Safe Reinforcement Learning with Contrastive Risk Prediction

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Abstract: As safety violations can lead to severe consequences in real-world robotic applications, the increasing deployment of Reinforcement Learning (RL) in robotic domains has propelled the study of safe exploration for reinforcement learning (safe RL). In this work, we propose a risk preventive training method for safe RL, which learns a statistical contrastive classifier to predict the probability of a state-action pair leading to unsafe states. Based on the predicted risk probabilities, we can collect risk preventive trajectories and reshape the reward function with risk penalties to induce safe RL policies. We conduct experiments in robotic simulation environments. The results show the proposed approach has comparable performance with the state-of-the-art model-based methods and outperforms conventional model-free safe RL approaches.

1 Introduction

Reinforcement Learning (RL) offers a great set of technical tools for robotics by enabling robots to automatically learn behavior policies through interactions with the environments and solving the decision-making problems in robotic environments [1]. The deployment of RL in robotic domains can range from small daily used robots [2, 3] to simulation robots with specific real-world applications [4] and humanoid robots [5]. Conversely, the applications in real-world robotic domains also pose important new challenges for RL research. In particular, many real-world robotic environments and tasks, such as human-related robotic environments [6], helicopter manipulation [7, 8], autonomous vehicle [9], and aerial delivery [10], have very low tolerance for violations of safety constraints, as such violation can cause severe consequences. This raises a substantial demand for safe reinforcement learning techniques.

Safe exploration for RL (safe RL) investigates RL methodologies with critical safety considerations, and has received increased attention from the RL research community. In safe RL, in addition to the reward function [11], a RL agent often deploys a cost function to maximize the discounted cumulative reward while satisfying the cost constraint [12, 13, 14]. A comprehensive survey of safe RL categorizes the safe RL techniques into two classes: modification of the optimality criterion and modification of the exploration process [15]. For modification of the optimality criterion, previous works mostly focus on the modification of the reward. Many works [16, 17, 18, 19, 20, 21] pursue such modifications by shaping the reward function with penalizations induced from different forms of cost constraints. For modification of the exploration process, safe RL approaches focus on training RL agents on modified trajectory data. For example, some works deploy backup policies to recover from safety violations to safer trajectory data that satisfy the safety constraint [22, 23, 24].

In this paper, we propose a novel risk preventive training (RPT) method to tackle the safe RL problem. The key idea is to learn a contrastive classification model to predict the risk—the probability of a state-action pair leading to unsafe states, which can then be deployed to modify both the exploration process and the optimality criterion. In terms of exploration process modification, we collect trajectory data in a risk preventive manner based on the predicted probability of risk. A trajectory is terminated if the next state falls into an unsafe region that has above-threshold risk values. Regarding optimality criterion modification, we reshape the reward function by penalizing it with the predicted risk for each state-action pair. Benefiting from the generalizability of risk prediction, the proposed approach can avoid safety constraint violations much early in the training phase and induce safe RL policies. We conduct experiments using four robotic simulation environments on MuJoCo [25]. Our model-free approach produces comparable performance with a state-of-the-art model-based safe RL
method SMBPO [20] and greatly outperforms other model-free safe RL methods. The main contributions of the proposed work can be summarized as follows:

- This is the first work that simultaneously learns a contrastive classifier to perform risk prediction while conducting safe RL exploration.
- With risk prediction probabilities, the proposed approach is able to perform both exploration process modification through risk preventive trajectory collection and optimality criterion modification through reward reshaping.
- As a model-free method, the proposed approach achieves comparable performance to the state-of-the-art model-based safe RL method and outperforms other model-free methods in robotic simulation environments.

2 Related Works

Safe Reinforcement Learning for Robotics. Reinforcement Learning (RL) offers a set of great tools for robotics and is becoming an important part of robotic learning. RL studies an agent’s decision-making at higher abstractive level, and enables a robot to learn an optimal behavior policy by interacting with the environment [1]. With the increasing application demands in robotic environments, new challenges are raised for reinforcement learning. For example, some robotic environments (in particular the human-related environments) have very low tolerance for violations of safety constraints, where safety is one most important concern [6]. Martín H et al. [7] and Koppejan et al. [8] studied the RL application on helicopters based on strict safety assumptions. Wen et al. developed a safe RL approach called Parallel Constrained Policy Optimization (PCPO) to specifically enhance the safety of autonomous vehicles [9]. Faust et al. developed a RL-based unmanned aerial vehicles (UAVs) system for aerial delivery tasks to avoid static obstacles [10]. Kahn et al. [26] propose a model-based collision avoidance approach that is applicable to robotics like a quadrotor and a RC car. Todorov et al. [25] developed a robotic simulation environment named MuJoCo, which promotes the study of the RL applications in robotic environments. Thomas et al. further modified the MuJoCo environment to define safety violations for robotic simulations [20].

