Creating Pro-Level AI for Real-Time Fighting Game with Deep Reinforcement Learning

Inseok Oh*, Seungeun Rho*, Sangbin Moon, Seongho Son, Hyoil Lee and Jinyun Chung†
NCSOFT
{ohinsuk, gloomymonday, sangbin, hingdoong, onetop21, jchung2050}@ncsoft.com

Abstract

Reinforcement learning combined with deep neural networks has performed remarkably well in many genres of game recently. It surpassed human-level performance in fixed game environments and turn-based two player board games. However, no research has ever shown a result that surpassed human level in modern complex fighting games, to the best of our knowledge. This is due to the inherent difficulties of modern fighting games, including vast action spaces, real-time constraints, and performance generalizations required for various opponents. We overcome these challenges and made 1v1 battle AI agents for the commercial game, “Blade & Soul”. The trained agents competed against five professional gamers and achieved 62% of win rate. This paper presents a practical reinforcement learning method including a novel self-play curriculum and data skipping techniques. Through the curriculum, three different styles of agents are created by reward shaping, and are trained against each other for robust performance. Additionally, this paper suggests data skipping techniques which increased data efficiency and facilitated explorations in vast spaces.

1 Introduction

Reinforcement learning (RL) is extending its boundaries to a variety of game genres. In PVE (player versus environment) settings such as Atari 2600 games, RL agents have exceeded human level performance using various methods including value-based methods [Mnih et al., 2015, Kapturowski et al., 2019] and actor-critic methods [Mnih et al., 2016, Espeholt et al., 2018]. Likewise, in PVP (player versus player) settings, neural networks combined with search-based methods beat the best human players in turn-based two player games, such as Go and Chess [Silver et al., 2018b]. Recently, the focus of RL research in game has shifted to complex video games like StarCraft2 [Vinyals et al., 2017], Quake3 [Jaderberg et al., 2018], Dota2 [OpenAI, 2018], and Vizdoom [Kempka et al., 2016]. Real-time fighting games are one of the most representative types of complex video games. Although some researches [Li et al., 2018; Firoiu et al., 2017; Kim et al., 2017] have made progress with real-time fighting games, they generally require simpler strategies compared to more complex modern games due to their smaller problem spaces. We created pro-level AI agents for complex fighting game “Blade & Soul (B&S) Arena Battle”.

B&S is a commercial massively multiplayer online role-playing game, which is famous for realistic martial arts movements. B&S supports duels between two players called “B&S Arena Battle (BAB)”. Figure 1 displays a scene from BAB. In BAB, two players fight each other to reduce their opponent's health point (HP) to zero within three minutes. If the match does not end in three minutes, the player who dealt more damage to the opponent wins.

To master BAB, an agent must be able to deal with real-time constraints and more complex challenges compared to classic board games. First, an agent must manage vast and complicated action and state spaces. The vast action space is a result of numerous combinations of skill and move decisions, while the vast state space is a result of the continuous nature of modern fighting games. Moreover, some skills are dependent on other skills; e.g., a skill may become available only for a short period of time following the use of another skill. As a result, out of the 45 skills in total (including “noop”), the set of skills available at a given time is continuously changing. The agent must also consider the characteristics of each skill because they each have different cool times and

*Equal contribution
†Corresponding author

Figure 1. A scene from the B&S Arena Battle
skill point (SP) consumption and serve one or more out of five different functions: damage dealing, crowd control (CC), resist, escape, and dash.

Additionally, an agent must be capable of facing any type of opponent. Because BAB is a real-time game, each player makes their skill decisions simultaneously. And because of the non-transitive hierarchies among the skills, BAB can be considered a series of rock-paper-scissors games. For example, when a player uses a resistance skill and the opponent uses a type of CC skill at the same time, the player gains advantage over the opponent. Therefore, an agent should be able to deal with the opponent’s skill decision that is unknown at decision time. As such, the essence of the problem is to make an agent perform well in general so that it can react appropriately to any opposing strategy.

To tackle these problems, we devised a new self-play curriculum with opponents with different fighting styles. We first introduced fighting styles through reward shaping, and created three agents with different fighting styles: aggressive, defensive and balanced. These agents were made to compete against each other and were reinforced together. This renders the agents capable of competing against various different opponents. Additionally, data skipping techniques were introduced to enhance explorations of vast space.

