Status-quo policy gradient in Multi-Agent Reinforcement Learning

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Abstract

Individual rationality, which involves maximizing expected individual return, does not always lead to high-utility individual or group outcomes in multi-agent problems. For instance, in multi-agent social dilemmas, Reinforcement Learning (RL) agents trained to maximize individual rewards converge to a low-utility mutually harmful equilibrium. In contrast, humans evolve useful strategies in such social dilemmas. Inspired by ideas from human psychology that attribute this behavior to the status-quo bias, we present a status-quo loss (SQLoss) and the corresponding policy gradient algorithm that incorporates this bias in an RL agent. We demonstrate that agents trained with SQLoss learn high-utility policies in several social dilemma matrix games (Prisoner’s Dilemma, Stag Hunt matrix variant, Chicken Game). We show how SQLoss outperforms existing state-of-the-art methods to obtain high-utility policies in visual input non-matrix games (Coin Game and Stag Hunt visual input variant) using pre-trained cooperation and defection oracles. Finally, we show that SQLoss extends to a 4-agent setting by demonstrating the emergence of cooperative behavior in the popular Braess’ paradox.

1 Introduction

In sequential social dilemmas, individually rational behavior can lead to outcomes that are suboptimal for each individual in the group [Hardin [1968], Ostrom [1990], Ostrom et al. [1999], Dietz et al. [2003]. Current state-of-the-art Multi-Agent Deep Reinforcement Learning (MARL) methods that train agents independently lead to agents that play individualistically, thereby receiving poor rewards, even in simple social dilemmas [Foerster et al. [2018], Lerer and Peysakhovich [2017].

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To illustrate why it is challenging to learn optimal policies in such dilemmas, we consider the Coin Game, which was first explored in [Foerster et al., 2018]. Each agent can play either selfishly (pick all coins) or cooperatively (pick only coins of its color). Regardless of the other agent's behavior, the individually rational choice for an agent is to play selfishly, either to minimize losses (avoid being exploited) or to maximize gains (exploit the other agent). However, when both agents behave rationally, they try to pick all coins and achieve an average long term reward of $-0.5$. In contrast, if both cooperate, then the average long term reward for each agent is $0.5$. Therefore, when agents cooperate, they are both better off. Training Deep RL agents independently in the Coin Game using state-of-the-art methods leads to mutually harmful selfish behavior (Section 2.2).

The problem of how independently learning agents develop optimal behavior in social dilemmas has been studied by researchers through human studies and simulation models [Fudenberg and Maskin, 1986; Green and Porter, 1984; Fudenberg et al., 1994; Kamada and Kominers, 2010; Abreu et al., 1990]. A large body of work has looked at the mechanism of evolution of cooperation through reciprocal behaviour and indirect reciprocity [Trivers, 1971; Axelrod, 1984; Nowak and Sigmund, 1992; 1993; 1998], through variants of reinforcement using aspiration [Macy and Flache, 2002], attitude [Damer and Gini, 2008] or multi-agent reinforcement learning [Sandholm and Crites, 1996; Wunder et al., 2010], and under specific conditions [Banerjee and Sen, 2007] using different learning rates [de Cote et al., 2006] similar to WoLF [Bowling and Veloso, 2002] as well as using embedded emotion [Yu et al., 2015], social networks [Ohtsuki et al., 2006; Santos and Pacheco, 2006].

However, these approaches do not directly apply to Deep RL agents [Leibo et al., 2017]. Recent work in this direction [Kleiman-Weiner et al., 2016; Julien et al., 2017; Peysakhovich and Lerer, 2018] focuses on letting agents learn strategies through interactions with other agents in a multi-agent setting. Leibo et al. [2017] defines the problem of social dilemmas in the Deep RL framework and analyzes the outcomes of a fruit-gathering game [Julien et al., 2017]. They vary the abundance of resources and the cost of conflict in the fruit environment to generate degrees of cooperation between agents. Hughes et al. [2018] defines an intrinsic reward (inequality aversion) that attempts to reduce the difference in obtained rewards between agents. The agents are designed to have an aversion to both advantageous (guilt) and disadvantageous (unfairness) reward allocation. This handcrafting of loss with mutual fairness develops cooperation, but it leaves the agent vulnerable to exploitation. LOLA [Foerster et al., 2018] uses opponent awareness to achieve high cooperation levels in the Coin Game and the Iterated Prisoner’s Dilemma game. However, the LOLA agent assumes access to the other agent’s network architecture, observations, and learning algorithms. This access level is analogous to getting complete access to the other agent’s private information and therefore devising a strategy with full knowledge of how they are going to play. Wang et al. [2019] proposes an evolutionary Deep RL setup to learn cooperation. They define an intrinsic reward that is based on features generated from the agent’s past and future rewards, and this reward is shared with other agents. They use evolution to maximize the sum of rewards among the agents and thus learn cooperative behavior. However, sharing rewards in this indirect way enforces cooperation rather than evolving it through independently learning agents.

Interestingly, humans develop individual and socially optimal strategies in such social dilemmas without sharing rewards or having access to private information. Several ideas in human psychology [Samuelson and Zeckhauser, 1988; Kahneman et al., 1991; Kahneman, 2011; Thaler and Sunstein, 2009] have attributed this cooperative behavior to the status-quo bias [Guney and Richter, 2018]. The status-quo bias is a decision-making bias that encourages humans to stick to the status-quo unless

![Figure 1: High-level architecture illustrated using coin game. Each agent runs GameDistill by performing steps (1), (2), (3) individually to obtain two oracles per agent. During game-play, each agent (with SQLoss) takes either the action suggested by the cooperation or the defection oracle](image-url)
doing so causes significant harm. This preference in humans for sticking to ‘comfortable’ states rather than seeking short-term exploitative gains is one explanation for emergent cooperative behavior in human groups. Inspired by this idea, we present the status-quo loss (SQLoss) and the corresponding status-quo policy gradient formulation for RL. Agents trained with SQLoss learn optimal policies in multi-agent social dilemmas without sharing rewards, gradients, or using a communication channel. Intuitively, SQLoss encourages an agent to stick to past actions provided these actions did not cause significant harm. Therefore, mutually cooperating agents stick to cooperation since the status-quo yields higher individual reward, while unilateral defection by any agent leads to the other agent also switching to defection since the status-quo is very harmful for the exploited agent. Subsequently, for each agent, the short-term reward of exploitation is overcome by the long-term cost of mutual defection, and agents gradually switch to cooperation.

To apply SQLoss to games where a sequence of non-trivial actions determines cooperation and defection, we present GameDistill, an algorithm that reduces a dynamic game with visual input to a matrix game. GameDistill uses self-supervision and clustering to extract distinct policies from a sequential social dilemma game automatically.

Our key contributions can be summarised as:

1. We introduce a Status-Quo loss (SQLoss, Sec. 2.3) and an associated policy gradient-based algorithm to learn optimal behavior in a decentralized manner for agents playing iterated matrix games where agents can choose between a cooperative and selfish policy at each step. We empirically demonstrate that agents trained with SQLoss learn optimal behavior in several social dilemma iterated matrix games (Sec. 4).

2. We extend SQLoss to social dilemma game with visual observations (Sec. 2.4) using GameDistill. We empirically demonstrate that GameDistill extracts cooperative and selfish policies for the Coin Game and Stag Hunt (Sec. 4.2). We further show that incorporating GameDistill in LOLA accelerates learning and achieves higher cooperation.

3. We also demonstrate that SQLoss extends in a straight forward manner to games with more than two agents due to its ego-centric nature (Sec. 6).

