
Normative Disagreement as a Challenge for Cooperative AI

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Abstract

Cooperation in settings where agents have both common and conflicting interests (mixed-motive environments) has recently received considerable attention in multi-agent learning. However, the mixed-motive environments typically studied have a single cooperative outcome on which all agents can agree. Many real-world multi-agent environments are instead bargaining problems (BPs): they have several Pareto-optimal payoff profiles over which agents have conflicting preferences. We argue that typical cooperation-inducing learning algorithms fail to cooperate in BPs when there is room for *normative disagreement* resulting in the existence of multiple competing cooperative equilibria, and illustrate this problem empirically. To remedy the issue, we introduce the notion of *norm-adaptive* policies. Norm-adaptive policies are capable of behaving according to different norms in different circumstances, creating opportunities for resolving normative disagreement. We develop a class of norm-adaptive policies and show in experiments that these significantly increase cooperation. However, norm-adaptiveness cannot address residual bargaining failure arising from a fundamental tradeoff between exploitability and cooperative robustness.

1 Introduction

Multi-agent contexts often exhibit opportunities for cooperation: situations where joint action can lead to mutual benefits [Dafoe et al., 2020]. Individuals can engage in mutually beneficial trade; nation-states can enter into treaties instead of going to war; disputants can settle out of court rather than engaging in costly litigation. But a hurdle common to each of these examples is that the agents will disagree about their ideal agreement. Even if agreements benefit all parties relative to the status quo, different agreements will benefit different parties to different degrees. These circumstances can be called *bargaining problems* [Schelling, 1956].

As AI systems are deployed to act on behalf of humans in more real-world circumstances, they will need to be able to act effectively in bargaining problems — from commercial negotiations in the

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nearer-term (e.g., Chakraborty et al. [2020]) to high-stakes strategic decision-making in the longer-term [Geist and Lohn, 2018]. Moreover, agents may be trained independently and offline before interacting with one another in the world. This raises concerns about future AI systems following incompatible norms for arriving at solutions to bargaining problems, analogously to disagreements about fairness which create hurdles to international cooperation on critical issues such as climate policy [Albin, 2001, Ringius et al., 2002].

Our contributions are as follows. We introduce a taxonomy of cooperation games, including bargaining problems (Section 3). We relate their difficulty to the degree of *normative disagreement*, i.e., differences over principles for selecting among mutually beneficial outcomes, which we formalize in terms of *welfare functions*. Normative disagreement does not arise in purely cooperative games or simple sequential social dilemmas [Leibo et al., 2017], but is an important obstacle for cooperation in what we call *asymmetric* bargaining problems. Following this, we introduce the notion of *norm-adaptive* policies – policies which can play according to different norms depending on the circumstances. In several multi-agent learning environments we highlight the difficulty of bargaining between norm-unadaptive policies (Section 4). We then contrast this with a class of norm-adaptive policies (Section 5) based on Lerer and Peysakhovich [2017]’s approximate Markov tit-for-tat algorithm. We show that this improves performance in bargaining problems. However, there remain limitations, most fundamentally a tradeoff between exploitability and the robustness of cooperation.

2 Related work

The field of multi-agent learning (MAL) has recently paid considerable attention to problems of cooperation in mixed-motive games, in which agents have conflicting preferences. Much of this work has been focused on *sequential social dilemmas* (SSDs) (e.g., Peysakhovich and Lerer 2017, Lerer and Peysakhovich 2017, Eccles et al. 2019). The classic example of a social dilemma is the Prisoner’s Dilemma, and the SSDs studied in this literature are similar to the Prisoner’s Dilemma in that there is a single salient notion of “cooperation”. This means that it is relatively easy for actors to coordinate in their selection of

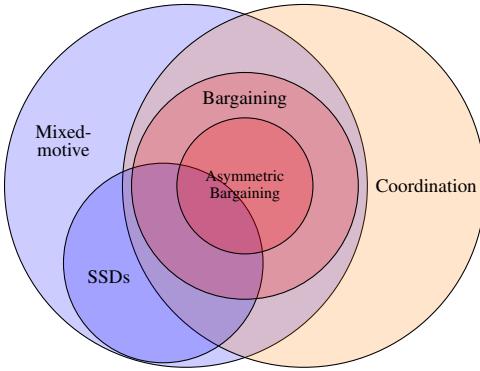


Figure 1: Venn diagram of cooperation problems.
policies to deploy in these settings.

Cao et al. [2018] look at negotiation between deep reinforcement learners, but not between independently trained agents. Several authors have recently investigated the board game Diplomacy [Paquette et al., 2019, Anthony et al., 2020, Gray et al., 2021] which contains implicit bargaining problems amongst players. Bargaining problems are also investigated in older MAL literature (e.g., Crandall and Goodrich 2011) as well as literature on automated negotiation (e.g., Kraus and Arkin 2001, Baarslag et al. 2013), but also not between independently trained agents. Considerable work has gone into understanding the emergence of norms in both human [Bendor and Swistak, 2001, Boyd and Richerson, 2009] and artificial societies [Walker and Wooldridge, 1995, Shoham and Tennenholtz, 1997, Sen and Airiau, 2007]. Especially relevant are empirical studies of bargaining across cultural contexts [Henrich et al., 2001]. There is also recent multi-agent reinforcement learning work on norms [Hadfield-Menell et al., 2019, Lerer and Peysakhovich, 2019, Köster et al., 2020] is also relevant here as bargaining problems can be understood as settings in which there are multiple efficient but incompatible norms. However, much less attention has been paid in these literatures to how agents with different norms are or aren't able to overcome normative disagreement.

There are large game-theoretic literatures on bargaining (for a review see Muthoo [2001]). This includes a long tradition of work on *cooperative bargaining solutions*, which tries to establish normative principles for deciding among mutually beneficial agreements [Thomson, 1994]. We will draw on this work in our discussion of normative (dis)agreement below.

Lastly, the class of norm-adaptive policies we develop in Section 5 — $\text{amTFT}(\mathcal{W})$ — can be seen as a more general variant of an approach proposed by Boutilier [1999] for coordinating in pure coordination games. As it implicitly searches for overlap in the agents' sets of allowed welfare

functions, it is also similar to Rosenschein and Genesereth [1988]’s approach to reaching agreement in general-sum games via sets of proposals by each agent.

3 Coordination, bargaining and normative disagreement

We are interested in a setting in which multiple actors (“principals”) train machine learning systems offline, and then deploy them into an environment in which they interact. For instance, two different companies might separately train systems to negotiate on their behalf and deploy them without explicit coordination on deployment. In this section, we develop a taxonomy of environments that these agents might face, and relate these different types of environments to the difficulty of bargaining.

