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# Group Distributionally Robust Reinforcement Learning with Hierarchical Latent Variables

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## Abstract

Reinforcement Learning (RL) agents may only have incomplete information about tasks to solve. Although inferring the latent task could improve the performance, blindly trusting the task estimates may cause significant performance drops due to inevitable inference errors. One dominant way to enhance robustness is to optimize over worst-possible tasks, which may generate overly conservative policies and have difficulties balancing the performance and robustness. Moreover, most sequential decision-making formulations assume tasks are i.i.d. sampled from a single distribution and overlook the existence of task subpopulations. This work aims to address both challenges in decision-making under task estimate uncertainty. We propose Group Distributionally Robust Markov Decision Process (GDR-MDP), which is flexible to encode prior task relationships via a latent mixture model, and leverage the prior by dynamically updating a belief distribution over mixtures. GDR-MDP has a distributionally robust decision criterion as finding the optimal policy that maximizes the expected return under the worst-possible qualified belief within an ambiguity set. Our theoretical analysis shows that GDR-MDP’s hierarchical structure further enhances the distributional robustness by adding regularization to the worst-possible outcomes. We then propose group distributionally robust RL training algorithms with temporal difference targets estimated with perturbed beliefs. Empirical results show that our algorithms generate robust policies over belief inference errors in autonomous driving and robotic control tasks.

## 1 Introduction

Reinforcement learning (RL) [1, 2, 3, 4] has demonstrated extraordinary capabilities in sequential decision-making, even for handling multiple tasks such as navigating autonomous vehicles in various scenarios. With policies conditioned on accurate task-specific contexts, RL agents are expected to perform better than ones without access to context information [5, 6]. However, one key challenge for contextual decision-making is that, in real deployments, RL agents may only have incomplete information about the task to solve.

In principle, agents could adaptively infer the latent context with data collected across an episode, and prior knowledge about tasks [7, 8, 9]. However, the context estimates may be inaccurate [10, 11] due to limited interactions, poorly constructed inference models, or intentionally injected adversarial perturbations. Blindly trusting the inferred context and performing context-dependent decision-making may lead to significant performance drops or catastrophic failures in safety-critical situations. For example, an autonomous vehicle will frequently interact with nearby drivers whose driving styles (such as aggressive or conservative) are unclear. With a misidentified driving style, the autonomous vehicle may follow a policy that leads to crashes.

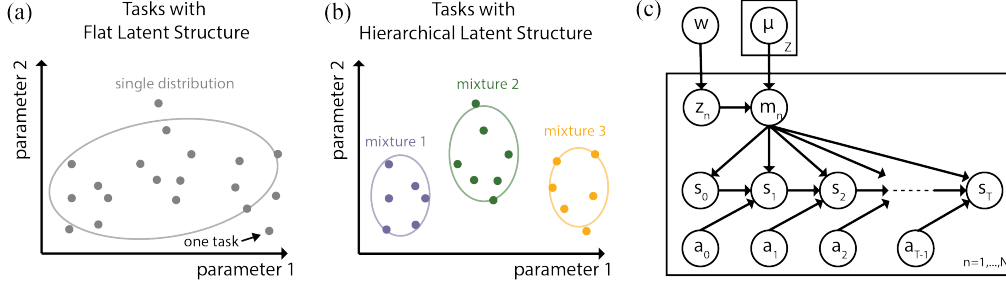


Figure 1: Illustration examples when modeling tasks with (a) a flat latent structure which uses one distribution for all tasks and (b) a hierarchical latent structure which clusters tasks to different mixtures. The graphical model with a hierarchical latent structure for both GDR-MDP and HLMDP is shown in (c). At episode  $n$ , a mixture  $z_n$  is first sampled from a prior distribution  $w$ . An MDP  $m$  is then sampled according to  $\mu_{z_n}(m)$  and controls the dynamics of the  $n$ 'th episode.

Therefore, in this work, we are motivated to study the problem of robust decision-making under the *task estimate uncertainty*. Prior works about robust RL involve optimizing over the worst-case qualified elements within one uncertainty set [12, 13]. To handle task estimate uncertainty, directly optimizing over the worst possible task may lead to *overly conservative policies* or even training instabilities [14, 15, 16]. The autonomous agent trained with robust methods may always assume the human driver is aggressive regardless of recent interactions and choose to wait until the road is clear, consequently blocking the traffic. Moreover, existing robust Markov Decision Process (MDP) formulations *lack the capacity to model task subpopulations* [12]. Thus the effect of task subpopulations on the policy's robustness is unexplored. In practice, it is common that tasks may share similar transition models and can be properly clustered into mixtures (Figure 1 (b)). For instance, an aggressive driver may also exploit some conservative policies but with a small probability.

To address the limitations above, we aim to propose robust RL formulations and algorithms to balance the robustness against task estimate uncertainties and the performance when conditioned on the task estimates. We consider that each task corresponds to an MDP fully specified by a context. In contrast to prior work [10] that leverages point estimates of latent contexts, we take a probabilistic point of view and represent the task estimate with a belief distribution. We consider an adaptive setting in line with system identification methods [17], where the ambiguity set of the belief distribution is updated during one episode, with streaming collected interaction data, as well as prior knowledge about models for each mixture. Our problem formation is related to the ambiguity modeling [18] inspired by human's bounded rationality to approximate and handle distributions, which has been studied in behavioral economics [19, 20] yet has not been widely acknowledged in RL. We highlight our main contributions as follows:

1. We formulate the Hierarchical-Latent MDP (HLMDP) in Section 4, which utilizes a mixture model over MDPs to encode task subpopulations. HLMDP has a high-level latent variable  $z$  as the mixture, and a low-level  $m$  to represent tasks (Figure 1 (c)).
2. We introduce the Group Distributionally Robust MDP (GDR-MDP) in Section 5 to handle the over-conservative problem, which formulates the robustness w.r.t. the ambiguity of the adaptive belief  $b(z)$  over mixtures. GDR-MDP builds on distributionally robust optimization [21, 22] and HLMDP to leverage rich distributional information.
3. We show the convergence property of GDR-MDP in the infinite-horizon case. We find that the hierarchical latent structure helps restrict the worst-possible outcome within the ambiguity set and thus helps generate less conservative policies with higher optimal values.
4. We design robust deep RL training algorithms based on GDR-MDP by injecting perturbations to beliefs stored in the data buffer. We empirically evaluate in three environments, including autonomous driving and robotic control tasks, demonstrating that the proposed algorithms outperform baselines in terms of robustness to belief noise.

## 2 Related Work

**Multitask RL** Learning a suite of tasks with an RL agent has been studied under different frameworks, such as Latent MDP [23], Multi-model MDP [5], Contextual MDP [24], Hidden Parameter MDP [25], and etc [26]. Our proposed HLMDP builds on the Latent MDP [23] which contains a finite number of MDPs, each accompanied by a weight. In contrast to Latent MDP utilizing a flat

structure to model each MDP’s probability, HLMDP leverages a rich hierarchical model to cluster MDPs to a finite number of mixtures. In addition, HLMDP is a special yet important subclass of partial observable MDP (POMDP) [27]. It treats the latent task mixture that the current environment belongs to as the unobservable variable. HLMDP resembles the recently proposed Hierarchical Bayesian Bandit [28] model but focuses on more complex MDP settings.

**Robust RL and distributionally robust RL** RL’s vulnerability to uncertainties has attracted large efforts to design proper robust MDP formulations accounting for uncertainties in MDP components [12, 13, 29, 30, 31, 32]. Existing robust deep RL algorithms [33, 34, 35, 36, 37, 30] are shown to generate robust policies with promising results in practice. However, it is also known that robust RL that optimizes over the worst-possible elements in the uncertainty set may generate over-conservative policies by trading average performance for robustness and may even lead to training instabilities [16]. In contrast, distributionally robust RL [38, 39, 40, 41, 42, 43, 44, 45] assumes that the *distribution* of uncertain components (such as transition models) is partially/indirectly observable. It builds on distributionally robust optimization [21, 22] which optimizes over the worst possible distribution within the ambiguity set. Compared with robust methods, distributionally robust RL embeds prior probabilistic information and generates less conservative policies with carefully calibrated ambiguity sets [38]. We aim to propose distributionally robust RL formulations and training algorithms to handle task estimate uncertainties while maintaining a trade-off between robustness and performance. One relevant work is the recently proposed distributionally robust POMDP [43] which maintains a belief over states and finds the worst possible transition model distribution within an ambiguity set. We instead hold a belief over task mixtures and find the worst possible belief distribution. [44] also maintains a belief distribution over tasks but models tasks with a flat latent structure. Moreover, [44] achieves robustness by optimizing at test-time, while we aim to design robust training algorithms to save computation when deployment.

**RL with task estimate uncertainty** Inferring the latent task as well as utilizing the estimates in decision-making have been explored under the framework of Bayesian-adaptive MDPs [46, 47, 48, 49, 17]. Our work is similar to Bayesian-adaptive MDPs in terms of updating a belief distribution with Bayesian update rules, but we focus on the robustness against task estimate uncertainties at the same time. The closest work to our research is [10], which optimizes a conditional value-at-risk objective and maintains an uncertainty set centered on a context point estimate. Instead, we maintain an ambiguity set over beliefs and further consider the presence of task subpopulations. [11] also considers the uncertainties in belief estimates but with a flat latent task structure.

### 3 Preliminary

This section introduces Latent MDP and the adaptive belief setting, which both serve as building blocks for our proposed HLMDP (Section 4) and GDR-MDP (Section 5).

**Latent MDP** An episodic Latent MDP [23] can be specified by a tuple  $(T, \mathcal{S}, \mathcal{A}, \mathcal{M}, \mu)$ . Here  $T$  is the episode length (planning horizon).  $\mathcal{S}$  and  $\mathcal{A}$  denote the joint state and action space.  $\mathcal{M}$  is a set of joint MDPs. Let  $|\mathcal{S}| = S$ ,  $|\mathcal{A}| = A$ ,  $|\mathcal{Z}| = Z$  and  $|\mathcal{M}| = M$ . Each MDP  $\mathcal{M}_m \in \mathcal{M}$  is a tuple  $(T, \mathcal{S}, \mathcal{A}, P_m, R_m, \nu_m)$  where  $P_m$  is the transition probability,  $R_m$  is the reward function and  $\nu_m$  is the initial state distribution.  $\mu$  is the mixing weight distribution of MDPs and  $\sum_{m=1}^M \mu(m) = 1$ .

Latent MDP assumes that at the beginning of each episode, one MDP from set  $\mathcal{M}$  is sampled based on weights  $\mu(m)$ . The goal of Latent MDP is to find a policy  $\pi$  that maximize the accumulated expected return  $V_{\mathcal{M}}^* = \max_{\pi} \sum_{m=1}^M \mu(m) \mathbb{E}_m^{\pi} \left[ \sum_{t=1}^T r_t \right]$ , where  $\mathbb{E}_m[\cdot]$  denotes  $\mathbb{E}_{P_m, R_m}[\cdot]$ .

**The adaptive belief setting** In general, a belief distribution contains the probability that the current environment belongs to each possible MDP. The adaptive belief setting [5] holds a belief distribution that is dynamically updated with streamingly observed interactions and prior knowledge about the MDPs. In practice, the prior knowledge may be acquired by rule-based policies or data-driven learning methods. For example, it is possible to pre-train in simulated complete information scenarios or exploit unsupervised learning methods based on online collected data [50]. There also exist multiple choices for updating the belief, such as applying the Bayesian rule as in POMDPs [27] and representing beliefs with deep recurrent neural nets [51].