2 Approach

2.1 Social Dilemmas modeled as Iterated Matrix Games

To remain consistent with previous work, we adopt the notations from Foerster et al. [2018]. We model social dilemmas as general-sum Markov (simultaneous move) games. A multi-agent Markov game is specified by $G = (S, A, U, P, r, n, \gamma)$. $S$ denotes the state space of the game. $n$ denotes the number of agents playing the game. At each step of the game, each agent $a \in A$, selects an action $u^a \in U$. $\bar{u}$ denotes the joint action vector that represents the simultaneous actions of all agents. The joint action $\bar{u}$ changes the state of the game from $s$ to $s'$ according to the state transition function $P(s'|\bar{u}, s) : S \times U \times S \rightarrow [0, 1]$. At the end of each step, each agent $a$ gets a reward according to the reward function $r^a(s, \bar{u}) : S \times U \rightarrow \mathbb{R}$. The reward obtained by an agent at each step is a function of the actions played by all agents. For an agent $a$, the discounted future return from time $t$ is defined as $R_t^a = \sum_{\tau=t}^{\infty} \gamma^{\tau-t} r^a_{t+\tau}$, where $\gamma \in [0, 1)$ is the discount factor. Each agent independently attempts to maximize its expected discounted return.

Matrix games are the special case of two-player perfectly observable Markov games [Foerster et al. 2018]. Table 1 shows examples of matrix games that represent social dilemmas. Consider the Prisoner’s Dilemma game in Table 1a. Each agent can either cooperate (C) or defect (D). Playing D is the rational choice for an agent, regardless of whether the other agent plays C or D. Therefore, if both agents play rationally, they each receive a reward of $-2$. However, if each agent plays C, then it will obtain a reward of $-1$. This fact that individually rational behavior leads to a sub-optimal group (and individual) outcome highlights the dilemma.

In Infinitely Iterated Matrix Games, agents repeatedly play a particular matrix game against each other. In each iteration of the game, each agent has access to actions played by both agents in the previous iteration. Therefore, the state input to an RL agent consists of both agents’ actions in the previous iteration of the game. We adopt this state formulation as is typically done in such games.
We describe below the formulation of SQLoss with respect to agent 1. The formulation for agent 2 is identical to that of agent 1. The formulation for agent 1. Let \( \tau_a = (s_0, u_0, u_1, r_1^1, \ldots, s_T, u_T^1, u_T^2, r_T^1) \) denote the collection of state, action, reward, and next state for agent 1.

### 2.2 Learning Policies in Iterated Matrix Games: The Selfish Learner

The standard method to model agents in iterated matrix games is to model each agent as an RL agent that independently attempts to maximize its expected total discounted reward. Several approaches to model agents in this way use policy gradient-based methods [Sutton et al., 2000, Williams, 1992]. Policy gradient methods update an agent’s policy, parameterized by \( \theta^a \), by performing gradient ascent on the expected total discounted reward \( \mathbb{E}[R^a_0] \). Formally, let \( \theta^a \) denote the parameterized version of an agent’s policy \( \pi^a \) and \( V^a_{\theta^a} \), \( V^b_{\theta^b} \) denote the total expected discounted reward for agent \( a \) and \( b \), respectively. Here, \( V^a \) is a function of the policy parameters \((\theta^1, \theta^2)\) of both agents. In the \( t \)\textsuperscript{th} iteration of the game, each agent updates \( \theta^a \) to \( \theta^a_{t+1} \), such that it maximizes its total expected discounted reward. \( \theta^a_{t+1} \) is computed using Eq. \( 1 \) For agents trained using reinforcement learning, the gradient ascent rule to update \( \theta^a_{t+1} \) is given by Eq. \( 2 \)

\[
\theta^a_{t+1} = \arg \max_{\theta^a} V^1(\theta^1, \theta^2_t) \quad \text{and} \quad \theta^b_{t+1} = \arg \max_{\theta^b} V^2(\theta^1_t, \theta^2) \tag{1}
\]

\[
f^a_{t+1} = \nabla_{\theta^a} V^1(\theta^1_t, \theta^2_t) \cdot \delta \quad \text{and} \quad \theta^a_{t+1} = \theta^a_t + \alpha f^a_{t+1}(\theta^1_t, \theta^2_t) \tag{2}
\]

where \( \delta \) is the step size of the updates. In the Iterated Prisoner’s Dilemma (IPD) game, agents trained with the policy gradient update method converge to a sub-optimal mutual defection equilibrium \((DD, DD)\) also leads to a sub-optimal equilibrium attained by Selfish Learners (SL).

### 2.3 Learning Policies in Iterated Matrix Games: The Status-Quo Aware Learner (SQLoss)

#### 2.3.1 SQLoss: Motivation and Theory

The status-quo bias instills in humans a preference for the current state provided the state is not harmful to them. Inspired by this idea, we introduce a status-quo loss (SQLoss) for each agent, derived from the idea of imaginary game-play (Figure 2). The SQLoss encourages an agent to imagine a future episode where the status-quo (current situation) is repeated for several steps. If an agent has been exploited in the previous iteration of the game (state \( DC \)), then SQLoss will encourage the agent to imagine a continued risk of exploitation and subsequently switch to defection and move to state \( DD \). Hence, for the exploiting agent, the short-term gain from exploitation (\( DC \)) is overcome by the long-term loss from mutual defection (\( DD \)). Conversely, if both agents cooperated in the previous iteration of the game (state \( CC \)), then SQLoss will encourage the agent to imagine a continued gain from mutual cooperation and subsequently stick to state \( CC \). Since state \( CC \) is more beneficial to both agents than \( DD \), and exploitation (\( DC \) and \( CD \)) also leads to \( DD \), agents move away from defection and converge to mutual cooperation (\( CC \)). Appendix C describes in detail how cooperation emerges between SQLoss agents.

#### 2.3.2 SQLoss: Formulation

We describe below the formulation of SQLoss with respect to agent 1. Let \( \tau_a = (s_0, u_0, u_1, r_1^1, \ldots, s_T, u_T^1, u_T^2, r_T^1) \) denote the collection...
where $\alpha$ The previous section focused on learning optimal policies in iterated matrix games that represent a reward of $X$ to the row and $Y$ to the column player. $C$, $D$, $H$, and $T$ denote the actions for the row and column players. In the iterated versions of these games, agents play against each other over several iterations. In each iteration, an agent takes an action and receives a reward based on the actions of both agents. Each matrix represents a different kind of social dilemma.

|   | $C$ | $D$ | $H$ | $T$ | $C$ | $D$ |
|---|-----|-----|-----|-----|-----|-----|
| $C$ | (-1, -1) | (-3, 0) | (+1, -1) | (-1, +1) | (0, 0) | (-4, -1) |
| $D$ | (0, -3) | (-2, -2) | (-1, +1) | (+1, -1) | (-1, -4) | (-3, -3) |

(a) Prisoners’ Dilemma (PD)  
(b) Matching Pennies (MP)  
(c) Stag Hunt (SH)

Table 1: Payoff matrices for the different games used in our experiments. $(X, Y)$ in a cell represents a reward of $X$ to the row and $Y$ to the column player. $C$, $D$, $H$, and $T$ denote the actions for the row and column players. In the iterated versions of these games, agents play against each other over several iterations. In each iteration, an agent takes an action and receives a reward based on the actions of both agents. Each matrix represents a different kind of social dilemma.

of an agent’s experiences after $T$ time steps. Let $R^1_t(\tau_1) = \sum_{t=0}^{T} \gamma^{t-1} r^1_t$ denote the discounted future return for agent 1 starting at $s_t$ in actual game-play. Let $\tau_1$ denote the collection of an agent’s imagined experiences. For a state $s_t$, where $t \in [0, T]$, an agent imagines an episode by starting at $s_t$ and repeating $u^1_{t-1}, u^2_{t-1}$ for $\kappa_t$ steps. This is equivalent to imagining a $\kappa_t$ step repetition of already played actions. We sample $\kappa_t$ from a Discrete Uniform distribution $\mathcal{U}\{1, z\}$ where $z$ is a hyper-parameter $\geq 1$. To simplify notation, let $\phi_t(s_t, \kappa_t)$ denote the ordered set of state, actions, and rewards starting at time $t$ and repeated $\kappa_t$ times for imagined game-play. Let $\hat{R}^1_t(\tau_1)$ denote the discounted future return starting at $s_t$ in imagined status-quo game-play.

