Pertanika J. Sci. & Technol. 28 (1): 211 - 225 (2020)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Logic Mining in League of Legends

Liew Ching Kho[1], Mohd Shareduwan Mohd Kasihmuddin[1]*, Mohd. Asyraf Mansor[2] and Saratha Sathasivam[1]

[1]*School of Mathematical Sciences, Universiti Sains Malaysia, 11800 USM, Minden, Pulau Pinang, Malaysia*
[2]*School of Distance Education, Universiti Sains Malaysia, 11800 USM, Pulau Pinang, Malaysia*

ABSTRACT

Since its debut in 2009, League of Legends (LoL) has been on a rise in becoming an extremely favoured multiplayer online battle arena (MOBA) game. This paper presented a logic mining technique to model the results (Win / Lose) of the LoL games played in 3 regions, namely South Korea, North America and Europe. In this research, a method named *k* satisfiability based reverse analysis method (*k*SATRA) was brought forward to obtain the logical relationship among the gameplays and objectives in the game. The logical rule obtained from the LoL games was used to categorize the results of future games. *k*SATRA made use of the advantages of Hopfield Neural Network and *k* Satisfiability representation. The data set used in this study included the data of all 10 teams from each region, which composed of all games from Spring Season 2018. The effectiveness of *k*SATRA in obtaining logical rule in LoL games was tested based on root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and CPU time. Results acquired from the computer simulation showed the robustness of *k*SATRA in exhibiting the performance of the LoL teams.

Keywords: 2 satisfiability, 2 satisfiability reverse analysis method, hopfield neural network, league of legends, logic mining

ARTICLE INFO

Article history:
Received: 09 May 2019
Accepted:12 September 2019
Published: 13 January 2020

E-mail addresses:
cindyklc90@gmail.com (Liew Ching Kho)
shareduwan@usm.my (Mohd Shareduwan Mohd Kasihmuddin)
asyrafman@usm.my (Mohd. Asyraf Mansor)
saratha@usm.my (Saratha Sathasivam)
* Corresponding author

ISSN: 0128-7680
e-ISSN: 2231-8526

INTRODUCTION

In these past few years, eSports has started to attain more fans and recognition from all over the globe. It is difficult to define eSports since the industry is comparatively new. Hence, several authors have written on what defines a sport and why eSports should be recognized as sports (Kane and Spradley, 2017; Jenny et al., 2017). While there is a vast number of studies on data mining for sports, such as, football (Nunes & Sousa, 2006; Baio & Blangiardo, 2010), swimming (Chen et al., 2007; Johnson et al., 2009) and basketball (Bhandari et al., 1997; Lamb et al., 2010), there is still an inadequate amount of researches exploring data mining in eSports.

League of Legends (LoL) is a multiplayer online battle arena (MOBA) game developed and published by Riot Games. LoL is a competitive eSports played in teams of five. In LoL, each players takes control of one “champion” and compete with another team of players. The aim is to knock down the opposing team’s “nexus”, a structure in the middle of the base. Reitman (2018) gave a complete introduction of gameplay for LoL for those unfamiliar with its distinct quirks and features. LoL has a global competitive scene. Major regional competition exist in North America (NA LCS), Europe (EU LCS), China (LPL), South Korea (LCK), Taiwan/Hong Kong/Macau (LMS) and various other regions. Teams that won in their respective regions will get the chance to compete in the annual World Championship. The 2018 World Championship had 99.6 million unique viewers and a total prize pool of over 6.45 million USD (Riot Games, 2018). As the eSports scene advances forward, the need to analyse game strategies arises. At present, most professional gaming teams recruit analysts to analyse their opponents, work out their strategies and come up with counterstrategies. Shout casters and analysts report their analyses during tournaments and matches. Nowadays, eSports players are lodged together with their team coaches, managers and strategists. With the fast growing level of competition, the need for strategies to enhance players’ performance also increases.

Kim et al. (2017) used collective intelligence to anticipate team performance in LoL. They showed that collective intelligence was able to anticipate the team performance based on the players’ tacit coordination. Nascimento Jr et al. (2017) divided teams’ performance into several groups. They evaluated the features in each group to find out how these features affected the results in LoL by applying machine learning and statistical analysis. Yang et al. (2014) modelled combat tactics in graphs and extracted features from the graphs to construct a decision tree that predicted the results of MOBA game. Lan et al. (2018) proposed a player behaviour model that allowed to predict the result of a MOBA game once enough data on the behaviour of the players were collected. They used recurrent neural network to process the interaction among the features of player behaviour variation and predict the outcome of a game. Johansson and Wikström (2015) showed that partial game data collected as the game progressed could be used to accurately predict the results of an ongoing game of Defense of the Ancients 2 (DotA 2) in real-time with the application of machine learning techniques. Wang (2016) used multi-layer feedforward neural networks to predict DotA 2 game outcome based on hero draft data. All these studies did not take gameplays or objectives in game into consideration while the main purpose of the game was to take down the objectives such as the turrets in order to win. Hence, we would like to propose a new method to determine the relationship among the gameplays or objectives and how they affect the outcome of the game.

