Abstract—In this paper, we propose a new framework, exploiting the multi-agent deep deterministic policy gradient (MADDPG) algorithm, to enable a base station (BS) and user equipment (UE) to come up with a medium access control (MAC) protocol in a multiple access scenario. In this framework, the BS and UEs are reinforcement learning (RL) agents that need to learn to cooperate in order to deliver data. The network nodes can exchange control messages to collaborate and deliver data across the network, but without any prior agreement on the meaning of the control messages. In such a framework, the agents have to learn not only the channel access policy, but also the signaling policy. The collaboration between agents is shown to be important, by comparing the proposed algorithm to ablated versions where either the communication between agents or the central critic is removed. The comparison with a contention-free baseline shows that our framework achieves a superior performance in terms of goodput and can effectively be used to learn a new protocol.

Index Terms—Multi-Agent Reinforcement Learning, Protocol Emergence, Wireless Communications.

I. INTRODUCTION

The current 5G networks are designed to support a wide range of services, including enhanced mobile broadband (eMBB), ultra-reliable and low-latency communications (uRLLC) and massive machine-type communications (mMTC), which in turn will support an important growth in the number of applications. This upsurge in novel services and applications is expected to also happen with 6G [1]. This heterogeneity of wireless networks may represent a challenge to protocol design. Therefore, protocols tailored to specific applications may perform better than general-purpose solutions [2].

Machine learning (ML) can be used to design protocols, boost the network capacity [3] and reduce the efforts and costs for future standardization [4]. It is possible to view a protocol as the language of a network, since the network nodes have to negotiate how to transmit data by exchanging messages. Then, the idea of emerging a new protocol would be similar to emerging communication between the network nodes. Reinforcement learning (RL) is one category of ML that provides the means to reach this goal.

During the last years, research on how to emerge communication in order to achieve collaboration between multiple agents received a growing attention [5]. This growth partly relies on recent advances in multi-agent reinforcement learning (MARL) for cooperative problems [6]. Learning to cooperate by leveraging communication is about teaching agents to either learn existing natural languages or to emerge a fully new communication protocol that would help them collaborate to solve a task.

Contribution: Our proposal is to leverage cooperative MARL augmented with communication to allow a fully new medium access control (MAC) protocol to emerge. The idea of learning a given protocol has already been addressed in a previous work [7], but to the best of the authors’ knowledge, there is no previous work on studying the emergence of a new MAC protocol (signalling included) with MARL. In the future, this idea may be used to develop application-tailored protocols that could perform better than the human-designed ones.

This work is structured as follows. In Section II, we briefly review the literature. In Section III, we give a short background overview of MARL and the algorithm used in this work. Section IV describes the system model used and in Section V, we present a new framework allowing the emergence of MAC protocols with MARL. Finally, Section VI illustrates the performance of our algorithm with our numerical results, where we compare the proposed solution with a baseline. The main conclusions are drawn in Section VII.

II. RELATED WORK

Several papers have applied RL to the MAC layer, mostly to solve radio resource management (RRM) problems such as scheduling [8], [9] and dynamic spectrum access [10], [11].

In [7], MARL is used to learn a predefined protocol and a new channel access policy. This is done by having a base station (BS) which uses a predefined protocol while the user equipments (UEs) are RL agents. The UEs are trained to learn the signaling and how to access the channel without any prior
knowledge. This way, they can learn their own channel-access policy, while respecting the target signaling policy. However, in this case the agents only learn to use an already known MAC signaling, rather than developing a new one.

In [2], a framework to design a protocol is proposed by considering the different functions a MAC protocol must perform. An RL agent designs a protocol by selecting which building function to use according to the network conditions. However, in this case, the RL agent still has a prior knowledge due to the use of the predefined protocol functions.

In [12], [13], cooperative MARL is used to emerge a coding scheme by joint learning of communication and cooperation to solve a task with the help of a noisy communication channel. The proposition of both works is to emerge a coding scheme that is tailored to the application. None of these works address the question of learning a new signaling protocol.

III. BACKGROUND ON MARL

RL is an area of ML that aims to find the best behavior for an agent interacting with a dynamic environment in order to maximize a notion of accumulated reward [14]. The goal of the RL agent is to find the best policy, which is the mapping of the perceived states to the actions to be taken. The action-value function $Q^\pi(s, a)$, also known as Q-function, is the overall expected reward for taking action $a$ in state $s$ and then following a policy $\pi$.