### 4 Hierarchical Latent MDP

In realistic settings, tasks share similarities, and task subpopulations are common. Although different MDP formulations are proposed to solve multi-task RL, the task relationships are in general overlooked. To fill in the gap, we first propose **Hierarchical Latent MDP (HLMDP)**, which utilizes

a hierarchical mixture model to represent MDP distributions. Moreover, we consider the adaptive belief setting to leverage prior information about tasks.

**Definition 1** (Hierarchical Latent MDPs). An episodic HLMDP can be specified by a tuple  $(T, \mathcal{S}, \mathcal{A}, \mathcal{M}, \mathcal{Z}, w)$ .  $\mathcal{Z}$  denotes a set of Latent MDPs and  $|\mathcal{Z}| = Z$ . Each Latent MDP  $\mathcal{Z}_z$  composes of a set of joint MDPs  $\{\mathcal{M}_m\}_{m=1}^M$  and their mixing weights  $\{\mu_z \in [0, 1]^M\}_{z \in [\mathcal{Z}]}$  satisfying  $\sum_{m=1}^M \mu_z(m) = 1$ .  $w$  is the mixing weight distribution of latent MDPs and  $\sum_{z=1}^Z w(z) = 1$ .

HLMDP includes extra task similarity information in conditional weights  $\mu_z(m)$  and mixing weights  $w(z)$ , where  $z$  and  $m$  indicate the latent mixture and MDP, respectively. HLMDP contains richer task information than Latent MDP [23]. We could always find one Latent MDP for each HLMDP. However, there may exist infinitely many corresponding HLMDPs given one Latent MDP. HLMDP assumes that at the beginning of each episode, the environment first sample a mixture  $z \sim w(z)$  and then sample an MDP  $m \sim \mu_z(m)$ . We provide a graphical model of HLMDP in Figure 1 (c).

The adaptive setting when solving multi-task RL problems is shown to help generate a policy with a higher performance [5] than the non-adaptive one since it leverages prior knowledge about the transition model. This work follows the adaptive belief setting and maintains a belief distribution over mixtures  $b(z)$  to model the probability that the current environment belongs to each mixture  $z$ .

**The optimal policy of HLMDP in adaptive belief setting** Let a policy  $\pi$  as a collection of  $T$  functions  $\{\pi_t : (\mathcal{S}, \mathcal{A})_{t-1} \times \mathcal{S} \rightarrow \mathcal{A}\}_{t \in [T]}$  that maps a history to an action. Following general notations in POMDPs, we denote the history at time  $t$  as  $h_t = (s_0, a_1, s_1, \dots, s_{t-1}, a_{t-1}, s_t) \in \mathcal{H}_t$ , where  $s$  and  $a$  denote state and action in each MDP, respectively. At timestep  $t$ , we use both the observed state  $s_t$  and the inferred belief distribution  $b_t(z)$  as the sufficient statistics for history  $h_t$ . Let  $\gamma$  denote the reward discount factor. Under the adaptive belief setting, the goal is to find an optimal policy  $\pi^*$  within a history-dependent policy class  $\Pi$ , under which the discounted expected cumulative reward is maximized. Let

$$\bar{V}^* = \max_{\pi \in \Pi} \sum_{z=1}^Z b_0(z) \cdot \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^\pi \left[ \sum_{t=1}^T \gamma^t r_t \right], \quad (1)$$

where  $r_t$  denotes the reward received at step  $t$ .  $b_0(z)$  is the initial belief prior at timestep 0.

## 5 Group Distributionally Robust MDP

The belief update function in HLMDP proposed in Section 4 may not be accurate, which motivates robust decision-making under belief estimation errors. In this section, we introduce **Group Distributionally Robust MDP (GDR-MDP)** which models task subpopulations and considers robustness against the belief ambiguity. We then study the convergence property of GDR-MDP in the infinite-horizon case in Section 5.1. We find that GDR-MDP’s hierarchical structure helps restrict the worst-possible value within the ambiguity set and provide the robustness guarantee in Section 5.2.

**Definition 2** (Group Distributionally Robust MDP). An episodic GDR-MDP is defined by a 8-tuple  $(T, \mathcal{S}, \mathcal{A}, \mathcal{M}, \mathcal{Z}, w, \mathcal{B}, SE)$ .  $T, \mathcal{S}, \mathcal{A}, \mathcal{M}, \mathcal{Z}, w$  are elements of an episodic HLMDP (Definition 1).  $\mathcal{B}$  is the belief distribution space.  $SE : \mathcal{B} \times \mathcal{S} \rightarrow \mathcal{B}$  is the belief updating rule. GDR-MDP aims to find a history-dependent policy  $\pi^* \in \Pi$  that obtains the following optimal value:

$$V^* = \max_{\pi \in \Pi} \min_{b \in \mathcal{C}_\mathcal{B}} \sum_{z=1}^Z b_0(z) \cdot \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^\pi \left[ \sum_{t=1}^T \gamma^t r_t \right], \quad (2)$$

where  $\mathcal{C}_\mathcal{B}$  is the ambiguity set for the inferred belief distribution.

GDR-MDP naturally balances robustness and performance by leveraging distributionally robust formulation and rich distributional information, including the inferred belief and prior task relationships embedded in the hierarchical structure. In contrast to HLMDP, which maximizes expected return over nominal adaptive belief distribution (Equation 1), GDR-MDP aims to maximize the expected return under the worst-possible beliefs within an ambiguity set  $\mathcal{C}_\mathcal{B}$ . We could assume that there exists an *adversary* which perturbs the belief distribution  $b(z)$  and finds the solution of the inner minimization problem. Equation 2 optimizes over fewer optimization variables than when directly perturbing MDP model parameters or states. It resembles the group distributionally robust optimization problem in supervised learning but focuses on sequential decision-making in dynamic environments [52, 53].

### 5.1 Convergence in the infinite-horizon case

It is known that with general ambiguity sets (e.g. the probability simplex  $\Delta$ ), calculating the optimal policy is intractable [45, 39]. We assume a belief-wise ambiguity set that follows the b-rectangularity in Assumption 1 to facilitate solving the proposed GDR-MDP. This assumption is motivated by the  $s$ -rectangularity first introduced in [29], which helps reduce a robust MDP formulation to an MDP formulation and thus get rid of the time-inconsistency problem [54].

**Assumption 1** (b-rectangularity). We assume a belief-wise ambiguity set,  $\mathcal{C}_B := \bigotimes_{b \in \Delta_s} \mathcal{C}_b$ , where  $\bigotimes$  represents Cartesian product and  $b$  serves as the nominal distribution of the ambiguity set  $\mathcal{C}_b$ .

More concretely, b-rectangularity means uncoupling the ambiguity set related to different beliefs. When conditioned on each belief, the adversary could select the worst-case realization unrelated to others. In the autonomous driving example, assuming the ambiguity sets at time step  $t$  and  $t + 1$  are the whole simplex, given different value functions, the adversary may assume the surrounding driver is purely aggressive ( $m = 1$ ) at time  $t$  and purely conservative ( $m = 0$ ) at time  $t + 1$ . Considering that the rectangularity assumption could lead to conservative policies, generalizations beyond rectangularity are recently explored in [55, 56].

To solve Equation 2 with dynamic programming, we derive Bellman equations under Assumption 1. Detailed proofs are in Appendix Section B.1.

**Proposition 1** (Group Distributionally Robust Bellman Equation). *Define the distributionally robust value of a arbitrary policy  $\pi$  as follows where  $b_{t+1} = SE(b_t, s_t)$ .*

$$V_t^\pi(b_t, s_t) = \min_{\hat{b}_{t:T} \in \mathcal{C}_{b_t:T}} \mathbb{E}_{\hat{b}_{t:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t:T}} \left[ \sum_{n=t}^T \gamma^{n-t} r_n | b_t, s_t \right]. \quad (3)$$

The Group Distributionally Robust Bellman expectation equation is

$$V_t^\pi(b_t, s_t) = \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi^t} \left[ \mathbb{E}_{R_m} [r_t] + \gamma \sum_{s_{t+1}} P_m(s_{t+1} | s_t, a_t) V_{t+1}^\pi(b_{t+1}, s_{t+1}) \right]. \quad (4)$$

**Lemma 1** (Contraction Mapping). *Let  $\mathcal{V}$  refer to a set of real-valued bounded functions on  $\Delta_s \times \mathcal{S}$  and  $\mathcal{LV}(b, s) : \mathcal{V} \rightarrow \mathcal{V}$  refer to the Bellman operator defined as*

$$\mathcal{LV}(b, s) = \max_{\pi \in \Pi} \min_{\hat{b} \in \mathcal{C}_b} \mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^\pi \left[ \mathbb{E}_{R_m} [r] + \gamma \sum_{s'} P_m(s' | s, a) V^\pi(SE(b, s), s) \right]. \quad (5)$$

$\mathcal{LV}(b, s)$  is a  $\gamma$  contraction operator on complete metric space  $(\mathcal{V}, \|\cdot\|_\infty)$ . That is, given  $\forall U, V \in \mathcal{V}$ ,  $\|\mathcal{LU} - \mathcal{LV}\|_\infty \leq \gamma \|U - V\|_\infty$ .

**Theorem 1** (Convergence in Infinite-horizon Case). *Define  $V_\infty(b, s)$  as the infinite horizon value function. For all  $b \in \mathcal{B}$  and  $s \in \mathcal{S}$ , we have  $V_\infty(b, s)$  is the unique solution to  $\mathcal{LV}_\infty(b, s) = V_\infty(b, s)$ , and  $\lim_{t \rightarrow \infty} \mathcal{LV}_t(b, s) = \mathcal{LV}_\infty(b, s)$  uniformly in  $\|\cdot\|_\infty$ .*

By repeatedly applying the contraction operator in Lemma 1, the value function will converge to a unique fixed point, which corresponds to the optimal value based on Banach fixed point theorem [57].

### 5.2 Robustness guarantee of GDR-MDP

This section shows how GDR-MDP's hierarchical task structure and distributionally robust formulation help balance the performance and robustness. We compare the optimal value of GDR-MDP denoted as  $V_{GDR}(\pi_{GDR}^*)$ , with three different robust formulations. Group Robust MDP is a robust version of GDR-MDP with its optimal value denoted as  $V_{GR}(\pi_{GR}^*)$ . Distributionally Robust MDP holds a belief over MDPs without the hierarchical task structure whose optimal value denoted as  $V_{DR}(\pi_{DR}^*)$ . Robust MDP is a robust version of Distributionally Robust MDP, denoted as  $V_R(\pi_R^*)$ .  $\pi^*$  denote optimal policies under different formulations. We achieve the comparison by studying how maintaining beliefs over mixtures affects the worst-possible outcome of the inner minimization problem and the resulting RL policy. Proofs are detailed in Appendix Section B.2.

We study the worst-possible value via the relationships between ambiguity sets projected to the space of beliefs over MDPs. We first define a discrepancy-based ambiguity set that is widely used in existing DRO formulations [58, 59, 60].

