Collaboration Promotes Group Resilience in Multi-Agent AI

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December 13, 2022

Abstract

AI agents need to be robust to unexpected changes in their environment in order to safely operate in real-world scenarios. While some work has been done on this type of robustness in the single-agent case, in this work we introduce the idea that collaboration with other agents can help agents adapt to environment perturbations in multi-agent reinforcement learning settings. We first formalize this notion of resilience of a group of agents. We then empirically evaluate different collaboration protocols and examine their effect on resilience. We see that all of the collaboration approaches considered lead to greater resilience compared to baseline, in line with our hypothesis. We discuss future direction and the general relevance of the concept of resilience introduced in this work.

1 Introduction

Reinforcement Learning (RL) agents are typically required to operate in dynamic environments, and must develop an ability to quickly adapt to unexpected perturbations in their environment. Promoting this ability is hard, even in single-agent settings Padakandla (2020). For a group this is even more challenging; in addition to the dynamic nature of the environment, agents need to deal with high variance caused by changes in the behavior of other agents.

Unsurprisingly, many recent Multi-Agent RL (MARL) works have shown the beneficial effect collaboration between agents has on their performance Xu, Rao, and Bu (2012); Foerster et al. (2016); Lowe et al. (2017); Qian et al. (2019); Jaques et al. (2019); Christianos, Schäfer, and Albrecht (2020). Our objective is to highlight the relationship between a group’s ability to collaborate effectively and the group’s resilience, which we measure as the group’s ability to adapt to perturbations in the environment. Thus, agents that collaborate not only increase their expected utility in a given environment, but are also able to recover a larger fraction of the previous performance after a perturbation occurs.

Contrary to investigations of transfer learning Zhu, Lin, and Zhou (2020); Liang and Li (2020) or curriculum learning Portelas et al. (2020), we do not have a stationary target domain in which

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the group of agents is going to be deployed, nor do we have a training phase dedicated to preparing agents for the deployment environment. Instead, we aim to measure a group’s ability to adapt to unexpected changes that can occur at random times and show that the ability to collaborate with other agents may increase resilience.

Recent literature is rich with different definitions of resilience and robustness, for both single and multi-agent settings Zhang, Zhang, and Gupta (2017); Vinitsky et al. (2020); Pattanaik et al. (2018). Most work focuses on resilience in the presence of deliberate adversary attacks on one or many agents in the system Saulnier et al. (2017). We focus instead on non-adversarial settings and measure group resilience according to the agents’ performance in the presence of unexpected and random environment perturbations, and on the ability to promote resilience by facilitating collaboration.

Our focus here is on multi-agent reinforcement learning (MARL) settings for which previous work demonstrates how collaboration allows a group to learn and operate efficiently in complex but stationary environments Jaques et al. (2019); Foerster et al. (2016); Christianos, Schäfer, and Albrecht (2020). We extend this to non-stationary environments and facilitate collaboration via communication using both existing protocols Jaques et al. (2019) as well as novel communication protocols according to which agents broadcast observations that are most misaligned with the agent’s current understanding of the environment.

Example 1 Consider Figure 1, which depicts a multi-agent variation of the Taxi domain Dietterich (2000). All taxis are associated with the same operator, who aims to maximize the group’s total revenue, but each taxi receives a direct payment from each passenger when it drops her off at her destination.

The designer monitors the taxis’ performance (revenue), and notices that taxis sometimes deviate from their usual routes. This may happen, for example, due to road construction, road congestion, or other reasons. In the attempt to maximize the group’s performance despite these changes, and with the intention of not overwhelming the communication channel, the designer instructs taxis to broadcast to the others experiences that correspond to actions that have unexpected outcomes. For example, when a taxi encounters a blocked road, and fails to drive through a street it has driven through regularly, it will broadcast this unsuccessful attempt to the other taxis. Similarly, the taxi will broadcast information about a vacant street that is typically busy. This may relieve the effect that perturbations have on the other taxis and help improve performance.

