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SciVerse ScienceDirect

Procedia - Social and Behavioral Sciences 47 (2012) 943 – 949

Procedia
Social and Behavioral Sciences

CY-ICER 2012

The factors effecting students' PC game types preferences

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Abstract

The aim of this study is to investigate the attitude of students' pc game and theme preferences (*action, strategy, sports etc.).* The data were collected from 722 students at the age of 11-14 in Istanbul and was analyzed using by Weka 3.7.0 that is a popular suite of machine learning software. At this point some classifiers and learning algorithms were used for determining which students play which types of games. The study reveals that there is a relation between students PC game types preferences and their demographic characteristics and the independent variables. The software predicts the game types truly in acceptable ratio.
Keywords: Machine learning, learning algorithms, computer games, game themes

1. Introduction

Computer games are perceived as one of the most popular leisure time activities that have gained an important role in the most of students' lives (Durkin & Barber, 2002; Can & Cagiltay, 2006). Young people in this century have spent years immersed in video games . Games are not only used in entertainment sector, but they also used in business sector to train staff, military sector to simulation, and health sector (Kirriemuir, 2002).

In the 1990s, the entertainment industry shifted focus from an individual player environment to virtual worlds and collaborative environments (Pellegrino&Scott,2004). By using advanced technologies and techniques in IT field, deep-rooted changes done in game sector. Kwak et al quoted from Wolf that video games are a multibillion dollar industry, generating more revenue than the film industry (Kwak et al, 2010)

In the literature, there are many studies showing the benefits of computer games for children and adults in terms of providing motivation, developing skills and encouraging collaboration. Games also have many benefits on children development. Critical thinking and scenario-based learning are very important elements of children's mental abilities. Games, on the other hand, are extremely good at engaging and motivating learners (Pellegrino & Scott, 2004; Westwood & Griffiths, 2010). Improving learning effectiveness has always been a constant challenge in software education and training. One of the primary tasks educators face is to motivate learners to perform to their best abilities. Using computer games is one means to encourage learners to learn.

Generally a game is defined as being rule-based, with a quantifiable outcome that can be either positive or negative. As we consider games, there is a growing body of literature about games on different platforms, however most of them did not identify their individual effects (Durkin & Barber, 2002). The features of games that are presented in this definition resemble the ones that are mentioned by Prensky (2001). He lists the following six basic elements of computer games: rules, goals and objectives, outcomes and feedback,

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doi:10.1016/j.sbspro.2012.06.761

conflict/competition/challenge/opposition, interaction, and representation or story. Games can be shortly defined as "organized play" (Prensky, 2001, p. 119). However, the phrases "video games" and "computer games" are usually used interchangeably because in both the game is viewed thorough a screen and an input device such as a joystick; keyboard or a keypad is used to play (Kirriemuir, 2002). The social interactions in playing games have to carefully design and embed in scenario. Interactions take place in various ways. Developing a science of games opens up a huge potential for the wider application of game based learning tools for being used to design effective learning opportunities.

Though much social scientific research and popular debate has focused on the effects of violent video game content (Ivory,2006; Williams & Skoric,2005; Nije Bijvank et al,2011; Willoughby&Adachi,2011). Oggins & Sammis state that some players said they felt addicted to games as soon as they started playing; others felt addicted over time; games might even remain on one's mind after quitting. Players also noted withdrawal symptoms and changes in mood associated with play (2010).

Some researches related to gender differences in computer games showed that boys were being as more successful about playing computer games than girls. Coyne,2011; Miller & Summers,2007; Hamlen,2010). There are many classifications of game type. Prensky classified a categorization of game type in generally; action, adventure, fighting, puzzle, role-playing, simulation, sports, strategy (2001, p. 130). All game players are different; each has a different preference for the pace and style of game play within a game, and the range of game playing capabilities between players can vary widely (Gibb et al.,1983). Therefore game-playing behaviors of players differ from each others.

2. Methods

This project was aimed to investigate the attitude of students pc game and theme preferences and designed as a survey research study. The data were collected through a questionnaire interviews.

2.1. Participants

722 students at the age of 11-14 from 16 different state schools in Istanbul Anatolian Side have formed the sample group. As presented in Table 1, %50 of the participants were female/male. As shown it is a balanced distribution of gender.

