Match or Replay: Self Imitating Proximal Policy

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Abstract

Reinforcement Learning (RL) agents often struggle with inefficient exploration, particularly in environments with sparse rewards, where traditional exploration strategies lead to slow learning and suboptimal performance. This inefficiency comes from unsystematic exploration, where agents fail to effectively exploit past successful experiences, hindering both temporal credit assignment and exploration. To address this, we propose a self-imitating on-policy algorithm that enhances exploration by bootstrapping policy learning with past successful state-action transitions. To incorporate self-imitation, our method uses optimal transport distance for dense reward environments to prioritize the state visitation distribution that matches the most rewarding past trajectory. In sparse reward environments, we uniformly replay self-encountered successful trajectories to provide structured exploration. Experimental results across diverse environments—including MuJoCo for dense rewards and the partially observable 3D Animal-AI Olympics and multi-goal PointMaze for sparse rewards—demonstrate significant improvements in learning efficiency. Our approach achieves faster convergence and significantly higher success rates than state-of-the-art self-imitating RL baselines. These findings suggest that self-imitation is a promising strategy for improving exploration and can be extended to more complex RL tasks.

1 Introduction

Deep Reinforcement Learning (DRL) (Li, 2017) has achieved remarkable success in solving complex problems across a variety of domains, including robotic manipulation (Han et al., 2023), flight control (Kaufmann et al., 2018), intelligent perception system (Chaudhary et al., 2023) and real-time strategy game-play (Andersen et al., 2018). However, despite these advancements, DRL algorithms still face significant challenges in efficient learning, resulting in poor sample inefficiency (Baker et al., 2019). A major contributing factor is the reliance on unguided exploration to discover optimal policies, leading to slow convergence, excessive policy divergence, or even forgetting behaviors, particularly in environments with sparse rewards.

Guided exploration using expert demonstrations has been proposed as a potential solution. Approaches such as those in (Salimans & Chen, 2018; Ecoffet et al., 2019; Xu et al., 2023; Duan et al., 2017; Zhou et al., 2019; Haldar et al., 2023) have explored the use of expert data to guide the agent's learning process. However, these methods often suffer from challenges such as acquiring expert demonstrations, the risk of bias, and the potential for suboptimal policies when demonstrations are not sufficiently informative.

This work addresses these challenges by exploiting the agent's past successful experiences to guide exploration. To this end, we propose a novel Self-Imitation Learning (SIL) (Oh et al., 2018) approach that allows RL agents to bootstrap policy learning with their past successes, enhancing temporal credit assignment (Sutton, 1984) and reducing the risk of forgetting behaviors. By leveraging successful past trajectories, our approach prevents the agent from deviating too far from previously learned successful behaviors, improving exploration and learning efficiency.

Even though, self-imitation learning has been applied to diverse complex tasks such as robotics (Luo & Schomaker, 2023; Luo et al., 2021), text-based games (Shi et al., 2023), procedurally generated environments (Lin et al., 2023), interactive navigation (Kim et al., 2023), and large language models (Xiao et al., 2024). Despite these advancements, no comprehensive approach remains that effectively addresses

self-imitation learning across state- and pixel-based observation while catering to dense and sparse reward settings. Motivated by this challenge, we aim to enhance the sample efficiency of on-policy deep reinforcement learning (DRL) agents in these diverse scenarios. To achieve this, we propose the Self-Imitating Proximal Policy (SIPP) algorithm, an extension of Proximal Policy Optimization (PPO) (Schulman et al., 2017), which incorporates two complementary strategies specifically designed to address the unique challenges posed by these reward structures.

For dense reward environments, we propose the Match strategy. This strategy uses optimal transport (Peyré et al., 2019), specifically the sinkhorn algorithm (Cuturi, 2013), to measure the similarity between state distributions of the current policy and the most rewarding episodic rollout from the past. By prioritizing state-action transitions that closely match these distributions, the Match strategy ensures that exploration focuses on the self-encountered regions of the state space with high expected rewards.

In sparse reward environments, we introduce the Replay strategy, which maintains an imitation buffer storing self-encountered successful trajectories. Instead of relying completely on the agent's current behavior, the replay strategy prioritizes past high-reward trajectories by adding them strategically to the learning process. This approach views self-imitation as an advantage-based prioritization, where the agent focuses on proven successful experiences. By emphasizing high-reward trajectories over arbitrary past transitions, the Replay strategy ensures that the agent benefits from useful past data while maintaining the stability of the on-policy learning framework. This selective sampling allows the agent to improve its policy without the risk of destabilizing updates, even in the absence of dense reward signals.

To summarize, our key contributions are as follows:

- Self-imitating on-policy algorithm: We propose Self-Imitating Proximal Policy (SIPP), a novel self-imitation learning algorithm that enhances exploration and sample efficiency in dense and sparse reward settings.
- Optimal transport-based prioritization: We introduce the Match strategy, which uses Optimal Transport (Peyré et al., 2019) and the Sinkhorn algorithm (Cuturi, 2013) to prioritize state-action transitions that closely match the state distribution of the most rewarding past episodic rollout, improving learning efficiency in dense reward environments.
- Replay strategy for sparse rewards: We develop the Replay strategy, which maintains an imitation buffer to store and replay self-encountered successful trajectories, effectively addressing the temporal credit assignment problem in sparse and binary reward environments.
- Mitigation of forgetting behavior and policy divergence: Our approach mitigates forgetting behaviors and excessive policy divergence by bootstrapping RL policy learning with past successful behaviors, stabilizing and enhancing the learning process.
- Diverse empirical validation: We validate SIPP through experiments across a wide range of environments, including complex MuJoCo (Towers et al., 2023) tasks, multi-goal PointMaze navigation (de Lazcano et al., 2023), and partially observable 3D Animal-AI Olympics (Crosby et al., 2019), demonstrating significant improvements in learning efficiency and performance over existing methods (Oh et al., 2018; Gangwani et al., 2018).

2 Related Work

Many attempts have addressed the sample efficiency and exploration problem in reinforcement learning. However, this literature has divided the long work history mainly into guided and unguided exploration.

Guided exploration paradigms aim to exploit expert trajectories to address RL agents' sample efficiency and exploration problems. Recently, in this direction, (Sontakke et al., 2024) presented an approach that uses a single demonstration and distilled knowledge contained in Video-and-Language Models (VLMs) to train a robotics policy. They use VLMs to generate rewards by comparing expert trajectories and policy rollouts. Another single demonstration guided approach was presented by (Libardi et al., 2021) for solving

three-dimensional stochastic exploration. They exploit expert trajectories and value estimate prioritized trajectories to learn optimal policy under uncertainty. Similarly, (Salimans & Chen, 2018) trained a robust policy using a single demonstration by replaying the demonstration for n steps, after which agents learned in a self-supervised manner. To make the agent robust to randomness, they monotonically decrease replay steps n. (Uchendu et al., 2023) present an expert-guided learning. They employ two policies to solve tasks: guide policy and exploration policy. The guide policy introduces a curriculum of initial states for the exploration policy, significantly easing the exploration challenge and facilitating rapid learning. As the exploration policy becomes more proficient, the reliance on the guide policy diminishes, allowing the RL policy to develop independently and continue improving autonomously. This progressive reduction in guide-policy influence enables the agent to transition to a fully autonomous exploration phase, enhancing its long-term performance and adaptability.

