

RODE: LEARNING ROLES TO DECOMPOSE MULTI-AGENT TASKS

Tonghan Wang[†], Tarun Gupta[‡], Anuj Mahajan[‡], Bei Peng[‡]

[†] Institute for Interdisciplinary Information Sciences, Tsinghua University

[‡] Univeristy of Oxford

tonghanwang1996@gmail.com

{tarun.gupta, anuj.mahajan, bei.peng}@cs.ox.ac.uk

Shimon Whiteson*

Univeristy of Oxford

shimon.whiteson@cs.ox.ac.uk

Chongjie Zhang*

Tsinghua University

chongjie@tsinghua.edu.cn

ABSTRACT

Role-based learning holds the promise of achieving scalable multi-agent learning by decomposing complex tasks using roles. However, it is largely unclear how to efficiently discover such a set of roles. To solve this problem, we propose to first decompose joint action spaces into restricted role action spaces by clustering actions according to their effects on the environment and other agents. Learning a role selector based on action effects makes role discovery much easier because it forms a bi-level learning hierarchy – the role selector searches in a smaller role space and at a lower temporal resolution, while role policies learn in significantly reduced primitive action-observation spaces. We further integrate information about action effects into the role policies to boost learning efficiency and policy generalization. By virtue of these advances, our method (1) outperforms the current state-of-the-art MARL algorithms on 10 of the 14 scenarios that comprise the challenging StarCraft II micromanagement benchmark and (2) achieves rapid transfer to new environments with three times the number of agents. Demonstrative videos are available at <https://sites.google.com/view/rode-marl>.

1 INTRODUCTION

Cooperative multi-agent problems are ubiquitous in real-world applications, such as crewless aerial vehicles (Pham et al., 2018; Xu et al., 2018) and sensor networks (Zhang & Lesser, 2013). However, learning control policies for such systems remains a major challenge. Joint action learning (Claus & Boutilier, 1998) learns centralized policies conditioned on the full state, but this global information is often unavailable during execution due to partial observability or communication constraints. Independent learning (Tan, 1993) avoids this problem by learning decentralized policies but suffers from non-stationarity during learning as it treats other learning agents as part of the environment.

The framework of centralized training with decentralized execution (CTDE) (Foerster et al., 2016; Gupta et al., 2017; Rashid et al., 2018) combines the advantages of these two paradigms. Decentralized policies are learned in a centralized manner so that they can share information, parameters, etc., without restriction during training. Although CTDE algorithms can solve many multi-agent problems (Mahajan et al., 2019; Das et al., 2019; Wang et al., 2020d), during training they must search in the joint action-observation space, which grows exponentially with the number of agents. This makes it difficult to learn efficiently when the number of agents is large (Samvelyan et al., 2019).

Humans cooperate in a more effective way. When dealing with complex tasks, instead of directly conducting a collective search in the full action-observation space, they typically decompose the task and let sub-groups of individuals learn to solve different sub-tasks (Smith, 1937; Butler, 2012). Once the task is decomposed, the complexity of cooperative learning can be effectively reduced

*Equal advising

because individuals can focus on restricted sub-problems, each of which often involves a smaller action-observation space. Such potential scalability motivates the use of roles in multi-agent tasks, in which each role is associated with a certain sub-task and a corresponding policy.

The key question in realizing such scalable learning is how to come up with a set of roles to effectively decompose the task. Previous work typically predefines the task decomposition and roles (Pavón & Gómez-Sanz, 2003; Cossentino et al., 2005; Spanoudakis & Moraitis, 2010; Bon-jean et al., 2014). However, this requires prior knowledge that might not be available in practice and may prevent the learning methods from transferring to different environments.

Therefore, to be practical, it is crucial for role-based methods to automatically learn an appropriate set of roles. However, learning roles from scratch might not be easier than learning without roles, as directly finding an optimal decomposition suffers from the same problem as other CTDE learning methods – searching in the large joint space with substantial exploration (Wang et al., 2020c).

To solve this problem, we propose a novel framework for learning ROles to DEcompose (RODE) multi-agent tasks. Our key insight is that, instead of learning roles from scratch, role discovery is easier if we first decompose joint action spaces according to action functionality. Intuitively, when cooperating with other agents, only a subset of actions that can fulfill a certain functionality is needed under certain observations. For example, in football games, the player who does not possess the ball only needs to explore how to move or sprint when attacking. In practice, we propose to first learn effect-based action representations and cluster actions into role action spaces according to their effects on the environment and other agents. Then, with knowledge of effects of available actions, we train a role selector that determines corresponding role observation spaces.

This design forms a bi-level learning framework. At the top level, a role selector coordinates role assignments in a smaller role space and at a lower temporal resolution. At the low level, role policies explore strategies in reduced primitive action-observation spaces. In this way, the learning complexity is significantly reduced by decomposing a multi-agent cooperation problem, both temporally and spatially, into several short-horizon learning problems with fewer agents. To further improve learning efficiency on the sub-problems, we condition role policies on the learned effect-based action representations, which improves generalizability of role policies across actions.

We test RODE on StarCraft II micromanagement environments (Samvelyan et al., 2019). Results on this benchmark show that RODE establishes a new state of the art. Particularly, RODE has the best performance on 10 out of all 14 maps, including all 9 hard and super hard maps. Visualizations of learned action representations, factored action spaces, and dynamics of role selections shed further light on the superior performance of RODE. We also demonstrate that conditioning the role selector and role policies on action representations enables learned RODE policies to be transferred to tasks with different numbers of actions and agents, including tasks with three times as many agents.

2 RODE LEARNING FRAMEWORK

In this section, we introduce the RODE learning framework. We consider fully cooperative multi-agent tasks that can be modelled as a Dec-POMDP (Oliehoek et al., 2016) consisting of a tuple $G = \langle I, S, A, P, R, \Omega, O, n, \gamma \rangle$, where I is the finite set of n agents, $\gamma \in [0, 1]$ is the discount factor, and $s \in S$ is the true state of the environment. At each timestep, each agent i receives an observation $o_i \in \Omega$ drawn according to the observation function $O(s, i)$ and selects an action $a_i \in A$, forming a joint action $\mathbf{a} \in A^n$, leading to a next state s' according to the transition function $P(s' | s, \mathbf{a})$, and observing a reward $r = R(s, \mathbf{a})$ shared by all agents. Each agent has local action-observation history $\tau_i \in \mathcal{T} \equiv (\Omega \times A)^*$.

Our idea is to learn to decompose a multi-agent cooperative task into a set of sub-tasks, each of which has a much smaller action-observation space. Each sub-task is associated with a role, and agents taking the same role collectively learn a role policy for solving the sub-task by sharing their learning. Formally, we propose the following definition of sub-tasks and roles.

Definition 1 (Role and Sub-Task). *Given a cooperative multi-agent task $G = \langle I, S, A, P, R, \Omega, O, n, \gamma \rangle$, let Ψ be a set of roles. A role $\rho_j \in \Psi$ is a tuple $\langle g_j, \pi_{\rho_j} \rangle$ where $g_j = \langle I_j, S, A_j, P, R, \Omega_j, O, \gamma \rangle$ is a sub-task and $I_j \subset I$, $\cup_j I_j = I$, and $I_j \cap I_k = \emptyset$, $j \neq k$. A_j is the action space of role j , $A_j \subset A$, $\cup_j A_j = A$, and we allow action spaces of different roles to overlap: $|A_j \cap A_k| \geq 0$, $j \neq k$. $\pi_{\rho_j} : \mathcal{T} \times A_j \rightarrow [0, 1]$ is a role policy for the sub-task g_j associated with the role.*

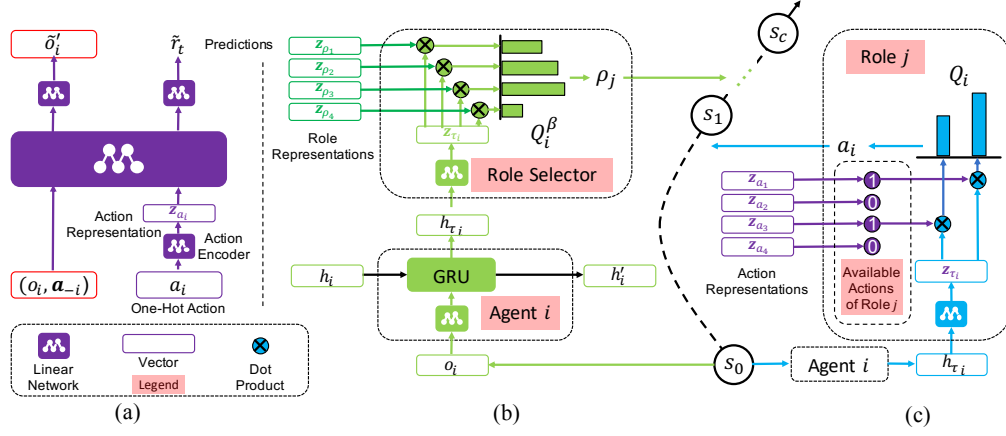


Figure 1: RODE framework. (a) The forward model for learning action representations. (b) Role selector architecture. (c) Role action spaces and role policy structure.

In our definition, a given set of roles specifies not only a factorization of the task but also policies for sub-tasks. This role-based formulation is effectively a kind of dynamic grouping mechanism where agents are grouped by roles. The benefit is that we can learn policies for roles instead of agents, providing scalability with the number of agents and reducing search space of target policies. In our framework, an agent decides which role to take by a *role selector* β that is shared among agents. Here, $\beta : \mathcal{T} \rightarrow \Psi$ is a deterministic function that is conditioned on local action-observation history.

Our aim is to learn a set of roles Ψ^* that maximizes the expected global return $Q^\Psi(s_t, \mathbf{a}_t) = \mathbb{E}_{s_{t+1:\infty}, \mathbf{a}_{t+1:\infty}} [\sum_{i=0}^{\infty} \gamma^i r_{t+i} | s_t, \mathbf{a}_t, \Psi]$. Learning roles involves two questions: learning sub-tasks and role policies. For learning sub-tasks, we need to learn the role selector, β , and to determine role action spaces, A_j . These two components determine the observation and action spaces of roles, respectively. We now introduce the framework to learn these components, which is shown in Fig. 1.

