On Solving Cooperative MARL Problems with a Few Good Experiences

Rajiv Ranjan Kumar*, Pradeep Varakantham
School of Information Systems, Singapore Management University
{rajivrk.2017@phdcs.smu.edu.sg, pradeepv@smu.edu.sg}

Abstract

Cooperative Multi-agent Reinforcement Learning (MARL) is crucial for cooperative decentralized decision learning in many domains such as search and rescue, drone surveillance, package delivery and fire fighting problems. In these domains, a key challenge is learning with a few good experiences, i.e., positive reinforcements are obtained only in a few situations (e.g., on extinguishing a fire or tracking a crime or delivering a package) and in most other situations there is zero or negative reinforcement. Learning decisions with a few good experiences is extremely challenging in cooperative MARL problems due to three reasons. First, compared to the single agent case, exploration is harder as multiple agents have to be coordinated to receive a good experience. Second, environment is not stationary as all the agents are learning at the same time (and hence change policies). Third, scale of problem increases significantly with every additional agent.

Relevant existing work is extensive and has focussed on dealing with a few good experiences in single-agent RL problems or on scalable approaches for handling non-stationarity in MARL problems. Unfortunately, neither of these approaches (or their extensions) are able to address the problem of sparse good experiences effectively. Therefore, we provide a novel fictitious self imitation approach that is able to simultaneously handle non-stationarity and sparse good experiences in a scalable manner. Finally, we provide a thorough comparison (experimental or descriptive) against relevant cooperative MARL algorithms to demonstrate the utility of our approach.

1 Introduction

Cooperative MARL is an important framework for learning agent policies in multiple domains such as disaster rescue [Parker et al., 2016], fire fighting [Oliehoek et al., 2008] and package delivery (box pushing) [Seuken and Zilberstein, 2012]. In these problems, a team of decentralized agents coordinate to accomplish tasks (find people, extinguish fires, and deliver boxes to destinations) in uncertain domains. There are multiple key challenges in these learning problems: (a) Uncertainty in movement or in accomplishing tasks; (b) Coordination of decentralized entities to accomplish tasks (e.g., big fires require multiple fire engines or delivering a large box may require multiple robots; (c) Affected global state: Global state (representing status of tasks) can be impacted by agent actions; and most importantly (d) Sparse good experiences: rewards are obtained only when tasks are accomplished and there are only a few tasks.

The problem of learning with a few good experiences or sparse rewards studied also in single agent RL [Oh et al., 2018] is exacerbated in MARL problems due to three reasons: (1) Exploration is significantly harder as multiple agents have to be coordinated; (2) Environment is not stationary (multiple agents are learning together); and (3) Scale of problem increases significantly with every additional agent. In summary, exploration to find good policies is challenging and even if we find good policies, addressing non-stationarity and scalability can result in forgetting those good policies.

Research of relevance to this paper has focussed on addressing: (a) A few good experiences [Pomerleau, 1991; Oh et al., 2018; Lee and Lee, 2019; Lerer and Peysakhovich, 2019] primarily in single agent RL and sparsely in multi-agent RL through imitation learning; (b) Non-stationarity (due to multiple agents learning simultaneously) in MARL [Palmer et al., 2018; Omidshafiei et al., 2017; Forster et al., 2018]; (c) Scalability in MARL by exploiting anonymity and homogeneity [Nguyen et al., 2017; Yang et al., 2018]. Even though the relevant research in MARL is extensive, there is not much research on handling sparse good experiences in MARL. Most importantly, the current best approaches are unable to provide good policies (as demonstrated in experimental results) for cooperative MARL problems with only a few good experiences.

To that end, we provide a novel approach that not only learns effectively from a few good experiences but is also decentralized and scalable. Specifically, we make the following key contributions: (i) we incorporate self imitation into a state of the art MARL approach called Neural Fictitious Self Play (NFSP), so as to replay past good experiences and ensure effective exploration; (ii) we introduce a modification to policy averaging in NFSP to ensure good policies remain relevant; (iii) we also provide theoretical intuition for why the new policy averaging method follows the generalized weakened fictitious play property, thereby guaranteeing convergence. Finally, we demonstrate that our approach is able to get significant improvement in performance over leading MARL approaches on three benchmark problem domains from literature.
2 Related Work

In this section, we highlight research of relevance to the contributions of this paper.