(Xu et al., 2023) uses expert demonstration to improve exploration in learning from demonstrations in sparse reward settings. They assign an exploration score to each demonstration and generated episode and train policy to imitate exploration behaviors. (Nair et al., 2018) design an auxiliary objective on demonstrations to solve hard exploration problems and anneal away the demonstration guidance once the policy performs better than the demonstration. (Huang et al., 2023) used a two-component approach: a novel actor-critic-based policy learning module that efficiently uses demonstration data to guide RL exploration and a non-parametric module that employs nearest-neighbor matching and locally weighted regression for robust guidance propagation at states distant from the demonstrated ones.

Unguided exploration approaches use self-experience, count-based methods, or some type of prioritized experience replay buffer to guide policy in hard exploration problems. In this literature, we focus only on approaches under the paradigm of Self-Imitation Learning (SIL) coined by (Oh et al., 2018). (Oh et al., 2018) presented an approach for self-imitation learning for off-policy algorithms. They store experiences in a replay buffer and learn to imitate state-action pairs in the replay buffer only when the return in the past episode is greater than the agent's value estimate. They also extended their approach to the on-policy algorithm. However, the proposed algorithm does not have a strong theoretical connection to the on-policy algorithms.

(Gangwani et al., 2018) introduces the Stein Variational Policy Gradient (SVPG), a self-imitating algorithm designed for on-policy reinforcement learning. In this approach, policy optimization is framed as a divergence minimization problem, where the objective is to minimize the difference between the visitation distribution of the current policy and the distribution induced by experience replay trajectories with high returns. The method incorporates an auxiliary objective that regularizes this divergence, allowing for improved exploration and more effective policy updates. However, their experiments are limited to episodic, delayed, or noisy reward settings, which may restrict the generalizability of their results to more complex environments.

(Chen & Lin, 2020) present a SIL technique for off-policy algorithms. In their approach, they provide a constant reward at each step in addition to an episodic environment reward. Further, they maintain two replay buffers, one with K highest episodic reward trajectories and the other with all agent-generated trajectories, and sample from these two replay buffers to train the policy. They limit their work to delayed episodic rewards. (Tang, 2020) presents a self-imitation learning approach for off-policy learning by extending the traditional Q-learning with a generalized n-step lower bound. They adopt SIL by leveraging trajectories where the behavior policy performs better than the current policy. (Ferret et al., 2020) proposes a self-imitating variant of DQN for dense reward environments. In this approach, they propose to adopt self-imitation using a modified reward function. They augment the true reward with a weighted advantage term, the difference between a true discounted reward and an expected future return.

(Kang & Chen, 2020) introduce the Explore-then-Exploit (EE) framework, which integrates Random Network Distillation (RND) (Burda et al., 2018) and Generative Adversarial Self-Imitation Learning (GASIL) (Guo et al., 2018). The framework tackles the exploration-exploitation trade-off by using RND to facilitate exploration and prevent the policy from stagnating at local optima. At the same time, GASIL accelerates policy convergence by leveraging past successful trajectories. Rather than directly combining these methods, which could confuse the agent, the authors propose an interleaving approach, where the agent switches between exploration and imitation based on specific criteria.

Recently, (Li et al., 2023) extended the SIL approach to Goal-Conditioned Reinforcement Learning. They achieve this by designing a target action values function that can effectively combine the training mechanism of self-initiated policy and actor policy. SILP (Luo et al., 2021) method utilizes a planning mechanism for robotic manipulation that identifies good policies from previous experiences, allowing the agent to imitate high-quality actions even when explicit demonstrations are unavailable. By incorporating planning into the SIL framework, the agent can efficiently explore and exploit past successful behaviors. The approach improves the exploration-exploitation balance and enhances learning stability.

The proposed approach aligns with unguided exploration with a focus on on-policy learning. The proposed approach uses past experiences to bootstrap policy learning, making a strong connection with the self-imitation learning paradigm.

3 Preliminaries

Markov Decision Process We formulate the problem as a Markov Decision Process (MDP) $M : \langle S, A, T, R, \gamma, S_0 \rangle$ with $S = \{s_1, ..., s_n\}$ being set of environment states, $A = \{a_1, ..., a_n\}$ being set of agents actions, $T : S \times A \to S$ is state transition function, $R : S \times A \times S \to R$ is reward function, $\gamma \in (0, 1)$ is discount factor, and S_0 is environment state at initial time $t = 0$. At each time step t, the agent observes the state of the environment s_t, samples an action a_t from action set A, and receives a reward r_t from the environment. The reinforcement learning agent is trained to maximize the expected reward collected from agent environment interaction (Sutton & Barto, 2018).

4 Method

In this work, we propose an approach that can guide an agent's exploration by combining the agent's current behavior and past successful trajectories for an on-policy RL algorithm. Unlike prior works (Oh et al., 2018; Li et al., 2023; Tang, 2020), which mostly addresses exploration and self-imitation for off-policy algorithms, we focus on on-policy algorithms. The key highlights are as follows:

- Our approach does not alter the base RL policy nor introduce new separate models requiring training, unlike prior works Gangwani et al. (2018); Kang & Chen (2020).
- Our approach does not modify the true reward, preventing any bias in learning, unlike (Chen & Lin, 2020).
- We address exploration by self-imitation for dense, sparse, and binary rewards encompassing state and pixel-based observations, unlike (Oh et al., 2018; Gangwani et al., 2018), which addressed only delayed and noisy rewards for state-based observation in an on-policy setting.

4.1 *Match*: Self-Imitating Proximal Policy

The *Match* strategy addresses the exploration for dense reward environments. The proposed approach connects with self-imitation learning by prioritizing experiences similar to the past most rewarding episodic rollout. We find the similarity or match between trajectories using optimal transport.

Optimal Transport (Cuturi, 2013; Peyré & Cuturi, 2020; Luo et al., 2023) offers a structured approach for comparing probability distributions. The squared Wasserstein distance between two discrete distributions, $\nu_x = \frac{1}{T}\sum_{t=1}^{T} \delta_{x_t}$ and $\nu_y = \frac{1}{T'}\sum_{t'=1}^{T'} \delta_{y_{t'}}$, is given by:

$$W^2(\nu_x, \nu_y) = \min_{\nu \in \zeta} \sum_{t=1}^{T} \sum_{t'=1}^{T'} c(x_t, y_{t'}) \nu_{t,t'}, \tag{1}$$

where $\zeta = \left\{ \nu \in \mathbb{R}^{T \times T'} : \nu \mathbf{1} = \frac{1}{T}\mathbf{1}, \nu^T \mathbf{1} = \frac{1}{T'}\mathbf{1} \right\}$ represents the set of coupling matrices, c is a cost function, and δ_x is the Dirac measure for x. The optimal coupling ν^* effectively matches the samples from ν_x and ν_y.

