The Enforcers: Consistent Sparse-Discrete Methods for Constraining Informative Emergent Communication

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Abstract

Communication enables agents to cooperate to achieve their goals. Learning when to communicate, i.e. sparse communication, is particularly important where bandwidth is limited, in situations where agents interact with humans, in partially observable scenarios where agents must convey information unavailable to others, and in non-cooperative scenarios where agents may hide information to gain a competitive advantage. Recent work in learning sparse communication, however, suffers from high variance training where the price of decreasing communication is a decrease in reward, particularly in cooperative tasks. Sparse communications are necessary to match agent communication to limited human bandwidth. Humans additionally communicate via discrete linguistic tokens, previously shown to decrease task performance when compared to continuous communication vectors. This research addresses the above issues by limiting the loss in reward of decreasing communication and eliminating the penalty for discretization. In this work, we successfully constrain training using a learned gate to regulate when to communicate while using discrete prototypes that reflect what to communicate for cooperative tasks with partial observability. We provide two types of “Enforcers” for hard and soft budget constraints and present results of communication under different budgets. We show that our method satisfies constraints while yielding the same performance as comparable, unconstrained methods.¹

1 Introduction

Multi-agent reinforcement learning (MARL) has seen general success in the performance of complex games. Notably, reinforcement learning has been able to play multiplayer competitive games such as Starcraft [Peng et al., 2017] and Dota-2 [Berner et al., 2019] where the reinforcement learning agents are trained versus other reinforcement learning agents and then compete against human teams. Recent work in using communication in Starcraft has aims towards enabling human-agent teaming at such games as well as other MARL tasks with emergent communication [Sukhbaatar et al., 2016; Singh et al., 2018; Jiang and Lu, 2018; Foerster et al., 2016].

Recently, there has been success in learning multiagent communication frameworks to solve partially observable tasks. In particular, these successes have been achieved using neural network architectures in conjunction with a reinforcement learning framework. Examples of recent work that has been successful in multiagent communication include CommNet [Sukhbaatar et al., 2016] and IC3Net [Singh et al., 2018]. They benefit from using individualized rewards for agents. However, their best results focus on continuous communication, which is unreasonable due to limited bandwidth in real-world settings.

While prior art in emergent communication establishes how agents may learn to communicate to accomplish their goals, the learned communication conventions often exhibit undesirable properties. Motivated by human communication in which people speak only when necessary, and using only a discrete set of words, we wish for agents to learn sparse (in time) and discrete communication. Recent work seeks to build such agents for agent-agent and human-agent teaming. Learning discrete prototypes shown to promote robustness in noisy communication channels, as well as human interpretability and zero shot generalization [Tucker et al., 2021]. However, these agents often perform suboptimally compared to agents trained with unconstrained communication [Lazaridou and Baroni, 2020; Freed et al., 2020; Agrawal, 2021]. Thus, state-of-the-art sparse communication requires a tradeoff between budget and task performance.

In this study, we propose to stably learn a communication-action policy such that the communication is discrete and sparse according to a limited bandwidth or budget. Specifically, the rate of communication needs to be minimized to essential communication or communication needs to be learned to maximize performance with a suboptimal bandwidth. We consider cooperative settings from [Singh et al., 2018] since these settings present unaddressed challenges in current work in sparse communication.

We adopt the IC3Net architecture, but modify it to stably learn sparse-discrete communication in cooperative environments. To achieve sparse communication, we employ a cur-
curriculum [Bengio et al., 2009] for the learned gating mechanism within the IC3Net model to first learn a useful language model and then enforce sparsity in communication. We consider two such Enforcers: a soft enforcer and a hard enforcer. The soft enforcer provides a communication constraint through the reward function, but allows exceeding the budget in training and testing. The soft enforcer is able to converge to any communication budget above an optimal budget and also can learn the optimal communication budget. The hard enforcer does not permit exceeding the budget during training and testing. This is useful when the bandwidth is below the optimal communication budget. The hard enforcer can constrain a suboptimal budget on the learned gate while maximizing the bounded suboptimal performance. To achieve discrete communication, we employ a fixed number of \( p \) discrete prototypes and show that our parameter tuning positively improves the performance to the same level as continuous vectors.