Safe Reinforcement Learning Methods. Many methods have been developed in the literature for safe RL. Altman et al. introduced the Constrained Markov Decision Process (CMDP) [27] to formally define the problem of safe exploration in reinforcement learning. Mihatsch et al. introduced the definition of risk into safe RL and intended to find a risk-avoiding policy based on risk-sensitive controls [12]. Hans et al. further differentiated the states as “safe” and “unsafe” states based on human-designed criteria, while a RL agent is considered to be not safe if it reaches “unsafe” states [13]. García et al. [15] presented a comprehensive survey on previous works on safe reinforcement learning, which categorizes the conventional safe RL methods into two classes: modification of the optimality criterion and modification of the exploration process. Ray et al. [16] presented a benchmark to measure the performance of RL agents on safety concerned environments. More recently, Bastani et al [22] and Thananjeyan et al. [23] focused on using backup policies of the safe regions, aiming to avoid safety violations. Tessler et al. applied the reward shaping technique in safe RL to penalize the normal training policy, which is known as Reward Constrained Policy Optimization (RCPO) [18]. Ma et al. propose a model-based Conservative and Adaptive Penalty (CAP) approach to explore safely by modifying the penalty in the training process [14]. Zhang et al. develop a reward shaping approach built upon Probabilistic Ensembles with Trajectory Sampling (PETS) [21]. It pretrains a predictor of the unsafe state in an offline sandbox environment and penalizes the reward of PETS in the adaptation with online environments. A similar work by Thomas et al [20] reshapes reward functions using a model-based predictor. It regards unsafe states as absorbing states and trains the RL agent with a penalized reward to avoid the visited unsafe states.

3 Preliminary

Reinforcement learning (RL) has been broadly used to train robotic agents by maximizing the discounted cumulative rewards. The representation of a reinforcement learning problem can be formulated as a Markov Decision Process (MDP) \( M = (\mathcal{S}, \mathcal{A}, T, r, \gamma) \) [11], where \( \mathcal{S} \) is the state space for all observations, \( \mathcal{A} \) is the action space for available actions, \( T : \mathcal{S} \times \mathcal{A} \to \mathcal{S} \) is the transition
dynamics, \( r : S \times A \rightarrow [r_{\min}, r_{\max}] \) is the reward function, and \( \gamma \in (0, 1) \) is the discount factor. An agent can start from a random initial state \( s_0 \) to take actions and interact with the MDP environment by receiving rewards for each action and moving to new states. Such interactions can produce a transition \( (s_t, a_t, r_t, s_{t+1}) \) at each time-step \( t \) with \( s_{t+1} = T(s_t, a_t) \) and \( r_t = r(s_t, a_t) \), while a sequence of transitions comprise a trajectory \( \tau = (s_0, a_0, r_0, s_1, a_1, r_1, \ldots, s_{|\tau|+1}) \). The goal of RL is to learn an optimal policy \( \pi^* : S \rightarrow A \) that can maximize the expected discounted cumulative reward (return): \( \pi^* = \arg \max_\pi J_r(\pi) = \mathbb{E}_{\tau \sim \mathcal{D}_\pi} \left[ \sum_{t=0}^{|\tau|} \gamma^t r_t \right] \)