Rojas (1996) mentioned that artificial neural network (ANN) learnt how the brain of human beings process information. One of the popular network used to solve several optimization problems is Hopfield Neural Network (HNN) (Hopfield & Tank, 1985). HNN shows outstanding learning behaviour. For example, productive learning and retrieval operation. Traditional HNN is susceptible to a few deficiencies (Gee et al., 1993), so HNN is embedded with logic programming to work as a single intelligent unit (Abdullah, 1992). HNN was proven to be effective in data mining (classification) with incomplete survey data (Wang, 2005). Gaber et al. (2000) presented an algorithm to solve data mining problems (association rule mining) using HNN. Logic mining in HNN was proposed by Sathasivam (2006) by applying Reverse Analysis method. This method could obtain the logical rule among neurons. Mean field theory applied to perform logic programming in HNN had proven to be fruitful in accelerating the computational ability of neuro symbolic integration by Velavan et al. (2015). Maknickas (2015) showed that 2 Satisfiability (2SAT) could further improve the representation of general SAT. Hence, it is appropriate to select 2SAT as the logical rules in HNN. It also lowers the logical complexity in learning the relationship between the variables in real life problems since only 2 literals per clause are taken into consideration. By hybridizing HNN, Reverse Analysis and 2SAT, a new method, 2 Satisfiability based Reverse Analysis method (2SATRA) will be utilized to obtain the logical rule of LoL games. In this paper, we will employ the 2 Satisfiability based Reverse Analysis method (2SATRA) to induce the best logical rule that shows how gameplays or objectives in game can affect the outcome of a game in 3 different regions, namely NA LCS, EU LCS and LCK.

The remaining of this paper is organized as follows. In Materials and methods section, 2SAT representation and logic programming in HNN will be discussed in detail. The implementation of 2SATRA in doing LoL data sets from 3 different regions is illustrated. Results and discussion section demonstrated the performance analysis of the data sets such as root mean square error, mean absolute error, mean absolute percentage error and computation time. Key findings from induced logic are summarized. Conclusion section concluded the research work with summary of findings and future works.

MATERIALS AND METHODS

2 Satisfiability Representation

Logical rule that is made up of 2 literals per clause is called 2 Satisfiability (2SAT). 2SAT is composed of a few elements (Kasihmuddin, 2017):

(a) A set of x variables, $v_1, v_2, v_3, ..., v_x$.

(b) A set of literals. A literal can be any variable or a negation of any variable.

(c) A set of y definite clauses, $C_1, C_2, C_3, ..., C_y$ linked by logical AND ($\vee$). Each clause contains only 2 literals connected by logical OR ($\vee$).

Each variable can take bipolar value of 1 or -1 only. It represents true or false respectively. Definition of the 2SAT formula P_{2SAT} is as follows

$$P_{2SAT} = \bigwedge_{i=1}^{y} C_i \qquad [1]$$

where C_i is a list of clause with 2 variables each,

$$C_i = \bigvee_{i=1}^{y} (m_i, n_i) \qquad [2]$$

The primary aim of 2SAT representation is to discover the consistent interpretation that makes formula P_{2SAT} become satisfied (Kasihmuddin et al., 2017). The focal point of the logic programming in this paper is to make sure in every execution, the program only considers 2 literals per clause. It has been proven that a great number of combinatorial problem can be directly or indirectly formulated by using 2SAT logical rule (Even et al., 1975; Miyashiro & Matsui, 2005; Mukherjee & Roy, 2015). In this paper, 2SAT logic will be embedded to HNN as a proposed logical rule.

Logic Programming in Hopfield Neural Network

Neural network is able to model complex relationships between inputs and outputs also look for patterns in data. Pattern recognition and function estimation are the reasons why neural networks are utilized in data mining (Singh & Chauhan, 2009). Hopfield Neural Network (HNN) is a widely used recurrent neural network model. Muezzinoglu et al. (2003) mentioned that HNN saved patterns as content addressable memory (CAM). HNN was chosen for logic mining because recurrent neural networks were able to learn the patterns of the data inputted to them, and used the pattern at one instant to assist in making prediction for the next instance (Craven & Shavlik, 1997). In HNN, each neuron's output and input are connected. The connection weight from neuron i to j is denoted by $w_{ij} = w_{ji}$. In HNN, $w_{ij} = w_{ji}$ (symmetric networks) and $w_{ii} = w_{jj} = 0$ (no self-feedback connections). Let θ be the state or output of the i th unit, θ is the pre-defined threshold of unit i. In an asynchronous network such as HNN, each neuron was "excited" at random time and changes its state to 1 or -1 independently according to the total excitation. For bipolar networks, S_i is either +1 or -1. HNN assumed that the individual units preserved their individual states until they were selected for a new update. General updating rule in HNN is given by:

$$S_i = \begin{cases} 1 & if \quad \sum_j w_{ij} S_j > \theta_i \\ -1 & Otherwise \end{cases} \quad [3]$$

The local field of the network is given by:

$$h_i(t) = \sum_j w_{ij}^{(2)} S_j + w_i^{(1)} \quad [4]$$

The updating rule of $h_i(t)$ is given by:

$$S_i(t+1) = sgn[h_i(t)] \quad [5]$$

where "sgn" represent the signum function. Signum function offers an output squashing mechanism to HNN.
The final state of neurons was examined by using Lyapunov energy function:

$$H_{P_{2SAT}} = -\frac{1}{2}\sum_i \sum_j w_{ij}^{(2)} S_i S_j - \sum_i w_i^{(1)} S_i \quad [6]$$

Final energy of HNN will without exception decrease with the dynamics. Minimum values from the energy function correspond to the stable state of the neurons. The aim of the HNN model is to ensure the solution move towards the lowest point. Lowest point (global minimum energy) corresponds to the optimal solution produced by HNN model. Learning phase of HNN model advanced by embedding the correct synaptic weight of 2SAT logic in HNN. 2SAT in HNN is abbreviated as HNN-2SAT model. Figure 1 shows the algorithm of implementation of HNN-2SAT models.