MARL is an extension of RL for to multi-agent systems (MAS), where multiple agents interact with a system, i.e. the environment. In this work, we use the decentralized partially observable Markov decision process (Dec-POMDP) formulation [15], augmented with communication. A Dec-POMDP for $n$ agents is defined by the global state space $S$, an action space $A_1, \ldots, A_n$, and an observation space $O_1, \ldots, O_n$ for each agent. In Dec-POMDP, the agent observation does not fully describe the environment state. All agents share the same reward and the action space of each agent is subdivided into one environment action space and a communication action space. The communication action represents the message sent by an agent and it does not affect the environment directly, but it may be passed to other agents. This formulation is shown in Fig. 1 where $o_i$ represents the observation received by the $i$th agent, $r$ represents the reward, $a_i$ and $c_i$ represent the environment and communication actions, respectively. In this work, the agent internal state $s_i$ may comprise not only the agent’s current observation, but also previous observations, actions and received messages.

MARL introduces some new challenges, such as partial observability and non-stationarity [16]. In this work, we adopt the multi-agent deep deterministic policy gradient (MADDPG) algorithm [17], an extension of the deep deterministic policy gradient (DDPG) algorithm [18] to multi-agent problems with centralized training and decentralized execution (CTDE). It addresses the non-stationarity problem by using a centralized critic. Each agent has an actor network that depends only on its own agent’s state in order to learn a decentralized policy $\mu_i$ with parameters $\theta_i$. During the training, each agent has a centralized critic that receives the agent states and actions of all agents in order to learn a joint action value function $Q_j(x, a)$ with parameters $\varphi_j$, where $x = (x_1, x_2, \ldots, x_n)$ is a vector containing all the agents’ states and $a = (a_1, a_2, \ldots, a_n)$ contains the actions taken by all of the agents.

The critic network parameters $\varphi$ are updated by minimizing the loss given by the temporal-difference error

$$L_i := \mathbb{E}_{x,a,r,x',D} [y_i - Q_j(x, a_1, \ldots, a_n; \varphi_j)]$$

where $D$ denotes the experience replay buffer in which the transition tuples $(x, a, r, x')$ are stored, $Q_j$ and $\mu_j$ represent the target critic network and the value of the target actor network, with parameters $\theta_j$ and $\varphi_j$, respectively, and $y_i$ is the temporal-difference target, given by

$$y_i := r + \gamma Q_j'(x', a'_1, \ldots, a'_n; \varphi'_j)|_{a'_j = \mu_j'(x_j)}$$

where $\gamma$ is the discount factor. The actor network parameters $\theta$ are updated using the sampled policy gradient

$$\nabla_{\theta_i} J = \mathbb{E}_{x,a,r} [\nabla_{a_i} Q_j(x, a) \nabla_{\theta_i} \mu_j(x_i) | a_i = \mu_i(x_i)] .$$

The target networks parameters are updated as

$$\varphi'_j \leftarrow \tau \varphi_j + (1 - \tau) \varphi'_j$$

$$\theta'_i \leftarrow \tau \theta_i + (1 - \tau) \theta'_i$$

where $\tau \in [0, 1]$ is the soft-update parameter. Smaller values of $\tau$ lead to slow target network changes and are generally preferred [18].

IV. SYSTEM MODEL

We consider a single cell with a BS serving $L$ UEs operating according to a time division multiple access (TDMA) scheme, where each UE needs to deliver $P$ service data units (SDUs) to the BS. We assume that each MAC protocol data unit (PDU) contains only one SDU. The network nodes can communicate, i.e. exchange information, using messages through the control channels. In the rest of this paper, we use the expressions UE and BS to refer to the UE MAC agent and the BS MAC agent, respectively.

The channel for the uplink data transmission is modeled as a packet erasure channel, where a transport block (TB) is incorrectly received with a probability given by a transport block error rate (TBLER). The downlink control messages (DCMs) and uplink control messages (UCMs) are transmitted over the downlink (DL) and uplink (UL) control channels,
which are assumed to be error free and without any contention or collision.

We assume that the sets of possible DL and UL control messages have cardinality \( D \) and \( U \), respectively. For example, the UCMs in an UL control vocabulary of size \( D = 8 \) would have a bitlength of \( \log_2 D = 3 \). This exchange is shown in Fig. 2 where dashed lines indicate control information and solid lines indicate user data.

Each UE has a transmission buffer of capacity \( B \) MAC SDUs that starts empty. At each time step \( t \), a new SDU is added to the buffer with probability \( p_u \), until a maximum of \( P \) SDUs have been generated for each UE.