3.1 Safe Exploration for Reinforcement Learning

Safe exploration for Reinforcement Learning (safe RL) studies RL with critical safety considerations. For a safe RL environment, in addition to the reward function, a cost function can also exist to reflect the risky status of each exploration step. The process of safe RL can be formulated as a Constrained Markov Decision Process (CMDP) [27], \( M = (S, A, T, r, \gamma, c, d) \), which introduces an extra cost function \( c \) and a cost threshold \( d \) into MDP. An exploration trajectory under CMDP can be written as \( \tau = (s_0, a_0, r_0, c_0, s_1, a_1, r_1, \ldots, s_{|\tau|+1}) \), where the transition at time-step \( t \) is \( (s_t, a_t, s_{t+1}, r_t, c_t) \), with a cost value \( c_t \) induced from the cost function \( c_2 = c(s_t, a_t) \). CMDP monitors the safe exploration process by requiring the cumulative cost \( J_c(\pi) \) does not exceed the cost threshold \( d \), where \( J_c(\pi) \) can be defined as the expected total cost of the exploration, \( J_c(\pi) = \mathbb{E}_{\tau \sim \mathcal{D}_\pi} \left[ \sum_{t=0}^{|\tau|} c_t \right] \) [16]. Safe RL hence aims to learn an optimal policy \( \pi^* \) that can maximize the expected discounted cumulative reward subjecting to a cost constraint, as follows:

\[
\pi^* = \arg \max_\pi J_r(\pi) = \mathbb{E}_{\tau \sim \mathcal{D}_\pi} \left[ \sum_{t=0}^{|\tau|} \gamma^t r_t \right], \quad \text{s.t. } J_c(\pi) = \mathbb{E}_{\tau \sim \mathcal{D}_\pi} \left[ \sum_{t=0}^{|\tau|} c_t \right] \leq d \quad (1)
\]

4 Method

Robot operations typically have low tolerance for risky/unsafe states and actions, since a robot could be severely damaged in real-world environments when the safety constraint being violated. Similar to [13], we adopt a strict setting in this work for the safety constraint such that any “unsafe” state can cause violation of the safety constraint and the RL agent will terminate an exploration trajectory when encountering an “unsafe” state. In particular, we have the following definition:

**Definition 1.** For a state \( s \) and an action \( a \), the value of the cost function \( c(s, a) \) can either be 0 or 1. When \( c(s, a) = 0 \), the induced state \( T(s, a) \) is defined as a safe state; when \( c(s, a) = 1 \), the induced state \( T(s, a) \) is defined as an unsafe state, which triggers the violation of safety constraint and hence causes the termination of the trajectory.

Based on this definition, the cost threshold \( d \) in Eq. (1) should be set strictly to 0. The agent is expected to learn a safe policy \( \pi \) that can operate with successful trajectories containing only safe states. Towards this goal, we propose a novel risk prediction method for safe RL. The proposed method deploys a contrastive classifier to predict the probability of a state-action pair leading to unsafe states, i.e., \( p(y = 1|s_t, a_t) \), where \( y \in \{0, 1\} \) denotes a random variable that indicates whether \( (s_t, a_t) \) leads to an unsafe state \( s_u \in S_u \). The set of unsafe states, \( S_u \), can be either pre-defined or collected during initial exploration. However, directly training a binary classifier to make
Figure 1: An overview of the risk preventive process. The blue area denotes the safe region of the trajectory. The dot \( s_U \) is an unsafe state. The red area around the unsafe state \( s_U \) denotes the unsafe region, bounded by the value of risk prediction \( p(y=1|s_t, a_t) \). The RL agent explores risk preventive trajectories by avoiding entering the unsafe region in the training process.

such predictions is impractical as it is difficult to judge whether a state-action pair is safe—i.e., never leading to unsafe states. For this purpose, we propose to train a contrastive classifier \( F_\theta(s_t, a_t) \) with model parameter \( \theta \) to discriminate a positive state-action pair \((s_t, a_t)\) in a trajectory that leads to unsafe states (unsafe trajectory) and a random state-action pair from the overall distribution of any trajectory. Such a contrastive form of learning can conveniently avoid the identification problem of absolute negative (safe) state-action pairs.

Let \( p(s_t, a_t|y=1) \) denote the presence probability of a state-action pair \((s_t, a_t)\) in a trajectory that leads to unsafe states, and \( p(y=1) \) denote the distribution probability of unsafe trajectory in the environment. The contrastive classifier \( F_\theta(s_t, a_t) \) can be expressed as:

\[
F_\theta(s_t, a_t) = \frac{p(s_t, a_t|y=1)p(y=1)}{p(s_t, a_t|y=1)p(y=1) + p(s_t, a_t)}
\] (2)

which contrastively identifies the state-action pairs in unsafe trajectories from pairs in the overall distribution.

