### Coordinating Policies Among Multiple Agents via an Intelligent Communication Channel

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### Abstract

In Multi-Agent Reinforcement Learning (MARL), specialized channels are often introduced to allow agents to communicate directly with one another. In this paper, we propose an alternative approach whereby agents communicate through an intelligent facilitator that learns to sift through and interpret signals provided by all agents to improve the agents’ collective performance. To ensure that this facilitator does not become a centralized controller, agents are incentivized to reduce their dependence on the messages it conveys, and the messages can only influence the selection of a policy from a fixed set, not instantaneous actions given the policy. We demonstrate the strength of this architecture over existing baselines on several cooperative MARL environments.

### 1 Introduction

Multi-agent reinforcement learning (MARL) addresses the sequential decision-making of two or more autonomous agents that operate in a common environment, each of which aims to optimize its own long-term return by interacting with the environment and with other agents [Busoniu et al. (2008)]. MARL is becoming more common in many real-world applications such as robotics, as well as in other applications involving complex, dynamic environments, such as video games. Largely, MARL algorithms can be placed into two categories depending on the type of setting they address. In the cooperative setting, agents collaborate to optimize a shared long-term return whereas in the competitive setting, an advantage for one agent results in a loss for another.

Early research in cooperative MARL focused on agents that operated independently and that did not explicitly communicate [Witt et al. (2020a); Foerster et al. (2018a); Tan (1997)]. However, when each agent has only a partial view of the environment, agents benefit from exchanging information with one another, allowing them to construct a more complete belief state and improve decision making. Even in fully observed environments, inter-agent communication can be beneficial to coordinate...
Step 2: SAF dynamically integrates the signals from the agents

Step 3: SAF modulates the behavior of other agents

Step 4: Pick policy from policy pool

Figure 1: Agents communicate through the SAF and pick a policy from the shared policy pool. First, each agent generates a message and competes for write-access into the SAF. Next, all agents read messages from the SAF and use it with their internal state to pick a policy from the shared policy pool.

behavior. Not surprisingly, performance advantages are obtained when agents have the ability to learn a communication protocol, whether implicitly or explicitly [Rashid et al. 2018a; Sunehag et al. 2018a; Lowe et al. 2017; Witt et al. 2020a]. Recent research on communication for deep MARL adopts an end-to-end training procedure based on a differentiable communication channel [Sukhbaatar et al. 2016; Foerster et al. 2016; Gupta et al. 2017; Singh et al. 2018; Das et al. 2019]. Essentially, each agent has the capability of generating messages and these messages can influence other agents’ policies. In these works, the message-generation subnet is trained using the gradient of other agents’ policy or critic losses.

In designing a MARL architecture, a key decision involves the nature of the communication channel. The simplest scenario involves direct agent-to-agent communication, where each of the $N$ agents can receive messages from all other agents. Communication costs are quadratic in $N$ and each agent faces the challenge of interpreting $N - 1$ simultaneous messages. Communication costs can be reduced by restricting the communication topology [Wang et al. 2017]. Message processing can be simplified using a learned key-value attention mechanism that condenses messages at either the side of the sender [Kim et al. 2020] or recipient [Das et al. 2019].

Intelligent communication channel. In previous approaches, the communication channel is passive, by which we mean that its role is to convey whatever message passes through the channel without alteration. We describe an approach in which the communication channel is active in that it can interpret and transform signals from one or more agents, and it is stateful in that its interpretations can depend on the recent history of messages transmitted. Because we endow the channel itself with intelligence, message communication complexity is reduced from quadratic to linear in $N$. In essence, the channel is a specialist agent aiming to facilitate coordination among the other agents. We refer to the channel as SAF, an acronym on stateful, active facilitator. SAF is itself adaptive and learns to improve the collective performance of the agents.

Maximizing agent independence. By endowing the communication channel with intelligence, there is a risk that SAF may simply become a centralized controller dictating actions to the agents, which is antagonistic to a multi-agent architecture. We therefore need to encourage independence of the agents, which could also lead to specialization of labor and thus faster learning. To the extent that independent agents can solve a task, independence is a clear advantage because the learning problem can be decomposed into smaller problems, i.e., each agent can learn without concern about the behavior of other agents. However, most tasks require some coordination among agents. We therefore pursue an approach that attempts to regularize toward independence: agents pay a penalty for modulating their behavior based on the information provided by SAF. This penalty, which is added to the primary task-based reward, discourages unnecessary use of the communication channel.

