Neural Fictitious Self-Play on ELF Mini-RTS

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Abstract

Despite the notable successes in video games such as Atari 2600, current AI is yet to defeat human champions in the domain of real-time strategy (RTS) games. One of the reasons is that an RTS game is a multi-agent game, in which single-agent reinforcement learning methods cannot simply be applied because the environment is not a stationary Markov Decision Process. In this paper, we present a first step toward finding a game-theoretic solution to RTS games by applying Neural Fictitious Self-Play (NFSP), a game-theoretic approach for finding Nash equilibria, to Mini-RTS, a small but nontrivial RTS game provided on the ELF platform. More specifically, we show that NFSP can be effectively combined with policy gradient reinforcement learning and be applied to Mini-RTS. Experimental results also show that the scalability of NFSP can be substantially improved by pretraining the models with simple self-play using policy gradients, which by itself gives a strong strategy despite its lack of theoretical guarantee of convergence.

Introduction

With the recent rise of deep neural networks, reinforcement learning has shown remarkable achievements in many complex environments. In the Atari 2600 video game environment, agents trained with deep reinforcement learning methods have succeeded in achieving human-level, or even superhuman performance in most of the games (Mnih et al. 2015; 2016; Van Seijen et al. 2017). However, in the domain of real-time strategy (RTS) games, which are considered to be one of the next grand AI challenges after Chess and Go (Tian et al. 2017; Silver et al. 2017), current AI is yet to defeat top human players (Vinyals et al. 2017).

To tackle this challenging domain, several platforms for conducting experiments on RTS games have been developed (Ontanon 2013; Synnaeve et al. 2016; Vinyals et al. 2017). The ELF platform (Tian et al. 2017) is such a platform and is an extensive, lightweight, and flexible platform designed for reinforcement learning research. It provides a small but nontrivial RTS game called Mini-RTS, and this game runs an order of magnitude faster than existing RTS environments, while capturing all the basic dynamics of RTS games, e.g., fog-of-war, resource gathering, troop building, and attacking with troops.

In this work, we aim to find a game-theoretic solution to Mini-RTS; that is, we attempt to compute an equilibrium strategy profile, as a first step toward solving more realistic and complex RTS games. Developing an AI for RTS involves many difficulties, including strategic and tactical decision making, real-time planning, and domain knowledge exploitation (Ontan et al. 2013; Robertson and Watson 2014). In this paper, we particularly focus on the multi-agent property: RTS games are multi-agent games and thus are not stationary for a learning agent, which breaks an assumption of single-agent reinforcement learning that the environment can be modeled as a Markov Decision Process (MDP).

Heinrich, Lanctot, and Silver (2015) proposed a game-theoretic self-play approach called Fictitious Self-Play (FSP). In FSP, an agent calculates the best response strategy to its opponents with reinforcement learning and averages its strategies in a sampling-based fashion. This process forms Fictitious Play (FP) (Brown 1951; Leslie and Collins 2006) in extensive-form games, and can be applied to a large-scale imperfect-information game. Since FP has a theoretical guarantee of convergence to a Nash equilibrium with minimal restrictions, FSP has a reliable theoretical background on convergence, and is more likely to converge than raw self-play methods. Neural Fictitious Self-Play (NFSP) (Heinrich and Silver 2016), a variant of FSP that uses deep reinforcement learning for its best response component, learned an approximate Nash equilibrium in small games of Poker without any prior domain knowledge.

In this paper, we show that NFSP can be effectively combined with policy gradient reinforcement learning and be used in the Mini-RTS domain. Our experimental results also show that the scalability of NFSP can be substantially improved by pretraining the models with simple self-play using a policy gradient method, which is efficient and by itself gives a strong strategy despite its lack of theoretical guarantee of convergence. To the best of our knowledge, this is the first attempt to find a convergent strategy profile in a nontrivial RTS game, hereby presenting a promising direction toward finding Nash equilibrium strategies for RTS games (i.e., solving RTS games).

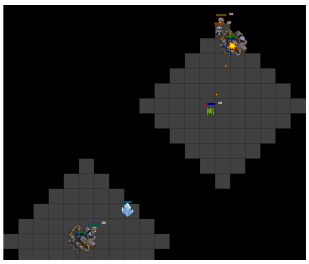


Figure 1: A game screenshot of Mini-RTS. Here the sight is for the lower-left agent whose health bars are enclosed by a blue line. Because of the fog-of-war, the agent cannot see the vicnity of the opponent's base, so it does not know whether the opponent has any troops or not.

Task

ELF and Mini-RTS

Our objective is to compute an equilibrium strategy that is not exploitable for the Mini-RTS game in the ELF platform.

In Mini-RTS, the goal of the agent is to destroy the opponent's base with its troops. Each agent has its base, units, and resource. With its base and some resource, the agent can build a worker. A worker can build a barrack, and some attackers with the barrack.

The ELF game engine is tick-driven: at each tick, each agent makes decisions by sending commands on units based on the observation. The game state changes according to the commands and new observations are given to the agents. Because there is fog-of-war in mini-RTS as in other RTS games, agents cannot observe units of its opponents in fog-of-war, and thus the game is imperfect information. A screenshot of the game is shown in Figure 1.

