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Deep learning in multiplayer online battle arena games

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Abstract. Multiplayer Online Battle Arena games, known as MOBA in abbreviation, are developing rapidly, and more and more new players are growing interests to it. But some parts of these games are quite complicate for those beginners, such as how to pick appropriate champions, how to choose suitable items for purchasing, what is the win rate for current game session and how to make correct strategy decisions. This paper summarized some works, that can help players to solve those complicate parts and understand the game well, using machine learning and deep learning models. These works have all proved their feasibility according to either their result comparing with other baseline methods, or simulating some game sessions played by or against AI using their champion picking, item purchasing and strategy making suggestions. There are also some limitations of these works and some improvements of using machine learning and deep learning in MOBA game industry mentioned in this paper.

Keywords: MOBA, Deep Learning, Transformer, League of Legends, Dota2.

1. Introduction

Games are becoming more and more popular among young generations nowadays. Among them, the most popular two categories of games are Multiplayer Online Battle Arena (henceforth referred to as MOBA) and First Person Shooter (henceforth referred to as FPS) games. Dota2, League of Legends and Honor of Kings (or Arena of Valor, which is its international version) are some examples of the MOBA games played most worldwide. For example, among the 10 most played esports tournaments in 2022, 7 of these tournaments are MOBA game events, top 1 and top 6 are League of Legends events, 2022 World Championship and 2022 Mid-Season Invitational respectively. Top 2 to 5 are Mobile Legends events, a mobile MOBA game, and top 8 is The International 2022, a Dota 2 esports tournament [1].

MOBA games are normally in the form of two teams of same amounts of players compete against opposing team, aiming to destroy their home base, meanwhile protect allied home base from being destroyed by opposing team. There are two forms of games in each MOBA game: Blind-pick and Draft-pick. Blind-pick refers to picking champions without banning champions and knowing enemies' pick, while players playing Draft-pick mode has champion banning and knows the champions which the opposing team has already selected.

Each player in MOBA games would control to a champion picked by the player themselves, and is assigned to a unique role. A simple example can be drawn from one of the most famous MOBA game, League of Legends, players are split into five roles: Top Laner, Jungle, Mid Laner, Bottom Laner and Support. Champions in the game have their own unique ability sets with different uses, for example,

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some of them could deal damage to enemies, while some of them might be able to heal allies. To destroy opposing team's home base, players should make themselves more powerful. Eliminating minions and neutral creatures, slaying enemy champions and destroying their turrets would help players gain in-game Gold, which can be used to buy useful and powerful items. Eliminating some of the neutral creatures could obtain extra buffs, which is beneficial for winning the game, as well.

There are a large number of champions in MOBA games, for example, there are currently 164 champions in the latest version of League of Legends and 124 champions in Dota2, and understanding their synergy and counter relationships would help a lot in winning the game. However, it is a challenging task to deeply understand those for players who is not well experienced in this game. There are also many items that each player could choose to buy, each player could buy up to 6 items and there are, for example, almost 160 items in League of Legends. So similar to the problem of champion selection, it is also difficult for players that is not well experienced to find items that suit the champion they selected.

There are a number of previous works did alleviate those problems, but there is no review about them. So, in this paper, those works are summarized and are put into four categories: Item recommendation, Draft recommendation, Outcome prediction and Strategy making, from Section 2.1 to Section 2.4 respectively, and Section 6 is the conclusion.

2. Methodology

2.1. Draft recommendation

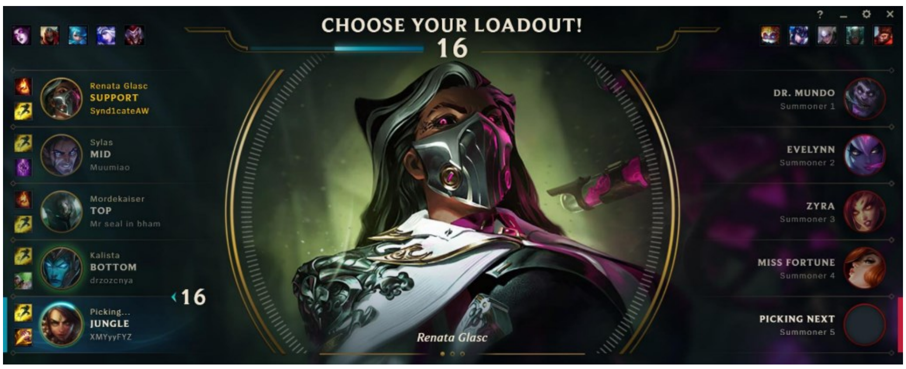

Figure 1. The UI of League of Legends drafting stage. 10 champions in the upper left and upper right corners in the figure are the champions banned by both allied team and enemy team, while left and right sides are the champions picked.