2 Satisfiability Based Reverse Analysis Method (2SATRA) in League of Legends

Logic mining will execute efficiently if the most favourable HNN-2SAT model is used. The neurons are represented in bipolar form {-1,1}. By acquiring the synaptic weight between 2 neurons, 2SATRA might be able to reveal the level of their connectedness. Therefore, Wan Abdullah's method was utilized in the learning phase of 2SATRA to figure out the accurate synaptic weight between the two neurons (Abdullah, 1992). By considering both neurons C and D where $S_D \in \{-1,1\}$ and $S_D \in \{-1,1\}$, Table 1 summarizes the feasible synaptic weight corresponding to the 2SAT clause.

As an example, given that neuron *C* and *D* exhibits 1 and -1, P_3 is going to be selected as the clause representation for the data set. In accordance with the nature of the neuron, 2SATRA will convert the data sets into 2SAT logic. Figure 2 shows the implementation of 2SATRA.

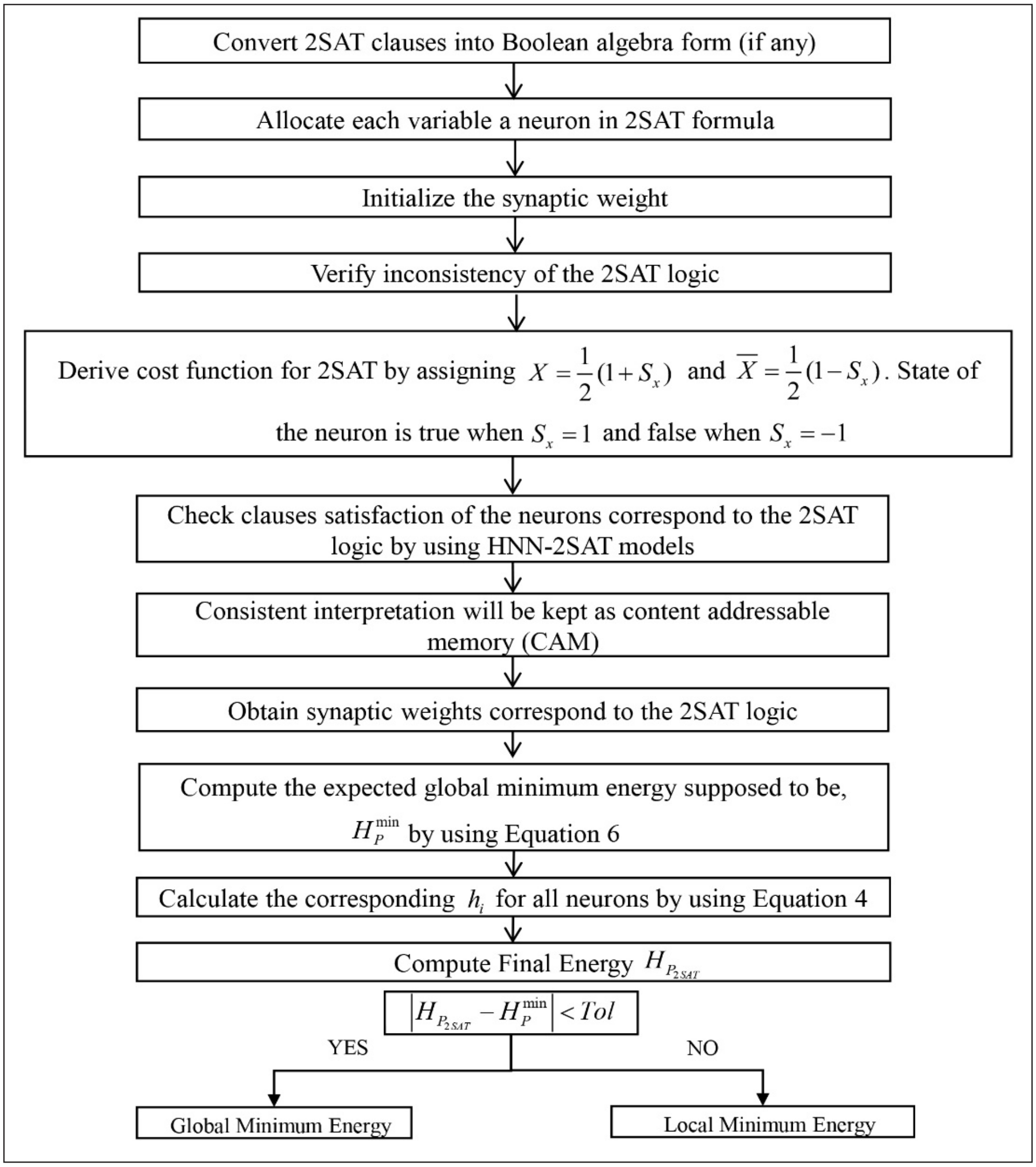

Figure 1. Algorithm of implementation of HNN-2SAT models

Table 1
Feasible synaptic weight corresponding to 2SAT logic

Synaptic Weight	$P_1 = C \vee D$	$P_2 = \neg C \vee D$	$P_3 = C \vee \neg D$	$P_4 = \neg C \vee \neg D$
W_C	0.25	-0.25	0.25	-0.25
W_D	0.25	0.25	0.25	-0.25
W_{CD}	-0.25	0.25	-0.25	-0.25