At each time step \( t \), the BS can send one control message to each UE and each UE can send one control message to the BS while being able to send data PDUs through the uplink shared channel (UL-SCH). Furthermore, the UEs can also delete a SDU from the buffer at each time step.

The transmission task is considered finished once all SDUs are received and all transmission buffers are empty. We define the goodput \( G \) (in SDUs/TTIs) as the number of MAC SDUs received by the BS per unit of time, without considering the retransmissions:

\[
G = \frac{N_{RX}}{N_{TTI}} \tag{6}
\]

where \( N_{RX} \) represents the number of SDUs received and \( N_{TTI} \) is the total time taken to finish the transmission task. The delivery-rate \( \Gamma_{RX} \) is the percentage of SDUs correctly received by the BS:

\[
\Gamma = \frac{N_{RX}}{PL}. \tag{7}
\]

V. EMERGING A MAC PROTOCOL WITH MARL

A. MARL Formulation

We can formulate the problem defined above as a MARL cooperative task, where the MAC layers of the network nodes (UEs and BS) are RL agents that need to learn how to communicate with each other to solve an uplink transmission task. In addition, the UE agents need to learn when to send data through the UL-SCH and when to delete an SDU, in other words, to learn how to correctly manage the buffer.

In order to decide how to act, an agent needs to consider the messages received from the other agents. In addition, the UEs also take into account their buffer status when taking actions, while the BS takes into account the state of the UL-SCH, i.e. idle, busy or collision-free reception.

We use the following notations:

- \( o_t^u \): Observation received by the \( u \)th UE at time step \( t \).
- \( n_t^u \): The UCM sent from the \( u \)th UE at time step \( t \).
- \( m_t^u \): The DCM sent to the \( u \)th UE at time step \( t \).
- \( a_t^u \): Environment action of the \( u \)th UE at time step \( t \).
- \( x_t^u \): Agent internal state of the \( u \)th UE at time step \( t \).
- \( x_t^b \): Agent internal state of the BS at time step \( t \).

The observation \( o_t^u \in \{0, \ldots, B\} \) is a integer representing the number of SDUs in the buffer of the UE \( u \) at that time \( t \). Similarly, the observation \( o_t^b \) received by the BS is a discrete variable with \( L + 2 \) possible states:

\[
o_t^b = \begin{cases} \emptyset, & \text{if the UL-SCH is idle} \\ u, & \text{if the UL-SCH is detected busy with a single PDU from UE } u, \text{ correctly decoded} \\ (L + 1), & \text{non-decodable energy in the UL-SCH} \end{cases} \tag{8}
\]

where \( u \in \{0, \ldots, L\} \). The environment action \( a_t^u \in \{0, 1, 2\} \) is interpreted as follows:

\[
a_t^u = \begin{cases} 0: & \text{do nothing} \\ 1: & \text{transmit the oldest SDU in the buffer} \\ 2: & \text{delete the oldest SDU in the buffer} \end{cases} \tag{9}
\]

We assume the episode ends when all the SDUs are correctly received by the BS or when a maximum number of steps \( t_{max} \) is reached. The reward given at each time step is:

\[
r_t = \begin{cases} +\rho, & \text{if a new SDU was received by the BS} \\ -\rho, & \text{if a UE deleted a SDU that has not been received by the BS} \\ -1, & \text{else} \end{cases} \tag{10}
\]

where \( \rho \) is a positive integer. This choice of reward is possible by leveraging the CTDE. During the centralized training, a centralized reward system can be used to observe the buffers of the BS and UEs in order to assign the reward.

B. Training Algorithm

The proposed RL solution is based on the MADDPG algorithm [17]. Each entity of the system has its own actor network which outputs the action of an agent given its state. Each agent also has a centralized critic network which outputs the Q-value given the actions and states of all agents. The critic networks are only used during the centralized training.

The actor and critic networks have the same architecture; a fully connected multilayer perceptron (MLP) with two hidden layers, of 64 neurons each. The activation function of all hidden layers is the rectified linear unit (ReLU).

The agent state at time step \( t \) is a tuple comprising the most recent \( k \) observations, actions and received messages:

\[
x_t = (o_t^u, \ldots, o_{t-k}^u, a_t^u, \ldots, a_{t-k}^u, m_t^u, \ldots, m_{t-k}^u)
\]

for \( u \)th UE; \( x_t^b = (o_t^b, \ldots, o_{t-k}^b, n_t, \ldots, n_{t-k}, m_t, \ldots, m_{t-k}) \), with \( n \) and \( m \) containing the messages from all the UEs.