2.1 DETERMINING ROLE ACTION SPACES BY LEARNING ACTION REPRESENTATIONS

Restricting the action space of each role can significantly reduce the policy search space. The key to our approach is to factor the action space according to actions' properties and thereby let roles focus on actions with similar effects, such as attacking enemy units of the same type in StarCraft II.

To this end, we learn action representations that can reflect the effects of actions on the environment and other agents. The effect of an action can be measured by the induced reward and the change in local observations. Therefore, we formulate an objective for learning action representations that incentivizes including enough information such that the next observations and rewards can be predicted when given the actions of other agents and current observations.

In practice, we use the predictive model shown in Fig. 1(a) to learn an action encoder $f_e(\cdot; \theta_e) : \mathbb{R}^{|A|} \rightarrow \mathbb{R}^d$. This encoder, parameterized by θ_e , maps one-hot actions to a d -dimensional representation space. We denote the representation of an action a in this space by \mathbf{z}_a , i.e., $\mathbf{z}_a = f_e(a; \theta_e)$, which is then used to predict the next observation o'_i and the global reward r , given the current observation o_i of an agent i , and the one-hot actions of other agents, \mathbf{a}_{-i} . This model can be interpreted as a forward model, which is trained by minimizing the following loss function:

$$\mathcal{L}_e(\theta_e, \xi_e) = \mathbb{E}_{(o, \mathbf{a}, r, o') \sim \mathcal{D}} \left[\sum_i \|p_o(\mathbf{z}_{a_i}, o_i, \mathbf{a}_{-i}) - o'_i\|_2^2 + \lambda_e \sum_i (p_r(\mathbf{z}_{a_i}, o_i, \mathbf{a}_{-i}) - r)^2 \right], \quad (1)$$

where p_o and p_r are predictors for observations and rewards, respectively, and parameterized by ξ_e . λ_e is a scaling factor, \mathcal{D} is an replay buffer, and the sum is carried out over all agents.

In the beginning, we initialize K roles, each with the full action space. After collecting samples and training the predictive model for t_e timesteps, we cluster the actions according to their latent representations and set the action space of each role to contain one of the clusters. For outliers, we

add them to all clusters to avoid action sets consisting of only one action. After this update, training begins and action representations and action spaces of each role are kept fixed during training.

In this paper, we simply use k -means clustering based on Euclidean distances between action representations, but it can be easily extended to other clustering methods. In practice, we find that the forward model converges quickly. For example, a well-formed representation space can be learned using $50K$ samples on StarCraft II micromanagement tasks, while the training usually lasts for $2M$ timesteps.

2.2 LEARNING THE ROLE SELECTOR AND ROLE POLICIES

Learning action representations to cluster actions based on their effects leads to a factorization of the action space, where each subset of actions can fulfill a certain functionality. To make full use of such a factorization, we use a bi-level hierarchical structure to coordinate the selection of roles and primitive actions. At the top level, a role selector assigns a role to each agent every c timesteps. After a role is assigned, an agent explores in the corresponding restricted role action space to learn the role policy. We now describe how to design efficient, transferable, and lightweight structures for the role selector and role policies.

For the role selector, we can simply use a conventional Q -network whose input is local action-observation history and output is Q -values for each role. However, this structure may not be efficient because it ignores information about action space of different roles. Intuitively, selecting a role is selecting a subset of actions to execute for next c timesteps, so the Q -value of selecting a role is closely related to its role action space. Therefore, we propose to base the role selector on the average representation of available actions. Fig. 1(b) shows the proposed role selector structure. Specifically, we call

$$\mathbf{z}_{\rho_j} = \frac{1}{|A_j|} \sum_{a_k \in A_j} \mathbf{z}_{a_k}, \quad (2)$$

the representation of role ρ_j , where A_j is its restricted action space. To select roles, agents share a linear layer and a GRU, parameterized by $\theta_{\tau\beta}$, to encode the local action-observation history τ into a fixed-length vector h_τ . The role selector, a fully connected network $f_\beta(h_\tau; \theta_\beta)$ with parameters θ_β , then maps h_τ to $\mathbf{z}_\tau \in \mathbb{R}^d$, and we estimate the expected return of agent i selecting role ρ_j as:

$$Q_i^\beta(\tau_i, \rho_j) = \mathbf{z}_{\tau_i}^\top \mathbf{z}_{\rho_j}. \quad (3)$$

Agents select their roles concurrently, which may lead to unintended behaviors. For example, all agents choosing to attack a certain unit type in StarCraft II causes overkill. To better coordinate role assignments, we use a mixing network to estimate global Q -values, Q_{tot}^β , using per-agent utility Q_i^β so that the role selector can be trained using global rewards. In this paper, we use the mixing network introduced by QMIX (Rashid et al., 2018) for its monotonic approximation. The parameters of the mixing network are conditioned on the global state s and are generated by a hypernetwork (Ha et al., 2016) parameterized by ξ_β . Then we minimize the following TD loss to update the role selector f_β :

$$\mathcal{L}_\beta(\theta_{\tau\beta}, \theta_\beta, \xi_\beta) = \mathbb{E}_{\mathcal{D}} \left[\left(\sum_{t'=0}^{c-1} r_{t+t'} + \gamma \max_{\rho'} \bar{Q}_{tot}^\beta(s_{t+c}, \rho') - Q_{tot}^\beta(s_t, \rho_t) \right)^2 \right], \quad (4)$$

where \bar{Q}_{tot}^β is a target network, $\rho = \langle \rho_1, \rho_2, \dots, \rho_n \rangle$ is the joint role of all agents, and the expectation is estimated with uniform samples from a replay buffer \mathcal{D} .

After a role is assigned, an agent follows it for the next c timesteps, during which it can only take actions in the corresponding role action space. Each role ρ_j has a role policy $\pi_{\rho_j} : \mathcal{T} \times A_j \rightarrow [0, 1]$ that is defined in the restricted action space. Similar to the role selector, the most straightforward approach to learning role policies is with a conventional deep Q -network that directly estimates the Q -values of each action. However, basing Q -values on action representations makes full use of the effect information of actions and can generalize better across actions.

Therefore, we use the framework shown in Fig. 1(c) for learning role policies. Specifically, agents again use a shared linear layer and a GRU which together encode a local action-observation history τ into a vector h_τ . We denote the parameters of these two networks by $\theta_{\tau\rho}$. Each role policy is a

fully connected network $f_{\rho_j}(h_\tau; \theta_{\rho_j})$ with parameters θ_{ρ_j} , whose input is h_τ . f_{ρ_j} maps h_τ to \mathbf{z}_τ , which is a vector in \mathbb{R}^d . Using action representations \mathbf{z}_{a_k} and \mathbf{z}_τ , we estimate the value of agent i choosing a primitive action a_k as:

$$Q_i(\tau_i, a_k) = \mathbf{z}_{\tau_i}^\top \mathbf{z}_{a_k}. \quad (5)$$

For learning Q_i using global rewards, we again feed local Q -values into a QMIX-style mixing network to estimate the global action-value, $Q_{tot}(s, \mathbf{a})$. The parameters of the mixing network are denoted by ξ_ρ . This formulation gives the TD loss for learning role policies:

$$\mathcal{L}_\rho(\theta_{\tau_\rho}, \theta_\rho, \xi_\rho) = \mathbb{E}_{\mathcal{D}} \left[\left(r + \gamma \max_{\mathbf{a}'} \bar{Q}_{tot}(s', \mathbf{a}') - Q_{tot}(s, \mathbf{a}) \right)^2 \right]. \quad (6)$$

Here, \bar{Q}_{tot} is a target network, θ_ρ is the parameters of all role policies, and the expectation is estimated with uniform samples from the same replay buffer \mathcal{D} as the one for the role selector. Moreover, two mixing networks for training the role selector and role policies are only used during training. By virtue of effect-based action representations, our framework is lightweight – in practice, we use a single linear layer without activation functions for role policies and a two-layer fully-connected network for the role selector. Basing the role selector and role policies on action representations also enable RODE policies to be rapidly transferred to new tasks with different numbers of agents and actions, which we discuss in detail in Sec. 4.3.

3 RELATED WORK

Hierarchical MARL To realize efficient role-based learning, RODE adopts a hierarchical decision-making structure. Hierarchical reinforcement learning (HRL) (Sutton et al., 1999; Al-Emran, 2015) has been extensively studied to address the sparse reward problem and to facilitate transfer learning. Single-agent HRL focuses on learning temporal decomposition of tasks, either by learning sub-goals (Nachum et al., 2018b;a; Levy et al., 2018; Ghosh et al., 2018; Sukhbaatar et al., 2018; Dwiel et al., 2019; Nair & Finn, 2019; Nasiriany et al., 2019; Dilokthanakul et al., 2019) or by discovering reusable skills (Daniel et al., 2012; Gregor et al., 2016; Warde-Farley et al., 2018; Shankar & Gupta, 2020; Thomas et al., 2018; Sharma et al., 2020). In multi-agent settings, many challenges, such as efficient communication (Ossenkopf et al., 2019) and labor division (Wang et al., 2020c) in large systems, necessitate hierarchical learning along the second dimension – over agents (Zhang et al., 2010). Ahilan & Dayan (2019) propose a hierarchy in FeUdal (Dayan & Hinton, 1993; Vezhnevets et al., 2017) style for cooperative multi-agent tasks, where managers and workers are predefined and workers are expected to achieve the goal generated by managers. Similar hierarchical organizations among agents have been exploited to control traffic lights (Jin & Ma, 2018). Lee et al. (2019); Yang et al. (2019) propose to use bi-level hierarchies to train (or discover) and coordinate individual skills. Vezhnevets et al. (2020) extend hierarchical MARL to Markov Games, where a high-level policy chooses strategic responses to opponents. RODE proposes to learn multi-agent coordination skills in restricted action spaces and is thus complementary to these previous works.

Dealing with Large Discrete Action Spaces In single-agent settings, being able to reason with a large number of discrete actions is essential to bringing reinforcement learning to a larger class of problems, such as natural language processing (He et al., 2016) and recommender systems (Ayush et al., 2020). Sallans & Hinton (2004); Pazis & Parr (2011) represent actions using binary code to reduce the size of large action spaces. Cui & Kharon (2016; 2018) address scalability issues of planning problems by conducting a gradient-based search on a symbolic representation of the state-action value function. Sharma et al. (2017) show that factoring actions into their primary categories can improve performance of deep RL algorithms on Atari 2600 games (Bellemare et al., 2013). All aforementioned methods assume that a handcrafted binary decomposition of raw actions is provided.

