DREAMERPRO: RECONSTRUCTION-FREE MODEL-BASED REINFORCEMENT LEARNING WITH PROTOTYPICAL REPRESENTATIONS

Anonymous authors
Paper under double-blind review

ABSTRACT

In model-based reinforcement learning (MBRL) such as Dreamer, the approaches based on observation reconstruction often fail to discard task-irrelevant details, thus struggling to handle visual distractions or generalize to unseen distractions. To address this issue, previous work has proposed to contrastively learn the latent representations and its temporal dynamics, but showed inconsistent performance, often worse than Dreamer. Although, in computer vision, an alternative prototypical approach has often shown to be more accurate and robust, it is elusive how this approach can be combined best with the temporal dynamics learning in MBRL. In this work, we propose a reconstruction-free MBRL agent, called DREAMERPRO, to achieve this goal. Similar to SWAV, by encouraging uniform cluster assignment across the batch, we implicitly push apart the embeddings of different observations. Additionally, we let the temporal latent state to 'reconstruct' the cluster assignment of the observation, thereby relieving the world model from modeling low-level details. We evaluate our model on the standard setting of DeepMind Control Suite, and also on a natural-background setting, where the background is replaced by natural videos irrelevant to the task. The results show that the proposed model is consistently better than the previous models.

1 INTRODUCTION

Model-Based Reinforcement Learning (MBRL) (Sutton & Barto, 2018; Sutton, 1991) provides a solution to many problems in contemporary reinforcement learning. It improves sample efficiency by training a policy through simulations of a learned world model. Learning a world model also provides a way to efficiently represent experience data as general knowledge simulatable and reusable in arbitrary downstream tasks. In addition, it allows accurate and safe decisions via planning.

Among recent advances in image-based MBRL, DREAMER is particularly notable as the first MBRL model outperforming popular model-free RL algorithms with better sample efficiency in both continuous control (Hafner et al., 2020) and discrete control (Hafner et al., 2021). Unlike some previous model-based RL methods (Kaiser et al., 2019), it learns a world model that can be rolled out in a compact latent representation space instead of the high-dimensional observation space. Also, policy learning can be done efficiently via backpropagation through the differentiable dynamics model.

In image-based RL, the key problem is to learn low-dimensional state representation and, in the model-based case, also its forward model. Although we can learn such representation directly by maximizing the rewards (Schrittwieser et al., 2020), it is usually very slow to do this due to the reward sparsity. Instead, it is more practical to introduce auxiliary tasks providing richer learning signal to facilitate representation learning without reward (or with sparse reward) (Sutton et al., 2011; Jaderberg et al., 2016). DREAMER achieves this by learning the representation and the dynamics model in a way to reduce the reconstruction error of the observed sequences. However, reconstruction-based representation learning has limitations. First, it is computationally expensive to reconstruct the high-dimensional inputs, especially in models like DREAMER that needs to reconstruct long-range videos. Second, it wastes the representation capacity to learn even the visual signals that are irrelevant to the task or unpredictable such as noisy background (Burda et al., 2018). Thus, in MBRL it is of particular interest to realize a version of DREAMER without reconstruction.

Recently, there have been remarkable advances in reconstruction-free representation learning in reinforcement learning (Laskin et al., 2020a;b; Yarats et al., 2021c). The currently dominant approach is via contrastive learning. This approach requires pair-wise comparisons to push apart different instances while pulling close an instance and its augmentation. Therefore, this method usually requires a large batch size (so computationally expensive) to perform accurately and robustly. An alternative is the clustering-based or prototype-based approach (Caron et al., 2020). By learning a set of clusters represented by prototypes, it replaces the instance-wise comparison by a comparison to the clusters and thereby avoids the problems of contrastive learning. This approach is shown to perform more accurately and robustly in many applications (Caron et al., 2020; 2021; Yarats et al., 2021b) than the contrastive method while also alleviating the need for maintaining a large batch size. The prototype structure can also be used to implement an exploration method (Yarats et al., 2021b).

However, for reconstruction-free MBRL only the contrastive approach like Temporal Predictive Coding (TPC) (Nguyen et al., 2021) has been proposed so far. Thus, it is important to investigate (1) how, in the MBRL setting, we can realize the improved robustness and accuracy of the prototypical representation as shown in computer vision, (2) whether and how temporal information available in MBRL can be combined with the prototypes to improve the representation further, and finally (3) what the challenges and benefits are in doing so. For instance, although TPC has shown to consistently outperform DREAMER in the noisy background settings, for standard DeepMind Control Suite (DMC) (Tassa et al., 2018) it showed quite inconsistent results by performing severely worse than DREAMER for some tasks. In this work, we therefore hypothesize that this inconsistent behavior may be fixed in the MBRL setting if the robustness and accuracy of the prototypical representation can be realized and further improved with the support of temporal information.

