Cooperative-Competitive Reinforcement Learning with History-Dependent Rewards

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ABSTRACT
Consider a typical organization whose worker agents seek to collectively cooperate for its general betterment. However, each individual agent simultaneously seeks to act to secure a larger chunk than its co-workers of the annual increment in compensation, which usually comes from a fixed pot. As such, the individual agent in the organization must cooperate and compete. Another feature of many organizations is that a worker receives a bonus, which is often a fraction of previous year’s total profit. As such, the agent derives a reward that is also partly dependent on historical performance. How should the individual agent decide to act in this context? Few methods for the mixed cooperative-competitive setting have been presented in recent years, but these are challenged by problem domains whose reward functions do not depend on the current state and action only. Recent deep multi-agent reinforcement learning (MARL) methods using long short-term memory (LSTM) may be used, but these adopt a joint perspective to the interaction or require explicit exchange of information among the agents to promote cooperation, which may not be possible under competition. In this paper, we first show that the agent’s decision-making problem can be modeled as an interactive partially observable Markov decision process (I-POMDP) that captures the dynamic of a history-dependent reward. We present an interactive advantage actor-critic method (IA2C+), which combines the independent advantage actor-critic network with a belief filter that maintains a belief distribution over other agents’ models. Empirical results show that IA2C+ learns the optimal policy faster and more robustly than several other baselines including one that uses a LSTM, even when attributed models are incorrect.\footnote{Preprint. Under review.}

KEYWORDS
Actor-critic, mixed setting, Organization, Reinforcement learning

1 INTRODUCTION
Real-world multi-agent domains involving interactions among agents are often not purely cooperative or competitive. For example, consider a typical organization whose worker agents seek to collectively cooperate for its general betterment. However, each individual agent simultaneously also seeks to act to secure a larger chunk than its co-workers of the annual increment in compensation, which usually comes from a fixed pot. Another feature of many organizations is that a worker receives a bonus, which is often a fraction of the previous year’s total profit. Thus, the agent derives a reward that partly depends on historical performance. The individual agent in an organization then faces a context where it must cooperate and compete while collecting history-dependent rewards.

A potential approach to solving the worker agents’ decision-making problem is multi-agent reinforcement learning (MARL). Interest in MARL has grown dramatically over the past decade. While traditional MARL has made significant strides in fields such as game playing (e.g., AlphaStar [14]) and robotics, it struggles in problems involving interactions where the individual and group interests may conflict with each other. In response to this challenge, MARL suited to both cooperative and competitive settings has received attention recently [3, 4, 9]. However, most of these recent methods take a joint perspective to the interaction and require explicit exchange of information among the learning agents, which may not be possible under competition.

In this paper, we first introduce and formalize the Organization problem as a quintessential domain involving mixed cooperation-competition, while exhibiting both partial observability and history-dependent rewards. Next, we show that the individual agent’s decision making can be modeled using an interactive partially observable Markov decision process (I-POMDP) [5] despite the presence of history-dependent rewards in the problem, and introduce an approach to MARL for this type of problems. In particular, we introduce an interactive advantage actor-critic (labeled IA2C+) algorithm, which combines an independent advantage actor-critic [10] with a belief filter that maintains a belief distribution over the other agents’ models, and updates the belief using private observations. We show that even when the set of models attributed to the other agents may not contain a grain of truth, agents using IA2C+ still converge to the optimal policy significantly faster than several relevant baselines, and remain consistent for greater levels of noise in their observations, compared to those baselines.

2 BACKGROUND
In this section, we briefly review the two main components on which this work is built: a well-known model of decision making in a multi-agent environment, and the actor-critic [8] reinforcement learning (RL) [12] approach used in our solution.

2.1 Overview of Interactive POMDPs
Interactive partially observable Markov decision processes are a generalization of POMDPs [6] to sequential decision-making in multi-agent environments [2, 5]. Formally, an I-POMDP for agent $i$ in an environment with one other agent $j$ is defined as,

$$I\text{-POMDP}_i = \{S_i, A_i, T_i, O_i, Z_i, R_i, OC_i\}$$

- $S_i$ denotes the interactive state space. This includes the physical state $S$ as well as models of the other agent $M_j$, which may be intentional (ascribing beliefs, capabilities and preferences) or subintentional [1]. Examples of the latter are probability distributions and
finite state machines. In this paper, we ascribe subintentional models to the other agent.

- \( A = A_i \times A_j \) is the set of joint actions of both agents.
- \( T_j \) represents the transition function, \( T_j: S \times A \times S \rightarrow [0,1] \). The transition function is defined over the physical states and excludes the other agent’s models. This is a consequence of the model non-manipulability assumption, which states that an agent’s actions do not directly influence the other agent’s models.
- \( O_i \) is the set of agent \( i \)’s observations.
- \( Z_j \) is the observation function, \( Z_j: A \times S \times O \rightarrow [0,1] \). The observation function is defined over the physical state space only as a consequence of the model non-observability assumption, which states that other’s model parameters may not be observed directly.
- \( R_i \) defines the reward function for agent \( i \), \( R_i: S \times A \rightarrow \mathbb{R} \). The reward function for I-POMDPs usually assigns preferences over the physical states and actions only.
- \( \mathcal{O}_C \) is the subject agent’s optimality criterion, which may be a finite horizon \( H \) or a discounted infinite horizon where the discount factor \( \gamma \in (0,1) \).