Our key contributions are threefold. First, we suggest a new measure of group resilience that corresponds to the group’s ability to adapt to unexpected changes. As a second contribution, and in order to promote resilience, we facilitate collaboration within the group. To support collaboration, we offer new communication protocols according to which agents notify each other about notable changes to their surroundings. Lastly, we offer an empirical evaluation that demonstrates how groups that collaborate are more resilient to changes in the environment.

2 Background

2.1 Markov Games

A Markov Decision Process (MDP) Bertsekas (1987) is a widely used formalization for sequential decision making in stochastic environments. A standard formulation of an MDP is a tuple $M =$
A Markov game, or stochastic game, is a generalization of the MDP to multi-agent settings Littman (1994). A Markov game is defined as a tuple $\langle S, A, R, T, \gamma \rangle$ with joint actions $A = \{A^i\}_{i=1}^n$ as a collection of action sets $A^i$, one for each of the $n$ agents, $R = \{R^i\}_{i=1}^n$ as a collection of reward functions $R^i$ defining the reward $r^i(a_t, s_t)$ that each agent receives when the joint action $a_t \in A$ is performed at state $s_t$, and $T$ as the probability distribution over next states when a joint action is performed. In the partially observable case, the definition also includes a joint observation function, defining the observation for each agent at each state. In this work, we refer to Markov games interchangeably as MDPs, games, domains, or environments, depending on the context.

2.2 Reinforcement Learning

Reinforcement learning (RL) deals with learning optimal policies for sequential decision making in environments for which the dynamics are not fully known Sutton and Barto (2018). These environments are typically modeled as an MDP for the single agent case, or a Markov Game for multi-agent settings.

Multi-Agent Reinforcement Learning (MARL) extends RL to multi-agent settings. The performance or utility of a group can be defined in various ways. In this work, we measure the group utility $U$ as the total discounted reward achieved by the group, which indicates the level of collaboration within the group (we will use group performance and group utility interchangeably).

A key challenge in MARL is that the policy of each agent changes during training. This causes the environment to be non-stationary from the perspective of an individual agent, which may not
be fully aware of the other agents and of their effect on the environment. This results in unstable learning and prevents the straightforward use of past experiences when deciding how to behave \cite{Lowe2017}. The high variance in the agent’s experience is intensified in the settings we consider here, in which the environment is randomly perturbed.

3 Measuring Group Resilience

We aim to promote the ability of a group to adapt to random perturbations in their environment. We refer to this ability as resilience, and formally define it below. We will then suggest promoting group resilience by facilitating collaboration.

To measure group resilience we take inspiration from the field of multi-agent robotics. Specifically, the work of Saulnier et al. \cite{Saulnier2017} aims to produce a control policy that allows a team of mobile robots to achieve desired performance in the presence of faults and attacks on individual members of the group. Accordingly, a group of robots achieves resilient consensus if the cooperative robots’ performance is in some desired range, even in the presence of up to a bounded number of non-cooperative robots.

Similarly to the definition above, we want group resilience to mean that if an environment undergoes an unexpected (but somehow bounded-in-magnitude) perturbation, agents can still achieve a fixed fraction of their original performance. However, we are interested in changes in the environment, rather than in the other agents, thus taking into consideration any kind of change that may occur in the environment. Accordingly, our definition of resilience is with regard to a distance measure $\delta(M, M')$ that quantifies the magnitude of the change between an original MDP $M$ and the modified MDP $M'$. It also relies on a utility measure $U(M)$, quantifying the performance of a group of agents in a given environment (e.g., total reward). Given these two user-specified measures, we require that a perturbation that results in an environment that is within a bounded distance $K$ from the original environment, will result in a decrease in performance by a factor of at most some constant $C_K$.

