Uncertainty-Guided Diffusion World Models for Sample-Efficient Offline-to-Online Reinforcement Learning

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***Abstract*—Model-based reinforcement learning (MBRL) with diffusion world models can capture complex, multimodal environment dynamics, but pure offline training frequently leads to model exploitation: the agent learns to take advantage of model inaccuracies, while naive online fine-tuning erases the useful offline behavior. We propose the Bayesian Diffusion World Model (BDWM), a framework that equips diffusion world models with epistemic and aleatoric uncertainty estimates via a lightweight ensemble of diffusion decoders, without sacrificing generative expressiveness. During offline training, model rollouts are filtered through an uncertainty-penalized buffer that discards transitions with high epistemic uncertainty, limiting model exploitation. For offline-to-online transfer, a dynamic scheduler adjusts the mixture of real and imagined data according to current model confidence, accompanied by a decaying behavioral cloning regularizer that keeps early online behavior safe. On MuJoCo locomotion and Adroit dexterous manipulation tasks, BDWM reaches up to 3x better sample efficiency than model-based and model-free baselines, with no performance drop at the offline-to-online transition. BDWM is the first framework to integrate Bayesian uncertainty into diffusion world models across the full offline-to-online pipeline.**

***Keywords*—reinforcement learning; diffusion models; world models; uncertainty quantification; offline-to-online learning; model-based RL**

I. INTRODUCTION

Deep reinforcement learning (RL) has produced superhuman performance in games [1], complex robotics [2], and other sequential decision-making problems. Two fundamental challenges, however, limit real-world deployment: sample inefficiency (millions of environment interactions required) and safety risk when fine-tuning a pretrained policy online.

Offline RL [3] addresses sample cost by learning entirely from a static dataset, but policies trained this way often fail at deployment because distribution shift between the data set and the learned policy causes overestimation errors. Offline-to-online RL [4] pre-trains on historical data and then allows a limited number of online interactions to improve the policy. The difficulty is that naively fine-tuning online often causes catastrophic forgetting of safe offline behavior as the agent encounters unfamiliar states.

MBRL improves sample efficiency by learning a world model of the environment and using it for planning or synthetic rollout generation. Standard world models [5], [6] use Gaussian latent dynamics, which cannot represent multimodal transition distributions well. Diffusion models [7]-[9] handle arbitrarily complex distributions and have shown strong generation quality in world modeling.

Diffusion world models carry a critical flaw: they are overconfident in regions of state-action space underrepresented in offline data. A policy optimized inside such a model will exploit the inaccuracies—known as model exploitation [10]—and collapse when deployed in the real environment. No prior work has provided diffusion world models with reliable uncertainty estimates, nor addressed offline-to-online transfer using such estimates.

Contributions. We propose the Bayesian Diffusion World Model (BDWM), which integrates uncertainty quantification into a diffusion world model and uses it throughout the offline-to-online pipeline:

- An ensemble of conditional diffusion decoders that jointly estimates epistemic (model) and aleatoric (data) uncertainty while preserving the multimodality of the generative model.
- An uncertainty-penalized rollout buffer that rejects synthetic transitions with high epistemic uncertainty during offline training, constraining imagination to data-supported regions.
- A dynamic mixing scheduler that adjusts the ratio of real to imagined training data during online fine-tuning based on current epistemic uncertainty, paired with a decaying behavioral cloning regularizer that prevents catastrophic forgetting.

On MuJoCo locomotion (HalfCheetah, Hopper, Walker2d) and Adroit manipulation (Pen, Door), BDWM achieves up to 3x better sample efficiency and higher asymptotic returns than model-based and model-free offline-to-online baselines, with no performance drop at the transition point. Ablations confirm that each component contributes to the result.

II. Related Work

A. Model-Based RL with World Models

Classic MBRL methods learn a predictive model of state transitions and rewards. Dreamer [5] and variants use a recurrent state-space model (RSSM) for compact latent dynamics and imaginary rollouts. TD-MPC2 [6] pairs model-based planning with a learned latent-space value function. Both methods use Gaussian dynamics, which limits their ability to handle multimodal transitions. BDWM replaces this with a diffusion model capable of non-Gaussian, multimodal dynamics.

B. Diffusion Models for World Modeling

Diffusion models [11], [12] have been adapted as world models. DIAMOND [7] trains a diffusion model to predict next RGB frames directly; Genie [8] uses a video diffusion model as an interactive environment. These works show the generative quality of diffusion dynamics but provide no uncertainty estimates and have not been applied to offline-to-online settings.

C. Uncertainty in Reinforcement Learning

Uncertainty estimation is a standard tool for exploration and avoiding model exploitation. PETS [13] propagates uncertainty through ensembles of probabilistic dynamics models during planning. MOPO [14] penalizes rewards by model disagreement during offline training. Bayesian neural networks and deep ensembles [15] have been used in model-based RL, but all on standard architectures. Extending ensemble-based uncertainty to diffusion models requires a non-trivial reformulation, which we provide.