Sparse Good Experiences

Imitation learning (IL) enables a learner to imitate expert behavior in an underlying MDP environment. A wide variety of IL methods have been proposed in the last few decades. The simplest IL method among those is Behavioral Cloning (BC) [Pomerleau, 1991] which: (i) collects demonstrations from expert(s); (ii) treat the demonstrations as i.i.d state-action pairs; (iii) learn policy using supervised learning. [Lerer and Peysakhovich, 2019] is another BC approach that is focussed on social dilemma. BC requires many demonstrations and unfortunately, it is typically not feasible to obtain many demonstrations from experts in real-world scenarios.

[Lee and Lee, 2019] employs demonstrations to improve multiagent learning. This paper is limited to problem settings where reasonable centralized policy can be obtained, therefore their method is only applicable to small 2 agents problems for which they can compute a centralized policy either from MMDP or MPOMDP. Since problems considered in the paper have more number of agents, it is not feasible to solve an MMDP or MPOMDP to obtain a centralized policy.

[Oh et al., 2018] provides a Self Imitation Learning (SIL) approach for single agent RL where (good) experiences generated during exploration are stored in a prioritized buffer (henceforth referred to as the $M_{SI}$ buffer) based on cumulative reward achieved. During training, it samples the experiences from this buffer and trains the neural networks only if the network is predicting a lower value for these experiences. SIL does not directly extend to multi-agent RL and in this paper, we provide an extension of SIL for multi-agent settings.

Non-Stationarity

There are two threads of relevant research in cooperative MARL for dealing with non-stationarity. First, we have team learning approaches [Haynes and Sen, 1995; Claus and Boutilier, 1998] where a single learner learns policies for a team of agents. Team learning approaches suffer from curse of dimensionality. Furthermore, it may not be realistic to assume centralization of information, especially if the agents themselves receive decentralized observations that cannot be shared with other agents at every step.

The second thread of research has focused on decentralized learning [Agogino and Tumer, 2006; Tampuu et al., 2017], where agents learn concurrently to avoid the curse of dimensionality and centralization of information. Since individual agents are changing their policies concurrently, RL problem experienced by each agent is no longer stationary and can result in unstable and divergent learning performance. In order to address this non-stationarity issue, a centralized critic is employed. One of the leading approaches in this space is called COMA [Foerster et al., 2018].

[Palmer et al., 2018] have applied “leniency” and [Omidshafiei et al., 2017] have applied Hysteric Q Learning to counter non-stationarity problem in MARL. Unfortunately, none of these approaches have a mechanism for handling the issues of exploration and forgetting of good policies arising due to having only a few good experiences.

Scalability

A leading approach is by [Nguyen et al., 2017] to solve cooperative problems with large numbers of homogeneous agents and anonymous interactions. However, it relies on having non-global states and transition function decomposability given number of agents. This is not feasible in domains of interest in this paper and since it is based on actor critic architecture, it has same issues as other MARL approaches with sparse rewards.

Another approach ([Yang et al., 2018]) along this line is based on mean field games [Lasry and Lions, 2007]. Unfortunately, approaches based in mean field, where indistinguishably property should hold - i.e. the game should be invariant under permutation of the agents’ indices, are not suitable as different types of agents (ambulances and fire trucks) can exist in MARL problems.

The last thread of relevant research has employed game theory to develop decentralized learning methods [Hu and Wellman, 2003; Heinrich et al., 2015; Heinrich and Silver, 2016]. One of the leading approaches is the neural fictitious self play method [Heinrich and Silver, 2016], which employs ideas from the well known fictitious play [Brown, 1951] method. Given the focus on equilibrium for game theoretic methods, these approaches can get stuck in bad local optima in the case of cooperative problems. However, a key advantage of relevance specifically of NFSP is being able to perform decentralized learning at scale.

3 Background

In this section, we describe key concepts/approaches on which we build upon in this paper, namely Generalized Weakened Fictitious Play and Neural Fictitious Self Play (NFSP).