Algorithm 1 ***Match***: Self-Imitating Proximal Policy

Initialize parameters θ
Initialize $\mathcal{B}_{\mathcal{I}} \leftarrow \{\}$
Initialize rollout buffer $\mathcal{D} \leftarrow \{\}$

for every update **do**
  Collect rollouts
  Update $\mathcal{B}_{\mathcal{I}}$
  Compute advantage estimates $\hat{A}_1, \hat{A}_2, ..., \hat{A}_T$ for trajectories in $\mathcal{D}$
  for every epoch **do**
    Sample transitions from $\mathcal{D}$ uniformly or weighted by Equation 3, controlled by IET (ϵ)
    Optimize L^{PPO} w.r.t. θ: $\theta \leftarrow \theta - \eta \nabla_\theta L^{PPO}$; where η is learning rate
  end for
  Empty rollout buffer $\mathcal{D} \leftarrow \{\}$
end for

Unlike measures such as the KL-divergence (Kullback & Leibler, 1951), the Wasserstein distance is a metric that considers the space's geometry.

Consider $\hat{q}_e = \frac{1}{T'} \sum_{t'=1}^{T'} \delta_{s_t^e}$ and $\hat{q}_\pi = \frac{1}{T} \sum_{t=1}^{T} \delta_{s_t^\pi}$ which represent the empirical state distributions of an expert policy π_e and a behavior policy π, respectively. The squared Wasserstein distance between the expert and behavior policies is then given by:

$$W^2(\hat{q}_\pi, \hat{q}_e) = \min_{\nu \in \zeta} \sum_{t=1}^{T} \sum_{t'=1}^{T'} c(s_t^\pi, s_{t'}^e) \nu_{t,t'} \tag{2}$$

Let ν^* denote the optimal coupling for this problem. The distance between each state can then be calculated as:

$$d_{OT}(s_t^\pi) = -\sum_{t'=1}^{T'} c(s_t^\pi, s_{t'}^e) \nu_{t,t'}^*, \tag{3}$$

The proposed approach does not rely explicitly on expert policy π_e. Instead, we adopt a more flexible framework by considering the distribution of the best episodic rollout generated by the behavior policy π as the surrogate expert policy. This removes the dependency on external expert trajectories and leverages the agent's high-performing experiences. We achieve this by maintaining an imitation buffer $\mathcal{B}_{\mathcal{I}}$, which dynamically stores the most rewarding episodic rollout encountered by the behavior policy. The state visitation distribution of the trajectory stored in $\mathcal{B}_{\mathcal{I}}$ serves as the expert distribution. This design ensures that the imitation buffer evolves continuously as the agent discovers better-performing trajectories, thus adapting the surrogate expert distribution over time.

Building on this, we compute the Wasserstein distance (Equation 3) between the state visitation distribution in the imitation buffer $\mathcal{B}_{\mathcal{I}}$ and the current state visitation distribution generated by the behavior policy. This distance measures alignment, quantifying how closely the agent's trajectory matches its past successful experiences. Using this metric, each transition in the rollout buffer $\mathcal{D}$ is assigned a sampling priority proportional to the computed distance. Transitions that are more similar to those in $\mathcal{B}_{\mathcal{I}}$ are given higher priority, effectively guiding the agent toward replicating its best-performing behaviors.

The effective balance between exploration (sampling diverse transitions) and exploitation (focusing on high-priority transitions) is governed by the hyperparameter Imitation-Exploration Trade-off (IET) coefficient ϵ. IET coefficient controls the probability of sampling transition for policy updates from rollout buffer $\mathcal{D}$ either uniformly or with a probability governed by Equation 3. This prioritization framework enhances sample efficiency and ensures that the agent's learning process is bootstrapped by past successful experiences,

Algorithm 2 ***Replay***: Self-Imitating Proximal Policy

Initialize parameters θ
Initialize $\mathcal{B}_{\mathcal{I}} \leftarrow \{\}$
Initialize rollout buffer $\mathcal{D} \leftarrow \{\}$

for every update **do**
  Sample τ from $\{\mathcal{B}_{\mathcal{I}}$,Env$\}$ controlled by IET (ϵ)
  if $\tau \in \mathcal{B}_{\mathcal{I}}$ **then**
    Replay a trajectory from $\mathcal{B}_{\mathcal{I}}$ and store transition in $\mathcal{D}$
  else if $\tau \in$ Env **then**
    Execute current policy and store transition in $\mathcal{D}$
  end if
  Compute advantage estimates $\hat{A}_1, \hat{A}_2, ..., \hat{A}_T$
  for trajectories in $\mathcal{D}$
  Optimize L^{PPO} wrt θ for K epoch $\theta \leftarrow \theta - \eta \nabla_\theta L^{PPO}$; where η is learning rate
  Update $\mathcal{B}_{\mathcal{I}}$
  Empty rollout buffer $\mathcal{D} \leftarrow \{\}$
end for

eliminating the need for external supervision. Algorithm 1 provides a detailed overview of the optimal transport-based trajectory-matching strategy.

4.2 *Replay*: Self-Imitating Proximal Policy

This section addresses the exploration challenge for sparse reward settings using self-imitation. Sparse reward environments often present significant challenges for learning agents due to the limited availability of positive feedback. To mitigate this challenge, we propose the *Replay* strategy, a variant of the *Match* strategy, tailored specifically for sparse reward scenarios. Unlike *Match*, which uses past trajectories to generate preferences for current trajectories, the *Replay* strategy focuses on directly replaying successful past behaviors. In this context, "replay" refers to including trajectories stored in the imitation buffer $\mathcal{B}_{\mathcal{I}}$ into the rollout buffer $\mathcal{D}$ and treating them as potential behaviors generated under the current policy. This ensures that the agent strategically encounters successful trajectories at each policy update to guide policy learning, even in sparse reward environments where most interactions yield little to no reward.

Replay strategy maintains an imitation buffer $\mathcal{B}_{\mathcal{I}}$ to store past successful trajectories. The imitation buffer is initialized as empty, and as the agent interacts with the environment, trajectories are added to $\mathcal{B}_{\mathcal{I}}$ based on the return for sparse reward and the FIFO strategy for binary reward environments, respectively. Each trajectory in $\mathcal{B}_{\mathcal{I}}$ is represented as $\tau = (s_0, a_0, s_1, a_1, ...)$, where policy $\pi_{\mathcal{I}}$ associated with the imitation buffer maps observations from the imitation buffer to the corresponding actions in the stored successful trajectories with a probability of one while assigning zero probability to all other actions. The policy $\pi_{\mathcal{I}}$ is used to replay trajectories from $\mathcal{B}_{\mathcal{I}}$, integrating them into the rollout buffer $\mathcal{D}$.

At each policy update epoch, trajectories are sampled from $\mathcal{B}_{\mathcal{I}}$ with probability ϵ, or generated by current policy with probability $1-\epsilon$. These trajectories are then added to the rollout buffer $\mathcal{D}$ from which transitions are sampled to update policy. This trajectory sampling mechanism ensures a balance between exploration and exploitation. The IET coefficient ϵ plays a crucial role in tuning this balance. A higher value of ϵ emphasizes exploitation by prioritizing trajectory sampling from $\mathcal{B}_{\mathcal{I}}$, while a lower value encourages exploration by focusing on trajectories generated from the agent's most recent interactions.

The presented *Replay* strategy, hence, offers a robust framework for addressing sparse and binary reward challenges by ensuring that successful behaviors are continually reinforced in policy learning. This selective reuse of high-value trajectories enhances sample efficiency and mitigates the risk of the agent getting stuck in unproductive exploration loops.

With this explicit focus on replaying successful past behaviors, the *Replay* strategy aligns with the principles of self-imitation learning while addressing the unique challenges posed by sparse reward environments.

