Multi-Objective RL With Multi-Agent Bidding

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Summary

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Contribution(s)

1. Provide a succinct but precise list of the contribution(s) of the paper. Use contextual notes to avoid implications of contributions more significant than intended and to clarify and situate the contribution relative to prior work (see the examples below). If there is no additional context, enter "None". Try to keep each contribution to a single sentence, although multiple sentences are allowed when necessary. If using complete sentences, include punctuation. If using a single sentence fragment, you may omit the concluding period. A single contribution can be sufficient, and there is no limit on the number of contributions. Submissions will be judged mostly on the contributions claimed on their cover pages and the evidence provided to support them. Major contributions should not be claimed in the main text if they do not appear on the cover page. Overclaiming can lead to a submission being rejected, so it is important to have well-scoped contribution statements on the cover page.
   Context: None

2. The submission template for submissions to RLJ/RLC 2025
   Context: Built from previous RLC/RLJ, ICLR, and TMLR submission templates

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

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 $M = \{\perp, 1, \ldots, m\}$ 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 $\mathcal{B}_{\mathcal{M}} = (\hat{S}, \hat{A}, \hat{T}, \hat{R}, \hat{\mu}_0)$ where*

- *$\hat{S} = S \times M$ is the original state space accompanied by an agent index,*

- *$\hat{A} = (A \times B)^m$ 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,*

$$\hat{T}((s, \_), ((a_1, b_1), \ldots, (a_m, b_m))) := \frac{1}{|B_{\max}|} \sum_{i \in B_{\max}} (T(s, a_i), i)$$

where $B_{\max} := \{i \mid b_i = \max\{b_1, \ldots, b_m\}\}$ 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 $\hat{S}$.

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

$$\hat{R}_k((s_0, \_), ((a_1, b_1), \ldots, (a_m, b_m)), (s, i)) := \begin{cases} R_k(s_0, a_k, s) - \rho b_k & i = k \\ R_k(s_0, a_i, s) & otherwise \end{cases}$$

29 • $\hat{\mu}_0 \coloneqq (\mu_0, \perp)$ *is the initial state distribution over $\hat{S}$ induced by μ_0 and the second component is*
30   *fixed to be $\perp$.*

31 Intuitively, in the above definition, a state $(s, i) \in \hat{S}$ encodes the agent that won the bidding and
32 chose the action to reach s in the previous step. At each step, each of the agents chose an action and
33 a bid, and an action amongst the set of highest bidders is chosen uniformly at random. The reward
34 function is designed so that the agent whose action was chosen receives a bidding penalty.

35 Given an MAB-MDP $\mathcal{B}_\mathcal{M}$, a *policy* for each agent indexed by $i \in \{1, \dots, m\}$ takes a similar form
36 $\pi_i : (\hat{S} \times \hat{A})^* \times \hat{S} \to \hat{A}$.

37 # References