In addition to the low- and micro-level commands like "move left by two pixels" for each unit, the ELF engine has more hierarchical and strategic commands like "make someone go to some available place and build a barrack" or "defend our base from the enemy's attackers" for its all units. We use these commands instead of raw commands. Specifically, agents have nine discrete strategic actions. Four of these are about building units: a worker, a barrack, a melee attacker, and a range attacker. The next four are about tactical commands: attack, attack-in-range, hit-and-run, and all-defend. The last command is Idle, which means doing nothing. These actions are global, i.e., they affect all units in one command. Agents receive a low-level observation matrix shaped $22 \times 20 \times 20$ at each tick, where 20×20 represents the resolution of the observation for the game map, and 22 channels contain the number of each kind of units like a worker or the base.

Background

Markov Decision Process and Reinforcement Learning

An MDP is an environment model for standard reinforcement learning. In reinforcement learning with an MDP, an agent interacts with an MDP environment $\mathcal{E}$. At each time step t, the agent receives a state $s_t \in \mathcal{S}$ and selects an action a_t from a set of possible actions $\mathcal{A}$ with a probability distribution $\pi : \mathcal{S} \times \mathcal{A} \to [0, 1]$, which is called a policy. In $\mathcal{E}$ the action is executed, and it returns a next state s_{t+1} with reward r_{t+1}. The goal of the agent is to maximize its expected cumulative reward $\mathbb{E}[R_t] = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k}\right]$, where γ is a discount factor.

If the agent cannot distinguish between some states of the environment, the environment is called a Partially Observable MDP (POMDP). In a POMDP environment $\mathcal{E}_p$, the agent receives an observation $o_t = O(s_t)$, where s_t is a true state of $\mathcal{E}_p$ and O is a function that maps a state to an observation of the agent. The agent selects an action a_t from $\mathcal{A}$ as in an MDP, but the policy π depends on the observation o_t and not on the state s_t, because the agent cannot observe the true state.

We will use the following standard definitions of the state-action value function $Q_\pi(s_t, a_t) = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k}\right]$, the value function $V_\pi(s_t) = \sum_{a \in \mathcal{A}} \pi(a \mid s_t) Q_\pi(s_t, a)$, and the advantage function $A_\pi(s_t, a_t) = Q_\pi(s_t, a_t) - V_\pi(s_t)$.

Extensive-Form Games

In this work, we regard RTS games as extensive-form games. An extensive-form game is a model for a sequential multi-agent game. The representation is based on a finite rooted game tree.

In an extensive-form game, for each agent $i \in \mathcal{N}$, there are some indistinguishable states. An information set $u_i \in U_i$ contains such states; namely, the agent i cannot distinguish s_1 and s_2 and is forced to act in the exact same way if the two states are in the same information set u_i. If the agents in the game never forget their acquired information, the game is called perfect recall. In a perfect recall game, the graph of information sets forms a tree. And if the game has only two agents and $R_1 + R_2 = 0$ for all states, the game is called a two-player zero-sum game.

Each agent has its own strategy π_i, which specifies the probability distribution over the possible actions $A(s)$ in the given state s. A strategy profile $\pi = \{\pi_1, \cdots, \pi_N\}$ is a tuple of strategies for all agents. We can consider the expected cumulative reward $R(\pi)$ given a fixed strategy profile. A strategy of the agent i is called the best response strategy to its opponents' strategy $\pi_{-i} = \{\pi_j \mid j \neq i\}$ if the strategy maximizes its expected reward $R(\cdot, \pi_{-i})$. A Nash equilibrium of an extensive-form game is a strategy profile such that for each agent its strategy is the best response strategy to the others' strategies.

We can combine this game-theoretic model with MDPs. In an extensive-form game, if we pick an agent and fix other agents' strategies, then the environment can be regarded as a single-agent POMDP for the picked agent. In addition, if the game is perfect recall, this POMDP can be converted into an MDP environment, because the probability distribution of reaching indistinguishable states is stationary and thus these states can be degenerated into one state.

Neural Fictitious Self-Play

NFSP (Heinrich and Silver 2016) is a variant of FSP that uses neural networks and Deep-Q Networks (DQN) (Mnih

et al. 2015) for its approximation functions. FSP is a scalable method that uses FP in extensive-form representations.

In FP, a popular game-theoretic model of learning, agents repeatedly play a game, choosing the best response strategy to their opponents' average strategies at each iteration. The average strategies converge to a Nash equilibrium when the game has certain properties, e.g., two-player zero-sum or potential games.

FP is a theory on a normal-form representation, where each agent acts only once per one game, which is not suited to large-scale applications. To overcome the limitation, Heinrich, Lanctot, and Silver (2015) proposed a full-width extensive-form fictitious play and FSP. Both methods are developed for an extensive-form representation, and the former is a full-width method and the latter is an appropriately approximated (hence scalable to large-scale games) method. As with FP, agents in FSP repeatedly play a game, storing their experience in memory. Instead of computing the full-width best response strategy, they learn an approximate best response using reinforcement learning (RL). And instead of averaging their full-width strategies, they learn an approximate average strategy by using supervised learning (SL).

NFSP is not a method that simply applied neural networks to FSP. In NFSP, agents memorize their experiences in a reservoir replay buffer (Vitter 1985) to avoid windowing experiences due to sampling from a finite memory. NFSP also uses anticipatory dynamics (Shamma and Arslan 2005) to enable each agent to effectively track changes in its opponents' behavior.