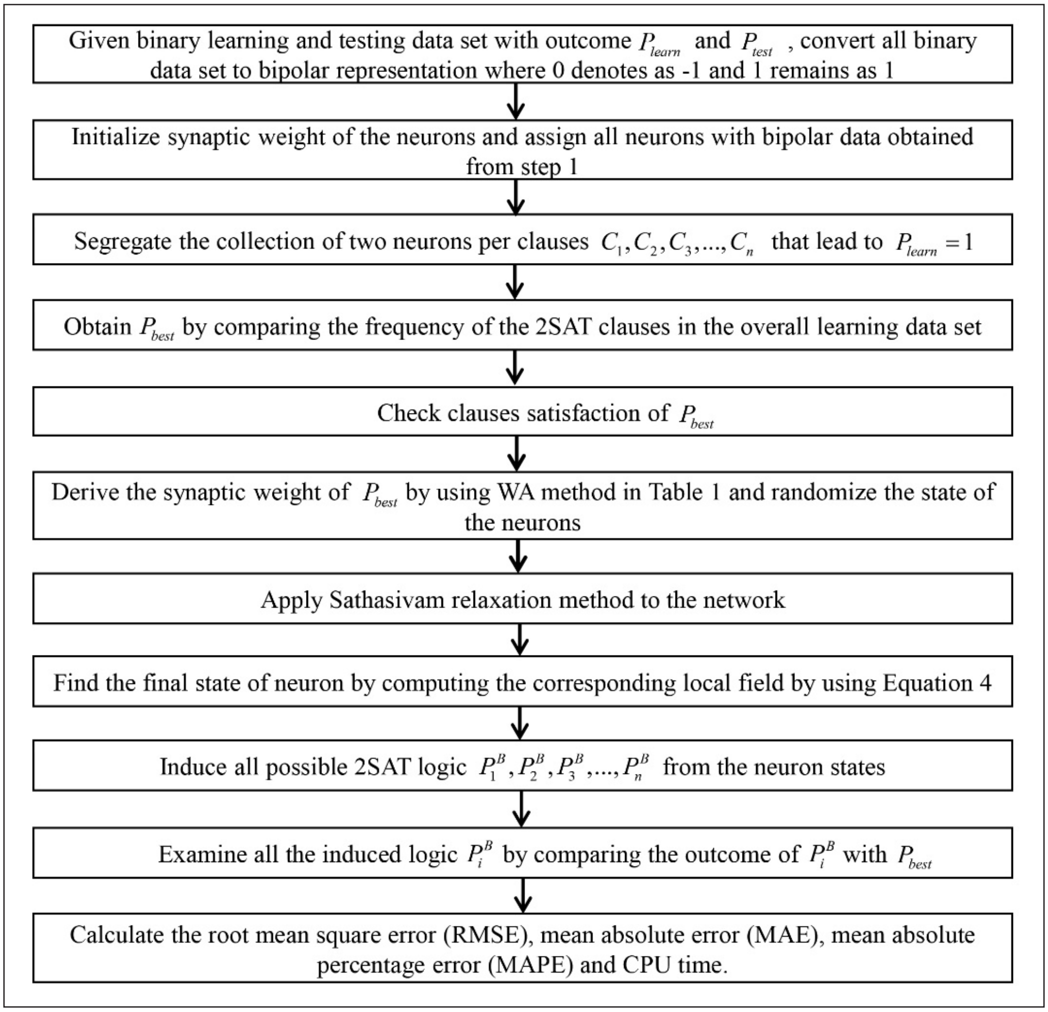

Figure 2. Algorithm of implementation of 2SATRA

In LoL, a split second decision or one team fight could turn the results of the game around. Hence, the coaches and players should be extra cautious when coming up with game strategies and their decisions in game. Logic mining is used in LoL to help the coaches and strategists in analysing the important gameplay or objectives in game. In this paper, 2SATRA is used to extract the logical relationship among the gameplay or objectives in game.

Experimental Setup

Every region has their own read on the game and hence there will be slight difference in the way they approach the game. Therefore, it is important to figure out the playing pattern of every region in order to win games. By using 2SATRA, it is possible to determine the relationship among the gameplay or objectives in game. In learning data set, {Win, Lose} would be converted into bipolar representation {1,-1} respectively. Each gameplay or objective taken would be represented in terms of neuron in 2SATRA. Hence, there would be a total of six neurons being considered in this data set. The respective gameplay or objective taken and neuron are summarized in Table 2. Explanation of the gameplay or objective is summarized in Table 3.

