et al., 1984; Thompson and Borrello, 1986; Capraro and Capraro, 2002). Myers and Briggs made the theory of psychological types described by Jung understandable and useful in people's lives. Nowadays, the MBTI is one of the most widely used assessments in the world to understand individual differences and uncover effective ways to work and interact with others. Basically, the MBTI sorts each person into one of 16 personality types based on a self-reported preference for one of each four dichotomous characteristics: (a) Extraversion/Introversion (E/I), (b) Sensing/Intuition (S/N), (c) Thinking/Feeling (T/F), and (d) Judging/Perceiving (J/P). The E/I dichotomy refers to our preferred energy source, either in the exterior world of action and interaction or in the inner world of ideas and concepts. The S/N dichotomy reflects our preference for taking in knowledge through our five senses or through the filter of intuition. The T/F dichotomy reflects our preference to make decision, objectively and impersonally or based on the individual's value system and the impact that decision will have on others. Finally, the J/P dichotomy refers to our orientation to the outer world, either a more structured and decided lifestyle, or a more flexible and adaptable one.

2.2. Personality Trait Detection

We can find some related work in the field of personality trait detection, especially in the area of learning style detection. In the past few years, several approaches for students' learning style detection have been proposed. In general, these approaches automatise this detection by observing how the students interact with an educational environment. To do this in an automatic way, several Machine Learning techniques have been applied, such as Neuronal Networks (Villaverde et al., 2006; Kolekar et al., 2010), Bayesian Networks (García et al., 2007, 2008), Decision Trees (Cha et al., 2006; Crockett et al., 2011; Özpolat and Akar, 2009), Association Rules (Chen et al., 2007), statistical analysis (Graf et al., 2009; Graf and Kinshuk, 2010), among others. Notice that these works focused on learning styles, but not on personality dichotomies detection.

One of the main features of video games is that many of them already embody sound learning theories in their designs even if the incorporation of those theories was not deliberate (Becker, 2007). Particularly, Myers-Briggs Sensitive-Intuitive personality dichotomy is well supported in video games (Becker, 2005; Feldman et al., 2014), since most video games require players to learn facts and understand processes (sensitive) but also understand concepts and synthesize relationships (intuitive). These intrinsic characteristics of video games make it feasible to associate video games features with personality traits.

Furthermore, several studies have reported positive results of employing video games to detect a wide range of students' characteristics such as learning preferences, personality traits and skills. For example, (Triberti et al., 2015) examined the relationship between moral positioning of video gamers (i.e. choosing evil/good game characters) and some personality traits such as empathy, extraversion, and agreeableness. The authors found that less empathic and extravert players are more likely to play as evil characters. In addition, (Teng, 2008) examined three personality features of online video game players: openness, conscientiousness, and extraversion. Results showed that online video games players obtained higher scores in personality traits that lead to personal success and self-efficacy. Also, in (Buelow et al., 2015), the authors analysed the effects of playing video game on decision making, problem solving, and risk-taking cognitive skills; founding that active video game play can improve cognition. Similarly, in (Boctor, 2013; Fraser et al., 2014), the authors investigated the relationship between learning and gaming; reporting positive effects.

There is not one standard classification of online video games, but they can be described by their genre (action, adventure, fighting, role-playing, simulations sports, and strategy) and the number of players (single player, multiplayer, and massively multiplayer) (Gros, 2007). In our work, we used single player action games to detect personality dichotomies. As we explain in the next section, we consider single player action games the most appropriate to infer personality traits.

Taking into account the literature review, we observe that had not been analysed the use of video games as medium to detect a user's dichotomies. For this reason, we based our research on the following research questions:

RQ1: Which classification algorithm is more suitable to detect a user's personality trait?

RQ2: Which online video games are more suitable to detect a user's personality trait?

RQ3: Is it possible to detect a user's personality trait by analysing how he/she interacts with online video games?