Our agents competed against professional players in the 2018 B&S World Championship Blind Match. The B&S World Championship is an annual event where a large number of professional gamers from around the world participate and compete. Our AI agents won three out seven matches.

2 Background

2.1 Reinforcement Learning

In reinforcement learning [Sutton and Barto, 1998], agent and environment can be formalized as a Markov decision process (MDP) [Howard, 1960]. For every discrete time step $t$, an agent receives a state $s_t \in S$ and sends an action $a_t \in A$ to the environment. Then, the environment makes a state transition from $s_t$ to $s_{t+1}$ with the state transition probability $P_{a_t}^{s_t} = P[s' | s, a]$ and gives a reward signal $r_t \in \mathbb{R}$ to the agent. Therefore, this process can be expressed with $\{S, A, P, R, \gamma\}$, where $\gamma \in [0, 1]$ is a discount factor, which represents the uncertainty of the future. Here, the agent samples an action from a policy $\pi(a_t | s_t)$, and the learning process modifies the policy to encourage good actions and suppress bad actions. The objective of learning is to find the optimal policy $\pi^*$ which maximizes the expected discounted cumulative reward.

$$\pi^* = \arg \max_{\pi} \mathbb{E}_\pi [\Sigma r_t \cdot \gamma^t]$$

2.2 Real-Time Two Player Game

In a real-time two player game, there are two players, namely, the agent and the opponent. Both of them send an action to the environment at the same time. Let’s denote the policy of the agent as $\pi^{ag}$, and the policy of the opponent as $\pi^{op}$. Both samples an action from its own policy for every time step.

$$a_t^{ag, op} \sim \pi^{ag, op}(a_t^{ag, op} | s_t)$$

Figure 2. Agent-environment plot in BAB

Then, the environment makes a state transition by considering those two actions jointly.

$$s_{t+1} \sim P(s_{t+1} | s_t, a_t^{ag}, a_t^{op}), r_{t+1} = R(s_t, a_t^{ag}, a_t^{op})$$

Here, MDP can be expressed as $\{S, A^{ag}, A^{op}, P, R, \gamma\}$. If $\pi^{ag}$ is fixed, then we can regard the opponent as a part of the environment by marginalizing the policy of the opponent.

$$P'(s_{t+1} | s_t, a_t^{ag}) = \sum_{a_t^{op}} \pi^{op}(a_t^{op} | s_t) \cdot P(s_{t+1} | s_t, a_t^{ag}, a_t^{op})$$

Then, the MDP expression turns into a simpler form with $P'$: $\{S, A^{ag}, P', R', \gamma\}$. This expression is coherent with the one player MDP. Therefore, any methods for the original MDP work in this form as well. However, $\pi^{op}$ is not fixed in general, and our agent does not know which $\pi^{op}$ it is going to face. We will propose a novel method regarding this in section 3.

2.3 BAB as MDP

Since the policy of the opponent can be marginalized into the environment, BAB can be expressed as an MDP. Figure 2 illustrates the agent-environment framework in BAB. LSTM [Hochreiter and Schmidhuber, 1997]-based agents operate in the BAB simulator, which corresponds to the environment. For every time step with 0.1 sec intervals, state $s_t$ is constructed from the history of observations $H_t = \{o_1, o_2, ..., o_t\}$. Any information provided to human players during the game is also given to the agent. To be specific, $s_t$ is the vector of about 600 real numbered and Boolean features, including HP, SP, cool time, position, etc. Then, the agent decides an action $a_t = (a_t^{skil}, a_t^{move})$ for every time step. The action is sent to the environment and a state transition occurs accordingly. Here, exact rewards should also be determined. Rewards are closely related to high performances in BAB. We provided $r_{WIN}^t$, which is the reward for winning a game, and $r_{HP}^t$, the reward for the changes in HP difference. These rewards are designed based on the assumption that the more you win with a larger HP margin, the better your performance is. $r_{WIN}^t$ is derived at the terminal step of each episode with +10 for win and -10 for loss. $r_{HP}^t$ may occur at every time step when
the agent deals damage to the opponent and vice versa. Since HP is normalized to [0, 10], $r_t^{WIN}$ and $r_t^{HP}$ have the same scale.

$$r_t = r_t^{WIN} + r_t^{HP}$$

$$r_t^{HP} = (H_t^{aq} - H_{t-1}^{aq}) - (H_t^{dp} - H_{t-1}^{dp})$$

These are fundamental rewards, and additional rewards for guiding battle styles will be described in section 3.2. The value of $\gamma$ is set to 0.995, which is close to 1.0, since all episodes in BAB are forced to terminate after 1,800 time steps (= 3 min).

