MULTI-AGENT REINFORCEMENT LEARNING IN OPENSPIEL

A REPRODUCTION REPORT

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ABSTRACT

In this report, we present results reproductions for several core algorithms implemented in the OpenSpiel [1] framework for learning in games. The primary contribution of this work is a validation of OpenSpiel’s re-implemented search and Reinforcement Learning algorithms against the results reported in their respective originating works. Additionally, we provide complete documentation of hyperparameters and source code required to reproduce these experiments easily and exactly.

Keywords OpenSpiel · Reinforcement Learning · Games

1 Introduction

The OpenSpiel framework provides a collection of environments and algorithm implementations for studying Reinforcement Learning (RL) in games. OpenSpiel includes many popular general-sum, zero-sum, perfect and imperfect information games with episodic interfaces suitable for training RL agents. The algorithms implemented in OpenSpiel are contemporary or state-of-the-art (SOTA) and are designed to be highly configurable and extensible. As stated in the documentation and provided example code, the given default parameters are (in the majority of cases) intended to solve the imperfect information poker variant Kuhn [2]. However, the papers originally proposing many of the OpenSpiel algorithms may not necessarily provide results for this environment and instead report results for more challenging games such as Leduc or Heads up No-Limit Texas Holdem. This limits OpenSpiel users’ ability to conveniently verify the correctness and performance of algorithm implementations using this tool. Therefore, it is interesting to validate that the partial results provided in the OpenSpiel paper [1] can be reliably reproduced with comparable performance \(^1\) to SOTA results present elsewhere in the literature.

We have conducted a comprehensive reproduction study in which we extract relevant metrics and hyperparameters from SOTA publications and attempt to replicate these studies as faithfully and exactly as possible. The motivation of this effort is to rigorously validate the algorithms implemented in OpenSpiel as well as provide complete hyperparameter sets so that SOTA baselines may be quickly reproduced by other researchers. In the course of this study, we identified several experimental nuances and parameter sensitivities which we will discuss later in the paper. We hope that addressing these small, often undocumented concerns will prove helpful to the Multi-Agent RL community by providing insight and (perhaps more importantly) saving valuable time and effort.

2 Quickstart & Usage

The source repository for reproducing these experiments can be found on github at aicenter/openspiel_reproductions. An example OpenSpiel docker image can be pulled from Docker Hub at waltonmyke/openspiel\(^2\). Individual experiments may be run using scripts in the algorithms folder. SLURM jobfiles can also be constructed and batch run with run.py.

\(^1\)For the purposes of this study, we aim to produce performances matching or exceeding those reported for their original implementations

\(^2\)We base our experiments on OpenSpiel release 0.2.0
Hyperparameter configurations to replicate the results in this paper can be found in the arguments defined in the
*.cfg files in config and in Appendix A. Finally, for methods that necessitated additional hyperparameter search, configurations of these procedures may be found under sweep.

We use Weights & Biases [3] for experiment configuration and results logging. If you prefer not to use this platform or do not have it configured for your environment, W&B logging may be deactivated and redirected to standard out with the --no_wandb flag.

3 Algorithms & Methods

While a rigorous technical survey of the methods utilized herein is outside the scope of this paper, we include high-level descriptions of each algorithm for proper attribution and to provide the reader with some context for relevant prior work. The reader may also refer to [4, 5] for more comprehensive surveys of recent techniques in Reinforcement Learning approaches to game solving.

Extensive Form Fictitious Play (XFP) & Fictitious Self Play (FSP)  [6] In classic fictitious play, players best respond to an average of their opponents’ strategies on each iteration (or a slightly perturbed average of opponent strategies as in [7]). However, vanilla fictitious play is only defined in normal form (an exponentially less efficient representation for extensive form games). To address this [6] proposed XFP which allows player strategy updates in the extensive form with linear time and space complexity. FSP is an approximation to XFP which replaces the best response computation with tabular reinforcement learning and estimates the average of opponent strategies using supervised learning over action probabilities.

Regression CFR (RCFR)  [8] estimates counterfactual regret using online updates to a function approximator and improves it’s strategy by minimizing the predicted regret of the estimator on each iteration. In the original work the authors proposed regression trees as a function approximator and empirically evaluate the impact of error tolerance at the leaf nodes on the quality of the strategies obtained. In OpenSpiel, RCFR regrets are estimated using a neural network.