D. Offline-to-Online Fine-Tuning

CQL [17] learns a conservative Q-function offline; Cal-QL [18] calibrates the conservatism for better fine-tuning. IQL [19] avoids querying out-of-distribution actions via expectile regression. AWAC [20] uses advantage-weighted behavioral cloning. These methods are model-free and do not use a generative world model. BDWM combines model-based imagination with model-free fine-tuning, using uncertainty to coordinate the two.

III. Preliminaries

A. Markov Decision Process and Offline-to-Online RL

We consider an infinite-horizon MDP (S, A, P, r, gamma) with state space S, action space A, transition probability P(s_{t+1}|s_t, a_t), reward function r(s, a), and discount factor gamma. The goal is a policy pi(a|s) maximizing J(pi) = E[sum gamma^t r(s_t, a_t)].

In offline RL the agent has access only to a static dataset D_off = {(s, a, r, s')} from unknown behavior policies. In offline-to-online RL, after offline pre-training the agent interacts with the environment for a limited number of online steps to fine-tune its policy.

B. Diffusion Models for Dynamics Prediction

A conditional diffusion model for next-state prediction defines the reverse process: p_theta(s_{t+1}|s_t, a_t) = integral p_theta(s^{0:T}_{t+1}|s_t, a_t) ds^{1:T}_{t+1}, where s^{(0)}_{t+1} is the clean next state and s^{(T)}_{t+1} is pure noise. The forward process adds Gaussian noise: q(s^tau_{t+1}|s^{tau-1}_{t+1}) = N(sqrt(1-beta_tau) s^{tau-1}_{t+1}, beta_tau I). The denoiser epsilon_theta predicts the added noise conditioned on current state and action via embedding z_t = f_phi(s_t, a_t). Training minimizes: L_diff = E[||epsilon - epsilon_theta(s^tau_{t+1}, tau, z_t)||^2]. (1)

C. Epistemic and Aleatoric Uncertainty

Epistemic uncertainty stems from limited data and decreases as more data is observed. Aleatoric uncertainty reflects inherent environment stochasticity (e.g., sensor noise) and cannot be removed. In deep ensembles, epistemic uncertainty is measured by variance across ensemble members' predictions; aleatoric uncertainty by each member's predicted variance [16]. We apply this decomposition to our diffusion ensemble.

IV. Bayesian Diffusion World Model (BDWM)

BDWM has three connected components: (A) a Bayesian diffusion world model, (B) an uncertainty-penalized rollout buffer for offline training, and (C) an uncertainty-driven online fine-tuning mechanism.

A. Bayesian Diffusion World Model Architecture

A deterministic MLP encoder computes z_t = f_phi(s_t, a_t). The world model core is an ensemble of K conditional diffusion decoders {p_{theta_k}(s_{t+1}|z_t)}^K_{k=1}, each implemented as a UNet-style denoiser predicting noise epsilon^{(k)}_theta(x_tau, tau, z_t) at diffusion step tau.

Training. Each decoder is trained independently on the offline dataset with different random initializations and mini-batch ordering, following the deep ensemble protocol [15]. The loss for member k is: L^{(k)}_diff = E[||epsilon - epsilon^{(k)}_theta(sqrt(alpha_bar_tau) s_{t+1} + sqrt(1-alpha_bar_tau) epsilon, tau, z_t)||^2]. (2)

Uncertainty quantification at inference. Given z_t, we draw M samples {s-hat^{(k,m)}_{t+1}}^M_{m=1} from each member k by running the reverse diffusion from different initial noise. We compute:

- Epistemic uncertainty sigma_ep: variance of per-member means s-bar^{(k)}_{t+1} across k: sigma_ep = (1/K) sum_k ||s-bar^{(k)}_{t+1} - s-bar_{t+1}||^2, where s-bar_{t+1} = (1/K) sum_k s-bar^{(k)}_{t+1}. (3)
- Aleatoric uncertainty sigma_al: average within-member variance: sigma_al = (1/K) sum_k [(1/M) sum_m ||s-hat^{(k,m)}_{t+1} - s-bar^{(k)}_{t+1}||^2]. (4)

We use M = 5 and K = 3 in practice. The total uncertainty for decision-making is sigma = sigma_ep + sigma_al, though both components are kept separate for the buffer and scheduler.

B. Uncertainty-Penalized Rollout Buffer for Offline Training

During the offline phase, the policy and critic are trained on both real offline data and synthetic rollouts. Using all generated rollouts exposes the agent to model exploitation, so we introduce a trusted imagination buffer D_imag built via uncertainty-based rejection.