The resulting NFSP algorithm is as follows. Each agent i has its RL network β_i, SL network π_i, and SL reservoir replay buffer $\mathcal{M}_i^{SL}$. At the beginning of the game, each agent decides whether it uses β_i or π_i as its strategy in this episode, with probability η and $1-\eta$, respectively. At each time step, agents sample an action from the selected strategy, and if the selected strategy is β_i, a tuple of the observation and the taken action is stored in $\mathcal{M}_i^{SL}$. β_i is trained as it maximizes the expected cumulative reward against π_{-i} and π_i is trained as it represents the probability distribution over actions in $\mathcal{M}_i^{SL}$. Since $\mathcal{M}_i^{SL}$ is a reservoir buffer and tuples in $\mathcal{M}_i^{SL}$ are taken from β_i, π_i demonstrates the average strategy over the past RL strategies. In addition, since the mixed strategy representated by choosing one from two extensive-form strategies at the beginning of episodes forms a realization equivalent strategy to the mixed strategy of the two normal-form strategy, the behavior strategy in each episode is $\eta\beta_i^t + (1-\eta)\pi_i^t = \pi_i^t + \eta(\beta_i^t - \pi_i^t) \simeq \pi_i^t + \eta\alpha\frac{d}{dt}\pi_i^t \simeq \pi_i^{t+\Delta t}$, which is a short-term prediction of π_i^t. Thus, for any agent i, it computes an approximated best response strategy to its opponents' average strategy (with some time prediction) π_{-i}, and an approximated average strategy over the past best response strategies β_i, which forms an approximated FP.

Proximal Policy Optimization

For the reason discussed later in the Method section, we do not use a value-based reinforcement learning method such as DQN as our reinforcement learning algorithm. Instead, we use a policy-based reinforcement learning method called Proximal Policy Optimization (PPO) (Schulman et al. 2017), which extends and simplifies Trust Region Policy Optimization (TRPO) (Schulman et al. 2015).

In TRPO, an objective function $\mathbb{E}_t\left[\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{\text{old}}}(a_t \mid s_t)}\hat{A}_t\right]$ is maximized, subject to a constraint on the policy update represented as the Kullback-Leibler divergence between $\pi_\theta(\cdot \mid s_t)$ and $\pi_{\theta_{\text{old}}}(\cdot \mid s_t)$, where θ_{old} is the fixed parameters before the update.

The constraint in this optimization problem is introduced to prevent an excessively large policy update. PPO uses a clipping term instead of this constraint, i.e., maximizing the following function under the unconstrained condition:

$$L(\theta) = \hat{\mathbb{E}}_t\left[\min\left(r_t\hat{A}_t,\, \text{clip}\left(r_t,\, 1-\epsilon,\, 1+\epsilon\right)\hat{A}_t\right)\right], \quad (1)$$

where r_t is the probability ratio $r_t = \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{\text{old}}}(a_t \mid s_t)}$, ϵ is a hyperparameter that determines the threshold, and $\hat{A}_t$ is an estimator of the advantage function A_t. This scheme is much simpler to implement and empirically has better performance than original TRPO.

Method

We regard RTS games as two-player zero-sum perfect recall extensive-form games and apply self-play methods to them. This view is justified as follows: although there are many units in an RTS game, agents can control all of them and have all information about them, and hence the game is essentially a two-player zero-sum game. Because of the existence of fog-of-war, the game is an imperfect information game. An RTS game is originally real-time and is not tick-driven, but in practice almost all of the RTS games have discrete time steps and therefore the game can be regarded as an extensive-form game. If each agent collects all observation histories and treats the set of them as a new observation, then the game is modeled as a perfect recall game. In this work we do not memorize past histories. We will discuss it in the section of future work.

While the original NFSP uses DQN with a replay buffer as its RL algorithm, there can be an on-policy problem. Value-based RL methods including DQN are known to be off-policy algorithms; that is, one can use any data sampled by any behavior policies to train the target policy. However, in NFSP, we cannot use the off-policy data because the opponents' strategies are not stationary. Although we do not need to sample the training data with the target policy, we still need to sample the data along the environment, and the transition rules of the environment now depends on the behavior policy of the opponent. Using a circular replay buffer in self-play requires the strict assumption that the training speed of its opponent is sufficiently slower than the reinforcement learning.

To exploit this fact efficiently, we use a policy gradient algorithm, which is by nature on-policy. Specifically, we combine NFSP and PPO, a state-of-the-art policy gradient al-

Algorithm 1 NFSP with PPO

Γ is an ELF interface and N is the number of agents

1: **function** MAIN(Γ, N)
2: **for** $p = 1, 2, \cdots, N$ in parallel **do** ▷ p is a learning agent
3: Γ.Initialize()
4: Γ.RegisterCallback(p, Trainer)
5: Γ.RegisterCallback(p, RL_Actor)
6: **for** $q = 1, \cdots, p-1, p+1, \cdots, N$ **do**
7: Γ.RegisterCallback(q, SL_Actor)
8: **end for**
9: **repeat**
10: **repeat**
11: batch$\leftarrow$ Γ.StepAndAccumulate() ▷ Multiple games are executed asyncronously and observation data is accumulated into the batch
12: **until** The number of accumulated data reaches certain batch size
13: Γ.CorrespondingCallback(batch)
14: **until** Time steps exceed the certain limits
15: **end for**
16: **end function**
17: **function** TRAINER(p, batch)
18: $\{S_\tau, A_\tau, \Pi_\tau, R_\tau\}_{\{\tau=t,\cdots,t+T-1\}} \leftarrow$ batch ▷ State, action, probability distribution, and reward ▷ Π_t is a probability distribution of NN_{RL} at t
19: Calculate $\mathcal{L}_{RL}$ with eq. (2)
20: Memorize $\{S_\tau, \Pi_\tau\}$ in buffer $\mathcal{M}_{SL}$
21: Sample $S, \Pi \leftarrow \mathcal{M}_{SL}$
22: Calculate $\mathcal{L}_{SL}$ with eq. (3)
23: Optimize NN_{RL} and NN_{SL} with $\mathcal{L}_{RL}$ and $\mathcal{L}_{SL}$
24: **end function**
25: **function** RL_ACTOR(p, batch)
26: $S \leftarrow$ batch
27: $\pi \leftarrow \text{NN}_{RL}(S)$
28: **return** Sampled $a \leftarrow \pi$
29: **end function**
30: **function** SL_ACTOR(p, batch)
31: $S \leftarrow$ batch
32: $\pi \leftarrow \text{NN}_{SL}(S)$
33: **return** Sampled $a \leftarrow \pi$
34: **end function**