Without loss of generality, let the subintentional model ascribed to \( j \) take the form \( m_j = (h_j, \pi_j, Z_j) \) where \( h_j \) is agent \( j \)’s action-observation history, \( \pi_j \) is a candidate policy, and \( Z_j \) is its observation function. Given agent \( i \)’s belief over interactive states \( b_i \), on action \( a_i \) and receiving observation \( o_i \), the belief is updated as:

\[
b_i'(i's) = \sum_{i'} b_i(is) \sum_{a_i} Pr(a_i|m_j) Z_j(s,a',o'_j) T_j(s,a,s') \times \delta_k(\text{APPEND}(h_j,o'_j),h'_j) Z_j(s',a,o'_j) \tag{1}
\]

where \( a \) is a normalizing constant, \( h_j \) and \( h'_j \) are part of \( m_j \) and \( m'_j \), respectively. \( \delta_k \) is the Kronecker-delta function, and APPEND returns a string with the second argument appended to the first.

Each belief state \( b_i \) is associated with a value given by:

\[
V(b_i) = \max_{a_i \in A_i} \left\{ \sum_{i} \sum_{a_j} R_j(s,a_i, a_j) Pr(a_j|m_j) b_i(is) + \gamma \sum_{o_i \in O_i} Pr(o_i|a_i, b_i) V(b_i'(i's)) \right\} \tag{2}
\]

where \( b_i'(i's) \) is obtained as shown in equation 1.

### 2.2 Actor-Critic RL

RL problems are typically modeled using Markov decision processes or MDPs [12], which is defined by the tuple \((S, A, T, R)\), where \( S \) is the set of perfectly observed environmental states; \( A \) is the set of agent’s actions;

\[ T(s,a,s') \]

is the state transition probability function specifying the probability of the next state in the Markov chain being \( s' \) on the agent selecting action \( a \) in state \( s \); \( R(s,a) \) is the reward function specifying the reward from the environment that the agent gets for executing action \( a \) in state \( s \) in \( S \). The agent’s goal is to learn a policy \( \pi : S \rightarrow A \) that maximizes the sum of current and future rewards from any state \( s \), given by:

\[ V^\pi(s) = E_{\pi} [ R(s,\pi(s)) + \gamma R(s',\pi(s')) + \gamma^2 \ldots ] \]

where \( s, s', \ldots \) are successive samplings from the distribution \( T \) following the Markov chain with policy \( \pi \), and \( \gamma \in (0,1) \) is a discount factor. This is sometimes facilitated by learning an action value function, \( Q(s,a) \) given by

\[ Q(s,a) = R(s,a) + \max_\pi \gamma \sum_{s'} T(s,a,s')V^\pi(s'). \tag{3} \]

There are two main categories of reinforcement learning: value-based and policy-based RL. On the one hand, value-based RL learns an optimal value function (e.g., \( V \) given above) that maps each state (or state-action pair) to a value. It is more sample efficient and stable compared to policy-based RL, but it usually requires that the action space be finite. On the other hand, policy-based RL learns the optimal policy directly, sometimes without using a value function. It is useful when the action space is continuous or stochastic, and it has a faster convergence due to directly searching the policy space.

Actor-critic methods take advantage of both value-based policy-based RL while eliminating some drawbacks. It splits the model into two components, an actor and a critic, where the actor controls how the agent acts by learning the optimal policy, and the critic evaluates the actor’s actions by computing the action value (\( Q \) value in equation 3) function, or directly the value function (\( V \)). The actor and the critic are optimized separately during the training. By having them interact with and complement each other, the architecture is more robust than if the two models were used individually.

Value-based RL methods typically display a high variance due to the uncertainty embedded in the agent’s experience. To mitigate this, instead of using the \( Q \) value for the critic, advantage actor-critic (A2C) uses advantage values, given for a policy \( \pi \) by

\[ A(s,a) = Q(s,a) - V^\pi(s) \]

Advantage represents how much better a particular action is at a state compared to the value of the state. While the critic can be optimized by reducing the mean square of the advantages estimated from samples, the actor, \( \pi_\theta \) (parametrized by \( \theta \)) can be optimized by gradient descent using gradients:

\[ E_{s \sim d^{\pi_\theta} \rightarrow A} \nabla_\theta \log \pi_\theta(a|s) A(s,a), \]

where \( d^{\pi_\theta}(s) = \sum_{t=0}^{\infty} \gamma^t Pr(s_t = s | s_0, \pi_\theta) \) is the discounted state distribution that results from following policy \( \pi_\theta \).

In an I-POMDP setting, the state is not directly observable; instead the learner receives an observation that is usually (noisily) correlated with the (hidden) state and other agents’ actions. The advantage function can be reformulated in terms of belief as

\[ A(b_i,a_i) = \sum_{i} \sum_{a_j} R_j(s,a_i,a_j) Pr(a_j|m_j) b_i(is) + \gamma \sum_{o_i} Pr(o_i|a_i, b_i) V^\pi(b_i'(i's)) - V^\pi(b_i(is)) \tag{4} \]

Assuming \( \pi_\theta \) maps beliefs to actions, its gradients are

\[ E_{b \sim d^{\pi_\theta} \rightarrow A} \nabla_\theta \log \pi_\theta(a|b) A(b,a), \tag{5} \]

where \( d^{\pi_\theta}(b) = \sum_{t=0}^{\infty} \gamma^t Pr(is = i|s_0, \pi_\theta) \) is the discounted belief distribution that results from following policy \( \pi_\theta \).
then joint action is a balance action. Balance joint action does not change the underlying state. If the number of agents who pick self is greater than the number of agents who pick group, the joint action will be a self action. Self joint action brings down the health level (the current state) by one when the current state is higher than \( s_{\text{hl}} \); otherwise, the state remains unchanged. If the number of agents who pick self is smaller than the number of agents who pick group, the joint action will be a group action. Group joint action increases the current health level by one when the current state is lower than \( s_{\text{hl}} \), otherwise, the state remains unchanged. Besides, if all agents performed group individual action, the state increases by two. Figure 2 demonstrates state transitions of the organization domain.