DeepCFR  [9] Similar to RCFR, DeepCFR uses function approximation to generalize across similar infosets obviating the need to calculate and accumulate regrets for each infostate. DeepCFR uses external sampling Monte Carlo CFR (MCCFR) to conduct a number of partial traversals of the game tree and update the values of states along the trajectory on each iteration. The observed values are stored in a memory buffer and used to update the parameters of a value prediction network which estimates the value of an action in an infostate. Because the average strategy of all CFR iterations converges to a Nash Equilibrium, it is insufficient to maintain a single parametric policy. To address this, DeepCFR maintains a separate policy network which approximates the average strategy by learning a distribution over actions selected for each infostate on each iteration.

Exploitability Descent (ED)  [10] directly updates the player’s policy against a worst case opponent in a two-player zero sum game. The exploitability of each player employing ED’s strategy converges asymptotically to zero; hence in self-play, the joint strategy converges to an approximate Nash Equilibrium. On each iteration, ED first computes a best response to each players’ policy. Next, update the policy using gradient ascent to maximize player expected utility wrt. to the best response of the other player.

Neural Fictitious Self Play (NFSP)  [11] augments FSP with deep learning by replacing the tabular Reinforcement Learning agent with a neural network (trained off-policy with ϵ-greedy Q-learning) and the (infostate, action)-pair visitation counts with an additional policy network which approximates average strategies by maximizing the log-probability of observed actions in each infostate. NFSP also incorporates a short-horizon prediction of opponent strategies using anticipatory dynamics for which the authors demonstrate improved empirical performance.

Policy Space Response Oracles (PSRO)  [12] generalizes fictitious play and the well-studied Double Oracle algorithm [13]. In general PSRO, an empirical game (much smaller in size than the original game) is incrementally constructed by playing the full game with a set of policies sampled from a portfolio. A meta-strategy is induced over a resultant empirical payoff table which is estimated by rolling out strategies currently in the portfolio. New policies are discovered by iteravely setting one player as the fixed-strategy oracle and training a new strategy as a best response. In general, a specific PSRO-family algorithm can be (principally) characterized by a particular choice of meta-strategy solver and oracle.
**Policy Gradient** [14], in the context of games, refers to a family of algorithms utilizing the policy gradient theorem from reinforcement learning [15]. More specifically, variations on Advantage Actor-Critic (A2C) [16] in which an advantage function is used to reduce the variance of estimates of the policy gradient. Several variations on this algorithm are evaluated in the original work and implemented in OpenSpiel: \textit{Q-based Policy Gradient} uses the action-values of all actions rather than only those executed during a rollout to estimate the policy gradient. Hence it is also referred to as Mean Actor-Critic (MAC) in the literature [17]. \textit{Regret Policy Gradient} takes inspiration from CFR and represents the loss in terms of regret represented as a relu-thresholded difference between action-values and the baseline. \textit{Regret Matching Policy Gradient} extends this further by weighting the A2C policy gradient by the thresholded regrets.

**Neural Replicator Dynamics (NeuRD)** [18] is another policy gradient algorithm which yields desirable theoretical properties and greatly improved empirical performance through a slight modification of vanilla softmax PG. NeuRD also has formal relationships to the Hedge algorithm and softmax-CFR; the latter of which guarantees convergence in the tabular case.

**Metrics** In cases where exact quantitative performance tables were not readily available or we would like to compare against convergence plots we extract estimated values from figures using \textit{webplotdigitizer} \footnote{Most original works present convergence plots on log-log scale. In the case where they are instead given on a linear scale, we present our replications in both linear and log. The aim is to clarify small differences between various parameters of each algorithm. However, note that small errors in the target curve traces extracted on linear scale may be exaggerated.}. Original works may report results and figures using Exploitability or NashConv, possibly expressed in terms of milliblinds per hand (mb/h) in the case of poker. For consistency, and as we only report results for two-player zero-sum games (more specifically poker) we measure the performance of all strategy profiles in terms of Exploitability following the definitions in equations 1 - 3.