3.1 Preliminaries

We formalize multi-agent environments as partially observable stochastic games (POSGs). For simplicity we assume two players, $i = 1, 2$. We will index player i ’s counterpart by $-i$. Each player has an action space \mathcal{A}_i . There is a space \mathcal{S} of states S^t which evolve according to a Markovian transition function $P(S^{t+1} | S^t, A_1^t, A_2^t)$. At each time step, each player sees an observation O_i^t which depends on S^t . Thus each player has an accumulating history of observations $\mathcal{H}_i^t = \{O_1^v, A_1^v\}_{v=1}^t$. We refer to the set of all histories for player i as $\mathcal{H}_i = \cup_{t=1}^{\infty} \mathcal{H}_i^t$ and assume for simplicity that the initial observation history is fixed and common knowledge: $h_1^0 = h_2^0 \equiv h^0$. Finally, principals choose among policies $\pi_i : \mathcal{H}_i \rightarrow \Delta(\mathcal{A}_i)$, which we imagine as artificial agents deployed by the principals. We will refer to policy profiles generically as $\pi \in \Pi := \Pi_1 \times \Pi_2$.

Each player has a reward function r_i , such that $r_i(S^t, A_1^t, A_2^t)$ is their reward at time t . We define the value to player i of policy profile π starting at history h_i^t as $V_i(h_i^t, \pi) = \mathbb{E}_\pi [\sum_{v=t}^{\infty} \gamma^{v-t} r_i(S^v, A_1^v, A_2^v) | H_i^t = h_i^t]$, where $\gamma \in [0, 1)$ is a discount factor, and the value of a policy profile to player i as $V_i(\pi) = V_i(h^0, \pi)$. A payoff profile is then a tuple $(V_1(\pi), V_2(\pi))$. We say that π is a (Nash) equilibrium of a POSG if $\pi_i \in \arg \max_{\pi'_i \in \Pi_i} V_i(h^0, \pi'_i, \pi_{-i})$ for $i = 1, 2$. We say that π is Pareto-optimal if for $i = 1, 2$ and $\pi' \in \Pi$ we have that $V_i(\pi') > V_i(\pi)$ implies $V_{-i}(\pi') < V_{-i}(\pi)$.

3.2 Coordination problems

We define a coordination problem as a game involving multiple Pareto-optimal equilibria (cf. Zhang and Hofbauer 2015), which require some coordinated action to achieve. That is, if the players disagree about which equilibrium they are playing, they will not reach a Pareto-optimal outcome. A *pure coordination problem* is a game in which there are multiple Pareto-optimal equilibria over which agents have identical interests. Although agents may still experience difficulties in pure coordination games, for instance due to a noisy communication channel, they are made easier by the fact that principals are indifferent between the Pareto-optimal equilibria.

3.3 Bargaining problems and normative disagreement

We define a *bargaining problem (BP)* to be a game in which there are multiple Pareto-optimal equilibria over which the principals have *conflicting* preferences. These equilibria represent more than one way to collaborate for mutual benefit, or put in another way, for sharing a surplus. Thus a bargaining problem is a mixed-motive coordination problem, in which there is conflicting interest between Pareto-optimal equilibria and common interest in reaching a Pareto-optimal equilibrium.

We can distinguish between BPs which are *symmetric* and *asymmetric* games. A 2-player game is symmetric if for any attainable payoff profile (a, b) there exists a profile (b, a) . The reason this distinction is important is that all (finite) symmetric games have a symmetric Nash equilibrium [Nash, 1990]; thus symmetric games have a natural set of focal points [Schelling, 1958] for aiding coordination in mixed-motive contexts, while asymmetric BPs may not. Similarly, given a chance to play a correlated equilibrium [Aumann, 1974], agents in a symmetric BP could play according to a correlated equilibrium which randomizes using a symmetric distribution over Pareto-optimal payoff profiles.

Figure 2 displays the payoff matrices of three coordination games: Pure Coordination, and two variants of Bach or Stravinsky (BoS), one of which is a symmetric BP and one of which is an

asymmetric BP. Pure Coordination is not a BP because it is not a mixed-motive game as the players only care about playing the same action. On the other hand, in the case of symmetric BoS the players do have conflicting interest, however, there is a correlated equilibrium – tossing a commonly observed fair coin – that is intuitively the most reasonable way of coordinating: It both maximizes the total payoff and offers each player the same expected reward.

	B S		B S		B S
B	1, 1 0, 0		B	3, 2 0, 0	
S	0, 0 1, 1		S	0, 0 2, 3	

Figure 2: Payoff matrices for Pure Coordination (left), BoS (middle), Asymmetric BoS (right).

To develop a better intuition for the sense in which equilibria can be more or less reasonable, consider a BoS with an extreme asymmetry, with equilibrium payoffs (15, 10) and (1, 11). Even though each of these equilibria is Pareto-optimal, the latter seems unreasonable or *uncooperative*: it yields a lower total payoff, more inequality, and lowers the reward of the worst-off player in the equilibrium. To formalize this intuition, we characterize the reasonableness of a Pareto-optimal payoff profile in terms of the extent to which it optimizes *welfare functions*: we can say that (1, 11) is unreasonable because there is no (impartial, see below) welfare function that would prefer it. Different welfare functions with different properties have been introduced in the literature (see Appendix A for an overview), but two uncontroversial properties of a welfare function are *Pareto-optimality* (i.e., its optimizer should be Pareto-optimal) and *impartiality*² (i.e., the welfare of a policy profile should be invariant to permutations of player indices). From the latter property we can observe that the intuitively reasonable choice of playing the correlated equilibrium with a *fair* correlation device in the case of symmetric games is also the choice which *all* impartial welfare functions recommend, provided that it is possible for the agents to play a correlated equilibrium.

By contrast, in the asymmetric BoS from Figure 2 we see that playing BB maximizes utilitarian welfare $w^{\text{Util}}(\pi) = V_1(\pi) + V_2(\pi)$, whereas playing SS maximizes the egalitarian welfare $w^{\text{Egal}}(\pi) = \min\{V_1(\pi), V_2(\pi)\}$ subject to π Pareto-optimal. Throwing a correlated fair coin to choose between the two would lead to an expected payoff that is optimal with respect to the Nash welfare $w^{\text{Nash}}(\pi) = V_1(\pi) \cdot V_2(\pi)$. Each of these different equilibria has a normative principle to motivate it.