Table 2
Respective gameplay/objective and neuron

Neuron	Gameplay/Objective
A	First Blood (*FB*)
B	First Turret (*FT*)
C	First Dragon (*FD*)
D	Rift Herald (*RH*)
E	Gold Ahead at 20 Minutes (*GA*)
F	First Baron Nashor (*FN*)

Table 3
Explanation for gameplay/objective

Gameplay/Objective	Explanation
First Blood	The first kill in the game.
First Turret	The first tower to fall in the game.
First Dragon	The first elemental drake secured in the game.
Rift Herald	Rift Herald secured in the game.
Gold Ahead at 20 Minutes	Gold lead exists at the 20^{th} minute mark of the game.
First Baron Nashor	The first Baron Nashor secured in the game.

The threshold CPU time was 24 hours and outputs that exceeded the time were all excluded. Dev C++ Version 5.11 was used to implement the HNN-2SAT model. Computer used was equipped with Intel Core i7 2.5GHz processor, 8GB RAM and Windows 8.1. In order to decrease the statistical error, the program ran 100 trials with 100 combination of neurons. (Sathasivam & Abdullah, 2011).

Performance Evaluation

In order to determine the efficiency of the HNN-2SAT model in doing 2SATRA, four performance evaluation metrics namely root mean square error, mean absolute error, mean absolute percentage error and computational time were analysed.

Root Mean Square Error

Root mean square error (RMSE) showed the differences between observed value and target value of a model. RMSE is defined as follows (Schwenker et al., 2001; Willmott et al., 1985)

$$RMSE = \sum_{i=1}^{n} \sqrt{\frac{1}{n}(f_{NC} - f_i)^2} \quad [7]$$

where f_i is the fitness of the solution in HNN-2SAT model, $f_i = f_{NC}$ is the total number of 2SAT clauses, and *n* is the number of iteration before $f_i = f_{NC}$. Lowest value of *RMSE* indicates the best HNN-2SAT model.

Mean Absolute Error

Mean absolute error (MAE) is derived from each difference of $f_{NC} - f_i$. MAE is defined by (Mansor et al., 2018).

$$MAE = \sum_{i=1}^{n} \frac{1}{n} \left| f_{NC} - f_i \right| \quad [8]$$

The best HNN-2SAT model has the least value of *MAE*.

Mean Absolute Percentage Error

Mean absolute percentage error (MAPE) is a measure of accuracy in percentage form. MAPE can be expressed as (Tayman & Swanson, 1999)

$$MAPE = \sum_{i=1}^{n} \frac{100}{n} \frac{\left| f_{NC} - f_i \right|}{\left| f_i \right|} \quad [9]$$

However, *MAPE* cannot be used if the observed value is zero as it will lead to division by zero. Lowest percentage of *MAPE* shows the best HNN-2SAT model.

Computational Time

CPU time is the time required by a HNN-2SAT model to finish one execution. CPU time implies the capability and stability of the HNN-2SAT model. Equation of CPU time is as follows (Sathasivam, 2010)

$$CPU\_Time = Learning\_Time + Retrieval\_Time \quad [10]$$

The best HNN-2SAT model would have the shortest CPU time since a good HNN-2SAT model is capable of reducing the computation time in learning phase of HNN.

RESULTS AND DISCUSSION

A total of 4 performance evaluation namely RMSE, MAE, MAPE and CPU time were analysed to determine the effectiveness, precision and steadiness of HNN-2SAT in doing 2SATRA. *NC* was the total number of clause and 1 clause had 2 neurons. Figure 3, Figure 4, Figure 5 and Figure 6 show the results of RMSE, MAE, MAPE and CPU time for all 3 regions. In this execution, 214 data points for LCK, 95 data points for NA LCS and 91 data points for EU LCS had been embedded to 2SATRA. The data points for LCK, NA LCS and EU LCS were obtained from the Riot Games website https://matchhistory.na.leagueoflegends.com. 60% were used as learning data and 40% used as testing data.

Based on Figure 3, Figure 4 and Figure 5, it can be observed that at *NC*=1, the HNN-2SAT model had the best results in terms of RMSE, MAE and MAPE. The reason behind this was when the number of clauses got larger, learning phase of 2SATRA got more complicated as HNN-2SAT had to discover the consistent interpretation for P_{best}. Conjointly, the learning error for 2SATRA increased as the number of neurons increased. 2SATRA achieved maximum value of RMSE, MAE and MAPE when *NC*=10. In this case,