$$\phi_t(s_t, \kappa_t) = [(s_t, u^1_{t-1}, u^2_{t-1}, r^1_{t-1}), \ldots, (s_t, u^1_{t-1}, u^2_{t-1}, r^1_{t-1}), (s_t, u^1_{t-1}, u^2_{t-1}, r^1_{t-1}), \ldots, (s_T, u^1_{T}, u^2_{T}, r^1_{T})]_{\kappa_t-1}$$

$$\hat{\tau}_1 = (\phi_t(s_t, \kappa_t), (s_{t+1}, u^1_{t+1}, u^2_{t+1}, r^1_{t+1}), \kappa_{t+1}, \ldots, (s_T, u^1_{T}, u^2_{T}, r^1_{T})_{\kappa_T})$$

$$\hat{R}^1_{t}(\tau_1) = \left(1 - \frac{\gamma^\kappa}{1 - \gamma}\right) r^1_{t-1} + \gamma^\kappa R^1_{t}(\tau_1) = \left(1 - \frac{\gamma^\kappa}{1 - \gamma}\right) r^1_{t-1} + \gamma^\kappa \sum_{t=1}^{T} \gamma^{t-1} r^1_t$$

$V^1_{\theta_1, z^2}$ and $\tilde{V}^1_{\theta_1, z^2}$ are approximated by $\mathbb{E}[R^1_{0}(\tau_1)]$ and $\mathbb{E}[\hat{R}^1_{0}(\tau_1)]$ respectively. These $V$ values are the expected rewards conditioned on both agents’ policies ($\pi^1, \pi^2$). For agent 1, the regular gradients and the Status-Quo gradient-like correction term, $\nabla_{\theta_1} \mathbb{E}[R^1_{0}(\tau_1)]$ and $f^1_{sqcor}$, can be derived from the policy gradient formulation as

$$\nabla_{\theta_1} \mathbb{E}[R^1_{0}(\tau_1)] = \mathbb{E}[R^1_{0}(\tau_1) \nabla_{\theta_1} \log \pi^1(\tau_1)] = \mathbb{E} \left[ \sum_{t=1}^{T} \nabla_{\theta_1} \log \pi^1(u^1_t|s_t) \gamma^t (R^1_{t}(\tau_1) - b(s_t)) \right]$$

$$f^1_{sqcor} = \mathbb{E} \left[ \sum_{t=1}^{T} \nabla_{\theta_1} \log \pi^1(u^1_{t-1}|s_t) \gamma^t \times \left( \left(1 - \frac{\gamma^\kappa}{1 - \gamma}\right) r^1_{t-1} + \gamma^\kappa \sum_{t=1}^{T} \gamma^{t-1} r^1_t - b(s_t) \right) \right]$$

Here, $f^1_{sqcor}$ in Eq. [7] is a biased term that has policy gradient-like structure and incorporates the prior action taken through the $u^1_{t-1}|s_t$ term. It should be noted that the $f^1_{sqcor}$ is not a gradient of the expected return of the imagined trajectory in Eq. [5] but the form of this expression is arrived at considering the policy gradient expression. Furthermore, $b(s_t)$ is a baseline-like term added for variance reduction in the implementation.

The update rule $f_{sql,pg}$ for the policy gradient-based Status-Quo Learner (SQL-PG) is defined by,

$$f^1_{sql,pg} = (\alpha \cdot \nabla_{\theta_1} \mathbb{E}[R^1_{0}(\tau_1)] + \beta \cdot f^1_{sqcor}) \cdot \delta$$

where $\alpha$, $\beta$ are the loss scaling factor for REINFORCE and imaginative game-play respectively.

2.4 Learning policies in Dynamic Non-Matrix Games using SQLoss and GameDistill

The previous section focused on learning optimal policies in iterated matrix games that represent sequential social dilemmas. In such games, an agent can take one of a discrete set of policies at each step. For instance, in IPD, an agent can either cooperate or defect at each step. However, in social dilemmas such as the Coin Game (Appendix A), cooperation and defection policies are composed of
a sequence of state-dependent actions. *SQLoss*, proposed above, works for matrix games but is not directly applicable to games with visual input to yield mutual cooperation. To apply the Status-Quo policy gradient to these games, we present *GameDistill*, a self-supervised algorithm that reduces a dynamic infinitely iterated game with visual input to a matrix game. *GameDistill* takes as input game-play episodes between agents with random policies and learns oracles (or policies) that lead to distinct outcomes. *GameDistill* (Figure 1) works as follows.

1. We initialize agents with random weights and play them against each other in the game. In these random game-play episodes, whenever an agent receives a reward, we store the sequence of states along with the rewards for both agents.
2. This collection of state sequences is used to train the *GameDistill* network, which is a self-supervised trajectory encoder. It takes as input a sequence of states and predicts the rewards of both agents during training.
3. We now cluster the embeddings extracted from the penultimate layer of the trained *GameDistill* network using Agglomerative Clustering [Friedman et al., 2001]. Each embedding is a finite-dimensional representation of the corresponding state sequence. Each cluster represents a collection of state sequences or transitions, that lead to a consistent outcome (w.r.t rewards). For CoinGame, when we use the number of clusters as two, we observe that one cluster consists of transitions that represent cooperative behavior (cooperation cluster) while the other contains transitions that lead to defection (defection cluster).
4. Using the state sequences in each cluster, we train an oracle to predict the next action given the current state. For the Coin Game, the oracle trained on state sequences from the cooperation cluster predicts the cooperative action for a given state. Similarly, the oracle trained on the defection cluster predicts the defection action for a given state. Each agent uses *GameDistill* independently to extract a cooperation and a defection oracle. Figure 15 (Appendix J) illustrates the cooperation and defection oracles extracted by the Red agent.

During game-play, an agent can consult either oracle at each step. In CoinGame, this is equivalent to either cooperating (consulting the cooperation oracle) or defecting (consulting the defection oracle). In this way, an agent reduces a dynamic game to its matrix equivalent using *GameDistill*. We then utilize the Status-Quo policy gradient to learn optimal policies in the reduced matrix game. For the Coin Game, this leads to agents who cooperate by only picking coins of their color (Figure 5). It is important to note that for games like CoinGame, we could have learned cooperation and defection oracles by training agents using the sum-of-rewards for both agents and individual reward, respectively [Lerer and Peyssakhovich, 2017]. However, *GameDistill* learns distinct policies without using hand-crafted reward functions. *GameDistill* is applicable only in games where cooperation and defection policies are clearly defined and lead to distinct payoffs (rewards) for both players.

Algorithm 1 in Appendix provides the pseudo-code for *GameDistill* with additional details in Appendix B.3. Appendix B.2 provides additional details about the architecture and the different components of *GameDistill*. Further, we have verified *GameDistill* empirically on the Coin Game and the Stag Hunt (results in Appendix G). Additional clustering visualizations for the trajectories and the experimental plots are provided in Appendix F and J.

3 Experimental Setup

In order to compare our results to previous work, we use the Normalized Discounted Reward or \( NDR = (1 - \gamma) \sum_{t=0}^{T} \gamma^t r_t \). A higher NDR implies that an agent obtains a higher reward in the environment. We compare our approach (Status-Quo Aware Learner or *SQLearner*) to Learning with Opponent-Learning Awareness (Lola-PG) [Foerster et al., 2018] and the Selfish Learner (SL) agents. For all experiments, we perform 20 runs and report average \( NDR \), along with variance across runs. The bold line in all the figures is the mean, and the shaded region is the one standard deviation region around the mean.