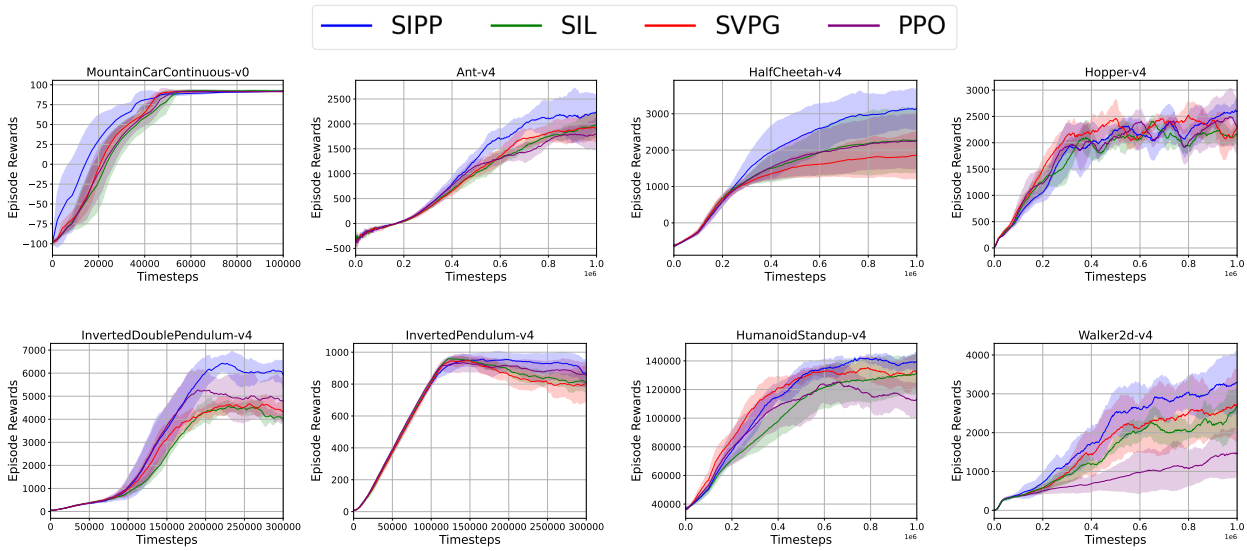


Figure 1: Results show the performance of 8 MuJoCo (Towers et al., 2023) continuous control tasks (refer to Figure 7 for results on all tasks). The plots are the learning curves and show the episodic rewards along the y-axis evaluated through current policy. The reported results are mean across 5 different seeds with shaded regions highlighting standard deviation. The proposed algorithms outperform all baselines across all tasks by being competitive or better than others.

Algorithm 2 provides a detailed outline of implementing this strategy, highlighting its integration into the policy optimization process.

5 Experiments

In this section, we aim to answer the following questions:

- Does bootstrapping policy learning, with its few past experiences, enhance sample efficiency and hard exploration across diverse tasks?
- Can a single past successful behavior be sufficient to guide policy learning in complex sequential continuous control tasks?
- Is replaying past successful trajectories sufficient for policy learning in multi-goal and partially observable sparse reward settings?

5.1 Implementation Details

For dense reward environments in MuJoCo (Towers et al., 2023), we implement the *Match* strategy. The network architecture utilizes a multi-layer perceptron (MLP) with two hidden layers containing 64 units and *tanh* as the activation function. The PPO policy is updated over 10 epochs per training iteration. Training batches are sampled uniformly or with priority based on the optimal transport distance between the current trajectories and past best episodic rollouts, controlled by the Imitation-Exploration Trade-off coefficient ϵ during each epoch. The imitation buffer is initiated with size 1. Further details about the hyperparameters and implementation can be found in the supplementary material Table 1.

For sparse reward settings, such as the multi-goal PointMaze (de Lazcano et al., 2023) navigation tasks, we adopt the *Replay* strategy. This setup shares the same MLP-based architecture used in MuJoCo environments. Similarly, for the Animal-AI Olympics (Crosby et al., 2019), a partially observable 3D environment

with binary rewards, we apply the *Replay* strategy but with a different architecture: a three-layer convolutional neural network (CNN). The input comprises the last four stacked frames (84×84 RGB pixels). In both PointMaze and Animal-AI tasks, the rollout buffer is populated with trajectories sampled either from the current policy with probability $1 - \epsilon$ or from the imitation buffer $\mathcal{B}_{\mathcal{I}}$ with probability ϵ. The imitation buffer is initialized with size 10. Comprehensive details of the hyperparameters for all environments are provided in the supplementary material Table 2.

5.2 Choice of Baselines:

Self-imitation learning (SIL) has been mainly explored to enhance exploration in off-policy reinforcement learning (RL) algorithms with a limited focus on on-policy RL algorithms. Further, recent works Luo & Schomaker (2023); Xiao et al. (2024); Shi et al. (2023) predominantly focus on problem-specific adoption of SIL rather than advancing SIL from a broader algorithmic perspective. Notably, there remains a limited analysis of SIL's potential in the context of on-policy RL algorithms to solve diverse problem settings, leaving a significant gap in understanding its general applicability. This limits the choice of baseline in the context of our problem.

PPO: PPO is vanilla proximal policy algorithm (Schulman et al., 2017), which does not impose any self-imitation learning paradigm.

SIL-PPO: SIL (Oh et al., 2018) is an off-policy RL algorithm that imitates past state-action pairs that have higher returns than agent value estimates. The proposed approach was also extended to the on-policy PPO (Schulman et al., 2017) algorithm with a focus on dense or delayed rewards. Further, as highlighted by (Oh et al., 2018), SIL lacks a theoretical connection with on-policy algorithms.

SVPG-PPO: SVPG (Gangwani et al., 2018) is another self-imitating on-policy algorithm. They use an auxiliary objective with the RL policy objective. The auxiliary term is a divergence minimization regularizer between current policy visitation and distribution induced by experience replay trajectories with high returns with a focus on dense, delayed, or noisy rewards only.

5.3 Performance of *Match* on Continuous Control Tasks

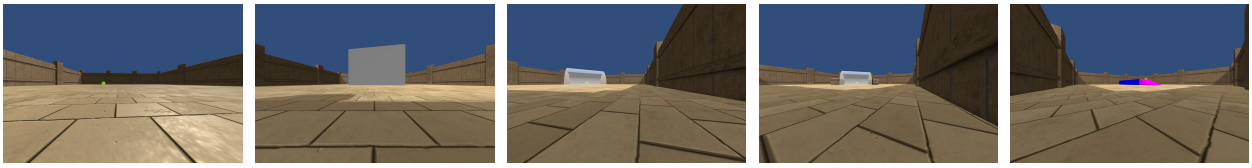
In this section, we investigate the effect of self-imitation on continuous control tasks with dense rewards. We evaluate the performance of our *SIPP-Match* strategy on 10 MuJoCo (Towers et al., 2023) tasks with chosen baselines.

Compared with all the baselines, the performance of the *Match* strategy on continuous control tasks is shown in Figure 1. The proposed *Match* algorithm outperforms PPO (Schulman et al., 2017) and SIL-PPO across all the tasks except SIL-PPO outperforming on Humanoid-v4 task, with SVPG+PPO lagging in most tasks except having competitive performance on Hopper-v4 and Humanoid-v4 tasks.