In the best case, all principals agree on the same welfare function as a common ground for coordination in asymmetric BPs. However, the principals may have reasonable differences with respect to which welfare function they perceive as fair, and so they may train their systems to optimize different welfare functions, leading to coordination failure when the systems interact after deployment. In cases where agents were independently-trained according to inconsistent welfare functions, we will say that there is *normative disagreement*. There may be different degrees of normative disagreement. For instance, the difference $|\max_{\pi} w^{\text{Util}}(\pi) - \max_{\pi} w^{\text{Egal}}(\pi)|$ differs across games.

To summarize, we relate the difficulty of coordination problems to the concept of welfare functions: In pure coordination problems, they are not needed. In symmetric bargaining problems, they all point to the same equilibria. And in asymmetric bargaining problems, they can serve to filter out intuitively unreasonable equilibria, but leave the possibility of normative disagreement between reasonable ones. This makes normative disagreement a critical challenge for bargaining. In the remainder of the paper, we will focus on asymmetric bargaining problems for this reason.

3.4 Norm-adaptive policies

When there is potential for normative disagreement, it can be helpful for agents to have some flexibility as to the norms they play according to.

A number of definitions of norms have been proposed in the social scientific literature (e.g., Gibbs [1965]), but they tend to agree that a norm is a rule specifying acceptable and unacceptable behaviors in a group of people, along with sanctions for violations of that rule. Game-theoretic work sometimes

²The requirement of impartiality is also called *symmetry* in the welfare economics literature, or *anonymity* in the social choice literature [Campbell and Fishburn, 1980].

identifies norms with *equilibrium selection devices* (e.g., Binmore and Samuelson 1994, Young 1996). Given that complex games generally exhibit many equilibria, some rule (such as maximizing a particular welfare function) is needed to select among them.

Normative disagreement arises (among other reasons) from the underdetermination of good behavior in complex multi-agent settings. This is exemplified by the problem of conflicting equilibrium selection criteria in asymmetric bargaining problems, but there are other possible cases of undeter-determination. One example is undetermination of the *beliefs* that a reasonable agent should act according to in games of incomplete information (cf. the common prior assumption in Bayesian games [Morris, 1995]). Thus our definition of norm will be more general than an equilibrium selection device, though in the remainder of the paper we will focus on the use of welfare functions to choose among equilibria.

Definition 3.1 (Norms). Given a 2-player POSG, a *norm* N is a tuple $N = (\Pi_1^N, \Pi_2^N, p_1, p_2, \Pi_1^P, \Pi_2^P)$, where Π_i^N are normative policies (i.e., those which comply with the norm); Π_i^P are “punishment” policies, which are enacted when deviations from a normative policy are detected; and p_i are rules for judging whether a deviation has happened and how to respond, i.e., $p_i : \mathcal{H}_i \rightarrow \{\text{True}, \text{False}\}$. A policy π_i is compatible with norm N if, for all $H_i \in \mathcal{H}_i$,

$$\pi_i(h) = \begin{cases} \pi_i^N(h), \pi_i^N \in \Pi_i^N, & \text{if } p_i(h) = \text{False}; \\ \pi_i^P(h), \pi_i^P \in \Pi_i^P, & \text{if } p_i(h) = \text{True}. \end{cases}$$

For example, in the iterated Asymmetric BoS, one norm is for both players to always play B (this is the normative policy), and for a player to respond to deviations by continuing to play B . A similar norm is given by both players always playing S instead. More generally, following the folk theorems [Mailath et al., 2006], an equilibrium in a repeated game corresponds to a norm, in which a profile of normative policies corresponds to play on the equilibrium path; the functions p_i indicate whether there is deviation from equilibrium play; and punishment policies π_i^P are chosen such that players are made worse off by deviating than by continuing to play according to the normative policy profile.

Now we formally define norm-adaptive policies.

Definition 3.2 (Norm-adaptive policies.). Take a 2-player POSG and a non-singleton set of norms \mathcal{N} for that game. Let $N_i : \mathcal{H}_i \rightarrow \mathcal{N}$ be a surjective function that maps histories of observations to norms (i.e., for each norm in \mathcal{N} , there are histories for which N_i chooses that norm.) Then, a policy π'_i is *norm-adaptive* if, for all h , there is a policy π_i such that π_i is compatible with $N_i(h)$ and $\pi'_i(h) = \pi_i(h)$.

That is, norm-adaptive policies are able to play according to different norms depending on the circumstances. As we will see below, the benefit of making agents explicitly norm-adaptive is that this can help to prevent or resolve normative disagreement. Lastly, note that we can define higher-order norms and higher-order norm-adaptiveness: a higher-order norm is a norm N such that policies Π_i^N are themselves norm-adaptive with respect to some set of norms. This framework allows us for discussing differing (higher-order) norms for resolving normative disagreement.

4 Multi-agent learning and cooperation failures in BPs

In this section, we illustrate how cooperation-inducing, but norm-*unadaptive*, multi-agent learning algorithms fail to cooperate in asymmetric BPs. In Section 5 we will then show how norm-adaptiveness improves cooperation. The environments and algorithms considered are summarized in Table 1.

4.1 Setup: Learning algorithms and environments

In order to both include algorithms which use an explicitly specified welfare function and ones which do not, we use the Learning with Opponent-Learning Awareness (LOLA) algorithm [Foerster et al., 2018] in its policy gradient and exact value function optimization versions as an example for the latter, and Generalized Approximate Markov Tit-for-tat ($\text{amTFT}(w)$) for the former.

We introduce $\text{amTFT}(w)$ as a variant of Lerer and Peysakhovich [2017]’s Approximate Markov Tit-for-tat. The original algorithm trains a cooperative policy profile on the utilitarian welfare, as well as a punishment policy, and switches from the cooperative policy to the punishment policy

when it detects that the other player is defecting from the cooperative policy. The algorithm has the appeal that it ‘‘cooperates with itself, is robust against defectors, and incentivizes cooperation from its partner’’ [Lerer and Peysakhovich, 2017]. We consider the more general class of algorithms that we call $\text{amTFT}(w)$ in which a cooperative policy is constructed by optimizing an arbitrary welfare function w . Note that although $\text{amTFT}(w)$ takes a welfare function as an argument, the resulting policies are not norm-adaptive.

To cover a range of environments representing both symmetric and asymmetric games, we use some existing multi-agent reinforcement learning environments (IPD, Coin Game [CG; Lerer and Peysakhovich 2017]) and introduce two new ones (IAsymBoS, ABCG).