3.1 Generalized Weakened Fictitious Play, GWFP

In Fictitious play (FP), a popular approach for computing Nash Equilibrium in normal-form single shot games, fictitious players choose exact best responses against their opponents’ average strategy at each iteration. FP is guaranteed to converge to a Nash equilibrium for zero-sum games, potential games and identical interest games (i.e., cooperative multi-agent problems). FP requires the computation of exact best response and [Leslie and Collins, 2006] relaxed this requirement by providing Generalized Weakened Fictitious Play (GWFP). GWFP works with approximate best responses as follows:

$$
\pi^{t+1} \in (1 - \eta^{t+1})\pi^t + \eta^{t+1} \cdot b_{\pi^t}(Q^t)
$$

where $\eta^t \rightarrow 0$, $\epsilon^t \rightarrow 0$, $||Q^t - R(\pi^t)|| \rightarrow 0$ as $t \rightarrow \infty$. $b_{\pi^t}(Q^t)$ is best response to the policy. $R(\pi^t)$ is the reward for an agent given that it is following policy ($\pi^t$). This generalized and weakened version has similar guarantees as the original FP algorithm and converges for potential games, identical interest and zero sum games.

3.2 Neural Fictitious Self Play (NFSP)

In order to overcome the scalability issue (particularly with respect to agents taking multiple decisions) with FP and its extensions. [Heinrich et al., 2015; Heinrich and Silver, 2016] proposed an appropriately approximated method for generalized weakened fictitious play referred to as Neural Fictitious Self Play (NFSP). Specifically,

- Instead of computing the exact best response strategy, NFSP learns an approximate best response using Deep Q-Networks (DQN) [Mnih et al., 2015]. Deep Q network
with parameters $\theta^Q$ is trained using the following loss function:

$$
L(\theta^Q) = E_{(s,a,r,s') \sim M_{RL}} \left[ (r + \max_{a'} Q(s',a'|\theta^Q) - Q(s,a|\theta^Q))^2 \right]
$$

where $M_{RL}$ refers to the stored RL experiences (i.e., past game transitions).

- Instead of averaging full exact strategies, each agent learns an approximate average strategy by using supervised learning (SL) with deep neural networks [Heinrich and Silver, 2016]:

$$
L(\theta^S) = E_{(s,a) \sim M_{SL}} \left[ -\log(\pi(s,a|\theta^S)) \right]
$$

where $M_{SL}$ refers to the stored Supervised Learning experiences (i.e., past best responses).

4 Neural Fictitious Self Imitation Play, NFSIP

In this section, we describe our main algorithm, NFSIP (pseudocode in Algorithm 1) for cooperative MARL problems in the presence of only a few good experiences. Here are the key contributions in NFSIP:

1. NFSIP implements self imitation for multi-agent settings in context of NFSP.
2. NFSIP provides novel insights on value and policy network updates that preserve the fictitious play property while dealing with the issue of few good experiences. This ensures guarantees on convergence under certain conditions.

There are four key steps to the NFSIP algorithm:

1. **Store experiences in appropriate replay buffers**: An NF-SIP agent interacts with its fellow agents and stores its experience of state transitions in $M_{RL}$ buffer and its own best response behaviour in $M_{SI}$ buffer (lines 6 in pseudocode). Once an episode ends, a copy of the individual experiences, $(s, a, r, s')$ updated to include cumulative rewards $R$ (i.e., $(s, a, R(s, a), s')$) are stored in the prioritized buffer, $M_{SI}$. Once episode ends, in lines 10-14, we update the self imitation buffer, $M_{SI}$ with experiences if social welfare (welfare of the entire system, including all agents) is higher than the set threshold for social welfare (bestReward achieved so far). These experiences are updated to include cumulative rewards.

2. **Learn from all experiences**: For each agent, in NFSIP, we update the average policy network and Q-network parameters based on all the experiences (good and bad).

3. **Learn from self imitation buffer**: Since there are only a few good experiences, it is imperative that updates from “good” experiences (i.e., ones that improve social welfare) are not overwritten by “bad” experiences. Therefore, in NFSIP, we have a separate self imitation loop at the end of each episode to not forget the learning from “good” experiences. In this self imitation loop, we update both the average policy and Q-network parameters based on difference in the reward obtained from the episode and the current value function estimate.

4. **Mixing the approximate average strategy and approximate best response**: The resulting Q-network (from the above parameter updates) for each agent is used in its approximate best response strategy, $b_{i}(Q)$, which selects a random action with probability $\epsilon$ and otherwise chooses the action that maximizes the predicted action values. On the other hand, we have the II-network which defines the agents’ average strategy so far. During execution, the agent chooses its actions from a mixture of its two strategies, $b_{i}(Q)$ and II. Line 4 ensures the mixing of average and approximate best response using the parameter $\eta$.