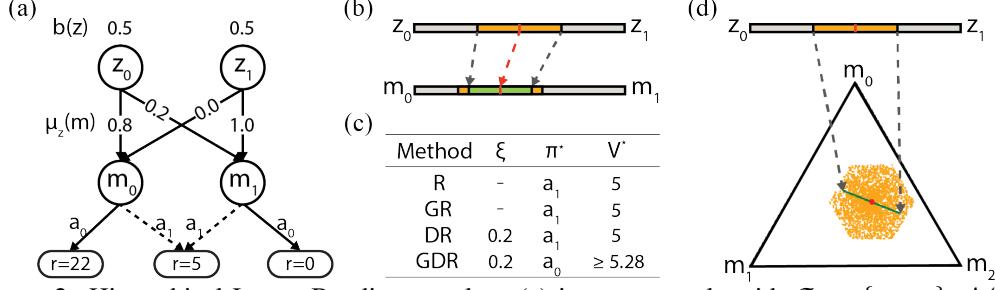


Figure 2: Hierarchical Latent Bandit examples. (a) is one example with  $\mathcal{Z} = \{z_0, z_1\}$ ,  $\mathcal{M} = \{m_0, m_1\}$  and  $\mathcal{A} = \{a_0, a_1\}$ . (b) shows the ambiguity sets of the example in (a). The orange sets denote the  $\xi$ -ambiguity sets for the beliefs over mixtures and MDPs. The green set denotes the ambiguity set projected from the  $\xi$ -ambiguity set for belief distributions over mixtures. We show that the mapped set is a subset of the original  $\xi$ -ambiguity set for the MDP belief distributions. (c) shows the optimal policy and value of different robust formulations for the example in (a). Our proposed GDR has the potential to get a less conservative policy with higher returns than other robust baselines. (d) follows the same notations in (b) but corresponds to an example with three possible MDPs. (b) and (d) together shows that the hierarchical structure helps regularize the adversary’s strength. The detailed procedure for getting the optimal policies is shown in Appendix A.

**Definition 3** (Ambiguity set with total variance distance). Consider a discrepancy-based ambiguity set defined based on total variance distance. Formally, the ambiguity set is

$$\mathcal{C}_{\nu_{\mathcal{X}}, d_{TV}, \xi}(X) = \{\nu'(X) : \sup_{X \in \mathcal{X}} |\nu'(X) - \nu_{\mathcal{X}}(X)| \leq \xi\},$$

where  $x \in \mathcal{X}$  is the support,  $\nu_{\mathcal{X}}$  is the nominal distribution over  $\mathcal{X}$  and  $\xi$  is the ambiguity set’s size.

To achieve reasonable comparison, we control the adversary’s budget  $\xi$  the same when perturbing the belief over mixtures and MDPs, which correspond to different model misspecification forms when there is a hierarchical latent structure about tasks.

**Theorem 2** (Value of different robust MDP formulations). Let  $U_m(\pi) = \mathbb{E}_m^\pi[\sum_{t=1}^T \gamma^t r_t]$ . Let  $\mathcal{C}_{b(m), d_{TV}, \xi}(m)$  and  $\mathcal{C}_{b(z), d_{TV}, \xi}(z)$  denote the ambiguity sets for beliefs over MDPs  $m$  and mixtures  $z$ , respectively.  $b(m)$  and  $b(z)$  satisfy  $b(m) = \sum_{\mathcal{Z}} \mu_z(m) b(z)$  and are the nominal distributions. For any history-dependent policy  $\pi \in \Pi$ , its value function under different robust formulations are:

$$\begin{aligned} V_{GDR}(\pi) &= \min_{\hat{b}(z) \in \mathcal{C}_{b(z), d_{TV}, \xi}(z)} \mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} [U_m(\pi)], & V_{GR}(\pi) &= \min_{z \in [Z]} \mathbb{E}_{\mu_z(m)} [U_m(\pi)], \\ V_{DR}(\pi) &= \min_{\hat{b}(m) \in \mathcal{C}_{b(m), d_{TV}, \xi}(m)} \mathbb{E}_{\hat{b}(m)} [U_m(\pi)], & V_R(\pi) &= \min_{m \in [M]} [U_m(\pi)]. \end{aligned}$$

We have the following inequalities hold:  $V_{GDR}(\pi) \geq V_{GR}(\pi) \geq V_R(\pi)$  and  $V_{GDR}(\pi) \geq V_{DR}(\pi)$ .

Theorem 2 shows that with a nontrivial ambiguity set, the distributionally robust formulation in GDR-MDP helps regularize the worst-possible value when compared with robust ones, including the group robust (GR) and task robust (R) formulations. It also shows that GDR-MDP’s hierarchical structure further helps restrict the effect of the adversary, resulting in higher values than the distributionally robust formulation with a flat latent structure (DR). To get Theorem 2, we first find that when projecting the  $\xi$ -ambiguity set for  $b(z)$  to the space of  $b(m)$ , the resulting ambiguity set is a subset of the  $\xi$ -ambiguity set for  $b(m)$ . Two illustration examples of the ambiguity set relationships are shown in Figure 2 (b) and (d). Our setting is different from [61] which states that DRO is a generalization of point-wise attack. The key difference is that when the adversary perturbs  $b(m)$ , we omit the expectation over the mixtures under  $b(z)$ .

**Theorem 3** (Optimal values of different robust formulations). Let  $\pi^*$  denote the converged optimal policy for different robust formulations, we have  $V_{GDR}(\pi_{GDR}^*) \geq V_{GR}(\pi_{GR}^*) \geq V_R(\pi_R^*)$  and  $V_{GDR}(\pi_{GDR}^*) \geq V_{DR}(\pi_{DR}^*)$ .

Based on Theorem 2, we can compare the optimal values for different robust formulations. Theorem 3 shows that imposing ambiguity set on beliefs over mixtures helps generate less conservative policies with higher optimal values at convergence compared with the other three robust formulations.

## 6 Algorithms

To solve the proposed GDR-MDP, we propose novel robust deep RL algorithms (summarized in Algorithm 2), including GDR-DQN based on Deep Q learning [1] for discrete action spaces, and GDR-SAC based on soft actor-critic [62] for continuous ones. We learn robust policies that take the inferred belief distribution over mixtures  $b(z)$  and the state  $s$  as input. To achieve a certain level of robustness over noisy inferred belief  $b(z)$ , we fix the ambiguity set size along with robust training, which is analogous to the adversary budget and the robustness level [42].

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### Algorithm 1: GDR-MDP Trajectory Rollout

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**Input:** Mixing weights  $w(z)$  and  $\mu_z(m)$ , episode index  $n$ , episode length  $T$ , belief update function  $SE$ , rollout policy  $\pi_\theta(b(z), s)$ , exploration  $\epsilon$

**Initialize** episodic history  $h = \{\}$  ;

Sample mixture  $z_n \sim w(z)$  ;

Sample MDP  $m_n \sim \mu_{z_n}(m)$  ;

Initialize belief  $b_0(z)$  as a uniform distribution ;

**for**  $t = 0$  **to**  $T$  **do**

Sample action  $a_t$  with the  $\epsilon$ -greedy method and rollout in MDP  $m$  ;

$b_{t+1}(z) = SE(b_t(z), s_{t+1})$  ;

Append the most recent data pair  $d = \{(b_t, s_t), a_t, r_t, (b_{t+1}, s_{t+1})\}$  to  $h$  ;

**Return:** history  $h$ , episode return

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### Algorithm 2: Group Distributionally Robust Training for GDR-DQN and GDR-SAC

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**Input:** Q-net  $Q_\theta(b(z), s, a)$  or Value-net  $V_\theta(b(z), s)$ , ambiguity set  $\mathcal{C}_{b'(z), d_{TV}, \xi}$ , training episodes  $N$

**Initialize** data buffer  $\mathcal{D}$  ;

**for**  $n = 0$  **to**  $N$  **do**

Rollout one episode with Algorithm 1 and append data pairs to  $\mathcal{D}$  ;

**if** *Update Q-net is true* **then**

Sample batch data from  $\mathcal{D}$  ;

**for** *Each  $d_i$  in the batch* **do**

Get  $b^{adv} \in \mathcal{C}_{b'(z), d_{TV}, \xi}$  with modified FGSM ;

Update Q-net  $\theta \leftarrow \theta - \alpha_\theta \nabla_\theta \mathcal{L}_{Q_\theta}$  or Value-net with  $\theta \leftarrow \theta - \alpha_\theta \nabla_\theta \mathcal{L}_{V_\theta}$  ;

**Return:** Q-net  $Q_\theta$  or Value-net  $V_\theta$

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**Group distributionally robust training** We update the Q-net in GDR-DQN and the critic net in GDR-SAC toward TD targets with perturbed beliefs. We follow Definition 3 to construct the ambiguity set  $\mathcal{C}_{b'(z), d_{TV}, \xi}$  which centers at the originally inferred  $b'(z)$  and satisfies the b-rectangularity assumption stated in Assumption 1. At each training step, we sample a batch data  $\{d = (b(z), s, a, r, b'(z), s', a', r')\}^N$  from the replay buffer  $\mathcal{D}$  to estimate the perturbed TD target. We update net parameters by minimizing losses as follows.

$$\mathcal{L}_{Q_\theta} = \sum_d \left( r + \min_{p(z) \in \mathcal{C}_{b'(z), d_{TV}, \xi}} \sum_{a \in \mathcal{A}} Q_\theta(p(z), s', a) - Q_\theta(b(z), s, a) \right)^2, \quad \text{if GDR-DQN,}$$

$$\mathcal{L}_{V_\theta} = \sum_d \left( r + \min_{p(z) \in \mathcal{C}_{b'(z), d_{TV}, \xi}} V_\theta(p(z), s) - V_\theta(b(z), s) \right)^2, \quad \text{if GDR-SAC.}$$

To obtain the worst case distribution  $b^{adv} \in \mathcal{C}_{b'(z), d_{TV}, \xi}$ , we iteratively apply a stochastic variant of fast gradient sign method (FGSM) [63] to make sure that the perturbed discrete distribution satisfies  $\sum_z p(z) = 1$ . For each attack to the belief distribution, we randomly sample an index  $i \in Z$ , and apply the attack to each element in  $p(z)$  as follows  $p(z)_j = p(z)_j + \alpha_b \cdot \text{sign}(\nabla_{p(z)_j} V(p(z), s'))$ ,  $\forall j \neq i$  and  $p(z)_i = p(z)_i - \sum_{j \neq i} p(z)_j$ .  $\alpha_b$  is the perturbation step size. To stabilize robust training, we pretrain first with exact one-hot beliefs to ensure that the value function could approximate the actual state value to some extent. We implement our algorithms with Tianshou [64]. More implementation details and hyperparameters are in Appendix Section D.

## 7 Experiments

We conduct experiments to empirically study (a) the effect of GDR-MDP's hierarchical structure on the robust training stability and (b) the policy's robustness to belief estimate error.

### 7.1 Environments

We evaluate GDR-DQN in HighwayMerge [65] and Lunarlander [66], GDR-SAC in Halfcheetah [67]. Table 1 shows a summary of environment setups. More details are in Appendix Section C.

**Driving scenario: HighwayMerge.** We consider a two-agent highway merging task, in which the RL agent aims to merge into a two-lane highway while maintaining a high speed and avoiding collisions. The surrounding vehicle's behavior is determined by the driving style and control policy. The aggressive surrounding vehicle tries to crash with the ego agent on the target lane.

Table 1: Environment setups. For all environments, we place equal weights on each possible combination of the two parameters. Both parameters affect the environment dynamics.

