# Diffusion Models for Reinforcement Learning: A Survey

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#### **Abstract**

Diffusion models surpass previous generative models in sample quality and training stability. Recent works have shown the advantages of diffusion models in improving reinforcement learning (RL) solutions. This survey aims to provide an overview of this emerging field and hopes to inspire new avenues of research. First, we examine several challenges encountered by RL algorithms. Then, we present a taxonomy of existing methods based on the roles of diffusion models in RL and explore how the preceding challenges are addressed. We further outline successful applications of diffusion models in various RL-related tasks. Finally, we conclude the survey and offer insights into future research directions. We are actively maintaining a GitHub repository for papers and other related resources in utilizing diffusion models in RL <sup>1</sup>.

## 1 Introduction

Diffusion models have emerged as a powerful class of generative models, garnering significant attention in recent years. These models employ a denoising framework that can effectively reverse a multistep noising process to generate new data [Song et al., 2021]. In contrast to earlier generative models such as Variational Autoencoders (VAE) [Kingma and Welling, 2013] and Generative Adversarial Networks (GAN) [Goodfellow et al., 2014], diffusion models exhibit superior capabilities in generating high-quality samples and demonstrate enhanced training stability. Consequently, they have made remarkable strides and achieved substantial success in diverse domains including computer vision [Ho et al., 2020; Lugmayr et al., 2022; Luo and Hu, 2021], natural language processing [Austin et al., 2021; Li et al., 2022], audio generation [Lee and Han, 2021; Kong et al., 2020], and drug discovery [Xu et al., 2022; Schneuing et al., 2022], etc.

Reinforcement learning (RL) [Sutton and Barto, 2018] focuses on training agents to solve sequential decision-making tasks by maximizing cumulative rewards. While RL has

achieved remarkable successes in various domains [Kober et al., 2013; Kiran et al., 2021], there are some longstanding challenges. Specifically, despite the considerable attention garnered by offline RL for overcoming low sample efficiency issue in online RL [Kumar et al., 2020; Fujimoto and Gu, 2021], conventional Gaussian policies may fail to fit the datasets with complex distributions for their restricted expressiveness. Meanwhile, although experience replay is used to improve sample efficiency [Mnih et al., 2013], there is still *data scarcity* problem in environments with high-dimensional state spaces and complex interaction patterns. A common usage of learned dynamic models in model-based RL is planning in them [Nagabandi et al., 2018; Schrittwieser et al., 2020; Zhu et al., 2021], but the perstep autoregressive planning approaches suffer from the compounding error problem [Xiao et al., 2019]. An ideal RL algorithm should be able to learn a single policy to perform multiple tasks and generalize to new environments [Vithayathil Varghese and Mahmoud, 2020; Beck et al., 2023]. However, existing works still struggle in *multitask generalizations*.

Recently, there has been a series of works applying diffusion models in sequential decision-making tasks, with a particular focus on offline RL. As a representative work, Diffuser [Janner et al., 2022] fits a diffusion model for trajectory generation on the offline dataset, and plans desired future trajectories by guided sampling. There have been many following works where diffusion models behave as different modules in the RL pipeline, e.g., replacing conventional Gaussian policies [Wang et al., 2023], augmenting experience dataset [Lu et al., 2023b], extracting latent skills [Venkatraman et al., 2023], among others. We also observe that planning and decision-making algorithms facilitated by diffusion models perform well in broader applications such as multitask RL [He et al., 2023a], imitation learning [Hegde et al., 2023], and trajectory generation [Zhang et al., 2022]. More importantly, diffusion models have already shed light on resolving those long-standing challenges in RL owing to their powerful and flexible distributional modeling ability.

This survey centers its attention on the utilization of diffusion models in RL, with additional consideration given to methods incorporating diffusion models in the contexts of trajectory generation and imitation learning, primarily due to the evident interrelations between these fields. Section 2 elaborates on the aforementioned RL challenges, and discusses

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<sup>1</sup>https://github.com/apexrl/Diff4RLSurvey

how diffusion models can help solve each challenge. Section 3 provides a background on the foundations of diffusion models and also covers two class of methods that are particularly important in RL-related applications: guided sampling and fast sampling. Section 4 illustrates what roles diffusion models play in RL among existing works. Section 5 discusses the contribution of diffusion models on different RL-related applications. Section 6 summarizes the survey with a discussion on emerging new topics.

## 2 Challenges in Reinforcement Learning

In this section, we list four challenges in RL algorithms and briefly discuss why diffusion models can address them.

### 2.1 Restricted Expressiveness in Offline Learning

Due to the low-sample efficiency, online RL [Sutton and Barto, 2018] is challenging to be applied in real-world scenarios. Offline RL [Fujimoto et al., 2019; Kumar et al., 2020] learns optimal policies from pre-collected datasets without environmental interaction, which can significantly improve sample efficiency. Directly applying off-policy RL to offline learning causes severe extrapolation errors [Fujimoto et al., 2019]. Existing works penalize value predictions on out-ofdistribution samples [Kumar et al., 2020] or limit the learning policy to be close to the data collecting policy [Kostrikov et al., 2021]. However, penalties imposed on the value function may result in an overly conservative policy [Lyu et al., 2022]; when imposing policy constraints on commonly used unimodal Gaussian parameterization, the restricted expressiveness makes it difficult to fit the possibly diverse dataset. Reinforcement learning via supervised learning framework (RvS) [Schmidhuber, 2019] is another important paradigm in offline RL, which eliminates Q-learning thus free of extrapolation errors. RvS learns a policy conditioned on the observed returns via supervised learning and then conditions it on a high return to generate desired behaviors [Chen et al., 2021]. Similar to policy constraining, RvS requires fitting the entire dataset. Therefore, the expressiveness of parameterized policies also matters in RvS. Diffusion models have the capability to represent any normalizable distribution [Neal and others, 2011], with the potential to effectively improve the performance of policy constraining and RvS algorithms on complex datasets.