Having only a few good experiences results in bad multi-agent cooperative learning for two reasons: (i) Good experiences are few so value updates can be lost due to bad experiences and non-stationarity. (ii) Policy averaging can result in bad policies overwriting the impact of good policies. To that end, we provide two sets of novel insights in NFSIP with respect to steps 3 and 4 above that help in learning good policies and good value functions even when there are only a few good experiences:

- **Self Imitation Learning for Cooperative MARL**: This is to ensure value updates corresponding to good experiences happen multiple times if the value is learned incorrectly for states involved in good experiences.

- **Good experience driven policy averaging**: This provides a novel way of weighted policy averaging in Fictitious Play to ensure good policies are not washed away.

4.1 SII for Cooperative MARL

Self imitation learning in single agent case imitates past good experiences multiple times (based on priority) and prioritizes learning with those good experiences. However, in multi-agent problems, due to simultaneous learning of agents, past good experience for an agent may not be a good experience if other agents have changed their policy. Therefore, our first insight here is to judge the goodness of any experience not just based on its own reward but also based on social welfare.

Due to non stationary environment we want to avoid utilizing old experiences, for this we periodically remove expert data (self) generated for self imitation process. We do so when we encounter a better social welfare solution. Our second insight here is to employ a threshold value that is slowly adjusted to ensure that there are always expert experiences for training that are not too old and provide higher social welfare.

Finally, we train only with experiences where neural network is predicting a lower value than the actual value (cumulative reward) of the agent. To ensure this, we employ the following term in value and policy parameter updates:

$$
[R(s, a) - V(s|\theta^Q)]_+ = \max(0, R(s, a) - V(s|\theta^Q))
$$

where, $W = \sum R(s, a)$ i.e., Welfare of the entire system (social welfare)

$$
W_T = \text{Threshold value for social welfare}
$$

Where $R(s, a) = \text{Cumulative reward of agent}$,
4.2 Good Experience Driven Policy Averaging

We first highlight the key issue with policy mixing in NFSP with regards to sparse rewards. NFSP employs maximum log likelihood (using loss as negative log likelihood) for learning the mixture of past policy, \( \pi' \) and current approximate best response policy, \( b_\pi(Q') \) based on the observed samples (i.e., best response actions taken at each iteration). The standard maximum likelihood principle implicitly places equal weight on each of the observations in the sample. Taking the example of coin toss, if after 1000 iterations, if we observed 700 heads and 300 tails, maximum likelihood will predict a biased coin with 0.7 and 0.3 probability. However, this is incorrect as the sampled data was biased. This issue is more prominent in RL problems where good experiences come by rarely. So, samples data is bound to have rare occurrences of them, causing maximum likelihood to result in bad local optima.

One way to improve the model is to use weighted maximum likelihood. Such methods have been employed in for risk management in Finance [Steude, 2011] and for image denoising in image processing [Deledalle et al., 2009]). [Steude, 2011] have shown that downweighting the observations that bear a high probability of being destructive outliers can considerably improve the forecast accuracy for a variety of data sets and different time series models. [Deledalle et al., 2009] derived the weights in a data driven manner. The weights are iteratively refined.

For solving MARL with a few good experiences, we build on similar ideas. Specifically, we increase weight for recent experiences in NFSP. For solving MARL with a few good experiences, we build on similar ideas. Specifically, we increase weight for recent experiences in NFSP. To achieve that, we add the following additional loss based on experiences in step t:

\[
L(\theta) = E_{(s,a,r,t)} \left[ -\log(\pi(s,a) \cdot \left( R(s,a) - V(s) \right)_+ \right]
\]

where, \( [R(s,a) - V(s)]_+ = \max(0, R(s,a) - V(s)) \)

On similar lines, we also add an additional weight to the Q-network loss based on self imitation memory, \( M_S \).

Theoretical Intuition

In this section, we provide the intuition for why good experience driven policy averaging in NFSP satisfies the GWFP property of Section 3.1. This is an important property as it justifies the convergence of NFSP for cooperative MARL problems.

Specifically, we show that if policy averaging in NFSP is:

\[
\pi^{t+1} \in (1 - \eta^{t+1})\pi^t + \eta^{t+1} \cdot b_\pi(Q') \text{ with } \eta^{t+1} = \frac{1}{t+1}
\]

then, policy averaging in NFSP is given by:

\[
\pi^{t+1} = \left(1 - \eta^{t+1}_NFSIP\right)\pi^t + \eta^{t+1}_NFSIP \cdot b_\pi(Q') \text{ with } \eta^{t+1}_NFSIP = \frac{1 + \Gamma}{t + 1}
\]

and \( \Gamma = \left[R(s,a) - V(s|\theta^t)\right]_+ \)

Intuitively, this is to say that NFSP just changes the mixing parameter (that satisfies all properties desired of the mixing parameter) in comparison to NFSP.