3 THE ORGANIZATION DOMAIN

We introduce the new Organization domain, which models a typical business organization featuring a mix of cooperation toward the overall improvement of the organization and individual competition. Notably, the reward function may not have the Markovian property. To be more specific, a proportion of the rewards from the past is added to the current reward as a bonus to the worker. For example, if the organization operated well in the past year, then it earned not only a profit from its business but also reputation about its business. Thus, the measure of its current reward must accommodate this carried-over influence from past rewards. We call this a history-dependent reward. The goal of each agent is to maximize the sum of all reward signals that it receives, which includes this history-dependent reward.

3.1 Specification

3.1.1 State and Observation Sets. The state space of the problem represents the organization’s financial health level, which is discretized into five states: very low (denoted as \( s_{\text{vl}} \)), low (\( s_l \)), medium (\( s_m \)), high (\( s_h \)), and very high (\( s_{\text{vh}} \)). Agents cannot directly observe the financial health level of the organization; instead, they only receive observations of the number of orders received by the organization as well as other agents’ actions. We assume that the observation is decomposed into public and private observations. While public observation is common to all agents and depends on the underlying state only, the private observation represents other agents’ actions and is perceived by the corresponding agent only. There are three possible public observations pertaining to the number of orders: meager \( (\alpha_1) \), several \( (\alpha_2) \), and many \( (\alpha_3) \), where \( \alpha_1 \) indicates the organization is in either \( s_{\text{vl}} \) or \( s_l \), \( \alpha_2 \) indicates the organization is in either \( s_m \) or \( s_h \), and \( \alpha_3 \) indicates the organization is in \( s_{\text{vh}} \). Three private observations represent the agents’ three possible actions, respectively. However, private observations are also noisy. Agents have 0.8 probability of perceiving the actual action of the other agent, and 0.2 probability of receiving either private observation corresponding to actions which the other agent did not take. Figure 1 illustrates the relationship between states and public observations.

3.1.2 Action Space and Transition Function. Each agent has three possible actions: self, balance, and group. The self action solely benefits the agent while the group action benefits the organization at the expense of self. The balance action benefits both self and the organization. A joint action is determined by the distribution of the individual agent’s actions. If the number of agents who picked self equals the number of agents who picked group, then joint action is a balance action. Balance joint action does not change the underlying state. If the number of agents who pick self is greater than the number of agents who pick group, the joint action will be a self action. Self joint action brings down the health level (the current state) by one when the current state is higher than \( s_{\text{hl}} \); otherwise, the state remains unchanged. If the number of agents who pick self is smaller than the number of agents who pick group, the joint action will be a group action. Group joint action increases the current health level by one when the current state is lower than \( s_{\text{hl}} \), otherwise, the state remains unchanged. Besides, if all agents performed group individual action, the state increases by two. Figure 2 demonstrates state transitions of the organization domain.

3.1.3 Reward Function. At time step \( t \), each agent receives a sum of individual and group rewards, and the bonus. The agent \( i \)'s individual reward, \( R_i \), depends on the state and its own action:

\[
R^i_t \leftarrow R_i(s^i_t, a^i_t).
\]

The group reward, common to all agents, depends on the current state and joint action:

\[
R^g_t \leftarrow R(s^g_t, a^g_t).
\]

The bonus or history dependent reward is a proportion of the total reward from the previous time step. For \( \phi \in (0, 1) \),

\[
R^b_{t-1} = \phi \left( \sum_{i} R^i_{t-1} + R^g_{t-1} \right).
\]

The goal of agent \( i \) is to optimize the expected sum of individual, group, and history rewards, \( \mathbb{E}[\text{trajectories}] \left[ \sum_t y^i (R^i_t + R^g_t + R^b_t) \right] \).

The Group action is cooperative giving \( R_i = 0 \) and \( R_g = r \), where \( r \in \mathbb{R} \). The Self action benefits an agent giving reward \( R_i = \beta r \) to the agent, where \( \beta > 1 \), and \( R_g = 0 \). Balance action gives \( R_i = \frac{\beta c + r}{1 + \beta} \), where \( 0 < c < 1 \) and \( r < \frac{1 + \beta}{\beta} \), and \( R_g = (1 - c) \frac{1 + \beta}{\beta} r \), thereby benefiting both the agent and the business. If the organization reaches state \( s_{\text{vl}} \), each agent receives a penalty of \( p \) no matter which individual action was picked.
3.2 Importance of History-Dependent Reward

In this subsection, we demonstrate the importance of history-dependent reward in the Organization domain. Suppose that policy $\pi_0$ leads to the reward sequence $\{b_r, \beta r, \ldots\}$ for an agent, and policy $\pi_1$ leads to the reward sequence $\{b_r, \beta r, \frac{1 + \beta}{a} r, \frac{1 + \beta}{a} r, \ldots\}$. For convenience, we set $d = \frac{1 + \beta}{a}$. For horizon $H = 4$, the total reward from performing policy $\pi_0$ is:

$$b_r + (\beta b_r + \beta r) + (\phi b_r + \beta b_r + \phi r + r) = \phi^3 b_r + 2\phi^2 b_r + 2\phi b_r + \phi r + 3\beta r + r$$

The total reward from performing policy $\pi_1$ is:

$$\beta r + (\phi \beta r + \beta r) + (\phi^2 \beta r + \phi b_r + \phi r + dr) = \phi^3 \beta r + 2\phi^2 \beta r + 2\phi \beta r + \phi dr + 2\beta r + 2\beta r + 2dr$$

Then we can compare the total rewards from these two policies with varying choices of $\beta$ and $\phi$. We use a simple program to check if $\phi$ can affect which of the two policies is optimal for horizon $H \geq 4$ when $d$ is set to $\frac{1}{2}$. The result shows that for every horizon from 4 to 100, the history-dependent parameter $\phi$ is always a deciding factor in finding optimal policy. Figure 3 shows the total reward from policy $\pi_0$ and $\pi_1$ with varying $\beta$ and $\phi$ for horizons 4 and 8. Notice that the parameter $\phi$ influences when each surface has the higher total reward.