Iterated asymmetric Bach or Stravinsky (IAsymBoS) is an asymmetric version of the iterated Bach or Stravinsky matrix game. At each time step, the game defined on the right in Figure 2 is played. We focus on the asymmetric variant due to the argument in Section 3.3 that players could resolve the symmetric version by playing a symmetric equilibrium; however, applying LOLA without modification would also lead to coordination failure in the symmetric variant. It should also be noted that IAsymBoS is not an SSD because it does not incentivize defection: agents cannot gain from miscoordinating. Thus we consider IAsymBos to be a minimal example for an environment that can produce bargaining failures out of normative disagreement.

For a more involved example we also introduce an asymmetric version of the stochastic gridworld Coin Game [Lerer and Peysakhovich, 2017] – asymmetric bargaining Coin Game (ABCG) – which is both an SSD and an asymmetric BP. In ABCG, a red and a blue agent navigate a grid with coins. Two coins simultaneously appear on this grid: a Cooperation coin and a Disagreement coin, each colored red or blue. Cooperation coins can only be consumed by both players moving onto them at the same time, whereas the Disagreement coin can only be consumed by the player of the same color as the coin. The game is designed such that w^{Util} is maximized by both players always consuming the Cooperation coin, however, this will make one player benefit more than the other. Due to the sequential nature of the game, this means that welfare functions which also care about (in)equity will favor an equilibrium in which the player who benefits less from the Cooperation coin is allowed to consume the Disagreement coin from time to time without retaliation.

Players move simultaneously in all games. Note that we assume each player to have full knowledge of the other player’s rewards as this is required by LOLA-exact during training and by $\text{amTFT}(w)$ both at training and deployment. We use simple tabular and neural network policy parameterizations, which are described in Appendix C along with learning algorithms.

Table 1: Summary of the environments and learning algorithms that we use to study sequential social dilemmas (SSDs) and asymmetric bargaining problems in this section.

Environment	Asymmetric BP	SSD	Learning algorithms
Iterated Prisoner’s Dilemma (IPD)	✗	✓	LOLA-Exact, $\text{amTFT}(w)$
Iterated Asymmetric BoS (IAsymBoS)	✓	✗	LOLA-Exact, $\text{amTFT}(w)$
Coin Game (CG)	✗	✓	LOLA-PG, $\text{amTFT}(w)$
Asymmetric bargaining Coin Game (ABCG)	✓	✓	LOLA-PG, $\text{amTFT}(w)$

4.2 Evaluating cooperative success

We train policies in environments listed in Table 1 with the corresponding MARL algorithms. After the training, we evaluate cooperative success in self-play and cross-play. *Self-play* refers to average performance between jointly-trained policies. *Cross-play* refers to average performance between independently-trained policies. We distinguish between two kinds of cross-play: that between agents trained using the same notion of collective optimality (such as a welfare function or an inequity aversion term in the value function), and between agents trained using different ones. For $\text{amTFT}(w)$ we use two welfare functions, w^{Util} and an inequity-averse welfare-function w^{IA} (see Appendix C).

Comparing cooperative success across environments is not straightforward: environments have different sets of feasible payoffs, and we should not evaluate cooperative success with a single welfare function, because our concerns about normative disagreement stem from the fact that it is not obvious what single welfare function to use. Thus we compute cooperative success as follows. First, we

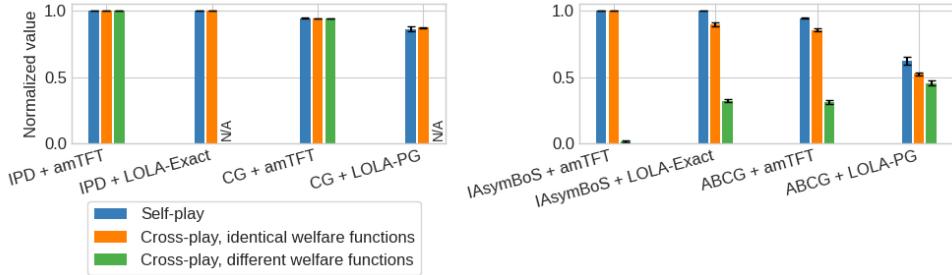


Figure 3: Comparison of cooperative success, measured by `NormalizedScore`, between SSDs (left) and asymmetric BPs (right). Small black bars are standard errors. For LOLA in asymmetric BPs, payoff profiles are collected into sets corresponding to the welfare functions they *implicitly* optimize, in order to obtain cross-play between identical and between different welfare functions.

take \mathcal{W} to be the set of welfare functions which we use in our experiments in the environment in question. For instance, for IAsymBoS and $\text{amTFT}(w)$ this is $\mathcal{W} = \{w^{\text{Util}}, w^{\text{IA}}\}$. Second, we define disagreement payoff profiles π^d corresponding to cooperation failure; in IAsymBoS the disagreement policy profile would be the one which has payoff profile $(0, 0)$. Then, for a policy profile π , we compute its normalized score as $\text{NormalizedScore}(\pi) \triangleq \max_{w \in \mathcal{W}} \frac{w(\pi) - w(\pi^d)}{\max_{\pi'} w(\pi') - w(\pi^d)}$. Under this scoring method, players do maximally well when they play a policy profile which is optimal according to some welfare function in \mathcal{W} .

Figure 3 illustrates the difference between cooperation in SSDs and bargaining problems. When there is a single "cooperative" equilibrium, as in the case of IPD and CG, cooperation-inducing learning algorithms typically achieve cooperation in cross-play. In contrast, in IAsymBoS and ABCG we observe mild performance degradation in cross-play where agents optimize the same welfare functions, and strong degradation when agents optimize different welfare functions.

5 Benefits and limitations of norm-adaptiveness

The cooperation-inducing properties of the algorithms in Section 4 are simple and are not designed to help agents resolve potential normative disagreement to avoid Pareto-dominated outcomes. The two main problems are (1) that the algorithms are ill-equipped for *reacting* to normative disagreement, and (2) that they may confuse normative disagreement with defection.

The former problem is already evident in IAsymBoS. There, playing according to incompatible welfare functions is not interpreted as defection by amTFT . This is not necessarily bad – we claim that normative disagreement *should* be treated differently to defection – but it does mean that amTFT lacks the policy space to react to normative disagreement. For the latter problem, we observe that in the ABCG the $\text{amTFT}(w)$ -agent does classify some of the opponent's actions as defection, even though they are aimed to optimize an impartial welfare function, and punishes accordingly.

