Multimodal Safety-Critical Scenarios Generation for Decision-Making Algorithms Evaluation

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Abstract—Existing neural network-based autonomous systems are shown to be vulnerable against adversarial attacks, therefore sophisticated evaluation on their robustness is of great importance. However, evaluating the robustness only under the worst-case scenarios based on known attacks is not comprehensive, not to mention that some of them even rarely occur in the real world. In addition, the distribution of safety-critical data is usually multimodal, while most traditional attacks and evaluation methods focus on a single modality. To solve the above challenges, we propose a flow-based multimodal safety-critical scenario generator for evaluating decision-making algorithms. The proposed generative model is optimized with weighted likelihood maximization and a gradient-based sampling procedure is integrated to improve the sampling efficiency. The safety-critical scenarios are generated by querying the task algorithms and the log-likelihood of the generated scenarios is with respect to the risk. Experiments on a self-driving task demonstrate our advantages in terms of testing efficiency and multimodal modeling capability. We evaluate six Reinforcement Learning algorithms with our generated traffic scenarios and provide empirical conclusions about their robustness.

I. INTRODUCTION

The robustness and safety are crucial factors to determine whether a decision-making algorithm (e.g. a robot) can be deployed in the real world [1]. However, most of the data collected from simulations or in the wild are skewed to redundant and highly safe scenarios, which leads to the long tail problem [2]. Furthermore, a self-driving vehicle has to drive hundreds of millions of miles to collect safety-critical data [3], resulting in expensive development and evaluation phases. Meanwhile, a large number of safe Reinforcement Learning (RL) algorithms [4] have been proposed recently, yet the evaluation of these algorithms mostly use uniform sampling scenarios, which have been proven to be insufficient due to poor coverage of rare risky events.

Adversarial attack [5], [6] is widely used to obtain specific examples when assessing the robustness of the model. This method only addresses extreme conditions, thus it does not provide comprehensive performance evaluations of the system. Researchers [7], [8] point out that there will always be loopholes in a neural network (NN) that can be attacked, hence, testing at different stress levels is deemed to provide more information about the robustness of the system. On the other hand, although the perturbation is limited during the attack, there is no guarantee that obtained samples are likely to occur in the real-world. It is a waste of resource to request robots to pass the tests that are unlikely to happen in practice.

The real-world scenarios are complicated with a huge number of parameters, and risk scenarios do not always happen within certain modality [9]. Multimodal distribution is a more realistic representation, for example, accidents could happen in different locations for a self-driving car as shown in Fig. 1. Though previous works [10], [11] tried to search the distribution of risk scenarios under the RL framework, they still use the single-mode Gaussian distribution. Covering diverse testing cases provides a more accurate comparison of algorithms. Even if a robot overfits to one specific risk modality, it will fail to handle other potential risk scenarios. To the best of our knowledge, few people have explored the multimodal estimation of safety-critical data.

In this paper, we use a flow-based generative model to estimate the multimodal distribution of safety-critical scenarios. We use the weighted likelihood [12] as the objective function, where the weight is related to the risk metric so that the log-likelihood of the sample will be approximately proportional to the risk level. We treat the algorithm that we want to evaluate as a black box, then get the risk value through the interaction with the simulation environment. To increase the generalization of generated scenarios, our generator also has a conditional input, so that the generated samples will be adaptively changed according to characteristics of the task.

We model the whole training process as an on-policy
optimization framework which shares the same spirit as Cross Entropy Method (CEM) [13], and we propose an adaptive sampler to improve the sample efficiency. Under this framework, we can dynamically adjust the region of interest of the sampler according to the feedback of the generator. The adaptive process is guided by the gradient estimated from the Natural Evolution Strategy (NES) method [14]. During the training stage, the sampler focuses on the unexplored and risky areas, and finally completes the multimodal modeling. We also consider the distribution of real-world data when designing the metric of risk to ensure that the generated data has a high probability of occurrence in the real world.

We carried out extensive experiments on the decision-making task of autonomous driving in an intersection environment. A safety-critical generator is trained, analyzed, and compared with traditional methods. Our generator outperforms others in terms of the efficiency and multimodal covering capability. We also evaluate the robustness of several RL algorithms and claim that our generator is more informative than uniform sampling methods. In summary, the contribution is three-fold:

- We propose a multimodal flow-based generative model that can generate adaptive safety-critical data to efficiently evaluate decision-making algorithms.
- We design an adaptive sampling method based on black-box gradient estimation to improve the sample efficiency of multimodal density estimation.
- We evaluate a variety of RL algorithms with our generated scenarios and provide empirical conclusions that can help the design and development of safe autonomous agents.