In order to improve training of our MADDPG solution, we make use of parameter sharing [19] for similar network nodes,
in this case the UEs. Similarly to the original work [17], we use the Gumbel-softmax [20] trick to soft-approximate the discrete actions to continuous ones. The Gumbel-softmax reparameterization also works to balance exploration and exploitation. The exploration-exploitation trade-off is controlled by the temperature factor $\zeta$.

After training finishes, we have successfully trained a population of $N_{\text{rep}} = 32$ protocols. We then select the protocol that performed best during the last $N_{\text{eval}} = 500$ evaluation episodes. This selection step can be seen as a "survival of the fittest" approach because only one protocol of the population of $N_{\text{rep}}$ is chosen going forward.

### VI. Results

#### A. Simulation Parameters

For simplicity, we assess the performance of a system with one BS and two UEs. The transmission buffer of each user starts empty and the SDU arrival probability $p_a$ is 0.5.

The system is trained for a fixed number of episodes $N_{\text{train}}$. At some points during the training, we evaluate the policy on a total of $N_{\text{eval}}$ evaluation episodes with disabled exploration and disabled learning in order to assess the current performance of the MAC protocol. The set of evaluation episodes remain the same in order to effectively compare the performance on the same set. At the end of the training procedure, we further evaluate the learned protocol by assessing its performance in $N_{\text{test}}$ episodes with exploration and learning disabled. This whole procedure represents a single training repetition. We evaluate a total of $N_{\text{rep}}$ repetitions, each with a different random seed.

A summary of the main simulation parameters is provided in Table I while the parameters of the MADDPG and DDPG algorithms are listed in Table II.

#### B. Baseline Solutions

We compare the proposed solution with a contention-free baseline. We also compare the proposed solution to two simplified approaches where either the communication between agents is not permitted or the centralized critic is disabled, i.e the DDPG algorithm. The ablation comparison helps to evaluate if communication and the centralized critic are needed to solve this task.

In the contention-free protocol, the UE sends a scheduling request (SR) if its transmission buffer is not empty and it only transmits if it has received a scheduling grant (SG). Similarly, it only deletes a TB from the transmission buffer after the reception of an acknowledgement (ACK). At each time step, the BS receives zero or more SRs. It then chooses one of the requesters at random to transmit in the next time-step, sending a SG to the selected UE. However, if the UE had made a successful data transmission simultaneously with an SR, the BS will send an ACK to this UE and its SR is ignored.

#### C. Results

We compare the MADDPG solution with three other solutions, the contention-free baseline, the MADDPG solution without communication, and the DDPG version of the proposed solution, i.e. the proposed solution without the centralized critic. For the RL solutions, the solid lines in Figs. 3 and 4 show the average performance in the evaluation episodes during the training and the shaded areas represent the 95% confidence interval (CI). The dashed lines show the average performance of the baseline.

In Fig. 3 we compare the performance in terms of goodput for the TBLER of $10^{-1}$. Figures 3a and 3b show the results when the UEs have to transmit one and two SDUs, respectively. After assessing the performance on the last $N_{\text{eval}}$ evaluation episodes, we select the best performing repetitions for each solution in terms of average goodput to compare using boxplots of the test episodes.

By comparing the results in both cases, the MADDPG has the best performance and the ablation without communication has the worst performance overall. In addition, the MADDPG shows a more stable performance during training, with less variation than both other RL solutions. The ablation without communication has the greatest variation of performance, demonstrated by the CIs and by the boxplots, indicating that communication helps achieving a more robust solution.

In Fig. 3a both the MADDPG and DDPG solutions outperform the contention-free baseline, whereas the ablation without

### Table I: Simulation Parameters

| Parameter                   | Symbol | Value |
|-----------------------------|--------|-------|
| Number of UEs               | $L$    | 2     |
| Size of transmission buffer | $B$    | 5     |
| Number of SDUs to transmit  | $P$    | $[1, 2]$ |
| SDU arrival probability     | $p_a$  | 0.5   |
| Transport block error rate  | $\text{TBLER}$ | $[10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}]$ |
| DCM vocabulary size         | $D$    | 3     |
| UCM vocabulary size         | $U$    | 2     |
| Max. duration of episode (TTIs) | $t_{\text{max}}$ | 24   |
| Reward function parameter  | $\rho$ | 3     |
| Number of training episodes | $N_{\text{train}}$ | 300k |
| Number of evaluation episodes | $N_{\text{eval}}$ | 500  |
| Number of test episodes     | $N_{\text{test}}$ | 5000 |
| Number of randomized repetitions | $N_{\text{rep}}$ | 32   |