5.1 $\text{amTFT}(\mathcal{W})$

To overcome both of these problems, we propose a norm-adaptive modification to $\text{amTFT}(w)$. As we only aim to illustrate the benefit of norm-adaptive policies, we keep the implementation simple:

Instead of a welfare function w the algorithm now takes a welfare-function set \mathcal{W} : $\text{amTFT}(\mathcal{W})$. The agent starts out playing according to some $w \in \mathcal{W}$. The initial choice can be made at random or according to a preference ordering between the $w \in \mathcal{W}$.

$\text{amTFT}(\mathcal{W})$ then follows a two-stage decision process. First, if the agent detects that their opponent is merely playing according to a different welfare function than itself, w gets re-sampled. Second, if the agent detects defection by the opponent, it will punish, just as in the original algorithm. However, by first checking for normative disagreement, we make sure that punishment does not happen as a result of a normative disagreement.

In Figure 5 we illustrate how, assuming uniform re-sampling from \mathcal{W} , $\text{amTFT}(\mathcal{W})$ can overcome normative disagreement and perform close to the Pareto frontier. Agents need not sample uniformly, though. For instance when the number of possible welfare functions is large, it would be beneficial to put higher probability on welfare functions which one's counterpart is more likely to be optimizing. Furthermore an agent might want to put higher probability on welfare functions that it prefers.

Notice that, when $w \in \mathcal{W}$, one player using $\text{amTFT}(\mathcal{W})$ rather than $\text{amTFT}(w)$ leads to a (weak) Pareto improvement. Beyond that, in anticipation of bargaining failure due to not having a way to resolve normative disagreement, players are incentivized to include more than just their preferred welfare function into \mathcal{W} . In both IAsymBoS (see Figure 5) and ABCG (see Table 5, Appendix D) we can observe significant improvement for cross-play when at least one player is norm-adaptive.

5.2 The exploitability-robustness tradeoff

As our experiments with $\text{amTFT}(\mathcal{W})$ show, agents who are more flexible are less prone to bargaining failure due to normative disagreement. However, they are prone to having that flexibility exploited by their counterparts. For instance, an agent which is open to optimizing either w^{Util} or w^{IA} will end up optimizing w^{IA} if playing against an agent for whom $\mathcal{W} = \{w^{\text{IA}}\}$. More generally, an agent who puts higher probability on a welfare function it has a preference for, when re-sampling w , will be less robust against counterparts who disprefer that welfare function and put a lower probability on it. An agent who tries to guess the counterpart's welfare function and tries to accommodate to this is exploitable to agents who do not.

6 Discussion

We formally introduce a class of hard cooperation problems – asymmetric bargaining problems – and situate them within a wider game taxonomy. We argue that they are hard because there can arise normative disagreement between multiple "reasonable" cooperative equilibria, characterized by divergence in the preferred outcomes according to different welfare functions. This presents a problem for those deploying AI systems without coordinating on the norms those systems follow. We have introduced the notion of *norm-adaptive* policies, which are policies that allow agents to change the norms according to which they play, giving rise to opportunities for resolving normative disagreement. As an example of a class of norm-adaptive policies, we introduced $\text{amTFT}(\mathcal{W})$, and showed in experiments that this tends to improve robustness to normative disagreement. On the other hand, we have demonstrated a *robustness-exploitability tradeoff*, under which methods that learn more normatively flexible strategies are also more vulnerable to exploitation.

There are a number of limitations to this work. We have throughout assumed that the agents have a common and correctly-specified model of their environment, including their counterpart's reward

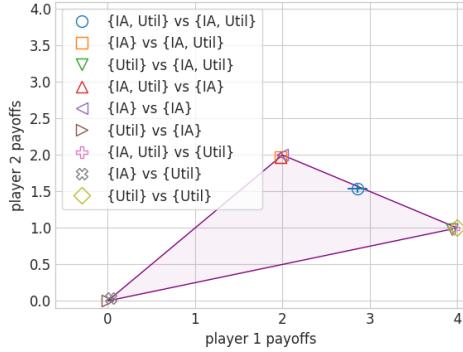


Figure 5: Average cross-play payoff profiles with standard errors for profiles of policies $(\text{amTFT}(\mathcal{W}_1), \text{amTFT}(\mathcal{W}_2))$. The legend shows various combinations of sets \mathcal{W}_1 and \mathcal{W}_2 . Coordination failure only occurs when $\mathcal{W}_1 \cap \mathcal{W}_2 = \emptyset$.

function. In real-world situations, however, principals may not have identical simulators with which to train their systems, and there are well-known obstacles to the honest disclosure of preferences [Hurwicz, 1972], meaning that common knowledge of rewards may be unrealistic. Similarly, we assumed a certain degree of reasonableness on part of the principals, see by the willingness to play the symmetric correlated equilibrium in symmetric BoS (Section 3), for instance. However, we believe this to be a minimal assumption as the deployers of such agents are aware of the risk of coordination failure as a result of insisting on equilibria that no impartial welfare function would recommend.

Future work should consider more sophisticated and learning-driven approaches to designing norm-adaptive policies, as amTFT(\mathcal{W}) relies on a finite set of user-specified welfare functions and a hard-coded procedure for switching between policies. One possibility is to train agents who are themselves capable of jointly deliberating about the principles they should use to select an equilibrium, e.g., deciding among the axioms which characterize different bargaining solutions (see Appendix A) in the hopes that they will be able to resolve initial disagreements. Another direction is resolving disagreements that cannot be expressed as disagreements over the welfare functions according to which agents play; for instance, disagreements over the beliefs or world-models which should inform agents’ behavior.

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A Welfare functions

Different welfare functions have been introduced in the literature. Table 2 gives an overview over commonly discussed welfare functions. Their properties are noted in Table 3.

Table 2: Welfare functions, adapted to the multi-agent RL setting where two agents with value functions V_1, V_2 are bargaining over the policy profile π to deploy. d_i , the *disagreement value*, is the value which player i gets when bargaining fails.