gorithm, applying PPO as the RL method of NFSP. Algorithm 1 shows the overview.

In this algorithm, action or training functions are formed into callbacks and registered to a game process. In steps from line 10 to line 13, multiple games are executed in parallel threads in the process, and one of the registered callback functions is called with appropriate batch information.

In this work, we launch N processes in parallel, and for each process we register agent p's action function that follows the strategy produced by the RL component and other agents' action functions that follow the strategies produced by the SL components, and build multiple game threads in parallel. Here N is the number of agents (in this work $N = 2$) and p is the index of a process.

This algorithm is different from the original NFSP, which mixes RL and SL actors and choose either of them at the beginning of each game. This is again due to an on-policy problem. In the original NFSP, an agent p has four types of experiences, namely, (π_p, π_{-p}), (π_p, β_{-p}), (β_p, π_{-p}), and (β_p, β_{-p}), where π is a SL strategy and β is a RL strategy. If the RL method is off-policy as in the original NFSP, then we can use all experiences. However, since it is now on-policy, we can only use $(\beta_p, \cdot)$ experiences, which significantly reduces its sample efficiency. Launching N processes in parallel and assigning each agent i for them, we can reduce inefficient data (π_p, π_{-p}) and (β_p, β_{-p}).

Here is another reason for the modification. Although the ELF platform is general and flexible, there is a difficulty in implementing original NFSP on the platform. In original NFSP, agents need to decide whether they follow the RL component to perform the best response strategy to its opponents, or the SL component to act as the average strategy of its past best response strategies, at the beginning of the game. However, in the ELF platform, in order to calculate the forward computing efficiently, observation data are accumulated, bundled, and sent with a callback function to a corresponding agent as a batch. We thus need to divide the given batch into RL and SL batches, and search for the terminal observation to decide which components to use in each game, spoiling the computing efficiency. The proposed algorithm overcomes the problem and is easier to implement than the original one, because we do not have to decide which component to follow, but just separately build N ELF processes in parallel.

During RL training in line 19, $\mathcal{L}_{RL}$ is calculated in almost the same way as in PPO. That is,

$$\mathcal{L}_{RL} = \mathcal{L}_{policy} + \alpha\mathcal{L}_{entropy} + \beta\mathcal{L}_{value}\,, \tag{2}$$

where $\mathcal{L}_{policy}$ is the main PPO cost function defined by the negation of the equation (1), $\mathcal{L}_{entropy} = \sum_a \pi_\theta(a \mid s) \log \pi_\theta(a \mid s)$ is a bonus term that encourages exploration for the agent, and $\mathcal{L}_{value}$ is a squared mean error between V_θ and the target value $V_{target} = \hat{A}_t + V_{\theta_{old}}$. The estimator $\hat{A}$ is calculated by $\hat{A}_t = \delta_t + k\delta_{t+1} + \cdots + k^{T-t+1}\delta_{T-1}$, where $\delta_t = r_t + \gamma V_\theta(s_{t+1}) - V_\theta(s_t)$.

Following the implementation in the OpenAI Baselines (Dhariwal et al. 2017), we use the clipped value loss as $\mathcal{L}_{value}$,

$$\begin{aligned}
V_{clip}(s) &= \text{clip}\left(V_\theta(s) - V_{\theta_{old}}(s), -\epsilon_v, \epsilon_v\right) + V_{\theta_{old}}(s)\,,\\
\mathcal{L}_{value}^{nonclip} &= \left(V_\theta(s_t) - V_{target}(s_t)\right)^2\,,\\
\mathcal{L}_{value}^{clip} &= \left(V_{clip}(s_t) - V_{target}(s_t)\right)^2\,,\\
\mathcal{L}_{value} &= \max\left(\mathcal{L}_{value}^{nonclip}, \mathcal{L}_{value}^{clip}\right)\,,
\end{aligned}$$

and normalize the average and variance of the advantages in a batch.

During SL training in line 22, $\mathcal{L}_{SL}$ is calculated by

$$\mathcal{L}_{SL} = -\sum_a \pi_{\theta_{RL}}(a|s_t) \log \pi_\theta(a|s_t)\,, \tag{3}$$

which is the cross entropy between the probability distribution of SL and RL.