We conduct experiments with variants of this general approach on a blind traffic junction environment and cooperative predator-prey environment of differential difficulty and show that our method learns when to communicate and how to encode the information in a discrete manner with a comparable measure of success to traditional IC3Net with a fixed gate. We also show that by varying parameters of the Enforcers, we see reduced variance, optimal communication when compared to analytical solutions, and near-optimal success on tasks with a suboptimal budget. We aim for our work to serve as an introductory bridge between MARL with communication and human-agent teaming with MARL.

2 Related Work

Communication is essential for partially observable multi-agent tasks. Recurrent networks have been shown to outperform Multi-Layer Perceptrons (MLPs) in MARL tasks [Singh et al., 2018] and help reduce redundant communication over time [Wang et al., 2020a]. Prior work in sparse communication has been able to reduce the total communication by over 75%, but at the cost of suboptimal task performance. Recent work also does not explore the benefits of moderate communication reductions, which may be useful when teaming with human partners, especially in memory intensive tasks. Attempts to reduce communication in MARL problems fall into one of three categories: gating, information bottleneck, and targeting.

Gating methods learn a gating function which decides whether or not an agent will communicate. By penalizing communication half the time during training and sending repeat messages, gating methods have reduced communication [Vijay et al., 2021]. However, this method is not able to choose a budget and requires repeated messaging, which is not required when training using our recurrent architecture. Gated Actor-Critic Message Learner (GACML) uses a set probability threshold value to determine gating and requires moderate pruning of communication to achieve its highest task performance [Mao et al., 2020]. Our method explores emergent gating through a soft threshold that can learn the optimal gating value. Additionally, our architecture also employs a hard enforcer to be able to further reduce the observed budget in the event of a stricter communication bandwidth.

Information bottleneck methods seek to minimize the entropy of messages between agents [Rashid et al., 2018; Wang et al., 2020b]. While information bottleneck techniques aim to only remove unnecessary communication, their results show that they decrease the overall reward, which leads to suboptimal task performance. These methods have one setting for reducing communication while our method offers both optimal and bounded suboptimal learned communication for any variable bandwidth.

Targeting methods learn with whom an agent should communicate. Methods have explored using attention, graph architectures, information bottlenecks for receiving information [Das et al., 2019; Agarwal et al., 2020; Goyal et al., 2020; Kim et al., 2019]. These reduce communication by targeting with whom to communicate with rather than reducing information overall. A separate line of work has developed a separate learned module called SchedNet to learn communication scheduling. SchedNet combines the targeting with a comparable method to rollover information from previous timesteps, which provides a similar benefit to the recurrent architecture used in our work. While our work does not address with whom an agent should communicate, these methods are complementary to our work and may be combined as an additional module. Targeting methods are easily combined with either the information bottleneck or gating methods such as in [Wang et al., 2020b].

3 Problem Setup

We formulate our multi-agent problem as a decentralized partially observable Markov Decision Process (Dec-POMDP) defined by the 7-tuple, \((S, A, T, R, O, \Omega, \gamma)\). We define \( S \) as the set of states, \( A_i \in [1, N] \) as the set of actions, which includes communication and task specific actions, for \( N \) agents. \( T \) is the transition between states due to the multi-agent joint action space \( T : S \times A_1, ..., A_N \rightarrow S \). \( \Omega \) defines the set of observations in our partially observable setting. The partial observability requires communication to complete the tasks successfully. \( O_i : A_{1_I}, ..., A_N \times S \rightarrow \Omega \) maps the joint actions and state to a distribution of observations for each agent. \( R \) defines the reward function and \( \gamma \) defines the discount factor. We use REINFORCE [Williams, 1992] to train both the gating function and policy network subject to the following constraints.

We define an optimal fraction of the total budget \( b^* \) at each uniform time unit, which defines the minimum communication between agents required to successfully complete a task. Our problem setup also considers the scenario when a fraction of the total budget \( b \) is less than optimal. Each agent needs to learn a joint action and communication policy which maximizes task performance, i.e. maximizing reward, while minimizing the difference, \( \min |c - b^*| \), between its observed fraction of total possible communication \( c \) and the optimal fraction of the total budget \( b^* \).

Continuous communication vectors have been shown to yield better performance than discrete communication tokens [Tucker et al., 2021]. Discrete prototypes are defined by the
number of discrete prototypes $N_p$ and the dimensionality of the prototype vector $d_p$. Our method seeks to minimize the difference between the reward from models with continuous communication vectors $R_c$ and reward from models with discrete prototype-based communication $R_p$. That is, our problem solves, $\min_{N_p,d_p} |R_c - R_p(N_p,d_p)|$.