We note that a range of subtly different formal definitions of group resilience can satisfy this intuitive requirement. We defer to the appendix a detailed discussion of some possible options, and provide here only the definitions that are relevant to our experiments. Specifically, the following definitions rely on the assumption that a designer might want to guarantee resilience over some subset $\mathcal{M}$ of perturbed environments within a specified distance. For example, instead of being resilient to arbitrary perturbations that may occur over the landscape, a taxi station’s manager might be interested in guaranteeing that a group of taxis is resilient under random road blockage.

**Definition 1 (Relative to Origin $C_K$-resilience)** Given a class of MDPs $\mathcal{M}$, a source MDP $M \in \mathcal{M}$, and a bound $K \in \mathbb{R}$, we say that a group of agents is $C_K$-resilient over $\mathcal{M}$ relative to origin $M$ if

\[
\forall M' \in \mathcal{M} : \delta(M, M') \leq K \implies U(M') \geq C_K \cdot U(M)
\]

Resilience over $\mathcal{M}$ allows us to choose a set $\mathcal{M}$ of environments of interest for which the distance condition is easily verified. However, this condition still requires that the bound on performance

\footnote{Notice that this is similar to the classical $\epsilon$-$\delta$-definition of the continuity of a function.}
holds for any \( M' \in \mathcal{M} \) (under the distance bound), which may be unreasonably strong and impractical in many cases. Therefore, equipped with a probability distribution (e.g., uniform distribution) \( \Psi \) over \( \mathcal{M} \), we further define resilience-in-expectation as follows.

**Definition 2 (Relative to Origin \( C_K \)-resilience in Expectation)** Given an MDP \( M \), a distribution over a class of MDPs \( \Psi \), and a bound \( K \in \mathbb{R} \), we say that a group of agents is \( C_K \)-resilient in expectation over \( \Psi \) relative to origin \( M \) if

\[
\mathbb{E}_{[M' \sim \Psi|\delta(M,M') \leq K]}[\mathcal{U}(M')] \geq C_K \cdot \mathcal{U}(M)
\]

Our definition above requires the expected performance of a group to fulfill a performance guarantee, where the expectation is over a sampled set of MDPs in \( \mathcal{M} \) within \( K \)-distance of \( M \). It is a known result that polynomially-many samples from \( \Psi \) are sufficient to achieve arbitrarily close approximations of the true expectation, with arbitrarily high probability. \(^2\)

Note that definitions 1 and 2 focus on comparing the performance of agents in a perturbed environment against their performance in the original one without considering its nominal value. This means that a group that follows a non-efficient policy (e.g., performing a no-op action repeatedly) may be associated with high resilience. Depending on the objective of the analysis, our suggested measures could therefore be considered in concert with the group’s measure of utility or normalized against some baseline.

### 3.1 Perturbations

In this work, we are interested in settings in which we have an initial environment and a set of perturbations that can occur. In general, a perturbation \( \phi : \mathcal{M} \rightarrow \mathcal{M} \) is a function transforming a source MDP into a modified MDP. An **atomic perturbation** is a perturbation that changes only one of the basic elements of the original MDP. In the following, given an MDP \( M = \langle S, A, R, P, \gamma \rangle \) and perturbation \( \phi \), the resulting MDP after applying \( \phi \) is denoted by \( M^\phi = \langle S^\phi, A^\phi, R^\phi, P^\phi, \gamma^\phi \rangle \).

Among the variety of perturbations that may occur, we focus here on three types of atomic perturbations. **Transition function perturbations** modify the distribution over next states for a single state-action pair. **Reward function perturbations** modify the reward of a single state-action pair. **Initial state perturbations** change the initial state of the MDP.

**Definition 3 (Transition Function Perturbation)** A perturbation \( \phi \) is a transition function perturbation if for every MDP \( M = \langle S, A, R, P, \gamma \rangle \), \( M^\phi \) is identical to \( M \) except that for a single action state pair \( s \in S \) and \( a \in A \), \( P^\phi_a[S] \neq P^\phi_a[S] \).