Another line of research uses continuous action representations to discover underlying structures of large discrete action spaces, thereby easing training. Van Hasselt & Wiering (2009) use policy gradients with continuous actions and select the nearest discrete action. Dulac-Arnold et al. (2015) extend this work to large-scale problems but use predefined action embeddings. Tennenholtz & Mannor (2019); Chandak et al. (2019) avoid pre-definitions by extracting action representations from expert demonstrations or without prior knowledge. Action representations have been used to solve natural language processing problems (He et al., 2016), enable generalization to unseen (Ayush et al., 2020) or under-explored (Chandak et al., 2019) actions in RL, learn linear dynamics that help

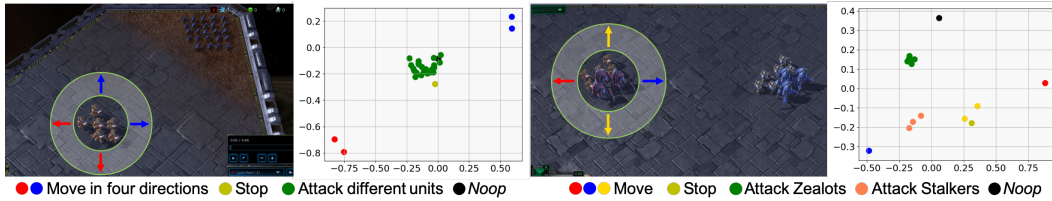


Figure 2: Action representations learned by our predictive model on `corridor` (left) and `3s5z_vs_3s6z` (right). Blue arrows indicate the directions moving towards enemies while red ones show the directions moving away from enemies.

exploration (Kim et al., 2019), and transfer policy across different tasks (Chen et al., 2019). By contrast, we use action representations to factor multi-agent tasks. Besides learning action representations, Czarnecki et al. (2018); Murali et al. (2018); Farquhar et al. (2020) propose to use curriculum learning over action spaces of increasing sizes to scale learning to large spaces. Although the large action space problem is more demanding in multi-agent settings, how to organize effective learning in them is largely unstudied – most algorithms directly search in the full action spaces. This is a key motivation for RODE, where search spaces are reduced by an effect-based action space factorization and a role-based hierarchical structure designed for efficient learning in these factored action spaces.

In Appendix E, we discuss how RODE is related to other role-based learning approaches and multi-agent reinforcement learning algorithms in detail.

4 EXPERIMENTS

We design experiments to answer the following questions: (1) Can the proposed predictive model learn action representations that reflect effects of actions? (Sec. 4.1) (2) Can RODE improve learning efficiency? If so, which component contributes the most to the performance gains? (Sec. 4.2) (3) Can RODE support rapid transfer to environments with different numbers of actions and agents? (Sec. 4.3) (4) Can the role selector learn interpretable high-level cooperative behaviors? (Appx. B)

We choose the StarCraft II micromanagement (SMAC) benchmark (Samvelyan et al., 2019) as the testbed for its rich environments and high complexity of control. The SMAC benchmark requires learning policies in a large action space. Agents can move in four cardinal directions, `stop`, take `noop` (do nothing), or select an enemy to attack at each timestep. Therefore, if there are n_e enemies in the map, the action space for each ally unit contains $n_e + 6$ discrete actions.

4.1 ACTION REPRESENTATIONS

For learning action representations, on all maps, we set the scaling factor λ_e to 10 and collect samples and train the predictive model for $50K$ timesteps using the loss function described by Eq. 1. The model is trained every episode using a batch of 32 episodes. In Fig. 2, we show the learned action representations on two maps, `3s5z_vs_3s6z` and `corridor`.

The map `corridor` features homogeneous agents and enemies, with 6 Zealots faced with 24 enemy Zerglings. In this task, all attack actions have similar effects because the enemies are homogeneous. Moreover, due to the symmetry of the map, moving northward and eastward exert similar influence on the environment – moving the agent towards enemies. Likewise, moving southward and westward have the same effect because both actions move agents away from enemies. The learned action encoder captures these underlying structures in the action space (Fig. 2 left). We can observe three clear clusters in the latent action representation space, which correspond to the aforementioned three types of actions, respectively. On the map `3s5z_vs_3s6z`, 3 Stalkers and 5 Zealots try to beat 3 enemy Stalkers and 6 Enemy Zealots. Unlike `corridor`, the enemy team consists of heterogeneous units, and attacking Stalkers and Zealots have distinct effects. Our predictive model highlights this difference – the attack actions are clustered into two groups (Fig. 2 right). Moreover, the learned action encoder also captures the dissimilarity between moving northward/southward and moving in other directions – these two move actions do not bring agents near to or far away from enemies.

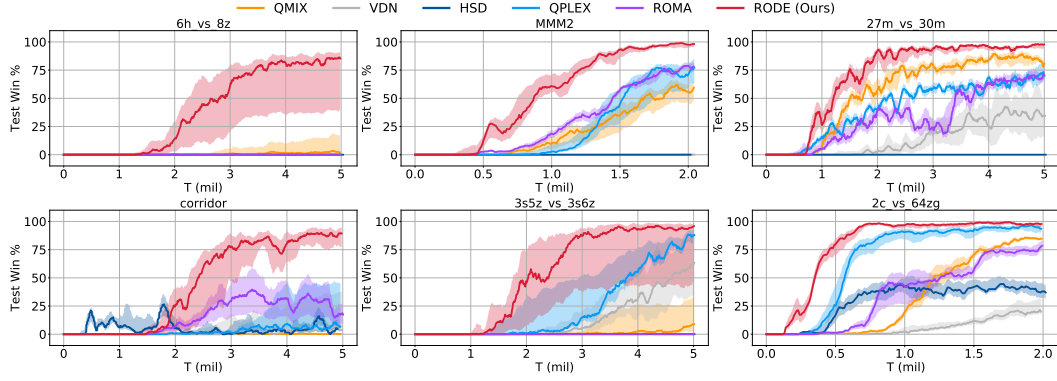


Figure 3: Performance comparison with baselines on *all super hard* maps and one *hard* map (2c_vs_64zg). In Appendix C.1, we show results on the whole benchmark.

Although we only show results on two maps, each with one random seed, similar action clusters can be observed on all the scenarios and are robust across different seeds. Therefore, we conclude that our predictive model effectively learns action representations that reflect the effects of actions.

4.2 PERFORMANCE AND ABLATION STUDY

For evaluation, all experiments in this section are carried out with 8 different random seeds, and the median performance as well as the 25-75% percentiles are shown. The detailed setting of hyperparameters is described in Appendix A.

We benchmark our method on all 14 scenarios in order to evaluate its performance across the entire SMAC suite, and the results are shown in Fig. 4. We compare with current state-of-the-art value-based MARL algorithms (VDN (Sunehag et al., 2018), QMIX (Rashid et al., 2018), and QPLEX (Wang et al., 2020b)), hierarchical MARL method (HSD (Yang et al., 2019)), and role-based MARL method (ROMA (Wang et al., 2020c)). RODE outperforms all the baselines by at least 1/32 on 10 of all 14 scenarios after $2M$ training steps.

Maps of the SMAC benchmark have been classified as *easy*, *hard*, and *super hard*. Hard and super hard maps are typically hard-exploration tasks. Since RODE is designed to help exploration by decomposing the joint action space, we are especially interested in the performance of our method on these maps. Fig. 3 shows the performance of RODE on all super hard scenarios and one hard scenarios. In Appendix C.1, we further show learning curves on the whole benchmark. We can see on all of 9 hard and super hard maps, RODE has the best performance. Moreover, RODE outperforms baselines by the largest margin on the maps that require more exploration: 3s5z_vs_3s6z, corridor, and 6h_vs_8z. In contrast, on 5 easy maps, RODE typically needs more samples to learn a successful strategy. We hypothesize that this is because these maps do not require substantial exploration, and the exploratory benefit brought by restricted action spaces is not obvious.

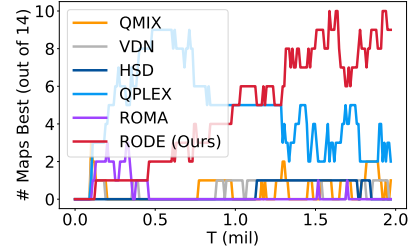


Figure 4: The number of scenarios (out of all 14 scenarios) in which the algorithm’s median test win % is the highest by at least 1/32.

Ablations To understand the superior performance of RODE, we carry out ablation studies to test the contribution of its four main components: (A) Restricted role action spaces; (B) Using action effects to cluster actions; (C) The integration of action representations into role policies and the role selector; (D) The hierarchical learning structure. To test component A and B, when updating role action spaces after $50K$ samples, we let each role action space contains all actions or a random subset of actions, respectively, while keeping other parts in the framework unchanged. For component B, we make sure the union of role action spaces equals the entire action space. To test component C, we can simply use conventional Q -networks for learning role policies and the role selector. The testing

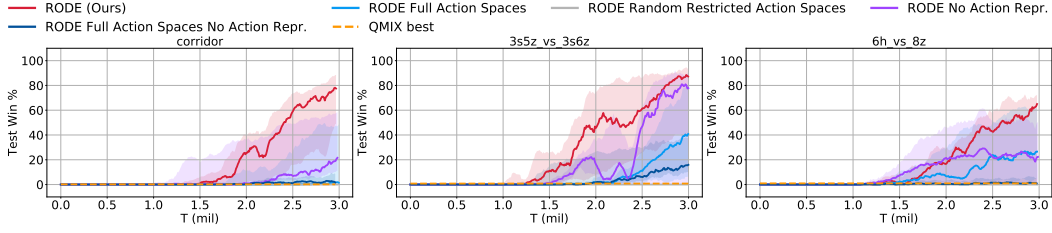


Figure 5: Ablation studies regarding each component of RODE. The best performance that can be achieved by QMIX is shown as horizontal dashed lines.

of component D is a bit different because we cannot ablate it separately while still using different roles. Therefore, we test it by ablating components A and C – using conventional deep Q -networks for role policies and the role selector and allowing role policies to choose from all primitive actions.