For memorizing the experiences in line 20, we use reservoir sampling (Vitter 1985) as a sampling method for the replay buffer like original NFSP (Heinrich and Silver 2016). A reservoir replay buffer $\mathcal{M}_{RRB}$ maintains N_{RRB} data tuples $\{s_{t_i}, \pi_{t_i}\}_{i=1,\cdots,N_{RRB}}$ and the number of given tuples M_{RRB}. When served $\{s_t, \pi_t\}$, $\mathcal{M}_{RRB}$ memorizes it with probability $\frac{N_{RRB}}{M_{RRB}+1}$, or otherwise rejects it. When a new tuple is memorized, each old tuple in $\mathcal{M}_{RRB}$ is discarded with equal probability, i.e., in $\frac{1}{N_{RRB}}$. It follows that for any time T, each data tuple $\{s_t, \pi_t\}_{t \leq T}$ is stored in $\mathcal{M}_{RRB}$ with probability $\frac{N_{RRB}}{M_{RRB}}$, which means that this replay buffer contains a uniform random sample of the given tuples.

We also use the raw self-play method with PPO. The algorithm is the same as the NFSP shown in Algorithm 1, except that the SL_Actor function and SL training in the Trainer function are omitted and all agents act with the RL_Actor function.

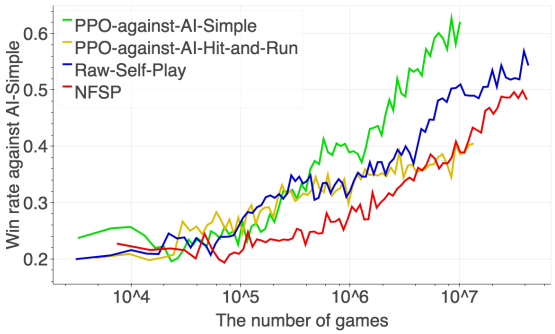
Experiments

Experimental Settings

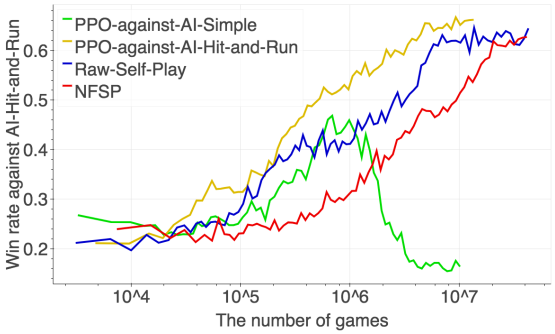
Unless otherwise specified, all experiments are conducted on the following settings. The batch size is 128 and the batch time is 50; namely, in line 18 in Algorithm 1 the batch contains 128 sequences of tuple $\{S_\tau, A_\tau, \Pi_\tau, R_\tau\}_{\{\tau=t,\cdots,t+T-1\}}$ where $T = 50$, and in line 26 and 31 the batch contains 128 states. In the reservoir sampling in line 21, we sample 512 states. The frame skip is set to 50, and thus each agent makes its decisions every 50 frames. In a process, 512 games are executed. We use Convolutional Neural Networks (CNNs) as the RL and SL models. Specifically, we use four blocks and some head layers for the CNN, where each block consists of a 3×3 convolutional layer with 64 channels and appropriate zero paddings, batch normalization, and leaky ReLU activation with $\alpha = 0.1$. For every two blocks, we use a 2×2 max pooling layer. The head layer is fully-connected and maps the flattened input to an output. There are three heads: π_{SL}, π_{RL}, and V_{RL}. The heads for π_{SL} and π_{RL} have nine outputs and a softmax layer to form a probability distribution, whereas the head for V_{RL} has only one output and does not have the softmax layer. The parameters of body blocks for π_{RL} and V_{RL} are shared, while π_{SL} and π_{RL} are not. Note that all agents use the same networks and their RL and SL networks are entirely shared. We use stochastic gradient descent with gradient clipping to optimize the models. The maximum gradient norm is set to 0.5. We use 0.01 and 0.001 for the learning rate of the RL model and the SL model respectively. In the RL loss function in the equation (2), we use $\alpha = 0.01$, $\beta = 0.5$, $\gamma = 0.99$, $k = 0.95$, and $\epsilon_v = 0.1$.

Self-Play and NFSP for Mini-RTS

We train agents with raw self-play and NFSP, and evaluate them with the win rate against rule-based AIs. In Mini-RTS, there are two rule-based built-in AIs: AI-Simple and AI-Hit-and-Run. AI-Simple simply builds five tanks and then attacks the opponent base. AI-Hit-and-Run is more aggressive and often harasses the opponent with its tanks. A human player has a win rate of 90% and 50% against AI-Simple and AI-Hit-and-Run respectively (Tian et al. 2017).



(a) Win rate against AI-Simple.



(b) Win rate against AI-Hit-and-Run.

Figure 2: Win rate in Mini-RTS with respect to the amount of experience in different methods. The horizontal axis is log-scale. NFSP is shown in the red line.

Because the game is a symmetric two-player zero-sum game, if an agent follows a strategy of a Nash equilibrium strategy profile, the agent is never exploitable, and thus it wins at least 50 percent against any strategies. If the game is sufficiently small, we can evaluate the exploitability of a strategy profile, which is the value that shows how close the strategy profile is to a Nash equilibrium (Johanson et al. 2011). However, ELF Mini-RTS is too large to calculate it. There are scalable methods to calculate the approximated or bounded exploitability such as local best response teqnique (LBR) (Lisy and Bowling 2017). Although LBR can calculate a lower bound of the given strategy profile, it cannot calculate an upper bound. In this work, we simply evaluate the agents with win rates against rule-based AIs, which is an estimator of a lower bound of the exploitability. Each evaluation consists of at least 1000 games.