**Definition 4 (Reward Function Perturbation)** A perturbation \( \phi \) is a reward function perturbation if for every MDP \( M = \langle S, A, R, P, \gamma \rangle \), \( M^\phi \) is identical to \( M \) except that for a single action state pair \( s \in S \) and \( a \in A \), \( r^\phi_a[S] \neq r^\phi_a[S] \).

**Definition 5 (Initial State Perturbation)** A perturbation \( \phi \) is a transition function perturbation if for every MDP \( M = \langle S, s_0, A, R, P, \gamma \rangle \), \( M^\phi \) is identical to \( M \) except that \( s_0 \neq s_0^\phi \).

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\(^2\)Assume that the utility function \( \mathcal{U}(M') \), considered as a random variable with \( M' \sim \Psi|\delta(M,M') \leq K \) as above, is i.i.d. for a random draw of \( M' \) and has a finite variance \( \sigma^2 \). Then it follows from Chebychev’s inequality that in order to be within \( \epsilon \) of the true mean with a probability of at least \( \delta \), it is sufficient to collect at least \( \frac{\sigma^2}{\epsilon^2(1-\delta)} \) samples.
Example 2 (Example 1 continued) In our multi-taxi domain, a road blockage can be modeled as an atomic transition function perturbation that reduces to zero the probability of transitioning to an adjacent cell through a wall. A change in a passenger’s destination can be represented by two atomic perturbations: one that replaces the reward for a dropoff at the original destination with a negative reward, and one that adds a positive reward for a dropoff at the new destination.

There are a variety of metrics for measuring the distance between two MDPs Song et al. (2016); Ammar et al. (2014). We want the magnitude of a perturbation to represent the extent by which a perturbed environment is different from the original one. Intuitively, the bigger the magnitude, the harder it would be for a set of RL agents to adapt.

A straightforward way to measure the distance \( \delta \) between two MDPs is to count the minimal number of atomic perturbations that transition the original MDP into the transformed one. This is a practical measure but it may denote as close environments that are in fact very different. For example, a single atomic perturbation that changes a positive reward to a negative one can dramatically change the behavior of RL agents. Another measure is the one suggested by Song et al. Song et al. (2016), where the distance between two MDPs \( M \) and \( M' \) is calculated by computing the accumulated distance between every state in \( M \) and its corresponding state in \( M' \). This definition holds for a setting where the two MDPs are homogeneous, such that there exists a correspondence (mapping) between the states, action spaces, and reward functions of the pair of MDPs. Given two homogeneous MDPs \( M \) and \( M' \), the distance \( d(s,s') \) between any two states \( s \in S_M \) and \( s' \in S_{M'} \) is defined as:

\[
d(s,s') = \max_{a \in A} \{|r^a_s - r'^a_{s'}| + c T_k(d)(P^a_s[S_M], P'^a_{s'}[S_{M'}])\}
\]

where \( r^a_s, P^a_s[S_M], r'^a_{s'}, \) and \( P'^a_{s'}[S_{M'}] \) are the immediate reward and transition probabilities for \( M \) and \( M' \) respectively, \( T_k(d) \) is the Kantorovich distance Dobrushin (1970) between the two probability distributions, and \( c \in [0,1] \) is a hyper-parameter defining the significance of the distance between the distributions. In our evaluation, we use perturbations that do not change the state space nor the action space, so \( \Phi(M) \) and \( M \) are homogeneous according to the definition above. We therefore use it to estimate the distance between an MDP and its perturbed variations.