Table 1 Participants' Characteristics

Class	**Gender**				**TOTAL#**	**TOTAL%**
	F#	F%	M#	M%		
5th	127	17,59	108	14,96	235	32,55
6	114	15,79	137	18,98	251	34,76
7	122	16,90	114	15,79	236	32,69
TOTAL	363	50,28	359	49,72	722	100

2.2. Instruments

The questionnaire is composed of two parts, with a total of 34 questions. The first part can be further divided into two sections, which deal with demographic and computer game-playing characteristics of the participants and their general perceptions toward playing computer games. The second part investigates the participants' perceptions regarding the use of computer games with educational features in education.

This questionnaire was developed by Gulfidan Can (Can & Cagiltay, 2006). But some questions inspired by an existing questionnaire developed for MIT's Games-to-Teach project (Squire & the Games-to-Teach Research Team, 2003) while Gulfidan Can had been developing the questionnaire. Questionnaire made up of 3 sections. The coefficient alpha value for the overall questionnaire is 0.87, for three sections they are 0.79, 0.64, and 0.85, respectively (Can&Cagiltay,2006). The first and the second sections of the questionnaire, developed by Gulfidan Can, is used in this study. The first section is changed according to the sampling's demographic characteristics.

2.3. Data Collection Procedure

The data were collected from 722 students in a three-week period, during the students' regular lesson hours. The questionnaire was used with the permission of the local government authority and teachers. The response rates were 100%. On average, the students completed the questionnaires in 20 minutes. The purpose of the research and the directions for the questionnaires were quoted verbally by the researcher before the participants were given the questionnaires.

2.4. Data Analysis Procedure

Arff type extension a text file used for raw data storage. The data were analyzed using by Weka 3.7.0 that is a popular suite of machine learning software. At this point some classifiers and learning algorithms were used for determining which students play which types of games.

2.4.1. Classifier used in the experiments: Decision Tree Classification

A decision tree is a hierarchical model for supervised learning. A decision tree consists of decision nodes and leaves in the end. Each decision node m, a test function applies fm(x). Each node, given an input, a test is applied, and one of the branches, is taken as a result. This process begins at the root and is repeated continuously until it reaches the leaf node (Alpaydın, 2004). Packed with features predictive and descriptive decision trees is the most common use in the classification models. Because, it is cheaper to organizations, can be easily integrated with database systems and better reliability (Sugumaran et al, 2007).

2.4.2. Evalution Criteria

2.4.2.1. Confusion Matrix

Confusion matrix is a matrix showing the predicted and actual classes. ℓ , is the number of different label values, the size of a Confusion Matrix is, $\ell \times \ell$ (Kohavi & Provost,1998). Table 2 shows 2x2 Confusion Matrix

Table 2 2x2 Confusion Matrix

		Predicted Class	
		positive	**negative**
Real Class	**positive**	*tp*	*fp*
	negative	*fn*	*tn*

2.4.2.2. Correctly Classified Instances(CCI)

All training data is the ratio of the number of correct predictions made. Using this criterion can give us information about how well our classifier was trained.

$$CCI= (tp+tn)/(tp+fp+fn+tn) \tag{1}$$

2.4.2.3. Precision

Correctly predicted positive samples predicted as positive examples are calculated as the ratio. Precision value, positive labeled data provides information on how much certainty is estimated. Precision value is a value of 0.5 and above.

$$Precision= tp/(tp+fp) \tag{2}$$

2.4.2.4. Recall

Correctly predicted as positive examples, which is really positive is calculated as the ratio of the samples. A value of 0.5 and above is generally acceptable for Recall

$$Recall= tp/(tp+fn) \tag{3}$$

2.4.2.5. F-Measure

F-Measure is the harmonic mean of Precision and recall values (Lewis&Gale, 1994). The use of harmonic mean in the calculation of the values involved in the case of a very high one, even this increase will not affect the result provides a very large extent. A value of 0.5 and above is generally acceptable for F-Measure. The closer the value is 1, the F-Measure is a good way of learning by each class and the classifier can be said.

$$F\ Measure= (2*Precision*Recall)/(Precision+Recall) \tag{4}$$

2.4.2.6. Root Mean Squared Error (RMSE)

Root mean-square error, calculated by taking the square root MSE. The formula of RMSE shown in (5). RMSE value takes a value between 0 and 1. . The closer the value is 0, can be said that made less errors during the predictions.