II. RELATED WORK

A. Deep generative model

Our method is based on deep generative models. The current popular generative models are mainly divided into three categories: normalizing flow [15] and autoregressive model [16] directly maximize the likelihood, Variational Auto-encoder (VAE) [17] optimizes the approximate likelihood using variational inference, and Generative adversarial network [18] implicitly computes the likelihood with a discriminator. The essence of these methods is to fit a distribution with parametric models that maximizes the likelihood according to the empirical data. In this paper, our data is collected from on-policy exploration. We select the flow-based model as the building block since we want to optimize the weighted likelihood directly and easily sample from the model.

B. Adversarial Attack

Another topic that is closely related to ours is the adversarial attack, which reduces the output accuracy of the target model by applying small disturbances to the original input samples. According to the information from the target model, this method falls into two types: white-box attack and black-box attack. Our method assumes that the internal information of the task algorithm cannot be obtained, so we are more relevant to the second one. This kind of method can be further divided into two mainstreams: substitute model [19] and query-based model [20]. The former is to train a completely accessible surrogate model to replace the target model, while the latter is based on the query of the target model to estimate the optimal attack direction. The NES gradient estimation method used in this paper has shown promising results in the latter method [21].

C. Safety-critical Scenario Generation

Some previous works have used the generative model to conduct safety-critical scenarios search. [22] modifies the last layer of a generative adversarial imitation learning model to generate different driving behaviors. [23] and [24] generate different levels of risky data by controlling the latent code of VAE. Besides, there are some frameworks [10], [11], [25] that combine RL and simulation environment to search for data that satisfies specific requirements. Adaptive stress test [26], [27] is also a kind of methods using the Monte Carlo Tree Search and RL to generate collision scenarios. Most of these methods use the Gaussian distribution policy to describe the result of searching, without considering the case of multiple modality. In addition, lots of literatures borrow the idea from evolution algorithms [28], reinforcement learning [29], Bayesian optimization [30], and importance sampling [31] to generate adversarial complex scenarios, resulting in diverse directions and platforms. In previous works, [32] is the most similar to this paper. They use the multilevel splitting method [33] to gradually extract risk scenarios by squeezing the searching area. However, it is sensitive to level partition and the efficiency of Monte Carlo Markov Chain (MCMC) method is limited by query times and data dimension.

D. Adaptive Sampler

In online decision-making, especially RL tasks, exploration has always been a popular topic. The adaptive sampler proposed in this paper can also be categorized into this field. For the simple multi-arm bandit problem, traditional solutions are Upper Confidence Bound (UCB) [34] and
Thompson sampling [35]. Recently, exploration methods based on curiosity [36], [37], and information gain [38], [39] also cause much attention. Also, works like [40], [41] are based on the disagreement of ensemble models. To some extent, all these methods aim at modeling the environment and the explored area, so as to guide the sampler with the desired direction.

The gradient information usually facilities samplers faster convergence. Hamiltonian Monte Carlo (HMC) is a variant of MCMC method that is more efficient than vanilla random walk counterparts. Motivated by this, our proposed adaptive sampler also use a black-box estimator to obtain the gradient of a non-differentiable target function.

### III. PROPOSED METHOD

#### A. Notation and Preliminaries

The variable \( x \in \mathcal{X} \) represents parameters that build a scenario, for instance, the initial position of a pedestrian or the weather conditions in the self-driving context. The variable \( y \in \mathcal{Y} \) represents the properties of the task, such as the goal position or target velocity. \( H(\mu|x, y) \) is the task algorithm that takes the scenario observation and task condition as input and outputs a decision policy \( \mu \in \mathcal{M} \). With a risk metric \( r : \mathcal{X} \times \mathcal{M} \rightarrow \mathcal{R} \), each scenario is corresponding to a value that indicates the safety under \( H \). For simplification, we omit the notation \( \mu \) in \( r(x, \mu) \).

