# Predicting Game Outcome in Multiplayer Online Battle Arena Games

Sang-Kwang Lee
*Electronics and Telecommunications Research Institute*
Daejeon, South Korea
sklee@etri.re.kr

Seung-Jin Hong
*School of ICT*
*University of Science and Technology*
Daejeon, South Korea
hsj9649@etri.re.kr

Seong-Il Yang
*Electronics and Telecommunications Research Institute*
Daejeon, South Korea
siyang@etri.re.kr

***Abstract*—Multiplayer online battle arena (MOBA) is currently one of most popular game genres in game artificial intelligence (AI). In this paper, we propose a method for predicting game outcome in MOBA games. Firstly, we extract features that contain the properties of the game outcome from game replay logs, taking into account game time. And then we implement a model for predicting the game outcome and interpret which features are important factors in the model. Experimental results show that the proposed method has high accuracy enough to predict the game outcome at a certain time point. It also analyzes the main play factors of game outcome for each game time zone.**

***Index Terms*—eSports, League of Legends, prediction model**

## I. Introduction

Recently, the multiplayer online battle arena (MOBA) is a major game genre that is the subject of game artificial intelligence (AI) research. In general, MOBA is subgenre of real-time strategy games in which each player controls a single character as part of a team competing against another team of players [1]. Typically, Valve's Dota 2 and Riot Games' League of Legends belong to games of this genre.

Game outcome prediction improves understanding of game characteristics and is the basis for strategy development for human and AI players. In addition, by looking at these characteristics over time, we can recognize the game meta information such as the most effective tactics available. [2] proposed a simple and interpretable model for Blizzard Entertainment's real-time tactics simulation (RTS) game, StarCraft II, using data obtained from a single player. [3] predicted the game outcome based on the champion data selected by each team for Dota 2, and [4] divided the factors determining the game output into individual and total states, and used it for modeling the output analysis.

In this paper, we present a game outcome prediction model based on player log data for League of Legends. The above described methods have a disadvantage in that they do not reflect game characteristics for each play time because they are modeling of game outcome using static features from the game start to end. In this work, we propose a modeling method for predicting game outcome that considers dynamic features according to characteristics of each play time zone.

## II. Proposed Prediction Method

### A. League of Legends

In general, League of Legends is a 5v5 match, with ten players split into two teams (called Blue and Purple). Teams work together to achieve a victory condition, typically destroying the core building called the Nexus in the enemy team's base [5]. Each team's Nexus is located on the top right and bottom left of the map, and the map has a generally symmetrical structure as shown in Fig. 1.

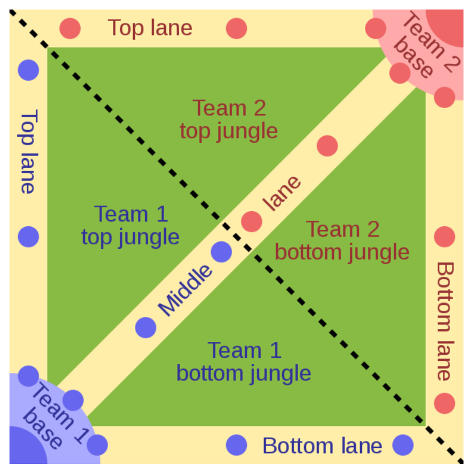


Fig. 1. Typical map of MOBA genre game [6]

### B. Prediction Modeling

To predict game outcome, we first consider the play elements that determine the outcome of the match. The play elements containing characteristics of the current state at a certain point in time are used as features of predicting game outcome. In this paper, we define the dynamic features to predict game outcome. Dynamic features are play elements that change continuously over time, such as amount of gold collection, kill score, tower destruction, and champion levels. In particular, we use the difference in gold collection, kill score, and tower destruction between the two teams, and for the champion levels, both teams' ten champion levels are all used as features (see Table I). Considering the characteristics of gameplay over time, we extract these features every five

TABLE I
DYNAMIC FEATURES

| Features | Remark |
|---|---|
| Gold collection difference | Blue minus Purple[b] |
| Kill score difference | Blue minus Purple |
| Tower deconstruction difference | Blue minus Purple |
| Champion levels[a] | - |

[a]Ten champion levels from both teams
[b]Feature value difference

minutes and implement a game outcome prediction model for each time zone using a random forest classifier.

## III. Experimental Results

In order to evaluate the performance of the proposed method, we collected 30,108 ranked games for the top tier players using the Riot Development API [7]. We created the dataset by extracting the dynamic features and win/loss labels from the collected game logs. And then we implemented the game outcome prediction model using scikit-learn [8], a Python-based machine learning library. Also, we used 90% of the dataset for training model and 10% for verifying model performance.

TABLE II
PERFORMANCE OF THE PROPOSED MODEL FOR EACH TIME ZONE

| Time zone(min) | Accuracy | Precision | Recall | F-score |
|---|---|---|---|---|
| 5 | 0.6225 | 0.6228 | 0.6225 | 0.6225 |
| 10 | 0.6788 | 0.6793 | 0.6788 | 0.6781 |
| 15 | 0.7318 | 0.7318 | 0.7318 | 0.7318 |
| 20 | 0.7649 | 0.7653 | 0.7649 | 0.7647 |
| 25 | 0.8037 | 0.8037 | 0.8037 | 0.8036 |
| 30 | 0.8613 | 0.8621 | 0.8613 | 0.8613 |
| 30 ∼ | 0.9608 | 0.9640 | 0.9608 | 0.9609 |