The results on the three most difficult scenarios from the benchmark are shown in Fig. 5. Generally speaking, performance of RODE using conventional deep Q -networks (*RODE No Action Repr.*) is close to that of RODE, and is significantly better than the other two ablations where role action spaces are not restricted. Therefore, using action representations in policy learning can help improve learning but the superior performance of RODE is mostly due to the restriction of the role action spaces. RODE with full role action spaces and conventional Q -networks (*RODE Full Action Spaces No Action Repr.*) has similar performance to QMIX, which demonstrates that the hierarchical structure itself does not contribute much to the performance gains. RODE with random restricted role action spaces also cannot outperform QMIX, highlighting the importance of using action effects to decompose joint action spaces.

In summary, by virtue of restricted role action spaces and the integration of action effect information into policies, RODE achieves a new state of the art on the SMAC benchmark. In Appendix B, we provide a case study to better understand why restricting role action spaces can improve performance. We study the effects of the interval between role selections in Appendix D.1.

4.3 POLICY TRANSFER

A bonus of basing role policies on action representations is that we can transfer the learned policies to tasks with new actions that have similar effects to old ones. To realize this, given a new task, we first collect some samples and train the action encoder. In this way, we identify the old actions that have similar functionality to the new actions. Then we use the average representation of these old actions as representations of new actions and add new actions to role action spaces to which the similar old actions belong. Moreover, in our framework, it is roles that are interacting with the environment, and agents only need to be assigned with roles. Therefore, our learned policies can also be transferred to tasks with different numbers of agents.

We test the transferability of our method on the SMAC benchmark. To keep the length of observations fixed, we sort allies and enemies by their relative distances to an agent and include the information of nearest N_a allies and N_e enemies in the visible range. In Fig. 6, we show win rates of the policy learned from map *corridor* on different maps without further policy training. In the original task, 6 Zealots face 24 enemy Zerglings. We set N_a to 5 and N_e to 24. We increase the number of agents and enemies, and the number of actions increases as the number of enemies grows. The transferability of RODE is attested by observing that the learned policy can still win 50% of the games on unseen maps with three times the number of agents. More details of this experiment is described in Appendix C.2. Besides rapid transfer, iteratively training

# Enemies	24	26	28	30	32	34	36
# Allies							
6	99.2	85.0	25.8	0.0	0.8	0.0	0.0
8	75.0	68.3	6.7	0.0	0.0	0.0	0.0
10	92.5	75.0	24.2	8.3	2.5	1.7	0.0
12	97.5	75.0	74.2	29.2	17.5	9.2	1.7
14	97.5	88.0	69.2	42.5	38.3	22.5	5.8
16	100	95.0	63.3	42.5	48.3	38.3	32.5
18	100	96.7	71.7	54.3	45.8	45.0	58.0

Figure 6: Win rates on unseen maps of the policy learned on *corridor*, where 6 ally Zealots face 24 Zerglings. We do not train policies on new maps.

the transferred policies on larger tasks may be a promising future direction to scaling MARL to large-scale problems.

5 CONCLUSION

How to come up with a set of roles that can effectively decompose the task is a long standing problem preventing role-based learning from realizing scalability. Instead of learning roles from scratch, in this paper, we find that role discovery becomes much easier if we first decompose joint action spaces according to action effects. With a specially designed hierarchical learning framework, we achieve efficient learning over these factored action spaces. We believe that the scalability and transferability provided by our method are crucial in building flexible and general-purpose multi-agent systems.

REFERENCES

- Sanjeevan Ahilan and Peter Dayan. Feudal multi-agent hierarchies for cooperative reinforcement learning. *arXiv preprint arXiv:1901.08492*, 2019.
- Mostafa Al-Emran. Hierarchical reinforcement learning: a survey. *International journal of computing and digital systems*, 4(02), 2015.
- Jain Ayush, Szot Andrew, and J. Lim Joseph. Generalization to new actions in reinforcement learning. In *Proceedings of the 37th International Conference on Machine Learning*, 2020.
- Bowen Baker, Ingmar Kanitscheider, Todor Markov, Yi Wu, Glenn Powell, Bob McGrew, and Igor Mordatch. Emergent tool use from multi-agent autocurricula. In *Proceedings of the International Conference on Learning Representations (ICLR)*, 2020.
- Marc G Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47: 253–279, 2013.
- Christopher Berner, Greg Brockman, Brooke Chan, Vicki Cheung, Przemyslaw Debiak, Christy Dennison, David Farhi, Quirin Fischer, Shariq Hashme, Chris Hesse, et al. Dota 2 with large scale deep reinforcement learning. *arXiv preprint arXiv:1912.06680*, 2019.
- Wendelin Böhmer, Vitaly Kurin, and Shimon Whiteson. Deep coordination graphs. In *Proceedings of the 37th International Conference on Machine Learning*, 2020.
- N Bonjean, W Mefteh, MP Gleizes, C Maurel, and F Migeon. Adelfe 2.0: Handbook on agent-oriented design processes, m. cossentino, v. hilaire, a. molesini, and v. seidita, 2014.
- Paolo Bresciani, Anna Perini, Paolo Giorgini, Fausto Giunchiglia, and John Mylopoulos. Tropos: An agent-oriented software development methodology. *Autonomous Agents and Multi-Agent Systems*, 8(3):203–236, 2004.
- Eamonn Butler. *The condensed wealth of nations*. Centre for Independent Studies, 2012.
- Lucas Cassano, Kun Yuan, and Ali H Sayed. Multi-agent fully decentralized value function learning with linear convergence rates. *arXiv preprint arXiv:1810.07792*, 2018.
- Yash Chandak, Georgios Theodorou, James Kostas, Scott Jordan, and Philip Thomas. Learning action representations for reinforcement learning. In *International Conference on Machine Learning*, pp. 941–950, 2019.
- Yu Chen, Yingfeng Chen, Yu Yang, Ying Li, Jianwei Yin, and Changjie Fan. Learning action-transferable policy with action embedding. *arXiv preprint arXiv:1909.02291*, 2019.
- Caroline Claus and Craig Boutilier. The dynamics of reinforcement learning in cooperative multi-agent systems. *AAAI/IAAI*, 1998(746-752):2, 1998.
- Massimo Cossentino, Salvatore Gaglio, Luca Sabatucci, and Valeria Seidita. The passi and agile passi mas meta-models compared with a unifying proposal. In *International Central and Eastern European Conference on Multi-Agent Systems*, pp. 183–192. Springer, 2005.

- Hao Cui and Roni Khordon. Online symbolic gradient-based optimization for factored action mdps. In *IJCAI*, pp. 3075–3081, 2016.
- Hao Cui and Roni Khordon. Lifted stochastic planning, belief propagation and marginal map. In *AAAI Workshops*, pp. 658–664, 2018.
- Wojciech Czarnecki, Siddhant Jayakumar, Max Jaderberg, Leonard Hasenclever, Yee Whye Teh, Nicolas Heess, Simon Osindero, and Razvan Pascanu. Mix & match agent curricula for reinforcement learning. In *International Conference on Machine Learning*, pp. 1087–1095, 2018.
- Christian Daniel, Gerhard Neumann, and Jan Peters. Hierarchical relative entropy policy search. In *Artificial Intelligence and Statistics*, pp. 273–281, 2012.
- Abhishek Das, Théophile Gervet, Joshua Romoff, Dhruv Batra, Devi Parikh, Mike Rabbat, and Joelle Pineau. Tarmac: Targeted multi-agent communication. In *International Conference on Machine Learning*, pp. 1538–1546, 2019.
- Peter Dayan and Geoffrey E Hinton. Feudal reinforcement learning. In *Advances in neural information processing systems*, pp. 271–278, 1993.
- Scott A DeLoach and Juan Carlos Garcia-Ojeda. O-mase: a customisable approach to designing and building complex, adaptive multi-agent systems. *International Journal of Agent-Oriented Software Engineering*, 4(3):244–280, 2010.
- Nat Dilokthanakul, Christos Kaplanis, Nick Pawlowski, and Murray Shanahan. Feature control as intrinsic motivation for hierarchical reinforcement learning. *IEEE transactions on neural networks and learning systems*, 30(11):3409–3418, 2019.
- Gabriel Dulac-Arnold, Richard Evans, Hado van Hasselt, Peter Sunehag, Timothy Lillicrap, Jonathan Hunt, Timothy Mann, Theophane Weber, Thomas Degris, and Ben Coppin. Deep reinforcement learning in large discrete action spaces. *arXiv preprint arXiv:1512.07679*, 2015.
- Zach Dwiel, Madhavun Candadai, Mariano Phielipp, and Arjun K Bansal. Hierarchical policy learning is sensitive to goal space design. *arXiv preprint arXiv:1905.01537*, 2019.
- Gregory Farquhar, Laura Gustafson, Zeming Lin, Shimon Whiteson, Nicolas Usunier, and Gabriel Synnaeve. Growing action spaces. In *Proceedings of the 37th International Conference on Machine Learning*, 2020.
- Jakob Foerster, Ioannis Alexandros Assael, Nando de Freitas, and Shimon Whiteson. Learning to communicate with deep multi-agent reinforcement learning. In *Advances in Neural Information Processing Systems*, pp. 2137–2145, 2016.
- Jakob N Foerster, Gregory Farquhar, Triantafyllos Afouras, Nantas Nardelli, and Shimon Whiteson. Counterfactual multi-agent policy gradients. In *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.
- Dibya Ghosh, Abhishek Gupta, and Sergey Levine. Learning actionable representations with goal conditioned policies. In *International Conference on Learning Representations*, 2018.
- Deborah M Gordon. The organization of work in social insect colonies. *Nature*, 380(6570):121–124, 1996.
- Karol Gregor, Danilo Jimenez Rezende, and Daan Wierstra. Variational intrinsic control. *arXiv preprint arXiv:1611.07507*, 2016.
- Carlos Guestrin, Daphne Koller, and Ronald Parr. Multiagent planning with factored mdps. In *Advances in neural information processing systems*, pp. 1523–1530, 2002a.
- Carlos Guestrin, Michail Lagoudakis, and Ronald Parr. Coordinated reinforcement learning. In *ICML*, volume 2, pp. 227–234. Citeseer, 2002b.
- Jayesh K Gupta, Maxim Egorov, and Mykel Kochenderfer. Cooperative multi-agent control using deep reinforcement learning. In *International Conference on Autonomous Agents and Multiagent Systems*, pp. 66–83. Springer, 2017.