4 Facilitating Collaboration via Communication

Equipped with a measure for group resilience, we now focus on maximizing the resilience of a group of RL agents. Recent work in MARL suggests various approaches for promoting efficient collaboration within a group of agents, including various communication protocols Foerster et al. (2016); Christianos, Schäfer, and Albrecht (2020), rewards that are provided for having influence on the behavior of others, Jaques et al. (2019), the introduction of models of other agents Mahajan et al. (2019); Rashid et al. (2018) and more. These frameworks promote collaboration in order to maximize the group’s performance in spite of the stochastic nature of the environment and the existence of other agents. We suggest promoting collaboration to promote resilience: we hypothesize that agents that learn to collaborate will adapt more quickly to changes in their environment.

In order to be effective and support collaboration, communication protocols need to produce messages that encode information that is valuable to the learning experience of other agents. Accordingly, we offer a novel communication protocol in which agents broadcast observations that are least aligned with their previous experiences. This is inspired by Prioritized Experience Replay
(PER [Schaul et al. 2016]), according to which a deep Q-Network (DQN) agent [Mnih et al. 2015] uses a buffer to maintain its past transitions, and uses importance weights to sample transitions from the buffer to update its policy. We use misalignment to measure the importance of an observation.

Let $\pi_p$ represent the policy of agent $p$ and $Q_{\pi_p}$ represent the $Q$ function of policy $\pi_p$. Also, let a transition $\tau = (s_t, a_t, s_{t+1}, r_t)$ represent the state $s_t$, the action $a_t$, the environment transitioned to after taking action $a_t$ in $s_t$, and the reward $r_t$ it receives. The estimated reward $\hat{r}_t$ is computed based on $Q_{\pi_p}$, s.t. $\hat{r}_t \approx Q_{\pi_p}(s_t, a_t) - Q_{\pi_p}(s_{t+1}, \pi_p(s_{t+1}))$. We measure the misalignment associated with a transition according to the extent by which $r_t$ differs from $\hat{r}_t$, and normalize it by $r_t$.

**Definition 6 (Misalignment)** Let $r_t$ and $\hat{r}_t$ be the observed and estimated reward of agent $p$ after taking action $a_t$ in $s_t$. The misalignment for agent $p$ at state $s_t$ after taking action $a_t$, denoted $J_{s_t,a_t}$, is defined as:

$$J^p_{s_t,a_t} = \frac{|r_t - \hat{r}_t|}{r_t}$$

Misalignment corresponds to the agents’ familiarity with the environment, which may increase due to perturbations. By communicating misaligned transitions, agents increase familiarity of the environment for the other agents. Within this framework, we support two settings: mandatory and emergent communication.

1. **Mandatory Broadcast**—each agent $p$ broadcasts at state $s_t$ its most misaligned experiences, i.e., transitions with the highest $J^p_{s_t,a_t}$. A message consists of the misaligned transitions $\tau$ observed by the agent. Messages are received by all other agents, and considered as part of their experience, i.e., they are inserted into their replay buffers, that contain their recent transitions. The number of transitions broadcast at each time step is bounded by a parameter $m_t$ that represents the channel’s bandwidth.

2. **Emergent Communication**—each agent $p$ broadcasts at each state $s_t$ a discrete communication symbol $m^p_t$ among a given set of symbols. Individual messages of all agents are concatenated into a single vector $m_t = [m^1_t \ldots m^N_t]$, which is included as an additional observation signal all agents receive at the next time step ($t+1$).

We distinguish between two sub-cases within this setting:

(a) **Emergent Self-Centric Communication:**

Each agent $p$ applies counterfactual reasoning and chooses a communication symbol $m^p_t$ that would have minimized its own misalignment at time step $t-1$. The loss function for $\pi_m$ is:

$$L_t = |\arg\min_m J^p_{s_{t-1},a_{t-1}} - J^p_{s_{t-1},a_{t-1}}|$$

where $J^p_{s_{t-1},a_{t-1}}$ is the misalignment level at $t-1$ had it received message $m$.