## 2.2 Data Scarcity in Experience Replay

Off-policy and offline RL methods use different levels of experience replay to improve sample efficiency. Note that experience replay in some literature only refers to data reuse in off-policy RL. Here, the term broadly refers to updating the current model with rollout data from other policies. Although all previous experiences can be used for policy learning in off-policy RL, the limitation of simulation speed and the potentially huge state and action spaces may still hinder policy optimization. In offline RL, policy learning is more limited by the quality and coverage of the dataset as no further interactions are allowed. Inspired by the success of data augmentation in computer vision, some works adopt similar augmentation in RL to reduce data scarcity. RAD [Laskin et

al., 2020] uses image augmentation such as random cropping or rotation to improve learning efficiency in vision-based RL. Imre [2021] and Cho et al. [2022] use generative models, VAE [Kingma and Welling, 2013] and GAN [Goodfellow et al., 2014], to augment the real dataset with generated synthetic data. However, existing works either lack fidelity when using random augmentation or are limited to simple environments due to insufficient modeling ability of particular generative models, making them difficult to be applied to more complex tasks. Diffusion models have demonstrated notable performances surpassing previous generative models in high-resolution image synthesis [Ho et al., 2020]. When applied to RL data, diffusion models are better suited for enhancing complex interactions.

## 2.3 Compounding Error in Model-based Planning

MBRL [Luo et al., 2022] fits a dynamic model from online rollout data or offline datasets to facilitate decision-making. Common dynamic models mimic single-step state transitions and rewards in the dataset. When predicting with a neural dynamic model, there could be single-step errors due to the limited data support and stochastic environment transitions. Cumulative single-step errors can make planned states deviate from the dataset distribution, which causes the compounding error problem when using the model for multistep planning [Xiao et al., 2019]. In contrast, diffusion models with powerful modeling ability of joint distributions can operate on the trajectory level and plan for multiple time steps simultaneously, improving temporal consistency and reducing compounding errors.

## 2.4 Generalization in Multitask Learning

Normal RL algorithms lack generalization abilities at the task level [Beck et al., 2023]. Even in the same environment, changing the reward function requires retraining a policy from scratch. Existing online multitask RL [Liu et al., 2021] works attempt to learn the same policy in different task environments, suffering from conflicting gradients across multiple tasks and low sample efficiency due to pure online learning. Recently, it has been a popular research direction to train a high-capacity model on multitask offline datasets and then deploy it on new tasks with or without online finetuning [Taiga et al., 2022]. Transformer-based pre-training decision models like Gato [Reed et al., 2022] excel at multitask policy learning. However, they typically require highquality datasets, large parameter sizes, and high training and inference costs. In multitask RL, designing an algorithm that can fit mixed-quality multitask datasets and generalize to new tasks emerges as a vital issue. As a powerful class of generative models, diffusion models can deal with multimodal distributions in multitask datasets, and adapt to new tasks by estimating the task distribution.

## 3 Foundations of Diffusion Models

We introduce the foundations of diffusion models, including two prominent formulations and several sampling techniques that are particularly important in RL tasks.

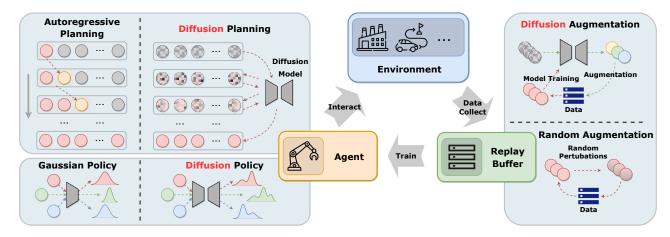


Figure 1: An illustration of how diffusion models play a different role in the classic Agent-Environment-Buffer cycle compared to previous solutions. (1) When used as a planner, diffusion models optimize the whole trajectory at each denoising step, whereas the autoregressive models generate the next-step output only based on previously planned partial subsequences. (2) When used as a policy, diffusion models can model arbitrary action distributions, whereas Gaussian policies can only fit the possibly diversified dataset distribution with unimodal distributions. (3) When used as a data synthesizer, diffusion models augment the dataset with generated data sampled from the learned dataset distribution, whereas augmentation with random perturbations might generate samples that deviate from data samples.