The penalty is expressed as the conditional mutual information between an agent’s behavior, $B$, and the information, $M$, obtained from SAF, given the agent’s current belief state, $S$, denoted $I(B; M | S)$. Previous work has shown how to optimize $I(B; M | S)$ using the framework of KL-Regularized RL [Teh et al. 2017; Galashov et al. 2019; Goyal et al. 2019; Tirumala et al. 2020]. This optimization encourages the agent to act according to a default or prior policy that is insensitive to SAF. To see that minimizing $I(B; M | S)$ is achieved by minimizing the KL divergence between an agent’s policy and the default one, note that $I(B; M | S) = \mathbb{E}_{\pi_0} [D_{KL}[\pi_\theta(B | S, M) || \pi_0(B | S)]]$, where $\pi_\theta(B | S, M)$ is the agent’s SAF-sensitive policy, $\pi_0(B | S) = \pi_\theta(B | S)$ is the default policy, $\mathbb{E}_{\pi_0}$
denotes an expectation over trajectories generated by \( \pi_\theta \), and \( D_{KL} \) is the Kullback-Leibler divergence. In past work, the information asymmetry obtained by prohibiting the default policy access to shared information has been shown to improve transfer and generalization [Galashov et al. (2019); Goyal et al. (2019); Tirumala et al. (2020)].

**Policy switching.** We were deliberately vague in describing \( B \) as an agent’s behavior. \( B \) might refer to the actions an agent takes [Goyal et al. (as it has in 2019); Galashov et al. (as it has in 2019); Tirumala et al. (as it has in 2020)], but in the present work, we endow agents with a discrete set of distinct policies to select from, and the agents have an explicit decision-making component that selects a policy stochastically conditioned on \( S \) and \( M \). The communicated information \( M \) is used only to select a policy, not to select actions conditioned on the policy. This mixture-of-policies approach limits the manner in which \( SAF \) can micromanage an agent’s behavior, and it has been shown to be effective in endowing agents with different behavior modes [Goyal et al. (2021c); Tirumala et al. (2020)].

In the previous paragraphs, we introduced three key ideas that operate synergistically. First, communication among agents is via an intelligent channel, \( SAF \). Second, each agent is incentivized to act independently and avoid relying on \( SAF \). Third, agents operate according to a mixture-of-policies, where \( SAF \) provides the signal to select the policy. To better appreciate how these ideas work in tandem, consider the naturalistic example of a herd of deer coordinating their behavior. By default, each animal’s policy is to graze in a field. But when one of the animals senses danger, the herd needs to escape. They need to move in unison because if they split up, it will be easier for a predator to trap them. Suppose that they can escape either to the north or the east, each characterized by a different policy. \( SAF \) in this case will relay the danger alert and will collect information from the individuals and suggest a direction so that the deer can escape in coordination. Each deer is responsible for avoiding obstacles and avoiding running into other deer, and thus they operate autonomously with only the high-level guidance from \( SAF \).

**Contributions.** The key contributions of our work are as follows: (a) we propose a novel architecture for multi-agent RL. Instead of agents communicating directly between one another, communication is mediated by a facilitator, \( SAF \), which itself uses the history of communication and active computation to improve the collective performance of all the agents, (b) To ensure agent autonomy, different agents are incentivized to minimize the influence of \( SAF \) on their behavior, (c) To further promote autonomy, agent behavior is only coarsely modulated by \( SAF \), much in the way that a Ph.D. student’s research direction is only guided at a high level by their advisor. In the case of our MARL architecture, this modulation comes in the form of policy selection, which is made explicit via a policy mixture model with a component that switches among policies (see Figure 1), (d) We show the performance of the proposed method on different MARL environments in cooperative setting. We also conduct various ablations and understand the role of different components namely the use of intelligent channel \( SAF \), maximizing agent independence and the use of policy pool. We show that the collective performance of the agent which uses all the three components is higher as compared to an agent which only uses one of the components.