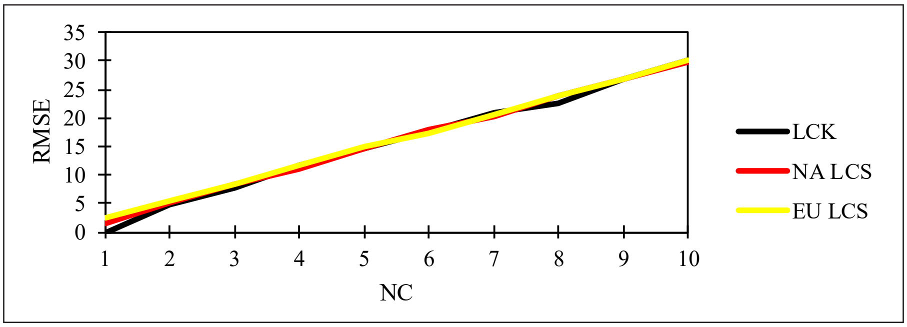

Figure 3. RMSE for HNN-2SAT model

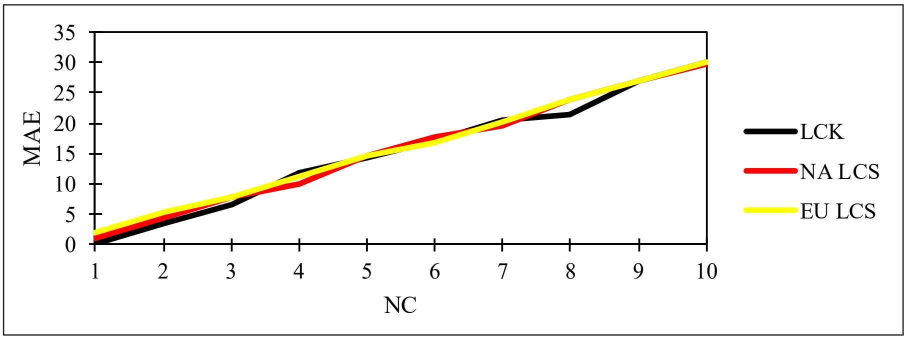

Figure 4. MAE for HNN-2SAT model

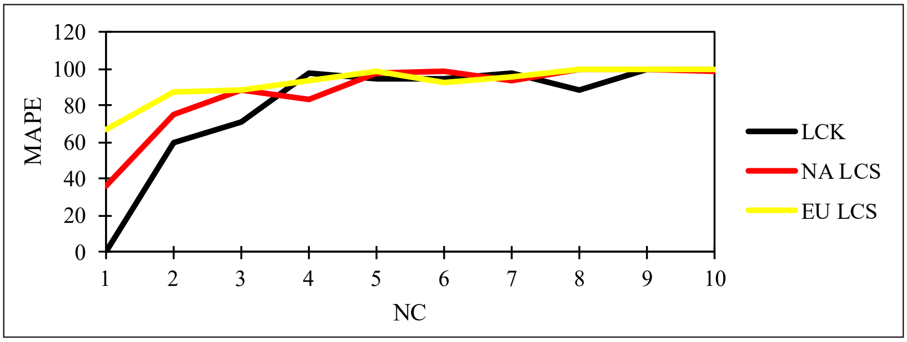

Figure 5. MAPE for HNN-2SAT model

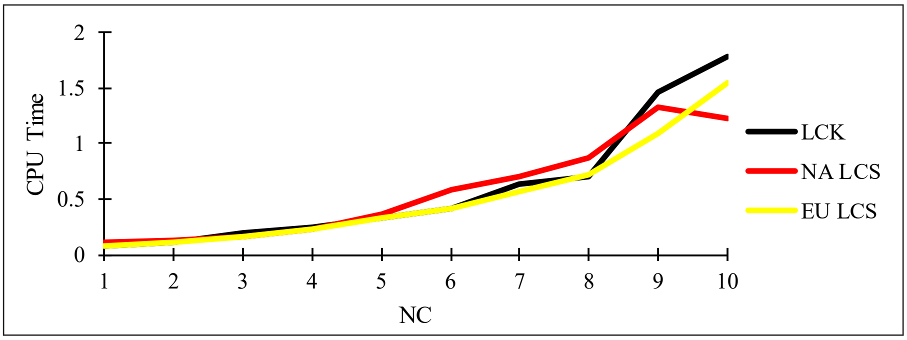

Figure 6. CPU Time for HNN-2SAT model

learning phase of HNN in 2SATRA reached a trial and error state. This phenomenon had a good agreement with the study by Sathasivam (2010). Figure 6 demonstrated the stability of 2SATRA in logic mining. 2SATRA was capable of inducing optimal P_i^B in moderate CPU time. At *NC*=4, 2SATRA was capable of inducing optimal P_i^B in 0.2 seconds. P_i^B induced by 2SATRA during the learning phase managed to accomplish an accuracy of 72% (LCK), 75% (NA LCS) and 73% (EU LCS). This is because the character of neuron in HNN, rather than oscillating, the neurons have always converged to minimum energy. Limitation of this model was the proposed gameplay or objective in game might not be the ones that will come out with the highest accuracy in 2SATRA. This was because in a LoL game, a lot of different factors will affect the outcome of the game. In this paper, we were only considering 6 of them. The results in this paper was not being compared to other existing methods because the approaches were different and incomparable. For example, Wang (2016) managed to achieve an accuracy of 61.04%. However, the research was done based on hero draft data while this paper was considering the gameplay or objectives in game. The best induced logic, $P_{inconsistent}$ and inconsistent interpretation, $P_{inconsistent}$ for each region are summarized in Table 4.

Table 4
Best induced logic and inconsistent interpretation

Region	Best induced logic, P_{best}	Inconsistent interpretation, $P_{inconsistent}$
LCK	$(\neg FB \vee FT) \wedge (FD \vee RH) \wedge (GA \vee FN)$	$(FB \wedge \neg FT) \vee (\neg FD \wedge \neg RH) \vee (\neg GA \wedge \neg FN)$
NA LCS	$(FB \vee FT) \wedge (FD \vee \neg RH) \wedge (GA \vee FN)$	$(FB \vee FT) \wedge (FD \vee RH) \wedge (GA \vee \neg FN)$
EU LCS	$(FB \vee FT) \wedge (FD \vee RH) \wedge (GA \vee \neg FN)$	$(\neg FB \wedge \neg FT) \vee (\neg FD \wedge \neg RH) \vee (\neg GA \wedge FN)$

According to Table 4, the relationship among the gameplays and objectives taken in game is shown. A list of key findings are summarized in Table 5.

