GOV-REK: Governed Reward Engineering Kernels for Designing Robust Multi-Agent Reinforcement Learning Systems

Extended Abstract

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ABSTRACT

For multi-agent reinforcement learning (MARL) systems, the problem task often involves massive problem-specific reward engineering effort. This effort is usually not directly transferable to other problems; worse, this problem is further exacerbated for sparse reward scenarios. We propose **GOV**erned **R**eward **E**ngineering **K**ernels (GOV-REK), which dynamically assign reward distributions to agents in MARLs during the learning stage. We also introduce governance kernels, which exploit the underlying structure in either state or joint action space for assigning meaningful agent rewards. We demonstrate, using a Hyperband-like problem-agnostic algorithm, that this approach successfully learns to solve different MARL problems by iteratively exploring multiple reward models.

KEYWORDS

Cooperative Multi-Agent Systems; Sparse Reinforcement Learning; Robust Multi-Agent Systems; Reward Shaping

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1 INTRODUCTION

The interactions formulated in MARLs are intricate to learn at larger scales, and this problem is further aggravated for sparse problem scenarios [10, 13, 19, 25]. Previously, many approaches have explored designing reward model problems in single-agent and multi-agent settings, but these efforts are problem-specific and often not generalizable to other MARLS [4–6, 15, 20, 27]. Past approaches have also improved sample efficiency by using novelties like attention [28], curiosity [1, 7], and experience sharing [8], but they have not directly influenced agent motivations. Therefore, building effective and robust reward models for agents in MARL tasks in an automated and problem-agnostic manner to improve baselines is still a challenging problem [30].

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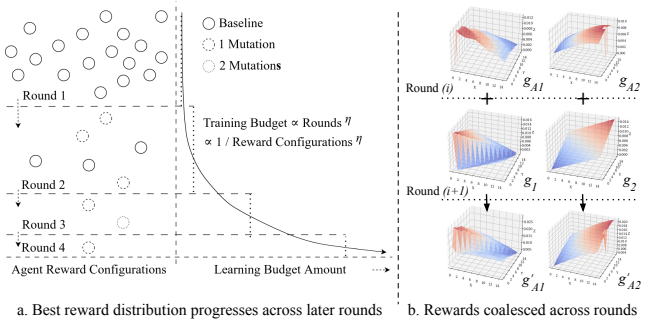

Figure 1: The reward model exploration and superposition mechanisms with increasing training timestep budgets.

Previously, reward shaping approaches that incorporate novel mechanisms, like learning ethical human behavior demonstrations [27], multi-objective reward shaping (MORS) [6], additional rewards for sub-goal completion [17], and context-sensitive rewards for agents [4], have shown further improvements. However, reward shaping is often susceptible to falling under continuous positive reward cycle traps, especially for sparse environments. For finding optimal policies, a multitude of systems like Autonomic Electronic Institutions (AEI) [3], Normative Multi-Agent Systems (NorMAS) [22], and Governed Multi-Agent Systems (GMAS) [24] have demonstrated their efficacy, where agents are provided with governing information for learning [9, 16, 26]. Our approach also proposes an intermediary governance layer between agents and environment, which directly incentivizes agents with additional rewards selected in an automated and problem-agnostic manner to improve the baseline MARL algorithms. Further, we define *governance kernels* for each agent, which are the reward distribution signals that generate similar additional rewards for similar states or joint actions depending on the MARL problem. Similar to problem-agnostic hyperparameter optimization algorithms like Successive Halving (SH) and Hyperband [18], the GOV-REK framework finds suitable reward models for agents by iteratively searching over different governance kernel configurations [2, 29]. Figure 1 demonstrates the execution of multiple SH rounds alongside the superposition of sample governance kernel configurations across these rounds.

We demonstrate the efficacy of this dynamic reward-based inductive bias to explore topologically similar state or joint-action spaces which incentivizes better cooperation amongst agents in MARLs.

