Boosting Robustness in Preference-Based Reinforcement Learning with Dynamic Sparsity

Extended Abstract

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ABSTRACT

To integrate into human-centered environments, autonomous agents must learn from and adapt to humans in their native settings. Preference-based reinforcement learning (PbRL) can enable this by learning reward functions from human preferences. However, humans live in a world full of diverse information, most of which is irrelevant to completing any particular task. It then becomes essential that agents learn to focus on the subset of task-relevant state features. To that end, this work proposes R2N (Robust-to-Noise), the first PbRL algorithm that leverages principles of dynamic sparse training to learn robust reward models that can focus on task-relevant features. In experiments with a simulated teacher, we demonstrate that R2N can adapt the sparse connectivity of its neural networks to focus on task-relevant features, enabling R2N to significantly outperform several sparse training and PbRL algorithms across simulated robotic environments.

KEYWORDS

Reinforcement learning; preference learning; sparse training

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1 INTRODUCTION

Recent advances in reinforcement learning (RL) are bringing us closer to a future in which RL agents aid humans in their daily lives [3, 5, 12]. Preference-based RL (PbRL) is a promising paradigm that allows RL agents to leverage human preferences to adapt their behavior to better align with human intentions [2, 7, 10]. However, to effectively integrate agents into human-centered environments, autonomous agents should be able to learn from humans in their natural settings. Unfortunately, human environments are inherently noisy. For example, suppose a household robot is tasked with learning to clean a toy room and a human provides the robot with preferences on how the room should be cleaned. In this scenario, the robot might receive distracting information, such as the sounds of children playing. Only a subset of the robot's perceptions is relevant to the task, and identifying this subset can boost performance. To that end, we present R2N, a novel *robust-to-noise* PbRL algorithm that leverages principles of dynamic sparse training (DST) to learn robust reward models in *extremely noisy environments*. R2N continually adjusts the network topology of both the reward model and RL agent networks to focus on task-relevant features.

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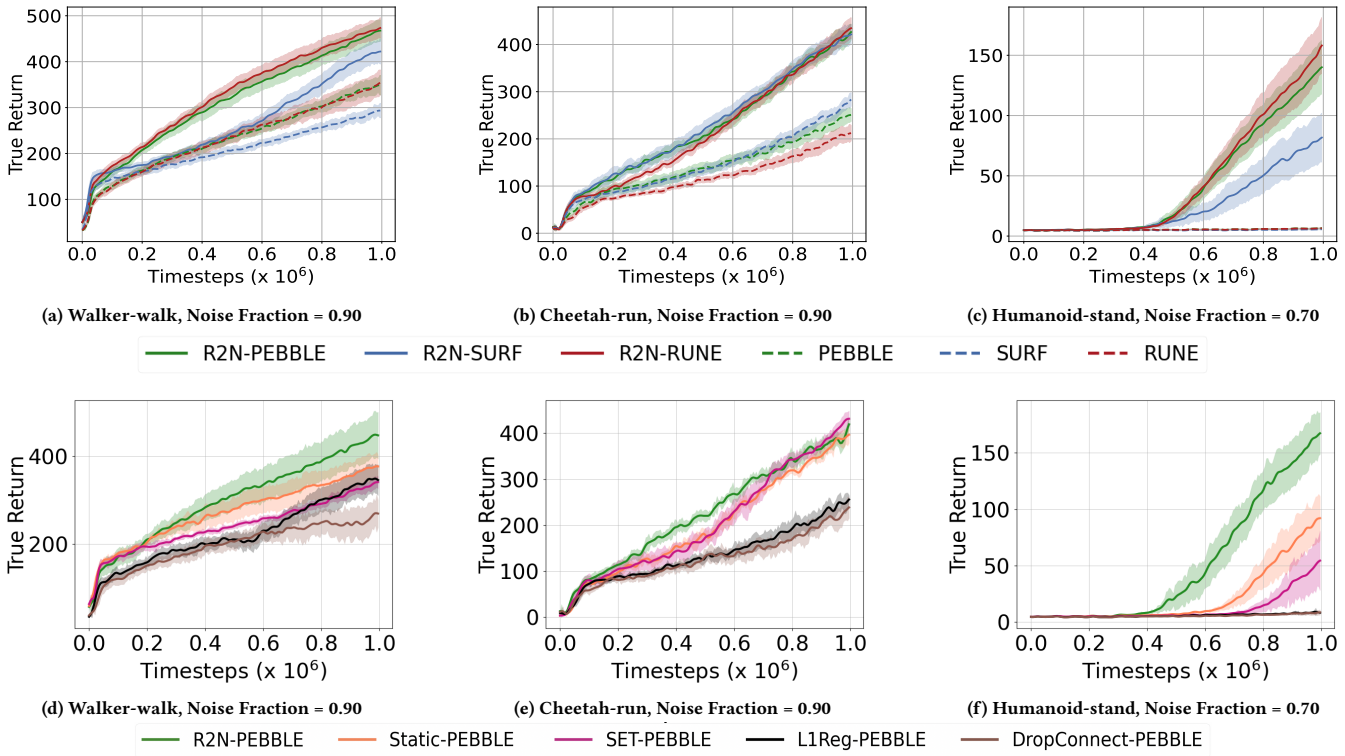
2 BACKGROUND