Name of welfare function w	Form of $w(\pi)$
Nash [Nash, 1950]	$[V_1(\pi) - d_1] \cdot [V_2(\pi) - d_2]$
Kalai-Smorodinsky [Kalai and Smorodinsky, 1975]	$\left \frac{V_1(\pi) - d_1}{V_2(\pi) - d_2} - \frac{\sup_\pi V_1(\pi) - d_1}{\sup_\pi V_2(\pi) - d_2} \right $ s.t. Pareto-optimal
Egalitarian [Kalai, 1977]	$\min \{V_1(\pi) - d_1, V_2(\pi) - d_2\}$ s.t. Pareto-optimal
Utilitarian [Harsanyi, 1955]	$V_1(\pi) + V_2(\pi)$

Pareto-optimality refers to the property that the welfare function's optimizer should be Pareto-optimal. *Impartiality*, often called symmetry, implies that the welfare of a policy profile should be invariant to permutations of player indices. These are treated as relatively uncontroversial properties in the literature. *Invariance to affine transformations* of the payoff matrix is usually motivated by the assumption that interpersonal comparison of utility is impossible. In contrast, the utilitarian welfare function assumes that such comparisons are possible. *Independence of irrelevant alternatives* refers to the principle that a preference for an equilibrium A over equilibrium B should only depend on properties of A and B. That is, a third equilibrium C should not change the preference ordering between A and B. *Resource monotonicity* refers to the principle that if the payoff for any policy profile increases, this should not make any agent worse off.

Table 3: Properties of welfare functions. For properties of Nash welfare here the set of feasible payoffs is assumed to be convex (Zhou [1997] describes properties in the non-convex case).

	Nash	Kalai-Smorodinsky	Egalitarian	Utilitarian
Pareto optimality	✓	✓	✓	✓
Impartiality	✓	✓	✓	✓
Invariance to affine transformations	✓	✓	✗	✗
Independence of irrelevant alternatives	✓	✗	✓	✓
Resource monotonicity	✗	✓	✓	✗

B Environments

B.1 Additional descriptions of environments

Coin Game

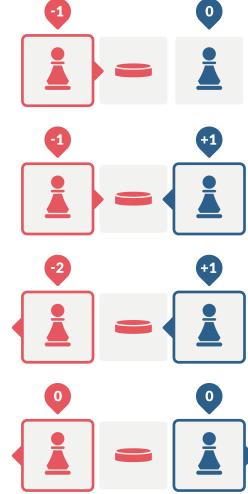


Figure 6: A pictorial description of agents' rewards in the Coin Game environment [Lerer and Peysakhovich, 2017]. A Red player and a Blue player navigate a grid and pick up randomly-generated coins. Each player gets a reward of 1 for picking up a coin of any color. But, a player gets a reward of -2 if the other player picks up their coin. This creates a social dilemma in which the socially optimal behavior is to only get one's own coin, but there is incentive to defect and try to get the other player's coin as well.

Asymmetric bargaining Coin Game

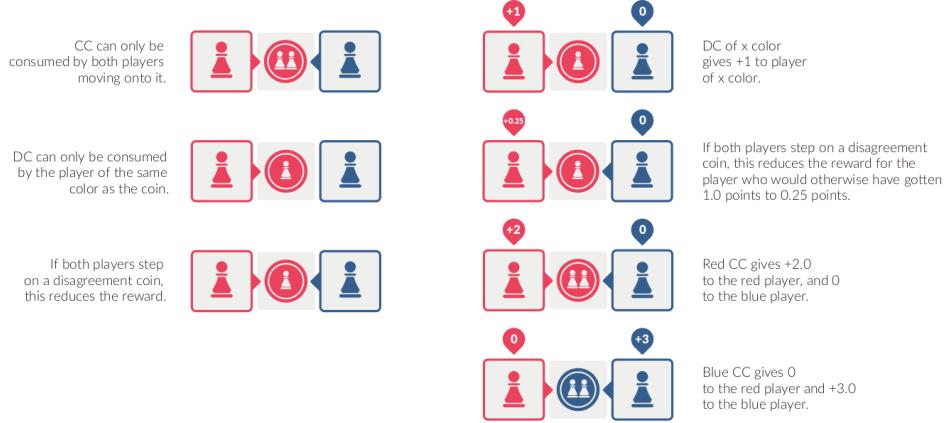


Figure 7: Illustration of the Asymmetric bargaining Coin Game described in Section 4. CC stands for Cooperative Coin and DC stands for Disagreement Coin.

B.2 Disagreement profiles for each environment

For computing the normalized scores in Figure 3, we use the following disagreement profiles, corresponding to cooperation failure. In IPD, the cooperation failures are only the joint defections

(D,D) producing a reward profile of (-3, -3). In IAsymBoS, they are the profiles (B, S) and (S, B), both associated with the reward profile (0, 0). In Coin Game, the cooperation failures are when both players pick all coins at maximum speed selfishly and this produce a reward profile of (0, 0). In Asymmetric bargaining Coin Game (ABCG), when the players fails to cooperates, they can punish the opponent by preventing any coin to be picked by waiting instead of picking their own defection coin (e.g. with `amTFT`). In these cooperation failures, the reward profile with perfect punishment is (0, 0).

C Experimental details

C.1 Learning algorithms

We use the discount factor $\gamma = 0.96$ for all the algorithms and environments unless specified otherwise in Table 4.

Approximate Markov tit-for-tat (`amTFT`)

We follow the `amTFT` algorithm from [Lerer and Peysakhovich, 2017] with two changes: 1) Instead of using a selfish policy to punish the opponent, we use a policy that minimizes the reward of the opponent. 2) We use the `amTFT` version that uses rollouts to compute the debit and the punishment length. We observed that using long rollouts to compute the debit increases significantly the variance on the debit and this leads to false positive detection of defection. To reduce this variance, we thus compute the debit without rollouts. We use the direct difference between the rewards given by the actual action and given by the simulated cooperative action. The rollout length used to compute the punishment length is 20.

We note that in asymmetric BoS, training runs using the utilitarian welfare function sometimes learn to produce, in self-play, the egalitarian outcome instead of the utilitarian outcome. In these cases the policy gets discarded.

The inequity-averse welfare w^{IA} is defined as follows:

$$w^{\text{IA}}(\pi) = V_1(\pi) + V_2(\pi) - \beta \cdot \mathbb{E} [|e_1^t(h_1^t, h_2^t) - e_2^t(h_1^t, h_2^t)|]$$

where $e_i^t(h_1^t, h_2^t) = \gamma \lambda e_i^{t-1}(h_1^{t-1}, h_2^{t-1}) + r_i(S^t, A_1^t, A_2^t)$ are smoothed cumulative rewards with a discount factor γ and a parameter β which controls how much unequal outcomes are penalized.