3 Self-Play Curriculum with Diverse Styles

In this section, we explain how we induced fighting styles through reward shaping, and present our self-play curriculum.

3.1 Guiding Battle Styles through Reward Shaping

One of the most noticeable elements in fighting styles is degree of aggressiveness. We have determined three dimensions of rewards to adjust the degrees of aggressiveness. The first dimension is the “time penalty”. The aggressive agent receives larger penalties per time step, and this motivates the agent to finish the match in a shorter amount of time. The second dimension is the relative importance of the agent’s HP to the opponent’s HP. Aggressive players will try to reduce the opponent’s HP rather than preserving their own HP, while defensive players tend to act the opposite way. The final dimension is the “distance penalty”. Defensive players tend to secure a certain distance from their opponents to respond appropriately against attacks, while aggressive players tend to approach their opponents to attack relentlessly. To realize these properties, the aggressive agent received larger penalties in proportion to the distance between itself and its opponent. The specific reward weights used for each style are shown in Table 1. Note that each of three dimensions can take continuous values. This means that it is possible to create a spectrum of different fighting styles with varying degrees of aggressiveness. However, to effectively demonstrate the viability of this method, we limited the number of fighting styles to three. Using any type of additional reward signals along with $r_t^{WIN}$ and $r_t^{HP}$, this method can be applied to other fighting games in general to create agents with varying fighting styles.

3.2 Our Self-Play Curriculum

Our agents were trained through a novel self-play curriculum. Existing self-play methods [Silver et al., 2017; Silver et al., 2018a] generally use opponent pools for training. Parameters of a network are stored at regular intervals to create a pool of past selves produced during training. And opponents are sampled from the pool using a variety of sampling distributions: from uniform random distribution to somewhat biased distributions toward recent models. Self-play methods have two

![Figure 3. Overview of self-play curriculum with three different styles](image-url)

Table 1: Reward weights of each style

<table>
<thead>
<tr>
<th></th>
<th>Aggressive</th>
<th>Balanced</th>
<th>Defensive</th>
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<tbody>
<tr>
<td>Time penalty</td>
<td>0.008</td>
<td>0.004</td>
<td>0.0</td>
</tr>
<tr>
<td>HP ratio</td>
<td>5:5</td>
<td>5:5</td>
<td>6:4</td>
</tr>
<tr>
<td>Distance penalty</td>
<td>0.002</td>
<td>0.0002</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Note that each of three dimensions can take continuous values. This means that it is possible to create a spectrum of different fighting styles with varying degrees of aggressiveness. However, to effectively demonstrate the viability of this method, we limited the number of fighting styles to three. Using any type of additional reward signals along with $r_t^{WIN}$ and $r_t^{HP}$, this method can be applied to other fighting games in general to create agents with varying fighting styles.
main advantages. First, the opponents continue to be reinforced along with the agent. Thus, the agent can gain increasingly high-quality training experiences. Secondly, the diversity of opponents helps improve generalization performance. When an agent is faced with a single opponent, it will learn how to exploit the opponent’s fixed fighting patterns but will fail to deal effectively against other opponents.

However, for games with larger problem spaces, not enough space is covered during vanilla self-play, unless an explicit incentive is provided to diversify the pool. Therefore, we enforced the diversity into the pool by introducing agents with a range of different battle styles. And these agents were made to compete against each other. In this section, we will focus on data skipping techniques that allow the agent to choose certain data during training and evaluating procedures. We will cover data skipping methods applied to skill spaces and move spaces, respectively.

4 Data Skipping Techniques

In this section, we will focus on data skipping techniques that enhance data efficiency and facilitate efficient exploration in vast spaces. Data skipping refers to the process of dropping certain data during training and evaluating procedures. We will cover data skipping methods applied to skill spaces and move spaces, respectively.