In MuJoCo benchmark environments, the agent benefits from continuous feedback via a smooth and dense reward structure, facilitating faster exploration and learning. Despite this, our experiments demonstrate that the optimal transport distance prioritized self-bootstrapping can further enhance exploration for the proximal policy. By prioritizing the most informative experiences, our method ensures that the agent focuses on high-value learning opportunities, accelerating convergence and improving policy robustness.

Additionally, the proposed approach stores only the states visited by the most rewarding past episodic rollout, making it straightforward compared to prior methods. Unlike our approach, (Oh et al., 2018) compares returns of past experiences with agent value estimates to select experiences for self-imitation, which can be noisy and introduce bias in policy learning (Libardi et al., 2021; Raileanu & Fergus, 2021). Furthermore, (Gangwani et al., 2018) uses KL-divergence as a regularizer to minimize divergence between state-action visitation distributions of the current policy and past rewarding experiences. However, their approach introduces bias in policy learning, which they address by simultaneously learning multiple diverse policies.

In summary, the proposed *Match* algorithm integrates seamlessly with PPO without introducing additional learning parameters and requires only one trajectory to guide self-imitation learning. It introduces a single hyperparameter IET coefficient (ϵ) to control whether training batches are uniformly sampled or priori-



(a) Goal (b) Goal-behind wall (c) Goal-tunnel (d) Goal-occluded tunnel (e) Goal-on wall

Figure 2: All tasks feature one goal and one agent. The positions of the agent and goal are selected randomly at the start of each episode from a predefined set of fixed initial positions. Each episode initializes the environment by sampling these positions, ensuring variability while maintaining a structured distribution. There is only one source of reward per environment, i.e., a binary reward is provided for reaching the goal. The agent observes the arena through a first-person view with partial visibility, reflecting the limitations of a partially observable environment.

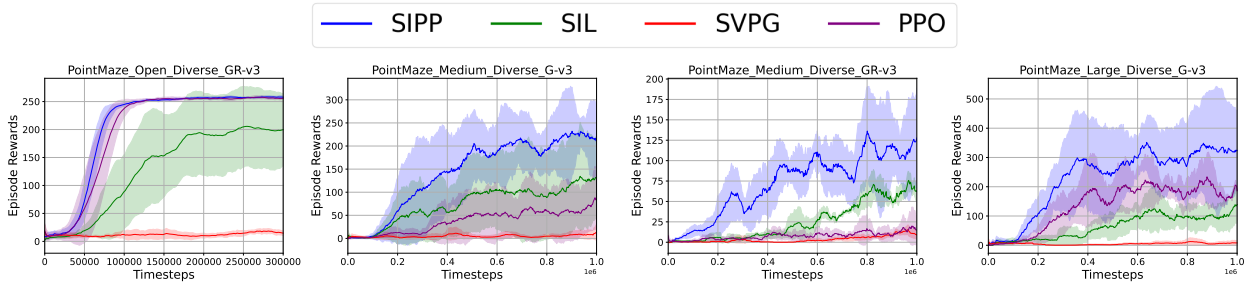


Figure 3: Results show the performance on 4 PointMaze (de Lazcano et al., 2023) multi-goal sparse reward tasks (refer to Figure 8 for results on all tasks). The plots are the learning curves and show the episodic rewards along the y-axis evaluated through current policy. The reported results are mean across 5 different seeds. The proposed algorithms outperform all the baselines by a significant margin.

tized using optimal transport distance based on past successful episodic rollouts. The single hyperparameter provides a simple mechanism to balance exploration and exploitation. This approach offers a practical and efficient solution to enhance reinforcement learning performance in complex environments.

5.4 Performance of *Replay* in Sparse Reward Tasks

In this section, we empirically evaluate self-imitation performance in sparse and binary reward settings. We believe that self-imitation can play a crucial role in such reward settings, as the ability of an agent to reach some success can be extremely difficult with sparse rewards. The previous works were limited to MuJoCo environments with dense or delayed rewards. Motivated by this, we evaluate the performance of *SIPP-Replay* on a diverse set of tasks, including multi-goal gymnasium-robotics PointMaze navigation sparse reward environments (de Lazcano et al., 2023) and partially observable 3-dimensional Animal-AI Olympics (Crosby et al., 2019) binary reward environments.

5.4.1 Task Definitions:

The PointMaze environment is a 2-dimensional maze. We use two variants of the PointMaze environment. First, with fixed agent position and varying goal position, i.e., the goal position is reinitialized at each episode. Second, both the goal and agent positions are reinitialized after every reset.

The Animal-AI Olympics (Crosby et al., 2019) is a partially observable 3-dimensional environment where an agent can navigate freely inside an arena. We design a total of 5 experiments. Each experiment has a different level of complexity based on the type of obstacles present in the arena. The descriptions of playgrounds are as follows :

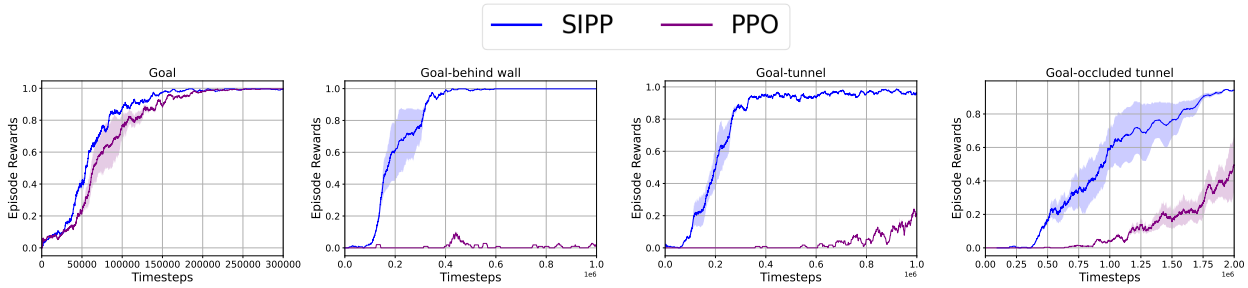


Figure 4: Results show the performance on 4 Animal-AI Olympics environment (Crosby et al., 2019) binary reward tasks (refer to Figure 9 for results on all tasks). The plots are the learning curves and show the episodic rewards (success rate) along the y-axis evaluated through current policy. The reported results are mean across 5 different seeds with shaded regions highlighting standard deviation across seeds. The proposed algorithms outperform PPO by a significant margin.

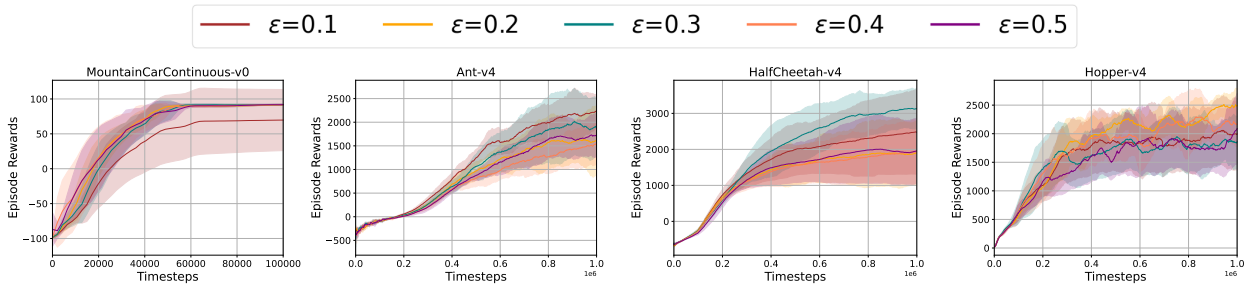


Figure 5: Results show the ablation study on 4 MuJoCo (Towers et al., 2023) continuous control tasks (refer to Figure 10 for complete results). The parameter ϵ controls the degree of exploration vs exploitation. The plots are the learning curves and show the episodic rewards along the y-axis evaluated through current policy with different ϵ. The reported results are mean across 5 different seeds with shaded regions highlighting standard deviation across seeds.