Policy Averaging in NFSP:

We begin with NFSP network updates for policy averaging in NFSP. The action-value network loss function is given by:

\[
L(\theta^Q) = E_{(s,a,r,t)} \left[ (r(s,a) + \max_a' Q(s',a'|\theta^Q) - Q(s,a|\theta^Q))^2 \right]
\]

(1)

The policy network loss function is given by:

\[
L(\theta^\pi) = E_{(s,a)} \left[ -\log(\pi(s,a|\theta^\pi)) \right]
\]

(2)

When we train the two networks (learning rates \( \alpha, \beta \)), the parameter updates for policy and action-value networks are as follows:

\textbf{1-network update:} \( \theta^\pi = \theta^\pi + \alpha \nabla \log(\pi(s,a|\theta^\pi)) \)

\textbf{Q-network update:}

\[
\theta^Q = \theta^Q - \beta \nabla \left( r + \max_a' Q(s',a'|\theta^Q) - Q(s,a|\theta^Q) \right)^2
\]

Since \( Q(s',a'|\theta^Q) \) is based on \( \theta^Q \) and not \( \theta^Q \)

\[
= \theta^Q + \beta \left( r + \max_a' Q(s',a'|\theta^Q) - Q(s,a|\theta^Q) \right) \nabla Q(s,a|\theta^Q)
\]

(4)

GWFP [Leslie and Collins, 2006] is defined as follows:

\[
\pi_{t+1} \in (1 - \eta_{t+1})\pi^t + \eta_{t+1} \cdot b_\pi(Q') \text{ with } \eta_{t+1} = \frac{1}{(t+1)}
\]

where \( \eta_{t+1} \rightarrow 0, \epsilon_t \rightarrow 0, \|Q' - R(\pi^t)\| \rightarrow 0 \) as \( t \rightarrow \infty \)

NFSP and standard FP typically employ: \( \eta_{t+1} = \frac{1}{(t+1)} \) in order to satisfy GWFP criterion above.

Network updates with only Self Imitation Learning (SIL):

NFSP employs self imitation loop on top of NFSP updates. We first compute the self imitation learning related updates and add it over the updates above for NFSP.

The action-value network loss function is given by:

\[
L(\theta^Q) = E_{(s,a,r,t)} \left[ (\left[R(s,a) - V(s|\theta^Q)\right])^2 \right]
\]

(5)

The policy network loss function is given by:

\[
L(\theta^\pi) = E_{(s,a,r,t)} \left[ -\log(\pi(s,a|\theta^\pi)) \cdot \left(R(s,a) - V(s|\theta^Q)\right)_+ \right]
\]

(6)

Where, \( [R(s,a) - V(s|\theta^Q)]_+ = \left\{ \begin{array}{ll} 0, & \text{if } [R(s,a) - V(s|\theta^Q)] \leq 0 \\ [R(s,a) - V(s|\theta^Q)], & \text{otherwise} \end{array} \right. \)

The parameter updates for the two networks are as follows:

\textbf{1-network update:}

For a baseline, \( V(s|\theta^Q) \) that is independent of current policy, \( [R(s,a) - V(s|\theta^Q)]_+ \) is constant. Therefore,

\[
\theta^\pi = \theta^\pi + \alpha ([R(s,a) - V(s|\theta^Q)]_+ \nabla \log(\pi(s,a|\theta^\pi))
\]

(7)

\textbf{Q-network update:}

Q network is optimized based on \( [R(s,a) - V(s|\theta^Q)]_+ \):

Case 1: \( [R(s,a) - V(s|\theta^Q)]_+ = 0 \) : This is trivial as there will be no update to Q network.