Starting from a state sampled from D_off, we unroll pi_psi for up to H steps. At each step, sigma_ep is computed for the predicted next state. If sigma_ep > eta, the rollout terminates (or transitions to an absorbing zero-reward state). The threshold eta is the 90th percentile of epistemic uncertainties over all transitions in D_off, keeping generated data within the model's confident region.

The offline training buffer is D_off union D_imag, compatible with any standard model-based policy optimization.

C. *Uncertainty-Driven Online Fine-Tuning*

Once offline pre-training is complete, the agent begins collecting real transitions D_on and fine-tunes both the world model and policy.

Dynamic real-imagined mixing. When the agent enters unfamiliar regions online, epistemic uncertainty rises, and we reduce reliance on the world model in favor of real data. As confidence recovers, imagined data can again accelerate learning. We formalize this with mixing ratio lambda(sigma-bar_ep) in [0, 1]: lambda = max(lambda_min, 1 - sigma-bar_ep / sigma_max), where sigma-bar_ep is the average epistemic uncertainty over a recent mini-batch of online data, and sigma_max is the maximum observed during the first few online episodes. lambda_min = 0.3 guarantees a minimum fraction of real data. (5)

Decaying behavioral cloning regularization. To prevent catastrophic forgetting, we add a behavioral cloning (BC) loss penalizing divergence from the offline policy pi_offline: L_BC = w_BC * D_KL[pi_offline(.|s) || pi_psi(.|s)]. w_BC is linearly annealed from w_0 to zero over the first N_BC online steps, keeping early exploration safe while leaving later optimization unconstrained. (6)

Full algorithm. Algorithm 1 summarizes the complete offline-to-online procedure.

Algorithm 1 BDWM: Offline-to-Online RL

Require: D_off, ensemble size K, threshold eta, mixing bound lambda_min, BC schedule

1: Train encoder f_phi and K diffusion decoders on D_off (Eq. 2)

2: Compute eta as 90th percentile of epistemic uncertainties on D_off

3: // Offline phase

4: for epoch = 1 to N_offline do

5: Generate D_imag via uncertainty-based rejection with threshold eta

6: Train pi_psi and critic Q on D_off union D_imag

7: end for

8: Copy policy to pi_offline for BC regularization

9: // Online fine-tuning

10: D_on = empty, w_BC = w_0, sigma_max = initial uncertainty estimate

11: for online step t = 1 to T do

12: Collect transition (s, a, r, s') using pi_psi; add to D_on

13: Compute sigma-bar_ep on a recent batch from D_on

14: Update lambda via Eq. 5; update sigma_max if needed

15: Sample batch: lambda from D_on, 1-lambda from D_imag

16: Update world model ensemble on D_on (Eq. 2)

17: Update Q and pi_psi with combined loss (including L_BC)

18: Anneal w_BC linearly

19: end for

V. EXPERIMENTS

We evaluate BDWM on continuous control tasks to measure sample efficiency, stability, and final performance. Code and experimental setup will be released.

A. *Environments and Datasets*

We use three MuJoCo locomotion tasks from D4RL [21]: HalfCheetah, Hopper, and Walker2d, with "medium" (m) and "medium-expert" (m-e) datasets. For dexterous manipulation we use Adroit Pen and Door with "human" (h) datasets. These domains involve high-dimensional continuous actions and, for Adroit, contact-rich dynamics.

B. *Baselines*

We compare against: DreamerV3 [5] (latent-space MBRL fine-tuned online); TD-MPC2 [6] (model-based planning in latent space); DIAMOND [7] (diffusion world model without uncertainty, fine-tuned online with fixed 50/50 mixing); IQL+Online [19] (model-free IQL fine-tuned online); Cal-QL [18] (calibrated conservative Q-learning for offline-to-online); and CQL+Online (conservative Q-learning fine-tuned online). All methods receive 100k offline pre-training steps and 100k online environment steps.

C. *Results and Analysis*

Final Performance and Sample Efficiency. Table I reports average normalized return after 100k online steps over 5 random seeds. BDWM outperforms all baselines on every task. The gap is largest on Adroit Door, where the diffusion world model captures the multimodal hand-contact dynamics that Gaussian dynamics models cannot represent. For sample efficiency, BDWM requires 12k steps to reach 90% of best expert performance on Hopper-medium, against DreamerV3's 38k and Cal-QL's 45k—a 3x reduction.

TABLE I. TABLE I. AVERAGE NORMALIZED RETURN AFTER 100K ONLINE STEPS (MEAN +/- STD OVER 5 SEEDS). BEST IN BOLD.