### 3.1 Denoising Diffusion Probabilistic Model

Assuming that the real data  $x^0$  are sampled from an underlying distribution  $q(x^0)$ , DDPM [Ho et~al., 2020] utilizes a parameterized diffusion process, represented as  $p_{\theta}(x^0) = \int p(x^T) \prod_{t=1}^T p_{\theta}(x^{t-1}|x^t) \, \mathrm{d}x^{1:T}$ , to model how the pure noise  $x^T = \mathcal{N}(\mathbf{0},\mathbf{I})$  is denoised into real data  $x^0$ . Each step of the diffusion process is represented by  $x^t$ , with T indicating the total number of steps. Note that both the diffusion process and RL involve time steps; thus, we denote diffusion steps as superscripts and RL time steps as subscripts. The sequence  $x^{T:0}$  is defined as a Markov chain with learned Gaussian transitions characterized by  $p_{\theta}(x^{t-1}|x^t) = \mathcal{N}(\mu_{\theta}(x^t,t),\Sigma(x^t,t))$ . If the process is reversed as  $x^{0:T}$ , each step is defined by the forward transition  $q(x^t|x^{t-1})$ , which is formulated as adding Gaussian noise to the data according to a variance schedule  $\beta^{1:T}$ :

$$x^{t} = \sqrt{\alpha^{t}} x^{t-1} + \sqrt{1 - \alpha^{t}} \epsilon^{t} , \qquad (1)$$

where  $\alpha^t = 1 - \beta^t$ ,  $\epsilon^t \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ . From Eq. (1), we can derive a direct mapping from  $x^0$  to  $x^t$ :

$$x^t = \sqrt{\bar{\alpha}^t} x^0 + \sqrt{1 - \bar{\alpha}^t} \epsilon(x^t, t) ,$$

where  $\bar{\alpha}^t = \prod_1^t \alpha^i.$  From Bayes theorem and relation between  $x^t$  and  $x^0,$  we have

$$q(x^{t-1}|x^t, x^0) = \mathcal{N}(\frac{1}{\sqrt{\alpha^t}}(x^t - \frac{\beta^t}{\sqrt{1 - \bar{\alpha}^t}}\epsilon(x^t, t)), \beta^t \mathbf{I}).$$

Eq. (2) allows us to sample  $x^T$  from Gaussian noise and denoise step by step until we obtain  $x^0$ . However, the noise  $\epsilon(x^t,t)$  is unknown. To address this, a parameterized network  $\epsilon_\theta$  is employed to predict the noise. Ho *et al.* [2020] propose the following simplified loss function for learning  $\epsilon_\theta$ , which is a weighted version of the evidence lower bound (ELBO):

$$\mathcal{L}(\theta) = \mathbb{E}_{x^0, \epsilon, t}[\|\epsilon - \epsilon_{\theta}(\sqrt{\bar{\alpha}^t}x^0 + \sqrt{1 - \bar{\alpha}^t}\epsilon, t)\|^2], \quad (3)$$
 where  $\epsilon$  is sampled from  $\mathcal{N}(\mathbf{0}, \mathbf{I})$ .

#### 3.2 Score-based Generative Models

Song et al. [2021] extend DDPM to continuous-time diffusion processes, and the sequence  $x^0, x^1, \ldots, x^T$  is replaced with a continuous function  $x^t, t \in [0, T]$ . The forwarding process can be described as a Stochastic Differential Equation (SDE):

$$dx = f(x,t) dt + g(t) dw,$$

where f(x,t) and g(t) are pre-defined functions, and  $\mathrm{d}w$  is the Brownian motion. According to Langevin dynamics, the reverse of the forwarding process is described by a reverse-time SDE:

$$dx = [f(x,t) - g^2(t)\nabla_x \log p_t(x)] dt + g(t) d\bar{w},$$

where  $\bar{w}$  is the reverse Brown motion,  $p_t(x)$  is the probability density of  $x^t$ , and  $s(x) = \nabla_x \log p_t(x)$  is called the score function of  $p_t(x)$ . In practice, a parameterized score model  $s_\theta$  is adopted to estimate the score function, which can be trained by minimizing

$$\mathcal{L}(\theta) = \mathbb{E}_{x^0, t, x^t} \left[ \| s_{\theta}(x^t, t) - \nabla_{x^t} \log p(x^t | x^0) \|_2^2 \right] .$$

## 3.3 Guided Sampling Methods

Guided sampling from diffusion models considers sampling from the conditional distribution p(x|y), where y is the desired attribute of generated samples. Two main categories of guidance are classifier-guidance and classifier-free guidance.

Classifier guidance. Classifier guided sampling relies on a differentiable classifier model  $p_{\phi}(y|x)$ . Specifically, since the guidance needs to be performed on each denoising step, the classifier model  $p(y|x^t)$  is trained on noisy samples of x and corresponding attribute y. The conditional reverse process can be written as

$$p_{\theta,\phi}(x^{t-1}|x^t,y) = Zp_{\theta}(x^{t-1}|x^t)p_{\phi}(y|x^{t-1}), \qquad (4)$$

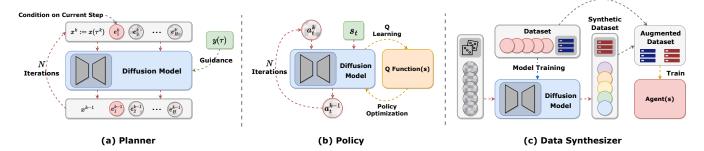


Figure 2: Different roles of diffusion models in RL. (a) Diffusion models as the planner. The sampling target is a part of trajectories whose components may vary from specific tasks. (b) Diffusion models as the policy. The sampling target is the action conditioned on the state, usually guided by the Q-function via policy gradient-style guidance or directly subtracting it from the training objective. (c) Diffusion models as the data synthesizer. The sampling target is also the trajectory, and both real and synthetic data are used for downstream policy improvement. For better visualizations, we omit the arrows for N denoising iterations in (c) and only show generated synthetic data from randomly sampled noise. Note that there are other roles that are less explored, and we introduce them in Section 4.4.

where Z is the normalization factor. Dhariwal and Nichol [2021] approximate Eq. (4) by another Gaussian distribution:

$$p_{\theta,\phi}(x^{t-1}|x^t,y) = \mathcal{N}(\mu^t + w\Sigma^t g, \Sigma^t), \qquad (5)$$

where  $g = \nabla_{x^t} \log p_{\phi}(y|x^t)|_{x^t = \mu^t}$  and w is the guidance scale to control the strength of conditions.  $\mu^t$  and  $\Sigma^t$  are the mean and the covariance matrix in Eq. (2), respectively.

