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Classification of Computer Game Addiction Level in Students in Secondary Education (M.1-3) using Neural Networks

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Abstract. This paper presents the classification of game addiction level in secondary school students (M.1-3) with a sample group of 32 students who play game in the residence daily. Data was collected during 18 May – 26 July 2011. We classified level of addiction using Backpropagation Neural Networks and compared the results to Decision Tree Learning. The accuracy of the obtained model was tested by the standard 10-fold Cross Validation approach. This research classifies computer games, based on their characteristic, into four categories: Long Term, Casual, Real Time and Turn-Based Games. The experimental results showed that accuracies of Backpropagation Neural Networks for Long Term Game, Casual Game, Real Time Game, and Turn Base Game are 97.75, 91.35, 90.0, and 97.73, while the accuracies of Decision Tree Algorithm are 88.76, 92.63, 87.5, and 90.91 respectively.

Keywords: backpropagation neural networks, decision tree learning, computer game addiction, classification

1. Introduction

Nowaday, more than 1.3 millions of Thai children and teenagers addict to on-line computer game [1]. Severe on-line computer game addiction leads to several problems such as personal, family, and social problems. It can lead to criminal cases such as using weapon to hurt other people, rob, or murder, because of the desire to imitate characters in the games [2,3]. Severity of on-line computer game addiction in children and teenagers varies on the condition of game addiction of each child or teenager. In Thailand, the Ratchanakarin Child and Adolescent Mental Health Institute, Department of Mental Health, Ministry of Public Health classifies the level of game addiction into three levels: like, fanaticize, and addict. In our preliminary stage, we interviewed the director of Ratchanakarin Child and Adolescent Mental Health Institute and found that treatment and prevention will be more effective if we can classify game addiction level of the children or adolescents. Anyhow, the monitoring of computer usage condition of Thai population showed that children and teenagers who study in the secondary education (M.1-3) in Bangkok are in the group of those who play on-line computer games at the high level [4]. Therefore, this research is aimed at classifying game addiction level in secondary school students (M.1-3) to provide benefits for the parents in monitoring children's game playing behaviors. This article presents the classification of the addiction level using Backpropagation Neural Networks in comparison with Decision Tree Model, as well as to evaluate the efficiency of each model using 10–fold cross validation.

This article is divided into five parts. The rest of the article contains Section 2: Review of Related Literatures and Researches, Section 3: Research Methodology, Section 4: Results, and Section 5: Conclusion.

2. Related Literatures and Researches

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2.1. Classification

In general, classification is an approach in machine learning, in which the goal is to categorize the data into classes. The process consists of two main parts, learning and classifying. We must first construct a model from a set of training examples each of which is a pair of the input variables and its target value. The obtained model is then used to classify unseen data.

The input variables we used in this research are sequences of actions captured from the users and the target value which is the class of the addiction level namely like, fanaticize, and addict.

2.2. Backpropagation Learning

Backpropagation is a well-known Neural Networks learning algorithm which is widely used to train multi-layer perceptrons to adjust the weight of connection between each perceptron. The adjustment depends on the different between output obtained from feeding forward step and target value. The detail of Backpropagation algorithm is illustrated below.

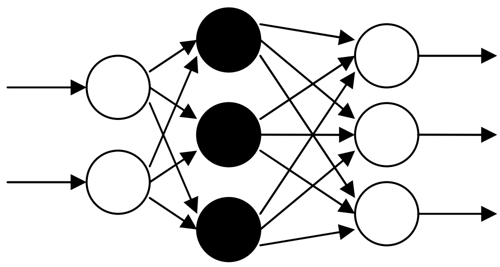

Fig. 1: An example of structure of multi-layer perceptrons

Figure 1 shows a structure of multi-layer perceptrons which consist of input, hidden, and output layer with connections linking from the input layer to the hidden layer and from the hidden layer to the output layer. There is no reverse connection in the structure we use in this research. Weight vectors of the backpropagation neural networks are adjusted backward from the output nodes to the hidden nodes. Definition of error value is illustrated in Equation (1).

$$E(\vec{w}) = \frac{1}{2}\sum_{d \in D}\sum_{k \in output\ nodes}(t_{kd} - o_{kd})^2 \quad (1)$$

Where t_{kd} and o_{kd} are expected output (or target value) and output obtained from node k when an input d is fed to the network. The objective of backpropagation learning algorithm is to determine the weight vector with minimum error over the whole training set.