In this paper, we propose a reconstruction-free MBRL agent, called DREAMERPRO, by combining the prototypical representation learning with temporal dynamics learning. Similar to SwAV, by encouraging uniform cluster assignment across the batch, we implicitly pull apart the embeddings of different observations. Additionally, we let the temporal latent state to 'reconstruct' the cluster assignment of the observation, thereby relieving the world model from modeling low-level details. We evaluate our model on the standard setting of DeepMind Control Suite, and also on a natural-background setting, where the background is replaced by natural videos irrelevant to the task. The results show that the proposed model is consistently more accurate than the previous models.

The contributions of the paper are (1) the first reconstruction-free MBRL agent based on the prototypical representation and its temporal dynamics and (2) the demonstration of the consistently improved accuracy and robustness of the proposed model in comparison to a contrastive reconstruction-free MBRL agent and Dreamer for both standard and natural background DMC tasks.

2 PRELIMINARIES

In this section, we briefly introduce the world model and learning algorithms used in DREAMERV2 (Hafner et al., 2021) which our model builds upon. To indicate the general DREAMER framework (Hafner et al., 2020; 2021), we omit its version number in the rest of the paper.

2.1 RECONSTRUCTION-BASED WORLD MODEL LEARNING

DREAMER learns a recurrent state-space model (RSSM, Hafner et al. (2019)) to predict forward dynamics and rewards in partially observable environments. At each time step t, the agent receives an image observation o_t and a scalar reward r_t (obtained by previous actions $a_{<t}$). The agent then chooses an action a_t based on its policy. The RSSM models the observations, rewards, and transitions through a probabilistic generative process:

$$p(o_{1:T}, r_{1:T} \mid a_{1:T}) = \int \prod_{t=1}^{T} p(o_t \mid s_{\leq t}, a_{<t})\, p(r_t \mid s_{\leq t}, a_{<t})\, p(s_t \mid s_{<t}, a_{<t})\, \mathrm{d}s_{1:T} \tag{1}$$

$$= \int \prod_{t=1}^{T} p(o_t \mid h_t, s_t)\, p(r_t \mid h_t, s_t)\, p(s_t \mid h_t)\, \mathrm{d}s_{1:T}\,, \tag{2}$$

where the latent variables $s_{1:T}$ are the agent states, and $h_t = \mathrm{GRU}(h_{t-1}, s_{t-1}, a_{t-1})$ is a deterministic encoding of $s_{<t}$ and $a_{<t}$. To infer the agent states from past observations and actions, a

variational encoder is introduced:

$$q(s_{1:T} \mid o_{1:T}, a_{1:T}) = \prod_{t=1}^{T} q(s_t \mid s_{<t}, a_{<t}, o_t) = \prod_{t=1}^{T} q(s_t \mid h_t, o_t)\,. \tag{3}$$

The training objective is to maximize the evidence lower bound (ELBO):

$$\mathcal{J}_{\text{DREAMER}} = \sum_{t=1}^{T} \mathbb{E}_q \big[\underbrace{\log p(o_t \mid h_t, s_t)}_{\mathcal{J}_{\text{O}}^t} + \underbrace{\log p(r_t \mid h_t, s_t)}_{\mathcal{J}_{\text{R}}^t} - \underbrace{D_{\text{KL}}(q(s_t \mid h_t, o_t) \parallel p(s_t \mid h_t))}_{\mathcal{J}_{\text{KL}}^t} \big]\,. \tag{4}$$

2.2 Policy learning by latent imagination

DREAMER interleaves policy learning with world model learning. During policy learning, the world model is fixed, and an actor and a critic are trained cooperatively from the latent trajectories imagined by the world model. Specifically, the imagination starts at each non-terminal state $\hat{z}_t = [h_t, s_t]$ encountered during world model learning. Then, at each imagination step $t' \geq t$, an action is sampled from the actor's stochastic policy: $\hat{a}_{t'} \sim \pi(\hat{a}_{t'} \mid \hat{z}_{t'})$. The corresponding reward $\hat{r}_{t'+1}$ and next state $\hat{z}_{t'+1}$ are predicted by the learned world model. Given the imagined trajectories, the actor improves its policy by maximizing the λ-return (Sutton & Barto, 2018; Schulman et al., 2018) plus an entropy regularizer that encourages exploration, while the critic is trained to approximate the λ-return through a squared loss.