## 2 Background and Notation

In this work, we consider a multi-agent version of Markov decision processes (MDPs) with partially observable Markov environments (POMDP). The environment is defined as \( (N, S, O, A, \Pi, \gamma) \). \( N = \{1, \ldots, N\} \) denotes the set of \( N > 1 \) agents. \( S \) describes all possible states of all agents. \( A = A_1 \times \cdots \times A_N \) denotes the joint action space and \( a_{i,t} \in A_i \) refers to the action of agent \( i \) at time step \( t \). \( O = O_1 \times \cdots \times O_N \) denotes the set of partial observation where \( o_{i,t} \in O_i \) stands for partial observation of agent \( i \) at time step \( t \). \( \Pi \) is the set of policies available to the agents. To choose actions, agent \( i \) uses a stochastic policy \( \pi_\theta_i : O_i \times A_i \rightarrow [0,1] \). Actions from all agents together produces the transition to the next state according to transition function \( T : (s_t, a_{1,t}, \ldots, a_{N,t}) \rightarrow s_{t+1} \) where \( s_t \in S \) is the joint state at timestep \( t \). \( R : S \times A \rightarrow \mathbb{R} \) is the global reward function conditioned on the joint state and actions. At timestep \( t \), the agent team receives a reward \( r_t = R(s_t, a_{1,t}, \ldots, a_{N,t}, \gamma) \) based on the current total state \( s_t \) and joint action \( a_{1,t}, \ldots, a_{N,t}, \gamma \) is the discount factor for future rewards. In this study, we focus on cooperative MARL with partial observations.
3 MARL with a Facilitator

We present our approach, first in terms of a high level overview of the mechanisms enabling inter-agent communication (Section 3.1), and then with a detailed description that steps through the algorithm (Section 3.2). For further details, see Algorithm 1 in Appendix A.1.

3.1 High Level Overview

Stateful active facilitator. The facilitator, SAF, consists of $l$ stateful memory slots, each a vector of $d_m$ elements. The slots are randomly initialized at the beginning of an episode. The state of the SAF is updated once per time step, where a time step corresponds to all agents performing one action. In this update, SAF integrates information provided by the agents into its slot memory and then outputs a message $M$ that any agent can use.

Policy switching using a shared policy pool. Although all agents operate in the same environment, their contexts and objectives may vary. A policy pool $\Pi = \{\pi^1, \ldots, \pi^U\}$, shared among agents, enables agents to exhibit diverse behaviors and have distinct goals. Each policy $\pi^u \in \Pi$ is associated with a learned signature key $k_{\pi^u}$. Using differentiable hard attention with Gumbel-softmax [Jang et al., 2016], an agent can dynamically select one of the policies at each time step via a query formed from its belief state, $S$, and the message conveyed by SAF, $M$.

Reducing agent dependence on SAF. To reduce an agent’s dependence on SAF, each agent is penalized according to the KL divergence $D_{KL}[\Pr(Z | S, M) || \Pr(Z | S)]$, where $Z$ is the agent’s policy choice.

3.2 Detailed Algorithm

Step 1: Agents pass messages to SAF. At step $t$, each agent $i$ receives a partial observation $o_{i,t}$ of the environment. This observation is used to update the agent’s belief state, $s_{i,t}$, which in turn is used to generate a message for SAF. The message, $m_{i,t} = g_{enc}(s_{i,t})$, is a vector of dimensionality $d_m$. We denote the set of messages generated by the agents at time step $t$ as $M_t = \{m_{i,t} | 1 \leq i \leq N\} \in \mathbb{R}^{N \times d_m}$.

Step 2: SAF integrates information from the agents. SAF dynamically integrates the information from all the agents and incorporates the information that it finds interesting into its state representation. The SAF slot memory at time step $t$ is a set of vectors $F_t \in \mathbb{R}^{l \times d_m}$, each row representing one of the $l$ slots. The state of SAF is updated based on agent messages, ensuring that only the important information is incorporated. SAF achieves this via the use of query-key-value attention mechanism [Bahdanau et al., 2014; Vaswani et al., 2017]. In this case, the query is a function of SAF’s state (a set of slots), represented by matrix $F_t$ (with one row per slot), i.e., $Q = F_t W^q$. Keys and values are a function of the messages from individual agents. Dot product attention is applied to obtain the updated state of the slots: $F_t \leftarrow \text{softmax} \left( \frac{Q_t^T W^r \kappa_{\pi^u}}{\sqrt{d_v}} \right) M_t W^v$. The use of softmax to write into $l$ slots leads to a standard soft competition among agents to influence the state of SAF. Next, self-attention is applied over the slots of SAF to obtain its updated state.