A Best Response $\text{BR}$ to a strategy profile including all players other than player $i$, denoted $\pi_{-i}$ is the set of strategies for a player $i$ which maximise their payoff function $u_i$ given the other players play $\pi_{-i}$

$$\text{BR}(\pi_{-i}) = \{ \pi_i' | \pi_i' = \arg\max_{\pi_i} u_i(\pi_i, \pi_{-i}) \} \quad (1)$$

The \textit{NashConv} of a strategy profile $\pi$ is defined as the sum over players $\mathcal{N}$ of each of their respective incentives to deviate from their current strategy to a best response, denoted $\delta_i(\pi) = u_i(\pi_i^b, \pi_{-i}) - u_i(\pi)$ where $\pi_i^b \in \text{BR}(\pi_{-i})$

$$\text{NashConv}(\pi) = \sum_{i \in \mathcal{N}} \delta_i(\pi) \quad (2)$$

When $|\mathcal{N}| = 2$, the exploitability of a strategy profile $\pi$ is

$$\text{Exploitability}(\pi) = \frac{\text{NashConv}(\pi)}{|\mathcal{N}|} = \frac{\sum_{i \in \mathcal{N}} \delta_i(\pi)}{n} = \frac{u_1(\pi_1^b, \pi_2) + u_2(\pi_1, \pi_2)}{2} \quad (3)$$

**4 Replications**

In this section we will summarize at a high-level the specific methods used to obtain each result. Unless otherwise specified, all hyperparameter search was conducted using the Hyperband [19] implementation provided in [3]. Hyperband is a bandit-based hyperparameter search algorithm which utilizes adaptive resource allocation and configurable early stopping criteria to speed up traditional hyperparameter search based on adaptive configuration selection with Bayesian optimization. In our experiments, we set the total number of brackets $s = 2$.

Reproducing the \textit{CFR & XFP} results using their respective OpenSpiel implementations is relatively trivial using the default configuration implemented in the provided examples (Figure 1). It is suggested, however, to use these reproductions as smoke-tests and sanity-checks for novel extensions to OpenSpiel (for instance the addition of new games) as their behavior is more predictable than more complex or harder to tune models.

**RCFR** Although the high-level RCFR algorithm implemented in OpenSpiel aligns with the original work proposing RCFR, some implementation details differ. Most importantly, the results in the original work used regression trees to estimate regrets whereas OpenSpiel uses neural network estimator. We further observed that the best result reported for the original RCFR implementation exceeded the performance reported in OpenSpiel. Using the network size reported
in the OpenSpiel paper (400 hidden units, two layer fully-connected), default batch size and number of epochs specified in the example code (200 and 100 respectively). These parameters yielded roughly approximate results to OpenSpiel. To match the performance of the original RCFR, we swept the learning rate over .1, .01, .001 and found .001 allowed the model to exceed the performance of the original regression tree based RCFR implementation, as demonstrated in Figure 2.

Figure 1: Extensive Form Fictitious Play. XFP Target from [6]

Figure 2: Comparison of RCFR & tabular CFR on Kuhn (left). Replication of results in Leduc (right). CFR Target and RCFR OpenSpiel Target extracted from [1] RCFR Original Target from [8]
DeepCFR  We provide results comparisons against [20] as this work demonstrated improved results for this algorithm over [9]. We used the suggested parameters from [9] however we also conducted a parameter search over the number of hidden units {64, 128, 256} the number of layers 3-5 and the number of external sampling iterations per iteration {15k, 30k, 100k}. As in [9] we re-initialized the value networks, trained the advantage network and policy network for 750 and 5000 gradient steps per iteration with a learning rate of $10^{-3}$ and minibatches of size 2048. As shown in Figure 3, we find that the implementation in OpenSpiel, using these parameters, improves slightly over the target baseline.

![Figure 3: DeepCFR. Target results from [9]](image)

Figure 4: Exploitability Descent. Target results Tabular ED and Neural Net ED in both domains from [10]
**Exploitability Descent** Our ED replications in both the tabular and approximate implementations closely match the results presented in [10] in the Kuhn domain. 4 We conducted parameter sweeps over the initial learning rate for powers of 2 and (in the neural network case) number of hidden layers 1-5, number of hidden units \{64, 128, 256\} and regularization weights from \([10^{-7}, 10^{-4}]\). We found that a three layer network with 256 hidden, and a regularization weight of .001 consistently outperformed other configurations, illustrated in Figure 4, and exhibited similar empirical convergence rates across multiple random seeds.