3 DreamerPro

To compute the DREAMER training objective, more specifically $\mathcal{J}_{\text{O}}^t$ in Equation 4, a decoder is required to reconstruct the image observation o_t from the state $z_t = [h_t, s_t]$. Because this reconstruction loss operates in pixel space where all pixels are weighted equally, DREAMER tends to allocate most of its capacity to modeling complex visual patterns that cover a large pixel area (e.g., backgrounds). This leads to poor task performance when those visual patterns are task irrelevant, as shown in previous work (Nguyen et al., 2021).

Fortunately, during policy learning, what we need is accurate reward and next state prediction, which are respectively encouraged by $\mathcal{J}_{\text{R}}^t$ and $\mathcal{J}_{\text{KL}}^t$. In other words, the decoder is not required for policy learning. The main purpose of having the decoder and the associated loss $\mathcal{J}_{\text{O}}^t$, as shown in DREAMER, is to learn meaningful representations that cannot be obtained by $\mathcal{J}_{\text{R}}^t$ and $\mathcal{J}_{\text{KL}}^t$ alone.

The above observations motivate us to improve robustness to visual distractions by replacing the reconstruction-based representation learning in DREAMER with reconstruction-free methods. For this, we take inspiration from recent developments in self-supervised image representation learning, which can be divided into contrastive (van den Oord et al., 2019; Chen et al., 2020; He et al., 2020) and non-contrastive (Grill et al., 2020; Caron et al., 2020) methods. We prefer non-contrastive methods as they can be applied to small batch sizes. This can speed up both world model learning and policy learning (in wall clock time). Therefore, we propose to combine DREAMER with the prototypical representations used in SWAV (Caron et al., 2020), a top-performing non-contrastive representation learning method. We name the resulting model DREAMERPRO, and provide the model description in the following.

DREAMERPRO uses the same policy learning algorithm as DREAMER, but learns the world model without reconstructing the observations. This is achieved by clustering the observation into a set of K trainable prototypes $\{c_1, \ldots, c_K\}$, and then predicting the cluster assignment from the state as well as an augmented view of the observation. See Figure 1 for an illustration.

Concretely, given a sequence of observations $o_{1:T}$ sampled from the replay buffer, we obtain two augmented views $o_{1:T}^{(1)}, o_{1:T}^{(2)}$ by applying random shifts (Laskin et al., 2020b; Yarats et al., 2021c) with bilinear interpolation (Yarats et al., 2021a). We ensure that the augmentation is consistent across time steps. Each view $i \in \{1, 2\}$ is fed to the RSSM to obtain the states $z_{1:T}^{(i)}$. To predict the cluster assignment from $z_t^{(i)}$, we first apply a linear projection followed by ℓ_2-normalization to obtain a vector $x_t^{(i)}$ of the same dimension as the prototypes, and then take a softmax over the dot

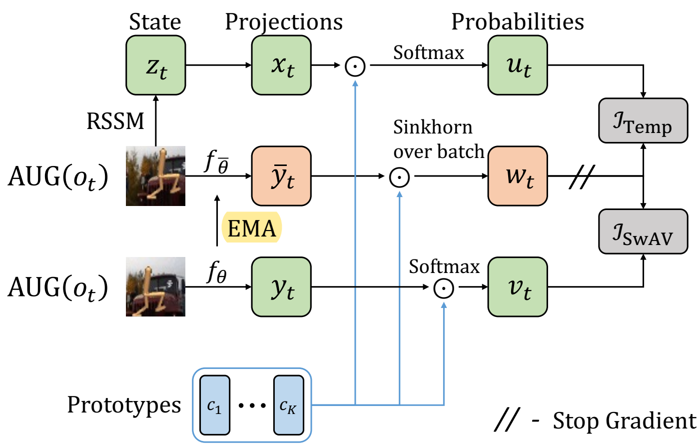

Figure 1: DREAMERPRO model.

products of $x_t^{(i)}$ and all the prototypes:

$$(u_{t,1}^{(i)}, \ldots, u_{t,K}^{(i)}) = \operatorname{softmax}\left(\frac{x_t^{(i)} \cdot c_1}{\tau}, \ldots, \frac{x_t^{(i)} \cdot c_K}{\tau}\right) . \tag{5}$$

Here, $u_{t,k}^{(i)}$ is the predicted probability that state $z_t^{(i)}$ maps to cluster k, τ is a temperature parameter, and the prototypes $\{c_1, \ldots, c_K\}$ are also ℓ_2-normalized.