- David Ha, Andrew Dai, and Quoc V Le. Hypernetworks. *arXiv preprint arXiv:1609.09106*, 2016.
- Ji He, Jianshu Chen, Xiaodong He, Jianfeng Gao, Lihong Li, Li Deng, and Mari Ostendorf. Deep reinforcement learning with a natural language action space. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1621–1630, 2016.
- Edward Hughes, Joel Z Leibo, Matthew Phillips, Karl Tuyls, Edgar Dueñez-Guzman, Antonio García Castañeda, Iain Dunning, Tina Zhu, Kevin McKee, Raphael Koster, et al. Inequity aversion improves cooperation in intertemporal social dilemmas. In *Advances in Neural Information Processing Systems*, pp. 3330–3340, 2018.
- Shariq Iqbal and Fei Sha. Actor-attention-critic for multi-agent reinforcement learning. In *International Conference on Machine Learning*, pp. 2961–2970, 2019.
- Max Jaderberg, Wojciech M Czarnecki, Iain Dunning, Luke Marris, Guy Lever, Antonio Garcia Castaneda, Charles Beattie, Neil C Rabinowitz, Ari S Morcos, Avraham Ruderman, et al. Human-level performance in 3d multiplayer games with population-based reinforcement learning. *Science*, 364(6443):859–865, 2019.
- Natasha Jaques, Angeliki Lazaridou, Edward Hughes, Caglar Gulcehre, Pedro Ortega, Dj Strouse, Joel Z Leibo, and Nando De Freitas. Social influence as intrinsic motivation for multi-agent deep reinforcement learning. In *International Conference on Machine Learning*, pp. 3040–3049, 2019.
- Raphaël Jeanson, Penelope F Kukuk, and Jennifer H Fewell. Emergence of division of labour in halictine bees: contributions of social interactions and behavioural variance. *Animal behaviour*, 70(5):1183–1193, 2005.
- Junchen Jin and Xiaoliang Ma. Hierarchical multi-agent control of traffic lights based on collective learning. *Engineering applications of artificial intelligence*, 68:236–248, 2018.
- Hyoungseok Kim, Jaekyeom Kim, Yeonwoo Jeong, Sergey Levine, and Hyun Oh Song. Emi: Exploration with mutual information. In *International Conference on Machine Learning*, pp. 3360–3369, 2019.
- Jelle R Kok and Nikos Vlassis. Collaborative multiagent reinforcement learning by payoff propagation. *Journal of Machine Learning Research*, 7(Sep):1789–1828, 2006.
- Angeliki Lazaridou, Alexander Peysakhovich, and Marco Baroni. Multi-agent cooperation and the emergence of (natural) language. In *Proceedings of the International Conference on Learning Representations (ICLR)*, 2017.
- Youngwoon Lee, Jingyun Yang, and Joseph J Lim. Learning to coordinate manipulation skills via skill behavior diversification. In *International Conference on Learning Representations*, 2019.
- Andrew Levy, George Konidaris, Robert Platt, and Kate Saenko. Learning multi-level hierarchies with hindsight. In *International Conference on Learning Representations*, 2018.
- Kemas M Lhaksmana, Yohei Murakami, and Toru Ishida. Role-based modeling for designing agent behavior in self-organizing multi-agent systems. *International Journal of Software Engineering and Knowledge Engineering*, 28(01):79–96, 2018.
- Ryan Lowe, Yi Wu, Aviv Tamar, Jean Harb, OpenAI Pieter Abbeel, and Igor Mordatch. Multi-agent actor-critic for mixed cooperative-competitive environments. In *Advances in Neural Information Processing Systems*, pp. 6379–6390, 2017.
- Sergio Valcarcel Macua, Aleksi Tukiainen, Daniel García-Ocaña Hernández, David Baldazo, Enrique Muñoz de Cote, and Santiago Zazo. Diff-dac: Distributed actor-critic for multitask deep reinforcement learning. *arXiv preprint arXiv:1710.10363*, 2017.
- Anuj Mahajan, Tabish Rashid, Mikayel Samvelyan, and Shimon Whiteson. Maven: Multi-agent variational exploration. In *Advances in Neural Information Processing Systems*, pp. 7611–7622, 2019.

- Adithyavairavan Murali, Lerrel Pinto, Dhiraj Gandhi, and Abhinav Gupta. Cassl: Curriculum accelerated self-supervised learning. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 6453–6460. IEEE, 2018.
- Ofir Nachum, Shixiang Gu, Honglak Lee, and Sergey Levine. Near-optimal representation learning for hierarchical reinforcement learning. In *International Conference on Learning Representations*, 2018a.
- Ofir Nachum, Shixiang Shane Gu, Honglak Lee, and Sergey Levine. Data-efficient hierarchical reinforcement learning. In *Advances in Neural Information Processing Systems*, pp. 3303–3313, 2018b.
- Suraj Nair and Chelsea Finn. Hierarchical foresight: Self-supervised learning of long-horizon tasks via visual subgoal generation. In *International Conference on Learning Representations*, 2019.
- Soroush Nasiriany, Vitchyr Pong, Steven Lin, and Sergey Levine. Planning with goal-conditioned policies. In *Advances in Neural Information Processing Systems*, pp. 14843–14854, 2019.
- Frans A Oliehoek, Christopher Amato, et al. *A concise introduction to decentralized POMDPs*, volume 1. Springer, 2016.
- Andrea Omicini. Soda: Societies and infrastructures in the analysis and design of agent-based systems. In *International Workshop on Agent-Oriented Software Engineering*, pp. 185–193. Springer, 2000.
- Marie Ossenkopf, Mackenzie Jorgensen, and Kurt Geihs. When does communication learning need hierarchical multi-agent deep reinforcement learning. *Cybernetics and Systems*, 50(8):672–692, 2019.
- Lin Padgham and Michael Winikoff. Prometheus: A methodology for developing intelligent agents. In *International Workshop on Agent-Oriented Software Engineering*, pp. 174–185. Springer, 2002.
- Juan Pavón and Jorge Gómez-Sanz. Agent oriented software engineering with ingenias. In *International Central and Eastern European Conference on Multi-Agent Systems*, pp. 394–403. Springer, 2003.
- Jason Papis and Ronald Parr. Generalized value functions for large action sets. In *Proceedings of the 28th International Conference on Machine Learning*, pp. 1185–1192, 2011.
- Huy Xuan Pham, Hung Manh La, David Feil-Seifer, and Aria Nefian. Cooperative and distributed reinforcement learning of drones for field coverage, 2018.
- Tabish Rashid, Mikayel Samvelyan, Christian Schroeder Witt, Gregory Farquhar, Jakob Foerster, and Shimon Whiteson. Qmix: Monotonic value function factorisation for deep multi-agent reinforcement learning. In *International Conference on Machine Learning*, pp. 4292–4301, 2018.
- Tabish Rashid, Mikayel Samvelyan, Christian Schroeder De Witt, Gregory Farquhar, Jakob Foerster, and Shimon Whiteson. Monotonic value function factorisation for deep multi-agent reinforcement learning. *arXiv preprint arXiv:2003.08839*, 2020.
- Brian Sallans and Geoffrey E Hinton. Reinforcement learning with factored states and actions. *Journal of Machine Learning Research*, 5(Aug):1063–1088, 2004.
- Mikayel Samvelyan, Tabish Rashid, Christian Schroeder de Witt, Gregory Farquhar, Nantas Nardelli, Tim GJ Rudner, Chia-Man Hung, Philip HS Torr, Jakob Foerster, and Shimon Whiteson. The starcraft multi-agent challenge. *arXiv preprint arXiv:1902.04043*, 2019.
- Tanmay Shankar and Abhinav Gupta. Learning robot skills with temporal variational inference. In *Proceedings of the 37th International Conference on Machine Learning*. JMLR. org, 2020.
- Archit Sharma, Shixiang Gu, Sergey Levine, Vikash Kumar, and Karol Hausman. Dynamics-aware unsupervised discovery of skills. In *International Conference on Learning Representations*, 2020.

- Sahil Sharma, Aravind Suresh, Rahul Ramesh, and Balaraman Ravindran. Learning to factor policies and action-value functions: Factored action space representations for deep reinforcement learning. *arXiv preprint arXiv:1705.07269*, 2017.
- Adam Smith. The wealth of nations [1776], 1937.
- Kyunghwan Son, Daewoo Kim, Wan Ju Kang, David Earl Hostallero, and Yung Yi. Qtran: Learning to factorize with transformation for cooperative multi-agent reinforcement learning. In *International Conference on Machine Learning*, pp. 5887–5896, 2019.
- Nikolaos Spanoudakis and Pavlos Moraitis. Using aseme methodology for model-driven agent systems development. In *International Workshop on Agent-Oriented Software Engineering*, pp. 106–127. Springer, 2010.
- Sainbayar Sukhbaatar, Rob Fergus, et al. Learning multiagent communication with backpropagation. In *Advances in Neural Information Processing Systems*, pp. 2244–2252, 2016.
- Sainbayar Sukhbaatar, Emily Denton, Arthur Szlam, and Rob Fergus. Learning goal embeddings via self-play for hierarchical reinforcement learning. *arXiv preprint arXiv:1811.09083*, 2018.
- Changyin Sun, Wenzhang Liu, and Lu Dong. Reinforcement learning with task decomposition for cooperative multiagent systems. *IEEE transactions on neural networks and learning systems*, 2020.
- Peter Sunehag, Guy Lever, Audrunas Gruslys, Wojciech Marian Czarnecki, Vinicius Zambaldi, Max Jaderberg, Marc Lanctot, Nicolas Sonnerat, Joel Z Leibo, Karl Tuyls, et al. Value-decomposition networks for cooperative multi-agent learning based on team reward. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*, pp. 2085–2087. International Foundation for Autonomous Agents and Multiagent Systems, 2018.
- Wesley Suttle, Zhuoran Yang, Kaiqing Zhang, Zhaoran Wang, Tamer Basar, and Ji Liu. A multi-agent off-policy actor-critic algorithm for distributed reinforcement learning. *arXiv preprint arXiv:1903.06372*, 2019.
- Richard S Sutton, Doina Precup, and Satinder Singh. Between mdps and semi-mdps: A framework for temporal abstraction in reinforcement learning. *Artificial intelligence*, 112(1-2):181–211, 1999.
- Ming Tan. Multi-agent reinforcement learning: Independent vs. cooperative agents. In *Proceedings of the tenth international conference on machine learning*, pp. 330–337, 1993.
- Guy Tennenholtz and Shie Mannor. The natural language of actions. In *International Conference on Machine Learning*, pp. 6196–6205, 2019.
- Valentin Thomas, Emmanuel Bengio, William Fedus, Jules Pongard, Philippe Beaudoin, Hugo Larochelle, Joelle Pineau, Doina Precup, and Yoshua Bengio. Disentangling the independently controllable factors of variation by interacting with the world. *arXiv preprint arXiv:1802.09484*, 2018.
- Hado Van Hasselt and Marco A Wiering. Using continuous action spaces to solve discrete problems. In *2009 International Joint Conference on Neural Networks*, pp. 1149–1156. IEEE, 2009.
- Alexander Sasha Vezhnevets, Simon Osindero, Tom Schaul, Nicolas Heess, Max Jaderberg, David Silver, and Koray Kavukcuoglu. Feudal networks for hierarchical reinforcement learning. *arXiv preprint arXiv:1703.01161*, 2017.
- Alexander Sasha Vezhnevets, Yuhuai Wu, Rémi Leblond, and Joel Z Leibo. Options as responses: Grounding behavioural hierarchies in multi-agent rl. In *Proceedings of the 37th International Conference on Machine Learning*. JMLR. org, 2020.
- Oriol Vinyals, Igor Babuschkin, Wojciech M Czarnecki, Michaël Mathieu, Andrew Dudzik, Junyoung Chung, David H Choi, Richard Powell, Timo Ewalds, Petko Georgiev, et al. Grandmaster level in starcraft ii using multi-agent reinforcement learning. *Nature*, 575(7782):350–354, 2019.