## 4 Proposed Methodology

Our method introduces learned discrete prototypes for recent communication networks and constraints on the gating function of IC3Net-G [Singh et al., 2018]. The discrete prototypes that we implement are based on those described in [Tucker et al., 2021]. Our model connects the hidden state of its LSTM to a prototype network before passing the corresponding discrete prototype communication to other agents. See figure 1.

![Figure 1: Above is our modified IC3Net architecture. For each agent, the observation from the environment is inputted to the LSTM. The hidden state from the LSTM goes to the learned gating function, $f^g$, which decides whether to communicate. The output is provided to the prototype network before being communicated to the other agents as a discrete prototype.](image)

The main element of our work is the use of The Enforcers to constrain (with low variance) communication for arbitrary budgets. To enable efficient convergence, we implement a communication curriculum that penalizes any restriction on communication, $R_c$. For the fraction of the budget, the learning rate is tapered to enable convergence of the joint communication and action policy. Dropout is also used on the communication vectors such that the entirety of the communication is zeroed for an agent when the dropout activates.

### 4.1 Soft Enforcer

The soft enforcer uses a tuned reward function to ensure that communication is within a budget. However, the soft enforcer allows the agent to exceed the budget as it sees fit. That is, there exists some $\epsilon_s$, we have, $|b - c| < \epsilon_s$, for the fraction of the budget $b$ and the learned observed fraction of total communication $c$, such that the $\epsilon_s$ is learned at the discretion of the model. We constrain the budget with an additional term $R_{\text{commSoft}}^i$ in the reward to penalize communication,

$$R^i = R_{\text{env}}^i - \lambda R_{\text{commMax}}^i$$

where, in this case,

$$R_{\text{commMax}}^i = |1 - c|$$

for some observed gated observed fraction of total communication $c$. After achieving the success criterion again with the new reward function, we allow The Enforcers to do their job to further constrain the communication. Once the fraction communication exhibited is within some $\epsilon$ of our fraction of the budget, the learning rate is tapered to enable convergence of the joint communication and action policy. Dropout is also used on the communication vectors such that the entirety of the communication is zeroed for an agent when the dropout activates.
The hyperparameters are tuned empirically. Note that the method limits the integral term such that \( |R^i_c| < K \) for some hyperparameter \( K \) for stability.

The defined reward has the effect of limiting the variance of the reward, which in turn, provides a soft limit of the change in gated observed fraction of total communication while guiding the gated observed fraction of total communication towards the defined budget. However, since it is only a soft limit, it allows for exploration, which guides the gated observed fraction of total communication towards a more stable equilibrium.

### 4.2 Hard Enforcer

The hard enforcer restricts any communication over the allowed budget during training and testing. If the network tries to communicate beyond the fraction of the budget through the learned gating function, the communication is hardcoded to be masked. That is, the learned communication is strictly below the allowed fraction of the budget \( b \). In order to avoid trying to communicate over the budget, we vary training with random masking. Additionally, the hard enforcer introduces a reward penalty term to mitigate the learned gating function’s attempts to communicate over the budget. The hard enforcer defines the following reward,

\[
R^i = R^i_{\text{env}} - \lambda R^i_{\text{commHard}},
\]

where,

\[
R^i_{\text{commHard}} = |c^i_{\text{hard}} - c^*|,
\]

where \( c^* \) is the attempted fraction of total communication and \( c^i_{\text{hard}} \) is the resulting masked fraction of total communication.

In order to minimize communication, the communication gate should start with a maximum budget and taper the budget until performance degrades considerably, which will mark at what value is the optimal minimum budget. One may also taper the budget at any intermediate value between the maximum budget and the optimal minimum budget. This method also works with suboptimal budget, that is, budgets below the optimal minimum budget, in case the available bandwidth is below the optimal minimum budget. When using a hard enforcer, one can bound the performance of a suboptimal budget to fit one’s needs. This is discussed more in section 5.3.