Analogously, to predict the cluster assignment from an augmented observation $o_t^{(i)}$, we feed it to a convolutional encoder (shared with the RSSM), apply a linear projection followed by ℓ_2-normalization, and obtain a vector $y_t^{(i)}$. We summarize this process as: $y_t^{(i)} = f_\theta(o_t^{(i)})$, where θ collectively denotes the parameters of the convolutional encoder and the linear projection layer. The prediction probabilities are again given by a softmax:

$$(v_{t,1}^{(i)}, \ldots, v_{t,K}^{(i)}) = \operatorname{softmax}\left(\frac{y_t^{(i)} \cdot c_1}{\tau}, \ldots, \frac{y_t^{(i)} \cdot c_K}{\tau}\right) , \tag{6}$$

where $v_{t,k}^{(i)}$ is the predicted probability that observation $o_t^{(i)}$ maps to cluster k.

To obtain the targets for the above two predictions (i.e., Equations 5 and 6), we apply the Sinkhorn-Knopp algorithm (Cuturi, 2013) to the cluster assignment scores computed from the output of a momentum encoder $f_{\bar{\theta}}$ (He et al., 2020; Grill et al., 2020; Caron et al., 2021), whose parameters $\bar{\theta}$ are updated using the exponential moving average of θ: $\bar{\theta} \leftarrow (1-\eta)\bar{\theta} + \eta\theta$. For each observation $o_t^{(i)}$, the scores are given by the dot products $(\bar{y}_t^{(i)} \cdot c_1, \ldots, \bar{y}_t^{(i)} \cdot c_K)$, where $\bar{y}_t^{(i)} = f_{\bar{\theta}}(o_t^{(i)})$ is the momentum encoder output. The Sinkhorn-Knopp algorithm is applied to the two augmented batches $\{o_{1:T}^{(1)}\}, \{o_{1:T}^{(2)}\}$ separately to encourage uniform cluster assignment within each augmented batch and avoid trivial solutions. We specifically choose the number of prototypes $K = B \times T$, where B is the batch size, so that the observation embeddings are implicitly pushed apart from each other. The outcome of the Sinkhorn-Knopp algorithm is a set of cluster assignment targets $(w_{t,1}^{(i)}, \ldots, w_{t,K}^{(i)})$ for each observation $o_t^{(i)}$.

Now that we have the cluster assignment predictions and targets, the representation learning objective is simply to maximize the prediction accuracies:

$$\mathcal{J}_{\text{SwAV}}^t = \frac{1}{2}\sum_{k=1}^{K}\left(w_{t,k}^{(1)} \log v_{t,k}^{(2)} + w_{t,k}^{(2)} \log v_{t,k}^{(1)}\right) , \tag{7}$$

$$\mathcal{J}_{\text{Temp}}^t = \frac{1}{2}\sum_{k=1}^{K}\left(w_{t,k}^{(1)} \log u_{t,k}^{(1)} + w_{t,k}^{(2)} \log u_{t,k}^{(2)}\right) . \tag{8}$$

Here, $\mathcal{J}^t_{\text{SwAV}}$ improves prediction from an augmented view. This is the same loss as used in SwAV (Caron et al., 2020), and is shown to induce useful features for static images. However, it ignores the temporal structure which is crucial in reinforcement learning. Hence, we add a second term, $\mathcal{J}^t_{\text{Temp}}$, that improves prediction from the state of the same view. This has the effect of making the prototypes close to the states that summarize the past observations and actions, thereby distilling temporal structure into the prototypes. From another perspective, $\mathcal{J}^t_{\text{Temp}}$ is similar to $\mathcal{J}^t_{\text{O}}$ in the sense that we are now 'reconstructing' the cluster assignment of the observation instead of the observation itself. This frees the world model from modeling complex visual details, allowing more capacity to be devoted to task-relevant features.

The overall world model learning objective for DREAMERPRO can be obtained by replacing $\mathcal{J}^t_{\text{O}}$ in Equation 4 with $\mathcal{J}^t_{\text{SwAV}} + \mathcal{J}^t_{\text{Temp}}$:

$$\mathcal{J}_{\text{DREAMERPRO}} = \sum_{t=1}^{T} \mathbb{E}_q[\mathcal{J}^t_{\text{SwAV}} + \mathcal{J}^t_{\text{Temp}} + \mathcal{J}^t_{\text{R}} - \mathcal{J}^t_{\text{KL}}] \, , \tag{9}$$

where $\mathcal{J}^t_{\text{R}}$ and $\mathcal{J}^t_{\text{KL}}$ are now averaged over the two augmented views.