4.1 Discarding Passive "No-op"

In fighting games, using skills generally consumes resources, such as SP and cool time. Therefore, if a player overuses a certain skill, it will not be available for use at actual times of need. Thus, players should strategically spare their skills to keep them available. To take this aspect into account, we concatenated a “no-op” action to the output of the policy network, allowing the agent to choose “no-op” and do nothing for a certain period if necessary. This means that our action space has 44 skills, plus an additional “no-op” action. In fact, human play logs of BAB show that “no-op” actions take up the largest portion of the entire game.

“No-op” decisions can be categorized into passive and active use cases. Passive usage of “no-op” means that an agent chooses “no-op” because there are no skills available for use. For example, when an agent is out of resources or is hit by an opponent’s CC skill. Active usage of “no-op” means that an agent selects “no-op” strategically, even though other skills are available for use.

We discarded passive “no-op” data from both the training and evaluation phases because passive “no-ops” had not been used deliberately by the agent. In addition, the method enables LSTM to reflect observations of longer time horizons because the data is not provided to the network. We will show in section 5.3 that skipping passive “no-ops” greatly improves learning efficiency. Note that this methodology is generally applicable to other domains where a set of available skills changes abruptly and “no-op” action is essential.

4.2 Maintaining Move Action

Although a single skill decision can have substantial influence on the subsequent states, the effect of a single move decision is relatively limited. The reason is that the distance a character moves for a single time step (0.1 sec) is very short considering its speed. In order for any moving decision to have a meaningful effect, the agent should make the same moving decision repeatedly for several ticks in a row. This allows the agent to literally “move”, and lead to the change of subsequent states and rewards. Therefore, it is difficult to train a move policy from the initial policy with random move decisions. Since the chance of random policy making the same decision consecutively is very low, exploration is extremely limited. So we propose maintaining move decision for fixed time steps.

Figure 4 shows how the method works with an example. If the agent selects a move action, it skips decision for the following n-1 time steps. This means that the agent maintains the same move decision for n steps in total. The larger n is, the less immediate the agent reacts but the more consistently the agent moves. In this case, the sweet spot was around 10 ticks of maintaining decision (equivalent to 1 sec).
Table 2: Win rate of three style of agents against baseline (1,000 games each)

<table>
<thead>
<tr>
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<th>Aggressive</th>
<th>Balanced</th>
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<tbody>
<tr>
<td>Vs. Baseline</td>
<td>59.5%</td>
<td>63.8%</td>
<td>63.2%</td>
<td>62.2%</td>
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</table>

Table 3: Generalization performance of three styles of agents for both with and without shared pool (7,000 games each)

<table>
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<th>Average</th>
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</thead>
<tbody>
<tr>
<td>Shared</td>
<td>64.8%</td>
<td>79.6%</td>
<td>75.3%</td>
<td>73.6%</td>
</tr>
<tr>
<td>Ind.</td>
<td>64.7%</td>
<td>72.1%</td>
<td>56.5%</td>
<td>64.4%</td>
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</tbody>
</table>

5 Experiments

5.1 Implementation Details

Architecture
The network is composed of LSTM-based architecture of depth 30 and has four heads with shared state representation layer. Each head is consisted of $\pi_{\text{skill}}$ (45 dims), $Q_{\text{skill}}$ (45 dims), $\pi_{\text{move}}$ (5 dims including “no-move”) and $Q_{\text{move}}$ (5 dims). $Q_{\text{skill}}$ and $Q_{\text{move}}$ are used for gradient update of $\pi_{\text{skill}}$ and $\pi_{\text{move}}$ respectively. After the softmax layer outputs of skill distribution, a Boolean vector indicating the availability of each skill is taken element-wise multiplication with the output. Then it is normalized to produce a sum of 1, resulting in the final probability distribution.

Algorithm
We used ACER [Wang et al., 2017] as the learning algorithm. It offers off-policy learning, which enables us to deal with policy lag between simulator and learner. Also, we could exploit the advantage of stochastic policy since it is an actor-critic based method. Stochastic policy responds more stably to changes in the environment due to smooth updates of policy, and it works well in the domain of games like rock-scissors-paper where deterministic policy is not optimal.

