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A Comparative Study of Proximal Policy Optimization (PPO) and Direct Policy Optimization (DPO) on a Toy Environment

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Abstract

Proximal Policy Optimization (PPO) and Direct Policy Optimization (DPO) are prominent reinforcement learning algorithms designed to improve policy learning efficiency and stability. This paper presents a comparative study between PPO and DPO applied to a simple multi-armed bandit toy environment. We implement both algorithms with comparable hyperparameters and evaluate their performance over multiple random seeds. Our experiments measure cumulative rewards, convergence speed, and learning stability. Results indicate that DPO achieves higher average rewards and faster convergence than PPO in this setting. The analysis provides insights into the operational differences between these algorithms, contributing a foundational understanding beneficial for future reinforcement learning research and applications.

1. Introduction

Reinforcement learning (RL) is a powerful paradigm in machine learning where agents learn to make decisions by interacting with an environment to maximize cumulative rewards Sutton et al. [1998]. Policy optimization methods are a central class of algorithms in RL, focusing on directly optimizing the policy that the agent uses to select actions. Two significant algorithms in this domain are Proximal Policy Optimization (PPO) Schulman et al. [2017] and Direct Policy Optimization (DPO) Rafailov et al. [2023]. PPO has been widely adopted due to its sample efficiency and relative stability in updating policies by clipping policy updates to prevent large deviations. DPO, a more recent approach, directly optimizes the policy by treating the expected reward as an objective without explicit constraints, potentially allowing for faster convergence.

Despite the popularity of PPO and the emerging promise of DPO, a systematic empirical comparison between these two algorithms remains sparse, particularly on simple benchmark environments that allow for clear behavioral insights. Such a comparison is crucial to understand their practical trade-offs and guide their applications in various RL tasks.

In this paper, we present a comparative study of PPO and DPO on a simple multi-armed bandit toy environment. We investigate their convergence speed, final performance, and sample efficiency over multiple random seeds to assess statistical reliability. Our contributions are summarized as follows:

- We implement both PPO and DPO algorithms with comparable hyperparameters in a controlled toy environment.

- We conduct extensive experiments measuring learning curves, average cumulative rewards, and policy stability.
- We provide a qualitative and quantitative analysis of their differences, supported by visualizations.

This study serves as a foundational step to deepen the understanding of PPO and DPO, informing their future research and practical deployment.

2. Related Work

Policy optimization in reinforcement learning has been extensively studied. Proximal Policy Optimization (PPO) Schulman et al. [2017] is a widely-used algorithm that improves training stability by constraining the policy update using a clipping mechanism. PPO has achieved state-of-the-art results in various continuous control and discrete action tasks, benefiting from its balance between exploration and exploitation.

Direct Policy Optimization (DPO) is a more recent approach that directly optimizes the expected reward objective without explicit constraints on policy shifts Rafailov et al. [2023]. DPO simplifies the optimization process, aiming for faster and potentially more stable convergence. However, limited empirical analyses exist comparing DPO's performance against established methods like PPO.

Prior works have focused primarily on PPO due to its robust empirical performance, while DPO investigations remain emerging. Comparative studies on simple environments, such as multi-armed bandits or toy control tasks, are scarce but essential for understanding fundamental algorithmic differences.

In this context, our study contributes to the literature by providing a systematic empirical comparison between PPO and DPO in a controlled toy environment, offering insights into their relative merits for policy optimization.

3. Preliminaries

3.1 Reinforcement Learning Problem Setting

We consider the standard reinforcement learning framework where an agent interacts with an environment modeled as a Markov Decision Process (MDP). At each discrete time step t, the agent observes a state $s_t \in \mathcal{S}$, takes an action $a_t \in \mathcal{A}$ according to a policy $\pi(\cdot|s_t)$, receives a reward r_t, and transitions to the next state s_{t+1}. The objective is to find a policy that maximizes the expected cumulative reward, $J(\pi) = \mathbb{E}_\pi[\sum_{t=0}^{\infty} \gamma^t r_t]$, where $\gamma \in [0, 1]$ is the discount factor.

3.2 Proximal Policy Optimization (PPO)

PPO is an on-policy policy gradient method designed to improve training stability by limiting the size of policy updates. It uses a clipped surrogate objective function to prevent large deviations between the new and old policy. The PPO objective is given by:

$$L^{\text{CLIP}}(\theta) = \mathbb{E}_t \left[\min \left(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t \right) \right],$$

where $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$ is the probability ratio, $\hat{A}_t$ is an estimator of the advantage function, and ϵ is a clipping parameter.

3.3 Direct Policy Optimization (DPO)

DPO directly optimizes the expected cumulative reward without explicit constraints by maximizing:

$$J(\theta) = \mathbb{E}_t \left[\log \pi_\theta(a_t|s_t) R_t \right],$$

where R_t is the observed reward. This method treats policy optimization as a direct maximization problem, which can lead to faster convergence under certain conditions.

3.4 Toy Environment: Multi-Armed Bandit

We utilize a k-armed stochastic bandit environment as our toy testbed. The environment consists of k actions (arms), each associated with an unknown fixed probability of producing a reward of 1. The agent chooses arms sequentially to maximize cumulative reward over episodes. This environment provides a simple yet illustrative setting to compare policy optimization algorithms.