### Table II: Training Algorithm Parameters

| Parameter                                      | Value     |
|-----------------------------------------------|-----------|
| Memory length                                 | 3         |
| Replay buffer size                            | $10^5$    |
| Batch size                                    | 1024      |
| Number of neurons per hidden layer            | $\{64, 64\}$ |
| Interval between updating policies            | 96        |
| Optimizer algorithm                           | Adam [21] |
| Learning rate                                 | $10^{-3}$ |
| Discount factor                               | 0.99      |
| Policy regularizing factor                    | $10^{-3}$ |
| Gumbel-softmax temperature factor             | 1         |
| Target networks soft-update factor            | $10^{-3}$ |
communication fails to effectively solve the task in this case. When we move from one SDU to two SDUs, in Fig. 3b, the DDPG solution does not outperform the baseline. Moreover, the difference in performance between the MADDPG and the baseline is reduced.

To better understand the goodput results of Fig. 3b, Fig. 4 shows the performance in terms of episode duration, Fig. 4a, and of percentage of the total SDUs received during the episode as defined in Eq. (7), Fig. 4b.

As shown in Fig. 4b, the DDPG algorithm achieves a high performance in terms of delivery-rate, but it takes more time to solve the task, thus the lower performance in terms of goodput when compared with the MADDPG and the baseline. Comparing the MADDPG with the contention-free solution in Fig. 4a, the proposed solution achieves a better goodput by finishing the task in less TTIs. The proposed solution has a delivery-rate lower than the contention-free baseline, although it is also very close to 100%.

By applying "survival of the fittest" to pick the best protocol in terms of goodput, the delivery-rate difference becomes even lower than shown in Fig 4b. The best protocol produced by the proposed solution has an average delivery-rate on the test episodes of $\Gamma_{\text{MADDPG}} = 99.973\%$, whereas the average of the contention-free baseline is of $\Gamma_{\text{base}} = 99.998\%$.

In Fig. 5, we compare the proposed MADDPG framework with the contention-free baseline for different TBLERs and with each UE having to transmit two SDUs. The performance is evaluated on $N_{\text{test}}$ test episodes by comparing the average goodput achieved. For the MADDPG solution, we also show the 95% CI across randomized repetitions. The proposed solution maintains a better performance than the baseline across the different TBLERs. Moreover, the lowest difference in performance between the baseline and the proposed solution occurs when the TBLER is equal to 0.1, showing that the proposed solution adapts well to lower TBLER regimes.
VII. CONCLUSIONS AND PERSPECTIVES

We have proposed a novel framework based on cooperative MARL augmented with communication, that provides us with the means to emerge a new protocol. In essence, the agents have to learn the signaling policy, representing the control messages they exchange, and the channel-access policy, representing the physical layer (PHY) control of the agents. Comparing with two ablations and a baseline, the results show that a solution capable to overcome the challenges in multi-agent systems is needed in order to emerge a protocol. The results also indicate that enabling communication between agents is needed in order to solve a transmission task. In addition, the results illustrate that the proposed solution can produce a protocol tailored to all TBLER regimes that outperforms a more general one.

Concerning future work, we highlight a study on the effect of the different parameters, such as the vocabulary sizes and TBLERs. Moreover, we envision a comparison with different MARL algorithms. Finally, the application of this framework to a more complex system model is planned.

ACKNOWLEDGMENT

The work of Mateus P. Mota is funded by Marie Skłodowska-Curie actions (MSCA-ITN-ETN 813999 WIND-MILL).

REFERENCES

[1] K. David and H. Berndt, “6G vision and requirements: Is there any need for beyond 5G?” IEEE Vehicular Technology Magazine, vol. 13, no. 3, pp. 72–80, 2018.

[2] H. B. Pasandi and T. Nadeem, “Towards a learning-based framework for self-driving design of networking protocols,” IEEE Access, vol. 9, pp. 34,829–34,844, 2021.

[3] J. Hoydis, F. A. Aoudia, A. Valcarce, and H. Viswanathan, “Towards a 6G AI-native air interface,” IEEE Communications Magazine, vol. 59, no. 5, pp. 76–81, 2021.

[4] S. Han, T. Xie, C.-L. I, L. Chai, Z. Liu, Y. Yuan, and C. Cui, “Artificial-Intelligence-Enabled air interface for 6G: Solutions, challenges, and standardization impacts,” IEEE Communications Magazine, vol. 58, no. 10, pp. 73–79, 2020.