2.3. An approach to detect personality dichotomies

As mentioned above, one of the four dichotomies of the Myers-Briggs model is the Sensing/Intuition (S/N) dichotomy. According to this dichotomy, sensitive people pay attention to physical reality, what they see, hear, touch, taste, and smell; intuitive people pay the most attention to impressions or the meaning and patterns of the information they get. Sensitive people like to see the practical use of things and learn best when they see how to use what they are learning. Intuitive people like to work with symbols or abstract theories, even if they do not know how they will use them. In other words, this dichotomy responds to the question: Do you pay more attention to information that comes in through your five senses (Sensing), or do you pay more attention to the patterns and possibilities that you see in the information you receive (Intuition)? For this reason, knowing this dichotomy allows us to personalise software applications. Traditionally personalization is based on taking into account various characteristics of the users (Brusilovsky, 2001). These characteristics include goals, knowledge, user interests and user's individual traits, among others. User's individual traits represent user features that together define a user as an individual: personality factors (e.g. sensitive/intuitive), cognitive factors, and learning styles (Brusilovsky, 2001; Brusilovsky and Peylo, 2003). Thus, we can assist a manager in a project planning application by adapting the information presented in a report to her/his S/N dichotomy. For example, if a problem is detected, the system can present an abstract chart representing the problem (Intuition) or a descriptive detail (Sensing).

In this paper, we present a novel approach to detect the users' S/N dichotomy by observing their gameplay. To do this, we build a profile to model the behaviour that the users exhibit when they play such games. Then, we train a classifier taking into account the information stored in the profiles. Once the classifier is trained, we can infer the S/N dichotomy of new users.

2.3.1. Building the user profile from a online video game

To build the user profile, we observe the user's behaviour when playing online video game. In this paper, we explore the use of different online video games to build the user profile. These games were selected because they exhibit features that match with the preference described for each dichotomy such as preferences about abstract concepts or repetitive tasks, among others. For this reason, we explore four categories of online games:

Puzzle: this category of game presents complex problems that cannot be solved in a predetermined way. Instead, players have to use their innovation to figure out how to solve them. In this context, we consider that puzzle games evidence players' innovation and their preferences for solving problems analysing complex patterns.

Memory: this type of game exercises players' memory capacity. Memory digital games present repetitive problems that require players to pay attention to details that have to be memorized. Therefore, we consider that memory games allow us to observe players' memorization skills and their preference for solving problems using their senses (sight).

Concrete: concrete games are video games that can be solved by using standard methods such as arithmetic, algebraic or logic operations. This type of game is characterized by being repetitive since the problems presented are solved by applying the same method over and over again. We think that concrete games allow us to evaluate players' preferences for solving repetitive problems through practice, and their capacity to apply standard methods to find out a solution.

Physics/Maths: this category includes video games that aim to teach abstract concepts and interpret symbols. In this context, we consider that physics/maths games allow us to observe players' preference for abstract theory, and their capacity for working with symbols.

According to these categories, the video games are the following:

- Equilibrium: is an abstract game to teach students abstract concepts such as force and torque. The game's goal is to put balloons and weights in a scale, so that the torque of the forces associated with them is zero. Category: physics/maths.
- Four Knights: is a puzzle game that consists of a 3x3 board with 2 knights at the top of it and 2 knights at the bottom. The game's goal is to invert the position of the knights, so that the ones that are at the top are placed at the bottom and vice versa. To move the knights, the player must honour the chess movement rules for the chess piece. Category: puzzle.
- Frogs: is a puzzle game that consists of a 7 cell row with 3 frogs on the left and 3 frogs on the right. The game's goal is to invert the position of the two groups of frogs, so that the ones that are on the left are placed on the right and vice versa. A frog can perform two types of jumps: 1) the frog can jump to an ahead free cell,

and 2) the frog can jump over another frog located ahead of a free cell. Category: puzzle.