Environment	Parameter 1 (Mixture)	Parameter 2	# Mixtures	# MDPs
HighwayMerge	Driving Style {Aggressive, Conservative}	Control Policy {Go Straight, Yield}	2	4
LunarLander	Engine Mode {Normal, Flipped}	Engine Power {3.0, 6.0}	2	4
HalfCheetah	Failure Joint {0,1,2,3,4,5}	Torso Mass {0.9, 1.0, 1.1}	6	18

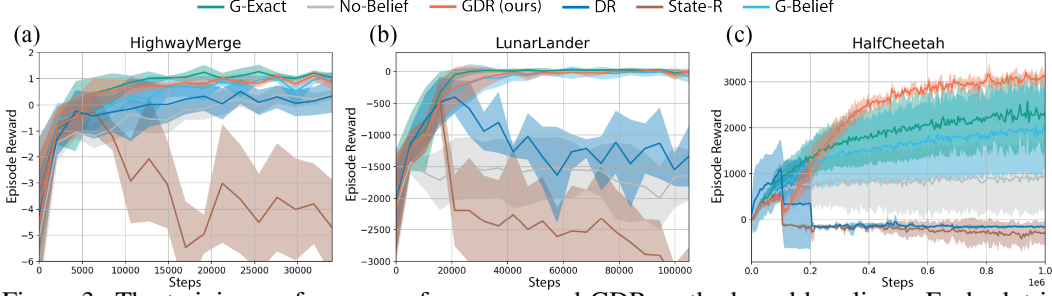


Figure 3: The training performance of our proposed GDR methods and baselines. Each plot is averaged with 5 runs. Our results show that GDR has better training stability than DR since GDR implicitly regularizes the adversary’s strength with the hierarchical structure.

**Box2D control task: LunarLander.** The Lunarlander’s dynamics are affected by the engine mode and engine power. In the flipped mode, the action turning on the left(or right) engine in normal mode will turn on the right (or left) engine instead.

**Mujoco control task: HalfCheetah.** Each task’s dynamics of HalfCheetah are controlled by both the torso mass and the failure joint, to which we cannot apply action. This environment is similar to the implementation in [10] but with a deterministic failure joint at each episode.

## 7.2 Baselines

In **G-Exact**, the RL agent is trained with the exact mixture information encoded in a one-hot vector. The agent in **DR** maintains a belief distribution  $b(m)$  and utilizes distributionally robust training over  $b(m)$ . It uses the same belief updating rule as in GDR to update  $b(z)$  at each timestep but projects  $b(z)$  to  $b(m)$  with  $\mu_z(m)$ . DR utilizes no mixture information and helps ablate the effect of the hierarchical latent structure. The agent in **No-Belief** has no access to the context information and generates action only based on state  $s$ . The No-Belief baseline helps show the importance of the adaptive belief setting. In **G-Belief**, the agent maintains belief  $b(z)$  and is trained towards a nominal TD target. Compared with GDR, G-Belief helps reveal the effect of distributionally robust training. The **State-R** agent takes both the inferred belief  $b(z)$  and state  $s$  as input. It updates towards a TD target with perturbed states along with training. For baselines with belief modules, we utilize the Bayesian update rule and leave the detailed likelihood calculation in Appendix Section D.

## 8 Results and Discussion

### 8.1 How does GDR-MDP’s hierarchical structure affect the robust training?

We investigate the effect of the hierarchical structure on the adversary’s strength based on training performances in Figure 3. We first validate the importance of mixture information since the No-Belief baseline consistently underperforms G-Exact during training in all three environments. It is worth noting that No-Belief in Lunarlander and HalfCheetah has a return much lower than G-Exact, since the kinematic observation feed into the neural net does not reveal any mixture information. However, in HighwayMerge, the performance gap between No-Belief and G-Exact is much smaller. This is because the states containing the kinematic information of the surrounding vehicle already encode partial information about the driving style.

Figure 3 shows that GDR achieves a higher average return at convergence compared with other robust training baselines, including DR and State-R in all environments. In LunarLander and HalfCheetah, DR which maintains a belief  $b(m)$  over MDPs induces significant training instability, instead of learning a meaningful conservative policy. Those observations empirically validate our theoretical



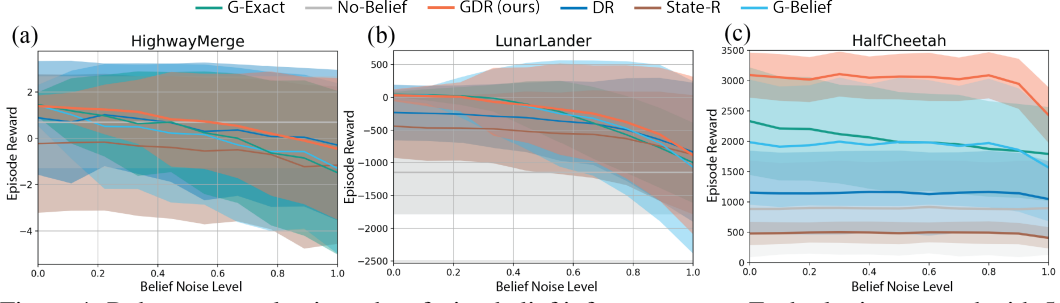


Figure 4: Robustness evaluation when facing belief inference errors. Each plot is averaged with 5 runs. GDR preserves higher robustness to belief inference errors compared with baselines.

result (Section 5.2) in the regime of deep RL, which is that, with the same ambiguity set size, perturbing  $b(m)$  omitting mixture information will lead to larger value perturbations than perturbing  $b(z)$  over mixtures. The State-R baseline leads to more considerable training instability than DR and fails to learn in all three environments.

GDR has comparable training performance with G-Exact and G-Belief in HighwayMerge and LunarLander. It shows that GDR successfully extracts task-specific information stored in the noisy beliefs and conditions on the beliefs for action generation. Moreover, GDR performs better than G-Exact in HalfCheetah. Although GDR leads to an immediate performance drop after pretraining (100000 steps), the robust training in GDR converges to higher performance. We conjecture that this is due to the perturbed belief helping the algorithm get out of local optima.

## 8.2 Does GDR-MDP generate policies robust to belief inference errors?

We test the robustness against belief noise of the best policies obtained with GDR and baselines along with training. The results are shown in Figure 4. We define the belief noise level, which indicates the inaccuracy of the likelihood when updating belief with the Bayesian rule. During robustness evaluation, G-Exact generate actions conditioned on the same noisy beliefs as GDR and G-Belief.

In HalfCheetah, GDR is consistently more robust to belief noise than baselines. In HighwayMerge and LunarLander, the mean reward of GDR is better than G-Exact when there is a high belief noise level and is better than DR when a low belief noise level. The large variances in HighwayMerge and LunarLander are due to the large penalty when crashes which are further exaggerated by the fixed episode length. Although GDR has its performance decreasing along with the increase of the belief noise level, its performance is still an upper bound of DR and G-Exact’s performances. These observations show that GDR successfully balances the information between belief distributions and states, and is more robust to belief inference errors. G-Exact is prone to injected belief noise since it heavily relies on accurate mixture information to achieve high performance. G-Belief does not show significant robustness improvement over G-Exact. It shows that the proposed group distributionally robust training procedure instead of the belief randomness along training helps improve the robustness.

## 8.3 Ablation study

We perform empirical sensitivity analysis to reveal the effect of uncertainty set size on GDR’s policy robustness in HalfCheetah. Figure 5 (a) shows that gradually increasing the ambiguity set size up to 0.2 helps improve the robustness. The ambiguity set whose size is greater or equal to 0.25, easily leads to training instability and thus decreases the robustness. In contrast, even with an ambiguity set of size 0.05 and pretraining for 300000 steps, DR without the mixture information still causes unstable training (see Appendix Section E). Figure 5 (b) provides the average belief errors at each time step corresponding to different belief noise levels. Figure 5 (b) and Figure 4 show that GDR only shows significant performance drops when the belief error is nonzero for a large portion of steps.

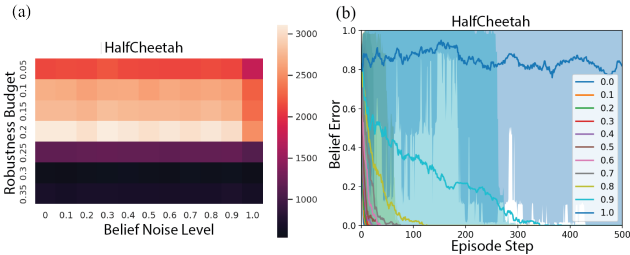


Figure 5: Ablation studies in HalfCheetah.

## 9 Conclusion

This paper considers robustness against task estimate uncertainties. We propose the GDR-MDP formulation that can leverage rich distribution information, including the adaptive inferred beliefs

and prior knowledge about task subpopulations. To the best of our knowledge, GDR-MDP is the first distributionally robust MDP formulation that models ambiguity over belief estimates in an adaptive setting. We theoretically show that GDR-MDP’s hierarchical latent structure helps enhance its distributional robustness compared with a flat task structure. We also empirically show that our proposed group distributionally robust training methods generate more robust policies than baselines when facing belief inference errors in realistic autonomous driving and continuous control tasks.

We hope this work that relies on prior distributional information to facilitate robustness will inspire future research on how diverse domain knowledge affects robustness and generalization. It is important to screen out misleading human-induced or data-induced biases in the mixture information to avoid negative social impacts when deploying our work. One exciting direction to explore in the future is to scale the group distributionally robust training idea to high-dimensional and continuous latent task distributions for a broader range of sequential decision-making applications.

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## A Toy Example: Hierarchical Latent Bandit

In this section, we show the process of getting the optimal policies for different robust formulations in the Hierarchical Latent Bandit problem as illustrated in Figure 2 (a).

The agent selects among two actions  $a_0$  and  $a_1$ . There are two possible mixtures  $z$  and two possible MDPs denoted as  $m$ . We have the conditional probability as  $p(m = 0|z = 0) = 0.8$ ,  $p(m = 1|z = 0) = 0.2$ ,  $p(m = 0|z = 1) = 0.0$ ,  $p(m = 1|z = 1) = 1.0$ . We assume the same type of ambiguity set measured by the total variance distance as in analysis. Let the current belief over contexts is  $b(z) = [0.5, 0.5]$  and the ambiguity set size  $\xi = 0.2$ .

We compare the optimal policies of four robust formulations, including our proposed GDR-MDP shorthand as **GDR** here, which utilizes both the hierarchical structure and distributionally robust formulation, Group Robust MDP (**GR**), which is a robust version of GDR-MDP, distributionally Robust MDP (**DR**), which holds a belief over MDPs without the hierarchical task structure, and Robust MDP (**R**), which is a robust version of Distributionally Robust MDP.

**Optimal policy for R.** **R** desires robustness over the worst possible MDPs. We can see that the worst possible MDP is  $m_1$  since the reward when choosing  $a_0$  or  $a_1$  in  $m_1$  is consistently smaller than the rewards when in  $m_0$ . Considering that with  $m_1$  the optimal policy is  $a_1$ , the optimal policy for **R** is  $a_1$ .

**Optimal policy for GR.** **GR** desires robustness over the worst-possible mixtures. The value for selecting  $a_0$  under mixture  $z_0$  is  $V(a_0|z_0) = 22*0.8 = 17.6$ . Similarly,  $V(a_1|z_0) = 5$ ,  $V(a_0|z_1) = 0$  and  $V(a_1|z_1) = 5$ . Assume the agent has a stochastic policy,  $\pi(p) = [p, 1-p]$ . The value of the policy under mixture  $z_0$  is  $V(\pi(p), z_0) = 0.8*(22p+5*(1-p))+0.2*(0*p+5*(1-p)) = 12.6p+5$ . The value of the policy under mixture  $z_1$  is  $V(\pi(p), z_1) = 0.5*(5p+0.0*(1-p))+0.5*(5p+0*(1-p)) = 5p$ . Since  $V(\pi(p), z_1) < V(\pi(p), z_0), \forall p \in [0, 1]$ . The worst possible mixture is thus  $z_1$  and the optimal policy for **GR** is  $a_1$ .