Classifier-free guidance. Classifier-free sampling relies on an extra conditional noise model  $\epsilon_{\theta}(x^t,y,t)$ . In practice, the conditional and unconditional models share the same set of parameters, and the unconditional model is represented by setting y as a dummy value  $\varnothing$ . Ho and Salimans [2022] state that the noise learning target in Eq. (3) is a scaled score function of  $p(x^t)$ , i.e.,  $\epsilon(x^t,t) = -\sigma^t \nabla_{x^t} \log p(x^t)$  and  $\sigma^t = \sqrt{\beta_t}$ . By using Bayes theorem, we have

$$\nabla_{x^t} \log p(y|x^t) = -1/\sigma^t (\epsilon(x^t, y, t) - \epsilon(x^t, t)).$$

According to Eq. (5), we can derive the guided noise predictor as  $\bar{\epsilon}_{\theta}(x^t,y,t) = \epsilon_{\theta}(x^t,t) - w\sigma^t\nabla_{x^t}\log p(y|x^t)$ . Replacing the score function with the noise model predictions, the noise used in classifier-guided sampling can be written as

$$\hat{\epsilon}_w(x^t, y, t) = w\epsilon_\theta(x^t, y, t) + (1 - w)\epsilon_\theta(x^t, t) .$$

## 3.4 Fast Sampling Methods

Various fast sampling methods are proposed to overcome the prolonged iterative sampling time of diffusion models. We summarize these methods into two categories: those that do not involve learning and those that require extra learning, and describe representative works in each category.

**Learning-free methods.** DDIM [Song *et al.*, 2022] is one of the seminal works on sampling acceleration. It extends DDPM to a non-Markovian formulation by learning another Markov chain  $q_{\theta}(x^{t-1}|x^t,x^0)$ . Some high-order solvers are proposed for diffusion sampling, such as DPM-solver [Lu *et al.*, 2022], which provides an excellent trade-off between sample quality and sampling speed. With DDIM as its first-order version, DPM-solver boosts the efficiency of solving PF-ODE, outperforming common numerical ODE solvers.

**Learning-based methods.** Learning-based sampling methods require extra training to obtain a higher sampling efficiency at a slight expense of sampling quality. A recent work, Truncate Diffusion Probabilistic Model (TDPM) [Zheng et al., 2023], demonstrates that both the noising and denoising process can be early terminated to reduce the iterative steps. Moreover, Watson et al. [2021] propose a strategy to select the best K time steps to maximize the training objective for the DDPMs, which also decreases the denoising steps.

#### 4 The Roles of Diffusion Models in RL

Fig. 1 illustrates how diffusion models play a different role in RL compared to previous solutions. Current works applying diffusion models on RL mainly fall into three categories: as planners, as policies, and as data synthesizers. It is essential to note that we include methods that generate action-only sequences as planners, even though some of the representative works have "policy" in their names, e.g., Diffusion Policy [Chi et al., 2023]. Generating multi-step action sequences can be viewed as planning in action space, and the use of diffusion models to ensure temporal consistency is similar to other planning-based diffusion methods. The following subsections will illustrate overall frameworks and representative papers for each category.

#### 4.1 Planner

Planning in RL refers to using a dynamic model to make decisions imaginarily and selecting the appropriate action to maximize cumulative rewards. This process usually explores various sequences of actions and states, thus improving decisions over a longer horizon. Planning is commonly used in the MBRL framework with a learned dynamic model. However, the planning sequences are usually simulated autoregressively, which may lead to severe compounding errors, especially in the offline setting due to limited data support. Diffusion models offer a promising alternative as they can generate multi-step planning sequences simultaneously.

A general framework of diffusion planners is shown in Fig. 2(a). Diffusion models are designed to generate clips of the trajectory  $\tau = (s_1, a_1, r_1, \dots, s_H, a_H, r_H)$ , denoted as

 $x(\tau)=(e_1,e_2,\ldots,e_H)$ . H is the planning horizon. Here  $e_t$  represents the selected elements from  $(s_t,a_t,r_t)$ , where various choices can be made as  $e_t=(s_t,a_t)$  [Janner et al., 2022; Liang et al., 2023a; He et al., 2023a],  $e_t=(s_t,a_t,r_t)$  [He et al., 2023a; Hu et al., 2023],  $e_t=s_t$  [Ajay et al., 2023; Zhu et al., 2023], or  $e_t=a_t$  [Chi et al., 2023; Li et al., 2023b]. RL datasets often contain trajectory data of varying quality. In order to make the diffusion planner generate high rewarded trajectories during evaluations, guided sampling techniques are widely adopted. The guidance can be either injected in the sampling stage following the classifier guided sampling or in both the training and sampling stages following the classifier-free sampling.

When deploying the trained diffusion planner for online evaluations, fast sampling methods are usually adopted to reduce the inference time. Besides, to ensure the planned trajectory is congruous with the agent's current state, before each denoising step, the first h ( $h \ge 1$ ) steps of the noisy trajectory are substituted with the h steps of historical states observed by the agent. Here, h is a hyperparameter where a larger h can better handle partially observable and non-Markovian settings but increases the modeling complexity.