Step 3: SAF modulates the behavior of other agents. SAF makes the updated state available to the agents should they deem to use it. We again utilize an attention mechanism to perform this reading operation. All the agents create queries $Q_i^s = \{q_i^s, | 1 \leq i \leq N\} \in \mathbb{R}^{l \times d_v}$, where $q_i^s$ is query generated using the encoded partial observations of agent $i$: $q_i^s = W^q_{\text{write}} s_{i,t}$. Generated queries are matched with the keys $\kappa = F_t W^c \in \mathbb{R}^{l \times d_k}$ from the updated state of SAF (a set of slots), forming the attention matrix $\alpha = \text{softmax} \left( \frac{Q_i^s T \kappa_{\pi^u}}{\sqrt{d_k}} \right)$. The slot values generated by each slot of SAF’s state and the attention weights are then made available to all the agents:

$M_t = \text{softmax} \left( \frac{Q_i^s T \alpha_{\pi^u}}{\sqrt{d_k}} \right) F_t W^u$

Here $M_t = \{m_{i,t} | 1 \leq i \leq N\}$, where $m_{i,t}$ is the message made available to the agent $i$.

Step 4: Policy switching. The encoded partial observation of an agent $s_{i,t}$ and the information made available to each agent $m_{i,t}$ is used to select a policy $\pi^u$ for that agent from the pool of policies $\Pi$.
E

where

As a result of this attention procedure, agent $i$ (2020) uses intentions represented as encoded imagined trajectories as messages where the encoding (2021b) propose the extension of single-agent DDPG and single-agent PPO respectively, to a multi-

Thus, we can instead maximize this lower bound on $J$ via a straight-through Gumbel-softmax attention mechanism to make a differentiable approximately

$$\sum_{i} \text{psel} = g_{psel}(s_{i,t}, m_{i,t})$$

where $g_{psel}$ is parameterized as a neural network.

$$\text{index}_i = \text{GumbelSoftmax} \left( \frac{q_{i,t}^{policy}(K_t^{\pi})^T}{\sqrt{d_m}} \right)$$

As a result of this attention procedure, agent $i$ selects a policy $\pi^{\text{index}_i}$. This operation is performed independently for each agent, i.e. each agent selects a policy from the policy pool.

**Step 5: Maximizing agent independence.** We minimize the dependence of agent on the information made available to each agent. We do this by optimizing the conditional mutual information by upper bounding the KL and penalizing $I(Z; M | S)$

Thus, we can instead maximize this lower bound on $J(\theta)$: $J(\theta) \geq \mathbb{E}_{\pi_a}[r] - I(Z; M | S)$

where $\mathbb{E}_{\pi_a}$ denotes an expectation over trajectories across different agents, $\beta > 0$ is a trade-off parameter and $r = \sum_{t=0}^{T} r_t$ is the total return up to the horizon $T$.

4 Related Work

**Centralized training decentralized execution (CTDE).** These approaches are among the most commonly adopted variations for MARL in cooperative tasks. They usually involve a centralized critic which takes in global information, i.e. information from multiple agents and decentralized policies which are guided by the critic. Foerster et al. (2018b) uses the standard centralized critic decentralized actors framework with a counterfactual baseline. Lowe et al. (2017) and Yu et al. (2015) propose the extension of single-agent DDPG and single-agent PPO respectively, to a multi-agent framework with a centralized critic and decentralized policies during training and completely decentralized execution. Li et al. (2021) uses an information theory based objective to promote novel behaviours in CTDE based approaches. Value Decomposition (Sunehag et al., 2018b, Rashid et al., 2018b, Wang et al., 2020, Mahajan et al., 2019) approaches learn a factorized action-value function. Sunehag et al. (2018b) proposes Value Decomposition Networks (VDN) which simply add the action-value function of each agent to get the final action value function. Rashid et al. (2018b) uses a mixing network to combine the action-value functions of each agent in a non-linear fashion.

**Communication in MARL.** Several approaches use emergent communication protocols for MARL. Communication involves deciding the message to be shared and determining how the message sending process is implemented. Foerster et al. (2016) and Sukhbaatar et al. (2015) have done work on learnable inter-agent communication protocols. Jiang and Lu (2018) first proposed using attention for communication where attention is used for integrating the received information as well as determining when communication is needed. Das et al. (2019) uses multiple rounds of direct pairwise inter-agent communication in addition to the centralized critic where the messages sent by each agent are formed by encoding it’s partial observation, location information, etc., and the messages received by each agent are integrated into it’s current state by using a soft-attention mechanism. Kim et al. (2020) uses intentions represented as encoded imagined trajectories as messages where the encoding is done via a soft-attention mechanism with the messages received by the agent. Wang et al. (2021) trains a model for each agent to infer the intentions of other agents in a supervised manner, where the communicated message denotes the intentions of each agent. The above mentioned approaches require a computational complexity which is quadratic in the number agents. Our approach has a computational complexity which is linear in the number of agents. Moreover, we show that our approach is able to outperform several standard baselines using messages which can be computed as simply the encoded partial observations of each agent.