- LightBot: is a puzzle game to teach students basic computer science concepts such as commands, functions and function calls. The game's goal is to move a robot from the initial to the target position by selecting the corresponding commands. There are 7 types of commands to move the robot: 1) move ahead, 2) turn clockwise, 3) turn counterclockwise, 4) jump, 5) highlight the current cell, 6) call the commands in function one, and 7) call the commands in function two. Category: puzzle.
- Memo Board: is a memory game where the player has to remember 12 cards shown in a 3x4 board. When the game starts the player watches the cards for a short period of time. Then, the cards are turn around and the game challenges the player to select the card from the board that matches a random card selected by the game. Category: memory.
- Simon Says: is a memory game that consists of four colored buttons. A round in the game consists of lighting up one or more buttons in a random order, after which the player must reproduce that order by pressing the buttons. Category: memory.
- Fractions: is a mathematical game whose goal is to group a sequence of numbers represented in different ways such as decimal, fractions and percentage. Category: physics/maths.
- Geometry: is a mathematical game that simulates the international television show "Who wants to be millionaire?". In this game, the player has to choose the correct answer from 4 possible responses to geometry questions. If the player is not sure about the answer he/she can use three different types of help. The first type is named "ask the audience" where the player is shown with the percentages of what the audience believe the correct answer to be. The second type is named "phone a friend", where the player is shown with the believed answer of a friend. Finally, the last type of help is called "50/50", where 2 incorrect answers are eliminated. Category: physics/maths.
- Hangman: is a traditional game. In this game, the player has to guess a requested word from a synonym. The player has 7 chances to choose incorrect letters until the hangman image is completely drawn. Category: concrete.

In each game, users start playing an initial level (Level 1) and move on to the next level when the proposed solution is correct. Intuitively, the complexity of level *i* is greater than level *i-1*. Each game has 10 levels, and if the proposed solution is wrong, the user must start at the initial level again. Moreover, the player has 120 seconds on each level to determine a solution.

Once described the games, we need to specify the information that will be stored in the user profile that best describes the S/N dichotomy. Since games represent different characteristics that can be preferred (or not) by a user according to his/her S/N dichotomy, we decide to include in the user profile information on how much the user played and the results he/she obtained during the games. Then, we collect the following information to build the user profile:

- Number of levels won: this field counts the number of levels won by a player in a game.
- Number of levels lost: this field counts the number of levels lost by a player in a game.
- Average time played by game's level: this field represents the average time played by a player in a game's level.
- Maximum level reached: this field represents the maximum level completed by a player in a game.
- Number of times played: this field counts the number of times a player played a game.

2.3.2. Building a classifier for users' S/N dichotomy detection

To detect the S/N dichotomy, we compare different classification algorithms in order to obtain the best accuracy. A classification algorithm finds a function or model that describes and distinguishes data classes or concepts, in order to use the model to predict the class of objects whose class label is unknown (Han et al., 2006). The classification algorithms explored in this work are the following:

- Bayesian Networks (*BN*): A BN is a compact, expressive representation of uncertain relationships among parameters in a domain. A BN is 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 parents. These tables are known as conditional probability tables. Tables for root nodes (or independent nodes) just contain unconditional probabilities.
- Naive Bayes Classifier (*NBC*): A NBC is a Bayesian classifier that simplifies learning by assuming that features (observable variables) are independent given the class (inferred variable). Despite this unrealistic assumption, the resulting classifier is remarkably successful in practice, often competing with much more sophisticated techniques (Rish, 2001).

- Decision Trees: is a method for approximating discrete-valued target functions, in which the learned function is represented by a decision tree. Learned trees can also be represented as sets of if-then rules to improve human readability. Decision trees classify instances by sorting them down the tree from the root to some leaf node, which provides the classification of the instance (Mitchell, 1997).
- Support Vector Machines (*SVM*): a SVM classifier blends linear modelling and instance-based learning. Support vector machines select a small number of critical boundary instances called support vectors from each class and build a linear discriminant function that separates them as widely as possible (Witten and Frank, 2005).