Instead of exploring the extreme scenarios that output low \( r(x) \) as in adversarial attack field, we aim at estimating a multimodal distribution \( p(x|y) \) where the log-likelihood is proportional to the value of risk measure. Then we can efficiently generate scenarios that have different risk levels by sampling from \( p(x|y) \). The condition \( q \) follows a distribution \( p(y) \). A sampler \( \pi(x|y) \) is used to collect training data. We also assume real-world data of similar scenarios is accessible and has a distribution \( q(x) \). The pipeline of our proposed evaluation method is shown in Fig. 2.

#### B. Mathematical Formulation

We formulate the safety-critical data generation as a density estimation problem. The traditional way to estimate the multimodal distribution \( p(x|y) \) by a parameterized generative model is maximizing the likelihood of data. To integrate the risk information, we solve the density estimation problem by the weighted likelihood maximization method [12]. For one data point \( x_i \), we have:

\[
L(x_i|y_i; \theta) = p(x_i|y_i; \theta)^w(x_i) \tag{1}
\]

\[
\log L(x_i|y_i; \theta) = w(x_i) \log p(x_i|y_i; \theta) \tag{2}
\]

where \( w(x_i) \) is the weight and \( p(x_i|y_i; \theta) \) is our generator with learnable parameter \( \theta \), corresponding to the \( i \)-th data point. Assume we have a sampling distribution \( \pi(x|y) \) of \( x \), then our objective is:

\[
\hat{\theta} = \arg\max_{\theta} \mathbb{E}_{x \sim \pi(x|y), y \sim p(y)} \log L(x|y; \theta) \tag{3}
\]

Since the goal is to find a distribution of safety-critical scenarios, \( w(x) \) should be relevant to \( r(x) \). At the same time, we should also consider the probability that each scenario happens in real-world to make the result practical. For that, we learn another generative model \( q(x; \psi) \) to approximate the distribution of the real data, and calculate the weight \( w(x_i) \) with:

\[
w(x_i) = r(x_i) + \beta q(x_i; \psi) \tag{4}
\]

where \( \beta \) is a hyperparameter to adjust the ratio between \( r(x) \) and \( q(x; \psi) \). Finally, we can rewrite the objective function \([3]\) as:

\[
\hat{\theta} = \arg\max_{\theta} \mathbb{E}_{x \sim \pi(x|y), y \sim p(y)} [(r(x) + \beta q(x; \psi)) \log p(x|y; \theta)] \tag{5}
\]

To evaluate the likelihood of sample \( x \) in \( q(x; \psi) \), we pre-train a prior model with the dataset \( D \) collected from real-world by maximizing the following likelihood:

\[
\hat{\psi} = \arg\max_{\psi} \mathbb{E}_{x \sim D} \log q(x; \psi) \tag{6}
\]

The uniform distribution is a common choice for \( \pi(x|y) \) to search the solution space. However, uniform sampling is inefficient in high-dimensional space, especially when the risky scenarios are rare events. Therefore, we propose an adaptive sampler that leverages the gradient information to gradually cover all modes of risky scenarios. Suppose we have a metric \( c(x) \) that indicates the exploration value: the higher \( c(x) \) is, the more worth exploring \( x \) is. We then use NES, a black-box optimization method, to estimate the
Then we have the following equation to calculate the exact distribution:

\[ p(x^t + 1) \leftarrow x^t + \alpha \nabla_x c(x^t) \]  

(7)

where \( \alpha \) is the step size. The gradient \( \nabla_x c(x^t) \) in (7) can be estimated by:

\[ \nabla_x c(x^t) = \nabla_x \mathbb{E}_{x \sim N(x^t, \sigma^2 I)} [c(x)] = \frac{1}{\sigma} \mathbb{E}_{x \sim N(0, I)} [\epsilon \cdot c(x^t + \sigma \epsilon)] \]  

(8)

In practice, we will approximate the above expectation with the Monte Carlo method:

\[ \nabla_x c(x^t) = \frac{1}{M} \sum_{i=1}^{M} \epsilon_i \cdot c(x^t + \sigma \epsilon_i), \quad \epsilon_i \sim \mathcal{N}(0, I) \]  

(9)

The design of \( c(\cdot) \) heavily influences the performance of the adaptive sampler. Inspired by some curiosity-driven literature [36], where the uncertainty, Bayesian surprise, and prediction error are used to guide the exploration, we choose a metric that involves the generative model \( p(x|y) \):

\[ c(x) = r(x) - \gamma p(x|y) \]  

(10)

where \( \gamma \) is a hyperparameter that balance the shape between \( r(x) \) and \( p(x|y) \). This metric changes according to the learnable generator \( p(x|y) \). Intuitively, when one mode (some similar risky scenarios) is well learned by \( p(x|y) \), the metric \( c(x) \) will decrease and force the sampler to explore other modes. Finally, the multimodal distribution will be captured by \( p(x|y) \). The diagram of this pipeline is shown in Fig. 3 with a Gaussian Mixture Model (GMM) example.