- Jianhao Wang, Zhizhou Ren, Beining Han, and Chongjie Zhang. Towards understanding linear value decomposition in cooperative multi-agent q-learning, 2020a.
- Jianhao Wang, Zhizhou Ren, Terry Liu, Yang Yu, and Chongjie Zhang. Qplex: Duplex dueling multi-agent q-learning. *arXiv preprint arXiv:2008.01062*, 2020b.
- Tonghan Wang, Heng Dong, Victor Lesser, and Chongjie Zhang. Roma: Multi-agent reinforcement learning with emergent roles. In *Proceedings of the 37th International Conference on Machine Learning*, 2020c.
- Tonghan Wang, Jianhao Wang, Wu Yi, and Chongjie Zhang. Influence-based multi-agent exploration. In *Proceedings of the International Conference on Learning Representations (ICLR)*, 2020d.
- Tonghan Wang, Jianhao Wang, Chongyi Zheng, and Chongjie Zhang. Learning nearly decomposable value functions with communication minimization. In *Proceedings of the International Conference on Learning Representations (ICLR)*, 2020e.
- Yihan Wang, Beining Han, Tonghan Wang, Heng Dong, and Chongjie Zhang. Off-policy multi-agent decomposed policy gradients. *arXiv preprint arXiv:2007.12322*, 2020f.
- David Warde-Farley, Tom Van de Wiele, Tejas Kulkarni, Catalin Ionescu, Steven Hansen, and Volodymyr Mnih. Unsupervised control through non-parametric discriminative rewards. In *International Conference on Learning Representations*, 2018.
- Ying Wen, Yaodong Yang, Rui Luo, Jun Wang, and Wei Pan. Probabilistic recursive reasoning for multi-agent reinforcement learning. In *Proceedings of the International Conference on Learning Representations (ICLR)*, 2019.
- Aaron Wilson, Alan Fern, and Prasad Tadepalli. Bayesian policy search for multi-agent role discovery. In *Twenty-Fourth AAAI Conference on Artificial Intelligence*, 2010.
- Michael Wooldridge, Nicholas R Jennings, and David Kinny. The gaia methodology for agent-oriented analysis and design. *Autonomous Agents and multi-agent systems*, 3(3):285–312, 2000.
- Zhao Xu, Yang Lyu, Quan Pan, Jinwen Hu, Chunhui Zhao, and Shuai Liu. Multi-vehicle flocking control with deep deterministic policy gradient method. *2018 IEEE 14th International Conference on Control and Automation (ICCA)*, Jun 2018. doi: 10.1109/icca.2018.8444355. URL <http://dx.doi.org/10.1109/ICCA.2018.8444355>.
- Jiachen Yang, Igor Borovikov, and Hongyuan Zha. Hierarchical cooperative multi-agent reinforcement learning with skill discovery. *arXiv preprint arXiv:1912.03558*, 2019.
- Yaodong Yang, Rui Luo, Minne Li, Ming Zhou, Weinan Zhang, and Jun Wang. Mean field multi-agent reinforcement learning. In *International Conference on Machine Learning*, pp. 5571–5580, 2018.
- Chongjie Zhang and Victor Lesser. Coordinated multi-agent reinforcement learning in networked distributed pomdps. In *Twenty-Fifth AAAI Conference on Artificial Intelligence*, 2011.
- Chongjie Zhang and Victor Lesser. Coordinating multi-agent reinforcement learning with limited communication. In *Proceedings of the 2013 international conference on Autonomous agents and multi-agent systems*, pp. 1101–1108. International Foundation for Autonomous Agents and Multiagent Systems, 2013.
- Chongjie Zhang, Victor R Lesser, and Sherief Abdallah. Self-organization for coordinating decentralized reinforcement learning. In *AAMAS*, volume 10, pp. 739–746, 2010.
- Kaiqing Zhang, Zhuoran Yang, Han Liu, Tong Zhang, and Tamer Basar. Fully decentralized multi-agent reinforcement learning with networked agents. In *International Conference on Machine Learning*, pp. 5872–5881, 2018.
- Yan Zhang and Michael M Zavlanos. Distributed off-policy actor-critic reinforcement learning with policy consensus. *arXiv preprint arXiv:1903.09255*, 2019.
- Haibin Zhu and MengChu Zhou. Role-based multi-agent systems. In *Personalized Information Retrieval and Access: Concepts, Methods and Practices*, pp. 254–285. Igi Global, 2008.

A ARCHITECTURE, HYPERPARAMETERS, AND INFRASTRUCTURE

In this paper, we use simple network structures for the role selector and role policies. Each role policy is a simple linear network without hidden layers or activation functions, and the role selector is a two-layer feed-forward fully-connected network with a 64-dimensional hidden layer. Agents share a trajectory encoding network consisting of two layers, a fully-connected layer followed by a GRU layer with a 64-dimensional hidden state. For all experiments, the length of action representations, d , is set to 20. The outputs of role policies and the outputs of role selector are each fed into their own separate QMIX-style mixing networks (Rashid et al., 2020) to estimate the global action values. The two mixing networks use the same architecture, containing a 32-dimensional hidden layer with ReLU activation. Parameters of the mixing networks are generated by hypernetworks conditioning on global states. These settings are the same to QMIX (Rashid et al., 2020). Moreover, it can be easily extended to other mixing mechanisms, such as QPLEX (Wang et al., 2020b), which may further improve the performance of RODE.

For all experiments, the optimization is conducted using RMSprop with a learning rate of 5×10^{-4} , α of 0.99, and with no momentum or weight decay. For exploration, we use ϵ -greedy with ϵ annealed linearly from 1.0 to 0.05 over $50K$ time steps and kept constant for the rest of the training. For three hard exploration maps—3s5z_vs_3s6z, 6h_vs_8z, and 27m_vs_30m—we extend the epsilon annealing time to $500K$, for both RODE and all the baselines and ablations. Batches of 32 episodes are sampled from the replay buffer, and the role selector and role policies are trained end-to-end on fully unrolled episodes. All experiments on the SMAC benchmark use the default reward and observation settings of the SMAC benchmark (Samvelyan et al., 2019). Experiments are carried out on NVIDIA GTX 2080 Ti GPU.

We use k -means clustering when determining role action spaces. The number of clusters, k , is treated as a hyperparameter. Specifically, on maps with homogeneous enemies, we set k to 3, and on maps with heterogeneous enemies, we set k to 5. If the task only involves one enemy, k is set to 2. We can avoid this hyperparameter by using more advanced clustering approaches.

For all baseline algorithms, we use the codes provided by their authors where the hyperparameters have been fine-tuned on the SMAC benchmark.

B CASE STUDY: ROLE DYNAMICS

In this section, we provide a case study to explore the dynamics of the role selector and give an example to explain why restricting action spaces of roles can improve learning performance.

We carry out our study on the map `corridor` from the SMAC benchmark. We choose this map because it presents a hard-exploration task. An optimal strategy for this scenario requires active state space exploration for the allied Zealots to learn to move to edges or to the choke point on the map, so as to not be surrounded by the enemy army. Previous state-of-the-art algorithms all learn a suboptimal strategy, where agents merely damage the enemy units for rewards, instead of first moving to edges and then attacking.

In Fig. 7, we show the roles assigned by the learned role selector at different timesteps in an episode. The first row shows game snapshots, and the second row presents the corresponding role assignments. Here, the action encoder gives three clusters of actions (see Fig. 2left) – move eastward & northward, attack, and move westward & southward. These clusters of actions form the action spaces of three roles. The color of circles indicates the role of an ally unit.

We see that all agents select *Role 2* in the beginning (Fig. 7 (a)) to help them move to the edges, which is the good strategy as discussed above. The agents also learn an effective cooperative policy – one of the agents (agent A) attracts most of the enemies (enemy group A) so that its teammates have an advantage when facing fewer enemies (enemy group B). After killing agent A, enemy group A goes through the choke point and arrives their destination. In Fig. 7 (b), the alive agents start to attack this group of enemies. However, the enemies are still very powerful. To win the game, ally agents learn to attract part of enemies and kill them. They achieve this by alternating between *Role 0* (retract in this case) and *Role 1* (attack), as shown in Fig. 7 (b-d).