$$RMSE= \sqrt{(((p_1- a_1)^2+ ...+ (p_n- a_n)^2)/n)} \tag{5}$$

2.4.2.7. Kappa Statistics

Kappa (Kılıçarslan et al.,2009) is an alternative to the measure of the value of the right to evaluate classifiers. kappa, which determines the growth of accuracy of a classifier is used as a criterion in the fild of machine learning (Kılıçarslan et al.,2009). In the case of more than two valuer the Kappa coefficient of Fless can be adabtable in the fild of machine learning (Fleiss, 1971). Cohen's Kappa measure is defined as follows

$$K= (Pr(a) - Pr(e))/(1-Pr(e)) \tag{6}$$

Kappa statistic is between -1 and 1. -1 Is an incompatibility (ie, fully no classification) and 1 in the perfect harmony (ie, 100% correct classification). A value greater than 0.4 shows an acceptable value beyond chance (Landis&Koch, 1977). In order to interpret the values obtained, Landis and Koch presented Table 3.

Table 3 2x2 Landis and Koch's Kappa value table

Kappa	Interpretation
< 0	No agreement
0.0 – 0.20	Slight agreement
0.21 – 0.40	Fair agreement
0.41 – 0.60	Moderate agreement
0.61 – 0.80	Substantial agreement
0.81 – 1.00	Almost perfect agreement

3. Results and Discusssion

After the application of questionnaires to students, 5 training sets prepared to be used for testing. J48 classifier results are shown that applied on sets of education in Table 4 separately for each training set. The accuracy table for the prepared training sets are shown in Table 5 . These results are evaluated according to the above-mentioned evaluation criteria, good level of learning classifier can be seen performed. This general reviews before, the priority of the criteria used for classifier must be specifying. Adequacy of the criterias used for the experiments in learning classifier is, in order, CCI, RMSE and Kappa. After more, for evaluation of each such class which located in the training data, F-Measure, Precision, Recall, TP and FP are criterion values.

As it can be seen in Table 4, CCI value is around %80. This value is acceptable for the value of ongoing hypothesis. Therefore, the classification performed by a good level of learning can be said. Additionally, RMSE value is closer to 0 ensures that the errors are acceptable. Kappa value is below 0.4 but, in training data with high levels of bugs kappa value is high, it is a contradiction. Therefore, Kappa value cannot be used for Measure of learning classifier in this type training data. The use of CCI and RMSE values Instead of Kappa, give more reliable results.

Table 4 The results of J48 on the classifier training data

Training Data	Number of correctly classified sample	Number of Samples misclassified	CCI	RMSE	Kappa
Action	580	142	80.3324 %	0.3969	0.0151
Adventure	584	138	80.8864 %	0.3903	-0.0016
Sports	599	123	82.964 %	0.376	0
Simulation	576	146	79.7784 %	0.4031	0.0519
Other	517	205	71.6066 %	0.4549	0.014

The best learning in the five training data is “sport” training data and after, in order, “adventure”, “action”, ”simulation” and “other (fighting, puzzle, role-playing, strategy)”

Table 5 Accuracy Table Prepared for Trainning Data

Training Data	TP Rate	FP Rate	Precision	Recall	F-Measure	Class
Action	0.022	0.012	0.3	0.022	0.041	yes
	0.988	0.978	0.81	0.988	0.89	no
Adventure	0.007	0.009	0.167	0.007	0.014	yes
	0.991	0.993	0.814	0.991	0.894	no
Sports	0	0	0	0	0	yes
	1	1	0.83	1	0.907	no
Simulation	0.098	0.058	0.255	0.098	0.141	yes
	0.942	0.902	0.836	0.942	0.885	no
Other	0.02	0.01	0.444	0.02	0.038	yes
	0.99	0.98	0.719	0.99	0.833	no

As shown in Table 5 class “yes” is not learned enough In all the training data by classifier. It can be seen when TP and FP values are examined, class “yes” is only slightly proportion of the true prediction and class “no” is a high proportion of the true prediction. Also accuracy of all the values for class “no” is greater than value 0.8. In this respect, it can be said that classifier learned from labeled “no” examples is a good way and classified them truly. When sports training set is examined, it can seen that class “yes” is not classified truly by the classifier. In generally class “yes” is not classified truly, because the number of class “yes” is not enough. In this case, “yes” and “no” classes are unbalanced.

As a result by the addition of “yes” labeled samples to the training sets, the proportion of true prediction of classifiers will increase. At this statement the proportion reaches to % 90-% 100 sections.

Acknowledgements

The authors thank the generous support of the many private donors who provided support for this project. The authors also thank the many students who assisted in conducting the data.

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