$\sum \pi_{ae}(z | S, M) p_{ae}(A | S, z)$

Galashov et al. (2019), Goyal et al. (2019) such that $\pi_o(A | S, M) = I(Z; M | S) \geq I(A; M | S)$

5
Option-critic in Multi-agent Hierarchical Reinforcement Learning

A classical approach within the Hierarchical Reinforcement Learning (HRL) literature is modeling agents’ intentions as options (Sutton et al., 1999), temporally extended actions that aim to achieve subgoals in a finite time horizon. Recently, Bacon et al. (2017) proposed an end-to-end option-critic architecture capable of learning both options and the related policy. However, despite the advantages brought by using options, due to the temporally-extended nature of options, agents’ responses can be inconsistent when the environment or other agents’ behaviour change. To tackle this problem, Han et al. (2019) proposed a dynamical termination scheme which allows an agent to flexibly terminate its current option. Although both option-critic and our approach use a pool of actors, in the former case actors model options, in the latter one actors model policies, preventing agents’ inconsistent behaviours. Moreover, although within the option-critic framework the optimality of the learned hierarchical policy can be theoretically guaranteed (Chakravorty et al., 2020), the learned options cannot be easily transferred to other tasks (Pateria et al., 2021). Furthermore, many works proposed within the option-critic framework (Klissarov et al., 2017; Riemer et al., 2018; Khetarpal et al., 2020) perform poorly on sparse reward tasks (Bagaria and Konidaris, 2020; Nachum et al., 2018), while experimental results show that our approach presents comparable performances with SOTA baselines even on that case (e.g., Waterworld Environment (Gupta et al., 2017)).

Independent Learning.

Independent Learning in MARL consists of each agent optimizing its policy locally using its observation and in the absence of any communication or centralized controller (as in CTDE). These approaches mainly consist of the extension of single-agent RL approaches to multi-agent settings where each agent learns independently using local observations, considering other agents as part of the environment. Tan (1993) proposed Independent Q-Learning (IQL) where each agent independently learns its own action-value function. Witt et al. (2020b) demonstrates that PPO, when used for independent learning in multi-agent settings (called Independent PPO or IPPO) is in fact capable of beating several state of the art approaches in MARL on competitive benchmarks such as StarCraft and can hence serve as a strong baseline.

Communication bottleneck.

With the emergence of modular deep learning architectures (Vaswani et al., 2017; Goyal et al., 2021a; Scarselli et al., 2008; Bronstein et al., 2017; Kipf et al., 2018; Battaglia et al., 2018), which require communication among different model components, there have been development of methods which introduce a bottleneck in this communication to a fixed bandwidth which helps communicating only the relevant information. Liu et al. (2021) uses a VQ-VAE (Oord et al., 2017) to discretize the information being communicated. Inspired by the theories in cognitive neuroscience (Baars 1988; Shanahan 2006; Dehaene et al., 2017), Goyal et al. (2021b) proposes the use of a generic shared workspace which acts as a bottleneck for communication among different components of multi-component architectures and promotes the emergence of specialist components. We use a SAF similar to the shared workspace in which different agents compete to write information to and read information from.

5 Experiments

We investigate how well SAF, policy switching, and maximizing independence work together to improve cooperative MARL. Next, we compare our method with a state-of-the-art cognitive science-inspired approach used in multi-agent communication and cooperation (Wang et al., 2021). Lastly, to understand if our method can be adapted to MARL methods that send different messages among agents, we integrate our machinery into a MARL algorithm that iteratively sends hypothetical actions among cooperative agents.

5.1 Environments

In this section, we describe the various MARL environments which we considered for our experiments.

GhostRun environment. We use the GhostRun Environment which is an adaptation of the Drone environment available from Jiang (2019). The environment consists of multiple drones, each with a partial view of the ground below them. The ground consists of ghosts - represented by red dots, trees - depicted by green dots, and obstacles - depicted by black dots. The ghosts move about randomly whereas the trees and obstacles are stationary (see Figure 2(a)). The task at hand is a cooperative task where the agents must work together to escape from ghosts. Hence, the number of ghosts in
each agent’s partial observation of the environment must be minimized. The reward received by each agent at each time step is the negative of the total number of ghosts in the view of all the agents and a step cost of -1 for each step taken.