### 4.2 Policy

Based on whether they rely on a dynamic model for making decisions, RL algorithms can be categorized into MBRL and model-free RL. Under such classification criteria, using diffusion models as planners is more akin to MBRL, as the generated trajectories encapsulate dynamics information. Another perspective is that diffusion planner can be seen as a combination of policy and dynamic model [Janner et al., 2022]. In contrast, using diffusion models as policies focuses on improving existing model-free RL solutions. Section 2.1 states the main drawbacks of current offline policy learning methods: over-conservatism and lack of expressiveness. Many works use diffusion models as the policy class in model-free RL to tackle these problems.

Diffusion-QL [Wang et al., 2023] first combines the diffusion policy with the Q learning framework and finds that it can perfectly fit on datasets collected by strong multi-modal behavior policies, where previous distance-based policy regularization approaches fail. Compared with using diffusion models as planners, the diffusion target of the diffusion policy is simply the action given the current state, as shown in Fig. 2(b). Suppose the noise predictor is  $\epsilon_{\theta}(a^k, k, s)$  parameterized by  $\theta$ , and the derived action mean is  $\mu_{\theta}(a|s)$ . To guide the model sampling actions that can lead to high returns, it is necessary to take Q(s,a) into consideration. Diffusion-QL includes a weighted Q maximization term into the diffusion training loss as

$$\mathcal{L}(\theta) = \mathbb{E}_{k,\epsilon,(s,a) \sim \mathcal{D}}[\|\epsilon - \epsilon_{\theta}(a^{k}, s, k)\|_{2}^{2}] - \frac{\eta}{\mathbb{E}_{(s,a) \sim \mathcal{D}}[Q(s,a)]} \cdot \mathbb{E}_{s \sim \mathcal{D}, a^{0} \sim \pi_{\theta}(\cdot \mid s)}[Q(s,a^{0})],$$

where  $\eta$  is a hyperparameter, and  $\mathcal{D}$  is the offline dataset. Some works [Chen *et al.*, 2023a; Lu *et al.*, 2023a; Hansen-Estruch *et al.*, 2023; Kang *et al.*, 2023] construct the policy by (advantage) weighted regression as

$$\pi_{\theta}(a|s) \propto \mu_{\theta}(a|s) \exp(\alpha Q(s,a))$$
,

where  $\alpha$  is the temperature hyperparameter. Following this, Chen et al. [2023a] decouple the policy learning into behavior learning and action evaluation, which allows more freedom in the choice of guidance. They also propose insample planning for Q-learning, avoiding extrapolation errors in previous offline RL methods. CEP [Lu et al., 2023a] further extends this framework to sample from the more general energy-guided distribution  $p(x) \propto q(x) \exp(-\beta \mathcal{E}(x))$ . Here,  $\mathcal{E}(x)$  is an energy function, and in the RL setting, it is trained via contrastive learning to match the in-sample softmax of Q functions. Since there are off-the-shelf Q functions or energy functions after training, some methods use those functions to further improve the sampling quality during evaluations. They first sample multiple candidate actions for a given state and use Q or energy values to perform weighted sampling or just select the best candidate.

Fast reaction is crucial when deploying policies in online environments. Therefore, almost all diffusion policies use smaller diffusion steps during sampling, usually about 15 steps. ODE solvers such as the DPM-solver [Lu et al., 2022] are also used to accelerate sampling [Chen et al., 2023a; Lu et al., 2023a; Kang et al., 2023; Li et al., 2023c]. Kang et al. [2023] introduce action approximation, which allows one-step action sampling in the training stage.

### 4.3 Data Synthesizer

In addition to fitting multi-modal distributions, a simple and common use of diffusion models is to create synthetic data, which has been widely applied in computer vision. Therefore, the diffusion model is a natural data synthesizer for RL datasets because data scarcity is a practical concern. To ensure consistency of synthetic data to the environment dynamics, previous data augmentation approaches in RL usually add minor perturbations to states and actions [Sinha *et al.*, 2021]. In contrast, Fig. 2(c) illustrates that diffusion models generate diverse and consistent data by learning the data distribution from the entire dataset  $\mathcal{D}_{\text{real}}$ . The diffusion model first learns the parameterized data distribution  $\rho_{\theta}(\tau)$  from the real data  $\mathcal{D}_{\text{real}}$ , and generates desired synthetic data by

$$\mathcal{D}_{\rm syn} = \{ \tau \sim \rho_{\theta}(\tau) \}$$
.

Then, real and synthetic data are combined together as

$$\mathcal{D} = \mathcal{D}_{\mathrm{real}} \cup \mathcal{D}_{\mathrm{syn}}$$
,

and  $\mathcal D$  is used for policy learning. In online settings, the policy interacts with the environment, collects more real data into  $\mathcal D_{\rm real},$  and updates the diffusion model. As a result, the diffusion model and the policy are updated alternately.

#### 4.4 Others

Besides the primary directions discussed above, other ways of improving RL with diffusion models are less explored. Mazoure *et al.* [2023] estimate value functions with diffusion models by learning the discounted state occupancy, combined with a learned reward estimator. Then, the value function can be directly computed by definition, where future states are sampled from the diffusion model. Venkatraman *et al.* [2023] first encode the high-level trajectories into semantically rich latent representations, then apply diffusion models to learn

the latent distribution. Conditioning on latent representations improves the capability of Q-functions and policies without significant extrapolation errors. Rigter *et al.* [2023] use a diffusion dynamic model and allow an online RL policy to collect synthetic trajectories on it. The interplay of the diffusion dynamic model and RL policy is done by alternating between state denoising and Langevin dynamics of policy actions.