[5] A. Lazaridou and M. Baroni, “Emergent multi-agent communication in the deep learning era,” arXiv preprint arXiv:2006.02419, 2020.

[6] A. Dafoe, E. Hughes, Y. Bachrach, T. Collins, K. R. McKee, J. Z. Leibo, K. Larson, and T. Graepel, “Open problems in cooperative AI,” arXiv preprint arXiv:2012.08630, 2020.

[7] A. Valcarce and J. Hoydis, “Towards joint learning of optimal MAC signaling and wireless channel access,” IEEE Transactions on Cognitive Communications and Networking, pp. 1–1, 2021.

[8] F. Al-Tam, N. Correia, and J. Rodriguez, “Learn to schedule (LEASCH): A deep reinforcement learning approach for radio resource scheduling in the 5G MAC layer,” IEEE Access, vol. 8, pp. 108,085–108,101, 2020.

[9] F. Al-Tam, A. Mazayev, N. Correia, and J. Rodriguez, “Radio resource scheduling with deep pointer networks and reinforcement learning,” in 2020 IEEE 25th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD), 2020, pp. 1–6.

[10] C. Bowyer, D. Greene, T. Ward, M. Menendez, J. Shea, and T. Wong, “Reinforcement learning for mixed cooperative/competitive dynamic spectrum access,” in 2019 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN), 2019, pp. 1–6.

[11] T. F. Wong, T. Ward, J. M. Shea, M. Menendez, D. Green, and C. Bowyer, “A dynamic spectrum sharing design in the DARPA spectrum collaboration challenge,” in Proceedings of the Government Microcircuit Applications and Critical Technology Conference (GOMACTech), 2020.

[12] A. Mostaani, O. Simeone, S. Chatzinotas, and B. Ottersten, “Learning-based physical layer communications for multiagent collaboration,” in 2019 IEEE 30th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), 2019, pp. 1–6.

[13] J. S. P. Roig and D. Gündüz, “Remote reinforcement learning over a noisy channel,” in GLOBECOM 2020 - 2020 IEEE Global Communications Conference, 2020, pp. 1–6.

[14] C. M. Bishop, Pattern Recognition and Machine Learning, 5th Edition, ser. Information Science and Statistics. Springer, 2007. [Online]. Available: http://www.worldcat.org/oclc/771008143

[15] F. A. Oliehoek, M. T. Spaan, and N. Vlassis, “Optimal and approximate q-value functions for decentralized pomdps,” Journal of Artificial Intelligence Research, vol. 32, pp. 289–353, 2008.

[16] T. T. Nguyen, N. D. Nguyen, and S. Nahavandi, “Deep reinforcement learning for multiagent systems: A review of challenges, solutions, and applications,” IEEE Transactions on Cybernetics, vol. 50, no. 9, pp. 3826–3839, 2020.

[17] A. Dafoe, E. Hughes, Y. Bachrach, T. Collins, K. R. McKee, J. Z. Leibo, K. Larson, and T. Graepel, “Open problems in cooperative AI,” arXiv preprint arXiv:2006.02419, 2020.

[18] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wu, “Continuous control with deep reinforcement learning,” in ICLR, 2016. [Online]. Available: http://dlp.loni.uCLA.de/db/conf/iclr/iclr2016.html#LillicrapHPHET15

[19] J. N. Foerster, Y. M. Assael, N. de Freitas, and S. Whiteson, “Learning from demonstration using latent spaces,” in Proceedings of the 30th International Conference on Neural Information Processing Systems, 2016, pp. 6379–6390.

[20] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wu, “Continuous control with deep reinforcement learning,” in ICLR, 2016. [Online]. Available: http://dlp.loni.uCLA.de/db/conf/iclr/iclr2016.html#LillicrapHPHET15

[21] J. N. Foerster, Y. M. Assael, N. de Freitas, and S. Whiteson, “Learning from demonstration using latent spaces,” in Proceedings of the 30th International Conference on Neural Information Processing Systems, 2016, pp. 2145–2153.

[22] E. Jang, S. Gu, and B. Poole, “Categorical reparameterization with Gumbel-Softmax,” in 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings, OpenReview.net, 2017. [Online]. Available: https://openreview.net/forum?id=r2kEYzi85e

[23] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, Y. Bengio and Y. LeCun, Eds., 2015. [Online]. Available: http://arxiv.org/abs/1412.6980