The originating study [10] also presents results for more complex domains such as Leduc and Goofspiel. However, in our experiments we were unable to reproduce the results presented using neural networks. The same parameter searches were conducted for each domain as they were in Kuhn. We observed that although the tabular model converged as expected, neural network estimators demonstrated inconsistent behavior and occasionally failed to improve at all over the number of iterations tested. We expect that more reliable convergence could be accomplished by taking several gradient steps on the for each iteration (i.e. without updating the best response for each iteration of gradient descent). This could be accomplished by modifying the OpenSpiel implementation to step the minimizer on the advantage and policy losses without re-computing a new best-response to the modified strategy for some variable number of timesteps. While this change is relatively simple, we defer modifications to OpenSpiel’s ED implementation for future work.

**NFSP** Instead of the default parameters provided with OpenSpiel, we use a similar configuration for the NFSP baseline reported in the recently proposed Advantage Regret Matching Actor Critic (ARMAC) [21] which demonstrates improved performance over the original reported OpenSpiel baseline. Specifically, we use the same network architecture with four fully-connected layers each with 128 hidden units. The anticipatory parameter \(\eta = 0.1\), the exploration parameter \(\epsilon\) is decayed during the first 20m iterations, the reservoir and replay buffer capacities are limited to 2m entries and 200k respectively. We then conducted search over the following hyperparameters using the method previously described: \(\epsilon\)-greedy starting values \{0.06, 0.24\}, RL learning rates \{0.1, 0.01, 0.001\}, SL learning rates \{0.01, 0.001, 0.005\}, and DQN target network update period of \{1000, 19200\}. We identified and report results using the following configuration for leduc: \(\epsilon\)-greedy starting value 0.6, RL learning rate 0.01, and update period 19200. As illustrated in Figure 5, our results using these parameters match those reported in ARMAC very closely.

**PSRO** We defer description of the hyperparemeters for PSRO in Appendix A as they are more numerous than other evaluated algorithms and thus, likely easier for the reader to parse in tabular form. Our experiments used the hyperparerete sweeps suggested in [22] and followed a similar experimental procedure. As in [22], we elect to measure exploitability

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4The implementation in OpenSpiel was found to have a (very minor) bug in the provided example code in release 0.2.0; this is patched in our repository as well as OpenSpiel commit 291c5e2.
in terms of Total Pool Length (the sum of the sizes of all players’ policy sets) rather than iteration. This preference is motivated in the original work to encourage fair comparison across meta-solvers as some can add more than one strategy to a player’s profile on a single iteration. As illustrated in Figure 6, our results for different metasolver choices track the baseline target from [22], however they do not match exactly for each choice of solver. It is likely that additional parameter sweeps for each solver independently could improve this correspondence, however for simplicity we leave this to the reader who may have specific motivations to more rigorously compare the properties of different metagame solvers in PSRO.

Figure 6: Policy Space Response Oracles for different choices of meta-solver: Nash, PRD (Projected Replicator Dynamics), Uniform and α-rank. Target is extracted from [22]. Note that the x-axis is the Total Pool Length rather than iteration.
Policy Gradients In our policy gradient experiments (QPG, RPG, RMPG) we conducted similar parameter sweeps to those specified in [14]: the learning rates for the policy and critic networks were swept over \{0.001, 0.01, 0.1\} independently for both networks. The number of hidden layers and hidden units ranged from 1-5 and \{64, 128, 256\} respectively. The entropy cost was swept over \{0, 0.01, 0.1, 0.15, 0.2\}. The batch size and \(N_q\) (the number of critic updates before a policy update) were selected from powers of 2 ranging 4-32 and 16-512 respectively. Although we were able to achieve comparable performance to the original study, the rates of convergence differed slightly in our replications. Interestingly, our results specifically improved the relative performance of RMPG (which in the prior work under-performed in Kuhn) over other policy gradient methods. In our experiments, we observed the convergence of all policy gradient methods evaluated strongly depend on the number of critic updates before updating the policy. This makes sense as improved estimates of the advantage function (regret in the case of RPG, RMPG) reduce the variance of the estimated policy gradient leading to smoother convergence. As illustrated in Figure 7, we were not able to quantitatively reproduce the target learning curves, however the OpenSpiel implementation demonstrates some modestly improved sample complexity early in training and converges to a comparable exploitability to [14] after \(10^7\) iterations.