2.3. Decision Tree Learning

In this research, we ran another standard learning algorithm, C4.5 [5] to compare the results with the neural networks. The decision tree learner in C4.5 builds a tree using greedy fashion based on the principles of Information Theory [6]. Internal nodes in the decision tree are the evaluation of attribute value which is used to divide examples, while the leaf nodes represent the class or the decision of the tree. The attribute with the best splitting power is placed in the tree first. Then, the leaf nodes consisting of example from different classes will be split using the same procedure until the proportion of the example in the new leaf node meets the stopping criteria. Finally, we can use the obtained decision tree to classify unseen examples.

2.4. Types of Computer Games Based on Playing Characteristics [7]

- Long Term Game: Games with long story or with continual scene. The players have to finish each scene first and then they can continue playing the next one. Samples of this type of games are RPG Game such as Final Fantasy, Tales Rockman, and Series Game such as Mario, Rockman, and DarkCloud.
- Casual Game: The players do not have to play this type of game according to the story. They can play with or without story. The scene of the game usually does not connect to each other. It might be only one scene but the difficulty will be increased until the player loses the game. Examples of this type of games are Puzzle Game, Dancing Game, Flash Game, and Strategy Games, etc.

- Real Time Game: It is the games with time rules. The movement in the game must be according to real time. Examples of this type of games are Action/Adventure Game or Fighting Game which focus on the realistic control that is suitable for the games that emphasize on responses or skill.
- Turn Base Game: The game has a time rule that does not refer to the real time. There are some breaks for the player to make a decision to do some specific mission and make a plan to manage the mission. Examples of this type of games are Board Game and Tactics Game or RPG Game such as Final Fantasy, Strategy Game such as Heroes of Might and Magic.

According to relevant researches, Nogueira [8] classified the internet users in Portuguese using neural networks. In addition, Kim et al. [9] studied the automatic detection of MMORPG Game. Attributes were specified in the research by analyzing the sequence of instructions given to Windows OS, such as total number of events, average time average time between mouse and keyboard events, average of time interval between specific mouse and keyboard events, etc. Moreover, standard machine learning algorithms such as Decision Tree and Multi-Layer Perceptrons were applied in data classification

3. Methodology

3.1. Data Collection

This article presents an approach which is aimed at classifing the computer game addiction level of 32 students in secondary education (M.1-3) in Bangkok. Our subjects were classified by experts in government agencies that are responsible to monitoring problem of child's game addiction. We developed an agent program that collects the keyboard pressing and mouse clicking. Data was gathered in a log file stored in students' computer and sent through the internet from 18 May 2011 to 26 July 2011. The system design is illustrated in Figure 2 and a sample of data in log file is illustrated in Figure 3.

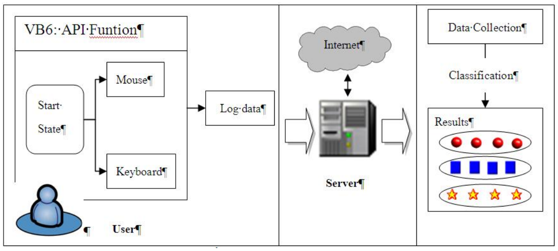

Fig. 2: System Design

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user1308;WinXP;&H90040;Left 4 Dead;2554-05-23;19:40:47:1247;x:318;y:240;EN;a
user1308;WinXP;&H90040;Left 4 Dead;2554-05-23;19:40:47:1247;x:309;y:240;EN;a
user1308;WinXP;&H90040;Left 4 Dead;2554-05-23;19:40:48:1248;x:315;y:240;EN;w
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user1308;WinXP;&H90040;Left 4 Dead;2554-05-23;19:40:50:1250;x:303;y:242;EN;w
user1308;WinXP;&H90040;Left 4 Dead;2554-05-23;19:40:50:1250;x:325;y:240;EN;w
user1308;WinXP;&H90040;Left 4 Dead;2554-05-23;19:40:51:1251;x:320;y:240;EN;w
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Fig. 3: samples of data being stored in log file