![Figure 3: The total reward from policy $\pi_0$ and $\pi_1$ with varying $\beta$ and $\phi$ for horizon of 4.](image)

3.3 Modeling the Org Domain as an I-POMDP

The I-POMDP framework is suitable for modeling the Organization domain from an individual agent’s perspective. We formulate such an I-POMDP in this section. Suppose that if we remove the history dependent rewards, then the residual environment has perfectly Markovian dynamics, with functions $T(s_f, a_i, a_j, s'_f, o_f)$, $Z(a_i, a_j, s_f, s'_f, o_f)$, and $R(s_f, a_i, a_j)$, where $s_f$ is an ordinary physical state and $o_f$ is an observation related to this state. (Note that we assume $Z$ depends on both $s_f$ and $s'_f$, unlike in Section 2.1, as this is needed for our formulation.) To preserve the Markov property even when $R_{-1}$ is introduced, we add a continuous-valued feature, $s_r \in \mathbb{R}$, to the state space, that memorizes the reward from the last step. The new I-POMDP for agent $i$ in the Organization domain with one other agent $j$ has an expanded definition:

$$\text{I-POMDP}_i = (I_i, A_i, T_i, \Omega_i, W_i, Z_i, O_i, R_i, O\mathsf{C}_i)$$

- The interactive state space $I_i$ now includes the physical state $s_f$, the history-reward state $s_r$, as well as models of the other agent $M_j$.
- We let the latter be subintentional in this domain.
- $A_i = A_i \times A_j$ is the set of joint actions of both agents.
- $T_i$ represents the transition function, now defined as:

$$T_i((s_f, s_r), a_i, a_j, (s'_f, s'_r))$$

$$= \begin{cases} 
T(s_f, a_i, a_j, s'_f), & \text{if } s'_r = R(s_f, a_i, a_j) + \phi \cdot s_r \\
0, & \text{otherwise}
\end{cases}$$

- $\Omega_i$ is the set of agent’s private observations.
- $W_i : A \times \Omega_i \rightarrow [0, 1]$ is the private observation function.
- $O_i = O_f \times O_r$ is the set of agent’s public observations, where $O_f$ informs about the state and $O_r = s_r$, allowing the agent to observe the past reward.
- $Z_i$ is the observation function, defined as:

$$Z_i(a_i, a_j, (s_f, s_r), (s'_f, s'_r), (o_f, o_r))$$

$$= \begin{cases} 
Z(a_i, a_j, s_f, s'_f, o_f), & \text{if } s'_r = R(s_f, a_i, a_j) + \phi \cdot s_r \\
0, & \text{otherwise}
\end{cases}$$

- $R_i$ defines the reward function for agent $i$:

$$R_i((s_f, s_r), a_i, a_j) = R(s_f, a_i, a_j) + \phi \cdot s_r$$

- $O\mathsf{C}_i$ is the subject agent’s optimality criterion, which may be a finite horizon $H$ or a discounted infinite horizon where the discount factor $\gamma \in (0, 1)$.

The belief update equation for the new I-POMDP formulation is:

$$b_i'(s_f' | b_i, a_i, o_i', o_i') = b_i'(s_f' | b_i, a_i, o_i', o_i') \times b_i'(m_j' | (s'_f, s'_r), b_i, a_i, o_i', o_i')$$

where the first term can be derived as:

$$b_i'(s_f' | b_i, a_i, o_i', o_i') \times T(s_f, a_i, a_j, s'_f, o_f) \times Z(a_i, a_j, s_f, s'_f, o_f')$$

Recall that $o_f'$ is a public observation received by both agents. We derive the second term of the belief update decomposition in the next subsection. For convenience, we summarize the full update as

$$V(b_i) = \max_{a_i} \left[ \sum_{s_f, s_r, a_i} R_i((s_f, s_r), a_i, a_j) Pr(a_j | m_j) b_i((s_f, s_r)) + \sum_{a_j} Pr(a_j | m_j) T(s_f, a_i, a_j, s'_f) \times b_i((s_f, s_r)) Z(a_i, a_j, s_f, s'_f, o_f') W_i(a_i, a_j, o_i') \tau(b_i, a_i, o_i', b_i', o_f') \right]$$