![GhostRun Environment](image_a)
![PistonBall Environment](image_b)
![MSTC Environment](image_c)

Figure 2: GhostRun, PistonBall and MSTC environments. In the GhostRun environment (left panel) each agent has its own partial view of the environment and the reward is to escape from ghosts (red dots). Different agents can communicate their encoded views with each other. In the PistonBall environment (middle panel) all agents (pistons) work together to move the ball from one side to the other. In the MSTC environment (right panel), sensors (gray dots) need to cover as many targets as possible (red dots). MSTC figure adapted from Wang et al. (2021)

**Multi-Sensor Target Coverage.** We use the multi-sensor multi-target tracking (MSTC) environment from Wang et al. (2021). There are sensors (which are the agents) and targets. The goal is for the sensors to observe as many targets as possible at once (see Figure 2 (c)). Each sensor has a partial observation of its surroundings and its view may be obstructed by obstacles. The targets can move according to one of two rules: according to a random walk, or along the shortest path to reach a previously sampled destination. At the beginning of each episode, the location of targets, sensors and obstacles is randomly sampled. The maximum episode length is 100 steps and the reward is defined as \( r = \frac{1}{m} \sum q T_q \) where \( T_q = 1 \) if the target \( T_q \) is observed by any sensor and 0 otherwise. If no target is observed (i.e. \( T_q = 0 \) \( \forall q \)) then \( r = -0.1 \).

**PistonBall Environment.** This is a simple physics-based cooperative game where the goal is to move the ball to the left wall of the game border by activating the vertically moving pistons. Each agent’s observation is an RGB image of the two pistons (or the wall) next to the agent and the space above them (see Figure 2 (b)). Every piston can be acted on at any time. The action space can be discrete: 0 to move down, 1 to stay still, and 2 to move up. Alternatively, the action space can be continuous: the action value in the range \([-1, 1]\) is proportional to the amount by which the pistons are raised or lowered. Continuous actions are scaled by a factor of 4, so that in both the discrete and continuous action space, the action 1 will move a piston 4 pixels up, and \(-1\) will move pistons 4 pixels down.

### 5.2 Baselines: Varying Along Different Axes

In our experiments, we consider multiple baselines which use some aspects of the proposed method, such as the use of stateful and active facilitator SAF, shared pool of policies and maximizing agent independence. In particular, we try to disentangle the contributions of these different components of the proposed architecture. The following baselines are evaluated:

**Multiple Agents with no communication** [I]: There are multiple independent agents with no communication between them.

**Multiple Agents with pairwise communication** [P]: Every pair of agents can communicate with each other via self-attention [Vaswani et al. (2017)].

**Multiple Agents with pairwise communication and shared pool of policies** [P + SP]: Every pair of agents can communicate with each other via self-attention and each agent can select a different policy from the shared pool of policies. The difference from the proposed method would be that this variant does not make use of SAF.

**Multiple Agents with SAF** [SAF]: Here, we consider multiple agents such that different agents communicate with each other via SAF, and all agents share the same policy.
Multiple Agents with SAF and policy pool [SAF + SP]: the agents can communicate with each other via SAF, and also share the pool of policies such that each agent can dynamically select a policy from the policy pool.

Multiple Agents with SAF, policy pool and maximizing agent dependence. [SAF + SP + KL]: The agents can communicate with each other via SAF, share the pool of policies, and also agents minimize the dependence of the policy on the information made available by SAF.

Hyperparameters. We consider two hyper-parameters in the proposed model: (1) number of policies in the pool \( (U = N_{\text{policies}}) \), (2) number of slots in the SAF \( (l = N_{\text{slots}}) \). For all our experiments, we use \( N_{\text{policies}} = 3 \).

Stateful and Active communication Facilitator (SAF) improves communication in MARL. We investigate the use of SAF for coordinating among different agents in the Ghost Run environment by comparing different communication schemes. (a) We compare three communication strategies [I], [P] and using SAF. We find that the proposed SAF based approach outperforms the other two settings and shows an improvement of about 45% over the other two baselines as shown in figure 4(a). This shows that introducing the SAF helps improve inter-agent communication. The SAF acts as a specialist agent / communication bottleneck for the messages sent by all agents. It filters out only the relevant information for providing the relevant context to each agent making it more robust, which may not be possible in pairwise communication i.e., where every pair of agents communicate with each other.