3.2. Data used in the Research

Before we can classify the data, we have to extract several attributes from the raw data. All attributes we used are illustrated in Table 1.

Table 1. List of Attributes

Feature Name	Description
1. EDU	3 groups of education levels. (M.1, M.2 and M.3)
2. SEX	2 groups of genders. (male/female)
3. DATE_TYPE	2 group of days of week. (normal day and holiday)
4. TIME_PER_DAY	Duration of playing game per day. (minutes)
5. TIMECLICK_PER_DAY	Duration of mouse clicking in game per day. (minutes)
6. TIMEKEY_PER_DAY	Duration of keyboard pressing in game per day. (minutes)
7. CLICKEY_PER_DAY	Total number of mouse clicking and keyboard using in game playing per day.
8. TOTCLICK_DAY	Total number of mouse clicking in game per day.
9. TOTKEY_DAY	Total number of keyboard pressing in game per day.
10. SWITCH_CLICKEY	Total number of switching from using mouse to keyboard or from using keyboard to mouse.
11. MAX_CLICK	Maximum number of mouse clicking before switching to keyboard using in game

	playing per day.
12. MAX_KEY	Maximum number of keyboard using before switching to mouse clicking in game playing per day.
13. MEANTIME_CLICKEY	Average time of mouse clicking and keyboard pressing in game playing per 1 minute.
14. MEANTIME_CLICK	Average time of mouse clicking in game playing per 1 minute.
15. MEANTIME_KEY	Average time of keyboard using in game playing per 1 minute.
16. LEV_ADDICTION	3 groups of computer game addition. (like, fanaticize, and addict)

3.3. Data Preparation for Learning Instruction

Data was classified based on four types of computer games according to their playing characteristic. The number of records in each type are as following a) 89 records for Long Term Game, b) 312 records for Casual Game, c) 240 records for Real Time Game, and d) 44 records for Turn-Based Game.

3.4. Learning Instruction

- Convert data to a suitable format such as data in the form of nominal scale or ordinal scale must be converted before being analyzed.
- Create a model using WEKA (Waikato Environment for Knowledge Analysis) [10] which is an open source software developed and published by a group of researchers in Waikato University, New Zealand. We have tested different parameters in order to find the best results from both learning method by adjusting the parameter to be best fit to construct the model.
- Separately compare the results using 10-fold cross validation method for each game type.

4. Results

Results from our experiments are illustrated in Table 2 and Figure 4-6.

Table 2. Comparison of Percentage of Accuracy for Each Type of Computer Game. Bnn And Dt Denote Backpropagation Neural Networks And Decision Tree, Respectively.

Type of computer game based on playing characteristic	Percentage of classification's accuracy		Percentage of clasification's error	
	BNN	DT	BNN	DT
1. Long Term	97.75%	88.76%	2.25%	11.24%
2. Casual	91.35%	92.63%	8.65%	7.37%
3. Real Time	90.0%	87.5%	10.0%	12.5%
4. Turn Base	97.73%	90.91%	2.27%	9.09%