**Optimal policy for DR.** **DR** desires robustness over the worst possible belief distribution over MDPs. The nominal  $m$ -level belief distribution is  $b(m) = [0.4, 0.6]$ , which is mapped from current  $z$ -level belief  $b(z) = [0.5, 0.5]$ . Considering that there always exists one deterministic policy  $\pi$  as the optimal policy for each belief distribution  $b'(m)$ , we directly analyze the value of the two actions with perturbed belief  $\hat{b}(m)$ . When the deterministic policy puts all mass on action  $a_1$ , perturbing belief doesn't affect the resulting value estimates since each  $m$  has the same reward 5 when selecting  $a_1$ . Therefore the value of  $a_1$  is always 5. When the deterministic policy puts all mass on action  $a_0$ , the worst possible belief decreases the weight of  $m_0$  by  $\xi$ , which is the maximum attack the adversary can apply. In this worst case, the value estimates of  $a_1$  is  $\hat{V} = (0.4 - \xi) * 22 = 4.4 < 5$ . Therefore the optimal policy is  $a_1$ .

Similar results can be derived with the value function. Formally, given  $\epsilon \in [-\xi, \xi] = [-0.2, 0.2]$ ,  $\pi(a_0) = p, \pi(a_1) = 1 - p$ , we want solve the following optimization problem

$$\begin{aligned} \max_p \min_{\epsilon} V(\pi(p), \mathcal{C}_{b(m), \xi}) &= \max_p \min_{\epsilon} (0.4 - \epsilon)[22p + 5(1 - p)] + (0.6 + \epsilon)[0p + 5(1 - p)] \\ &= \max_p \min_{\epsilon} -22p\epsilon + 3.8p + 5 \end{aligned}$$

Since  $\frac{\partial}{\partial \epsilon} V(\pi(p), \mathcal{C}_{b(m), \xi}) = -22p, p \in [0, 1]$ , we have  $\arg \min_{\epsilon} V(\pi(p), \mathcal{C}_{b(m), \xi}) = 0.2$ .

$$\max_p \min_{\epsilon} V(\pi(p), \mathcal{C}_{b(m), \xi}) = \max_p -0.6p + 5$$

Therefore when  $p = 0$ , the value is maximized. It shows that the optimal policy is  $a_1$ .

**Optimal policy for GDR.** **GDR** instead desires robustness over the worst possible belief distribution over contexts. Similar to the analysis for DR, the value estimate of  $a_1$ ,  $\hat{V}(a_1)$ , is always equal to 5 regardless of the perturbed  $\hat{b}(z)$ . Now need to investigate the value when selecting deterministic policy as  $a_0$ . The weight on  $z_0$  in the perturbed belief lies in range  $\hat{b}(z_0) \in [0.5 - \xi, 0.5 + \xi] = [0.3, 0.7]$ . The value estimate for  $a_0$  is thus  $\hat{V}(a_0) = \hat{b}(z_0) * 0.8 * 22 = 17.6\hat{b}(z_0) \in [5.28, 12.32]$ . Since the lower bound is larger than the value of  $\hat{V}(a_1) = 5$ , the optimal policy for GDR is  $a_0$ .

Similarly, we can also write out the value function and the optimization problem.

$$\begin{aligned}
& \max_p \min_{\epsilon} V(\pi(p), \mathcal{C}_{b(z), \xi}) \\
&= \max_p \min_{\epsilon} (0.5 - \epsilon)[0.8 * (22p + 5(1 - p)) + 0.2 * (0p + 5(1 - p))] + (0.5 + \epsilon)[0p + 5(1 - p)] \\
&= \max_p \min_{\epsilon} -17.6p\epsilon + 3.8p + 5
\end{aligned}$$

Since  $\frac{\partial}{\partial \epsilon} V(\pi(p), \mathcal{C}_{b(z), \xi}) = -17.6p$ ,  $p \in [0, 1]$ , we have  $\arg \min_{\epsilon} V(\pi(p), \mathcal{C}_{b(z), \xi}) = 0.2$ .

$$\max_p \min_{\epsilon} V(\pi(p), \mathcal{C}_{b(z), \xi}) = \max_p 0.28p + 5$$

Therefore when  $p = 1$ , the value is maximized. It shows that the optimal policy is  $a_0$ .

To sum up, the Hierarchical Latent Bandit example shows that our proposed GDR-MDP has the potential to find a less conservative policy compared with other robust formulations.

## B Proofs

### B.1 Proofs for Section 5.1: Convergence of GDR-MDP in infinite-horizon case

This section proves the convergence of GDR-MDP in the infinite-horizon case. We first prove the Bellman expectation equation and Bellman optimality equation in Section B.1.1. We then show the contraction operator build on the Bellman optimality equation is a contraction operator in Section B.1.2. Finally, we show the convergence of GDR-MDP in Section B.1.3.

#### B.1.1 Proofs for Proposition 1

We show the proof for Bellman expectation equation as follows. Starting from the definition of  $V_t^\pi(b_t, s_t)$ , we first separate the elements at time step  $t$  from future timesteps. We then find that the elements related to future timesteps starting from step  $t + 1$  could be aggregated to the group distributionally robust value at step  $t + 1$ .

$$\begin{aligned}
V_t^\pi(b_t, s_t) &= \min_{\hat{b}_{t:T} \in \mathcal{C}_{b_t:T}} \mathbb{E}_{\hat{b}_{t:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t:T}} \left[ \sum_{n=t}^T \gamma^{n-t} r_n | b_t, s_t \right] \\
&= \min_{\hat{b}_{t:T} \in \mathcal{C}_{b_t:T}} \mathbb{E}_{\hat{b}_{t:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t:T}} \left[ \{r_t + \gamma \sum_{n=t+1}^T \gamma^{n-t-1} r_n\} | b_t, s_t \right] \\
&= \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_t} \left[ \{r_t + \gamma \cdot \right. \\
&\quad \left. \min_{\hat{b}_{t+1:T} \in \mathcal{C}_{b_{t+1:T}}} \mathbb{E}_{\hat{b}_{t+1:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t+1:T}} \left[ \sum_{n=t+1}^T \gamma^{n-t-1} r_n \right] \} | b_t, s_t \right] \\
&= \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi_t} \left[ \{\mathbb{E}_{\mathbf{R}_m}[r_t] + \gamma \cdot \sum_{s_{t+1}} \mathbf{P}_m(s_{t+1} | s_t, a_t) \cdot \right. \\
&\quad \left. \min_{\hat{b}_{t+1:T} \in \mathcal{C}_{b_{t+1:T}}} \mathbb{E}_{\hat{b}_{t+1:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t+1:T}} \left[ \sum_{n=t+1}^T \gamma^{n-t-1} r_n \right] \} | b_t, s_t \right] \\
&= \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi_t} \left[ \mathbb{E}_{\mathbf{R}_m}[r_t] + \gamma \cdot \sum_{s_{t+1}} \mathbf{P}_m(s_{t+1} | s_t, a_t) \cdot \right. \\
&\quad \left. \min_{\hat{b}_{t+1:T} \in \mathcal{C}_{b_{t+1:T}}} \mathbb{E}_{\hat{b}_{t+1:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t+1:T}} \left[ \sum_{n=t+1}^T \gamma^{n-t-1} r_n | b_{t+1} = SE(b_t, s_t), s_{t+1} \right] \right] \\
&= \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi_t} \left[ \mathbb{E}_{\mathbf{R}_m}[r_t] + \gamma \sum_{s_{t+1}} \mathbf{P}_m(s_{t+1} | s_t, a_t) V_{t+1}^\pi(b_{t+1}, s_{t+1}) \right].
\end{aligned}$$



Therefore, the Group Distirbutionally Robust Bellman expectation equation is

$$V_t^\pi(b_t, s_t) = \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi_t} \left[ \mathbb{E}_{\mathbf{R}_m} [r_t] + \gamma \sum_{s_{t+1}} \mathbf{P}_m(s_{t+1}|s_t, a_t) V_{t+1}^\pi(b_{t+1}, s_{t+1}) \right].$$

**Proposition 2.** *The Group Distirbutionally Robust Bellman optimality equation is*

$$V_t^{\pi^*}(b_t, s_t) = \max_{\pi_t} \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi_t} \left[ \mathbb{E}_{\mathbf{R}_m} [r_t] + \gamma \sum_{s_{t+1}} \mathbf{P}_m(s_{t+1}|s_t, a_t) V_{t+1}^{\pi^*}(b_{t+1}, s_{t+1}) \right].$$

Follow similar process, we could also prove the Bellman optimality equation as follows.

$$\begin{aligned} V_t^{\pi^*}(b_t, s_t) &= \max_{\pi_{t:T}} \min_{\hat{b}_{t:T} \in \mathcal{C}_{b_{t:T}}} \mathbb{E}_{\hat{b}_{t:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t:T}} \left[ \sum_{n=t}^T \gamma^{n-t} r_n | b_t, s_t \right] \\ &= \max_{\pi_{t:T}} \min_{\hat{b}_{t:T} \in \mathcal{C}_{b_{t:T}}} \mathbb{E}_{\hat{b}_{t:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t:T}} \left[ \{r_t + \gamma \sum_{n=t+1}^T \gamma^{n-t-1} r_n\} | b_t, s_t \right] \\ &= \max_{\pi_t} \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_t} \left[ \{r_t + \gamma \cdot \right. \\ &\quad \left. \max_{\pi_{t+1:T}} \min_{\hat{b}_{t+1:T} \in \mathcal{C}_{b_{t+1:T}}} \mathbb{E}_{\hat{b}_{t+1:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t+1:T}} \left[ \sum_{n=t+1}^T \gamma^{n-t-1} r_n \right] \} | b_t, s_t \right] \\ &= \max_{\pi_t} \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi_t} \left[ \{ \mathbb{E}_{\mathbf{R}_m} [r_t] + \gamma \cdot \sum_{s_{t+1}} \mathbf{P}_m(s_{t+1}|s_t, a_t) \cdot \right. \\ &\quad \left. \max_{\pi_{t+1:T}} \min_{\hat{b}_{t+1:T} \in \mathcal{C}_{b_{t+1:T}}} \mathbb{E}_{\hat{b}_{t+1:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t+1:T}} \left[ \sum_{n=t+1}^T \gamma^{n-t-1} r_n \right] \} | b_t, s_t \right] \\ &= \max_{\pi_t} \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi_t} \left[ \mathbb{E}_{\mathbf{R}_m} [r_t] + \gamma \cdot \sum_{s_{t+1}} \mathbf{P}_m(s_{t+1}|s_t, a_t) \cdot \right. \\ &\quad \left. \max_{\pi_{t+1:T}} \min_{\hat{b}_{t+1:T} \in \mathcal{C}_{b_{t+1:T}}} \mathbb{E}_{\hat{b}_{t+1:T}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}_m^{\pi_{t+1:T}} \left[ \sum_{n=t+1}^T \gamma^{n-t-1} r_n | b_{t+1} = SE(b_t, s_t), s_{t+1} \right] \} \right] \\ &= \max_{\pi_t} \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi_t} \left[ \mathbb{E}_{\mathbf{R}_m} [r_t] + \gamma \sum_{s_{t+1}} \mathbf{P}_m(s_{t+1}|s_t, a_t) V_{t+1}^{\pi^*}(b_{t+1}, s_{t+1}) \right]. \end{aligned}$$

Therefore, the Group Distirbutionally Robust Bellman optimality equation is

$$V_t^{\pi^*}(b_t, s_t) = \max_{\pi_t} \min_{\hat{b}_t \in \mathcal{C}_{b_t}} \mathbb{E}_{\hat{b}_t(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^{\pi_t} \left[ \mathbb{E}_{\mathbf{R}_m} [r_t] + \gamma \sum_{s_{t+1}} \mathbf{P}_m(s_{t+1}|s_t, a_t) V_{t+1}^{\pi^*}(b_{t+1}, s_{t+1}) \right].$$

### B.1.2 Proof of Lemma 1

Let  $\mathcal{V}$  refer to a set of real-valued bounded functions on  $\Delta_{\mathcal{Z}} \times \mathcal{S}$  and  $\mathcal{LV}(b, s) : \mathcal{V} \rightarrow \mathcal{V}$  refer to the Bellman operator defined as

$$\mathcal{LV}(b, s) = \max_{\pi \in \Pi} \min_{\hat{b} \in \mathcal{C}_b} \mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^\pi \left[ \mathbb{E}_{\mathbf{R}_m} [r] + \gamma \sum_{s'} \mathbf{P}_m(s'|s, a) V^\pi(SE(b, s), s) \right].$$

Now we start the proof to show that the Bellman operator above is a contraction operator. For notation simplicity, let

$$\mathcal{L}_b^\pi = \mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^\pi \left[ \mathbb{E}_{\mathbf{R}_m} [r] + \gamma \sum_{s'} \mathbf{P}_m(s'|s, a) V^\pi(SE(b, s), s) \right], \text{ and } \mathcal{LV}(b, s) = \max_{\pi \in \Pi} \min_{\hat{b} \in \mathcal{C}_b} \mathcal{L}_b^\pi$$

Given arbitrary  $U, V \in \mathcal{B}$  and based on the definition of the operator  $\mathcal{LV}$  above,  $\mathcal{LU}, \mathcal{LV}$  are real-valued and bounded.