We also compare [SAF+SP] against a graph-based communication baseline Wang et al. (2021) that we simply name GRAPH, on the MSTC environment. In GRAPH, the agents generate a message from their observation and communication is done through a fully-connected graph whose nodes are the
updated messages. These are used to optimize the agents’ policies. We show the test reward in Table 1.

|                  | [SAF+SP]       | GRAPH               |
|------------------|----------------|---------------------|
| **Expected Return** | 71.26±5.81    | 61.22±8.15          |

Policy switching using shared policy pool improves performance. We investigate the significance of using policy switching using a shared pool of policies for each agent. We experiment with two settings: SAF and SAF + SP. The inter-agent communication in both settings is facilitated via the use of SAF. The results are shown in Figure 4(b). Using a shared pool of policies with dynamic selection shows a relative improvement of 25% over the fixed policy setting. This shows that the mixture of policies helps to transfer knowledge about different behaviors across different agents.

Minimizing dependence on SAF. Here, we investigate the effect of minimizing the dependence of each agent’s policy on the information that is available from the SAF in the form of its state, quantified by the conditional mutual information \( I(Z; M | S) \), where \( Z \) is the agent’s policy choice. One can directly optimize it as discussed in eq.1. We also experimented with different values of the coefficients (\( \beta \)) of the KL based regularization loss. Figure 4(c) shows that minimizing the dependence of each agent on the information from SAF helps improve convergence.

We also compare the effect of directly optimizing the conditional mutual information \( I(A; M | S) \) i.e., where the information from SAF is used to also select actions (as compared when information from SAF is only used to select the policy) and the agent is optimized to minimize dependence on information from SAF. We call the method where we optimize the mutual information directly on actions as regularized action selection, and the method where we optimize the upper bound on mutual information as regularized policy selection. Figure 4(d) compares the effect of regularizing action as compared to regularizing the policy selection, and shows that regularizing the policy selection (i.e., upper bound) achieves better results as compared to regularizing the action selection.

SAF is significantly helpful for MARL training with large number of agents. Here we investigate how the proposed method scales with increasing the number of agents. Learning a stateful, active facilitator SAF which integrates information across agents should scale better as compared to using a communication protocol where every agent interacts with every other agent. To test this hypothesis, we compare the performance of five different approaches: SAF, [SAF+SP], [P], [P + SP], [I] by varying the number of agents. Figure 3 shows the result of these different methods by varying the number of agents. As the number of agents increases, the relative difference between the proposed method and the different baselines ([I], [P], [P+SP]) increase significantly.

Flexible plug-in tool for many different MARL settings. In the previous sections, we showed that SAF, shared policy, and maximizing independence boost performance on cooperative MARL.
tasks in which agents communicate messages generated as a function of the observed environment. In this section, we investigate the possibility of applying the proposed method on cooperative MARL algorithms in which agents iteratively communicate hypothetical actions with each other before taking actions. The performance of the proposed method is compared with two recent approaches that communicate hypothetical actions, namely consensus update and iterative reasoning (IR) [Zhang et al., 2018]. Consensus update conducts graph-based local communication and IR communicate hypothetical actions among agents such that an agent’s policy is conditional on its teammates. Our experimental results show that our method achieves higher cumulative rewards in the PistonBall environment while doing so in a lower number of iterations, both of which indicate better performance (see Figure 5). This suggests the potential of the proposed method as a flexible plug-in tool in many MARL settings.

6 Future Work

Here, we introduced three key ideas that operate synergistically. First, communication among agents is conducted via an intelligent channel, SAF. Second, each agent is incentivized to act independently and avoid relying on SAF. Third, agents operate according to a mixture-of-policies, where SAF provides the signal to select the policy. Through extensive experiments we show the utility of all the different components. We also show that the proposed method scales better on increasing the number of the agents and achieves higher returns as compared to various different baselines. Future work may involve scaling the proposed method to more complex multi-agent problems like Starcraft [Vinyals et al., 2019] and Google Research Football [Kurach et al., 2019].

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Appendix

A.1 Algorithm

A.2 MARL environments

GhostRun environment is a cooperative multi-agent game adapted from Jiang et al. 2021 (Jiang and Amato (2021)). GhostRun environment consists of multiple agents with partial view of a 2D
for $t \leftarrow 1$ to $T$ do

Step 1: Each agent $i$ having state information $s_{i,t}$ (encoded partial observation), generates a message.

\[ \forall i \in \{1, \ldots, N\}, m'_{i,t} = f_\theta(s_{i,t}) \]

\[ M'_t = (m'_{1,t}, m'_{2,t}, \ldots, m'_{N,t}) \]

Step 2: SAF integrates information from all agents

\[ Q = F_t W^q \]

\[ F_t \leftarrow \text{softmax} \left( \frac{Q(M'_t W^v)^T}{\sqrt{d_e}} \right) M'_t W^v \]

Self-attention over $F_t$ to update the SAF state.