C. Flow-based Scenario Generator

The prior model \( q(x; \psi) \) and generator model \( p(x|y) \) are two density estimators and require the exact likelihood inference. Thus, we use the normalizing flow model as our building block to implement them. In flow-based model, a simple distribution \( p(z) \) is transformed to a complex distribution \( p(x) \) by the change of variable theorem. Suppose we choose \( z \sim \mathcal{N}(0, I) \) to be the simple distribution. Then we have the following equation to calculate the exact likelihood of data:

\[ p(x) = p(z) \left| \frac{\partial z}{\partial x} \right| = p(f(x)) \left| \frac{\partial f(x)}{\partial x} \right| \]  

(11)

where we have an invertible mapping \( f : \mathcal{X} \to \mathcal{Z} \). In our implementation, we use the structure of RealNVP [42] to realize this deterministic function.

One modified version to the original flow-based model is introducing the conditional input, which has been explored in [43]. Suppose \( y \in \mathcal{Y} \) is the conditional input, then the mapping function should be \( f : \mathcal{X} \times \mathcal{Y} \to \mathcal{Z} \) and \( p(x) \) will be rewritten as:

\[ p(x|y) = p(f(x|y)) \left| \frac{\partial f(x|y)}{\partial x} \right| \]  

(12)

In our method, we use \( (12) \) to represent the generator model \( p(x|y; \theta) \) and \( (11) \) to represent the prior model \( q(x; \psi) \). The data for training the generator comes from the exploration of our adaptive sampler, while the data for training the prior model comes from real-world dataset \( \mathcal{D} \). After training, scenarios can be generated by \( x = f^{-1}(z) \) where \( z \) is sampled from \( \mathcal{N}(0, \sigma) \). A smaller \( \sigma \) will make the samples more concentrated, therefore generated scenarios will have higher likelihood. Since our model is trained with WMLE, the high likelihood samples are also corresponding to high risk. Details about the network structure and hyperparameters can be found in Appendix.

IV. EXPERIMENTS

In this section, we firstly demonstrate the advantage of our proposed adaptive sampler with a toy example. After that, we show the generated safety-critical scenarios with different settings in an intersection environment. Finally, we evaluate the robustness of several popular RL algorithms using our generated scenarios and provide conclusions about their robustness.

A. Efficiency of Adaptive Sampler

As discussed in Section III-B, we shall expect that the estimated gradient of \( c(x) \) improves the efficiency of the sampling procedure and the design of \( c(x) \) plays a significant role. To assess this, we compare our method with two baselines. In the first one, we use \( c(x) = r(x) \), a straightforward and common choice in the adversarial attack literature. In the second baseline, we use the variance of the posterior
of Gaussian Processes (GP) to model the uncertainty of search space and combine this uncertainty with \( r(x) \). The comparison of these two baselines using a GMM example is displayed in Fig. 4. Both two baselines are facing the mode collapse problem to varying degrees, while our method effectively covers all modes.

The reasoning is as follows. The first baseline uses only limited information about the multimodal landscape, thus is easily trapped into one modality. The second baseline, which gradually decreases the importance of the explored points, can cover all modes even other unimportant points. However, the rapidly descending uncertainty and the lack of adaptivity to the generator \( p(x) \) lead to suboptimal results and unbalanced data collection. Our proposed method uses the feedback of the generator that gives the sampler both the capability of uncertainty exploration and balanced data collection, hence attaining all the modalities.

### B. Safety-critical Scenario Generation

**Environment settings.** An intersection environment is used to conduct our experiment in the Carla simulator[45]. We represent one scenario as a 4-dimensional vector \( x = [x, y, v_x, v_y] \), which represents the initial position and initial velocity of a cyclist. The cyclist is spawned in the environment and travels at a constant speed. Then we place an ego vehicle controlled by an intelligent driver model with a predefined route reference. The minimal distance between the cyclist and ego vehicle is used to calculate \( r(x) \geq 0 \), where a lower distance corresponds to higher \( r(x) \). This scenario is defined as a pre-crash scenario in [46] and also adopted in 2019 Carla Autonomous Driving Challenge [47]. This setting allows us to test the collision avoidance capability of decision-making algorithms \( H \). Other more intelligent algorithms can replace the current agent during the evaluation stage.