Let  $(b_U, \pi_U)$  and  $(b_V, \pi_V)$  be the saddle points for  $\mathcal{L}U$  and  $\mathcal{L}V$ , respectively.

Observe that,  $\mathcal{L}_{b_U}^{\pi_U} U(b, s) \leq \mathcal{L}_{b_U}^{\pi_U} U(b, s)$  and  $\mathcal{L}_{b_V}^{\pi_V} V(b, s) \geq \mathcal{L}_{b_V}^{\pi_V} V(b, s)$ .

$$\begin{aligned}
& \|\mathcal{L}U(b, s) - \mathcal{L}V(b, s)\|_\infty \\
&= \|\mathcal{L}_{b_U}^{\pi_U} U(b, s) - \mathcal{L}_{b_V}^{\pi_V} V(b, s)\|_\infty \\
&\leq \|\mathcal{L}_{b_V}^{\pi_U} U(b, s) - \mathcal{L}_{b_V}^{\pi_U} V(b, s)\|_\infty \\
&= \|\mathcal{L}_{b_V}^{\pi_U} (U(b, s) - V(b, s))\|_\infty \\
&= \|\mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^\pi \left[ \gamma \sum_{s'} \mathbf{P}_m(s'|s, a) \cdot (U(SE(b, s, \mu), s) - V(SE(b, s, \mu), s)) \right]\|_\infty \\
&\leq \gamma \mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} \mathbb{E}^\pi \left[ \sum_{s'} \mathbf{P}_m(s'|s, a) \cdot \|U(SE(b, s, \mu), s) - V(SE(b, s, \mu), s)\|_\infty \right] \\
&\leq \gamma \|U(SE(b, s, \mu), s) - V(SE(b, s, \mu), s)\|_\infty \\
&= \gamma \|U(b', s) - V(b', s)\|_\infty.
\end{aligned}$$

Considering that  $0 < \gamma < 1$ , we conclude that  $\mathcal{L}V(b, s)$  is a contraction operator on complete metric space  $(\mathcal{V}, \|\cdot\|_\infty)$ .

### B.1.3 Proof for Theorem 1

Since  $\mathcal{L}V(b, s)$  is a contraction operator based on Lemma 1, we directly follow the Banach's Fixed-Point Theorem [68] to show that (a) there exist a unique solution for  $\mathcal{L}V_\infty(b, s) = V_\infty(b, s)$ , and (b) the value function initiating from any value converge uniformly by iterative applying the Bellman update built in finite horizon case.

## B.2 Proofs for Section 5.2: Robustness Guarantee for GDR-MDP

In this section, we prove the robustness guarantee of our proposed GDR-MDP. We compare the GDR-MDP's optimal value with three different robust formulations. We achieve the comparison by studying how maintaining beliefs over mixtures affects the worst-possible outcome of the inner minimization problem and the resulting RL policy. We study the worst-possible value via the relationships between ambiguity sets projected to the space of beliefs over MDPs.

### B.2.1 Ambiguity set projection and set relationships

Recall that we consider a discrepancy-based ambiguity set defined based on total variance distance in Definition 3. Formally, the ambiguity set is

$$\mathcal{C}_{\nu_{\mathcal{X}}, d_{TV}, \xi}(X) = \{\nu'(X) : \sup_{X \in \mathcal{X}} |\nu'(X) - \nu_{\mathcal{X}}(X)| \leq \xi\},$$

where  $x \in \mathcal{X}$  is the support,  $\nu_{\mathcal{X}}$  is the nominal distribution over  $\mathcal{X}$  and  $\xi$  is the ambiguity set's size.

Define a column stochastic matrix  $\mathbf{A} = ((a_{ij})) \in \mathbb{R}^{M \times Z}$ ,  $i \in [M]$ ,  $j \in [Z]$ , where  $a_{ij} = \mu_{z=j}(m=i)$  represents a conditional probability equal to the  $i$ -th element of  $\mu_{z=j}$  defined in GDR-MDP.

Based on the total probability theorem, the matrix  $\mathbf{A}$  maps distributions over  $\mathcal{Z}$  to distributions over  $\mathcal{M}$ . Formally,  $\forall \mathbf{p}(z) \in [0, 1]^Z$ ,  $\sum_{\mathcal{Z}} \mathbf{p}(z) = 1$ , there exists  $\mathbf{p}(m) = \mathbf{A}\mathbf{p}(z)$ ,  $\mathbf{p}(m) \in [0, 1]^M$ ,  $\sum_m \mathbf{p}(m) = 1$ .

We now define the operator that maps an ambiguity set over distribution for mixtures to an ambiguity set over distributions for MDPs.

**Definition 4** (Ambiguity Set Projection). The operator  $T_{\mathbf{A}}$  projects an ambiguity set for distributions over  $\mathcal{Z}$  to an ambiguity set for distributions over  $\mathcal{M}$ , and

$$T_{\mathbf{A}}(\mathcal{C}_{b(z), d, \xi}(z)) = \{\mathbf{p}'(m) : \mathbf{p}'(m) = \mathbf{A}\mathbf{p}(z), \forall \mathbf{p}(z) \in \mathcal{C}_{b(z), d, \xi}(z)\}.$$

$\mathcal{C}_{b(m), d, \xi}(m)$  is the ambiguity set for admissible distributions over supports  $\mathcal{M}$ , where  $b(m)$  is the nominal distribution.  $d$  is the distance metric.  $\xi$  is the set size and also the adversary's perturbation budget around the nominal distribution. Similarly,  $\mathcal{C}_{b(z), d, \xi}(z)$  is the ambiguity set for admissible distributions over supports  $\mathcal{Z}$ .

With the set projection operator  $T_{\mathbf{A}}$ , we can derive the relationships between the projected ambiguity set  $T_{\mathbf{A}}(\mathcal{C}_{b(z),d,\xi}(z))$  and the  $\xi$ -ambiguity set  $\mathcal{C}_{b(m),d,\xi}(m)$  which directly represents the model misspecifications over different MDPs. We state the results in Proposition 3.

**Proposition 3** (Ambiguity Set Regularization with the Hierarchical Latent Structure). *Consider two adversaries with the same attack budget  $\xi$ . One adversary perturbs the  $z$ -level distribution by selecting the worst possible distribution within  $\mathcal{C}_{b(z),d,\xi}(z)$  and the other perturbs the  $m$ -level distribution by selecting the worst possible distribution within  $\mathcal{C}_{b(m),d,\xi}(m)$ . Given the nominal distribution for  $\mathcal{Z}$  as  $b(z)$ , we have the following statements hold:*

1.  $b(m) = \mathbf{A}b(z)$ .
2.  $T_{\mathbf{A}}(\mathcal{C}_{b(z),d,\xi}(z)) \subseteq \mathcal{C}_{b(m),d,\xi}(m)$ . The  $m$ -level ambiguity set projected from a  $z$ -level  $\xi$ -ambiguity set is a subset of the  $m$ -level  $\xi$ -ambiguity set when directly perturbing  $m$ -level distributions. It means the hierarchical structure imposes extra regularization/constraints to the adversary.

The second statement in Proposition 3 shows that the hierarchical structure imposes extra regularization/constraints to the adversary by shrinking the ambiguity set. The actual regularization reflected on the perturbed value of  $(b, s)$  is related to the rank of the matrix  $\mathbf{A}$  and the loss function of downstream tasks (e.g. the transition models in the group of RL). The hierarchical latent structure in GDR-MDP as well as in HLMDP can be viewed as a mixture model with random variables as  $m \in [M]$  such that  $\mathcal{M}_m \in \mathcal{M}$ , and latent variables as  $z \in [Z]$ . The results in Proposition 3 are applicable for general mixture models.

We now provide the proof for Proposition 3 as follows.

*Proof for Proposition 3.* Item (1) directly follows the definition of operator  $T_{\mathbf{A}}$  in Definition 4.

Define the ambiguity sets based on Definition 3, where the cost function is the cost total variance distance.

$$\begin{aligned}\mathcal{C}_{b(m),d_{TV},\xi}(m) &= \{\mathbf{p}(m) : \sup_{M \in \mathcal{M}} |\mathbf{p}(m) - b(m)| \leq \xi\}, \\ \mathcal{C}_{b(z),d_{TV},\xi}(z) &= \{\mathbf{p}(z) : \sup_{Z \in \mathcal{Z}} |\mathbf{p}(z) - b(z)| \leq \xi\}\end{aligned}$$

Consider an arbitrary  $\mathbf{p}'(m) \in T_{\mathbf{A}}(\mathcal{C}_{b(z),d,\xi}(z))$ , there exists a distribution  $\mathbf{p}(z) \in \mathcal{C}_{b(z),d,\xi}(z)$ , such that  $\mathbf{p}'(m) = \mathbf{A}\mathbf{p}(z)$ . Therefore,

$$\mathbf{p}'(m) - b(m) = \mathbf{A}\mathbf{p}(z) - b(m) = \mathbf{A}\mathbf{p}(z) - \mathbf{A}b(z) = \mathbf{A}(\mathbf{p}(z) - b(z))$$

Let  $g = \mathbf{p}'(m) - b(m)$ . Denote the  $i$ -th element of  $g$  as  $g_i, i \in [n]$ . Let  $a_i \in [0, 1]^{1 \times m}$  denote the  $i$ -th row of  $\mathbf{A}$ .