4 EXPERIMENTS

Environments. We evaluate our model and the baselines on six image-based continuous control tasks from the DeepMind Control (DMC) suite (Tassa et al., 2018). We choose the set of tasks based on those considered in PLANET (Hafner et al., 2019). Specifically, we replace Cartpole Swingup and Walker Walk with their more challenging counterparts, Cartpole Swingup Sparse and Walker Run, and keep the remaining tasks. In addition to the standard setting, we also consider a natural background setting (Zhang et al., 2021; Nguyen et al., 2021), where the background is replaced by task-irrelevant natural videos randomly sampled from the 'driving car' class in the Kinetics 400 dataset (Kay et al., 2017). Following TPC (Nguyen et al., 2021), we use two separate sets of background videos for training and evaluation. Hence, the natural background setting tests generalization to unseen distractions. We note that the recently released Distracting Control Suite (DCS, Stone et al. (2021)) serves a similar purpose. However, the background distractions in DCS seem less challenging, as there are fewer videos and the ground plane is made visible for most tasks. In our preliminary experiments, our model and all the baselines achieved close to zero returns on Cartpole Swingup Sparse in the natural background setting. We therefore switch back to Cartpole Swingup in this setting.

Baselines. Our main baselines are DREAMER (Hafner et al., 2021) and TPC (Nguyen et al., 2021), the state-of-the-art for reconstruction-based and reconstruction-free model-based reinforcement learning, respectively. In particular, TPC has shown better performance than CVRL (Ma et al., 2020) and DBC (Zhang et al., 2021) on the same datasets. The recently proposed PSE (Agarwal et al., 2021) has demonstrated impressive results on DCS. However, it is only shown to work in the model-free setting and requires a pretrained policy, while our model learns both the world model and the policy from scratch.

Implementation details. We implement our model based on a newer version of DREAMER[1], while the official implementation of TPC[2] is based on an older version. For fair comparison, we re-implement TPC based on the newer version. We adopt the default values for the DREAMER hyperparameters, except that we use continuous latents and `tanh_normal` as the distribution output by the actor. We find these changes improve DREAMER's performance in the standard DMC, and therefore use these values for all models in both the standard and the natural background setting. Following TPC, we increase the weight of the reward loss $\mathcal{J}^t_{\text{R}}$ to 1000 for all models in the natural background setting to further encourage extraction of task-relevant information. While in the original TPC, this weight is chosen separately for each task from $\{100, 1000\}$, we find the weight of 1000 works consistently better in our re-implementation, which also obtains better results than reported in the original paper.

[1] https://github.com/danijar/dreamerv2/tree/e783832f01b2c845c195587158c4e129edabaebb

[2] https://github.com/VinAIResearch/TPC-tensorflow

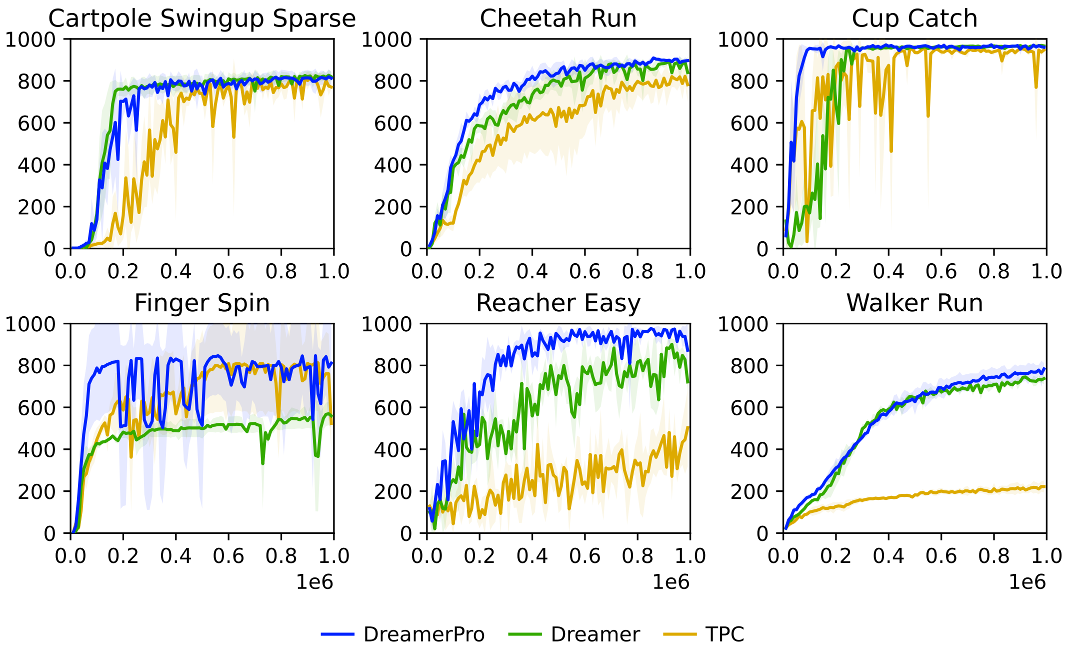

Figure 2: Performance curves in standard DMC. While TPC underperforms DREAMER on most tasks, DREAMERPRO greatly outperforms DREAMER on Finger Spin and Reacher Easy, achieves better data efficiency on Cup Catch, and is comparable or better than DREAMER on other tasks.