**Real-world data distribution.** There are numerous datasets collected in the intersection traffic environment. We train our prior model \( q(x) \) with trajectories from the InD dataset [44]. A well-trained prior model can be used to infer the likelihood of a given sample and generate new samples as well. We display the position and velocity direction of some generated samples in Fig. 5. These samples roughly describe the distribution of a cyclist in an intersection.

**Generated scenarios display.** We train a generator \( p(x|y) \) to generate safety-critical scenarios given the route condition \( y \). In Fig. 6 we compare the samples from two generators: one does not use prior (middle) and the other uses \( q(x) \) as the prior model (right), where the same color map is used as in Fig. 5. The left column of Fig. 6 shows the collected scenarios by our adaptive sampler for training both generators. Each of these samples is corresponding to a risk value that is not shown in the figure. In Fig. 6, it is clear that without real-world data prior, the generator learns the distribution of all risky scenarios collected by the sampler. After incorporating the prior model, the generator concentrates more on the samples that are more likely to happen in the real world. This results in the removal of samples that has opposite directions to the real data.

**Baseline and metric settings.** We select seven algorithms as our baseline. The details of each algorithm is discussed below:

- **Grid Search:** We set the searching step for all parameters to 100. Since we \( x \) has four dimensions, the entire searching iterations should be \( 10^8 \).
- **Human Design:** We use the rules defined in Carla AD Challenge, which basically trigger the movement of the cyclist according to the location of the ego vehicle.
- **Uniform:** The scenario parameter \( x \) is uniformly sampled from the entire space. This method is widely used in the evaluation of safety decision-making algorithms. For instance, obstacles are randomly generated to test the collision avoidance performance in the Safety-Gym
environment [48].

- **REINFORCE [11]**: This method uses the REINFORCE framework with a single Gaussian distribution policy. This kind of policy can only represent single modality.
- **REINFORCE+GMM**: The policy distribution of [11] is replaced with a GMM. The purpose is to explore the multimodal capability of the REINFORCE algorithm.
- **Ours-Uniform**: We replace the adaptive sampler in our method with a uniform sampler.
- **Ours-HMC**: We replace the adaptive sampler in our method with a HMC sampler to explore the efficiency of gradient-based MCMC method.

We use the query time and collision rate as our metrics. The query time means the number of times the algorithm queries the simulation during the training stage. Methods without training have 0 query time. The value of query time is recored when the distribution of samples is stable. It is a rough number since we measure the stability by human. The second metric is collision rate, which is calculated after the training stage. We sample 1000 scenarios for 10 different routes and get a collision rate for each route. We then calculate the mean and variance across the 10 numbers.

**Comparison with baseline methods.** The results are shown in Table. Grid search is the most trivial way comparable with our method in finding the multimodal risk scenarios. However, the query time grows exponentially as the dimension of \( x \) and the step size increase. In the simulation, human design is a possible way to reproduce the risk scenarios happen in the real world, but these scenarios are fixed and not adaptive to the changes of the task parameters \( y \), leading to a low collision rate. Our experiment also found that the uniform method attains less than 10% collision rate. In dense reward situations, uniform sampling could be a good choice, while in most real-world cases, the rare events risk scenarios makes this method quite inefficient. REINFORCE-Single searches the risk scenario under RL framework [11]. Although this method converges faster than ours, it cannot handle the multimodal cases with a single Gaussian distribution policy. The REINFORCE-GMM method extends the original version with a multimodal policy module. However, it has similar results as REINFORCE-Single. The reason is that on-policy sampling method in REINFORCE is easy to be trapped into a single modality, even the policy itself is multimodal. The final weight in GMM is highly imbalanced and only one component dominates. The ablation study reveals that our adaptive sampler (Ours-Adaptive) is more efficient than the uniform version (Ours-Uniform). The MCMC version (Ours-HMC) requires less query time than our adaptive sampler, while its samples only concentrate on one modality.