3.1 Iterated Matrix Game Social Dilemmas

For our experiments with social dilemma matrix games, we use the Iterated Prisoners Dilemma (IPD) [Luce and Raiffa, 1989], Iterated Matching Pennies (IMP) [Lee and Louis, 1967], and the
Iterated Stag Hunt (ISH) [Fang et al., 2002]. Each matrix game in Table 1 represents a different dilemma. In the Prisoner’s Dilemma, the rational policy for each agent is to defect, regardless of the other agent’s policy. However, when each agent plays rationally, each is worse off. In Matching Pennies, if an agent plays predictably, it is prone to exploitation by the other agent. Therefore, the optimal policy is to randomize between $H$ and $T$, obtaining an average NDR of 0. The Stag Hunt game represents a coordination dilemma. In the game, given that the other agent will cooperate, an agent’s optimal action is to cooperate as well. However, each agent has an attractive alternative at each step, that of defecting and obtaining a guaranteed reward of $-1$. Therefore, the promise of a safer alternative and the fear that the other agent might select the safer choice could drive an agent to select the safer alternative, thereby sacrificing the higher reward of mutual cooperation.

In iterated matrix games, at each iteration (iter), agents take an action according to a policy and receive the rewards in Table 1. To simulate an infinitely iterated game, we let agents play 200 iters of game against each other, and do not provide an agent with any information about the number of remaining iters. In an iter, state for an agent is the actions played by both agents in the previous iter.

3.2 Iterated Dynamic Game Social Dilemmas

For our experiments on a social dilemma with extended actions, we use the Coin Game (Figure 7) [Forster et al., 2018] and the non-matrix variant of the Stag Hunt (Figure 8). We provide details of the games in Appendix A due to space considerations.

4 Results

4.1 Learning optimal policies in Iterated Matrix Dilemmas

Iterated Prisoner’s Dilemma (IPD): We train different learners to play the IPD game. Figure 3 shows the results. For all learners, agents initially defect and move towards an NDR of $-2.0$. This initial bias towards defection is expected, since, for agents trained with random game-play episodes, the benefits of exploitation outweigh the costs of mutual defection. For Selfish Learner (SL) agents, the bias intensifies, and the agents converge to mutually harmful selfish behavior (NDR of $-2.0$). Lola-PG agents learn to predict each other’s behavior and realize that defection is more likely to lead to mutual harm. They subsequently move towards cooperation, but occasionally defect (NDR of $-1.2$). In contrast, SQLearner agents quickly realize the costs of defection, indicated by the small initial dip in the NDR curves. They subsequently move towards close to 100% cooperation, with an NDR of $-1.0$. Finally, it is important to note that SQLearner agents have close to zero variance, unlike other methods where the variance in NDR across runs is significant.

Iterated Matching Pennies (IMP): We train different learners to play the IMP game. Figure 4 shows the results. SQLearner agents learn to play optimally and obtain an NDR close to 0. Interestingly, Selfish Learner (SL) and Lola-PG agents converge to an exploiter-exploited equilibrium where one agent consistently exploits the other agent. This asymmetric exploitation equilibrium is more pronounced for SL agents than for Lola-PG agents. As before, we observe that SQLearner agents have close to zero variance across runs, unlike other methods where the variance in NDR is significant.

Iterated Chicken Game (ICG): Appendix H shows additional results for the ICG game.

4.2 Learning Optimal Policies in Iterated Dynamic Dilemmas

GameDistill: To evaluate the clustering step in GameDistill, we make two t-SNE [Maaten and Hinton, 2008] plots of the 100-dimensional feature vectors extracted from the penultimate layer of the trained GameDistill network in Figure 9 of Appendix F. In the first plot, we color each point (or state sequence) by the rewards obtained by both agents in the format $r_1|r_2$. In the second, we color each point by the cluster label output by the clustering technique. GameDistill correctly discovers two clusters, one for transitions that represent cooperation (Red cluster) and the other for transitions that represent defection (Blue cluster). We experiment with different values for feature vector dimensions and clustering techniques, and obtain similar results (see Appendix B). Results on Stag Hunt using GameDistill are presented in Appendix F and G. To evaluate the trained oracles that represent cooperation and a defection policy, we modify the CoinGame environment to contain only a single agent (the Red agent). We then play two variations of the game. In the first variant, the
Figure 3: Average NDR values for different learners in IPD. SQLearner agents obtain a near-optimal NDR value (−1) for this game.

Figure 4: Average NDR values for different learners in IMP. SQLearner agents avoid exploitation by randomising between H and T to obtain a near-optimal NDR value (0).

Figure 5: Probability that an agent will pick a coin of its color in CoinGame. SQLearner agents achieve a cooperation rate close to 1.0 while Lola-PG agents achieve rate close to 0.8.

Figure 6: Impact of using pretrained GameDistill oracles in CoinGame. SQLearner agents (w/ GameDistill oracles) achieve close to 100% cooperation. Lola-PG agents eventually (after roughly 4000 epochs) achieve close to 80% cooperation. Interestingly, Lola-PG agents trained w/ GameDistill oracles converge to higher cooperation rate of 85% in 300 epochs.

Red agent executes the actions as suggested by the first oracle. We observe that Red agent picks only 8.4% of Blue coins, indicating a high cooperation rate, which represents a cooperation policy. In the second variant, Red agent executes the actions suggested by the second oracle. We observe that Red agent picks 99.4% of Blue coins, indicating high defection rate, which represents a defection policy.

SQLoss: During game-play, at each step, an agent follows either the action suggested by its cooperation oracle or defection oracle. We compare approaches using the degree of cooperation between agents, measured by the probability that an agent will pick the coin of its color [Foerster et al., 2018]. Figure 5 shows the results. The probability that an SQLearner agent will pick the coin of its color is close to 1.0. This high probability indicates that the other SQLearner agent is cooperating with this agent and only picking coins of its color. In contrast, the probability that a Lola-PG agent will pick a coin of its color is close to 0.8, indicating higher defection rates. As expected, the probability of an agent picking its own coin is the smallest for Selfish Learner.

To evaluate the impact of GameDistill, we compare SQLearner agents to Lola-PG agents trained using GameDistill oracles. Figure 6 shows the results. Interestingly, Lola-PG agents trained with GameDistill oracles converge to a higher cooperation rate (0.88) than Lola-PG agents trained directly on visual input.

5 SQLoss for social dilemma matrix games

For a given matrix game, SQLoss will work on an equivalent version of the game in which all rewards have been transformed to non-positive values. For the matrix games described in our paper, we have used their variants with negative rewards to remain consistent with the LOLA paper. For a general matrix game, we can subtract the maximum reward (or any number larger than it) from each reward value to make rewards negative and then use SQLoss. We consider the social dilemma class of matrix games from Leibo et al. [2017],

\[
\begin{pmatrix}
C & R, R & S, T \\
D & T, S & P, P
\end{pmatrix}
\]

where the first row corresponds to
Leibo et al. [2017] define the following rules that describe different categories of social dilemmas: (i) If \( R > P \), then mutual cooperation is preferred to mutual defection. (ii) If \( R > S \), then mutual cooperation is preferred to being exploited by a defector. (iii) If \( 2R > T + S \), this ensures that mutual cooperation is preferred to an equal probability of unilateral cooperation and defection. (iv) Either greed \( (T > R: \text{Exploit a cooperator preferred over mutual cooperation}) \) or fear \( (P > S: \text{Mutual defection preferred over being exploited}) \) should hold. These rules have been reproduced from Leibo et al. [2017].

1. When “greed” \( (T > R) \) as well as “fear” \( (P > S) \) conditions hold, we have \( T > R > P > S \). The Iterated Prisoner’s Dilemma (IPD) is an example of this game. If we subtract \( T \) from each reward, we get the matrix game, \[
\begin{pmatrix}
C & R - T & R - T \\
D & S - T & 0 \\
0 & S & P - T, P - T
\end{pmatrix},
\] where all entries are non-positive and therefore Lemma 3 and Lemma 4 hold as before.

2. When “greed” holds but not “fear” we have \( T > R > S >= P \). The Chicken Game (CG) is an example of this game. If we subtract \( T \) from each reward as before, we get the equivalent matrix game with non-positive entries and Lemmas 3 and 4 hold.