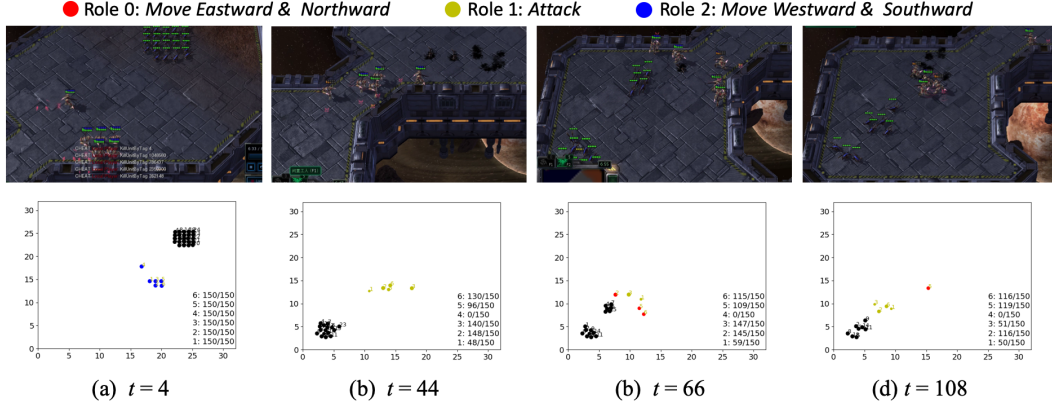


Figure 7: Visualization of roles in one episode on corridor. The first row shows game snapshots. In the second row, black circles are enemies and circles in other colors are ally agents, with different colors indicating different assigned roles. The size of circles is proportional to the remaining health points of units. The remaining and maximum health points are also shown in the lower right corner of the figures.

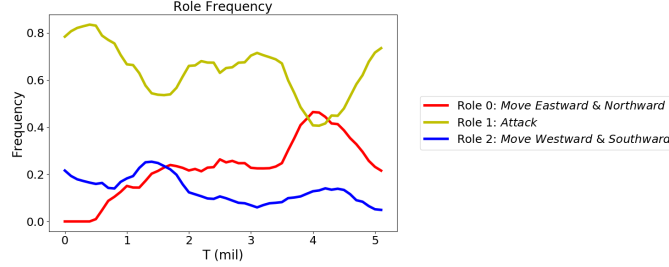
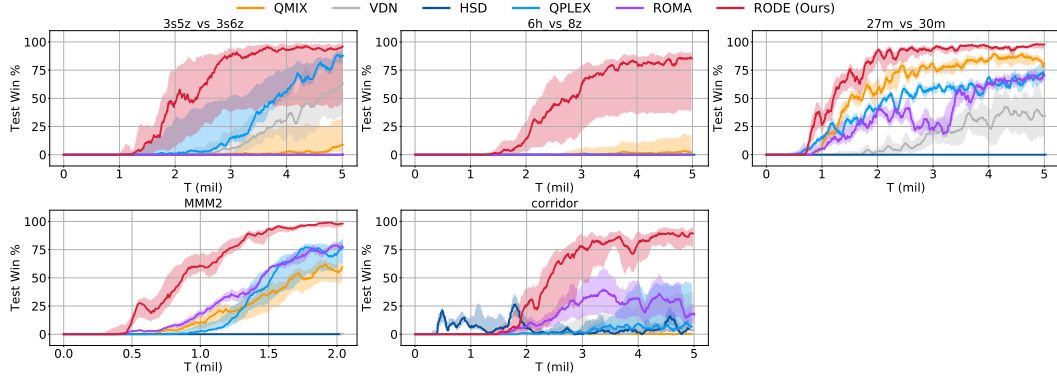
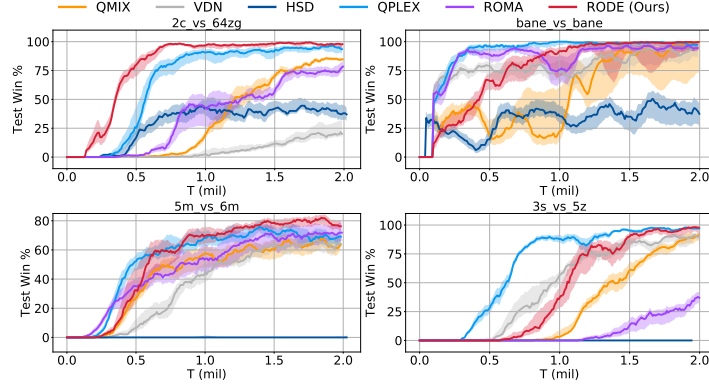


Figure 8: Frequencies of taking each role during training on corridor. Correspond to Fig. 7. The frequencies of two roles which help exploration (*Role 0* and *Role 2*) first increase and then decrease.

Why do restricted action spaces work? Our effect-based action clustering decomposes the full action spaces into smaller role action spaces, each of which focuses on a smaller subset of actions having similar effects. As each role learns on a smaller action space which has similar actions, it enables agents to efficiently explore and results in each role being able to learn different strategies, like spread and retracting. Moreover, exploration in the much smaller role space makes the coordination of these sub-strategies easily.

Exploring in the hierarchically decomposed action spaces also provides a bias in exploration space. For example, on corridor, *Role 0* and *Role 2* motivate agents to explore the state space in a certain direction which help them learn several important strategies on this map: 1) Agents first move to the edges (*Role 0*) to avoid being surrounded by the enemies (Fig. 7 (a)), and 2) Agents alternate between attacking (*Role 1*) and retracting (*Role 2*) to attract and kill part of the enemies, gaining an advantage in numbers (Fig. 7 (b-d)). The fact that *Role 0* and *Role 2* help exploration is also supported by Fig. 8 – their frequencies first improve as the agents explore more, and then decrease when cooperation strategies gradually converge.

On other maps, restricted role action spaces may help agents solve the task in other ways. For example, on the map 3s5z_vs_3s6z, agents learn more efficiently because the action encoder decomposes the task into two sub-tasks, one focusing on attacking Zealots and another one focusing on attacking Stalkers. Learning policies for these restricted sub-problems significantly reduces the learning complexity. In summary, action effects provide effective information to decompose joint action spaces. Clustering actions according to their effects makes role discovery much easier, and learning cooperative strategies in smaller action spaces makes learning more tractable.

Figure 9: Comparisons between RODE and baselines on all **super hard** maps.Figure 10: Comparisons between RODE and baselines on all **hard** maps.

C EXPERIMENTAL DETAILS

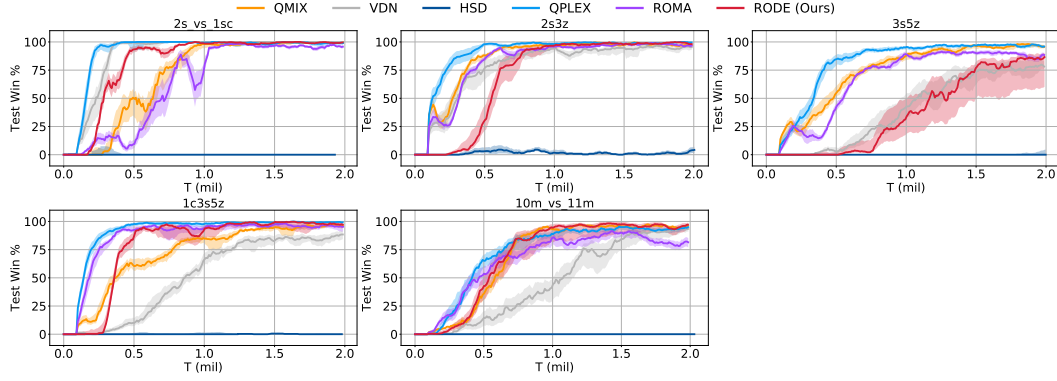
In this section, we provide more experimental results supplementary to those presented in Sec. 4.2. We also discuss the details of experimental settings of rapid policy transfer and analyze the results.

C.1 BENCHMARKING ON STARCRAFT II MICROMANAGEMENT TASKS

In Sec. 4.2, we show the overall performance of RODE on the SMAC benchmark. In this section, we further show the performance of our method on all maps. All experiments in this section are carried out with 8 random seeds. Median win rate, together with 25-75% percentiles, is shown.

The SMAC benchmark (Samvelyan et al., 2019) contains 14 maps that have been classified as easy, hard, and super hard. In Fig. 9, we compare the performance of RODE with baseline algorithms on all super hard maps. We can see that RODE outperforms all the baselines by a large margin, especially on those requiring the most exploration: 3s5z_vs_3s6z, corridor, and 6h_vs_8z. These results demonstrate that RODE can help exploration and solve complex tasks, in line with our expectations of it.

On hard maps, RODE still has superior performance compared to baselines, as shown in Fig. 10. However, on easy maps (Fig. 11), RODE tends to use more samples to achieve similar performance to baselines. We hypothesize that this is because easy maps do not require substantial exploration – ally agents can win by merely engaging in fight and damaging the enemy units for reward. Under these circumstances, RODE still explores a lot, which prevents it from performing better.

Figure 11: Comparisons between RODE and baselines on all **easy** maps.

In summary, RODE establishes a new state of the art on the SMAC benchmark by outperforming all baselines on 10 out of 14 scenarios. Notably, its superiority is particularly obvious on all of the hard and super hard maps.

C.2 POLICY TRANSFER

In this section, we describe the setting of the policy transfer experiment introduced in Sec. 4.3.

Policy transfer experiments are based on the assumption that new actions have similar functionalities to some old actions. We train an action encoder on the new task to cluster the actions. In this way, we can distinguish old actions a_{i_1}, \dots, a_{i_m} that have similar effects to a new action a_{n_i} . We then use $\frac{1}{m} \sum_{j=1}^m z_{a_{i_j}}$ as the representation for a_{n_i} , where $z_{a_{i_j}}$ is the representation for a_{i_j} on the original task, and we add a_{n_i} to role action spaces to which a_{i_1}, \dots, a_{i_k} belong. For each new action, we repeat these operations. The number of roles does not change during this process. This process enables the role selector and role policies learned in original task to be rapidly transferred to a similar task.

To test our idea, we train RODE on the map corridor, where 6 ally Zealots face 24 enemy Zerglings, for 5 million timesteps and rapidly transfer the learned policy to similar maps by increasing the number of agents and enemies. The number of actions also increases because a new attack action is added for every new enemy unit. The results are shown in Fig. 6.