- **Goal:** In this arena the agent has to reach the goal position. The agent and goal can be anywhere in the arena. There are no obstacles in the arena.
- **Goal-behind wall**: The goal is hidden behind a wall in this arena. The agent and goal position are different in each configuration. The agent needs to learn to find the goal, which is hidden behind the wall.
- **Goal-tunnel**: This arena has a transparent tunnel that is open from both ends. The agent can not penetrate the tunnel walls and must enter the tunnel to find the goal.
- **Goal-occluded tunnel:** This arena is identical to the previous one, except the tunnel entrances are occluded with movable boxes. The agent must learn to move the boxes to find the goal inside the tunnel.
- **Goal-on wall:** In this arena we place the goal on an L-shape wall. The agent must learn to find a ramp to climb on the wall and avoid falling off the wall to reach the goal.

5.4.2 Empirical Analysis:

The performance of *SIPP-Replay* is shown in Figures 3 and 4. The choice of baselines for the PointMaze environment is consistent with the MuJoCo tasks, as both involve fully observable MDPs. However, for the Animal-AI Olympics task, the choice of baselines is restricted to PPO. This limitation arises because the official implementations of baselines, SIL and SVPG, are tailored specifically to fully observable environments like MuJoCo and do not extend support to the Animal-AI Olympics. Further, Baselines SIL and SVPG rely

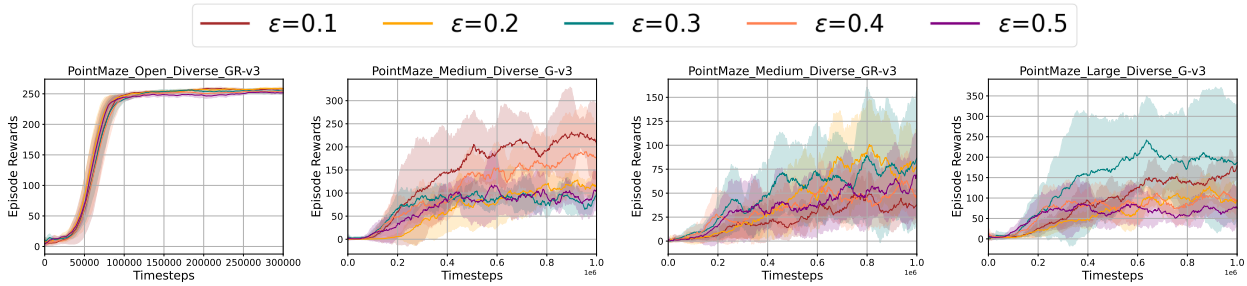


Figure 6: Results show the ablation study on 4 PointMaze (de Lazcano et al., 2023) multi-goal sparse reward tasks (refer to Figure 11 for complete results). The parameter ϵ controls the replay frequency to balance exploration vs exploitation. The plots are the learning curves and show the episodic rewards along the y-axis evaluated through current policy with different ϵ. The reported results are across 5 different seeds.

on state visitation distributions to design self-imitation mechanisms. Under partial observability, these state visitation measures lose relevance as the agent only has access to partial observations of the environment. Consequently, their performance would degrade significantly, making comparisons with them unfair. This also highlights the border applicability of our approach, which does not make any underlying assumption about the environment. Our is the first approach that has used self-imitation in such a diverse scenario.

The performance of our proposed algorithm exceeds all the baselines on the Maze navigation task, as shown in Figure 3. We believe that under sparse reward conditions, the credit assignment problem plays a crucial role, and we tackle this by replaying past trajectories. Unlike baseline methods, which prioritize state-action pairs, SIPP focuses on episodic trajectory-level prioritization rather than state visitation distributions. This helps the agent to understand which actions contribute to future rewards. To incorporate successful trajectories in the replay buffer, we consider it as the possible behavior of the agent in the current environment. The *Replay* strategy results in even superior performance, Figure 4, for partially observable environments due to its inherent design capability to adapt to partial observability. The results show that PPO agents encounter some success but fail to learn due to forgetting behaviors. However, the proposed *Replay* strategy stores those behaviors and keeps replaying them. This addresses the forgetting behaviors, and the agent eventually learns to mimic those successful behaviors.

To summarize, it is evident from the results that self-imitation can help agents learn in both dense or sparse reward settings. In a dense reward setting, prioritizing state visitation that matches the past successful state is sufficient, as a dense reward structure can guide the agent to learn the long-term consequences of actions taken in those states. However, a more exploitative strategy is required in sparse reward settings, such as replaying past successful episodic trajectories.

5.5 Tuning Self-Imitation vs. Exploration

The proposed strategy uses the exploitation of the agent's past behaviors. However, it is crucial to explore for the agent to learn an optimal policy. This balance between exploitation and exploration in SIPP is achieved through the Imitation-Exploration Trade-off (IET) coefficient ϵ. In *SIPP-Match* this parameter indicates the probability of sampling training batches uniformly or with a priority proportional to the optimal transport distance with the most successful past trajectory. In *SIPP-Replay* this parameter controls the trajectory replay probability from the imitation buffer $\mathcal{B}_{\mathcal{I}}$.

The effect of IET for *SIPP-Match* strategy is shown in Figure 5. The ablation study shows maximum performance improvement for $\epsilon = 0.1, 0.2$ or 0.3 across all tasks. This highlights the importance of exploration as a more greedy imitation results in sub-optimal performance. However, for simpler tasks such as MountainCarContinuous, the performance is mostly similar as these simpler environments require less exploration and even an aggressive imitation strategy results in similar performance.

A similar analysis was performed to find the balance between the exploration and exploitation trade-off of the PointMaze navigation environments. The results of this ablation study are shown in Figure 6. We didn't perform a similar analysis of the Animal-AI Olympics environment. However, the IET coefficient for the Animal-AI Olympics environment was kept $\epsilon = 0.3$ based on the insights from the above ablation studies.

6 Conclusion

This paper proposed a self-imitating proximal policy framework to address exploration and credit assignment challenges in dense and sparse reward environments. Through extensive experimentation, we demonstrated that bootstrapping policy learning with past rewarding experiences effectively mitigates forgetting behavior and reduces policy divergence, leading to enhanced exploration and stability. The simplicity and efficacy of the proposed algorithm highlight its versatility across different problem settings. Furthermore, we showed that self-imitation and exploration are inherently complementary, enabling agents to leverage prior successes for guided learning. Our results suggest dynamically integrating self-imitation with adaptive exploration strategies can provide a promising avenue for future research. Extending the proposed framework to more complex tasks, including partially observable and multi-agent settings, could unlock further potential and establish broader applicability across reinforcement learning domains.