Learning System
There are three learning processes in total, and each learning process consists of a learner and 100 simulators. If an agent is trained for a week, each agent accumulates experience equivalent to two-years of game play.

5.2 Effect of Self-Play Curriculum with Three Styles
In order to show the effects of the proposed self-play curriculum, we trained agents with both the vanilla method and the proposed curriculum. The baseline agent was trained with the vanilla self-play curriculum without any style-related rewards (only win reward and HP reward are included) and used pool of past selves. On the other hand, three agents of different styles were trained with the self-play curriculum with shared pool that we proposed. Then our aggressive, balanced and defensive agents played 1,000 matches each against the baseline agent to measure the performance. As shown in Table 2, agent learned from our curriculum defeated the baseline agent.

Next, we conducted the ablation study to see how the shared pool helps generalization. We wanted to know whether an agent would be able to deal with opponents of unseen style, if it experienced only a limited range of opponents during training. Thus, we have created three styles of agents that are trained in exactly the same way, except that they had their own opponent pools independently. Let’s denote the three types of agents using shared pools as $\pi_{\text{agg}}$, $\pi_{\text{bal}}$, and $\pi_{\text{def}}$, and three type of agents using independent pools as $\pi_{\text{agg}}$, $\pi_{\text{bal}}$, and $\pi_{\text{def}}$. All of six agents are trained for 5M steps (equivalent to 6 days) each.

Our assumption is that the agent learned with the shared pool is more robust when it faces opponents it never met. So we compared the win rate of $\pi_{\text{agg}}$ vs. $\{\pi_{\text{bal}}, \pi_{\text{def}}\}$ and $\pi_{\text{agg}}$ vs. $\{\pi_{\text{ind, ind}}, \pi_{\text{ind}}\}$. This experiment setting is based on three key ideas. First, $\pi_{\text{agg}}$ and $\pi_{\text{ind}}$ have the same training settings except for sharing the pool. Second, $\pi_{\text{agg}}$ and $\pi_{\text{agg}}$ are evaluated against the same opponents. Finally, although $\pi_{\text{agg}}$ have met other styles from the pool, it has not met $\{\pi_{\text{ind}}, \pi_{\text{ind}}\}$ for they were trained with independent opponent pools. If the assumptions are correct, $\pi_{\text{agg}}$ should have higher win rate. Note that $\pi_{\text{bal}}$ and $\pi_{\text{def}}$ are not single model, but 10 models each sampled from a pool at fixed intervals. We then conducted the same experiments for the remaining two styles of agents. The results are presented in Table 3. As shown in the table, agents trained with shared pool outperforms their counterparts.

However, the effect of shared pool is marginal in the case of an aggressive agent. It indicates that the spaces in which of defensiveness of an agent’s game play. The results were as follows: 66.6 sec for the aggressive, 91.7 sec for the balanced, and 179.9 sec for the defensive agent.

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2 We measured how the average game length differs for each style because game length is a good proxy for assessing the degree
training takes place are similar whether or not various opponents are provided. This seems to be related to the nature of the fighting game in which one side should fight back if the other side approaches and starts a brawl. Thus, in the case of an aggressive agent that attacks consistently, there is a little difference in the experience regardless of the diversity of the opponent.

5.3 Effect of Discarding Passive “No-op”
As discussed in Section 4.1, the “no-op” decision may be active or passive. Passive “no-op” happens when there is no other available skill to choose from besides “no-op” at that time step. We conducted an experiment to investigate the effect of discarding such passive “no-op” data from learning. The sparring partner for the experiment was the B&S built-in AI. Its performance is comparable to the top 20% of players. We measured how fast the agent learned to defeat the built-in AI. The result is shown in Figure 5 (a). If “no-op” ticks are discarded from the learning data, it reaches the win rate of 80% after 70k steps, whereas 170k steps are required when “no-op” ticks are included. The amount of time steps required to reach 90% of win rate was also twice less when skipping passive “no-op” data. This experiment confirms that the training performance is improved by discarding passive “no-op” from the learning data.