D ROLE INTERVAL AND RECURRENT ROLE SELECTOR

D.1 ROLE INTERVAL

In our framework, the role selector assigns roles to each agent every c timesteps. We call c the role interval. The role interval decides how frequently the action spaces change and may have a critical influence on the performance. To get a better sense of this influence, we change the role interval while keeping other parts unchanged and test RODE on several environments. In Fig. 12, we show the results on 2 easy maps (10m_vs_11m and 1c3s5z), 1 hard map (3s_vs_5z), and 1 super hard map (6h_vs_8z). Generally speaking, the role interval has a significant influence on performance, but 5 or 7 can typically generate satisfactory results. In this paper, we use a role interval of 5 on most of the maps.

D.2 RECURRENT ROLE SELECTOR AND FULLY-CONNECTED ROLE SELECTOR

The role selector is supposed to learn a decomposition of observation space. However, we base this component on local action-observation history. In this section, we discuss the influence of using GRUs in the role selector. In Fig. 13, we compare RODE to *RODE with a fully-connected role selector* conditioned on local observations. As expected, a recurrent role selector performs better than a selector based on local observations. Even though this conclusion is not surprising, we are

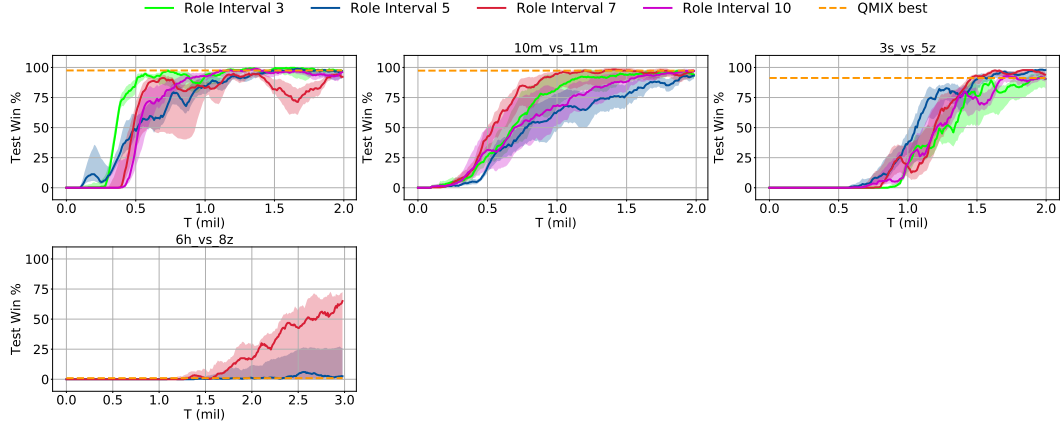


Figure 12: Influence of the role interval (the number of timesteps between two consecutive role selections).

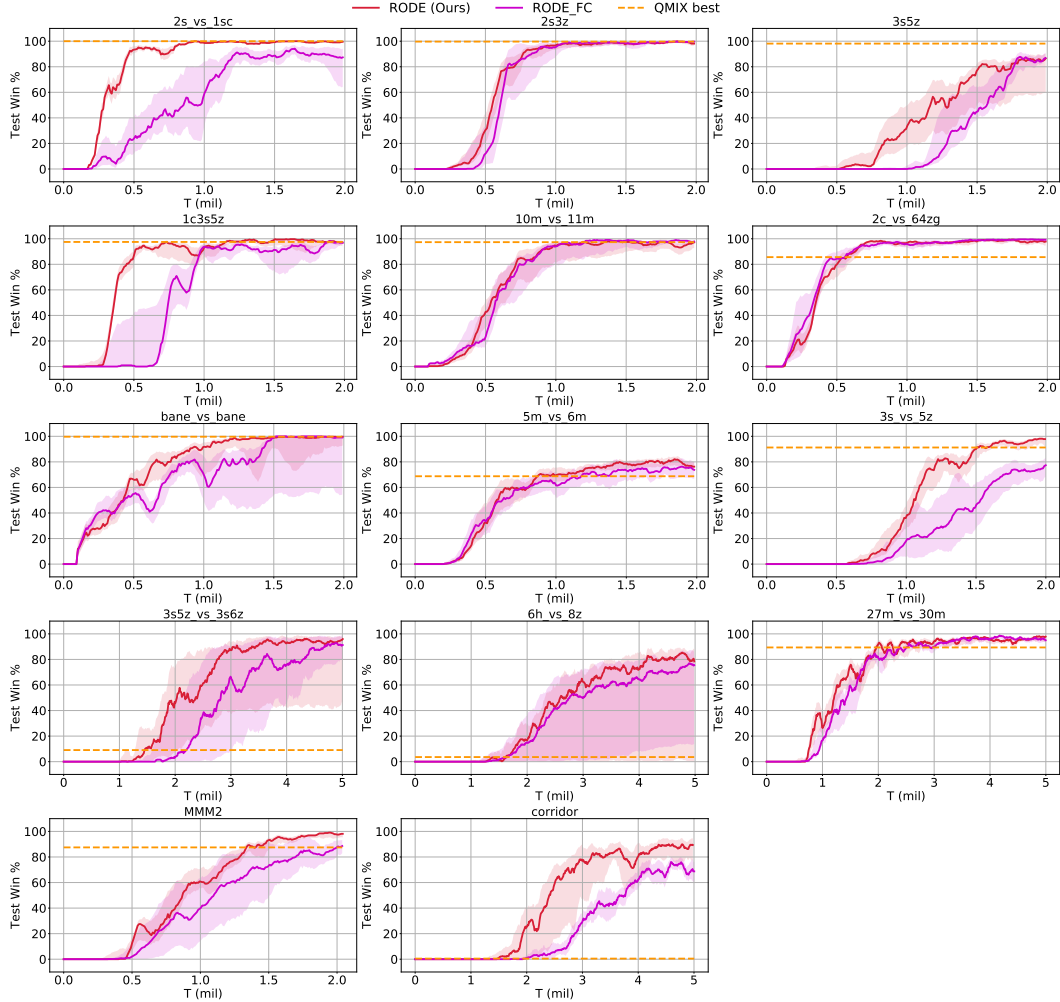


Figure 13: Comparisons between RODE with a recurrent role selector (RODE) and a fully-connected role selector conditioned on local observations (RODE-FC).

interested in those environments where a recurrent role selector can not perform better. For map 10m_vs_11m, together with the results presented in Fig. 12, we see that RODE with a role interval of 7 has similar performance to a fully-connected role selector, but underperforms when the role interval is set to other values. This indicates that the role interval has a sophisticated interaction with exploration, optimization, and learning stability. We leave the study of this as future work. In the previous section, we give more examples showing the influence of the role interval.

E RELATED WORKS

Role-Based Learning Our approach is an attempt to integrate roles into deep multi-agent reinforcement learning. Many natural systems feature emergent roles, such as ants (Gordon, 1996), bees (Jeanson et al., 2005), and humans (Butler, 2012). In these systems, roles are closely related to the division of labor and is critical to labor efficiency. These benefits inspired multi-agent system designers, who try to reduce the design complexity by decomposing the task and specializing agents with the same role to certain sub-tasks (Wooldridge et al., 2000; Omicini, 2000; Padgham & Winikoff, 2002; Pavón & Gómez-Sanz, 2003; Cossentino et al., 2005; Zhu & Zhou, 2008; Spanoudakis & Moraitis, 2010; DeLoach & Garcia-Ojeda, 2010; Bonjean et al., 2014). However, roles and the associated responsibilities (or subtask-specific rewards (Sun et al., 2020)) are pre-defined using prior knowledge in these systems (Lhaksmana et al., 2018). Although pre-definition can be efficient in tasks with a clear structure, such as software engineering (Bresciani et al., 2004), it hurts generalization and requires prior knowledge that may not be available in practice. To solve this problem, Wilson et al. (2010) use Bayesian inference to learn a set of roles and Wang et al. (2020c) design a specialization objective to encourage the emergence of roles. However, these methods search the optimal task decomposition in the full state-action space, resulting in inefficient learning in hard-exploration tasks. RODE avoids this shortcoming by first decomposing joint action spaces according to action effects, which makes role discovery much easier.

Multi-Agent Reinforcement Learning (MARL) Many challenging tasks (Vinyals et al., 2019; Berner et al., 2019; Samvelyan et al., 2019; Jaderberg et al., 2019) can be modelled as multi-agent learning problems. Many interesting real-world phenomena, including the emergence of tool usage (Baker et al., 2020), communication (Foerster et al., 2016; Sukhbaatar et al., 2016; Lazaridou et al., 2017; Das et al., 2019), social influence (Jaques et al., 2019), and inequity aversion (Hughes et al., 2018) can also be better explained from a MARL perspective.

Learning control policies for multi-agent systems remains a challenge. Centralized learning on joint action space can avoid non-stationarity during learning and may better coordinate the learning process of individual agents. However, these methods typically can not scale well to large-scale problems, as the joint action space grows exponentially with the number of agents. The coordination graph (Guestrin et al., 2002b;a; Böhrer et al., 2020) is a promising approach to achieve scalable centralized learning. It reduces the learning complexity by exploiting coordination independencies between agents. Zhang & Lesser (2011); Kok & Vlassis (2006) also utilize the sparsity and locality of coordination. These methods require the dependencies between agents to be pre-supplied. Value function decomposition methods avoid using such prior knowledge by directly learning centralized but factored global Q -functions. They implicitly represent the coordination dependencies among agents by the decomposable structure (Sunehag et al., 2018; Rashid et al., 2018; Son et al., 2019; Wang et al., 2020e;b).

Multi-agent policy gradient algorithms enjoy stable theoretical convergence properties compared to value-based methods (Gupta et al., 2017; Wang et al., 2020a) and hold the promise to extend MARL to continuous control problems. COMA (Foerster et al., 2018) and MADDPG (Lowe et al., 2017) propose the paradigm of centralized critic with decentralized actors (CCDA). PR2 (Wen et al., 2019) and MAAC (Iqbal & Sha, 2019) extend the CCDA paradigm by introducing the mechanism of recursive reasoning and attention, respectively. DOP (Wang et al., 2020f) solves the centralized-decentralized mismatch problem in the CCDA paradigm and enables deterministic multi-agent policy gradient methods to use off-policy data for learning. Another line of research focuses on fully decentralized actor-critic learning (Macua et al., 2017; Zhang et al., 2018; Yang et al., 2018; Cassano et al., 2018; Suttle et al., 2019; Zhang & Zavlanos, 2019).