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A Appendix

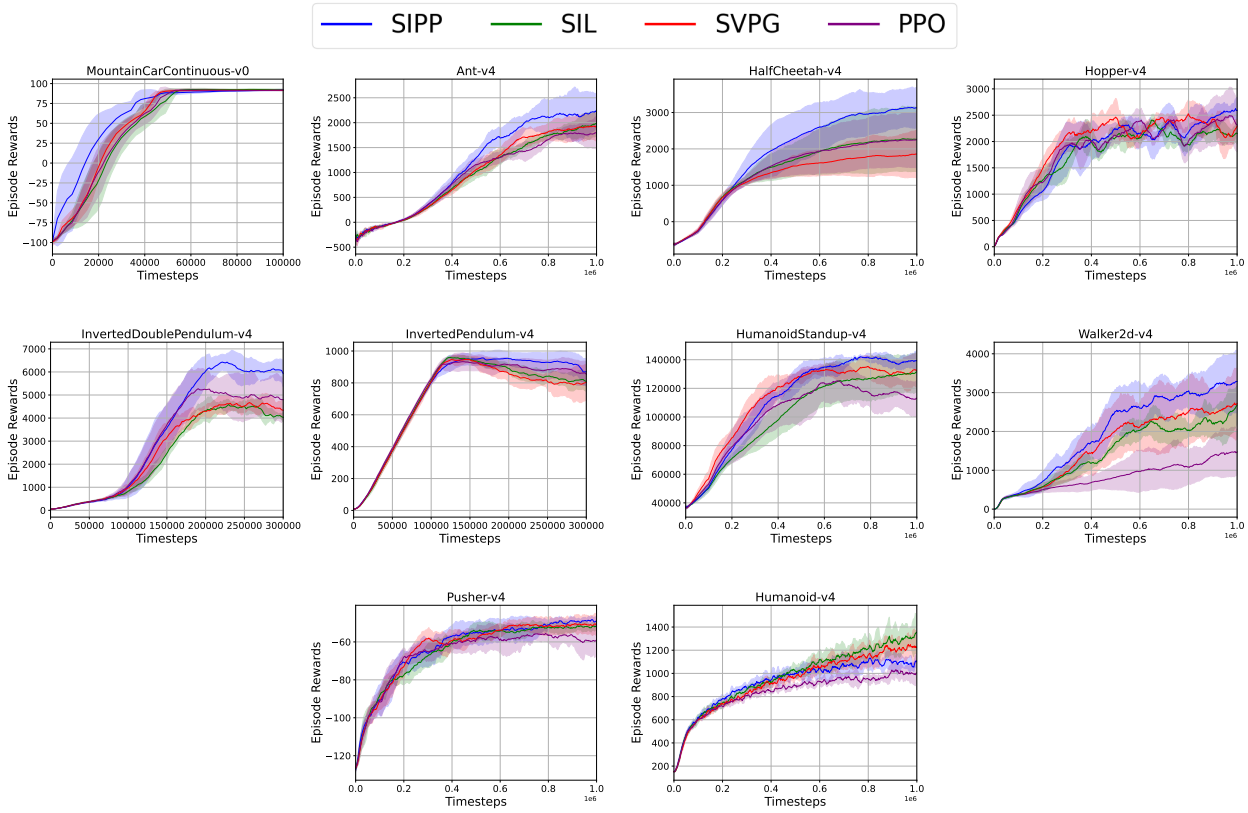

Figure 7: Results show the performance of 10 MuJoCo (Towers et al., 2023) continuous control tasks. The plots are the learning curves and show the episodic rewards along the y-axis evaluated through current policy. The reported results are mean across five different seeds. The proposed algorithms outperform all baselines across all tasks by being competitive or better than others.

Table 1: Parameters For Animal-AI Olympics Environment

Parameter	Values
episode length	1000
image size (RGB)	$84 \times 84 \times 3$
initial reward threshold	0
frame-skip	2
frame-stack	4
discount factor (λ)	0.99
gae-gamma (γ)	0.95
value loss coefficient (c_1)	0.1
entropy loss coefficient (c_2)	0.02
learning rate	10^{-4}
ppo-epoch	4
number-mini-batch	7
value-clip	0.15
policy-clip	0.15
buffer size ($\mathcal{B}_{\mathcal{I}}$)	10

Table 2: PPO Hyper-parameters

Parameter	Values
learning rate	$3e^{-4}$
n-steps	2048
batch size	64
n-epochs	10
discount factor	0.99
gae-gamma	0.95
clip-range	0.2
normalize advantage	True
vf-coef	0.5
max-grad-norm	0.5

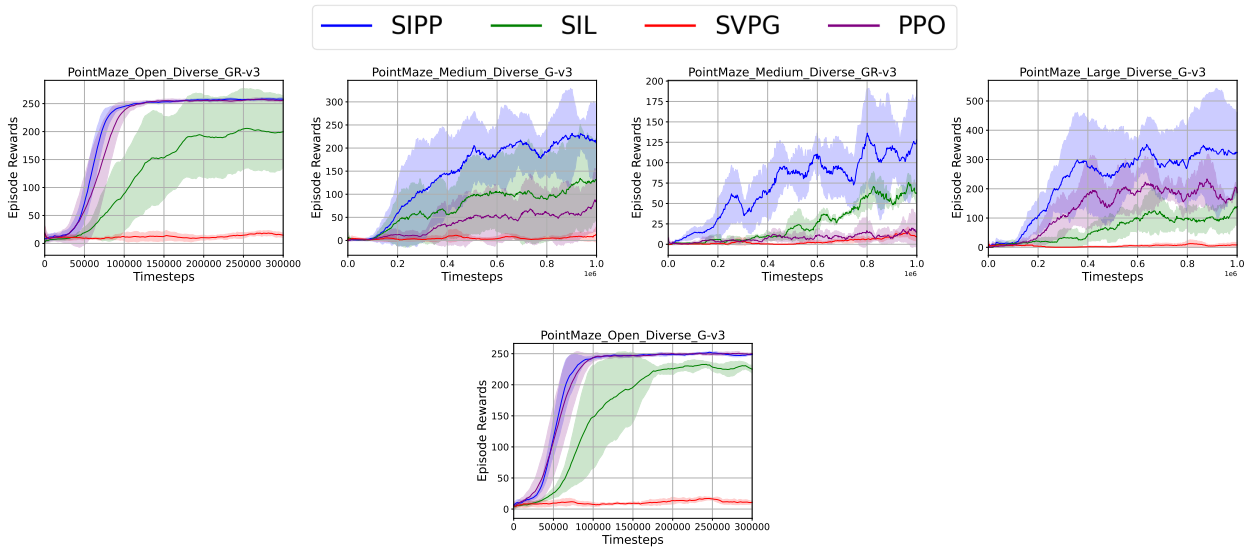

Figure 8: Results show the performance on all 5 PointMaze multi-goal sparse reward tasks. The plots are the learning curves and show the episodic rewards along the y-axis evaluated through current policy. The reported results are across five different seeds. The proposed algorithms outperform all the baselines by a significant margin.