(10)
### 3.4 Model Belief Update

The belief update in equation 9 updates the belief over states and other agent’s model simultaneously. The state belief update and model belief update can be separated in case when the two parts are not handled by a single network. In a two-agent setting, agent j’s model set at time step t is denoted as Mj, where Mj contains a finite number of pre-defined models mj. Given agent i’s action ai, public observation (o′ j, o′ r), private observation o′ i, and previous belief b1, the model belief update is defined as below:

\[
b_i'(m_j')(s_j', s_r', b_j, a_i, o_i', o'_j, \text{omega} i) = \frac{Pr(m_j' | o_i'(s_j', s_r'), a_i, o'_r, b_1)}{Pr(o_i', s_j', s_r', a_i, o'_r, b_1)}
\]

\[
\propto \sum_{m_j} b_j(m_j)Pr(m_j' | o_i'(s_j', s_r'), a_i, o'_r, m_j)
\]

\[
\propto \sum_{m_j} b_j(m_j)Pr(m_j' | o_i'(s_j', s_r'), a_i, o'_r, m_j)Pr(a_i | s_j', s_r', m_j)
\]

\[
\propto \sum_{m_j} b_j(m_j)Pr(a_i | m_j)Pr(o'_j | m_j')Pr(a_i | s_j', s_r', m_j)
\]

\[
\propto \sum_{m_j} b_j(m_j)Pr(a_i | m_j, m_j')Pr(o'_i | m_j')Pr(s_j', s_r', a_i, o'_j, m_j, m_j')
\]

\[
\propto \sum_{m_j} b_j(m_j)Pr(a_i | m_j)\sum_{a_j} W_i(a_i, a_j, o'_i)Pr(m_j' | a_i, a_j, o'_j, m_j, m_j').
\]

(11)

The last equation follows because the private observation function does not condition the private observation on the physical state. To simplify the term Pr(\(m_j'|o_i', m_j\)), we substitute \(m_j'\) with its components: \(m_j' = (\pi_j', h_j')\), where \(h_j'\) is agent j’s action-observation history at next time step and \(\pi_j'\) is j’s policy.

\[
Pr(m_j' | a_i, a_j, o'_i, m_j) = Pr(\pi_j', h_j' | a_i, a_j, o'_i, h_j)
\]

\[
= Pr(h_j' | \pi_j', a_i, a_j, o'_i, h_j)Pr(\pi_j' | a_i, a_j, o'_i, h_j)
\]

\[
= Pr(h_j' | \pi_j', a_i, a_j, o'_i, h_j)\delta h_k(\pi_j, \pi_j')
\]

where \(\pi_j'\) is j’s policy contained in \(m_j'\) (note that the action-observation history in a model expands with time steps, but the policy in the model does not change).

By substituting \(Pr(m_j' | a_i, a_j, o'_i, m_j)\) with equation 12, we can rewrite equation 11 as

\[
b_i'(m_j')(s_j', s_r', a_i, o'_i, o'_j, w_i, b_i) \propto \sum_{m_j} b_j(m_j)\sum_{a_j} Pr(a_j | m_j)\]

\[
W_i(a_i, a_j, o'_i, \delta h_k(\pi_j, \pi_j'))\]

\[
\sum_{o'_j} \delta h_k(\text{APPEND}(h_j, a_j, o'_j), h_j')
\]

(13)

The second Kronecker-delta function \(\delta h_k\) is 1 if the updated history matches the one in \(m_j'\), it is 0 otherwise.

### 4 INTERACTIVE A2C+

Most current deep reinforcement learning methods require explicit exchange of information among agents. Some methods use maximum likelihood estimation (MLE) to predict other agents’ actions from historical information in scenarios where agents cannot exchange information. However, the result is unsatisfactory in complex domains with large state and action spaces, as comparative evaluations have shown [9]. In this paper, we present I2A2C+, which extends advantage actor-critic by maintaining predictions of other agents’ actions based on dynamic beliefs over models. We implement A2C with one hidden layer with \(\tanh\) activation for input processing. For simplicity, we assume that both the critic and the actor networks map observations rather than beliefs, and that the critic maps observations to joint action values, \(Q((\sigma_f, o_f), a_i, a_j))\). We estimate equation 4 as:

\[
A((\sigma_f, o_f), a_i, a_j) = \text{avg}[r + yQ((\sigma_f', o_f'), a_i, a_j) - Q((\sigma_f, o_f), a_i, a_j)]
\]

while the actor’s gradient (equation 5) is estimated as:

\[
\text{avg}[\nabla_{a_i} \log p_{\pi}(a_i | o_f, a_j)]\cdot A((o_f, a_f), a_i, a_j)
\]

where \(r, (\sigma_f', o_f')\) and \(a_i'\) are samples, \(a_j\) and \(a_j'\) are predicted actions (see next section), and the avg is taken over sampled trajectories.

#### 4.1 Belief Filter

We implement a Bayesian belief filter, integrated with the critic within the deep RL pipeline, to complete the model belief update. We further decompose the model belief update of equation 13 into two steps. The first step is the prediction, which accounts for other agent’s actions.

\[
b_i'(m_j') = \sum_{m_j} b_j(m_j)\sum_{a_j} Pr(a_j | m_j)\delta h_k(\pi_j, \pi_j')\delta h_k(\text{APPEND}(h_j, a_j, o'_j), h_j')
\]

Second step corrects the predictions using perceived observations.

\[
b_i'(m_j') = \sum_{m_j} b_j(m_j)\sum_{a_j} W_i(w_j', a_i, a_j)
\]

![Figure 4: Belief filter samples agent i’s action based on model distribution, and passes the predicted action to agent i’s interactive A2C network.](image)

Note that at each time step, the belief is represented by a \(\|M_j| \times |O_f| \times |O_r|\) tensor. To keep the dimension of the belief matrix finite, we round \(O_r\) to one decimal place. The prediction step is done
by performing convolution on belief tensors using \(|A|\)-many convolution filters. After the convolution, we obtain \(|A|\) belief vectors corresponding to each possible joint action. Then the correction step is executed by multiplying each belief vector with the probability of perceiving its corresponding private observation. Finally, we sum up all result vectors and index all possible models by public observations. This step represents the Kronecker-delta function. We use model leveraging to sample a predicted action of the other agent.