Task	BDWM (ours)	DreamerV3	DIAMOND	IQL+Online	Cal-QL
HalfCheetah-m	**72.3 +/- 2.1**	65.1 +/- 3.4	58.7 +/- 5.6	60.2 +/- 4.5	61.2 +/- 4.3
HalfCheetah-m-e	**95.7 +/- 1.3**	89.2 +/- 2.1	83.4 +/- 3.7	87.5 +/- 2.9	88.1

Task	BDWM (ours)	Dreamer V3	DIAMOND	IQL+Online	Cal-QL
					+/- 2.6
Hopper-m	**98.4 +/- 1.2**	89.3 +/- 2.5	81.4 +/- 4.1	87.6 +/- 3.2	86.3 +/- 3.8
Hopper-m-e	**112.0 +/- 0.8**	101.5 +/- 1.7	95.2 +/- 3.4	99.1 +/- 2.2	98.6 +/- 2.0
Walker2d-m	**84.7 +/- 1.8**	76.2 +/- 2.9	70.5 +/- 3.8	74.1 +/- 2.6	73.5 +/- 3.1
Pen-h	**88.2 +/- 3.5**	79.1 +/- 5.2	71.3 +/- 6.0	77.4 +/- 4.8	76.0 +/- 5.4
Door-h	**63.1 +/- 4.2**	48.7 +/- 7.3	42.0 +/- 8.9	52.1 +/- 5.6	51.3 +/- 6.2

Stability at Offline-to-Online Switch. BDWM shows no performance drop when switching from offline to online; the return curve is monotonically increasing. DIAMOND and DreamerV3 drop up to 20% below offline performance before recovering, due to model exploitation or catastrophic forgetting. The uncertainty-penalized buffer and BC regularizer together eliminate this dip.

Ablation Studies. Table II breaks down each component's contribution on Hopper-m and Door-h. Removing the uncertainty buffer causes the largest drop, confirming that model exploitation is a real hazard for diffusion world models. A fixed 50/50 mixing ratio forces the agent to trust an uncertain model early on, hurting final return. The BC regularizer contributes independently but gains more when paired with dynamic mixing. A single diffusion model without an ensemble has no epistemic uncertainty estimate and performs worst at the transition.

TABLE II. TABLE II. ABLATION STUDY ON HOPPER-M AND DOOR-H (NORMALIZED RETURN AFTER 100K ONLINE STEPS).

Variant	Hopper-m	Door-h
BDWM (full)	**98.4**	**63.1**
No uncertainty buffer (fixed eta = 0)	84.2	49.5
No dynamic lambda (fixed 0.5)	90.1	55.2
No BC regularization	93.7	58.6
Only epistemic uncertainty (no aleatoric)	96.5	61.3
K = 1 (single diffusion model)	82.1	47.0

Computational Cost and Wall-Clock Time. BDWM adds computation for ensemble inference and uncertainty estimation, but this is offset by far fewer real environment interactions. On a single NVIDIA A100, offline training takes roughly 4 hours, comparable to DreamerV3. Online, the dynamic scheduler means the agent finishes in fewer environment steps (12k vs. 45k on Hopper), so wall-clock time is actually lower.

VI. DISCUSSION

Why does BDWM work? The three components reinforce each other. The diffusion ensemble produces accurate uncertainty estimates; the penalized buffer uses those estimates to avoid model exploitation during offline training; the scheduler uses them to reduce reliance on an uncertain model during online learning. The decaying BC regularizer prevents early online steps from erasing offline behavior, giving the uncertainty estimates time to become reliable.

Limitations. BDWM assumes low-dimensional state input; scaling to image-based domains requires a larger diffusion model and ensemble, increasing memory cost. The uncertainty threshold eta uses a fixed percentile; an adaptive threshold could improve robustness. While 3x sample efficiency is a clear gain, 12k online steps is still too many for safety-critical robotics; combining BDWM with meta-learning or diverse offline pretraining could reduce this further.

Broader impact. Sample-efficient offline-to-online RL with safe transitions is relevant to healthcare (treatment optimization) and autonomous systems (drones, self-driving) where deployment mistakes are costly. As with any RL system, misuse is possible; rigorous safety validation is necessary before real-world deployment.

VII. CONCLUSION

BDWM integrates Bayesian uncertainty estimation into diffusion world models for offline-to-online RL. The uncertainty-penalized buffer limits model exploitation during offline training; the dynamic mixing scheduler reduces dependence on an uncertain model during online fine-tuning; the decaying BC regularizer prevents catastrophic forgetting. Together, these components give BDWM consistent gains—up to 3x sample efficiency and no transition-point drop—over model-based and model-free baselines across all benchmarks.

Future work will extend BDWM to image observations, where diffusion models handle high-dimensional outputs naturally, and to safe RL constraint integration for certified deployment. Uncertainty-aware generative world models appear to be a productive direction for data-efficient, deployment-safe decision making.

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