Case 2: \( [R(s,a) - V(s|\theta^Q)]_+ > 0 \Rightarrow [R(s,a) - V(s|\theta^Q)]_+ = 0 \)

\[
\theta^Q = \theta^Q + \alpha ([R(s,a) - V(s|\theta^Q)]_+ \nabla Q(s,a|\theta^Q))
\]
\[ V(s|\theta^Q)_+ = [R(s, a) - V(s|\theta^Q)] \]

Considering \( V(s|\theta^Q) = (1/|A|) \sum_a Q(s, a|\theta^Q) \), we have
\[
\nabla (\langle [R(s, a) - V(s|\theta^Q)]_+ \rceil s, a \theta^Q) = 2(1/|A|) \sum_a Q(s, a|\theta^Q) \nabla (-Q(s, a|\theta^Q))
\]
Therefore,
\[
\theta^Q = \theta^Q + \beta 2(1/|A|) \langle [R(s, a) - V(s|\theta^Q)]_+ \rceil s, a \theta^Q \nabla (-Q(s, a|\theta^Q))
\]

**Policy Averaging for NFSIP:**

We now combine NSFSP (3, 4) and SIL updates (7, 9).

**Pi-network update:**
\[
\theta^{\pi} = \left( \theta^{\pi} - \alpha \nabla \left( \log(\pi(s, a|\theta^{\pi})) \right) \right) - \alpha \langle [R(s, a) - V(s|\theta^Q)]_+ \rceil s, a \theta^Q \nabla \log(\pi(s, a|\theta^{\pi}))
\]

\[
= \theta^{\pi} + \alpha (1 + [R(s, a) - V(s|\theta^Q)]_+) \nabla \log(\pi(s, a|\theta^{\pi}))
\]

\[ Q\text{-network update:} \]
\[
\theta^Q = \left( \theta^Q + \beta 2(r + \max_{a'} Q(s', a'|\theta^Q) - Q(s, a|\theta^Q)) \nabla Q(s, a|\theta^Q) \right)
\]
\[
+ \beta 2(1/|A|) \langle [R(s, a) - V(s|\theta^Q)]_+ \rceil s, a \theta^Q \nabla Q(s, a|\theta^Q)
\]
\[
= \theta^Q + \beta 2(r + \max_{a'} Q(s', a'|\theta^Q) - Q(s, a|\theta^Q)) \nabla Q(s, a|\theta^Q)
\]
\[
+ (1/|A|) \langle [R(s, a) - V(s|\theta^Q)]_+ \rceil s, a \theta^Q \nabla Q(s, a|\theta^Q)
\]

NFSP satisfies GWFP with \( \eta = \frac{1}{t+1} \). With policy and Q update as given in 10 and 11 respectively, NFSP satisfies GWFP property in the same way as NSFIP:
\[
\pi^{t+1} = (1 - \eta^{t+1}_{\text{NFSIP}}) \pi^t + \eta^{t+1}_{\text{NFSIP}} \cdot b_{\epsilon^t}(Q^t)
\]
with \( \eta^{t+1}_{\text{NFSIP}} = (1 + \Gamma)/(t + 1) \) and \( \Gamma = [R(s, a) - V(s|\theta^Q)]_+ \), where \( \eta_{\text{NFSIP}} \to 0, \epsilon^{t+1} \to 0, ||Q^{t+1} - R(\pi^{t+1})|| \to 0 \) as \( t \to \infty \).

GWFP holds exactly when the baseline, \( V(s|\theta^Q) \) is independent of policy. However, when the baseline is dependent on policy (e.g., \( V(s|\theta^Q) = \sum_a \pi(s, a|\theta^Q) Q(s, a|\theta^Q) \)), there is an additional term with respect to policy, \( \pi \) in the update expression of Q-network. In practice, we see that the performance converges in all our examples when we use a baseline dependent on policy.

5 Experimental Results

In this section, we evaluate the performance of our approach (NFSIP) in comparison to leading approaches for cooperative MARL. We perform the comparison on three different benchmark problems from literature: (a) Box Pushing [Seuken and Zilberstein, 2012]; (b) Fire Fighting [Oliehoek et al., 2008]; and, (c) Search and Rescue [Nanjanath et al., 2010; Parker et al., 2016]. We extend these problem settings to ones with many agents and larger state space, so as to make good experiences sparse. We compare against the following leading approaches for cooperative MARL: (a) COMA; (b) NSFSP; (c) AC-SIL: Multi-agent extension of SIL; (d) COMA-SIL: An SIL extension for COMA.

We now provide details of the benchmark problems:

- **Box pushing problem** [Seuken and Zilberstein, 2012]: Multiple agents need to coordinate and push boxes of different sizes to their goal locations in a grid world. Each agent has 6 possible actions to take: {move left, move right, move up, move down, act on the task, stay}. To successfully push a box, certain number of agents need to act on it. For this domain, we created simpler instances with a 4x4 grid, 4 boxes and 5-agents in box pushing. We created different versions of this problem with smaller grid sizes as benchmark algorithms were unable to learn at all on larger problem instances.