Figure 2 shows the results of self-play methods, with the results of PPO agents. Evaluated against AI-Simple, the PPO agent trained against the same AI has the highest win rate. However, it fails to generalize its strategy against AI-Hit-and-Run and thus its strategy is far from Nash equilibria. The PPO agent trained against AI-Hit-and-Run also fails to exploit the AI-Simple.

The win rate of the agent trained with NFSP steadily increases as the number of experienced games increases. Although the rate is lower than the rate of the appropriate PPO agent, the NFSP agent does not fall into a specialized best response strategy but gradually acquires a less exploitable strategy.

The agent trained with raw self-play reaches the same result as the NFSP agent in the AI-Hit-and-Run evaluation, and even better result in the AI-Simple evaluation. Although there is no theoretical guarantee that a self-play algorithm converges, it can reach a Nash equilibrium if it converges (Foerster et al. 2018), and it is faster than NFSP because NFSP agent has to learn both the best response strategy to its opponent and the averaged strategy. Note that Klimov and Schulman (2017) show a counter example that a self-play method oscillates and thus does not converge. In this experiment such an oscillation is not observed.

Note that we do not conduct an experiment with the combined AI, namely, an AI that acts as AI-Simple in 50% and acts as AI-Hit-and-Run in 50%, unlike Tian et al. (2017), because we evaluate the strategies with these built-in AIs and we have to make at least one of them unknown to the trained agent to evaluate its performance against unseen opponents.

From Figure 2 we can see that even the highly specialized agent wins in at most 65% of the games. This is because the Mini-RTS game has considerable randomness at the beginning of the game. When the game starts, resources, bases, and units are randomly placed in the game field. Because of the frame skip, if an agent has no tank and its opponent has some tanks at the beginning of the game, and the opponent decides to attack with them, the agent has no way to defend against the rush. Even the agent trained with PPO in 10^7 games against a pure random agent loses in 29% of the game against the same random agent.

Analysis of the acquired agents

We further analyze the acquired agents. To evaluate how exploitable the agent is, we train another PPO agent against the target agent. If the PPO algorithm converges to its optimal strategy, the win rate of the agent is equal to the exploitability of the target agent in imperfect recall settings.

The results are shown in Table 1. Compared with other agents, the self-play agents are less exploitable, and do not lose over 50 percent against the PPO algorithm. This result suggests that the obtained agents are not exploitable by strategies that do not use the past histories of observations.

We observe the details of some games between the NFSP agent and the PPO agent trained against the NFSP agent. Figure 3 shows some screenshots of the game. The NFSP agent first builds two melee attackers, next builds a range attacker, and then rushes to the opponent's base. Because of the fog-of-war, agents cannot be aware of its opponent's attack until the opponent's tanks get closer, and thus melee attackers are suited for defense while range attackers are suited for attacking. Hence, the behavior of the NFSP agent is very rational for humans: first build some defense units to prepare for its opponent's attacking, secondly build an attacking unit with keeping the previously built defense units, and finally attack the opponent's base with all tanks.

Agent	Win rate
Random	0.71
AI-Simple	0.62
AI-Hit-and-Run	0.65
PPO against AI-Simple	$0.80^{\dagger}$
PPO against AI-Hit-and-Run	0.56
Raw self-play with PPO	**0.45**
NFSP with PPO	**0.44**

Table 1: Win rates of the trained PPO agent against each AI. All agents are trained with 10^7 games except the results with †, which means the number of training games is less than 10^7. The self-play agents have the lowest win rate, and hence they are less exploitable.

(a) (b)

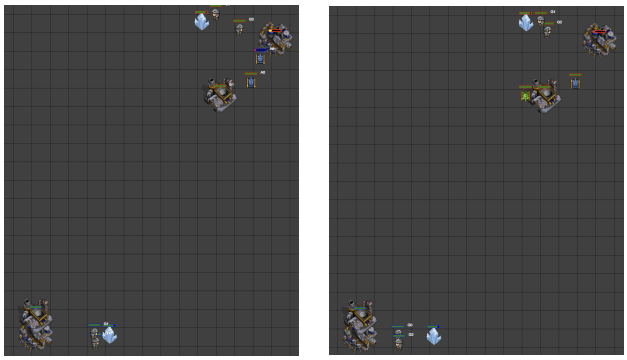
Figure 3: Screenshots of a game between the NFSP agent (red, bottom left) and the PPO agent trained against it (blue, top right). The blue tanks are melee attackers and the green tanks are range attackers. The NFSP agent (a) first builds a melee attacker, which is suited for defense, then (b) builds a range attacker, which is suited for attacking, and rushes to the opponent's base.

We show another example. In the game shown in Figure 4, at the initial state the NFSP agent has a large disadvantage due to the randomness of ELF games: it does not have a barrack while its opponent does, and it does not know the disadvantage because of the fog-of-war. Having the disadvantage, the NFSP agent is attacked by the opponent's tanks, but it builds a range attacker (suited for attacking) unit, and successfully counterattacks with it. Because in this game an agent must attack with all tanks it has, the NFSP agent knows that the opponent has now no tanks. Although an agent does not know or memorize the state of the opponent, the NFSP agent successfully exploits the rule and estimates the unknown state without any prior knowledge or even any built-in rule-base AIs.