3. When “fear” holds but not “greed” we have \( R >= T > P > S \). The Iterated Stag Hunt is an example of this game. If we subtract \( R \) from each reward, we get the equivalent matrix game with non-positive entries then Lemmas [2] and 4 (Appendix C) hold.

In our experiments, we have considered games from each of the classes mentioned above, and the use of \( SQLoss \) leads to cooperation in all these examples.

6 Games with more than 2 players

Our formulation of \( SQLoss \) has the distinct advantage of being fully ego-centric, i.e., the learning agent does not require any information regarding its opponents. This feature enables a straightforward extension of \( SQLoss \) beyond the two agent setting, without any change in each agent’s learning algorithm. In order to test this extension of \( SQLoss \) beyond 2-players, we consider as an example, the problem described in the popular Braess’ paradox [Braess, 1968], which is a well-known extension of the Prisoner’s Dilemma problem to more than 2 agents. We performed additional experiment in this game with 4 agents. We simulated the result when all agents are selfish learners (the SL agent(s)) and also when all agents use \( SQLoss \) (the \( SQLearner(s) \)). We observe that when using selfish learners, all agents converge to Defection and when using \( SQLoss \), all agents converge to Cooperation. Detailed explanation of the game, experimental setup and results are shown in Appendix D.

7 Conclusion

We presented a status-quo policy gradient that encourages an agent to imagine the consequences of sticking to the status quo. We demonstrated how \( SQLoss \) outperforms LOLA on standard benchmark matrix games. To work with dynamic games, we further proposed \( GameDistill \), an algorithm that reduces a dynamic game with visual input to a matrix game. We combined \( GameDistill \) and \( SQLoss \) to demonstrate how agents learn optimal policies in dynamic social dilemmas with visual observations. We empirically demonstrated that \( SQLoss \) obtains near-optimal rewards in various social-dilemma games such as IPD, IMP, Chicken, Stag-Hunt and Coin Game (both matrix and variant with visual observations).

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Appendix for
Status-Quo Policy Gradient in Multi-agent Reinforcement Learning

A  Description of Environments Used for Dynamic Social Dilemmas

The three matrix games tested in the paper are canonical games that appear in the sequential social dilemma literature. Hence, we selected these to demonstrate the effectiveness of SQ policy gradient approach. We have not tested our approach beyond the social dilemma setting and hence limit our claims to the same.

A.1  Coin Game

Figure 7 illustrates the agents playing the Coin Game. The agents, along with a Blue or Red coin, appear at random positions in a $3 \times 3$ grid. An agent observes the complete $3 \times 3$ grid as input and can move either left, right, up, or down. When an agent moves into a cell with a coin, it picks the coin, and a new instance of the game begins where the agent remains at their current positions, but a Red/Blue coin randomly appears in one of the empty cells. If the Red agent picks the Red coin, it gets a reward of $+1$, and the Blue agent gets no reward. If the Red agent picks the Blue coin, it gets a reward of $+1$, and the Blue agent gets a reward of $-2$. The Blue agent’s reward structure is symmetric to that of the Red agent.

A.2  Stag-Hunt

Figure 8 shows the illustration of two agents (Red and Blue) playing the visual Stag Hunt game. The STAG represents the maximum reward the agents can achieve with HARE in the center of the figure. An agent observes the full $7 \times 7$ grid as input and can freely move across the grid in only the empty cells, denoted by white (yellow cells denote walls that restrict the movement). Each agent can either pick the STAG individually to obtain a reward of $+4$, or coordinate with the other agent to capture the HARE and obtain a better reward of $+25$.

B  GameDistill: Oracles, Network Architecture and pseudo-code

B.1  Oracles from GameDistill

The oracles are important in games with visual input. The agent uses these oracles to reduce the games to their matrix equivalents. While we call the two oracles learned from GameDistill as Cooperation and Defection oracles, we do not need the notion of cooperation or defection, nor do we need to explicitly label these clusters as ‘cooperation’ or ‘defection’ to learn these oracles. These oracles are learned by clustering the outcomes of random play into two distinct clusters. In social dilemmas, these two distinct clusters represent cooperation and defection outcomes. Hence, we use the names ‘Cooperation’ and ‘Defection’ oracles for the oracles learned from these clusters. It is
important to mention that SQLoss (without oracles) achieves high-degree of cooperation in matrix games.

**Algorithm 1** Pseudocode for *GameDistill*

1: **Input:** Game Environment *env*, Agents *agents*, Clustering Technique *AggClustering*
2: **for** agent in *agents* **do**
3: \(t_{data} = \text{collect}_{data}(env, \text{agent})\) \(//\) Collect trajectory data
4: \(\text{rewardPredNet} = \text{createNetwork}()\)
5: \(\text{train}_{network}(\text{rewardPredNet}, t_{data})\)
6: \(\text{feats} = \text{get}_{features}(\text{rewardPredNet}, t_{data})\) \(//\) Extract shared features & cluster
7: \(\text{clus}_{ids} = \text{AggClustering}(n = 2).\text{fit}(\text{feats})\)
8: \(\text{oracle}_{nets} = []\) \(//\) Train oracles corresponding to each cluster
9: **for** \(k\) in range(2) **do**
10: \(\text{index} = \text{np.where}(\text{clus}_{ids} == k)\)
11: \(\text{cluster}_{data} = t_{data}[\text{index}]\)
12: \(\text{oracle}_{nets}[k] = \text{create}_{oracle}_{net}(env)\)
13: \(\text{train}_{oracle}(\text{oracle}_{nets}[k], \text{cluster}_{data})\)
14: **end for**
15: **end for**
16: **Output:** Trained oracle networks *oracle_{nets}*

In visual-input games with complex actions (such as up, down, left, right, eat-coin, etc.), it is not clear which action or sequence of actions constitute cooperation or defection. In such games, the role of the cooperation oracle is to recommend, at each step, which action (out of up down, left, right, eat-coin, etc.) constitutes *cooperative* behavior. Similarly, the role of the defection oracle is to recommend, at each step, which action constitutes *defection* behavior. Algorithm 1 describes (at a high level) how agents train and use these oracles in the game-play life cycle. Algorithm 6 (in Appendix B) describes how the oracles are trained.

We also provide details about the oracle network architecture from in Appendix B.1 in the supplementary material.

**B.2 GameDistill: Architecture Details**

*GameDistill* consists of two components.

The **first component is the state sequence encoder** that takes as input a sequence of states (input size is \(4 \times 4 \times 3 \times 3\), where \(4 \times 3 \times 3\) is the dimension of the game state, and the first index in the state input represents the data channel where each channel encodes data from both all the different colored agents and coins) and outputs a fixed dimension feature representation. We encode each state in the sequence using a common trunk of 3 convolution layers with *relu* activations and kernel-size \(3 \times 3\), followed by a fully-connected layer with 100 neurons to obtain a finite-dimensional feature representation. This unified feature vector, called the trajectory embedding, is then given as input to the different prediction branches of the network. We also experiment with different dimensions of this embedding and provide results in Figure 9.

The two branches, which predict the self-reward and the opponent-reward (as shown in Figure 1), independently use this trajectory embedding as input to compute appropriate output. These branches take as input the trajectory embedding and use a dense hidden layer (with 100 neurons) with linear activation to predict the output. We use the *mean-squared error (MSE)* loss for the regression tasks in the prediction branches. Linear activation allows us to cluster the trajectory embeddings using a linear clustering algorithm, such as Agglomerative Clustering \cite{Friedman2001}. In general, we can choose the number of clusters based on our desired level of granularity in differentiating outcomes. In the games considered in this paper, agents broadly have two types of policies. Therefore, we fix the number of clusters to two.