Considering that elements in  $a_i$  are non-negative and lie in interval  $[0, 1]$ , we have

$$\begin{aligned}g_i &= a_i^T (\mathbf{p}(z) - b(z)) \\ &\leq a_i^T (\mathbf{p}(z) - b(z))_+ \quad ((\cdot)_+ \text{ is an operator that replaces negative elements with 0}) \\ &\leq \sum a_i (\mathbf{p}(z) - b(z))_+ \quad (\text{each element in } a_i \text{ is in } [0, 1]) \\ &= d_{TV}(\mathbf{p}(z), b(z)) \\ &\leq \xi, \forall i \in [n].\end{aligned}$$

Similarly, we can prove  $-g_i \leq \xi, \forall i \in [n]$ .

$$\begin{aligned}-g_i &= -a_i^T (\mathbf{p}(z) - b(z)) = a_i^T (b(z) - \mathbf{p}(z)) \leq a_i^T (b(z) - \mathbf{p}(z))_+ \\ &\leq \sum a_i (b(z) - \mathbf{p}(z))_+ = d_{TV}(\mathbf{p}(z), b(z)) \\ &\leq \xi, \forall i \in [n].\end{aligned}$$

Therefore, we have elements in  $g$  bounded by  $\xi$ :  $|g_i| \leq \xi, \forall i \in [n]$ .

$$\begin{aligned}
& |g_i| \leq \xi, \forall i \in [n] \\
& \Rightarrow |\mathbf{A}\mathbf{p}(z) - b(m)| \leq \xi, \forall z \in [Z] \quad (\text{because of the definition of } g_i) \\
& \Rightarrow \sup_{z \in \mathcal{Z}} |\mathbf{A}\mathbf{p}(z) - b(m)| \leq \xi \\
& \Rightarrow T_{\mathbf{A}}(\mathcal{C}_{\mu_{\mathcal{Z}}, d, \xi}(z)) \subseteq \mathcal{C}_{\mu_{\mathcal{M}}, d, \xi}(m).
\end{aligned}$$

□

**Remark**  $\mathbf{A}$  is not a stochastic row matrix, which makes the proof different from the contraction mapping proof in tabular RL settings where the transition matrix is a stochastic row matrix.

### B.2.2 Proof for Theorem 2

With the ambiguity set relationships in Proposition 3, we are now ready to prove Theorem 2.

Recall that for notation simplicity, let  $U_m(\pi) = \mathbb{E}_m^\pi[\sum_{t=1}^T \gamma^t r_t]$ . Let  $\mathcal{C}_{b(m), d_{TV}, \xi}(m)$  and  $\mathcal{C}_{b(z), d_{TV}, \xi}(z)$  denote the ambiguity sets for beliefs over MDPs  $m$  and mixtures  $z$ , respectively.  $b(m)$  and  $b(z)$  satisfy  $b(m) = \sum_{\mathcal{Z}} \mu_z(m) b(z)$  and are the nominal distributions. For any history-dependent policy  $\pi \in \Pi$ , its value function under different robust formulations are:

$$\begin{aligned}
V_{GDR}(\pi) &= \min_{\hat{b}(z) \in \mathcal{C}_{b(z), d_{TV}, \xi}(z)} \mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} [U_m(\pi)], & V_{GR}(\pi) &= \min_{z \in [Z]} \mathbb{E}_{\mu_z(m)} [U_m(\pi)], \\
V_{DR}(\pi) &= \min_{\hat{b}(m) \in \mathcal{C}_{b(m), d_{TV}, \xi}(m)} \mathbb{E}_{\hat{b}(m)} [U_m(\pi)], & V_R(\pi) &= \min_{m \in [M]} [U_m(\pi)].
\end{aligned}$$

*Proof for Theorem 2.* First prove item (1) which is  $V_{GDR}(\pi) \geq V_{GR}(\pi) \geq V_R(\pi)$ :

Given an arbitrary policy  $\pi \in \Pi$ , we have

$$\begin{aligned}
V_{GDR}(\pi) &= \min_{\hat{b}(z) \in \mathcal{C}_{b(z), d_{TV}, \xi}(z)} \mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} [U_m(\pi)] \\
&\geq \min_{\hat{b}(z) \in \Delta_Z} \mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} [U_m(\pi)] \\
&= \min_{z \in [Z]} \mathbb{E}_{\mu_z(m)} [U_m(\pi)] \\
&= V_{GR}(\pi)
\end{aligned}$$

It means that with nontrivial ambiguity set  $\mathcal{C}_{b(z), d_{TV}, \xi}(z)$ , the distributionally robust value is more optimistic than the group robust formulation.

$$\begin{aligned}
V_{GR}(\pi) &= \min_{z \in [Z]} \mathbb{E}_{\mu_z(m)} [U_m(\pi)] \\
&\geq \min_{z \in [Z]} \min_{m \sim \mu_z(m)} [U_m(\pi)] \\
&\geq \min_{m \in [M]} [U_m(\pi)] \\
&= V_R(\pi)
\end{aligned}$$

Therefore, we have  $V_{GDR}(\pi) \geq V_{GR}(\pi) \geq V_R(\pi)$ .

**Remark** The belief robust method with  $V_{GR}$  is compatible with a non-adaptive robust problem, where the policy of the decision maker is a Markov policy that only depend on current state. In contrast, the belief distributionally robust method with  $V_{GDR}$  corresponds to an adaptive robust problem, where the decision maker utilizes a history-dependent policy. In other words, it considers both the current state and the information gather along interaction. A similar argument but in non-robust version is presented as Proposition 1. in [5].

Now prove the inequality relationship in item (2) which is  $V_{GDR}(\pi) \geq V_{DR}(\pi)$ :

Based on the projection operator in Definition 4, we change the minimization over belief distribution on mixtures to an equivalent expression which has minimization over belief distribution on MDPs instead.

$$\begin{aligned}
V_{GDR}(\pi) &= \min_{\hat{b}(z) \in \mathcal{C}_{b(z), d_{TV}, \xi}(z)} \mathbb{E}_{\hat{b}(z)} \mathbb{E}_{\mu_z(m)} [U_m(\pi)] \\
&= \min_{\hat{b}(z) \in \mathcal{C}_{b(z), d_{TV}, \xi}(z)} \mathbb{E}_{m \sim \sum_z \hat{b}(z) \mu_z(m)} [U_m(\pi)] \\
&= \min_{\hat{b}(m) \in T_{\mathbf{A}}(\mathcal{C}_{b(z), d, \xi}(z))} \mathbb{E}_{\hat{b}(m)} [U_m(\pi)] \quad (\text{based on Definition 4})
\end{aligned}$$

Then with Proposition 3 which shows the set relationships, we have,

$$\begin{aligned}
V_{GDR}(\pi) &= \min_{\hat{b}(m) \in T_{\mathbf{A}}(\mathcal{C}_{b(z), d, \xi}(z))} \mathbb{E}_{\hat{b}(m)} [U_m(\pi)] \\
&\geq \min_{\hat{b}(m) \in \mathcal{C}_{b(m), d_{TV}, \xi}(m)} \mathbb{E}_{\hat{b}(m)} [U_m(\pi)] \quad (\text{because of } T_{\mathbf{A}}(\mathcal{C}_{b(z), d, \xi}(z)) \subseteq \mathcal{C}_{b(m), d, \xi}(m)) \\
&= V_{DR}(\pi).
\end{aligned}$$

It shows that in general, distributionally robust over high level latent variable  $z$  is more optimistic than that over low level latent variable  $m$ . The hierarchical mixture model structure help regularize the strength of the adversary and generate less conservative policies than flat model structure.

Therefore, we have the following inequalities hold:  $V_{GDR}(\pi) \geq V_{GR}(\pi) \geq V_R(\pi)$  and  $V_{GDR}(\pi) \geq V_{DR}(\pi)$ .  $\square$

### B.2.3 Proof for Theorem 3

Based on Theorem 2, we can derive the relationships between the optimal values for different formulations.

*Proof for Theorem 3.* First prove that  $V_{GDR}(\pi_{GDR}^*) \geq V_{DR}(\pi_{DR}^*)$ .

Since  $\pi_{GDR}^*$  is the optimal policy for GDR-MDP, we have

$$V_{GDR}(\pi_{GDR}^*) \geq V_{GDR}(\pi_{DR}^*).$$

Since  $V_{GDR}(\pi) \geq V_{DR}(\pi), \forall \pi$ , base on Theorem 2, we have

$$V_{GDR}(\pi_{DR}^*) \geq V_{DR}(\pi_{DR}^*).$$

Therefore we have

$$V_{GDR}(\pi_{GDR}^*) \geq V_{DR}(\pi_{DR}^*).$$

Following similar procedures, we prove that  $V_{GDR}(\pi_{GDR}^*) \geq V_{GR}(\pi_{GR}^*) \geq V_R(\pi_R^*)$ .

$$\begin{aligned}
V_{GDR}(\pi_{GDR}^*) &\geq V_{GDR}(\pi_{GR}^*) && (\text{since } \pi_{GDR}^* \text{ is the optimal policy for GDR-MDP}) \\
&\geq V_{GR}(\pi_{GR}^*) && (\text{since } V_{GDR}(\pi) \geq V_{GR}(\pi), \forall \pi \text{ in Theorem 2}) \\
&\geq V_{GR}(\pi_R^*) && (\text{since } \pi_{GR}^* \text{ is the optimal policy for group robust MDP}) \\
&\geq V_R(\pi_R^*) && (\text{since } V_{GR}(\pi) \geq V_R(\pi), \forall \pi \text{ in Theorem 2})
\end{aligned}$$

Therefore, we have shown the following inequalities hold:  $V_{GDR}(\pi_{GDR}^*) \geq V_{GR}(\pi_{GR}^*) \geq V_R(\pi_R^*)$  and  $V_{GDR}(\pi_{GDR}^*) \geq V_{DR}(\pi_{DR}^*)$ .  $\square$

## C Environment Details

### C.1 HighwayMerge

We build a two-agent highway merging scenario based on highway-env [65]. The ego agent (the green vehicle) aims to merge into the middle lane at high speed while avoiding collisions with the adversary vehicle (the yellow vehicle). It has a 6-dimensional continuous observation that captures

Table 2: Observation and action space in HighwayMerge

Dim.	Continuous Observation Space	range
0-1	ego vehicle: $x, y$	$[-1, 1]$
2-3	surrounding vehicle (relative): $x, y$	$[-1, 1]$
4-5	ramp endpoint (relative): $x, y$	$[-1, 1]$
Index	Discrete Action Space	
0	change lane left	
1	idle	
2	change lane right	
3	increase target speed	
4	decrease target speed	

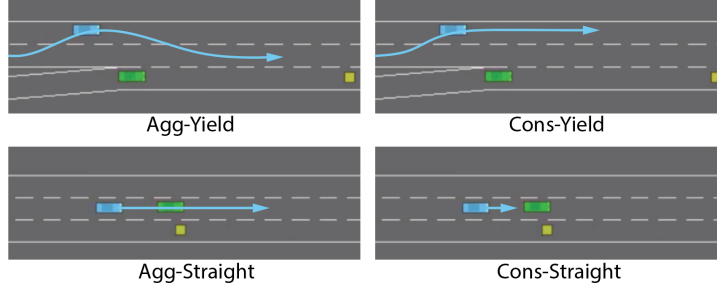


Figure 6: Visualization of the challenger vehicle’s possible behaviors in Merging task.

the kinematic information of road participants, and a discrete action space that represents high-level control commands. Detailed descriptions of ego vehicle’s observation and action space, and adversary’s action space are listed in Table 2.

At each time step, the ego vehicle receives a reward which consists of three components,

$$\begin{aligned}
 r &= r_{Collide} + r_{HighSpeed} + r_{RightLane} \\
 r_{Collide} &= -1 * \mathbb{I}_{Collide} \\
 r_{HighSpeed} &= 0.2 * v_{pro}/v_{max} \\
 r_{RightLane} &= 0.1 * \mathbb{I}_{RightLane}
 \end{aligned}$$

The surrounding vehicle adapts non-stationary behaviors and samples its policy at the beginning of each training episode. We visualize the behaviors of the challenger vehicle as in Figure 6.