Learning with Opponent-Learning Awareness (LOLA)

Write $V_i(\theta_1, \theta_2)$ as the value to player i under a profile of policies with parameters θ_1, θ_2 . Then, the LOLA update [Foerster et al., 2018] for player 1 at time t with parameters $\delta, \eta > 0$ is

$$\theta_1^t = \theta_1^{t-1} + \delta \nabla_{\theta_1} V_1(\theta_1, \theta_2) + \delta \eta [\nabla_{\theta_2} V_1(\theta_1, \theta_2)]^\top \nabla_{\theta_1} \nabla_{\theta_2} V_2(\theta_1, \theta_2).$$

C.2 Policies

We used RLlib [Liang et al., 2018] for almost all the experiments. It is under Apache License 2.0. All activation functions are ReLU if not specified otherwise.

Matrix games (IPD and IBoS) with LOLA-Exact

We used the official implementation of LOLA-Exact from <https://github.com/alshedivat/lola>. We slightly modified it to increase the stability and remove a few confusing behaviors. Following Foerster et al. [2018]'s parameterization of policies in the iterated Prisoner's Dilemma, we use policies which condition on the previous pair of actions played, with the difference that instead of using one parameter for every possible previous action profile, we use N parameters for every one of the previous action profile to always play in larger action space (N actions possible).

Matrix games (IPD and IBoS) with amTFT

We use a Double Dueling DQN architecture + LSTM for both simple and complex environments when using amTFT. This architecture is non-exhaustively composed of a shared fully connected layer (hidden layer size 64), an LSTM (cell size 16), a value branch and an action-value branch both composed of a fully connected network (hidden layer size 64).

Coin games (CG and ABCG) with LOLA-PG

We used the official implementation from <https://github.com/alshedivat/lola>, which is under MIT license. We slightly modified it to increase the stability and remove a few confusing behaviors. Especially, we removed the critic branch, which had no effect in practice. We use a PG+LSTM architecture composed of two convolution layers (kernel size 3x3 and feature size 20), an LSTM (cell size 64) and a final fully connected layer.

ABCG + LOLA-PG mainly generates policies that are associated with an egalitarian welfare function. Within this set of policies, some are a bit closer to the utilitarian outcome than others, which we used as a basis to classify them as "utilitarian" for the purpose of comparison in Figures 3 and 8. However, because the difference is small, we do not observe a lot of additional cross-play failure compared to cross-play between the "same" welfare function. It should also be noted that we chose to discard the runs in which none of the agents becomes competent at picking any of the coins.

Coin games (CG and ABCG) with amTFT

We use a Double Dueling DQN architecture + LSTM for both simple and complex environments when using amTFT. The architecture used is non-exhaustively composed of two convolution layers (kernel size 3x3 and feature size 64), an LSTM (cell size 16), a value branch and an action-value branch both composed of a fully connected network (hidden layer size 32).

C.3 Code assets

The code that we provide allows to run all of the experiments and to generate the figures with our results. All instructions on how to install and run the experiments are given in the ‘README.md’ file. The code to run the experiments from Section 4 is in the folder “base_game_experiments”. The code to run the experiments from Section 5, is in the folder ‘base_game_experiments’. The code to generate the figures is in the folder ‘plots’.

An anonymized version of the code is available at <https://github.com/68545324/anonymous>.

C.4 Hyperparameters

Table 4: Main hyperparameters for each cross-play experiment.

Env. (Algo.)	LR	Episodes	Episode length	Gamma	LSTM
Matrix games (LOLA-Exact)	1.0	N/A	N/A	0.96	N/A
Matrix games (amTFT)	0.03	800	20	0.96	✓
CG (LOLA-PG)	0.05	2048000	40	0.90	✓
ABCG (LOLA-PG)	0.1	2048000	40	0.90	✓
CG and ABCG (amTFT)	0.1	4000	100	0.96	✓

All hyperparameters can be found in the code provided as the supplementary material. They are stored in the “params.json” files associated with each replicate of each experiment. The experiments are stored in the “results” folders.

The hyperparameters selected are those producing the most welfare-optimal results when evaluating in self-play (the closest to the optimal profiles associated with each welfare function). Both manual hyperparameter tuning and grid searches were performed.

D Additional experimental results

Table 5: Cross-play normalized score of amTFT(\mathcal{W}) in ABCG.

	$\{w^{\text{Util}}\}$	$\{w^{\text{IA}}\}$	$\{w^{\text{Util}}, w^{\text{IA}}\}$
$\{w^{\text{IA}}\}$	0.82	0.12	0.69
$\{w^{\text{Util}}, w^{\text{IA}}\}$	0.92	0.95	0.95
$\{w^{\text{Util}}, w^{\text{IA}}\}$	0.85	0.91	0.91