We use the *Adam* \cite{Kingma2014} optimizer with learning-rate of \(3e - 3\). We also experiment with K-Means clustering in addition to Agglomerative Clustering, and it also gives similar results. We provide additional results of the clusters obtained using *GameDistill* in Appendix E.
Figure 9: Representation of the clusters learned by GameDistill for Coin Game. Each point is a t-SNE projection of the feature vector (in different dimensions) output by the GameDistill network for an input sequence of states. For each of the sub-figures, the figure on the left is colored based on actual rewards obtained by each agent ($r_1 | r_2$). The figure on the right is colored based on clusters as learned by GameDistill. GameDistill correctly identifies two types of trajectories, one for cooperation and the other for defection.

component is the oracle network that outputs an action given a state. For each oracle network, we encode the input state using 3 convolution layers with kernel-size $2 \times 2$ and relu activation. To predict the action, we use 3 fully-connected layers with relu activation and the cross-entropy loss. We use L2 regularization, and Gradient Descent with the Adam optimizer (learning rate $1e^{-3}$) for all our experiments.

B.3 GameDistill: Pseudo-Code

Algorithm 3 Pseudo-code for create_network

1: net = conv(states_placeholder, kernel = 3, num_outputs = 64, activation = relu)
2: net = conv(net, kernel = 3, num_outputs = 64, activation = relu)
3: net = conv(net, kernel = 3, num_outputs = 64, activation = relu)
4: feat = flatten(net)  // the trajectory embedding
5:
6: self_ft, opp_ft = FC(feat, num_outputs = 100), FC(feat, num_outputs = 100)
7:  // Predict the opponent and the self rewards
8: s_reward_pred = FC(self_ft, num_outputs = 1)
9: o_reward_pred = FC(opp_ft, num_outputs = 1)
10: return s_reward_pred, o_reward_pred
Algorithm 2 Pseudo-code for collect_data

1: Input: Game Environment Env, Minimum Samples min_samples = 2000, Batch Size batch = 100, look_back = 5
2: env = Env.spawn(batch)
3: state_q = Queue(batch, look_back)
4: reward_seq_dict = dict()
5: keep_running = True
6: while keep_running do
7:     actions = random(env.actions, size = (batch, env.n_agents))
8:     rewards, moves, states = env.step(actions)
9:     check = False
10:     for b in range(batch) do
11:         if state_q[b].full() then
12:             state_q[b].pop()
13:         end if
14:         state_q[b].put(states[b])
15:     end for
16:     // for any non zero reward tuple
17:     if abs(rewards).sum() > 0 then
18:         reward_tpl = tuple(rewards)
19:         if reward_tpl not in reward_seq_dict then
20:             reward_seq_dict[reward_tpl] = []
21:         end if
22:         obs = state_q[b].pop_all()
23:         reward_seq_dict[reward_tpl].append(obs)
24:         check = True
25:     end if
26: end for
27: if check then
28:     keys = env.get_all_possible_reward_tuples()
29:     count_stop = 0
30:     for k in keys do
31:         if len(reward_seq_dict[k]) > min_samples then
32:             count_stop+ = 1
33:         end if
34:     end for
35:     if count_stop >= len(keys) then
36:         keep_running = False
37:     end if
38: end if
39: end while
40: train_data = []  // Collect the final training data
41: for rewards_tpl in reward_seq_dict.keys() do
42:     for traj in t_data[rewards_tpl] : min_samples] do
43:         // trajectory has shape [look_back,h,w,c] and “rewards_tpl” is tuple of rewards of agents
44:         traj = traj.permute(1, 2, 3, 0).reshape(h, w, -1)
45:         train_data.append((traj, rewards_tpl))
46:     end for
47: end for
48: return shuffle(train_data)
Algorithm 4 Pseudo-code for \textit{train\_network}

1: \textbf{Input:} Reward Prediction Network as net, data \textit{train\_data}, loss term weights \(A\) and \(B\)
2: optimizer = Adam(lr = 0.003)
3: \textbf{while} convergence \textbf{do}
4: \hspace{1em} \text{state, reward} = \text{sample}(\textit{train\_data})
5: \hspace{1em} \text{my\_reward, opp\_reward} = \text{net}.\text{forward}(\text{state})
6: \hspace{1em} \text{loss} = A \ast \text{l2\_loss}(\text{my\_reward, reward}(0)) + B \ast \text{l2\_loss}(\text{opp\_reward, reward}(1))
7: \hspace{1em} \text{loss}.\text{backward}(), \text{optimizer}.\text{step}()
8: \textbf{end while}

Algorithm 5 Pseudo-code for \textit{create\_oracle\_net}

1: \textbf{Input:} Game Environment \textit{env}
2: \text{net} = \text{conv(\textit{state\_placeholder}, kernel = 2, num\_outputs = 128, activation = relu)}
3: \text{net} = \text{conv(\text{net}, kernel = 2, num\_outputs = 128, activation = relu)}
4: \text{net} = \text{conv(\text{net}, kernel = 2, num\_outputs = 64, activation = relu)}
5: \text{net} = \text{flatten(\text{net})}
6: \text{net} = \text{fc(\text{net}, num\_outputs = 128, activation = relu)} \quad \text{// Encode the environment state}
7: \text{logits} = \text{fc(\text{net, num\_outputs = env.num\_actions})}
8: \text{action\_predict} = \text{softmax(\text{logits})}
9: \textbf{return} Action predictions \text{action\_predict}

Algorithm 6 Pseudo-code for \textit{train\_oracle}

1: \textbf{Input:} Oracle Network \textit{net}, Clustered trajectory data \textit{train\_data}
2: \text{actions\_data} = []
3: \textbf{for} \text{data} \textbf{in} \textit{train\_data} \textbf{do}
4: \hspace{1em} \text{states} = \text{data}[0]
5: \hspace{1em} \textbf{for} \text{i} \textbf{in} \text{range}(1, \text{len(\text{states}))} \textbf{do}
6: \hspace{2em} \text{action} = \text{deduce\_move(\text{states}[i - 1], \text{states}[i])}
7: \hspace{2em} \text{actions\_data}.\text{append}((\text{states}[i - 1], \text{action}))
8: \hspace{1em} \textbf{end for}
9: \textbf{end for}
10: \text{optimizer} = \text{SGD(lr = 0.01)}
11: \textbf{while} not convergence \textbf{do}
12: \hspace{1em} \text{state, action} = \text{sample(\text{actions\_data})}
13: \hspace{1em} \text{my\_action} = \text{net}.\text{forward}(\text{state})
14: \hspace{1em} \text{loss} = \text{cross\_entropy(\text{my\_action, action})}
15: \hspace{1em} \text{loss}.\text{backward}(), \text{optimizer}.\text{step}()
16: \textbf{end while}

C $SQLoss$: Emergence of Cooperation

Equation \ref{eq:standard_loss} (Section 2.3.2) describes the gradient for standard policy gradient. It has two terms. The $\log \pi^1(u_t|s_t)$ term maximises the likelihood of reproducing the training trajectories $[(s_{t-1}, u_{t-1}, r_{t-1}), (s_t, u_t, r_t), (s_{t+1}, u_{t+1}, r_{t+1}), \ldots]$. The return term pulls down trajectories that have poor return. The overall effect is to reproduce trajectories that have high returns. We refer to this standard loss as Loss for the following discussion.