- **Firefighting problem** [Oliehoek et al., 2008]: In this problem setting we have a 4x4 grid with 10 agents (fire trucks), fires are spread over different locations. Number of trucks needed to put out the fire depends on its intensity (low/high).

- **Search and Rescue** [Parker et al., 2016]: Different types of agents (such as firetrucks and ambulances) need to coordinate with each other. In this problem setting we have a 4x4 grids with 5 ambulances and 5 firetrucks. Number of firetrucks and ambulances range from 1 to 5.

\[ \text{Algorithm 1 Neural Fictitious Self Imitation and Play, NFSIP} \]

1: Initialize \( \theta^{\pi}, \theta^Q \) and \( \theta^Q \) networks
2: bestReward = \(-\infty\)
3: while Not Converged do
4: policy = \( \begin{cases} b_{\eta}(Q) & \text{with probability } \eta \\ \pi & \text{with probability } 1 - \eta \end{cases} \)
5: for every time step do
6: Sample from \( M_{RL} \), train \( \theta^Q \) using Q-Loss (Eq 1)
7: Sample from \( M_{SL} \), train \( \theta^Q \) using \( \pi \)-Loss (Eq 2)
8: if episodeReward > bestReward then
9: Reset \( M_{SI} \) and bestReward = Episode reward
10: if episodeReward >= bestReward then
11: Compute cumulative reward, \( R \)
12: Store experiences in \( M_{SI} \) prioritized on \( R \)
13: for some iteration do
14: for all agents do
15: Sample from prioritized replay buffer, \( M_{SI} \)
16: Train \( \theta^Q \) using SIL Q-loss (Eq 5)
17: Train \( \theta^Q \) using SIL \( \pi \)-loss (Eq 6)
20: Update target action-value network, \( \theta^Q \) periodically
ambulances needed to complete the task depends on difficulty of the scenario. We created different versions of the problem. All results are averaged over multiple runs. We ran NFSIP, NFSP and AC-SIL for 5 times each. In results we plot average over 5 runs (line plot) as well as variance over different runs (shaded region). Due to counterfactual baseline computation for every action, COMA is very slow (and took 1-2 weeks for training) as compared to our approach (which took 1-2 days). Here are the key observations from Figures 1 and 2:

- On the simplest problems, i.e., ones in box pushing, COMA is able to learn good policies. However, NFSIP and AC-SIL perform the best even on these simplest problems.
- NFSIP is able to outperform both NFSP and COMA on all 6 scenarios.
- NFSIP is able to perform as good as or better than AC-SIL. In the last scenario (Search and Rescue V2), NFSIP is able to get a result that is 5 times that of AC-SIL.
- NFSIP not only outperformed COMA-SIL, AC-SIL and NFSP, variance is also low in case of NFSIP as compared to other approached compared here.

5.1 Neural network Architecture and Training:

Policy/Q network in NFSIP has 2 hidden layers (32 nodes in each layer). We used same number of hidden layers/nodes in all experiments/methods. After every hidden layer we used layer norm. In all experiments we start with exploration rate of 10% (NFSP/NFSIP: $\eta = 0.2, \epsilon = 0.5$ and $\epsilon = 0.2 \times 0.5 = 0.1$ for other methods). After every 500 iteration we reduce epsilon to a factor of 0.98. In NFSP/NFSIP all agents share parameters in both networks. i.e, there is one policy network and one best response network that takes agents Ids as input to distinguish between them. We used learning rate of $10^{-3}$ for actor/policy and $10^{-4}$ Q/Critic network. We wan SIL loop 5 times (line 19 of Algorithm 1). Hyper parameters were coarsely tuned on the box pushing scenario and then used for firefighting and 'Search and Rescue'. The most sensitive parameter was exploration parameter. In all methods we periodically discarded older experiences (except the SL buffer in NFSP/NFSIP). And used batch training with batch size of 32.

For tuning the social welfare threshold value we experimented with different techniques, But since here in all problem setting reward is discrete therefore we went with most logical choice of tuning it, which is whenever we encounter the experiences for which social welfare is higher than cur-
rent threshold, we update the threshold value to current social welfare and discarded old experiences.

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