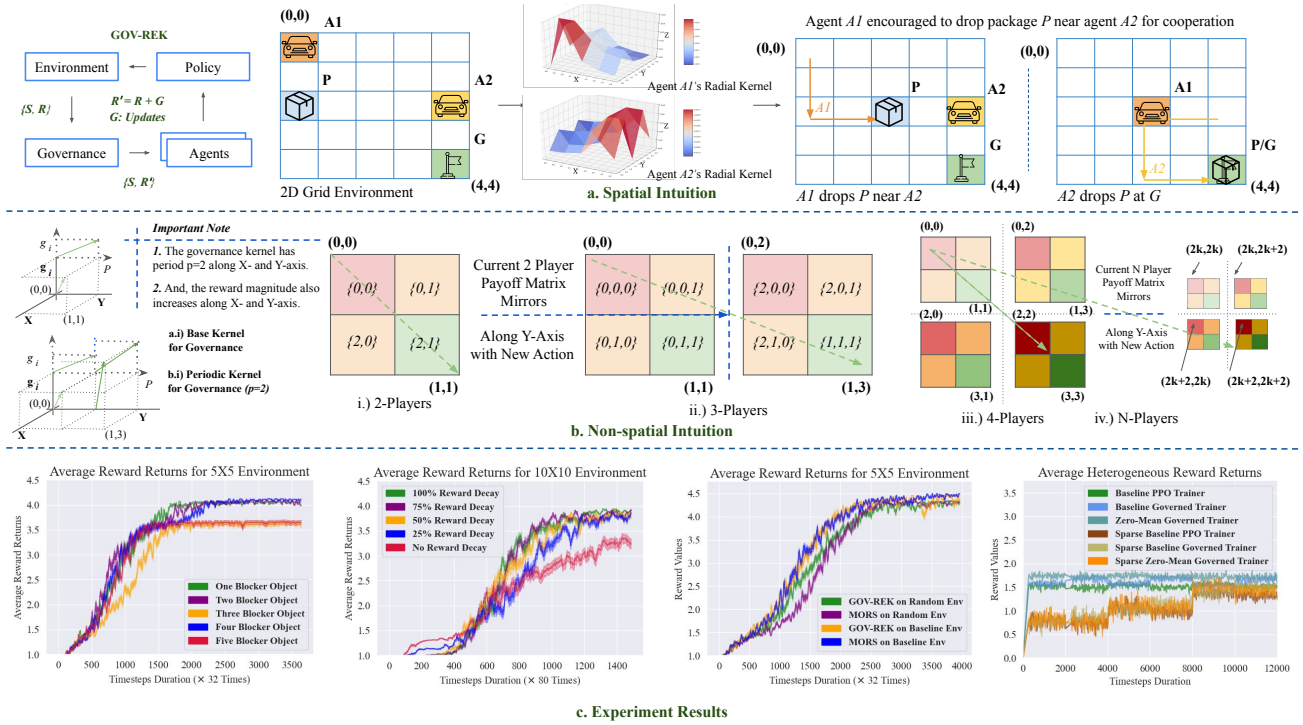

Figure 2: *a.* The additional sample radial governance kernels in the package delivery cooperative MARL problem are represented, where the kernels encourage higher local exploration to promote cooperation. *b.* The topological trend in the flattened joint-action space for the non-spatial social dilemma problem is exploited to define increasing periodic governance kernels that incentivize cooperation. *c.* The experiment demonstrates approach efficacy in four aspects: i.) robustness against the blocker objects, ii.) scalability with reward decays usage for the already explored states, iii.) better performance against manually defined MORS rewards, iv.) extensibility with higher average reward accumulation for the social dilemma problem.

2 APPROACH FORMULATION

We assume that the underlying learning algorithm is highly curious to select diverse actions, where all the relevant solution trajectories between the state-action transition pairs are explored, and define this as the *exploration expectation assumption*. Hence, we take an expectation with respect to the explored actions from the solution trajectories to define our reward models only as a function of state similarity, which is mathematically denoted by $E_a[R(s,a,s')] \rightarrow R'(s,s')$, and we extend our results to joint-action spaces as well. This allows us to define governance kernels independent of agent transitions, and this is expressed by the relations $r'_i = r_i + g_{r,i}$ and $R' = R + G_r$ for agent-specific and agent-agnostic kernels respectively. In its generalized mathematical form, we express our governance kernels as $g_i(s_{a_i}) = \sigma^2\kappa(s_{a_i}, s'_{a_i}) + \xi$ in agent-specific and $G(s) = \sigma^2\kappa(s,s') + \xi$ in agent-agnostic non-parametric variations respectively, while staying compliant with a Potential Based Reward Shaping (PBRS) constraint for policy invariance [11, 12, 23]. Here, the kernel function is represented by κ, while σ upscales or downscales function values much similar to Gaussian kernels in Gaussian processes [14, 21], (s_{a_i}, s'_{a_i}) or (s,s') quantifies the magnitude variation between agent-specific or agent-agnostic states, and ξ represents the uniform noise in the kernel function. The GOV-REK framework uses repeated Hyperband executions and iteratively manipulates governance kernel configurations to find suitable agent reward models[1].

3 EXPERIMENTS

We evaluate the GOV-REK framework in CTCE and CTDE settings for a two-agent *sparse cooperative package delivery problem* and a sixteen-agent *heterogeneous social dilemma problem*. Figure 2 summarizes the experimental results quantifying robustness, scalability, performance and extensibility criteria with average expected reward returns for MARL tasks. Notably, we also observed a performance detriment at larger scales and asymmetric agent contribution problem in the CTCE setting experimentation.

4 CONCLUSION AND FUTURE WORK

We demonstrate that our proposed GOV-REK framework which defines simplistic reward models based on state or joint-action topological similarities helps agents to learn different MARL tasks effectively. Building upon this result, exploring a paradigm that trades between our rigid and simplistic reward exploration method against wholly fluid and complex state similarity learning methods is part of our future research effort [1, 28].

[1]The complete manuscript and experiment implementations are available at the repository: github.com/arana-initiatives/gov-rek-marls

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