Abstract

Artificial intelligence (AI) technology has made great progress in recent years and has been used for various applications in society. Games are one such application, and research has long focused on the goal of creating strong AI players. The advent of AlphaZero and Deep Q-Network provides evidence that such a goal can be achieved. Since then, it has become increasingly important to pursue other goals such as "entertaining human players" or "teaching human players."

The role of entertaining or teaching is not necessarily played only by AI players who appear as enemies or teammates in the games. To elaborate, procedural content generation (PCG) is another important role for entertaining or teaching human players. These content generators do not directly appear in the games, but they may create levels that are fun to play or provide practice. AI technologies such as machine learning and generative AI are often used in this field as well.

In addition to fully automatically generating game content, there are some attempts to generate game content collaboratively with humans. One example is to use AI as test players to evaluate human-generated content for adjusting the game balance. This allows for reduced workload and high-quality content generation while respecting the intentions of human designers.

Collectible card games (CCG) are a game genre in which players collect cards and select a set of cards (deck) to play against other players, mainly one-on-one. Some CCGs, such as Yu-Gi-Oh! and HearthStone, have histories of more than 10 years and are widely played. Each game provides players with hundreds to over 10,000 cards. Cards have basic parameters such as mana cost, health points, and attack. In addition, many cards have special "effects" such as "attacking twice," "taking over enemy attacks on behalf of teammates," or "increasing teammates' attack by one." When combined appropriately, these effects can have a significant interaction, making players enjoy considering appropriate combinations of cards. These cards are added gradually, and the game must be attractive and balanced, taking into account the interactions between the new and existing cards. This is a challenging task and a costly collaboration between skilled game designers and a large number of test players.

In recent years, researchers have applied AI technologies to adjust the balance of card games. For example, Mesentier Silva et al. used a multi-objective optimization algorithm to obtain a set of Pareto optimal solutions (deck parameters) that satisfy the following two objectives: (1) the win rate between decks should be approximately 50%, and (2) the parameters of the decks should not differ too much from the original values in order to keep the concepts of the cards or the decks.

However, we consider it unsatisfactory to merely have 50Not limited to card

games, there are various factors that are necessary to make games interesting to play. When considering card games specifically, the following cases are likely to cause players' dissatisfaction: "Win or loss is determined by whether or not a certain card is drawn early in the game," or "it is easy to have overwhelming wins or losses."

Therefore, in this study, we first considered what factors contribute to the enjoyment of card games. Among the many candidate factors, some of them had little to do with the adjustment of card parameters, and some were difficult to quantify by computer. More specifically, in addition to the two factors mentioned above, the following lists required factors to form good card sets: (3) Games should not end in overwhelming wins or losses. (4) Games that are too long should be few. (5) Games that are too short should be few. (6) Cards that are rarely used should be few. (7) Cards that are too powerful should be few, where "too powerful" means that the winners are determined by whether the players can draw the cards or not.

We employed a genetic algorithm to adjust the deck parameters to satisfy the above-mentioned factors. Our target game was a simplified version of HearthStone that consisted of three decks with different characteristics (aggro, control, and spell). We optimized the 16 cards in the three decks, which contained a total of 38 parameters. Since a 7-objective optimization would result in too many candidate solutions, we defined the weights for each enjoyment factor and conducted single-objective optimizations instead.

Our experiments showed that when only (1) and (2) are optimized, (3) to (7) are likely to be sacrificed, while when all of (1) to (7) are considered, many factors can be improved without sacrificing (1) and (2) too much. Among the 38 parameters, averagely 5 were changed after the optimization; thus, we concluded that the original concept of the cards or decks was not changed significantly. Looking at the optimized parameters, we found that the mana costs, i.e., costs of playing cards, in aggro decks were often increased. With such adjustments, the ratio that aggro decks won quickly against control decks reduced (factors 1, 3, and 5), which also increased the chances for the control decks to use cards with high costs (factor 6). In addition, the number of minions on the board for aggro decks was reduced, lowering the power of cards that attack all enemies in spell decks (factor 7). In this study, we investigated a small set of cards and left the following as future work: improving the algorithm to allow for larger-scale parameter adjustments and improving the evaluation function for enjoyable decks through subject experiments.