TABLE III
RELATIVE FEATURE IMPORTANCE

| Features \ Time zone(min) | 10 | 15 | 20 | 30 |
|---|---|---|---|---|
| **Gold collection difference** | **0.4308** | 0.3395 | 0.3220 | **0.3048** |
| Kill score difference | 0.1537 | 0.1690 | 0.1877 | 0.1692 |
| Tower deconstruction difference | **0.0041** | 0.1215 | 0.1306 | **0.1464** |
| Champion level(Blue Top) | 0.0465 | 0.0441 | 0.0367 | 0.0350 |
| Champion level(Blue Jungle) | 0.0434 | 0.0479 | 0.0442 | 0.0455 |
| Champion level(Blue Middle) | 0.0420 | 0.0397 | 0.0348 | 0.0341 |
| Champion level(Blue Bottom) | 0.0338 | 0.0369 | 0.0350 | 0.0371 |
| Champion level(Blue Support) | 0.0417 | 0.0405 | 0.0338 | 0.0391 |
| Champion level(Purple Top) | 0.0460 | 0.0443 | 0.0352 | 0.0352 |
| Champion level(Purple Jungle) | 0.0436 | 0.0489 | 0.0433 | 0.0432 |
| Champion level(Purple Middle) | 0.0414 | 0.0410 | 0.0351 | 0.0351 |
| Champion level(Purple Bottom) | 0.0325 | 0.0378 | 0.0371 | 0.0386 |
| Champion level(Purple Support) | 0.0407 | 0.0400 | 0.0336 | 0.0369 |

Table II shows the model performance for each time zone. As the game time elapses, the prediction performance increases. In addition, it can be seen that when the game time is over fifteen minutes, the prediction performance has a more than 70% accuracy. It is high accuracy enough to predict the game outcome. Table III shows the results of calculating the relative feature importance to analyze the main play factors that determine the game outcome through the prediction model. Gold collection plays the most important role in the entire time period, however, it tends to decrease over time. On the other hand, each champion level has a minor impact on the prediction of game outcome. Also, it can be seen that tower destruction is a major factor after fifteen minutes of game time and the importance increases as the game time elapses.

Fig. 2 and Fig. 3 show the gold collection difference and game win probability prediction over time, respectively. The game outcome prediction graph follows the gold collection difference graph similarly. We can see that gold collection difference is a key feature in predicting game outcome.

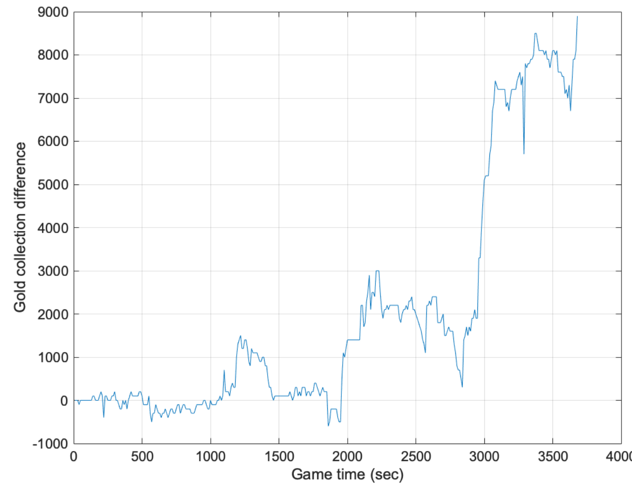


Fig. 2. Gold collection difference

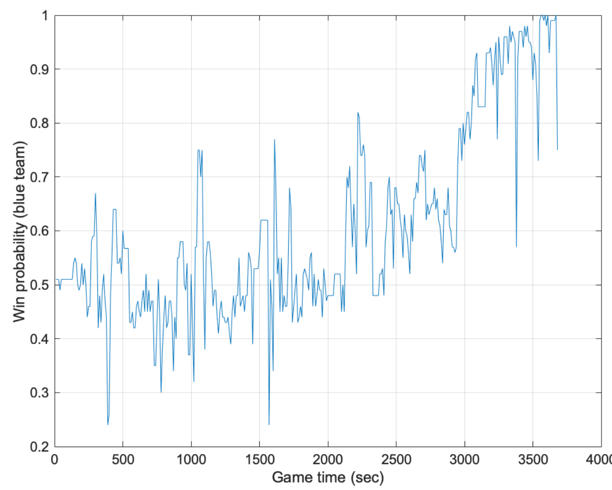


Fig. 3. Win probability prediction

## IV. Conclusion

Understanding characteristics of games provides successful commercialization of the game as well as game AI technology development. In this paper, we proposed the game outcome prediction model, considering play characteristics for each time zone. In addition, we analyzed the factors that play a major role in the game outcome by calculating the importance of each feature. In future works, we will consider more diverse play elements, apply deep neural networks that can analyze input features, and expand on games of other genres such as RTS, first person shooting (FPS).

## Acknowledgment

This research is supported by Ministry of Culture, Sports and Tourism and Korea Creative Content Agency(Project Number: R2019020067).

## References

[1] https://en.wikipedia.org/wiki/Multiplayer_online_battle_arena
[2] V. Volz et al., "Towards Embodied StarCraft II Winner Prediction," Workshop on Computer Games, 2018.
[3] W. Wang, "Predicting Multiplayer Online Battle Arena (MOBA) Game Overcome Based on Hero Draft Data," Masters thesis, Dublin, National College of Ireland, 2016.
[4] L. Yu et al., "MOBA-Slice: A Time Slice Based Evaluation Framework of Relative Advantage between Teams in MOBA Games," Workshop on Computer Games, 2018.
[5] https://en.wikipedia.org/wiki/League_of_Legends
[6] https://commons.wikimedia.org/wiki/File:Map_of_MOBA.svg
[7] https://developer.riotgames.com/apis
[8] https://scikit-learn.org