The whole workflow of agent's A2C with belief filter is shown in Figure 4. Other agents have a similar network architecture.

5 EXPERIMENTS

We evaluate the performance of the A2C method with belief filtering, labeled as IA2C+, on the cooperative-competitive Organization domain using four sets of experiments. First, we show that a method that does not account for the history-dependent rewards fails to reach optimality. Second, we explore the need for cooperation in Organization and that agents using the IA2C+ can learn to cooperate. Third, we explore the performances of other recent deep MARL methods on the Organization domain and compare them with IA2C+. Finally, we explore the impact of increasing noise levels in the observations on the convergence to the optimal policy by the various methods.

In order to model the partial observability of the problem, we extend the public observation \((\omega_f, \omega_r)\) used in the indexing procedure to a short-term observation history that contains the current public observation as well as the previous public observation, i.e. \(\{(\omega_{f,t}^{-1}, \omega_{r,t}^{-1}), (\omega_{f,t}^{-1}, \omega_{r,t}^0), (\omega_{f,t}^0, \omega_{r,t}^0), (\omega_{f,t}^0, \omega_{r,t}^1), (\omega_{f,t}^1, \omega_{r,t}^1), (\omega_{f,t}^1, \omega_{r,t}^0)\}\). We include 5 models of the other agent in the pre-defined model set \(M\). Three models lead to solely picking self, balance, and group action, respectively, no matter which observation sequence is perceived. One model picks group action for observation sequences \(\{(\omega_{f,t}^{-1}, \omega_{r,t}^{-1}), (\omega_{f,t}^{-1}, \omega_{r,t}^0), (\omega_{f,t}^0, \omega_{r,t}^0), (\omega_{f,t}^0, \omega_{r,t}^1), (\omega_{f,t}^1, \omega_{r,t}^1), (\omega_{f,t}^1, \omega_{r,t}^0)\}\). We use \(\{(\omega_{f,t}^{-1}, \omega_{r,t}^{-1}), (\omega_{f,t}^{-1}, \omega_{r,t}^0), (\omega_{f,t}^0, \omega_{r,t}^0), (\omega_{f,t}^0, \omega_{r,t}^1), (\omega_{f,t}^1, \omega_{r,t}^1), (\omega_{f,t}^1, \omega_{r,t}^0)\}\). The last model picks self action for observation sequences \(\{(\omega_{f,t}^{-1}, \omega_{r,t}^{-1}), (\omega_{f,t}^{-1}, \omega_{r,t}^0), (\omega_{f,t}^0, \omega_{r,t}^0), (\omega_{f,t}^0, \omega_{r,t}^1), (\omega_{f,t}^1, \omega_{r,t}^1), (\omega_{f,t}^1, \omega_{r,t}^0)\}\). We include 5 models of the other agent in

5.1 History-Dependent Rewards

We introduce a baseline method, IA2C−, which runs in the Organization domain that does not include the extra state and observation feature revealing the history-dependent rewards. To compensate, it utilizes the LSTM for both actor and critic networks, in order to model the dependence of its immediate rewards on the history of interactions. We establish the need for utilizing recurrence in this case, and thereby the need to correctly model the dependence on history, by comparing its performance with IA2C− that does not use LSTMs, using convolutional neural networks (CNN) instead in the actor and critic.

Notice from Figure 5 that the IA2C− without LSTM converges, but not to the optimal policy in contrast to IA2C+ with LSTM that converges to the optimal policy. From this observation, we conclude that our approach to accommodation of history in Section 3.3 is not only sufficient but also necessary, because if an alternative I-POMDP model existed that exhibited Markovian dynamics without requiring the extra features to enable optimal decisions, then IA2C− without LSTM should have reached the optimal policy as well. We will use IA2C− with LSTM as a baseline method to compare with IA2C+.

5.2 Cooperation in the Organization Domain

The optimal policy for the Organization domain involves performing the group joint action in response to observation history that pertain to states \(s_{ld}, s_l\), and \(s_m\); the balance joint action in response to observations that pertain to state \(s_b\); and the self action in response to observations that pertain to state \(s_{dh}\). Notice that this involves cooperation among the agents at various states. To quantify this, we compare the value of the optimal policy with that of performing the self joint action for all observations and the balance joint action for all observations. Table 1 shows a significant difference between the three values indicating that both cooperation as well as self-interestedness play a role in this domain.

![Figure 5: IA2C− without LSTM (uses a CNN instead) exhibits poor rewards for low numbers of episodes as we may expect, and eventually converges to a policy that is not optimal.](image)

| Optimal | Only Group | Only Balance |
|---------|------------|--------------|
| 226.9   | 132        | 198          |

Table 1: Values of the optimal policy and other default behaviors for two agents.

We hypothesize that independently learning agents may not converge to the cooperation needed in this domain. Consequently, we compare the performance of agents utilizing IA2C+ with CNN as the neural net architecture with those utilizing IA2C− and independent actor-critic (IAC) without belief filter on Organization with four learning agents. Figure 6a shows that agents learning using IA2C+ and IA2C− learn the optimal policy within 30,000 episodes. We show the mean and standard deviation of 5 runs of each method in this chart. Four agents learn to unanimously pick the group individual action to raise the organization’s financial health level. When the organization is in a better financial health level, the four agents coordinated to pick two group actions, one balance action, and one self action in order to maximize the total reward. However, IA2C+ converges faster than IA2C− with the former requiring 20,000 episodes.
While IA2C worst performance as we may expect, and fails to converge to the optimal policy. As such, this simulates the effect of private observations, and makes the optimal policy was learned as a function of the noise levels in private observations. IA2C among the MARL techniques allowing for noise up to 0.3 while still learning the optimal policy.