5.4 Effect of Maintaining Move
To examine the effect of maintaining move, we prepared two learning processes. Both processes learn on a self-play basis. The first process makes a moving decision at every time step, while the second process sends a decision, and repeats the same decision for the next nine successive time steps. We use entropy of moving policy as a metric to compare the effect. Entropy $H(x)$ is defined as follows:

$$H(x) = -\sum p(x) \cdot \log p(x)$$

Generally, entropy gradually decreases as learning progresses. Figure 5 (b) shows how the entropy of the move policy decreases for each learning process. There was a noticeable change in the movement of the trained agent after this technique was applied. Previously, there was no enhancement from random motion, but the agent learned to approach and retreat according to the situation with the technique.

6. Pro-Gamer Evaluation
Our agent had pre-test with two prominent professional gamers before the Blind Match. This section will address the results of both pre-test and the Blind Match, and conditions to ensure fairness to humans.

6.1 Conditions for Fairness
Reaction Time
When human confronts AI in a real-time fighting game, the most important factor that affects the result is the reaction time. In the case of human, it takes some time to recognize the skill used by the opponent and press a button by moving his / her hand. We applied an average of 230ms delay until the decision of the AI was reflected in the game so that the AI does not take advantage. This amount of delay is equivalent to the reaction time of professional players in BAB.

Class of the Character
There are 11 classes in the B&S, and each class has different characteristics. Some classes use magic from a distance, while some other classes deal damage to nearby opponents with axes and swords. Still another class use a sudden approach and retreat as a main weapon, by moving quickly and stealthily. As such, the inherent characteristics of each class are so different that there exists relative superiority among classes. Since these factors can affect the fairness of the match, we have fixed the class of both AI and pro-gamer as “Destroyer”. Destroyer is a class that has infighting style and steadily appears in the B&S world championship.

Skill Tree
Even if both players’ classes are the same, their skill tree can still be different from each other. Since each skill’s exact effect varies according to the skill tree chosen by the player, AI’s and pro-player’s skill trees were set equally for the fair match. The skill tree used for test had chosen based on the statistics of BAB users and followed the skill tree that the majority of users picked.

6.2 Evaluation Results
We invited two prominent pro-gamers, Yuntae Son (GC Busan, Winner of 2017 B&S World Championship), and Shingyeom Kim (GC Busan, Winner of 2015 and 2016 B&S World Championship), to test our agents before the Blind Match. Note that the total number of games played is different for each style because the testers played as many games as they wanted for each style of agent. After the pre-test, we went for the Blind Match of 2018 World Championship. Our agents had matches against three pro-gamers: Nicholas Parkinson (EU), Shen Haoran (CHN), and Sungjin Choi (KOR). Highlight video can be found at https://youtu.be/_KL5iU_nXEs.

The results of both the pre-test and the Blind Match are provided in Table 4. As can be seen in the table, the aggressive agent dominated the game, while other two types of agents had rather intense games. According to the interview after the pre-test, we have found out that this was partly because human players often need some breaks between fights thinking about the current state and high-level strategy. However, the aggressive agent does not allow human to have a break between battles, but only pours on attacks.

<table>
<thead>
<tr>
<th></th>
<th>Aggressive</th>
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<tbody>
<tr>
<td>Pro-Gamer 1</td>
<td>5-1</td>
<td>2-1</td>
<td>1-2</td>
</tr>
<tr>
<td>Pro-Gamer 2</td>
<td>4-0</td>
<td>2-4</td>
<td>4-1</td>
</tr>
<tr>
<td>Blind Match</td>
<td>2-0</td>
<td>1-2</td>
<td>0-2</td>
</tr>
<tr>
<td>Total</td>
<td>11-1</td>
<td>5-7</td>
<td>5-5</td>
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Table 4: Final score of AI - Human
7 Conclusion

Using deep reinforcement learning, we have created AI agents that competed evenly with professional players in the B&S Arena Battle, a 3D real-time fighting game. To do this, we proposed a method to guide fighting style with reward shaping. With three styles of agents, we introduced a novel self-play curriculum to enhance generalization performance. We also proposed data-skipping techniques to improve data efficiency and enable efficient exploration. Consequently, our agents were able to compete with the best BAB pro-gamers in the world. The proposed methods are generally applicable to other fighting games.

References