Table 1: Final performance in standard DMC.

Task	DREAMER	TPC	DREAMERPRO
Cartpole Swingup Sparse	$\mathbf{820 \pm 23}$	770 ± 9	$\mathbf{813 \pm 32}$
Cheetah Run	840 ± 74	782 ± 82	$\mathbf{897 \pm 8}$
Cup Catch	$\mathbf{967 \pm 3}$	948 ± 7	$\mathbf{961 \pm 10}$
Finger Spin	559 ± 54	524 ± 127	$\mathbf{811 \pm 232}$
Reacher Easy	721 ± 51	503 ± 185	$\mathbf{873 \pm 127}$
Walker Run	737 ± 26	222 ± 29	$\mathbf{784 \pm 28}$
Mean and STD of NDB (↓)	0.101 ± 0.12	0.284 ± 0.272	$\mathbf{0.002 \pm 0.003}$

Evaluation protocol. For each task, we train each model for 1M environment steps (equivalent to 500K actor steps, as the action repeat is set to 2). The evaluation return is computed every 10K steps, and averaged over 10 episodes. In all figures and tables, the mean and standard deviation are computed from 3 independent runs. In addition to the episode returns, we also report the Normalized Distance to the Best (NDB). Given the performance $x_{\tau,\alpha}$ of an algorithm α on a task τ, the NDB $\beta_{\tau,\alpha}$ is defined as:

$$\beta_{\tau,\alpha} = \frac{\max_{\hat{\alpha}}(x_{\tau,\hat{\alpha}}) - x_{\tau,\alpha}}{\max_{\hat{\alpha}}(x_{\tau,\hat{\alpha}})} \, . \tag{10}$$

We report the mean and variance of $\beta_{\tau,\alpha}$ for each algorithm α over all tasks τ, which indicate the bestness and consistency of algorithm α, respectively. An optimal algorithm that consistently achieves the best performance across all tasks will have zero mean and zero variance.

4.1 PERFORMANCE IN STANDARD DMC

We show the performance curves in Figure 2 and the final performance in Table 1 for the standard setting. In contrast to TPC which underperforms DREAMER on most tasks (most severely on Reacher Easy and Walker Run), DREAMERPRO achieves comparable or even better performance