Step 3: Information from SAF is made available to each agent

\[ \begin{align*}
q^i_{s,t} &= W^q_{\text{write}} s_{i,t} \\
\kappa &= (F_t W^v)^T \\
\alpha &= \text{softmax} \left( \frac{Q^i_{s,t}}{\sqrt{d_e}} \right) \\
M_t &= \text{softmax} \left( \frac{Q^i_{s,t}}{\sqrt{d_e}} \right) F_t W^v
\end{align*} \]

Step 4: Policy Selection from the pool

\[ \forall i \in \{1, \ldots, N\}, \begin{cases} 
q^{\text{policy}}_{i,t} = f_{\text{psel}}(s_{i,t}, m_{i,t}) \\
\text{index}_t = \text{GumbelSoftmax} \left( \frac{q^{\text{policy}}_{i,t}(K \Pi_t)^T}{\sqrt{d_m}} \right)
\end{cases} \]

Step 5: Minimizing dependence on information made available by SAF.

end

Algorithm 1: MARL with SAF, Maximizing Agent Independence and Policy Switching

Figure 6: Sensitivity of our approach to key hyperparameters: (a.) Dependence on number of policies ($U$) (b.) Dependence on number of SAF slots ($l$). We use the Ghost Run environment.

world of square shape. There are ghosts randomly moving around in the environment. Each agent receive a negative reward of $-10 \times N_{\text{ghost}}$ at each time step where $N_{\text{ghost}}$ is the number of ghosts in the agent’s partial view of the environment. In addition, there is a step cost of -1 for each agent at each time step. The goal of the game is to maximize the sum of rewards from all agents in the team. We conducted the experiments using fixed number of 100 ghosts and various number of agents.

Multi-agent Particle-World Environment (MPE) (results to be added) was introduced in Lowe et al. (Lowe et al. (2017)). MPE consist of various multi-agent games in a 2D world with small particles navigating within a square box. We consider a cooperative task from the original set called “SimpleSpread”. In the task there are various number agents and landmarks. The team reward is calculated by the distance between each landmark and its nearest agents. In this study, 2 landmarks and various number agents are used.
Table 2: Multi-agent reinforcement learning environments used in this work along with the number of agents and the task to solve for each environment.

| ENV | N AGENTS | TASK               |
|-----|----------|--------------------|
| GHOSTRUN | 5       | HIDE FROM GHOSTS   |
| MSTC   | 3        | OBSERVE TARGETS    |
| PISTONBALL | 5      | MOVE THE BALL     |

A.3 Training details

The optimization algorithm for each agent in our SAF method is PPO. Baselines IPPO, CPPO and MAPPO share the same or similar architectures of actor and critic as in SAF. Hyperparameters such as batch sizes, number of training episodes and learning rates of these PPO backbone are obtained from the original publication [Yu et al., 2021a].

Architectures and hyperparameters of SAF method were tuned. All the baselines are implemented in a way that their performance either matches or exceeds the results in the original publications if available.

A.4 Hyperparameters and sensitivity to SAF specific hyperparameters

Common hyperparameters used in SAF and other PPO derived method are shown in table 3. Other baselines uses hyperparameters from original publications.

In this section we study our approach’s sensitivity to two key hyperparameters: the number of slots \( l = N_{\text{slots}} \) and the number of policies \( U = N_{\text{policies}} \). In our findings that we summarize in Figure 6 we find that SAF is robust to variation in the number of slots. For the number of policies however, we find that the performance is best for \( N_{\text{policies}} = 3 \) and decreases for bigger values.

Table 3: Common hyperparameters used in SAF and other PPO baselines

| HYPERPARAMETERS            | VALUES               |
|----------------------------|----------------------|
| GAMMA                      | 0.99                 |
| BATCH SIZE                 | 15                   |
| OPTIMIZER                  | ADAM                 |
| OPTIMIZER EPSILON          | 0.01                 |
| WEIGHT DECAY               | 0                    |
| FEATURE NORMALIZATION      | BATCH NORM           |
| REWARD NORMALIZATION       | BY BATCH             |