Draft recommendation is literally helping the players to select the most suitable champions in the current game. As shown in Figure 1, champions in the upper left and upper right corners in the figure are the champions banned by both allied team and enemy team, while left and right sides are the champions picked.

As Sheng Chen et al [2]'s research, they built their method according to leveraging neural networks and Monte-Carlo tree search (henceforth referred to as MCTS), they used MCTS with a value network and policy network, the value network analyzes the value of current game state while the policy network samples actions for next draft. They tested their model on two datasets individually, based on both matches played by AI and human. They have implemented an AI system for playing the actual game, and tested on the AI datasets for 30 million matches. Champions' drafting data and game outcome, which contains win-lose of the game and many other data, was collected. For their human matches dataset, there is also 30 million matches played by top 5% players recorded, with the same data categories that the AI dataset has collected. They compared their winning rate predictor (Neural Network) with two baseline methods Gradient Boosted Decision Tree and Logistic Regression (henceforth referred to as LR). These methods are also trained on those two individual datasets respectively as well.

Their metrics are accuracy (henceforth referred to as ACC), area under ROC curve and the harmonic mean of the precision and recall for each method. Their Neural Network performs best on all metrics for both AI and human datasets. And all these methods had lower performances when using human dataset than using AI dataset, they believed that the reason is, all the AIs play under similar policies and strategies, while different human players game style varies, which makes it difficult to predict. They compared their model with three other strategies: DraftArtist, Highest Winning Rate (henceforth referred to as HWR) and RD for the champion recommendation task, they also compared with their model without long-term value mechanism. DraftArtist is pure MCTS without their trained value network and policy network, HWR selects the champion whose winning rate is the highest in the champion pool. And their results show that their method beats all the other baseline methods in both single-round (BO1: Best of 1) and multi-round (BO3: Best of 3 and BO5: Best of 5).

However, the experiment above did not consider the preference of the players and the champions which the players are good at. Hojoon Lee et al [3] also did some experiments to solve this problem. Their Transformer-based model include two networks, match network and player network. The player network would encode the match histories of the players, which include their champions used and their game data for each match, this indicates their preference of champions selection. If a champion has the highest use rate and win rate, that champion could be considered as that player's best-played champion. Then these encoded match history data were taken by the match network as input, recommends bans and picks of champions according to players' champion preference, team they belong to, champions banned and picked by enemy team. Match outcome is also predicted by their model. They used 279,893 League of Legends higher-ranked match data and 50,000 Dota2 match data as their dataset. They compared their model with 5 personalized recommendation baselines (POP, NCF, DMF, S-POP and SASRec) to verify the recommendation performance, and 6 baselines (Majority Class, LR, Neural Network, OptMatch and NeuralAC) for their match outcome prediction. Their metrics for the recommendation task, Hit Ratio (henceforth referred to as HR), Normalized Cumulative Gain (henceforth referred to as NG), varying rank k from {1, 5, 10} and ACC, Mean Absolute Error (MAE) for outcome prediction. The higher the value is, the better performance would be, for all metrics except MAE. They trained their model for two times, i.e., with match history and without match history. Results show that modelling the players' preferences could improves recommendation performance. Their model has the highest performance against all the other baselines for all these chosen metrics and datasets except HR at rank 1 and NG at rank 5 in Dota2, they speculated that the reason is the lack of players' history in Dota2 dataset, this situation made it harder for analyzing player's preferences. For the outcome prediction, their results indicate that knowing the players' preference would have superior prediction performance.

To make the draft recommendation more successful, the synergy and opposition relationships between champions are required, and Zhengxing Chen et al [4] made a model named Game Avatar Embedding which is able to analyze the different relationships between different champions. And to validate the sensibility of the results that their model made, they compared the synergy and opposition relationships made by their model with human experts' suggestion, and apparently, the result of their model is better than the baselines they have chosen.

2.2. Item recommendation

Figure 2. The UI of League of Legends' in-game shop, a large number of items that can be chosen.

Figure 3. The UI of a player's inventory in a League of Legends game. Up to 6 items allowed for each player to buy.

This task is about recommending which items should the players buy. As shown in Figure 2, there are a large number of items that can be chosen in the in-game shop and as show in Figure 3, each player's in-game inventory only allows each player to buy up to 6 items.