**Lemma 1.** For agents trained with random exploration in the IPD, $Q_\pi(D|s_t) > Q_\pi(C|s_t)$ for all $s_t$. 

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Let $Q_\pi(a_t|s_t)$ denote the expected return of taking $a_t$ in $s_t$. Let $V_\pi(s_t)$ denote the expected return from state $s_t$.

$$Q_\pi(C|CC) = 0.5 \times (-1) + V_\pi(CC) + 0.5 \times (-3) + V_\pi(CD)$$
$$Q_\pi(C|CC) = -2 + 0.5 \times (V_\pi(CC) + V_\pi(CD))$$
$$Q_\pi(D|CC) = -1 + 0.5 \times (V_\pi(DC) + V_\pi(DD))$$
$$Q_\pi(D|CC) = -2 + 0.5 \times (V_\pi(CC) + V_\pi(CD))$$
$$Q_\pi(C|CD) = -2 + 0.5 \times (V_\pi(CC) + V_\pi(CD))$$
$$Q_\pi(D|CD) = -1 + 0.5 \times (V_\pi(DC) + V_\pi(DD))$$
$$Q_\pi(C|DD) = -2 + 0.5 \times (V_\pi(CC) + V_\pi(CD))$$
$$Q_\pi(D|DD) = -1 + 0.5 \times (V_\pi(DC) + V_\pi(DD))$$

Since $V_\pi(CC) = V_\pi(CD) = V_\pi(DC) = V_\pi(DD)$ for randomly playing agents, $Q_\pi(D|s_t) > Q_\pi(C|s_t)$ for all $s_t$.

**Lemma 2.** Agents trained to only maximize the expected reward in IPD will converge to mutual defection.

This lemma follows from Lemma 1. Agents initially collect trajectories from random exploration. They use these trajectories to learn a policy that optimizes for a long-term return. These learned policies always play $D$ as described in Lemma 1.

Equation 7 describes the gradient for $SQLoss$. The $\log \pi^1(u^1_{t-1}|s_t)$ term maximises the likelihood of taking $u^1_{t-1}$ in $s_t$. The imagined episode return term pulls down trajectories that have poor imagined return.

**Lemma 3.** Agents trained on random trajectories using only $SQLoss$ oscillate between $CC$ and $DD$.

For IPD, $s_t = (u^1_{t-1}, u^2_{t-1})$. The $SQLoss$ maximises the likelihood of taking $u^1_{t-1}$ in $s_t$ when the return of the imagined trajectory $\hat{R}_t(\tau_1)$ is high.

Consider state $CC$, with $u^2_{t-1} = C$. $\pi^1(D|CC)$ is randomly initialised. The $SQLoss$ term reduces the likelihood of $\pi^1(C|CC)$ because $\hat{R}_t(\tau_1) < 0$. Therefore, $\pi^1(D|CC) > \pi^1(C|CC)$.

Similarly, for $CD$, the $SQLoss$ term reduces the likelihood of $\pi^1(C|CD)$. Therefore, $\pi^1(D|CD) > \pi^1(C|CD)$. For $DC$, $\hat{R}_t(\tau_1) = 0$, therefore $\pi^1(D|DC) > \pi^1(C|DC)$. Interestingly, for $DD$, the $SQLoss$ term reduces the likelihood of $\pi^1(D|DD)$ and therefore $\pi^1(C|DD) > \pi^1(D|DD)$.

Now, if $s_t$ is $CC$ or $DD$, then $s_{t+1}$ is $DD$ or $CC$ and these states oscillate. If $s_t$ is $CD$ or $DC$, then $s_{t+1}$ is $DD$, $s_{t+2}$ is $CC$ and again $CC$ and $DD$ oscillate. This oscillation is key to the emergence of cooperation as explained in section 2.3.1.

**Lemma 4.** For agents trained using both standard loss and $SQLoss$, $\pi(C|CC) > \pi^1(D|CC)$.

For $CD$, $DC$, both the standard loss and $SQLoss$ push the policy towards $D$. For $DD$, with sufficiently high $\kappa$, the $SQLoss$ term overcomes the standard loss and pushes the agent towards $C$. For $CC$, initially, both the standard loss and $SQLoss$ push the policy towards $D$. However, as training progresses, the incidence of $CD$ and $DC$ diminish because of $SQLoss$ as described in Lemma 3. Therefore, $V_\pi(CD) \approx V_\pi(DC)$ since agents immediately move from both states to $DD$. Intuitively, agents lose the opportunity to exploit the other agent. In equation 9, with $V_\pi(CD) \approx V_\pi(DC)$, $Q_\pi(C|CC) > Q_\pi(D|CC)$ and the standard loss pushes the policy so that $\pi(C|CC) > \pi(D|CC)$. This depends on the value of $\kappa$. For very low values, the standard loss overcomes $SQLoss$ and agents defect. For very high values, $SQLoss$ overcomes standard loss, and agents oscillate between cooperation and defection. For moderate values of $\kappa$ (as shown in our experiments), the two loss terms work together so that $\pi(C|CC) > \pi(D|CC)$.
D Games with more than 2 players

Our formulation of $SQLoss$ has the distinct advantage of being fully ego-centric, that is, the agent that is learning does not require any information regarding its opponents. This feature enables a straightforward extension of $SQLoss$ beyond the two agent setting, without any change in each agent’s learning algorithm. In order to test this extension of $SQLoss$ beyond 2-players, we consider as an example, the problem described in the popular Braess’ paradox, which is a well-known extension of the Prisoner’s Dilemma problem to more than 2 agents. We construct a simplified environment to interpret the policies in the problem given in Braess’ paradox as a sequential social dilemma problem. This problem, which we henceforth refer to as the Braess’ problem, is concerned with traffic flow from a source to a destination with two alternative paths, through two intermediate locations. This is illustrated in Fig. 10.

In this, each agent has to travel from the source (Start) to the destination (End) by choosing one of these paths. Each path has two segments separated by the respective intermediate location and the cost of traversing each segment (proportional to the time of travel) is either fixed or is determined based on the number of agents using that segment. This cost function is shown in Eq. 10. In the original setup, the two intermediate locations are not connected and each agent has to only choose between one of these paths. The equilibrium solution in this case is for half the agents to choose one path and the remaining half the other. The modification that entails is the paradox is connecting the two intermediate locations with a cost free directed bridge, thus leading a third possible path for all agents. This modification shifts the equilibrium in such a way that all agents now prefer to choose the new path that uses this directed bridge, although this results in a per-agent cost that is higher than each agent’s original cost in the absence of this new path. This problem has been well studied and the paradox highlights the fact that in strategic settings, increase in the number of available options for all agents, may also lead to decrease in utility for all agents individually and collectively.

We model this problem as a sequential social dilemma, where we define the initial strategy of the agents to choose one of the two original paths as Cooperation and the strategy that results in an agent choosing the new path with the directed bridge as Defection. For simplicity of exposition, we assign integer IDs to agents and define Cooperation for agents with odd-IDs as choosing the path Start-A-End in Fig. 10 and Cooperation for agents with even-IDs as choosing the path Start-B-End in Fig. 10. In this notation, the Defection can be defined as an agent choosing the path Start-A-B-End. In the Fig. 10 we provide reward numbers, such that the paradox is realized.

As described earlier, in this game, Cooperate and Defect have the following interpretation:

1. For an odd numbered vehicle – Cooperation implies taking the Start-A-End route.
2. For an even numbered vehicle – Cooperation implies taking the Start-B-End route (This and above point follow from the assumption that before addition of the new edge A-B, the vehicles were in this equilibrium).

3. For any vehicle – Defection implies taking the Start-A-B-End route.

Let \( n_{X-Y} \) denote the number of agents using the edge \( X-Y \). Then the reward structure for the odd-numbered vehicles (denoted by \( R_{odd} \)) and the even-numbered vehicles (denoted by \( R_{even} \)) is computed as shown below.

\[
\begin{align*}
N_0 &= \text{Total no. of agents} \\
R_0 &= \text{base reward for the agents} = (2.5 \times N_0)/2 \\
R_{odd} &= \begin{cases} 
-(n_{\text{Start-A}} + n_{\text{B-End}}) & \text{if Defection} \\
-(n_{\text{Start-A}} + R_0) & \text{if Cooperation}
\end{cases} \\
R_{even} &= \begin{cases} 
-(n_{\text{Start-A}} + n_{\text{B-End}}) & \text{if Defection} \\
-(R_0 + n_{\text{B-End}}) & \text{if Cooperation}
\end{cases}
\end{align*}
\]

We performed two separate set of experiments in this game with 4 and 6 agents. For each setup, we simulated the result when all agents are selfish learners (the SL agent(s)) and also when all agents use SQLoss (the SQLearner(s)). For both these setups, as expected, we observe that when using selfish learners, all agents converge to Defection and when using SQLoss, all agents converge to Cooperation. We present the results for the Braess’ Paradox experiment in Figure 11.