Table 5
Key findings from induced logic

Region	Key Findings
LCK	In LCK, first blood is the least deciding factor of the game. Players should focus on contesting other objectives on the map such as first turret, first dragon, rift herald and first baron nashor. They should also maintain a gold lead at 20 minutes to increase their chances of winning the game.
NA LCS	For games in NA LCS, rift herald does not have much impact on the outcome of the game. Hence, teams should give priority on getting first blood, first turret, first dragon and first baron nashor. It is also important to maintain a gold lead at 20 minutes.
EU LCS	The winning rate is higher when a team gets first blood, first turret, first dragon, rift herald and gold lead at 20 minutes. The impact of first baron nashor in the game is not huge. Therefore, teams should not give away free kills or objectives to contest the first baron nashor of the game.

Every different regions have their own playstyle and hence the best induced logic, P_{best} for all 3 regions, LCK, NA LCS and EU LCS are different. The results have shown that 2SATRA has decent potential to obtain the logical rule that classifies the results of win or lose for a LoL game. It is extremely important to understand the playstyle of each region especially during the LoL World Championships. This is because the teams are not only competing with another team from their own region, they are also competing with top teams from other regions. The induced logic can help the coaches, managers and strategists in deciding the strategies in game. Game casters could also use the induced logic to provide expert discussion during a LoL game.

CONCLUSION

In this research, 2SATRA is shown to be a decent relationship extraction system to model the results of LoL games. The effectiveness of 2SATRA in doing logic mining is examined by using 3 data sets from 3 different regions. The results acquired showed that 2SATRA has decent potential to obtain optimal logic from learned data set. Future research could be done by using other gameplays such as first buff stolen, first success gank, numbers of turret plating fallen, first inhibitor taken and vision score at 20 minutes. Another logical rule such as randomized kSAT where $k > 2$ could also be utilized. Metaheuristic algorithm such as Ant Colony Optimization, Artificial Bee Colony and Artificial Immune System could also be utilized to accelerate the process of learning phase of 2SATRA.

ACKNOWLEDGEMENT

This research is supported by Short Term Grant (304/PMATHS/6315226) by Universiti Sains Malaysia (USM).

REFERENCES

Abdullah, W. A. T. W. (1992). Logic programming on a neural network. *International Journal of Intelligent Systems, 7*(6), 513-519.

Baio, G., & Blangiardo, M. (2010). Bayesian hierarchical model for the prediction of football results. *Journal of Applied Statistics, 37*(2), 253-264.

Bhandari, I., Colet, E., Parker, J., Pines, Z., Pratap, R., & Ramanujam, K. (1997). Advanced scout: data mining and knowledge discovery in NBA data. *Data Mining and Knowledge Discovery, 1*, 121-125.

Chen, I., Homma, H., Jin, C., & Yan, H. H. (2007). Identification of elite swimmers' race patterns using cluster analysis. *International Journal of Sports Science and Coaching, 2*, 293-303.

Craven, M. W., & Shavlik, J. W. (1997). Using neural networks for data mining. *Future Generation Computer Systems, 13*(2-3), 211-229.

Even, S., Itai, A., & Shamir, A. (1975, October 13-15). On the complexity of time table and multi-commodity flow problems. In *16th Annual Symposium of Foundations of Computer Science* (pp. 184-193). Washington, DC, USA.

Gaber, K., Bahi, M. J., & El-Ghazawi, T. (2000, November 15). Parallel mining of association rules with a Hopfield type neural network. In *Proceedings of 12th IEEE Internationals Conference on Tools with Artificial Intelligence* (pp. 90-93). Vancouver, BC, Canada.

Gee, A. H., Aiyer, S. V., & Prager, R. W. (1993). An analytical framework for optimizing neural networks. *Neural Networks, 6*(1), 79-97.

Hopfield, J. J., & Tank, D. W. (1985). "Neural" computation of decisions in optimization problems. *Biological Cybernetics, 52*(3), 141-152.

Jenny, S. E., Manning, R. D., Keiper, M. C., & Olrich, T. W. (2017). Virtual(ly) athletes: where eSports fit within the definition of "Sport". *Quest, 69*(1), 1-18.

Johansson, F., & Wikström, J. (2015). *Result prediction by mining replays in dota 2* (Master Thesis). Blekinge Institute of Technology, Sweden.

Johnson, M. B., Edmonds, W. A., Jain, S., & Cavados, J. J. (2009). Analysis of elite swimming performances and their respective between-gender differences over time. *Journal of Quantitative Analysis in Sports, 5*(4), 1-18.

Kane, D., & Spradley, B. D. (2017). Recognizing eSports as a sport. *The Sport Journal, 21*, 1-9.

Kasihmuddin, M. S. M. (2017). *Satisfiability logic programming incorporating metaheuristics in Hopfield neural networks* (PhD Thesis). Universiti Sains Malaysia, Malaysia.