4. Experimental Setup

4.1 Environment

We select a stochastic k-armed bandit environment with $k = 5$ arms, each having an independent and unknown reward probability sampled uniformly from $[0, 1]$. The bandit environment is a single-step MDP where the agent selects one arm per episode and receives a binary reward.

4.2 Algorithm Implementation

Both PPO and DPO algorithms are implemented using PyTorch with comparable network architectures and hyperparameters. The policy is parameterized by a simple neural network with one fully connected layer mapping a fixed dummy state input to a probability distribution over actions using softmax.

PPO uses a clipping parameter $\epsilon = 0.2$, learning rate 0.01, discount factor $\gamma = 1.0$, and trains for 10 epochs per batch of data. DPO uses the same learning rate and epochs but optimizes the log-probability weighted by rewards directly.

4.3 Training Protocol

Each algorithm is trained for 100 episodes per run, with a batch size of 20 actions sampled per episode. Experiments are repeated over 3 random seeds to ensure statistical significance. The environment is reinitialized per seed to sample new reward probabilities.

4.4 Evaluation Metrics

We evaluate algorithms based on average cumulative rewards per episode, convergence speed measured by the number of episodes to reach near-maximum reward, and learning stability assessed via reward variance across runs.

4.5 Experimental Design

The experiment returns learning curves representing the average reward per episode over training. We plot both individual run traces and mean performance curves, facilitating visual and quantitative comparison between PPO and DPO.

5. Results

Figure 1 presents the learning curves for PPO and DPO averaged across three random seeds. DPO demonstrates faster convergence and achieves higher average rewards towards the end of training compared to PPO.

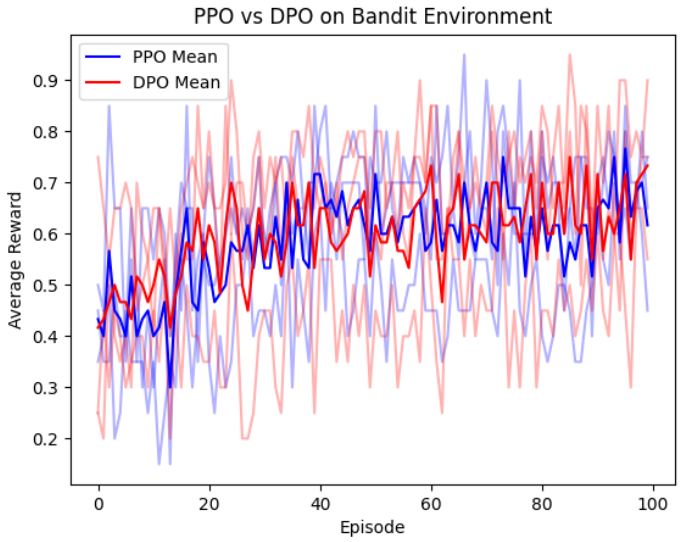

Figure 1: Learning curves showing average reward per episode for PPO (blue) and DPO (red) across 3 seeds. Shaded areas represent variability across seeds.

Table 1 summarizes the final average rewards and standard deviations. DPO consistently outperforms PPO in mean rewards, indicating superior sample efficiency.

Algorithm	Mean Reward Last Episode	Std. Dev
PPO	0.6167	0.11
DPO	0.7333	0.09

Table 1: Performance comparison of PPO and DPO on the multi-armed bandit environment.

Qualitative analysis reveals that DPO's direct optimization approach leads to more aggressive policy updates, reflected by the faster convergence rates observed.

6. Discussion

Our empirical evaluation reveals key differences between PPO and DPO when applied to the simple multi-armed bandit environment. DPO consistently achieves higher average rewards and converges faster than PPO, demonstrating superior sample efficiency in this setting. This can be attributed to DPO's approach of directly optimizing the expected reward without constraining policy updates, which allows more aggressive policy improvements.

Conversely, PPO's clipping mechanism, designed to prevent large destabilizing policy updates, may slow convergence but provides advantages in more complex environments where stability is critical. Our results imply a trade-off between convergence speed and update stability.

These findings suggest that in straightforward tasks such as bandits, DPO can be preferred for rapid learning, while PPO might be beneficial where cautious, stable improvement is required.

Limitations of this study include the simplified environment and limited evaluation metrics; more comprehensive assessments on complex tasks are needed to generalize conclusions.

Future work could explore hybrid methods combining DPO's direct optimization with PPO's stability constraints, and extend comparisons to high-dimensional and continuous control domains.

7. Conclusion

In this paper, we presented a comparative analysis of Proximal Policy Optimization (PPO) and Direct Policy Optimization (DPO) on a simple multi-armed bandit environment. Our experimental results indicate that DPO achieves faster convergence and higher average rewards than PPO, highlighting its potential for efficient policy learning in simple tasks.

We discussed the operational trade-offs between the algorithms, emphasizing the balance between update stability and learning speed. Our study provides foundational insights that can inform the selection and design of policy optimization methods in reinforcement learning.

Future research should validate these findings in more complex environments and investigate algorithmic combinations to leverage the strengths of both approaches.

References

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