Pretraining NFSP with Raw Self-Play

In the previous experiments, we observe that the NFSP agent successfully acquires a less exploitable strategy profile, but the learning process is slower than other methods. In contrast, the raw self-play algorithm is fast but lacks the guarantee of convergence. If the NFSP agent can be pretrained with the raw self-play algorithm, we can take the advantages of both algorithms.

This insight is also seen in CounterFactual Regret Min-



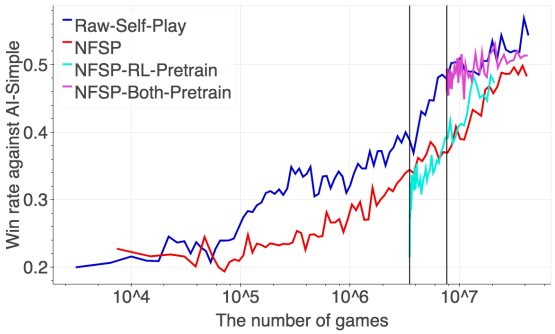
(a) (b)

Figure 4: Screenshots of a game between the NFSP agent (red, top right) and the PPO agent trained against it (blue, bottom left). (a) The NFSP agent's base is now very fragile because of its opponent's attack. (b) It builds a range attacker (to attack) and not a melee attacker (to defend), because in this settings agents cannot attack with a part of its tanks but must attack with all tanks, and thus its opponent must have now no tanks.

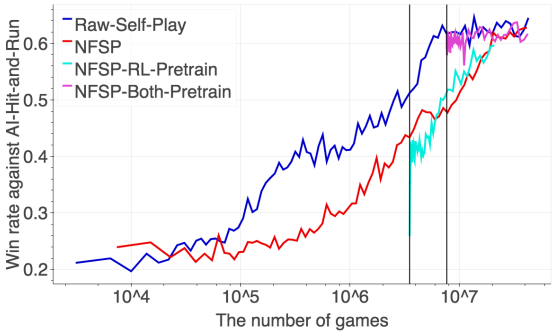
imization+ (CFR+) (Tammelin 2014). In a regret matching algorithm, which is a basis of CFR+, the average strategy of the regret-based strategies converges to a Nash equilibrium. This schema is similar to the fictitious play: in a fictitious play algorithm, we compute a best response strategy instead of the regret-based strategy, and average them. In CFR+, Tammelin (2014) uses delayed averaging, namely, accumulates the strategies from the middle of them. It significantly improves the result. The pretraining of NFSP is regarded as a kind of delayed averaging, because in PPO we do not accumulate the strategies and then switch to NFSP and begin to averaging them.

First we pretrain the RL model in NFSP with raw self-play. The light-blue lines in Figure 5 show the result. Although the learning is slightly faster than the NFSP agent, it does not improve the performance as we expected. This result can be explained as follows: in NFSP, the SL component averages the RL strategy and the RL component computes the best response strategy to the SL strategy. When we pretrain the RL strategy, the SL component can accumulate the pretrained strategies, and thus its learning process is accelerated. However, because the RL component computes the best response to the non-pretrained SL component, training in the RL component is not accelerated at all, making it fail to improve the performance.

To solve this problem, we also pretrain the SL model with the same parameters used in the RL model. We use the π_{RL} head of the PPO agent to pretrain the π_{SL} head of the NFSP agent, and simply discard the V_{RL} head of the PPO agent. The purple lines in Figure 5 show the result. Although the result is worse than the raw self-play, it successfully maintains the result of its base strategy, and is even slightly fine-tuned from the strategy in the AI-Simple evaluation. This result suggests that we can extend the results from a faster but more unstable self-play algorithm as pretraining for NFSP.



(a) Win rate against AI-Simple.



(b) Win rate against AI-Hit-and-Run.

Figure 5: Win rate of the pretrained agents with respect to the amount of experience. The horizontal axis is log-scale. The blue line shows the base self-play results, the light-blue line is the NFSP whose RL component is pretrained, the purple line is the NFSP whose both RL and SL components are pretrained, and the red line is the non-pretrained NFSP. The vertical black lines show the beginning of the pretraining.

Conclusion and Future Work

In this paper, we regard the Mini-RTS game as a two-player zero-sum extensive-form game, and apply self-play methods. The obtained agent is less exploitable for the PPO algorithm than other best response-based agents. We also observe that the obtained agent performs rationally to humans.

The contribution of this paper is that we show that NFSP can be combined with policy gradient reinforcement learning and be applied to Mini-RTS, which can be a first step toward solving more realistic and complex RTS games. We also show that we can improve the scalability of NFSP by pretraining the models with simple self-play using policy gradients, which is faster but lacks the theoretical guarantee of convergence. It significantly reduces the computational time and could be applied even when the self-play algorithm oscillates. However, the experimental results show that the learning process of NFSP is much slower than raw self-play with PPO, and actually raw self-play successfully acquires reasonable strategies despite its lack of convergence guarantees. We will further analyze the results and the differences between NFSP and raw self-play methods.

In this paper we do not have the agents memorize past histories. This makes the game essentially imperfect recall,

which breaks the assumption of the FSP. To solve this, we could use a recurrent neural networks as a controller of the RL component as in Hausknecht and Stone (2015). However, to ensure that the game is a perfect recall game, we need to use the same memorizing architecture for the SL reservoir replay buffer, which significantly reduces the size of the buffer. We will also further investigate to solve this problem as future work.