Figure 7: Policy Gradients. Our replication of QPG, RPG & RMPG in the Kuhn domain vs. the RMPG results presented in [14]

Neural Replicator Dynamics We observed that the default parameters in OpenSpiel examples and unit tests do not perform particularly well in the Leduc domain. Therefore, we conducted a hyperparameter search similar to the procedure described in [18]. Our results substantially improve over those provided in OpenSpiel, however they do not quite match those reported in the original NeurD paper. We swept the number of hidden units and depth of the network over \{64, 128, 256\} and \{2,3,4\} layers respectively. The step size was sampled from \{.5, .9, 1., 1.5, 2., 2.5, 3., 3.5, 4.\} we also varied the logit threshold parameter from 1-3 (although the original work set the threshold to 2, we observed a slightly higher threshold to improve performance in our experiments). In a practical implementation of NeurD, the threshold parameter is used to improve the numerical stability of the algorithm during training. In our experiments, parameter searches consistently resulted in a preference for higher threshold values. As illustrated in Figure 8, OpenSpiel’s implementation matches the original work closely.

5 Conclusion

In this study, we have conducted a thorough battery of replications for the multi-agent reinforcement learning algorithms implemented in OpenSpiel. Where possible, we utilized network architectures and hyperparameter settings suggested elsewhere in the literature. We also conducted extensive parameter sweeps in settings where configurations suggested in

5There is a small discrepancy between the threshold implementation described in original work and the OpenSpiel implementation. For the interested reader, issue 148 addresses this concern
prior work was insufficient to achieve expected behaviors of the evaluated algorithms. In the majority of cases, we were able to match or exceed the best-reported performance for each algorithm in OpenSpiel. As there are still several cases we were unable to address in this study, we intend to continue maintaining the provided source-code as well as this document if the expected behavior for current failure-cases can be accomplished. To this ends, we invite other OpenSpiel users to contribute if, in the course of their research, they address one of the limitations of this study. This may take the form of pull-requests on the associated git repository or other experimental documentation sufficient for exact reproduction. It is our hope that others working on reinforcement learning in games will benefit from this effort as a quick reference and a tool for improved reproducibility of their experiments.

References

[1] Marc Lanctot, Edward Lockhart, Jean-Baptiste Lespiau, Vinicius Zambaldi, Satyaki Upadhyay, Julien Pérolat, Sriram Srinivasan, Finbarr Timbers, Karl Tuyls, Shayegan Omidshafiei, Daniel Hennes, Dustin Morrill, Paul Muller, Timo Ewalds, Ryan Faulkner, János Kramár, Bart De Vyld, Brennan Saeta, James Bradbury, David Ding, Sebastian Borgeaud, Matthew Lai, Julian Schrittwieser, Thomas Anthony, Edward Hughes, Ivo Danihelka, and Jonah Ryan-Davis. OpenSpiel: A framework for reinforcement learning in games. CoRR, abs/1908.09453, 2019.

[2] H.W. Kuhn and A.W. Tucker. Contributions to the Theory of Games (AM-24), Volume I. Annals of Mathematics Studies. Princeton University Press, 2016.

[3] Lukas Biewald. Experiment tracking with weights and biases, 2020. Software available from wandb.com.

[4] Yaodong Yang and Jun Wang. An overview of multi-agent reinforcement learning from game theoretical perspective, 2020.

[5] Pablo Hernandez-Leal, Bilal Kartal, and Matthew E. Taylor. A survey and critique of multiagent deep reinforcement learning. Autonomous Agents and Multi-Agent Systems, 33(6):750–797, Oct 2019.