### 5 Applications of Diffusion Models

In this section, we conduct a complete review of existing works. We divide them into five groups based on the tasks they are applied: offline RL, online RL, imitation learning, trajectory generation, and data augmentation. For each group, we provide a detailed explanation of how each method uses diffusion models to handle the task.

#### 5.1 Offline RL

Offline RL aims to learn a policy from previously collected datasets without online interaction. Assuming there is a static dataset  $\mathcal{D}$  collected by some (unknown) behavior policy  $\pi_{\beta}$ , offline RL requires the learning algorithm to derive a policy  $\pi(a|s)$  that attains the most cumulative reward:

$$\pi^* = \arg\max_{\pi} \mathbb{E}_{\tau \sim p_{\pi}(\tau)} \left[ \sum_{t=0}^{H} \gamma^t r(s_t, a_t) \right].$$

The fundamental challenge in offline RL is the distributional shift. This refers to the discrepancy between the dataset distribution used to train the function approximators (*e.g.*, policies and value functions) and the distribution on which the policy is evaluated. This mismatch often results in subpar online performance. High-dimensional and expressive function approximation generally exacerbates this issue.

Several methods use diffusion models to help tackle or avoid the above challenges. Janner et al. [2022] first propose to generate optimal trajectories through iterative denoising with classifier-guided sampling. Subsequent works [Wang et al., 2023; Chen et al., 2023a; He et al., 2023b; Ada et al., 2023; Brehmer et al., 2023; Hansen-Estruch et al., 2023] represent the policy as a diffusion model to capture multimodal distributions and enhance the expressiveness of the policy class, which is beneficial to relieve the approximation error between the cloned behavior policy and true behavior policy. Ajay et al. [2023] alleviate the distribution shift problem by generating state sequences with conditional diffusion models followed by inverse dynamic functions to derive executable actions, which propose a novel approach to use classifier-free guidance with low-temperature sampling to denoise out return-maximizing trajectories. LatentDiffuser [Li, 2023] performs diffusion planning over a learned latent space with separate decoders to recover raw trajectories. Benefiting from a more compact planning space, it achieves superior performances on long-horizon and high-dimensional tasks. In order to improve the generation ability of diffusion models for RL, Lu et al. [2023a] propose a new guidance method named contrastive energy prediction and Hu et al. [2023] capture more temporal conditions. By incorporating control-theoretic invariance into the diffusion dynamics, SafeDiffuser [Xiao et al., 2023] guarantees the safe generation of planning trajectories. HDMI [Li et al., 2023a] adopts a hierarchical structure to tackle long-horizon decision-making problems, which uses a reward-conditional model to discover sub-goals and a goalconditional model to generate actions. Dong et al. [2023] condition the diffusion planner on diverse behavior attributes and learn from human preferences to generate trajectories that can match user-customized behaviors. CPQL [Chen et al., 2023d] leverages consistency models as the policy class for fast training and sampling, while EDP [Kang et al., 2023] achieves speed-up during training by using single-step model predictions as action approximations. Diffusion models are also used as the value function [Mazoure et al., 2023] and representation model [Venkatraman et al., 2023] to facilitate training of normal RL policies. Recent research has made progress in using diffusion models to improve the performance of policies in multitask and multi-agent offline RL.

Multitask offline RL. Diffusion models are verified to have the potential to address the challenge of multi-task generalization in offline RL. He *et al.* [2023a] first extend the conditional diffusion model to be capable of solving multitask decision-making problems and synthesizing useful data for downstream tasks. LCD [Zhang *et al.*, 2023a] leverages a hierarchical structure to achieve long-horizon multitask control. MetaDiffuser [Ni *et al.*, 2023] demonstrates that incorporating the conditional diffusion model into the context of task inference outperforms previous meta-RL methods. AdaptDiffuser [Liang *et al.*, 2023a] combines bootstrapping and diffusion-based generative modeling together to enable the model to adapt to unseen tasks.

**Multi-agent offline RL.** Using diffusion models in multiagent RL helps model discrepant behaviors among agents and reduces approximation error. MADiff [Zhu *et al.*, 2023] uses an attention-based diffusion model to model the complex coordination among behaviors of multiple agents, which is well-suited to learning complex multi-agent interactions. DOM2 [Li *et al.*, 2023c] incorporates the diffusion model into the policy classes to enhance learning and makes it possible to generalize to shifted environments well.

#### 5.2 Online RL

Recently, there have been some works showing that diffusion models can also boost online RL training. Value estimations in online RL are noisier and change with the current policy, which poses additional challenges on training a multistep diffusion model. DIPO [Yang et al., 2023a] proposes an action relabeling strategy to perform policy improvement at the data level, bypassing the potentially unstable value-guided training. Actions in the online rollout dataset are updated with gradient ascent, and the diffusion training objective is just supervised learning on the relabeled dataset. Chen et al. [2023d] conduct experiments to verify that consistency models with one-step sampling can naturally serve as online RL policies and achieve a balance between exploration and exploitation. Instead of using diffusion models as policies, Rigter et al. [2023] build a diffusion dynamic model to generate synthetic trajectories that are consistent with online RL policies. Applications of diffusion models in online RL are less explored

Table 1: Summary of papers on diffusion models for RL.