Kasihmuddin, M. S. M., Mansor, M. A., & Sathasivam, S. (2017). Hybrid genetic algorithm in the Hopfield network for logic satisfiability problem. *Pertanika Journal of Science and Technology, 25*(1), 139-152.

Kim, Y. J., Engel, D., Woolley, A. W., Lin, J. Y. T., McArthur, N., & Malone, T. W. (2017, February 25 - March 01). What makes a strong team?: Using collective intelligence to predict team performance in League of Legends. In *Proceedings* of *2017 ACM Conference on Computer Supported Cooperative Work and Social Computing* (pp. 2316-2329). Portland, Oregon, USA.

Lamb, P., Bartlett, R., & Robins, A. (2010). Self-organising maps: An objective method for clustering complex human movement. *International Journal of Computer Science in Sport, 9*, 20-29.

Lan, X., Duan, L., Chen, W., Qin, R., Nummenmaa, T., & Nummenmaa, J. (2018). A player behavior model for predicting win-loss outcome in MOBA games. In *International Conference on Advanced Data Mining and Applications* (pp. 474-488). Cham, Switzerland: Springer.

Maknickas, A. A. (2015). How to solve kSAT in polynomial time. *International Journal of Operational Research, 23*(3), 257-267.

Mansor, M. A., Sathasivam, S., & Kasihmuddin, M. S. M. (2018). 3 satisfiability logic programming approach for cardiovascular diseases diagnosis. *AIP Conference Proceedings, 1974*(1), 020022.

Miyashiro, R., & Matsui, T. (2005). A polynomial-time algorithm to find an equitable home-away assignment. *Operations Research Letters, 33*(3), 235-241.

Muezzinoglu, M. K., Guzelis, C., & Zurada, J. M. (2003). A new design method for the complex-valued multistate Hopfield associative memory. *IEEE Transactions on Neural Networks, 14*(4), 891-899.

Mukherjee, S., & Roy, S. (2015, June 26-29). Multi terminal net routing for island style FPGAS using nearly-2-sat computation. In *19th International Symposium on VLSI Design and Test (VDAT)* (pp. 1-6). Ahmedabad, India.

Nascimento Jr, F. F. D., Melo, A. S. D. C., da Costa, I. B., & Marinho, L. B. (2017, October 17-20). Profiling Successful Team Behaviors in League of Legends. In *Proceedings of the 23rd Brazilian Symposium on Multimedia and the Web* (pp. 261-268). Gramado, RS, Brazil.

Nunes, S., & Sousa, M. (2006, January 9). Applying data mining techniques to football data from European championships. In *Actas da 1ª Conferência de Metodologias de Investigação Científica (CoMIC'06)* (pp. 4-16). University of Porto, Portugal.

Reitman, J. G. (2018). Distributed cognition and temporal knowledge in league of legends. *International Journal of Gaming and Computer-Mediated Simulations (IJGCMS), 10*(1), 23-41.

Riot Games. (2018). *2018 events by the numbers*. Retrieved April 27, 2019 from https://nexus.leagueoflegends.com/en-us/2018/12/2018-events-by-the-numbers/

Rojas, R. (1996). *Neural networks: a systematic introduction*. Berlin, Germany: Springer.

Sathasivam, S. (2006). *Logic Mining in Neural Networks* (PhD Thesis). Universiti Malaya, Malaysia.

Sathasivam, S. (2010). Upgrading logic programming in Hopfield network. *Sains Malaysiana, 39*(1), 115-118.

Sathasivam, S., & Abdullah, W. A. T. W. (2011). Logic mining in neural network: reverse analysis method. *Computing, 91*(2), 119-133.

Schwenker, F., Kestler, H. A., & Palm, G. (2001). Three learning phases for radial-basis-function networks. *Neural Networks, 14*(4-5), 439-458.

Singh, Y., & Chauhan, A. S. (2009). Neural networks in data mining. *Journal of Theoretical and Applied Information Technology, 5*(1), 37-42.

Tayman, J., & Swanson, D. A. (1999). On the validity of mape as a measure of population forecast accuracy. *Population Research and Policy Review, 18*(4), 299-322.

Velavan, M., Yahya, Z. R., Halif, M. N. A., & Sathasivam, S. (2015). Mean field theory in doing logic programming using Hopfield network. *Modern Applied Science, 10*(1), 154-160.

Wang, S. (2005). Classification with incomplete survey data: a Hopfield neural network approach. *Computers and Operations Research, 32*(10), 2583-2594.

Wang, W. (2016). *Predicting multiplayer online battle arena (MOBA) game outcome based on hero draft data* (PhD Thesis). National College of Ireland, Dublin.

Willmott, C. J., Ackleson, S. G., Davis, R. E., Feddema, J. J., Klink, K. M., Legates, D. R., … & Rowe, C. M. (1985). Statistics for the evaluation and comparison of models. *Journal of Geophysical Research: Oceans, 90*(C5), 8995-9005.

Yang, P., Harrison, B. E., & Roberts, D. L. (2014, April 3-7). Identifying patterns in combat that are predictive of success in MOBA games. In *9th International Conference on the Foundations of Digital Games* (pp. 1-8). Liberty of the Seas, Caribbean.