According to Andrés Villa and et al [5]'s paper, they build the model based on Transformer. It would take a match information as input, including champions selected, roles assigned to champions, and team they belong to (Red team and Blue team), and the model would output the probabilities that the champion would select, so the model could recommend a list of six most probable items. They are inspired by the BERT model, they generated a clear description of each player, including their champions, their roles and the team information, and use these descriptions as the input of the model. Then they used the transformer encoder to obtain the contextual embeddings of each input respectively. And finally obtain the recommendation probabilities through the full-connected layer followed by a sigmoid function. They have chosen Precision, Recall, F1, and MAP as their evaluation metrics, and their dataset contains 184,070 ranked game sessions. As their experimental results show, compared with 4 different baselines (decision tree, LR, convolutional neural network and artificial neural network), their model appears to be statistically significant improved.

Alexander Dallmann et al [6] thought Sequential Item Recommendation model is effective in many different domains, and they explored how capable the models in the item recommendation in Dota2. They used the dataset that is created by themselves and found out that models which consider the order of buying items turned out to be more effective.

2.3. Outcome prediction

The methods to predict the game outcome might varies, Kodirjon Akhmedov and Anh Huy Phan [7]'s method is dependent on the time-lagged correlation to rows (the number of steps ahead of predicting the game.) and multi-forward steps (the number of joining rows). Those parameters can manually be adjusted by users. Their dataset is constructed using these two parameters above, and they have chosen three machine learning models: Neural Networks, LR and Long Short-Term Memory (henceforth referred to as LSTM). Their results show that all those models have achieved fairly good accuracy, and they could see the performance of them. They were concerned about the accuracy, but they had a firm belief that the accuracy fluctuates over the range of datasets after several experiments. After they altered some parameters and data, the range did not drop much.

Meanwhile, Zelong Yang et al [8] had a different idea, they divided some features of the game that might influence the game outcome, and calculated probabilities base on each of those features individually. Their model is a Two-Stage Spatial-Temporal Network that could interpret the MOBA outcome in real-time. During the first stage, they split the in-game features into six categories, and the proceed to Spatial-Stage to compute individual prediction for each category, and then pass those individual predictions to the Temporal-Stage to generate the final outcome prediction which is computed by combining with time-dependent importance weights. Their dataset contains 184,362 match information, 10,000 of them were randomly chosen for testing. 90% of the rest of them were the training dataset and the remained 10% for validation. They compared their model with Heuristic, Fully-Connected, LR and LSTM, and chose ACC at different time-points as evaluation metrics. They also entrusted three human specialists for predicting the winner of each game manually, all of them were the top 0.1% ranked player, as higher ranked players' prediction might be more accurate. Randomly chose 200 matches as it is impossible to predict all the 10,000 matches annually. The result showed that the accuracy of their model was higher than Heuristic model but a slightly lower than the Fully-Connected Network all the time, and their model might be higher and lower than LSTM as time-point varies.

Meanwhile, other two methods of predicting outcome also achieved good progress. Tiffany D. Do et al [9] proposed a method that can predict game results via a deep neural network, and their accuracy achieved 75.1%. And Dong-Hee Kim et al [10]'s method is a confidence-calibration method for game winner prediction. Their method considered data uncertainty as a factor, and their results achieved a lower expected calibration error than using another conventional temperature scaling method.

2.4. Strategy making

After recommending the draft picking and item purchase, one more way to help players winning the game is making strategy. As everyone knows, MOBA games are originated from RTS (Real-Time Strategy) games, which means both the two categories of game requires more or less strategy respectively. Although human would not have better execution on the strategies given than AI, having a better strategy are believed to be effective for winning the game.

Bin Wu et al [11] proposed a Hierarchical Macro Strategy Model, which would make strategy decisions and guide for the strategy execution, and different strategies individually. They have used their strategy model on Game AI, and the result is their AI team with strategy given had a 48% winning rate, when playing against top 1% ranked players teams.

3. Conclusion

This paper brings together four main tasks of improving players' MOBA game experiences, using machine learning models and deep learning models. Each experiment has solved those tasks respectively well, and has also proved their model worked successfully. After analyzing those experiments, most of those datasets used are the game data obtained from the official API or directly from the game company, but have to be limited to the games through only one game version. In the other word, those recommendation and prediction training should be updated frequently, as some of the in-game values is not changed annually, games like League of Legends might have many hot fixes to change in-game values frequently. And for the item recommendation task, the influence of in-game state can also be considered as a factor, such as, use the data of enemies' items as an extra parameter, to improve accuracy of the recommended items and make the recommendation be in real-time.

Generally speaking, deep learning's application in MOBA games is quite matured and can really help people playing the game well. And people can look forward to use it in other game categories and the whole game industry.

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