### 5 Experiments

In this section, first we discuss the experiment setup. Then we discuss observed issues with gated learning and our observations when using a curriculum to solve these issues. Next, we demonstrate the importance of hyperparameter tuning to successfully enable effective discrete tokens. Finally, we analyze the effects of sparsity. We compare the analytical optimal communication fraction of the budget \( b^* \) to the learned optimal communication budget found with the soft enforcer. We analyze the performance of the soft enforcer at various expected communication budgets. For the hard enforcer, we show when it is necessary and analyze the bounded suboptimal performance.

We follow a similar training setup to related work described in IC3Net [Singh et al., 2018; Sukhbaatar et al., 2016] in cooperative environments of traffic junction and cooperative predator-prey over various difficulties. Traffic junction studies multiple agents traversing through a traffic junction without vision of where other agents are located. Predator-prey has multiple agents use communication to cooperate to find the prey. Our communication is restricted to one round of communication before choosing an action. Both the communication and action occur during 1 timestep. We train with a large batch size. We use 16 parallel processes where each has a batch size of 500 for a total of 8000 datapoints averaged over 10 gradient updates at each backpropagation at the end of an epoch. This reduces variance of training and encourages faster learning. The results, unless specified otherwise, are averaged over 3 seeds. Our training use an RMSProp optimizer with a global learning rate of 0.001.

We analyze "Fixed-Cts", which is the continuous communication with continuous communication vectors from IC3Net, and "Gated-Cts", which uses learned gating communication from IC3Net-G with continuous communication vectors. Our experiments compare these methods with methods that use discrete prototypes ("Proto") rather than continu-

| No. of Protos | Converg. Epoch | Final Avg. Reward |
|---------------|----------------|-------------------|
| 16            | 96             | 7.119             |
| 58            | 73             | 7.145             |
| 100           | 114            | 6.90              |

Table 2: **Cooperative Predator-Prey**: The number of epochs for convergence and the final average reward for all agents is shown above. Lower epochs and higher success rate is better.
Table 4: Traffic Junction: The above table compares the convergence epoch and success rate for fixed (continuous) vs. gated (sparse) communication and continuous vector vs. prototype-based (discrete) tokens in two traffic junction environments. The success rate shows that our tuned parameters for the prototype methods are able to enable similar performance comparable to continuous vectors. Our enforcer method is able to stably maximize success while using optimal communication $b^*$ and discrete prototypes. The enforcer method requires few additional epochs in addition to the “Fixed” method to converge to the optimal fraction of total communication.

Table 5: Traffic Junction: The table above shows the results of training using the soft enforcer with different fractions of the budget $b$. We compare the fraction of total communication \ success rate for each budget. The soft enforcer is able to yield consistent performance while the observed fraction of total communication is above the optimal fraction of the budget threshold $b^*$.

Table 6: Traffic Junction: The table above shows the performance of our model using the hard enforcer with different fractions of the budget $b$. We compare the fraction of total communication \ success rate for each budget. Our results show that even with a suboptimal bandwidth, the hard enforcer is able to constrain communication while maximizing performance.

5.1 Reduced Variance Through Curriculum Learning

Dual communication and policy learning is a high variance method. Shown in table 3 and 4, the gated methods, which decide for the model when to communicate, perform suboptimally with respect to task performance. This is due to convergence to a suboptimal fraction of total communication: that is, there is more communication required in order to increase the task performance (e.g. success rate in traffic junction). This may also occur when the communication "language" learned is not suitable for the task. The success rate or reward will be unable to increase to the same level as continuous communication due to the learned encoded "language". One can see this when the optimal fraction of total budget (as found by other models or analytically) is less than the observed fraction of total communication when the success or reward level is subpar.

Our gated curriculum avoids this instability by ensuring that the learned gate communicates over 90% of the time before introducing a soft/hard enforcer to begin reducing the learned communicate rate. Our method only takes an extra 10-20% training epochs to exhibit the expected communication properties. Additionally, the method converges nicely to slightly below the expected fraction of total communication (lower is better when working with a constrained bandwidth) when the expected fraction of total communication is above the optimal fraction of the budget $b^*$ (See figure 3).

