Multi-Objective RL With Multi-Agent Bidding

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Paper under double-blind review

Keywords: Multi-Objective RL, Multi-Agent RL

Summary

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   Context: None
2. The submission template for submissions to RLJ/RLC 2025
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3. *[Example of one contribution and corresponding contextual note for the paper "Policy gradient methods for reinforcement learning with function approximation" (**?**).]*
   This paper presents an expression for the policy gradient when using function approximation to represent the action-value function.
   Context: Prior work established expressions for the policy gradient without function approximation (**?**).

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Abstract

1 Introduction

2 A Multi-Agent Bidding Approach for Multi-Objective RL

Definition 1 (MO-MDP)**.** *A multi-objective Markov decision process (MO-MDP) with $m \in \mathbb{Z}_{>0}$ objectives is specified by a tuple $\mathcal{M} = (S, A, T, R, \mu_0)$, where*

- *S is the set of states,*
- *A is the set of actions,*
- *$T : S \times A \to \mathbb{D}(S)$ is the transition function mapping a state-action pair to a distribution over states,*
- *$R : S \times A \times S \to \mathbb{R}^m$ is the reward function with each output component corresponding to the different objectives, and*
- *$\mu_0 \in \mathbb{D}(S)$ is the initial state distribution.*

A *policy* in an MO-MDP $\mathcal{M}$ is a function $\pi : (S \times A)^* \times S \to \mathbb{D}(A)$ that maps a history of state-action pairs and the current state to a distribution over actions.

Definition 2 (MAB-MDP)**.** *Let $\mathcal{M} = (S, A, T, R, \mu_0)$ be an MO-MDP with m objectives and let $b \in \mathbb{Z}_{>0}$ be the bid upper bound. Also, define $M = \{1, \ldots, m\}$ be indices of the m agents corresponding to the m objectives along with $\perp$ representing a null agent. Lastly, let $B = \{0, \ldots, b\}$ be the range of bids and $\rho > 0$ be the bid penalty factor. We define the multi-agent bidding Markov decision process (MAB-MDP) as a tuple $\mathcal{B}_{\mathcal{M}} = (\hat{S}, \hat{A}, \hat{T}, P, \hat{R}, \mu_0)$ where*

- *$\hat{S} = M \times S$ is the new state space augmented with the index of the agent that won the previous round of bidding,*
- *$\hat{A} = A^m \times B^m$ represents the action space of the m agents in which each agent selects an action from A and a bid from B,*
- *$\hat{T} : \hat{S} \times \hat{A} \to \mathbb{D}(\hat{S})$ is the new transition function defined as,*

  $$\hat{T}((\_, s), (\mathbf{a}, \mathbf{b})) \coloneqq \frac{1}{|B_{\max}|} \sum_{i \in B_{\max}} (T(s, a_i), i)$$

  where $B_{\max} \coloneqq \{i \mid b_i = \max\{b_1, \ldots, b_m\}\}$ is the set of agents with maximal bids. The tuple $(T(s, a_i), i)$ represents the distribution over $\hat{S}$ induced by the original transition function T such that the second component is fixed, and the weighted sum represents taking the weighted sums of the distributions over $\hat{S}$.
- *$P : \hat{A} \times M \to \mathbb{R}^m$ is the bidding penalty for the m agents and the second component is the index of the agent that won the bidding.*

- $\hat{R} : \hat{S} \times \hat{A} \times \hat{S} \to \mathbb{R}^m$ *is the reward function for the* m *agents with*

$$\hat{R}_k((\_, s_0), (\mathbf{a}, \mathbf{b}), (i, s)) \coloneqq R_k(s_0, a_i, s) - P_k((\mathbf{a}, \mathbf{b}), i)$$

  where $i \in M$ *is the index of the agent that won the bid and chose the action.*

- $\hat{\mu}_0 \coloneqq (\mu_0, 1)$ *is the initial state distribution over* $\hat{S}$ *induced by* μ_0 *and the second component is fixed to be* 1 *without loss of generality.*

Given an MAB-MDP $\mathcal{B}_{\mathcal{M}}$, a *policy* for each agent indexed by $i \in \{1, \ldots, m\}$ takes a similar form: $\pi_i : (\hat{S} \times \hat{A})^* \times \hat{S} \to \hat{A}$. Intuitively, a state $(i, s) \in \hat{S}$ encodes the agent that won the bidding and chose the action to reach s in the previous step. At each step, each of the agents choose an action and a bid, and an action amongst the set of highest bidders is chosen uniformly at random. The reward function includes a penalty term that captures the desired bidding mechanism.

References