Finally, we vary the noisiness of the private observations to test the robustness of the methods to increasing uncertainty. We gradually increase the private observation noise level from 0 to 0.5, where noise level 0 means that the other agent’s actions are perfectly observed, and noise level 0.5 means that there is only a 0.5 probability that the received observations indicate the correct actions of the other agent.

We record the number of runs out of 10 for which each method learned the optimal policy for various noise levels. Figure 6c shows the result of this experiment. IA2C+ is able to consistently learn the optimal policy when the private observation noise level is increased up to 0.3. Between noise levels 0.3 and 0.5, we observe an increasing number of runs where it fails to learn the optimal policy, failing completely beyond noise level 0.5. IA2C+ with LSTM has a slightly higher performance than IA2C+ with CNN, however, it requires almost twice as many episodes as IA2C+ with CNN to converge. In contrast, COMA and MADDPG start to fail from noise level of around 0.1, and fail completely beyond noise levels 0.35 and 0.4, respectively. We conclude that IA2C+ demonstrates consistent learning and robustness to higher levels of noise compared to the baselines in the Organization domain.

Figure 6: (a) Four agents, each utilizing IAC or IA2C+, converges (value loss becomes zero) to the optimal policy whereas IAC converges but not to the optimal policy. (b) IA2C+ requires fewer episodes to converge to the optimal policy compared to MADDPG, COMA, and IAC. (c) Number of runs (out of 10) in which the optimal policy was learned as a function of the noise levels in private observations. IA2C+ shows the most robust performance among the MARL techniques allowing for noise up to 0.3 while still learning the optimal policy.

5.3 Comparison with MARL Techniques
Next, we explore the performance of previous state-of-the-art MARL methods such as MADDPG [9] and COMA [4] on the two-agent Organization domain. We also include the results of IA2C+ mentioned in Section 5.1 and a variant of IA2C+ with LSTM. We disabled the policy exchange among agents as performed by MADDPG; instead each agent receives a noisy action whose noise probabilities are the same as those of the private observations in the Organization domain. As such, this simulates the effect of private observations, and makes it directly comparable to IA2C+. As COMA employs a centralized critic, we noise the action sent by each actor to the critic to simulate the private observations.

We show the results in Figure 6b. We point out that all methods eventually converge as their respective value losses become zero. While IA2C+ with CNN and IA2C+ with LSTM converges to the optimal policy at 20,000 episodes, and IA2C− converge to the optimal policy at 30,000 episodes, both MADDPG and COMA do not converge within these many episodes, instead requiring almost twice as many episodes. IA2C+ with CNN has similar performance with IA2C+ with LSTM while only using half the time to train. Closer inspection revealed that the belief filtering often predicted the true action of the other agent with a high probability despite the noisy observations. This more accurate prediction of the other agent’s actions in about 88.6% of the episodes, despite none of the models in $N_j$ being individually correct, results in faster convergence to the optimal policy for each agent. IAC without belief filter shows the worst performance as we may expect, and fails to converge to the optimal policy as seen in the previous subsection.

5.4 Varying Private Observation Noise
Finally, we vary the noisiness of the private observations to test the robustness of the methods to increasing uncertainty. We gradually increase the private observation noise level from 0 to 0.5, where noise level 0 means that the other agent’s actions are perfectly observed, and noise level 0.5 means that there is only a 0.5 probability that the received observations indicate the correct actions of the other agent.

We record the number of runs out of 10 for which each method learned the optimal policy for various noise levels. Figure 6c shows the result of this experiment. IA2C+ is able to consistently learn the optimal policy when the private observation noise level is increased up to 0.3. Between noise levels 0.3 and 0.5, we observe an increasing number of runs where it fails to learn the optimal policy, failing completely beyond noise level 0.5. IA2C+ with LSTM has a slightly higher performance than IA2C+ with CNN, however, it requires almost twice as many episodes as IA2C+ with CNN to converge. In contrast, COMA and MADDPG start to fail from noise level of around 0.1, and fail completely beyond noise levels 0.35 and 0.4, respectively. We conclude that IA2C+ demonstrates consistent learning and robustness to higher levels of noise compared to the baselines in the Organization domain.

6 RELATED WORK
While multi-agent RL mainly addresses purely cooperative or competitive tasks, there has been some work recently that address a mix of the two settings. We first discuss one prominent integrative work, the cooperative-competitive process (CCP), and then discuss recent work in MARL more generally, relating them to our contributions.

6.1 Organization Domain as a CCP
The CCP [15] is a framework for modeling mixed cooperative-competitive sequential decision problems. It blends both cooperative and competitive multi-agent modeling by introducing a slack parameter which controls the amount of cooperation versus competition. A group-dominant CCP (GD-CCP) first maximizes the group reward, then optimizes the individual reward while allowing a deviation of up to the slack from the optimal group reward. Individual-dominant CCP (ID-CCP) follows a similar pattern but with a reversed preference. Non-linear programming (NLP) is used for solving the CCPs. Our work can be seen as a pragmatic generalization of the CCP, situated in a MARL context, as discussed in the next paragraph. Instead
of manually defining a parameter to choose between cooperate or compete, Kleiman-Weiner et al. [7] present a hierarchical model that integrates low-level action plans to high-level strategy. An agent can infer other agents’ high level strategy before deciding whether to select a cooperative or a competitive strategy, and thus perform corresponding low-level actions specified by selected strategies.