We assume that it is possible to detect whether a user is sensitive (pays more attention to information that comes in through the senses) or intuitive (pays more attention to the patterns and possibilities of the received data) by observing the information stored in the user profile. Thus, classifier inputs are: S/N dichotomy (the dichotomy extracted from the MBTI), Result (number of levels won minus number of levels lost), Total (number of times played), Time (average time played by game's level) and Level (maximum level reached). The S/N dichotomy variable has 2 possible states: Intuitive or Sensitive. In contrast, Result, Total, Time and Level variables are numeric. To build each classifier, we used the classification module of the Weka[1] tool.

3. Methodology

We have evaluated our proposed approach with 82 Computer Engineering students, 19 women and 63 men, aged 22-26, who had previously completed the MBTI instrument[2]. We asked users to play the video games enumerated in Section 2.3.1 that were published online[3]. In total, the users played 11,034 levels. The proportion of S/N dichotomies was: 58 sensitive (70.73 %) and 24 intuitive users (29.27 %). It is worth noticing that this proportion is within the estimated frequencies of the dichotomy types reported by Lawrence et al. (2001). In that work, the estimated frequencies for the S/N dichotomy are 66-74% (S) and 26-34% (N). Table 1 shows the number of players who played each game and the distribution of S/N dichotomy.

The users played the video games during 2 weeks. It is important to notice that the students were not forced to play any particular game. In other words, students were free to

[1] http://www.cs.waikato.ac.nz/ml/weka/
[2] http://www.myersbriggs.org/
[3] http://game2d-unicen.rhcloud.com/

Game	Total	Sensitive		Intuitive	
		Total	%	Total	%
Equilibrium	55	36	65.45%	19	34.55%
Four Knights	52	38	73.08%	14	26.92%
Frogs	32	22	68.75%	10	31.25%
LightBot	32	25	78.13%	7	21.88%
Memo Board	43	34	79.07%	9	20.93%
Simon Says	25	22	88.00%	3	12.00%
Fractions	31	23	74.19%	8	25.81%
Geometry	40	30	75.00%	10	25.00%
Hangman	32	23	71.88%	9	28.13%

Table 1: Number of players by game and S/N dichotomy proportion.

choose which games they wanted to play with. After the playing period, the information gathered was stored in the user profiles. Then, we built a dataset for each game in which we stored classifier inputs according with the information stored in the profiles. Finally, we build four classifiers for each dataset using the techniques described in Section 2.3.2. To build each classifier, we used the classification module of the Weka tool.

We evaluated the proposed model by applying leave-one-out-cross-validation (Han et al., 2006; Korb and Nicholson, 2010). Thus, the dataset was splitted in N subsets of size 1. During the training phase, each classifier was trained with the information of N - 1 subsets. Then, during the testing phase, the classifier was evaluated by using the remaining subset. To carry out this evaluation, we computed the following well-known metrics: precision (*pr*, Equation 1), recall (*rec*, Equation 2), and accuracy (*acc*, Equation 3).

$$precision = \frac{correctly\,classified\,positives}{total\,predicted\,as\,positive} \tag{1}$$

$$recall = \frac{correctly\,classified\,positives}{total\,positives} \tag{2}$$

$$accuracy = \frac{total\,correctly\,classified}{total\ instances} \tag{3}$$

4. Results

Table 2 shows the values of the metrics Precision, Recall and Accuracy obtained according with the game used to build the user profile and the classification algorithm applied to build the classifier. For each game and each classifier, we computed the weighted average (*WA*) precision, precision by class (*int* and *sen* according with Intuitive and Sensitive dichotomies), accuracy (*acc*), weighted average recall, and recall by class (*int* and *sen*). Below, we analyse the results from the point of view of the research questions.