(b) **Emergent Group-Centric Communication:**

Agents observe the misaligned observations of all other agents at each time step. Each agent $p$ is rewarded for choosing a communication symbol $m^P_t$ that would have minimized the total misalignment level of the group at $t-1$ (reward is received at the next step). Agents maintain a model that predicts the global (average) misalignment of the other agents given an observation and messages. The loss function for $\pi_m$ is thus:

$$L_t = |\arg\min_m J^P_{s_{t-1},a_{t-1}} - J^P_{s_{t-1},a_{t-1}}|$$
Figure 2: Emergent Communication: the network of each agent. Input is the observation from the environment, as well as the concatenated messages of the other agents $m_{t-1}$. The network outputs the action to perform (via policy $\pi_e$), as well as the message to broadcast (via policy $\pi_m$).

Where $\hat{J}_{P_{y_{t-1},a_{t-1}}}$ is the counterfactual predicted average misalignment of the other agents, having received message $m$, and $J_{P_{y_{t-1},a_{t-1}}}$ is the average misalignment level of the other agents.

While for the mandatory protocol a message corresponds to a transition $\tau$ for which the semantic meaning is preset, with the emergent communication protocol arbitrary symbols are associated with semantic meaning via a decentralized learning process in which agents operate in the same environment. Another difference is that while in the mandatory case the agents’ policy is only over actions, for the emergent case agents learn to output an additional messaging action. Specifically, in our neural network implementation (depicted in Figure 2) the network of each agent receives the messages of the other agents and outputs a message symbol via a separate head.

|                  | CleanUp       | Harvest       | Taxis        |
|------------------|---------------|---------------|--------------|
|                  | $C_{K=50}$    | $C_{K=150}$  | $C_{K=200}$  | $tt$         |
| No communication | 0.62 (0.25)   | 0.64 (0.15)  | 0.67 (0.14)  | 141.35 (40.59) |
| Social Influence | 0.78 (0.17)   | 0.72 (0.14)  | 0.70 (0.17)  | 221.25 (51.63) |
| Mandatory       | 0.99 (0.19)   | 0.72 (0.14)  | 0.74 (0.13)  | 174.73 (46.33) |
| Emergent Global-Centric | 0.71 (0.16) | 0.81 (0.11)  | 0.74 (0.11)  | 149.45 (39.76) |
| Emergent Self-Centric | 0.64 (0.21) | 0.74 (0.14)  | 0.67 (0.14)  | 140.15 (40.42) |

Table 1: Average $C_K$-resilience over different domains and algorithms.

5 Empirical Evaluation

The objective of our empirical evaluation is to assess the effect collaboration has on group resilience. Specifically, we measure and compare the average total group reward in randomly perturbed environments, where each group uses a different communication protocol.
5.1 Environments

Our dataset consists of three environments. The Multi-taxi domain is described in Example 1. The other two domains are Harvest and Cleanup from Leibo et al. (2017). In both, agents gain reward by harvesting apples, but are subject to some joint tragedy-of-the-commons style dilemma. In Cleanup, the dilemma arises due to an adjacent river that must be cleaned so apples can grow. In Harvest, apples grow at rate that is proportional to the amount of nearby apples. Agents therefore need to coordinate the rate and locations from which they harvest apples.

We train our RL agents using a separate neural network per agent. Agents are implemented using Distributed Asynchronous Advantage Actor-Critic (A3C) Mnih et al. (2016). Our neural networks’ structure is inspired by the architecture presented by Jaques et al. (2019) and is depicted in Figure 2 and includes an LSTM unit Gers, Schmidhuber, and Cummins (1999).

5.2 Perturbations

Given an environment $M$ and a perturbation $\Phi$, we measure the perturbation’s magnitude as the sum of distances between all matching states as suggested by Song et al. Song et al. (2016) and described in Section 3. We experiment with perturbation bounds of 50, 150 and 200. We use initial state perturbations (e.g. changing the agent starting position), obstacles (e.g. adding walls to the map) and reward and resource reallocations (e.g. moving passenger or apple locations).