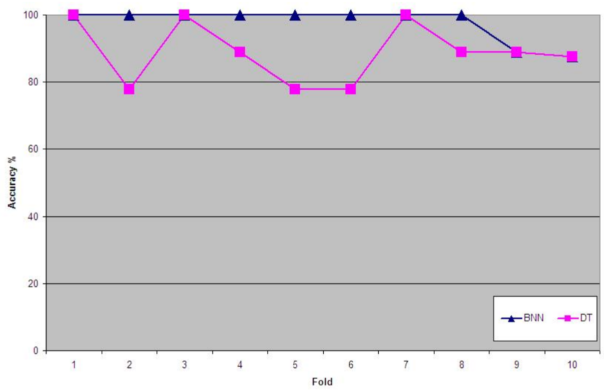

Fig. 4. The accuracy of the Long Term Game

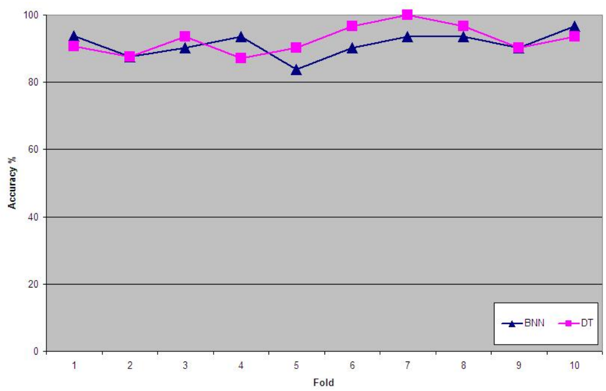

Fig. 5. The accuracy of the Casual Game

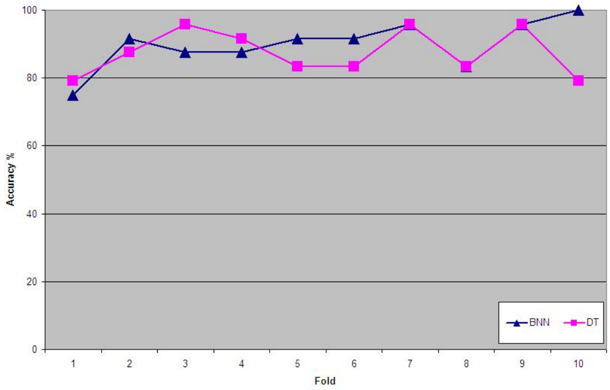

Fig. 6. The accuracy of the Real Time Game

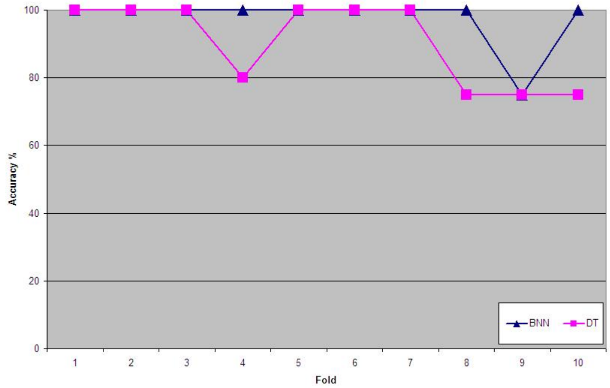

Fig. 7. The accuracy of Turn Base Game

Table 2 shows that the results obtained from the Neural Networks yields higher percentage of accuracy than Decision Tree in Long Term Game, Turn Base Game, and Real Time Game, with average percentage of accuracy of 97.75, 97.73, and 90.0 respectively. However, in the case of Casual Game, the percentage of accuracy obtained from Decision Tree Algorithm is higher than Neural Networks with the percentage of accuracy 92.63.

5. Conclusions

The classification of computer game addiction level in students in secondary education (M.1-3) is one of the tools which can be used as an alarm tool to monitor children's game playing behavior. Our program detects the mouse clicking and keyboard pressing while the samples were playing computer game. In our research, the computer games are classified into four types based on playing characteristics: a) Long Term Game, b) Casual Game, c) Real Time Game, and d) Turn-Based Game. Data was analyzed using two standard learning algorithms, Backpropagation Neural Networks and Decision Tree Learning. The accuracy of model was tested by using 10–fold Cross Validation in order to compare the accuracies obtained from both models.

6. References

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