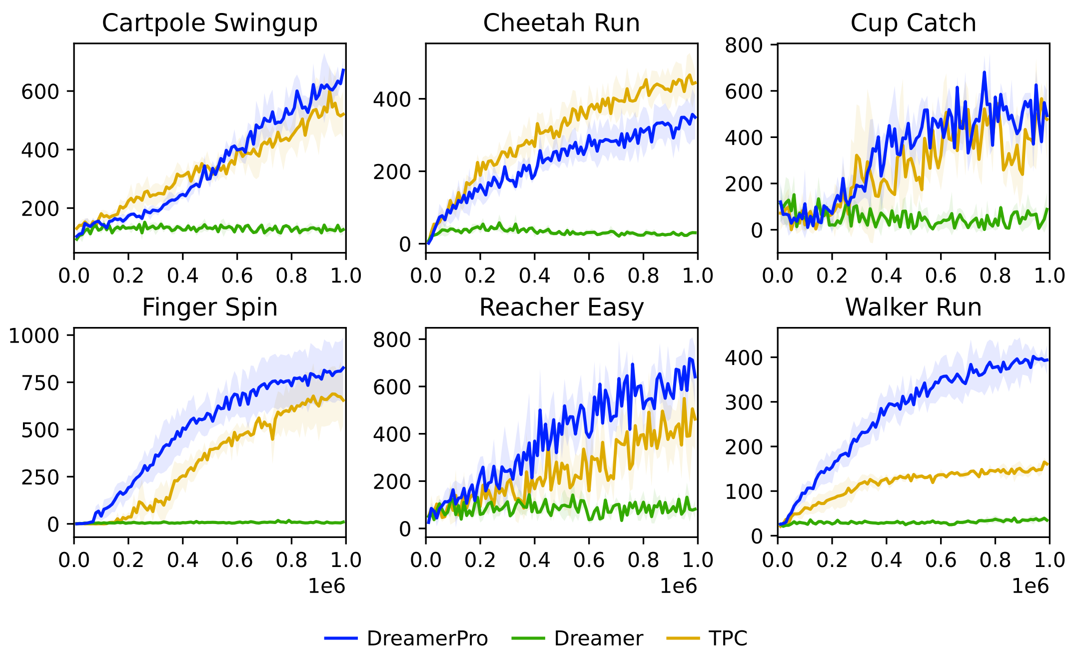

Figure 3: Performance curves in natural background DMC. DREAMERPRO significantly outperforms TPC on Cartpole Swingup, Finger Spin, Reacher Easy, and Walker Run, while DREAMER completely fails on all tasks.

Table 2: Final performance in natural background DMC.

Task	DREAMER	TPC	DREAMERPRO
Cartpole Swingup	126 ± 16	521 ± 80	$\mathbf{671 \pm 42}$
Cheetah Run	30 ± 2	$\mathbf{444 \pm 35}$	349 ± 61
Cup Catch	88 ± 73	477 ± 175	$\mathbf{493 \pm 109}$
Finger Spin	10 ± 1	655 ± 133	$\mathbf{826 \pm 162}$
Reacher Easy	82 ± 39	462 ± 130	$\mathbf{641 \pm 123}$
Walker Run	35 ± 4	161 ± 6	$\mathbf{394 \pm 33}$
Mean and STD of NDB ($\downarrow$)	0.890 ± 0.063	0.222 ± 0.237	$\mathbf{0.036 \pm 0.096}$

than DREAMER on all tasks. Notably, DREAMERPRO outperforms DREAMER by a large margin on Finger Spin and Reacher Easy, and demonstrates better data efficiency on Cup Catch. We notice a large variance in DREAMERPRO's performance on Finger Spin. Further investigation reveals that DREAMERPRO learned close to optimal behavior (with average episode returns above 950) on two of the seeds, while converged to a suboptimal behavior (with average episode returns around 500) on the other seed. Our results suggest for the first time that prototypical representations (and reconstruction-free representation learning in general) can be beneficial to MBRL even in the absence of strong visual distractions.

4.2 PERFORMANCE IN NATURAL BACKGROUND DMC

Figure 3 and Table 2 respectively show the performance curves and final evaluation returns obtained by all models in the natural background setting. DREAMER completely fails on all tasks, showing the inability of reconstruction-based representation learning to deal with complex visual distractions. In contrast, DREAMERPRO achieves the best performance on 5 out of 6 tasks, with large performance gains from TPC on Cartpole Swingup, Finger Spin, Reacher Easy, and Walker Run. These results indicate that the advantage of prototypical representations over contrastive learning in computer vision can indeed be transferred to MBRL for better robustness to visual distractions.

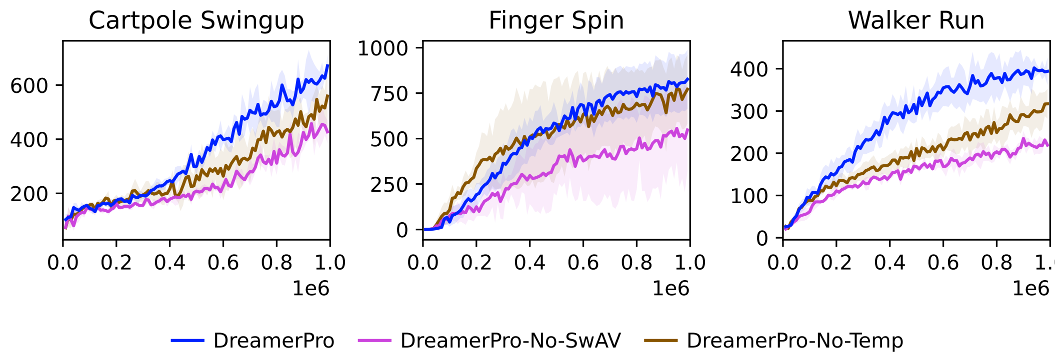

Figure 4: Ablation study. Both $\mathcal{J}^t_{\mathrm{SwAV}}$ and $\mathcal{J}^t_{\mathrm{Temp}}$ are necessary for achieving good performance.