From the definition of \( F_\theta(s_t, a_t) \) in Eq.(2), one can easily derive the probability of interest, \( p(y = 1|s_t, a_t) \), by Bayes’ theorem, as follows:

\[
p(y = 1|s_t, a_t) = \frac{p(s_t, a_t|y=1)p(y=1)}{p(s_t, a_t)} = \frac{F_\theta(s_t, a_t)}{1 - F_\theta(s_t, a_t)}
\] (3)

Although the normal output range for the probabilistic classifier \( F_\theta(s_t, a_t) \) should be \([0, 1]\), this could lead to unbounded \( p(y = 1|s_t, a_t) \in [0, \infty] \) through Eq.(3). Hence we propose to rescale the output of classifier \( F_\theta(s_t, a_t) \) to the range of \([0, 0.5]\).

We optimize the contrastive classifier’s parameter \( \theta \) using maximum likelihood estimation (MLE). The log-likelihood objective function can be written as:

\[
L(\theta) = E_{p(s_t, a_t|y=1)p(y=1)}[\log F_\theta(s_t, a_t)] + E_{p(s_t, a_t)}[\log(1 - F_\theta(s_t, a_t))]
\] (4)

During the training process, the positive state-action pair \((s_t, a_t)\) for the first term of this objective can be sampled from the observed unsafe examples, while the state-action pair \((s_t, a_t)\) for the second term can be sampled from the overall distribution.

### 4.2 Risk Preventive Trajectory

Based on Definition 1, a trajectory terminates when the RL agent encounters an unsafe state and triggers safety constraint violation. It is however desirable to minimize the number of such safety violations even during the policy training process and learn a good policy in safe regions. The risk prediction classifier we proposed above provides a convenient tool for this purpose by predicting the probability of a state-action pair leading to unsafe states, \( p(y = 1|s_t, a_t) \). Based on this risk prediction, we have the following definition for unsafe regions:

**Definition 2.** A state-action pair \((s_t, a_t)\) falls into an **unsafe region** if the probability of \((s_t, a_t)\) leading to unsafe states is greater than a threshold \( \eta \): \( p(y = 1|s_t, a_t) > \eta \), where \( \eta \in (0, 1) \).

With this definition, a RL agent can pursue risk preventive trajectories to avoid safety violations by staying away from unsafe regions. Specifically, we can terminate a trajectory before violating the
Without a doubt, the threshold $\eta$ is a key for determining the length $T = |\hat{\tau}|$ of an early stopped risk preventive trajectory $\hat{\tau}$. To approximate a derivable relation between $\eta$ and $T$, we make the following assumption and lemma:

**Assumption 1.** For a trajectory $\tau = \{s_0, a_0, r_0, c_0, s_1, \ldots, s_H\}$ that leads to an unsafe state $s_H \in S_U$, the risk prediction probability $p(y = 1|s_t, a_t)$ increases linearly along the time steps.

**Lemma 1.** Assume that Assumption 1 holds. Let $H \in \mathbb{N}$ denote the length of an unsafe trajectory $\tau = \{s_0, a_0, r_0, c_0, s_1, a_1, r_1, \ldots, s_H\}$ that terminates at an unsafe state $s_H \in S_U$. The number of transition steps, $T$, along this trajectory to the unsafe region determined by $\eta$ in Definition 2 can be approximated as: $T \approx \frac{\eta - p_0}{1 - p_0} H$.

Proof. According to assumption 1, the probability for $(s_t, a_t)$ leading to unsafe states $p(y_t = 1|s_t, a_t)$ increases linearly along time steps. Let $p_0$ denote the probability starting from the initial state $s_0$: $p_0 = p(y_t = 1|s_0, a_0)$. For a probability threshold $\eta \in (0, 1)$ for unsafe region identification in Definition 2, the ratio between the number of environment transition steps $T$ to the unsafe region and the unsafe trajectory length $H$ will be approximately (due to integer requirements over $T$) equal to the ratio between the probability differences of $\eta - p_0$ and $1 - p_0$. That is, $T \approx \frac{\eta - p_0}{1 - p_0}$. Hence $T$ can be approximated as: $T \approx \frac{\eta - p_0}{1 - p_0} H$.