[6] Johannes Heinrich, Marc Lanctot, and David Silver. Fictitious self-play in extensive-form games. In Francis Bach and David Blei, editors, Proceedings of the 32nd International Conference on Machine Learning, volume 37 of Proceedings of Machine Learning Research, pages 805–813, Lille, France, 07–09 Jul 2015. PMLR.

[7] David S. Leslie and E.J. Collins. Generalised weakened fictitious play. Games and Economic Behavior, 56(2):285 – 298, 2006.

[8] Kevin Waugh, Dustin Morrill, J. Andrew Bagnell, and Michael Bowling. Solving games with functional regret estimation, 2014.
[9] Noam Brown, Adam Lerer, Sam Gross, and Tuomas Sandholm. Deep counterfactual regret minimization, 2019.
[10] Edward Lockeart, Marc Lanctot, Julien Pérolat, Jean-Baptiste Lespiau, Dustin Morrill, Finbarr Timbers, and Karl Tuyls. Computing approximate equilibria in sequential adversarial games by exploitability descent. CoRR, abs/1903.05614, 2019.
[11] Johannes Heinrich and David Silver. Deep reinforcement learning from self-play in imperfect-information games. CoRR, abs/1603.01121, 2016.
[12] Marc Lanctot, Vinicius Zambaldi, Audrunas Gruslys, Angeliki Lazaridou, Karl Tuyls, Julien Perolat, David Silver, and Thore Graepel. A unified game-theoretic approach to multiagent reinforcement learning, 2017.
[13] H. Brendan McMahan, Geoffrey J. Gordon, and Avrim Blum. Planning in the presence of cost functions controlled by an adversary. In Proceedings of the Twentieth International Conference on International Conference on Machine Learning, ICML’03, page 536–543. AAAI Press, 2003.
[14] Sriram Srinivasan, Marc Lanctot, Vinicius Flores Zambaldi, Julien Pérolat, Karl Tuyls, Rémi Munos, and Michael Bowling. Actor-critic policy optimization in partially observable multiagent environments. CoRR, abs/1810.09026, 2018.
[15] Richard Sutton, David Mcallester, Satinder Singh, and Yishay Mansour. Policy gradient methods for reinforcement learning with function approximation. Adv. Neural Inf. Process. Syst., 12, 02 2000.
[16] Volodymyr Mnih, Adria Puigdomènech Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. CoRR, abs/1602.01783, 2016.
[17] Cameron Allen, Kavosh Asadi, Melrose Roderick, Abdel rahman Mohamed, George Konidaris, and Michael Littman. Mean actor critic, 2018.
[18] Daniel Hennes, Dustin Morrill, Shayegan Omidshafiei, Remi Munos, Julien Perolat, Marc Lanctot, Audrunas Gruslys, Jean-Baptiste Lespiau, Paavo Parmas, Edgar Duenez-Guzman, and Karl Tuyls. Neural replicator dynamics, 2020.
[19] Lisha Li, Kevin G. Jamieson, Giulia DeSalvo, Afshin Rostamizadeh, and Ameet Talwalkar. Neural replicator optimization and infinitely many armed bandits. CoRR, abs/1603.06560, 2016.
[20] Eric Steinberger. Single deep counterfactual regret minimization. CoRR, abs/1901.07621, 2019.
[21] Audrunas Gruslys, Marc Lanctot, Remi Munos, Finbarr Timbers, Martin Schmid, Pérolat Julien, Dustin Morrill, Vinicius Zambaldi, Jean-Baptiste Lespiau, John Schultz, Mohammad Azar, Michael Bowling, and Karl Tuyls. The advantage regret-matching actor-critic. In open review, 08 2020.
[22] Paul Muller, Shayegan Omidshafiei, Mark Rowland, Karl Tuyls, Julien Pérolat, Siqi Liu, Daniel Hennes, Luke Marris, Marc Lanctot, Edward Hughes, Zhe Wang, Guy Lever, Nicolas Heess, Thore Graepel, and Rémi Munos. A generalized training approach for multiagent learning. CoRR, abs/1909.12823, 2019.