This work assumes an MDP\R setting, where access to the environmental reward function is not provided. The goal is to learn a good policy while simultaneously estimating a reward function, $\hat{r}_\theta$, from human preferences. PbRL considers trajectory segments σ, where each segment consists of a sequence of state-action pairs. The teacher compares two segments, σ^0 and σ^1, assigning $y = 1$ if σ^1 is preferred, $y = 0$ if σ^0 is preferred, and $y = 0.5$ if both are equally preferred. As feedback is provided, it is stored as tuples (σ^0, σ^1, y) in a dataset. Then, we follow the Bradley-Terry model [1] to define a preference predictor P_θ using the reward function estimator, $\hat{r}_\theta$. Intuitively, if segment σ^i is preferred over segment σ^j, then the cumulative predicted reward (under $\hat{r}_\theta$) for σ^i should be greater than for σ^j. To train the reward function, we can use supervised learning where the teacher provides the labels y. We can then update $\hat{r}_\theta$ by minimizing the binary cross-entropy objective. The learned reward function, $\hat{r}_\theta$, is then used in place of the environmental reward function in the typical RL interaction loop.

3 ROBUST-TO-NOISE PBRL

The goal of R2N is to learn reward functions from feedback in environments with many task-irrelevant features. To achieve this, R2N applies DST techniques to PbRL algorithms to enable the learned reward model to focus on relevant features. R2N consists



(a) Walker-walk, Noise Fraction = 0.90 (b) Cheetah-run, Noise Fraction = 0.90 (c) Humanoid-stand, Noise Fraction = 0.70

(d) Walker-walk, Noise Fraction = 0.90 (e) Cheetah-run, Noise Fraction = 0.90 (f) Humanoid-stand, Noise Fraction = 0.70

Figure 1: Learning curves comparing R2N against various PbRL algorithms (top row) and sparse training methods (bottom row).

of two primary steps. First, at initialization, R2N randomly prunes the input layer of the reward model to a pre-defined sparsity level s^R. This is important, as prior works have shown that sparse neural networks can outperform their dense counterparts in both the supervised learning and RL settings [4, 9, 14]. Second, after every ΔT^R weight updates in the training loop, we prune the weakest active connections in the reward model's input layer. The strength of a connection is defined by the absolute value of its weight. After dropping a fraction $d_f^R \in (0, 1)$ of active connections, R2N regrows an equal number in new locations, maintaining a consistent sparsity level throughout training. To choose which inactive connections to grow, we use RigL [4], which activates connections with the highest gradient magnitude. We also apply the DST procedure, SET [9], to the input layers of the actor and critic networks in the RL agent, following a noise-filtering algorithm for standard RL [6].

4 EXPERIMENTS

We consider the Extremely Noisy Environment (ENE) [6], where noise is treated as a distracting feature in the environment. Specifically, the state space is expanded such that a fraction $n_f \in [0, 1)$ of the total state space consists of noise features. The PbRL algorithms must identify the most relevant features to (1) learn a robust reward function and (2) learn an adequate policy. We evaluate R2N in three DMControl environments [15]: Walker-walk, Cheetah-run, and Humanoid-stand. To assess its effectiveness, we compare R2N against four sparse training baselines: SET [9], Static Sparse Training, L1 Regularization [11], and DropConnect [16], each integrated into the reward learning module of the PbRL algorithm PEBBLE [7]. To further examine R2N's applicability across diverse PbRL algorithms, we integrate it with two additional approaches: SURF [13] and RUNE [8]. For PbRL baselines, we use a simulated teacher that provides preferences between trajectory segments based on the ground truth reward function. We train all algorithms for 1 million timesteps and evaluate performance every 5000 timesteps. Evaluation is based on the average offline performance over ten episodes using the ground truth reward function. Results are averaged over 14 or 5 seeds (Figure 1—top and bottom, respectively), with shaded regions representing the standard error.

In all environments, R2N-PEBBLE is the only algorithm that *consistently* achieves superior performance. Furthermore, in Figure 1 - top, the addition of R2N significantly improves both the learning efficiency and final return of the base PbRL algorithm. In Figure 1 - bottom, R2N-PEBBLE significantly outperforms L1-Regularization and DropConnect in learning efficiency. While Static-PEBBLE and SET-PEBBLE are more competitive, R2N maintains a performance advantage in Humanoid-stand and Cheetah-run.

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