4.1. Which classification algorithm is more suitable to detect a user's personality trait? (RQ1)

Comparing the results by classification algorithm, Table 2 shows that the best results were obtained when we built a Naive Bayes Classifier (NBC). Particularly, Bayesian Network (BN) and Support Vector Machine (SVM) were extremely sensitive to the unbalanced datasets (in this case, the number of sensitive users was higher than intuitive ones in most of the games). In consequence, the precision and recall obtained for intuitive users was 0.00, due to the fact that all instances were classified as sensitive. Something similar happened with the J48 algorithm, although to a lesser degree. Notice that the number of intuitive people is usually smaller than sensitive ones (Felder and Silverman, 1988). However, still with Equilibrium, in which the percentage of intuitive users was higher, NBC obtained the best results. In contrast, J48 obtained better results with Four Knights. These results show that the Naive Bayes Classifier was the most accurate algorithm for the personality trait detection, and was not affected by the unbalanced dataset.

Games			Equilibrium	Four Knights	Frogs	LightBot	Memo Board	Simon Says	Fractions	Geometry	Hangman
NBC	Pr	WA	0.76	0.71	0.68	0.72	0.73	0.76	0.71	0.59	0.56
		Int	0.75	0.42	0.41	0.40	0.40	0.00	0.33	0.17	0.20
		Sen	0.77	0.82	0.80	0.82	0.82	0.86	0.85	0.74	0.70
	Acc %		76.36	67.31	59.38	75.00	76.74	76.00	54.84	65.00	62.50
	Rec	WA	0.76	0.67	0.59	0.75	0.77	0.76	0.55	0.65	0.63
		Int	0.47	0.57	0.70	0.29	0.22	0.00	0.75	0.10	0.11
		Sen	0.92	0.71	0.55	0.88	0.91	0.86	0.48	0.83	0.83
BN	Pr	WA	0.42	0.53	0.47	0.61	0.63	0.77	0.55	0.56	0.51
		Int	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		Sen	0.64	0.73	0.69	0.78	0.79	0.88	0.74	0.75	0.71
	Acc %		61.81	73.08	68.75	78.13	79.07	88.00	74.19	75.00	68.75
	Rec	WA	0.62	0.73	0.69	0.78	0.79	0.88	0.74	0.75	0.69
		Int	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		Sen	0.94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96
J48	Pr	WA	0.55	0.77	0.47	0.61	0.63	0.77	0.66	0.56	0.68
		Int	0.35	0.53	0.00	0.00	0.00	0.00	0.33	0.00	0.50
		Sen	0.66	0.86	0.69	0.77	0.79	0.88	0.77	0.75	0.75
	Acc %		56.36	75.00	68.75	75.00	79.07	84.00	64.52	75.00	71.88
	Rec	WA	0.56	0.75	0.69	0.75	0.79	0.84	0.65	0.75	0.72
		Int	0.32	0.64	0.00	0.00	0.00	0.00	0.38	0.00	0.22
		Sen	0.69	0.79	1.00	0.96	1.00	0.96	0.74	1.00	0.91
SVM	Pr	WA	0.70	0.53	0.47	0.61	0.63	0.77	0.55	0.56	0.52
		Int	0.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		Sen	0.72	0.73	0.69	0.78	0.79	0.88	0.74	0.75	0.72
	Acc %		70.91	73.08	68.75	78.13	79.07	84.00	74.19	75.00	71.88
	Rec	WA	0.71	0.73	0.69	0.78	0.79	0.84	0.74	0.75	0.72
		Int	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		Sen	0.92	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00

NBC: Naive Bayes Classifier. BN: Bayesian Network. SVM: Support Vector Machine. Pr: Precision. Rec: Recall. Acc: Accuracy. WA: Weighted Average.

Table 2: Results by game and classification algorithm.

4.2. Which online video games are more suitable to detect a user's personality trait? (RQ2)

Comparing the results by game, the best results were obtained with Equilibrium (76.36% of accuracy with NBC), Four Knights (75%, with J48), LightBot (75%, with

NBC) and Memo Board (76.74%, with NBC). Particularly, Equilibrium and Four Knights datasets have the highest number of total users (55 and 52) and intuitive users (19 and 14). However, with Equilibrium we obtained a better and more balanced precision by dichotomy (intuitive, 0.75; and sensitive, 0.77) than Four Knights (0.53 and 0.86). In contrast, LightBot dataset has a smaller number of instances (32) and is more unbalanced (21.88% of the instances correspond to intuitive dichotomy). Similarly, Memo Board is unbalanced (20.93% of the instances correspond to intuitive dichotomy), but the NBC classifier obtained an accuracy of 76.74%. In this way, online video games with features that better match with the S/N dichotomy preferences are more suitable to the personality trait detection.