With Assumption 1, the proof of Lemma 1 is straightforward. This Lemma clearly indicates that a larger $\eta$ value will allow more effective explorations with longer trajectories, but also tighten the unsafe region and increase the possibility of violating safety constraints.

### 4.3 Risk Preventive Reward Shaping

With Definition 1, the safe RL formulation in Eq. (1) can hardly induce a safe policy since there are no intermediate costs before encountering an unsafe state. With the risk prediction classifier proposed above, we can rectify this drawback by defining the cumulative cost function $J_c(\pi)$ using the risk prediction probabilities, $p(y = 1|s_t, a_t)$, over all encountered state-action pairs. Specifically, we adopt a reward-like discounted cumulative cost as follows: $J_c(\pi) = \mathbb{E}_{\tau \sim \mathcal{D}_{\pi}} \left[ \sum_{t=0}^{T} \gamma^t p(y = 1|s_t, a_t) \right]$, which uses the predicted risk at each time-step as the estimate cost. Moreover, instead of solving safe RL as a constrained discounted cumulative reward maximization problem, we propose using Lagrangian relaxation [28] to convert the constrained maximization CMDP problem in Eq. (1) to an unconstrained optimization problem, which is equivalent to shaping the reward function with risk penalties:

$$\min_{\lambda \geq 0} \max_{\pi} \left[ J_c(\pi) - \lambda (J_c(\pi) - d) \right]$$

(5)

$$\iff \min_{\lambda \geq 0} \max_{\pi} \left[ J_r(\pi) - \lambda J_c(\pi) \right]$$

(6)

$$\iff \min_{\lambda \geq 0} \max_{\pi} \mathbb{E}_{\tau \sim \mathcal{D}_{\pi}} \left[ \sum_{t=0}^{T} \gamma^t (r_t - \lambda p(y = 1|s_t, a_t)) \right]$$

(7)

The Lagrangian dual variable $\lambda$ controls the degree of reward shaping with the predicted risk value.

**Theorem 1.** To prevent the RL agent from falling into known unsafe states, the penalty factor (i.e., the dual variable) $\lambda$ for the shaped reward $\hat{r}_t = r_t - \lambda p(y_t = 1|s_t, a_t)$ should have the following lower bound, where $H$ and $\eta$ are same as in Lemma 1:

$$\lambda > \frac{(1 - \gamma^H)(r_{\text{max}} - r_{\text{min}})}{\eta \gamma^H \frac{\eta - p_0}{1 - p_0} H (1 - \gamma^H \frac{\eta - p_0}{1 - p_0} H)}$$

(8)

Proof. For a trajectory with length $H$ that leads to an unsafe state $s_H \in S_U$, the largest penalized return of the unsafe trajectory should be smaller than the lowest possible unpenalized return from any safe trajectory with the same length:

$$\sup_{\tau} \left[ \sum_{t=0}^{H-1} \gamma^t (r - \lambda p_t) \right] < \inf_{\tau} \left[ \sum_{t=0}^{H-1} \gamma^t r \right]$$

(9)
where \( p_t = p(y = 1|s_t, a_t) \). With this requirement, the RL agent can learn a policy to explore safe states and prevent the agent from entering unsafe states \( S_U \) through unsafe regions. As the reward function \( r \) is bounded within \([r_{min}, r_{max}]\), we can further simplify the inequality in Eq. (9) by seeking the supremum of its left-hand side (LHS) and the infimum of its right-hand side (RHS).

Based on Definition 2 and Lemma 1, we can split an unsafe trajectory \( \tau \) with length \( H \) into two sub-trajectories: a sub-trajectory within the safe region, \( \tau_1 = (s_0, a_0, r_0, c_0, \ldots, s_{T-1}, a_{T-1}, r_{T-1}, c_{T-1}) \), where \( p_t \leq \eta \) and a sub-trajectory \( \tau_2 = (s_T, a_T, c_T, \ldots, s_H) \) after entering the unsafe region determined by \( p_t > \eta \). With Assumption 1, we have \( p_t > \eta \) for all state-action pairs in the sub-trajectory \( \tau_2 \). Then the LHS and RHS of Eq. (9) can be upper bounded and lower bounded respectively as follows:

\[
LHS \leq \sum_{t=0}^{H-1} \gamma^t r_{\text{max}} - \left( \sum_{t=0}^{T-1} \gamma^t \lambda \cdot 0 + \sum_{t=T}^{H-1} \gamma^t \lambda \eta \right) \tag{10}
\]
\[
RHS \geq \sum_{t=0}^{H-1} \gamma^t r_{\text{min}} \tag{11}
\]