Model & Paper	Role of Diffusion Models	Keyword(s)	Guidance
Diffuser [Janner et al., 2022] AdaptDiffuser [Liang et al., 2023a] EDGI [Brehmer et al., 2023] TCD [Hu et al., 2023] LatentDiffuser [Li, 2023] HDMI [Li et al., 2023a]		Offline Offline Offline Offline Offline Offline; Hierarchical	Classifier Classifier Classifier Classifier-free Energy Function Classifier-free
SafeDiffuser [Xiao et al., 2023] MADiff [Zhu et al., 2023] MTDiff-p [He et al., 2023a] MetaDiffuser [Ni et al., 2023] Diffusion Policy [Chi et al., 2023] Crossway Diffusion [Li et al., 2023b] AVDC [Ko et al., 2023] SkillDiffuser [Liang et al., 2023b] MLD [Chen et al., 2022] MDM [Tevet et al., 2022] UniSim [Yang et al., 2023b] ReMoDiffuse [Zhang et al., 2023b] SinMDM [Raab et al., 2023] EquiDiff [Chen et al., 2023] MoFusion [Dabral et al., 2022] MotionDiffuse [Zhang et al., 2022] MPD [Carvalho et al., 2023]	Planner	Offline; Safe Offline; Multi-agent Offline; Multi-agent Offline; Multitask Offline; Multitask Imitation; Robotics Imitation; Robotics Imitation; Multitask; Hierarchical Trajectory Generation	None Classifier-free Classifier-free Classifier-free None None None Classifier-free Classifier-free Classifier-free Classifier-free Classifier-free None None None None Classifier-free
MotionDiffuser [Jiang et al., 2023] AlignDiff [Dong et al., 2023]		Trajectory Generation; Multi-agent RLHF	Classifier Classifier-free
Diffusion-QL [Wang et al., 2023]     SRDP [Ada et al., 2023]     EDP [Kang et al., 2023]     SfBC [Chen et al., 2023a]  IDQL [Hansen-Estruch et al., 2023b]     CPQL [Chen et al., 2023b]     CPQL [Chen et al., 2023d]     CEP [Lu et al., 2023a]     DOM2 [Li et al., 2023c]     NoMaD [Sridhar et al., 2023]     BESO [Reuss et al., 2023]     Pearce et al. [2023]     Yoneda et al. [2023]     PlayFusion [Chen et al., 2023c]     XSkill [Xu et al., 2023]     CoDP [Ng et al., 2023]	Policy	Offline Offline Offline Offline Offline Offline Offline Offline; Online Offline; Image Synthesis Offline; Multi-agent Imitation; Robotics Imitation Imitation Imitation; Robotics	Q-loss Q-loss Q-loss Q-loss Sample & Reweight Sample & Reweight Convex Optimization Q-loss Energy Function Q-loss None Classifier-free Classifier-free None None None
GenAug [Chen <i>et al.</i> , 2023e] ROSIE [Yu <i>et al.</i> , 2023] SynthER [Lu <i>et al.</i> , 2023b] MTDiff-s [He <i>et al.</i> , 2023a]	Data Synthesizer	Robotics Robotics Offline; Online Offline; Multitask	None None None Classifier-free
LDCQ [Venkatraman et al., 2023]	Latent Representation	Offline	Classifier-free
DVF [Mazoure et al., 2023]	Value Function	Offline	None
PolyGRAD [Rigter et al., 2023]	Dynamic Model	Online	None

compared to offline settings and merit further investigation.

### 5.3 Imitation Learning

The goal of imitation learning (IL) is to reproduce behavior similar to experts in the environment by extracting knowledge from expert demonstrations. Recently, many works [Hegde et al., 2023; Ng et al., 2023; Chen et al., 2023c; Kapelyukh et al., 2022] have demonstrated the efficacy of representing policies as diffusion models to capture multi-modal behavior. Pearce et al. [2023] apply diffusion models to imitate human behavior in sequential environments, in which diffusion models are compared with other generative models and viable approaches are developed to improve the quality of behavior sampled from diffusion models. Chi et al.; Xian et al. [2023; 2023] generate the robot's behavior via a conditional denoising diffusion process on robot action space. Experiment results show that Diffusion models are good at predicting closed-loop action sequences while guaranteeing temporal consistency [Chi et al., 2023]. Li et al. [2023b] improve the models in Chi et al. [2023] by incorporating an auxiliary reconstruction loss on intermediate representations of the reverse diffusion process. Beneficial from its powerful generation ability, leveraging diffusion models to acquire diverse skills to handle multiple manipulation tasks is promising [Chen et al., 2023c; Mishra et al., 2023; Xu et al., 2023; Ha et al., 2023]. Diffusion models are already applied to goal-conditioned IL: Reuss et al. [2023] use a decoupled score-based diffusion model to learn an expressive goalconditional policy. In contrast, Sridhar et al. [2023] build a unified diffusion policy to solve both goal-directed navigation and goal-agnostic exploration problems. Liang et al. [2023b] adopt a hierarchical structure where the high-level skills are determined by the current visual observation and language instructions. Therefore the low-level skill-conditioned planner can satisfy the user-specified multitask instructions.