## C.2 LunarLander

We modify the LunarLander environment [66] by changing the engine mode and engine power. The mixture index set  $\mathcal{Z}$  has cardinality two:  $z = 0$  and  $z = 1$  correspond to two different engine operation modes: normal mode and left-right-flip mode. When in left-right-flip mode, the action turning on the left engine in normal mode will turn on the right engine instead, and the action turning on the right engine in normal mode will turn on the left instead. The engine power has two choices which are 3.0 and 6.0. The MDP set  $\mathcal{M}$  has carnality four corresponding to four combinations of engine mode and engine power. Detailed descriptions of the state and action space are shown in Tble 3.

## C.3 HalfCheetah

We modify the joint failure and torso mass of HalfCheetah and build 18 tasks with different dynamics. The joint failure has six choices which correspond to 6 joints of HalfCheetah. For instance, when the joint failure index is 0, we cannot apply control torque (action) to joint 0. The torso mass has three choices, which are 0.9, 1.0, and 1.1 times the original torso mass. Detailed descriptions of the state and action space are shown in Table 4.

Table 3: Observation and action space in LunarLander

Dim.	Continuous Observation Space	range
0	x position	$[-\text{inf}, \text{inf}]$
1	y position	$[-\text{inf}, \text{inf}]$
2	x velocity	$[-\text{inf}, \text{inf}]$
3	y velocity (relative): $x, y, v_x, v_y$	$[-\text{inf}, \text{inf}]$
4	angle	$[-\pi, \pi]$
5	angular velocity	$[-\text{inf}, \text{inf}]$
6	if left leg contact with ground	$\{0, 1\}$
7	if right leg contact with ground	$\{0, 1\}$
Index	Discrete Action Space	
0	Idle	
1	Turn on left engine (normal mode)/Turn on right engine (left-right-flip mode)	
2	Turn on main engine	
3	Turn on right engine (normal mode)/Turn on left engine (left-right-flip mode)	

Table 4: Observation and action space in HalfCheetah

Dim.	Continuous Observation Space
0-8	positional information
9-16	velocity information
Dim	Continuous Action Space
0-5	control torque

## D Implementation Details

**Trajectory rollout** In both training and testing, we initialize the environment by sampling first a mixture and then a MDP realization. The sampled mixture and MDP is fixed throughout one episode. In our environments with discrete mixtures and MDPs, we can represent the ground truth mixture index  $\hat{z}$  with a one-hot vector  $e_{\hat{z}}$ , which is used in the pretraining phase of all baselines and in the whole training phase of baseline **G-Exact**. For baselines with belief module including **GDR**, **G-Belief**, **DR**, **State-R**, the actual mixture  $\hat{z}$  and MDP weights  $\mu(m|\hat{z})$  are unknown to the RL agent. Instead, the RL agent is given the number of possible mixtures  $Z$  and is able to infer a belief over mixtures  $b(z)$  based on a belief update function  $SE$ . A detailed algorithm for trajectory rollout is Algorithm 1. For baseline **No-Belief**, we mask out the beliefs in the input by replacing with zeros.

**Belief update mechanism** In our implementation (Section 7), we use Bayesian update rule to update beliefs based on the interaction at each timestep. At the beginning of each episode, we initialize a uniform belief distribution  $b_0(i) = 1/(|Z|), \forall i \in [|Z|]$ . At timestep  $t$ , we update the belief as follows

$$b_{t+1}(j) = \frac{b_t(j)L(j)}{\sum_{i \in [|Z|]} b_t(i)L(i)}, \forall j \in [|Z|],$$

where  $L$  represents the likelihood. Let  $\hat{z}$  denote the true mixture index for the episode. We let the likelihood  $L$  vector be a soft version of the actual one-hot mixture encoding  $e_{\hat{z}}$ .

More concretely, at each time step, we first sample a noisy index  $j$  where  $j = \hat{z}$  with probability  $\epsilon_l$  and  $j$  is uniformly sampled from  $[Z]$  otherwise. The likelihood  $L$  is a vector with dimension  $|Z|$ , and  $\forall i \in [|Z|]$ , the  $i$ -th element  $L(i)$  is

$$L(i) = \begin{cases} l, & \text{if } i = j \\ (1 - l)/(|Z| - 1), & \text{if } i \neq j \end{cases}$$

There are lots of literature on accurate belief updates [69]. In this work, we utilize a simple but controllable belief update mechanism above, which is more suitable for robustness evaluations since we could explicitly vary the hyperparameters. We leave a more sophisticated design of belief update mechanism for future work.

**Belief noise level** During robustness evaluation in Section 8, we control the belief noise level  $\epsilon_{\hat{z}}$  which affects the likelihood  $L$ . More concretely, we add another layer of randomness on the estimate of  $\hat{z}$ . Define the noisy mixture index at test-time as  $z_{test}$ , we have

$$z_{test} = \begin{cases} \hat{z} & \text{with probability } \epsilon_{\hat{z}} \\ \text{a random index uniformly samples from } [|Z|], & \text{otherwise} \end{cases}$$

During robust evaluation, the likelihood  $L_{test}$  is calculated base on  $z_{test}$ . More concretely, at each time step, we first sample a noisy index  $j$  where  $j = z_{test}$  with probability  $\epsilon_l$  and  $j$  is uniformly sampled from  $[Z]$  otherwise. The likelihood and belief update are as follows:

$$L_{test}(i) = \begin{cases} l, & \text{if } i = j \\ (1-l)/(|Z|-1), & \text{if } i \neq j \end{cases}, \text{ and } b_{t+1}(j) = \frac{b_t(j)L_{test}(j)}{\sum_{i \in [|Z|]} b_t(i)L_{test}(i)}, \forall j \in [|Z|].$$

**Distributionally robust training with belief distribution over MDPs (DR)** **DR** has an agent that takes the belief distribution  $b(m)$  and state  $s$  as inputs. **DR** uses the same belief updating rule as in **GDR** to update  $b(z)$  at each timestep and then project  $b(z)$  to  $b(m)$  with  $\mu_z(m)$ .

This is a variant of our proposed Group Distributionally Robust DQN which has a perturbed target taking  $m$ -level belief distribution as part of its input. Note that in **DR**, we still update  $z$ -level belief  $b(z)$  based on the same belief updating function  $SE$  as in **GDR**. However, in **DR**, for data pair  $d$ , the ambiguity set  $\mathcal{C}_{b'(m), d_{TV}, \xi}$  is centered at  $b'(m) = T_A(b'(z))$  which is mapped from  $b'(z)$ . We also modify the fast gradient sign attack over  $b(m)$  accordingly. We first sample  $i \in [M]$  and apply attacks as  $p(m)_j = p(m)_j + \alpha_b \cdot \text{sign}(\nabla_{p(m), j} V(p(m), s'))$ ,  $\forall j \neq i$  and  $p(m)_i = p(m)_i - \sum_{j \neq i} p(m)_j$ . We iteratively apply the gradient sign attack to find  $b^{adv}(m) = \arg \min_{p(m) \in \mathcal{C}_{b'(m), d_{TV}, \xi}} \sum_{a \in \mathcal{A}} Q_\theta(p(m), s', a)$ .

## D.1 Hyperparameters

We show the hyperparameters for training Merging, Lunarlander and Halfcheetah in Table 5, Table 6 and Table 7, respectively. We select hyperparameters via grid search.

Table 5: Hyperparameters for the highway merging task

reward decay	1.0
net hidden structure	[64, 64]
net activation function	ReLU
value function learning rate	0.01
value function learning rate decay	0.999
epoch	10
gradient steps per epoch	5000
adv budget	0.4
adv step size	0.02
adv max step	50
batch size	128

Table 6: Hyperparameters for the LunarLander task

reward decay	0.95
net hidden structure	[128, 128]
net activation function	ReLU
value function learning rate	0.01
value function learning rate decay	0.999
epoch	20
gradient steps per epoch	5000
adv budget	0.4
adv step size	0.02
adv max step	50
batch size	256



Table 7: Hyperparameters for the Halfcheetah

reward decay	0.99
net hidden structure	[256, 256]
net activation function	ReLU
value function learning rate	0.001
value function learning rate decay	0.999
epoch	200
gradient steps per epoch	5000
adv budget	0.2
adv step size	0.02
adv max step	50
batch size	256

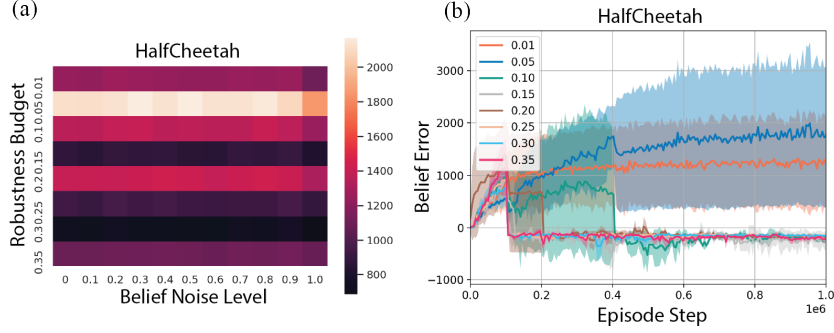


Figure 7: Ablation study about the effect of ambiguity set budget on **DR**'s robustness and training stability. We choose the ambiguity set size among 0.01, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, and 0.35.

## E Additional Ablation Study

In this section, we show how the ambiguity set size and the pretrain episodes affect the training stability and robustness of **DR** which maintains a belief over MDPs. Compared with our proposed **GDR**, **DR** omits the hierarchical structure.

Figure 7 shows the effect of the ambiguity set in HalfCheetah. All curves in Figure 7 are pre-trained in the first 100000 episodes. With ambiguity set size 0.01 and 0.05, the **DR** does not crash and converge to a non-negative value. Comparing Figure 7 (b) for **DR** with Figure 3 (c) for **GDR**, we can conclude that **GDR** is less sensitive to the ambiguity set size along training since it converge to a non-negative value with a larger range of ambiguity set size. Comparing Figure 5 (a) with Figure 4 (c) for our proposed **GDR**, we can conclude that the hierarchical structure enhances the robustness to belief noise since the robustness performance for **GDR** consistently outperforms that of **DR** for different ambiguity set sizes.

Figure 8 shows the effect of the pretrain episodes in HalfCheetah. All curves in Figure 8 has an ambiguity set size 0.2. Figure 8 shows that even pretraining for 900000 episodes, **DR** still will crash after the pretraining phase. It shows that **DR** is less sensitive to the pretraining episodes compared with the ambiguity set size.

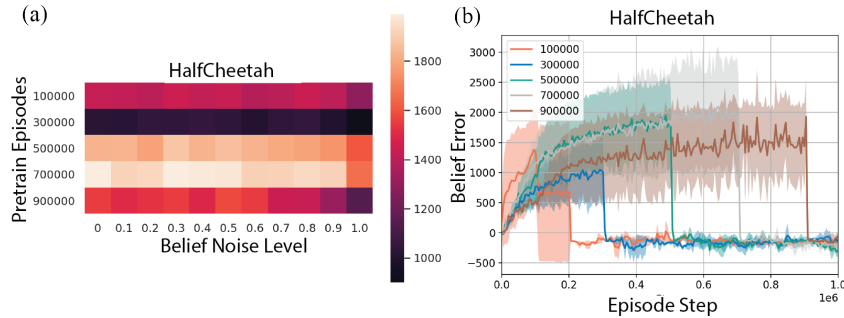


Figure 8: Ablation study about the effect of pretrain episodes on **DR**'s robustness and training stability. We choose the number of pretrain episodes among 100000, 300000, 500000, 700000, and 900000.