To ensure the satisfaction of the requirement in Eq. (9), we then enforce the follows:

\[
\sum_{t=0}^{H-1} \gamma^t r_{\text{max}} - \left( \sum_{t=0}^{T-1} \gamma^t \lambda \cdot 0 + \sum_{t=T}^{H-1} \gamma^t \lambda \eta \right) < \sum_{t=0}^{H-1} \gamma^t r_{\text{min}} \tag{12}
\]
\[
\iff \frac{(1 - \gamma^H) r_{\text{max}}}{1 - \gamma} - \frac{\lambda \eta^T (1 - \gamma^H) r_{\text{min}}}{1 - \gamma} < \frac{(1 - \gamma^H) r_{\text{min}}}{1 - \gamma} \tag{13}
\]
\[
\iff \lambda > \frac{(1 - \gamma^H)(r_{\text{max}} - r_{\text{min}})}{\eta^T (1 - \gamma^H) r_{\text{min}}} \tag{14}
\]

With Assumption 1 and Lemma 1, we can estimate the length \( T \) for the safe sub-trajectory as \( T = \left\lfloor \frac{\eta - p_0}{1 - p_0} H \right\rfloor \). With this estimation, the lower bound for \( \lambda \) in Eq. (8) can be derived.

\[
\text{Algorithm 1 Risk Preventive Training}
\]

\[\text{Input Initial policy } \pi_\phi, \text{ classifier } F_\theta, \text{ trajectory set } D = \emptyset, \text{ set of unsafe states } S_U, \text{ threshold } \eta, \text{ penalty factor } \lambda, \text{ set of unsafe trajectory length } H = \emptyset \]

\[\text{Output Trained policy } \pi_\phi \]

1: \text{for } k = 1, 2, \ldots, K \text{ do}
2: \quad \text{for } t = 1, 2, \ldots, T_{\text{max}} \text{ do}
3: \quad \quad \text{Sample transition } (s_t, a_t, r_t, c_t, s_{t+1}) \text{ from the environment with policy } \pi_\phi.
4: \quad \quad \text{if } c_t > 0 \text{ then}
5: \quad \quad \quad \text{Add risky state-action } (s_t, a_t) \text{ into the unsafe state set } S_U.
6: \quad \quad \quad \text{Add length } t \text{ to } H. \text{ Increase } \lambda \text{ if the lower bound increases with } H = t \text{ and Eq. (8).}
7: \quad \quad \quad \text{Stop trajectory and break.}
8: \quad \quad \text{Sample next action } a_{t+1} \text{ based on policy } \pi \text{ and next state } s_{t+1}: a_{t+1} = \pi_\phi(s_{t+1}).
9: \quad \quad \text{Calculate } p_t \text{ and } p_{t+1} \text{ using Eq. (3)}
10: \quad \quad \text{Penalize reward } r_t \text{ with } p_t: \hat{r}_t = r_t - \lambda p_t
11: \quad \quad \text{Add transition to the trajectory set: } D = D \cup (s_t, a_t, \hat{r}_t, s_{t+1})
12: \quad \quad \text{if } p_{t+1} > \eta \text{ then}
13: \quad \quad \quad \text{Stop trajectory and break.}
14: \quad \text{Sample risky state-action pairs from } S_U
15: \quad \text{Sample transitions from history: } (s_t, a_t, \hat{r}_t, s_{t+1}) \sim D
16: \quad \text{Update classifier } F_\theta \text{ by maximizing the likelihood } L(\theta) \text{ in Eq (4)}
17: \quad \text{Update policy } \pi_\phi \text{ with the shaped rewards } J_\pi(\pi) \text{ in Eq (7)}

4.4 Risk Preventive Training Algorithm

Our overall risk preventive RL training procedure is presented in Algorithm 1, which simultaneously trains the risk prediction classifier and performs reinforcement learning with risk preventive trajectory exploration and risk preventive reward shaping.
5 Experiment

We conducted experiments on four robotic simulation environments based on the MuJoCo simulator [25]. In this section, we report the experimental setting and empirical results.