4.3. *Is it possible to detect a user's personality trait by analysing how he/she interacts with online video games? (RQ3)*

As we commented above, the best results were obtained with (a) online video games with features that match with the S/N dichotomy preferences, and (b) classification algorithms that are not affected by unbalanced dataset. This is the case of Equilibrium and NBC (76.36% of accuracy) and Memo Board and NBC (76.74% of accuracy). In contrast, the worst results were obtained with SVM and BN. This can be observed in the recall values of intuitive and sensitive class (0 and 1, respectively). This occurred because the classifier only predicted sensitive class.

5. Discussion

In this work, we have presented an approach to detect the users' S/N dichotomy, which is a key dichotomy of the Myers-Briggs model, by using online video games. Our approach detects the S/N dichotomy of a user by analysing how he/she interacts with online video games. To validate our approach, we have analysed different video games and classification algorithms.

Experimental results have demonstrated that it is possible to obtain a high precision in this detection by using some video games whose features match with the preferences of each dichotomy. Thus, puzzle and physics games, whose characteristics strongly match with intuitive users' preferences, and memory games, whose characteristics match with sensitive users' preferences, showed the better results. For example, users that play Equilibrium need to deal with abstract concepts, which is clearly a preference of intuitive users. Similarly, Four Knights and LightBot are puzzle games that require that users solve a complex problem that cannot be solved in a repetitive way. This feature also matches with the preferences of intuitive users. On the other hand, Memo Board is a pure memory game in which the visual sense is very important. Therefore, it matches with the preferences of sensitive users.

Moreover, experimental results have shown that the Naive Bayes classifier performed better than Bayesian Networks, Decision Trees (J48), and Support Vector Machine classifiers; satisfactorily dealing with the unbalanced number of users in each dichotomy. The results showed that dealing with unbalanced datasets is a key feature that the classification algorithms should exhibit, since it is natural that the frequencies of the dichotomies types are unbalanced (Lawrence and Martin, 2001). Another factor that influenced the performance of the classifier was the amount of users that played each game. Intuitively, if this amount increases, the classification algorithm has more information to train the model. For these reason, we did not probably obtain good results with some of the games (i.e. Fractions and Simon Says).

As the main contribution, games have been presented as a promising environment in which the users' dichotomies can be detected. In the context of personality trait detection, we conclude that video games have several advantages over the manuscript test and other type of software application. By using games, users do not need to have previous experience as in other software applications. Furthermore, the information needed to predict the S/N dichotomy using games is little. In addition, it is worth noticing that the time elapsed to gather the information needed to detect the S/N dichotomy is considerably littler than using the manuscript test and previous experience was not necessary to reach this high precision. The extent of the study means that, whilst the findings are not generalisable, they do offer insights into the detection of Myers-Briggs dichotomies using games.

This study has two limitations. First, online video games are extremely varied. However, we focused on simple games instead of complex games (e.g. massively multiplayer online role-playing games). For this reason, future work will concentrate on the analysis of other kind of games. Second, we analysed variables that are common to all games (e.g. number of levels won). However, there are other particular variables of each game that could be analysed. For example, we could detect the patterns used by the users to put balloons and weights in the scale, and then we could observe if some patterns are related to the S/N dichotomy. Consequently, future research will focus on the analysis of particular characteristics of the games as well as other variables that can influence the detection of the dichotomies. For example, we will also focus on detecting the reasons for which the users do not play the game or when the users start to change their behaviours due to the fact that they have learnt how to play. Finally, we wish to extend our approach to detect other dichotomies of the Myers-Briggs model.

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