### 5.4 Trajectory Generation

Trajectory generation aims to produce a dynamically feasible path that satisfies a set of constraints. We focus on using diffusion models to generate human pose and robot interaction sequences, which are more related to the decision-making scenario. Many works [Zhang et al., 2022; Jiang et al., 2023; Tevet et al., 2022; Zhang et al., 2023b; Chen et al., 2022; Dabral et al., 2022] have remarked that the conditional diffusion models perform better than traditional methods which use GAN or Transformer. Employing a denoising-diffusionbased framework, they achieve diverse and fine-grained motion generation with various conditioning contexts [Chen et al., 2023b; Carvalho et al., 2023]. Recent works [Du et al., 2023b; Ko et al., 2023; Du et al., 2023a] harness diffusion models to synthesize a set of future frames depicting its planned actions in the future, after which control actions are extracted from the generated video. This approach makes it possible to train policies solely on RGB videos and deploy learned policies to various robotic tasks with varying dynamics [Black et al., 2023; Gao et al., 2023]. UniSim [Yang et al., 2023b] uses diffusion models to build a universal simulator of real-world interaction by learning through combined diverse datasets. It can be used to train both high-level vision-language planners and low-level RL policies, demonstrating powerful emulation ability.

### 5.5 Data Augmentation

Since diffusion models perform well in learning over multimodal or even noisy distributions, they can model original data distribution precisely. What is more, they are capable of generating diverse data points to expand original distribution while maintaining dynamic accuracy. Recent works [Yu et al., 2023; Chen et al., 2023e] consider augmenting the observations of robotic control using a text-guided diffusion model while maintaining the same action. The recently proposed SynthER [Lu et al., 2023b] and MTDiff-s [He et al., 2023a] generate complete transitions of trained tasks via a diffusion model. Lu et al. [2023b] directly train the diffusion model from the offline dataset or the online replay buffer and then generate samples for policy improvement. Analysis shows that both diversity and accuracy of data generated by diffusion models are higher than those generated by prior data augmentation methods. He et al. [2023a] deploy diffusion synthesizer on multi-task offline datasets and achieve better performance than that on single-task datasets. They claim that fitting on multiple tasks may enable implicit knowledge sharing across tasks, which also benefits from the multi-modal property of diffusion models. These works demonstrate that diffusion augmentation can bring significant improvement in policy learning for IL, online RL, and offline RL.

### **6** Summary and Future Prospects

This survey offers a comprehensive overview of contemporary research endeavors concerning the application of diffusion models in the realm of RL. According to the roles played by diffusion models, we categorize existing methods into using diffusion models as planners, policies, data synthesizers, and less popular roles such as value functions, representation models, etc. By comparing each class of methods to traditional solutions, we can see how the diffusion model addresses some of the longstanding challenges in RL, i.e., restricted expressiveness, data scarcity, compounding error, and multitask generalization. It is worth emphasizing that the incorporation of diffusion models into RL remains an emerging field, and there are many research topics worth exploring. Here, we outline four prospective research directions, namely, generative simulation, integrating safety constraints, retrieval-augmented generation, and composing different skills.

Generative simulation. As shown in Fig. 1, existing works use diffusion models to overcome certain limitations of previous solutions in both the agent and buffer parts. However, there has been a scarcity of research focused on using diffusion modeling to improve the environment. Gen2Sim [Katara et al., 2023] uses text-to-image diffusion models to generate diverse objects in simulation environments, where RL policies are trained to learn robot manipulation skills. Besides generating objects in the scene, diffusion models have the potential for broader applications in generative simulation, such

as the generation of various possible dynamics functions, reward functions, or opponents in multi-agent learning.

Integrating safety constraints. Making decisions in real tasks often necessitates compliance with various safety constraints. Several safe RL methods transform a constrained RL problem to its unconstrained equivalent [Achiam et al., 2017], which is then solved by generic RL algorithms. Policies acquired through these methods remain tailored to the specific constraint threshold specified during training. A recent research [Liu et al., 2023] has extended the applicability of decision transformers to the context of safety-constrained settings, thereby enabling a single model to adapt to diverse thresholds by adjusting the input cost-to-go. Similarly, diffusion models have the potential to be deployed in safe RL by viewing safety constraints as sampling conditions. Ajay et al. [2023] demonstrate that a diffusion-based planner can combine different movement skills to produce new behaviors. Also, classifier-guided sampling can include new conditions by learning additional classifiers, while the parameters of the diffusion model remain unchanged [Dhariwal and Nichol, 2021]. This makes the diffusion model promising for scenarios with new safety requirements after model training.

Retrieval-enhanced generation. Retrieval techniques are employed in various domains such as recommender systems [Qin et al., 2020] and large language models [Kandpal et al., 2023] to enhance the model capacity and handle longtail distributed datasets. Some works utilize retrieved data to boost text-to-image and text-to-motion diffusion generation [Sheynin et al., 2022; Zhang et al., 2023b], promoting better coverage of uncommon condition signals. During online interactions, RL agents may also encounter states that are rare in the training dataset. By retrieving relevant states as model inputs, the performance of diffusion-based decision models can be improved in these states. Also, if the retrieval dataset is constantly updated, diffusion models have the potential to generate new behaviors without retraining.

Composing different skills. From the perspective of skill-based RL, it is promising to break down complex tasks into smaller, more manageable sub-skills. Diffusion models excel in modeling multi-modal distributions, and since multiple sub-skills can be viewed as distinct modes within the distribution of possible behaviors, they offer a natural fit for this task. Combining with classifier guidance or classifier-free guidance, diffusion models are possible to generate proper skills to complete the facing task. Experiments in offline RL also suggest that diffusion models can share knowledge across skills and combine them up [Ajay et al., 2023], thus having the potential for zero-shot adaptation or continuous RL by composing different skills.

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