For each initial, unperturbed environment $M$, and perturbation bound $K$, we sample perturbed environments $M'$ such that $\delta(M, M') \leq K$. We generate perturbed environments using a stochastic process, iteratively applying random atomic perturbations until we reach a combined magnitude of $K$. We introduce a perturbation at $t_{pert}$ time steps of training, after agents have reached a reasonable performance level.

A detailed description of our benchmarks, our source code, and the complete set of our results can be found in the appendix.
5.3 Communication Protocols

We compare the following communication protocols.

1. **No Communication:** Agents do not communicate.

2. **Social influence:** As suggested by [Jacques et al. (2019)](https://example.com), agents choose to broadcast messages that will have the maximal influence on the immediate behavior of others.

3. **Mandatory communication:** Agents broadcast the top $m$ most misaligned transitions as described in Section 4.

4. **Emergent Self-Centric Communication:** Agents broadcast at each step a discrete symbol that would have minimized their misalignment at the previous step, as described in Section 4.

5. **Emergent Global-Centric Communication:** Agents observe other agents’ current misalignment level and broadcast at each step a discrete symbol trying to minimize the overall misalignment level of the group.

5.4 Results

To measure the effect of perturbations on group performance, we measure the average utility over a period of time before and after perturbation, averaged over 8 repeated experiments. For each experiment (initial environment), we use the process described above to generate perturbations by uniformly sampling $M'$ within the specified distance. To measure resilience we use Definition 2.

Table 1 shows the mean $C_K$-resilience under perturbations with magnitude $K = 50$, $K = 150$, and $K = 200$ alongside the utility $U$ of the group in the non perturbed environment, with standard deviation in parenthesis. Figure 3 shows learning curves per domain before and after a perturbation of up to 200 magnitude occurs after agents operate for 100k episodes in the environment.

As expected, the utility $U$ for groups that collaborate (before perturbation) is higher in all domains. But crucially, we observe that all of the collaborative approaches also show higher resilience than the no-communication approach, supporting our main hypothesis. This includes both the social influence approach as well as the three communication protocols we introduce. The effect is more pronounced for larger-magnitude perturbations, e.g. $0.27 \pm 0.08$ for emergent global-centric communication compared to $0.06 \pm 0.05$ for no communication in the Cleanup domain with $K = 200$. We also observe that the global-centric approach generally outperforms the self-centric approach (higher or similar resilience, and higher initial performance). This further reinforces that collaboration helps resilience in that agents can recover after perturbation a larger fraction of their previous performance, even if they are self-interested.

6 Conclusion

The ability of autonomous agents, individually or as a group, to adapt to changes in the environment is highly desirable in real-world settings where dynamic environments are the rule, not the

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4Due to space limitations, the rest of our results for different perturbations’ magnitudes are provided in the Appendix
exception. Therefore, if a group is to reliably pursue its objective function, it should be able to handle unexpected environmental changes.

In support of this agenda, we introduced novel formulations to evaluate group resilience based on the group’s ability to adapt to perturbations in the environment. To the best of our knowledge, this is the first measurement of group resilience that is relevant to MARL settings. In addition, we presented several communication approaches specifically aimed at high performance under such conditions. Our experimental results show that collaboration via communication can significantly increase resilience to changing environments.

While we examined our approach on MARL settings with homogeneous agents that collaborate via communication, as a next step we intend to examine additional methods for collaboration in settings with heterogeneous groups of agents. Additionally, we intend to explore resilience in real-world domains, including multi-robot settings.

It is noteworthy that the recent global pandemic perturbed many aspects of the environments in which we operate. In such cases, people used to certain kinds of collaboration before the pandemic may have found it easier adjusting to the unfamiliar constraints that were imposed. We believe our results reflect a quite specific kind of benefit that automated agents can derive from collaborating with one other. We do note that many usual caveats on AI research apply, for instance, where the original task itself is not of societal benefit. We leave this for future work and note potential solutions in existing work on differential privacy or federated learning.

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