5.2 Discrete Prototype Analysis

There are two important hyperparameters to enable successful discrete prototype-based communication: the dimension of the communication vector and the number of discrete prototypes. Ensuring the correct dimension of the communication vector is necessary to mimic the performance of continuous vector-based communication. Finding the required number of discrete prototypes is task specific. Since the observation of an agent’s current grid cell directly influences the communication, we assume the emergent communication vectors must be similar to the cell locations. For easy traffic junction, the number of cells in the environment is 14. Table 1 analyzes the number of epochs required for the model to converge to above a 95% success rate while varying the communication vector dimension and number of prototypes in the traffic junction environment. Our results show that redundant prototypes help converge to a better solution quality while a larger communication vector dimension helps decrease the number of epochs required for convergence. However, too large of a communication vector dimension will lower performance and may take longer to converge.

We run a similar analysis varying the number of prototypes required in the predator-prey environment. Agents have a vi-
sion of 1 (i.e. agents view a $3 \times 3$ area around their current cell), which means that the number of states needed to cover the entire $10 \times 10$ environment is lower than the number of cells. Note that the minimum number of cells necessary to view the entire environment is 16. Table 2 yields a similar conclusion to the traffic junction experiments. One can do well with the minimum number of prototypes, but added redundancy improves the overall performance and lowers the numbers of epochs required for convergence. However, using too many prototypes will hurt overall performance.

5.3 Sparsity Analysis

Analytical sparsity analysis. Before comparing the soft and hard enforcers, it is helpful to get a baseline for an optimal communication budget. We implement a version of expectimax [Wikipedia contributors, 2020] (with memory for pruning) on the easy traffic junction environment to understand the maximum performance without communication. The algorithm yields 35.3% of cases in traffic junction easy that result in collision. From the success score, we can determine what percentage of cases require communication to be successful, which serves as a lower bound of an optimal communication budget. However, due to the recurrent nature of our training, this is not necessarily a strict lower bound. Due to combinatorial complexity, we do not compute analytical solutions for more complex environments.

Our results for the soft enforcer show that the method is best used in cases where one wants to maintain maximal performance while decreasing the fraction of total communication within the bounds of the optimal communication budget. Table 5 shows the results of the soft enforcer with different values for the fraction of the budget $b$. For the easy traffic junction environment, the model is able to attain high success rates with various fractions of total communication between 30-100%. The soft enforcer also reveals that the true optimal fraction of total communication is around 30% for our recurrent model since performance degrades at 20%. In more difficult problems, the medium traffic junction environment, the soft enforcer is able to converge to a variety of fractions of the total budget as shown in figure 3. However, since this is a more difficult problem, there is a small performance loss as communication decreases, which shows that the optimal communication budget is quite high.

Note that this performance requires an adequately pre-trained network with optimizer settings and tuned constant hyperparameters for the soft enforcer such that exploration is allowed. Our method used $K = 0.1$, $K_p = 1$, $K_d = 1.6$, and $K_i = 0.026$.

The soft enforcer is unable to converge to ultra-low levels of communication due to their suboptimal nature contradicting with the joint communication and task performance reward. The hard enforcer explores the model’s performance in suboptimal communication budget scenarios. Since there is a fixed bound rather than a learned bound (soft) on the overall budget, the model can learn to best adapt to a suboptimal budget. Table 6 shows the results of the hard enforcer with different values for the suboptimal communication fraction of the budget $c_{hard}$. The hard enforcer is able to minimize the loss of performance while enforcing the bandwidth.

Our soft and hard enforcers are able to do better than the average performance of the previous gating model of IC3Net. Tables 3 and 4 show that our enforcer method is able to perform better than the the IC3Net-G method while still having comparable performance to the IC3Net-Fixed method, which has no constraint on communication. Our enforcer methods is able to achieve a similar success rate to the continuous “Fixed” method while communicating at an optimal fraction of the total fraction of the budget $b^*$ consistently. Our enforcer method is able to outperform the high variance gated methods, which sometimes learn to reduce communication and do not match the performance of continuous “Fixed” methods. Our enforcer method only requires a small number of additional epochs as compared with the “Fixed-Proto” method to achieve optimal sparsity.

6 Conclusion and Future Work

Sparse-discrete methods have long suffered from inconsistent suboptimal performance. In this paper, we have introduced a soft enforcer to reduce communication to an optimal budget and hard enforcer to learn emergent behavior when there is a suboptimal budget. The enforcers are able to match the performance of continuous, unconstrained methods. We also show how to properly tune discrete prototypes. While minimizing the number of discrete prototypes creates a more efficient model, some redundancy helps to minimize performance loss and find solutions faster. Our method also serves as a precursor to methods that will help bridge the gap with human-agent teaming.

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