**Relationship between risk level and log-likelihood.** Since our generator is trained with weighted likelihood estimation, we make usage of all collected samples rather than only the risky ones as in [32]. We compare two generators that are trained with MLE and WMLE and plot the results in Fig.7. The generator trained with MLE by only using the risk data concentrates on the high-risk area, while our WMLE generator has a linear relationship between the risk and log-likelihood. Therefore, our generator can not only generate risky scenarios but also generate scenarios with different risk levels by considering the likelihood of samples.

**C. Evaluation of RL algorithms**

To prove that our generated scenarios help improve the evaluation of algorithms, we implemented six popular RL agents (DQN, A2C, PPO, DDPG, SAC, Model-based RL) as \( H(\mu|x, y) \) on the navigation task in the aforementioned environment. The target is to arrive at a goal point and avoid reaching the non-driving area. At the same time, we place a cyclist on the intersection to create a traffic scenario. The agents should also avoid colliding the cyclist otherwise they will receive a penalty. The reward consists of three parts:

\[
R(x) = r_g + r_s \times I_s(x) + r_c \times I_c(x)
\]  

(13)

where \( r_g \) is calculated by reduction of distance between the agent and the goal, \( r_s \) and \( r_c \) indicates the penalty of non-driving area violation and cyclist collision. \( I_s(x) \) and \( I_c(x) \) are two indicator functions that equal to 1 when the two events happen. The episode terminates when the agent collides into the cyclist or the agent reaches the target. We implement DQN and A2C on discrete action space with a controller that follows a pre-defined route. Their action space only influences the acceleration. The other agents have continuous action space that controls throttle and steering.

Firstly, we train six agents with uniformly sampled \( x \) of the cyclist. Then we test those agents on both uniform risk scenarios (URS) and scenarios created by our multimodal generator (MRS) with \( \sigma = 0.2 \). The reward and collision rate results are shown in Fig.8. We find that agents tested on URS have similar final rewards and collision rates. These nearly indistinguishable results make it difficult to compare...
different algorithms. In contrast, the results on MRS show a great discrepancy, which helps us obtain clearer conclusions. To obtain further comparison, we train and test all agents both on MRS, and the results are displayed in the third column of Fig. 8. The last column shows the results of agents that are trained on MRS and tested on URS. We note that those agents do not sacrifice their generalization to uniformly sampled scenarios since the performance is similar to the first column. According to Fig. 8, we can also draw the following conclusions of different RL algorithms:

- **Model-based RL agent** has the highest reward and lowest collision rate, indicating its robustness to challenging scenarios. One potential reason is the pre-defined intrinsic cost function. The entire task is divided into two modules and an accurate state prediction module will lead an agent to appear robust in risk scenarios. This conclusion may provide additional information for future researches on safety model-based RL.

- **DDPG and SAC agents** perform similarly but SAC converges faster and has a higher final reward. The DDPG agent usually suffers from the exploration problem. The $\epsilon$-greedy method is easy to make the agent unstable especially in the diverse risk scenarios.

- **On-policy methods** (A2C and PPO) have poor performance and PPO performs quite unstable in risk scenarios. The potential reason is that the on-policy methods do not have a replay buffer that memorizes the diverse risk scenarios, therefore shows instability when the environment dramatically changes from one scenario to another.

Note that the above empirical conclusions might only be valid for in this environment. Further comparison of these RL algorithms should be carefully designed in multiple other settings. Nevertheless, our generator indeed is proven to be more insightful than the uniform sampler. Beyond RL algorithms, our proposed generating framework can also be used to efficiently evaluate other decision-making methods that are developed for dealing with more risky scenarios.

**V. CONCLUSION**

In this paper, we train a flow-based generative model using the objective function of weighted likelihood to realize the generation of multimodal safety-critical scenarios. Our generator can generate scenarios with various risk levels, providing efficient and diverse evaluations of decision-making algorithms. To speed up the training process, we propose an adaptive sampler based on feedback mechanism, which can adjust the sampling region according to the learning progress of the generator, and finally cover all risk modes in a faster way. We test six RL algorithms with scenarios generated by our generator in a navigation task and obtain some conclusions that are not easy to get with traditional uniform sampling evaluation. This achievement provides an efficient evaluation and comparison test-bed for the safety decision-making algorithms which have recently attracted more and more attention. A potential extension of this work is combining the evaluation and training process to build an adversarial training framework. We expect this combination can boost existing algorithms under safety-related tasks.

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