The Figure 11a shows the results for 4 SL-agents playing in the environment. From the figure it is clear that if 4 SL agents play in the environment, then they eventually end up defecting i.e. \( \lim_{E \to \infty} P(\text{Cooperation}) \to 0 \), where \( E \) denotes the epoch. Figure 11b illustrates the behaviour of the SQLearner agents. The SQLearner agents eventually learn to cooperate and thus the \( \lim_{E \to \infty} P(\text{Cooperation}) \to 1 \). To the best of our knowledge, this is the first demonstration of selfish agents learning to cooperate in a sequential social dilemma with more than 2 agents.

E Experimental Details

E.1 Infrastructure for Experiments

We performed all our experiments on an AWS instance with the following specifications. We use a 64-bit machine with Intel(R) Xeon(R) Platinum 8275CL CPU @ 3.00GHz installed with Ubuntu 16.04LTS operating system. It had a RAM of 189GB and 96 CPU cores with two threads per core. We use the TensorFlow framework for our implementation.

E.2 SQLoss

For our experiments with the Selfish and Status-Quo Aware Learner (SQLearner), we use policy gradient-based learning to train an agent with the Actor-Critic method [Sutton and Barto, 2011]. Each agent is parameterized with a policy actor and critic for variance reduction in policy updates. During training, we use \( \alpha = 1.0 \) for the REINFORCE and \( \beta = 0.5 \) for the imaginative game-play. We use gradient descent with step size, \( \delta = 0.005 \) for the actor and \( \delta = 1 \) for the critic. We use a batch size of 4000 for Lola-PG [Foerster et al., 2018] and use the results from the original paper. We use a batch size of 200 for SQLearner for roll-outs and an episode length of 200 for all iterated matrix games. We use a discount rate (\( \gamma \)) of 0.96 for the Iterated Prisoners’ Dilemma, Iterated Stag Hunt, and Coin Game. For the Iterated Matching Pennies, we use \( \gamma = 0.9 \) to be consistent with earlier works. The high value of \( \gamma \) allows for long time horizons, thereby incentivizing long-term rewards. Each agent randomly samples \( \kappa \) from \( U \in (1, z) \) (\( z = 10 \), discussed in Appendix [K] at each step.

F Visualizing clusters obtained from GameDistill

Figures[2] and [12] show the clusters obtained for the state sequence embedding for the Coin Game and the dynamic variant of Stag Hunt respectively.

In the figures, each point is a t-SNE projection of the feature vector (in different dimensions) output by the GameDistill network for an input sequence of states. For each of the sub-figures, the figure
on the left is colored based on actual rewards obtained by each agent \((r_1 | r_2)\). The figure on the right is colored based on clusters, as learned by GameDistill. GameDistill correctly identifies two types of trajectories, one for cooperation and the other for defection for both the games Coin Game and Stag-Hunt.

Figure 9 also shows the clustering results for different dimensions of the state sequence embedding for the Coin Game. We observe that changing the size of the embedding does not have any effect on the results.

G Results for Visual Stag-Hunt game with GameDistill and SQLoss

Figure 14 shows the results for the SQLearner agents using the trained oracles obtained from GameDistill along with SQLoss in the visual StagHunt environment.

H Results for the Iterated Chicken Game (ICG) using SQLoss

Figure 2 presents the payoff matrix for the Chicken Game. In Figure 13 we compare the results of a SQLearner agent on the ICG Game with a LOLA agent. The payoff matrix for the game is shown in the Table 2. From the payoff, it is clear that the agents may defect out of greed. In this game also, SQLearner agents coordinate successfully to obtain a near-optimal NDR value (0) for this game.

I SQLoss vs GameDistill

In this section we present the results for the additional experiments we do to disentangle the effect of GameDistill and SQLoss for the performance in Figure 5 by training a variant of LOLA that uses the oracles learned by GameDistill.

To discuss the observation regarding how much of the performance shown in Figure 5 is attributable to GameDistill, we further discuss Figures 3 and 5. Figure 3 shows the different methods applied...
to the matrix formulation of the Iterated Prisoner’s Dilemma (IPD) game. In this formulation, each method (SQLearner, LOLA, etc.) uses the same reduced action space consisting of cooperation and defection. Figure 3 shows how agents trained using SQLoss outperform those trained using LOLA in this setting. For our experiments on the Coin Game (Figure 5), we use (GameDistill + SQLoss) against LOLA.

From the results above, it is clear that the performance of the SQLearner agent is due to the SQLoss which promotes cooperation (as shown in multiple matrix games), the GameDistill algorithm further expands this gain by reducing the dimensionality of the games with visual input. The other baselines, e.g. Lola-PG and SL do not use GameDistill. To further test this hypothesis, we use the oracles developed using GameDistill with the SL agents, and observe that the SL agents with GameDistill do converge faster to DD than traditional SL agents, motivating us to use GameDistill.

J Illustrations of Trained Oracle Networks

J.1 Coin Game

Figure [13] shows the predictions of the oracle networks learned by the Red agent using GameDistill in the Coin Game. We see that the cooperation oracle suggests an action that avoids picking the coin of the other agent (the Blue coin). Analogously, the defection oracle suggests a selfish action that picks the coin of the other agent. Empirically, we train the Cooperation and Defection oracles and obtain a probability of picking self-colored coin (or $P(\text{Cooperation})$) close to 0.916 and 0.006 respectively.

J.2 StagHunt

GameDistill produces two oracles when trained on the StagHunt environment. One of the trained oracles results in both the agents capturing the Stag 99% of the times i.e. $\text{Probability (Capturing a Stag|Stag, Hare)} = 0.99$, while the other oracle forces the agents to eat the Hare with similar probability of 0.99. Both the oracles learn to accurately capture the desired item in the environment.

K SQLoss: Effect of $z$ on convergence to cooperation

We explore the effect of the hyper-parameter $z$ (Section 2) on convergence to cooperation, we also experiment with varying values of $z$. In the experiment, to imagine the consequences of maintaining the status quo, each agent samples $\kappa_i$ from the Discrete Uniform distribution $\mathbb{U}(1, z)$). A larger value of $z$ thus implies a larger value of $\kappa_i$ and longer imaginary episodes. We find that larger $z$ (and hence $\kappa$) leads to faster cooperation between agents in the IPD and Coin Game. This effect plateaus for
Figure 15: Illustrative predictions of the oracle networks learned by the Red agent using GameDistill in the Coin Game. The numbers in red/blue show the rewards obtained by the Red and the Blue agent respectively. The cooperation oracle suggests an action that avoids picking the coin of the other agent while the defection oracle suggests an action that picks the coin of the other agent

$z > 10$. However varying and changing $\kappa_t$ across time also increases the variance in the gradients and thus affects the learning. We thus use $\kappa = 10$ for all our experiments.

L SQLearner: Exploitability and Adaptability

Given that an agent does not have any prior information about the other agent, it must learn its strategy based on its opponent’s strategy. To evaluate an SQLearner agent’s ability to avoid exploitation by a selfish agent, we train one SQLearner agent against an agent that always defects in the Coin Game. We find that the SQLearner agent also learns to always defect. This persistent defection is important since given that the other agent is selfish, the SQLearner agent can do no better than also be selfish. To evaluate an SQLearner agent’s ability to exploit a cooperative agent, we train one SQLearner agent with an agent that always cooperates in the Coin Game. In this case, we find that the SQLearner agent learns to always defect. This persistent defection is important since given that the other agent is cooperative, the SQLearner agent obtains maximum reward by behaving selfishly. Hence, the SQLearner agent is both resistant to exploitation and able to exploit, depending on the other agent’s strategy.