A Hyperparameters

Hyperparameter configurations for each algorithm for each game may be found in the *.cfg files in the config/ folder. We provide them here as well for ease of reference.

| Parameter  | Value |
|------------|-------|
| num_hidden | 128   |
| num_layers | 2     |

| Parameter  | Value |
|------------|-------|
| init_lr    | 1     |
| lr_scale   | .01   |

Table 2: exp_descent

| Parameter  | Value |
|------------|-------|
| init_lr    | 1.0   |
| lr_scale   | .01   |

| Parameter  | Value |
|------------|-------|
| init_lr    | 1     |
| lr_scale   | .01   |

| Parameter  | Value |
|------------|-------|
| regularizer_scale | 0.001 |
| num_hidden    | 256   |
| num_layers    | 3     |
| Parameter               | Value    |
|-------------------------|----------|
| num_hidden              | 128      |
| num_layers              | 2        |
| batch_size              | 4        |
| entropy_cost            | 0.1      |
| critic_learning_rate    | 0.01     |
| pi_learning_rate        | 0.01     |
| num_critic_before_pi    | 128      |

Table 5: neurd

| Parameter                        | Value  |
|----------------------------------|--------|
| num_hidden_layers                | 2      |
| num_hidden_units                 | 128    |
| num_hidden_factors               | 0      |
| use_skip_connections             | True   |
| batch_size                       | 100    |
| threshold                        | 2.0    |
| step_size                        | 1.0    |
| autoencode                       | False  |

Table 6: rcfr

| Parameter                              | Value       |
|----------------------------------------|-------------|
| bootstrap                              | False       |
| truncate_negative                      | False       |
| buffer_size                            | -1          |
| num_hidden_layers                      | 2           |
| num_hidden_units                       | 400         |
| num_hidden_factors                     | 0           |
| use_skip_connections                   | True        |
| num_epochs                             | 200         |
| batch_size                             | 100         |
| step_size                              | 0.001       |

Table 7: deep_cfr

| Parameter                              | Value       |
|----------------------------------------|-------------|
| num_traversals                         | 1500        |
| batch_size_advantage                   | 2048        |
| batch_size_strategy                    | 2048        |
| num_hidden                             | 64          |
| num_layers                             | 3           |
| reinitialize_advantage_networks_learning_rate | True     |
| learning_rate                          | 1e-3        |
| memory_capacity                        | 1000000     |
| policy_network_train_steps             | 5000        |
| advantage_network_train_steps          | 750         |

Table 8: nfsp

| Parameter                        | Value       |
|----------------------------------|-------------|
| eval_every                       | 10000       |
| hidden_layers_sizes              | 128,128,128,128 |
| replay_buffer_capacity           | 2000000     |
| reservoir_buffer_capacity        | 2000000     |
| min_buffer_size_to_learn         | 1000        |
| anticipatory_param               | 0.1         |
| batch_size                       | 128         |
| learn_every                      | 128         |
| rl_learning_rate                 | 0.01        |
| sl_learning_rate                 | 0.01        |
| optimizer_str                    | sgd         |
| update_target_network_every      | 19200       |
| discount_factor                  | 1.0         |
| epsilon_decay_duration           | 20000000    |
| epsilon_start                    | 0.06        |
| epsilon_end                      | 0.001       |
| evaluation_metric                | exploitability |

Table 9: psro

| Parameter                              | Value       |
|----------------------------------------|-------------|
| n_players                              | 2           |
| meta_strategy_method                   | nash        |
| number_policies_selected               | 1           |
| sims_per_entry                         | 1000        |
| gpsro_iterations                       | 100         |
| symmetric_game                         | False       |
| prd_iterations                         | 50000       |
| training_strategy_selector            | probabilistic |
| oracle_type                            | BR          |
| number_training_episodes               | 10000       |
| self_play_proportion                   | 0.0         |
| hidden_layer_size                      | 256         |
| batch_size                             | 32          |
| sigma                                  | 0.0         |
| optimizer_str                          | adam        |
| num_q_before_pi                        | 8           |
| n_hidden_layers                        | 4           |
| entropy_cost                           | 0.001       |
| critic_learning_rate                   | 0.01        |
| pi_learning_rate                       | 0.001       |
| dqn_learning_rate                      | 0.01        |
| update_target_network_every            | 1000        |
| learn_every                            | 10          |
| seed                                   | 1           |
| verbose                                | True        |