References

Brown, G. W. 1951. Iterative solution of games by fictitious play. *Activity analysis of production and allocation* 13(1):374–376.

Dhariwal, P.; Hesse, C.; Klimov, O.; Nichol, A.; Plappert, M.; Radford, A.; Schulman, J.; Sidor, S.; and Wu, Y. 2017. Openai baselines. `https://github.com/openai/baselines`. Last visited 2018-08-29.

Foerster, J.; Chen, R. Y.; Al-Shedivat, M.; Whiteson, S.; Abbeel, P.; and Mordatch, I. 2018. Learning with opponent-learning awareness. In *AAMAS*, 122–130.

Hausknecht, M., and Stone, P. 2015. Deep recurrent q-learning for partially observable MDPs. In *AAAI Fall Symposium on Sequential Decision Making for Intelligent Agents*.

Heinrich, J., and Silver, D. 2016. Deep reinforcement learning from self-play in imperfect-information games. *arXiv:1603.01121*.

Heinrich, J.; Lanctot, M.; and Silver, D. 2015. Fictitious self-play in extensive-form games. In *ICML*, 805–813.

Johanson, M.; Waugh, K.; Bowling, M.; and Zinkevich, M. 2011. Accelerating best response calculation in large extensive games. In *IJCAI*, 258–265.

Klimov, O., and Schulman, J. 2017. Roboschool. `https://blog.openai.com/roboschool/`. Last visited 2018-08-29.

Leslie, D. S., and Collins, E. 2006. Generalised weakened fictitious play. *Games and Economic Behavior* 56(2):285 – 298.

Lisy, V., and Bowling, M. 2017. Equilibrium approximation quality of current no-limit poker bots. In *AAAI Workshop on Computer Poker and Imperfect Information Games*.

Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A. A.; Veness, J.; Bellemare, M. G.; Graves, A.; Riedmiller, M.; Fidjeland, A. K.; Ostrovski, G.; Petersen, S.; Beattie, C.; Sadik, A.; Antonoglou, I.; King, H.; Kumaran, D.; Wierstra, D.; Legg, S.; and Hassabis, D. 2015. Human-level control through deep reinforcement learning. *Nature* 518:529–533.

Mnih, V.; Badia, A. P.; Mirza, M.; Graves, A.; Lillicrap, T.; Harley, T.; Silver, D.; and Kavukcuoglu, K. 2016. Asynchronous methods for deep reinforcement learning. In *ICML*, 1928–1937.

Ontan, S.; Synnaeve, G.; Uriarte, A.; Richoux, F.; Churchill, D.; and Preuss, M. 2013. A survey of real-time strategy game ai research and competition in starcraft. *IEEE Transactions on Computational Intelligence and AI in Games* 5(4):293–311.

Ontanon, S. 2013. The combinatorial multi-armed bandit problem and its application to real-time strategy games. In *AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, 58–64.

Robertson, G., and Watson, I. 2014. A review of real-time strategy game AI. *Ai Magazine* 35:75–104.

Schulman, J.; Levine, S.; Abbeel, P.; Jordan, M.; and Moritz, P. 2015. Trust region policy optimization. In *ICML*, 1889–1897.

Schulman, J.; Wolski, F.; Dhariwal, P.; Radford, A.; and Klimov, O. 2017. Proximal policy optimization algorithms. *arXiv:1707.06347*.

Shamma, J. S., and Arslan, G. 2005. Dynamic fictitious play, dynamic gradient play, and distributed convergence to nash equilibria. *IEEE Transactions on Automatic Control* 50(3):312–327.

Silver, D.; Hubert, T.; Schrittwieser, J.; Antonoglou, I.; Lai, M.; Guez, A.; Lanctot, M.; Sifre, L.; Kumaran, D.; Graepel, T.; et al. 2017. Mastering chess and shogi by self-play with a general reinforcement learning algorithm. *arXiv:1712.01815*.

Synnaeve, G.; Nardelli, N.; Auvolat, A.; Chintala, S.; Lacroix, T.; Lin, Z.; Richoux, F.; and Usunier, N. 2016. Torchcraft: a library for machine learning research on real-time strategy games. *arXiv:1611.00625*.

Tammelin, O. 2014. Solving large imperfect information games using CFR+. *arXiv:1407.5042*.

Tian, Y.; Gong, Q.; Shang, W.; Wu, Y.; and Zitnick, C. L. 2017. ELF: An extensive, lightweight and flexible research platform for real-time strategy games. In *NIPS*, 2659–2669.

Van Seijen, H.; Fatemi, M.; Romoff, J.; Laroche, R.; Barnes, T.; and Tsang, J. 2017. Hybrid reward architecture for reinforcement learning. In *NIPS*, 5392–5402.

Vinyals, O.; Ewalds, T.; Bartunov, S.; Georgiev, P.; Vezhnevets, A. S.; Yeo, M.; Makhzani, A.; Küttler, H.; Agapiou, J.; Schrittwieser, J.; Quan, J.; Gaffney, S.; Petersen, S.; Simonyan, K.; Schaul, T.; van Hasselt, H.; Silver, D.; Lillicrap, T. P.; Calderone, K.; Keet, P.; Brunasso, A.; Lawrence, D.; Ekermo, A.; Repp, J.; and Tsing, R. 2017. StarCraft II: A New Challenge for Reinforcement Learning. *arXiv:1708.04782*.

Vitter, J. S. 1985. Random sampling with a reservoir. *ACM Transactions on Mathematical Software* 11(1):37–57.