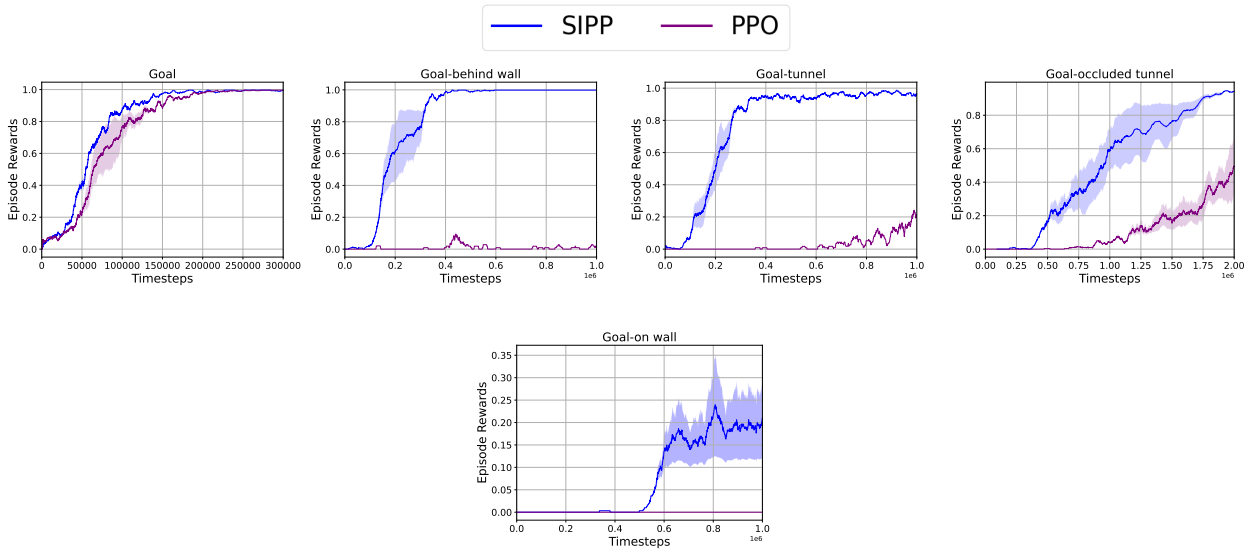

Figure 9: Results show the performance on all 5 Animal-AI Olympics environment sparse reward tasks. The plots are the learning curves and show the episodic rewards (success rate) along the y-axis evaluated through current policy. The reported results are across 5 different seeds. The proposed algorithms outperform all the baselines by a significant margin.

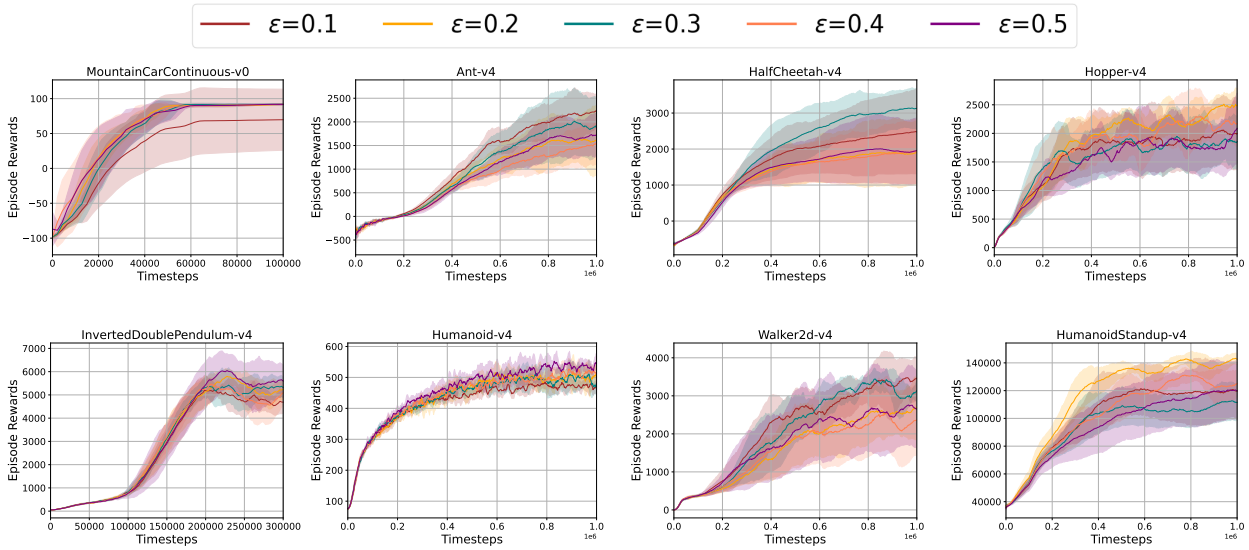

Figure 10: Results show the ablation study on 8 MuJoCo (Towers et al., 2023) continuous control tasks. The parameter ϵ controls the degree of exploration vs exploitation. The plots are the learning curves and show the episodic rewards along the y-axis evaluated through current policy with different ϵ. The reported results are mean across five different seeds.

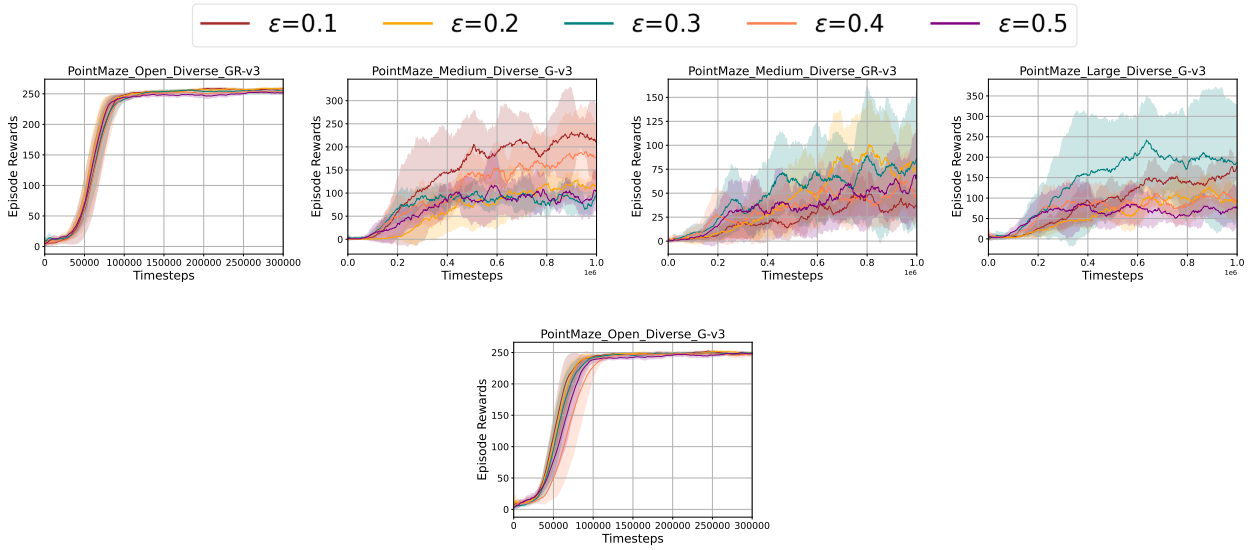

Figure 11: Results show the ablation study on all 5 PointMaze multi-goal sparse reward task . The parameter ϵ controls the replay frequency to balance exploration vs exploitation. The plots are the learning curves and show the episodic rewards along the y-axis evaluated through current policy with different ϵ. The reported results are across five different seeds.