5.1 Experimental Settings

Experimental Environments Following the experimental setting in [20], we adopted four robotics simulation environments, Ant, Cheetah, Hopper, and Humanoid, using the MuJoCo simulator [25]. In MuJoCo environments, a violation is presented when the robot enters an unsafe state. For Ant, Cheetah, and Hopper, a robot violates the safety constraint when it falls over. For Humanoid, the human-like robot violates the safety constraint when the head of the robot falls to the ground. The RL agent reaches the end of the trajectory once it encounters the safety violation.

Comparison Methods We compare our proposed Risk Preventive Training (RPT) approach with three state-of-the-art safe RL methods: SMBPO [20], RCPO [18], and LR [16].

- **Safe Model-Based Policy Optimization (SMBPO):** This is a model-based method that uses an ensemble of Gaussian dynamics based transition models. Based on the transition models, it penalizes unsafe trajectories and avoid unsafe states under certain assumptions.
- **Reward Constrained Policy Optimization (RCPO):** This is a policy gradient method based on penalized reward under safety constraints.
- **Lagrangian relaxation (LR):** Its uses Lagrangian relaxation for the safety constrained RL.

Implementation Details Implementations for LR and RCPO algorithms are adapted from the recovery RL paper [22]. For fair comparisons, following the original setting of LR and RCPO, we disable the recovery policy of the recovery RL framework, which collects offline data to pretrain the agent. For MBPO, we adopted the original implementation from the MBPO paper [20]. Both SMBPO and RCPO are built on top of the Soft-Actor-Critic (SAC) RL method [29]. In the experiments, we also implemented the proposed RPT approach on top of SAC, although RPT is a general safe RL methodology. We used $0.9$ as the threshold $\eta$ for risk preventive trajectory exploration. We collected the mean episode return and violation for $10^6$ time-steps.
5.2 Experimental Results

We compared all the four methods by running each method three times in each of the four MuJoCo environments. The performance of each method is evaluated by presenting the corresponding return vs. the total number of violations obtained in the training process. The results for all the four methods (LR, RCPO, SMBPO, and RPT) are presented in Figure 2, one plot for each robotic simulation environment. The curve for each method shows the learning ability of the RL agent with limited safety violations. From the plots, we can see both RPT and SMBPO achieve large returns with a small number of violations on all the four robotic tasks, and largely outperform the other two methods, RCPO and LR, which have much smaller returns even with large numbers of safety violations. The proposed RPT produces slightly inferior performance than SMBPO on Ant and Cheetah, where our method requires more examples of unsafe states to yield good performance at the initial training stage. Nevertheless, RPT outperforms SMBPO on both Hopper and Humanoid. As a model-free safe RL method, RPT produces an overall performance with the model-based method SMBPO.

To compare the overall performance of the comparison methods across all the four environments, we need to take the average of the results on all four environments using an environment-independent measure. We propose to use the measure that divides the ratio between the return and the number of violations by the maximum trajectory return—i.e., the ratio between the trajectory normalized return and the number of violations, and report the average performance of each method under this measure across all four environments. The results are presented in Figure 3. We can see RPT produces comparable or even better performance on certain region of time-steps than SMBPO, and greatly outperforms RCPO and LR. This again demonstrates that the proposed RPT produces the state-of-the-art performance for safe RL on robotic environments.

6 Conclusion

Inspired by the increasing demands for safe exploration of Reinforcement Learning in Robotics, we proposed a novel mode-free risk preventive training method to perform safe RL by learning a statistical contrastive classifier to predict the probability of a state-action pair leading to unsafe states. Based on risk prediction, we can collect risk preventive trajectories that terminate early without triggering safety constraint violations. Moreover, the predicted risk probabilities are also used as penalties to perform reward shaping for learning safe RL policies, with the goal of maximizing the expected return while minimizing the number of safety violations. We compared the proposed approach with a few state-of-the-art safe RL methods using four robotic simulation environments. The proposed approach demonstrates comparable performance with the state-of-the-art model-based method and outperforms the model-free safe RL methods.
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