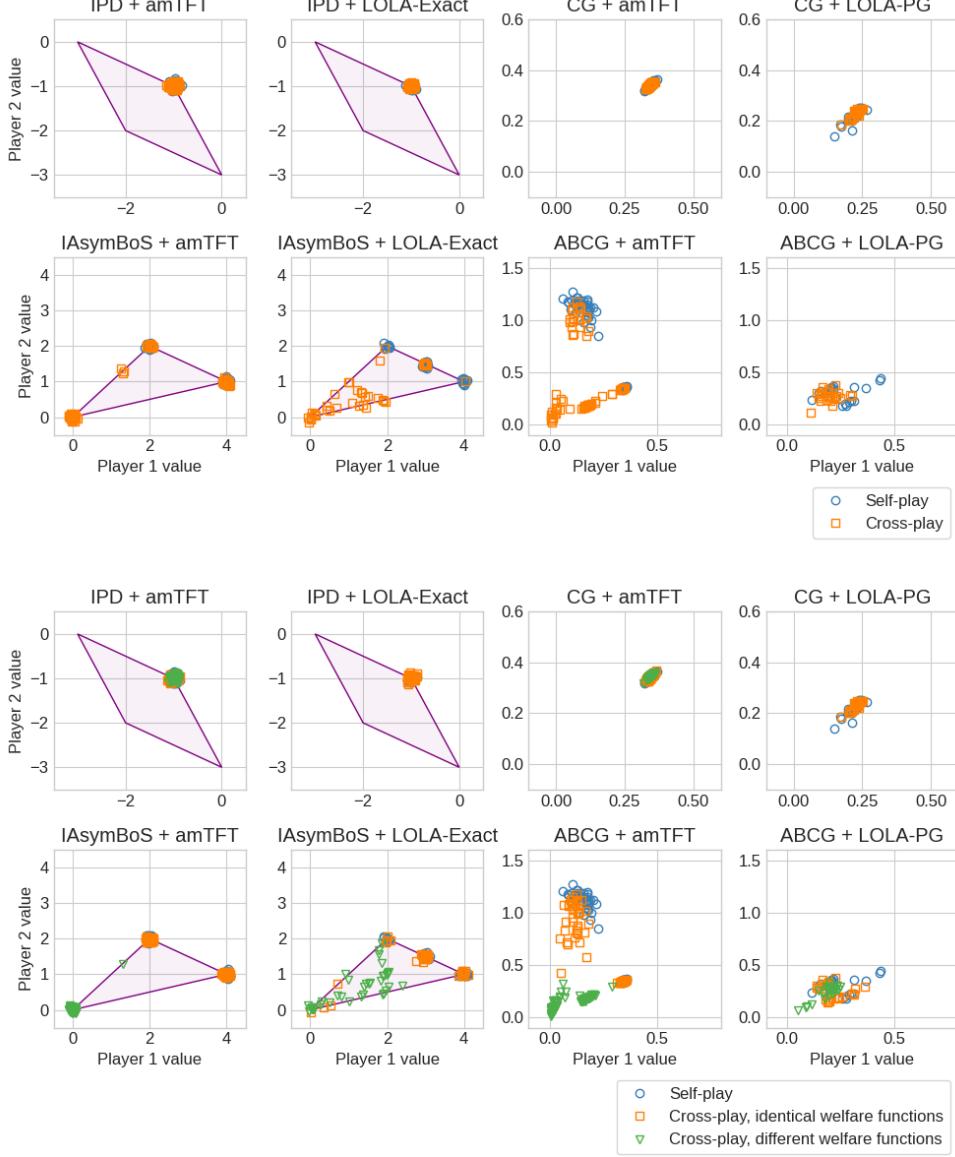


Figure 8: Mean reward of policy profiles for environments and learning algorithms given in Table 1. The purple areas describe sets of attainable payoffs. In matrix games, a small amount of jitter is added to the points for improved visibility. The plots on top compare self-play with cross-play, whereas the plots below compare cross-play between policies optimizing same and different welfare functions.

E Exploitability-robustness tradeoff

In this section, we provide some theory on the tradeoff between exploitability and robustness. Consider some asymmetric BP, with welfare functions w, w' optimized in equilibrium, such that for any two policy profiles $\pi^w, \pi^{w'}$, the cross-play policy profile $(\pi_1^w, \pi_2^{w'})$ is Pareto-dominated. Note that the definition implies that the welfare functions must be distinct.

We can derive an upper bound for how well players can do under the cross-play policy profile. It follows from the fact that both π^w and $\pi^{w'}$ are in equilibrium that for $i = 1, 2$, it is

$$V_i(\pi_1^w, \pi_2^{w'}) \leq \min\{V_i(\pi^w), V_i(\pi^{w'})\}. \quad (1)$$

This is because, otherwise, at least one of the two profiles cannot be in equilibrium, since a player would have an incentive to switch to another policy to increase their value.

From the above, it also follows that the cross-play policy must be strictly dominated. To see this, assume it was not dominated. This would imply that one player has equal values under both profiles. So that player would be indifferent, while one of the profiles would leave the other player worse off. Thus, that profile would be weakly Pareto dominated, which is excluded by the definition of a welfare function.

It is a desirable quality for a policy profile maximizing a welfare function in equilibrium to have values that are close to this upper bound in cross-play against other policies. For instance, if some coordination mechanism exists for agreeing on a common policy to employ, it may be feasible to realize this bound against any opponent willing to do the same.

Moreover, the bound implies that whenever we try to be even more robust against players employing policies corresponding to other welfare functions (e.g., a policy which reaches Pareto optimal outcomes against a range of different policies), our policy will cease to be in equilibrium. In that sense, such a policy will be exploitable, while unexploitable policies can only be robust against different opponents up to the above bound. Note that this holds even in idealized settings, where coordination, e.g., via some grounded messages, is possible.

Lastly, note that if no coordination is possible, or if no special care is being taken in making policies robust, then equilibrium profiles that maximize a welfare function can perform much worse in cross-play than the above upper bound.

We show this formally in a special case in which our POSG is an iterated game, i.e., it only has one state. Moreover, we assume that it is an asymmetric BP, and that for both welfare functions w, w' in question, an optimal policy $\pi^w, \pi^{w'}$ exists that is deterministic. Denote $V_i(t, \pi) \triangleq V_i(H_t, \pi)$ (where H_t denotes the joint observation history up to step t) as the return from time step t onwards, under the policy π . We also assume that for any player i , the minimax value $\min_{a_{-i}} \max_{a_i} \frac{1}{1-\gamma} r_i(a)$ is strictly worse than the values of their preferred welfare function maximizing profile. Then we can show that policies maximizing the welfare functions exist such that after some time step, their returns will be upper bounded by their minimax return.

Proposition 1. *In the situation outlined above, there exist policies $\tilde{\pi}^w, \tilde{\pi}^{w'}$ optimizing the respective welfare functions and a time step t such that*

$$V_i(t, \tilde{\pi}_1^w, \tilde{\pi}_2^{w'}) \leq \min_{a_{-i}} \max_{a_i} \frac{1}{1-\gamma} r_i(a)$$

for $i = 1, 2$.

Proof. Define $\tilde{\pi}^w$ as the policy profile in which player i follows π_i^w , unless the other player's actions differ from π_{-i}^w at least once, after which they switch to the action $a_i \triangleq \arg \min_{a_i} \max_{a_{-i}} r_i(a)$. Define $\tilde{\pi}^{w'}$ analogously. Note that both profiles are still optimal for the corresponding welfare functions.

As argued above, the cross-play profile $(\pi_1^w, \pi_2^{w'})$ must be strictly worse than their preferred profile, for both players. So there is a time t' after which an action of a player i must differ from $-i$'s preferred profile and thus $-i$ switches to the minimax action a_{-i} . We have $V_i(t', \pi_i^w, a_{-i}) \leq \min_{a'_{-i}} \max_{a'_i} \frac{1}{1-\gamma} r_i(a')$, i.e., the value i gets after step t' must be smaller than their minimax value,

and by assumption, the minimax value is worse for i than the value of their preferred welfare-maximizing profile. Hence, there must be a time step $t - 1 \geq t'$ after which i also switches to their minimax action.

From t onwards, both players play a , so

$$V_i(t, \tilde{\pi}) = \frac{1}{1-\gamma} r_i(a) \leq \max_{a'_i} \frac{1}{1-\gamma} r_i(a_{-i}, a'_i) = \min_{a'_{-i}} \max_{a'_i} \frac{1}{1-\gamma} r(a').$$

□