Because the CCP as is cannot model the organization domain, we generalize it to a history-dependent CCP by adding $R_{-1}$ to the reward vector, indicating the history-dependent component of the rewards. In addition, we further decompose the observation into public and private. Public observations depend on the state and the joint action, while private observations depend on other agent’s individual actions. Also, the individual rewards $R_i$ depend on agent $i$’s individual action only, instead of the joint action in the original CCP definition. The history-dependent CCP for Organization is given below.

- $I = \{1, 2, \ldots, n\}$ is the set of $n$ agents
- $S = S_f \times S_r$, where $S_f = \{s_1, s_2, s_3, s_4\}$ and $S_r$ is the continuous state feature for memorizing the previous reward
- $A = (self, balance, group)$ is the set of 3 joint actions, determined by the majority choices of the $n$ agents, as given in Section 3.1.2
- $T: S \times A \times S \rightarrow [0, 1]$ is the state transition function mapping state $s$ and joint action $a$ to successor state $s'$, such that $T(s, a, s') = Pr(s'|s, a)$
- $O = \{o_o, o_p, o_m\}$ is the set of public observations
- $Z: A \times S \times O \rightarrow [0, 1]$ is the public observation function mapping joint action $a$ and successor state $s'$ to a public observation such that $Z(\tilde{a}, s', o) = Pr(o|\tilde{a}, s')$
- $\Omega = \{\omega_1, \omega_2, \omega_3\}$ is the set of 3 private observations of each agent
- $W: A \times \Omega \rightarrow [0, 1]$ is the private observation function mapping individual action $a_j$ to a private observation $\omega_i$ such that $W(a_j, \omega_i) = Pr(\omega_i|a_j)$
- $\Phi = [R_{-1}, R_0, R_1, R_2, \ldots, R_n]$ is the vector of rewards; for each state $s$, $R_0(s, \bar{a})$ is a group reward for all agents and $R_i(s, a_i)$ is an individual reward for each agent $i$. $R_{-1}$ is the discounted history-dependent component of the reward, $R_{-1}(s_f, s_r) = \phi \cdot s_r$.

When $\phi = 0$ and $\Omega$ is empty, the history-dependent CCP reduces to the original CCP. While Wray et al. [15] solve the original CCP in a centralized manner for all agents, our approach is analogous to solving this variant from each individual agent’s perspective.

### 6.2 Multi-agent RL

Multi-agent deep deterministic policy gradient (MADDPG) [9] is a multi-agent RL algorithm that can be applied to mixed cooperative-competitive settings. It extends actor-critic by exchanging policies among agents’ critic, while the actor only has access to local information. After training is completed, only the actors are deployed in the environment. When direct policy exchange is not possible, each agent maintains an approximation to the true policies of the other agents. The approximation is done by maximizing the log likelihood of the other agents’ actions (which the learner is able to observe). However, when the other agents’ actions are not perfectly observed due to noise, MADDPG is unable to learn the optimal policy, as our experiments on Organization have shown.

Learning with opponent-learning awareness (LOLA) [3] is another actor-critic method where the agents attempt to directly influence the policy updates of other agents. Instead of learning the best response, LOLA learns to maximize the expected return after the opponent updates its policy with one naive learning step. In this way, a LOLA learner explicitly accounts for the learning of other agents in the environment, within its own learning. LOLA is suitable for both cooperative and competitive problems. Nevertheless, LOLA requires that the agents have access to each others’ exact gradients. LOLA with opponent modeling (LOLA-OM) removes this limitation of accessing other agent’s policy gradients, by estimating the other agent’s gradients from the trajectories, using maximum likelihood estimation. However, it is not straightforward to accommodate either the exact gradients or the estimated ones as private observations, in a manner consistent with the private observations of IA2C+, or those of our modified MADDPG and COMA for Organization, thus precluding a fair comparison with these methods in our experiments. For this reason, we have excluded LOLA from our set of baselines.

Independent deep Q-Learning (IQL) [13] extend deep Q-Learning network (DQN) [11] architecture to multi-agent settings by allowing the agents to select actions independently, and to receive separated individual rewards from the environment. IQL can learn policies ranging from fully cooperative to competitive by tuning the reward function. It demonstrates the possibility of decentralized learning in complex multi-agent environments. As we have already included IAC in our set of baselines, and Q-learning is an off-policy technique compared to the on-policy actor-critic based algorithms used in our experiments, we exclude IQL from our set of baselines.

Counterfactual multi-agent policy gradients (COMA) [4] is also an actor-critic method which consists of a centralized critic and multiple (decentralized) actors. COMA uses a centralized critic to compute the agent-specific advantage functions that compares the estimated return for the current joint action to a counterfactual baseline that marginalizes out one single agent’s action at a time, while keeping all other agents’ actions fixed. However, COMA requires access to the true state or the joint action-observation history.

### 7 CONCLUDING REMARKS

We introduced the Organization domain, inspired by typical real-world businesses, where agents must both cooperate and compete to attain optimal behavior. Agents in this domain not only receive noisy observations about the state and others’ actions, but also obtain rewards that, in part, depend on the total reward of the previous time step, analogous to bonus pay. Subsequently, the Organization domain offers substantially more realistic challenges than previous MARL domains. The presence of history-dependent rewards challenges the applicability of traditional decision-making frameworks and the need for cooperation precludes independent learning in this domain. We presented a new method that combined decentralized actor-critic based learning with maintaining beliefs over a finite set of candidate models of the other agents. This method is comparatively robust to noisy observations and converges significantly faster to the optimal policy in the Organization domain compared to previous state-of-the-art MARL baselines. An immediate avenue of future work is to further scale the number of agents beyond four to better simulate real-world business organizations.

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