4.3 Ablation study

We now show the individual effect of the two loss terms, $\mathcal{J}^t_{\mathrm{SwAV}}$ and $\mathcal{J}^t_{\mathrm{Temp}}$, in Figure 4. Here, each of the ablated versions, DreamerPro-No-SwAV and DreamerPro-No-Temp, removes one of the loss terms. We did not investigate removing both terms, as its failure has been shown in DREAMER (Hafner et al., 2020). We observe that both terms are necessary for achieving good performance. In particular, naively combining SWAV with DREAMER (i.e., DreamerPro-No-Temp) leads to inferior performance, as it ignores the temporal structure. On the other hand, $\mathcal{J}^t_{\mathrm{Temp}}$ alone is not sufficient to provide meaningful cluster assignment targets and learning signals for the convolutional encoder.

5 Related work

Self-supervised representation learning for static images. Recent works in self-supervised learning have shown its effectiveness in learning representations from high-dimensional data. CPC (van den Oord et al., 2019) learns representations by maximizing the mutual information between the encoded representations and its future prediction using noise-contrastive estimation. SimCLR (Chen et al., 2020) shows that the contrastive data can be generated using the data in the training mini-batch by applying random augmentations. MOCO (He et al., 2020), on the other hand, improves the contrastive training by generating the representations from a momentum encoder instead of the trained network. Despite the success in some tasks, one weakness of the contrastive approaches is that it require the model to compare a larger amount of samples, which demands large batch sizes or memory banks. To address this problem, some works propose to learn the image representations without discriminating between samples. Particularly, BYOL (Grill et al., 2020) introduces a momentum encoder to provide target representations for the training network. SwAV (Caron et al., 2020) proposes to learn the embeddings by matching them to a set of learned clusters. And DINO (Caron et al., 2021) replace the clusters in SwAV with categorical heads and uses the centering and sharpening technique to prevent representations collapsing. Unlike our model, these works treat each image independently and ignore the temporal structure of the environment, with is crucial in learning the policy in RL tasks.

Representation learning for model-free reinforcement learning. It has been shown that adopting data augmentation techniques like random shifts in the observation space enables robust learning from pixel input in any model-free reinforcement learning algorithm (Laskin et al., 2020b; Yarats et al., 2021c;a). Recent works have also shown that self-supervised representation learning techniques can bring significant improvement to reinforcement learning methods. For example, CURL (Laskin et al., 2020a) performs contrastive learning along with off-policy RL algorithms and shows that it significantly improves sample-efficiency and model performance over pixel-based methods. Other works aim to improve the representation learning quality by combining temporal prediction models in the representation learning process (Schwarzer et al., 2021a;b; Stooke et al., 2021; Yarats et al., 2021b; Guo et al., 2020; Gregor et al., 2019). However, the main purpose of the temporal prediction models in these works is mainly to obtain the abstract representations of the observations, and they are not shown to support long-horizon imagination.

Model-based reinforcement learning with reconstruction. Model based reinforcement learning from raw pixel data can learn the representation space by minimizing the observation reconstruction loss. World Models (Ha & Schmidhuber) learn the latent dynamics of the environment in a two-stage process to evolve their linear controllers in imagination. SOLAR (M. Zhang & Levine., 2019) models the dynamics as time-varying linear-Gaussian and solves robotic tasks via guided policy search. (Hafner et al., 2020) jointly learns the RSSM and latent state space from observation reconstruction loss. (Gelada et al., 2019) also propose a latent dynamics model-based method that uses bisimulation metrics and reconstruction loss in Atari. However, reconstruction based methods are susceptible to noise and objects irrelevant to the task in the environment (Nguyen et al., 2021; Okada & Taniguchi, 2021). Furthermore, in a few cases, the latent representation fails to reconstruct small task-relevant objects in the environment(Okada & Taniguchi, 2021).

Reinforcement learning under visual distractions. A large body of works on robust representation learning focuses on contrastive objectives. For example, CVRL (Ma et al., 2020) proposes to learn representations from complex observations by maximizing the mutual information between an image and its corresponding embedding using contrastive objectives. However, the learning objective of CVRL encourages the representation model to learn as much information as possible, including task-irrelevant information. Dreaming (Okada & Taniguchi, 2021) and TPC (Nguyen et al., 2021) tackle this problem by incorporating a dynamic model and applying contrastive learning in the temporal dimension, which encourages the model to capture controllable and predictable information in the latent space. Bisimulation metrics method such as DBC (Zhang et al., 2021) and PSE (Agarwal et al., 2021) is another type of representation learning robust to visual distractions. Using the bisimulation metrics that quantify the behavioral similarity between states, these methods make the mode robust to task-irrelevant information. However, DBC cannot generalize to unseen backgrounds (Nguyen et al., 2021), and PSE requires a pre-trained policy to compute the similarity metrics while our model learns the policy from scratch.

6 CONCLUSION

In this work, we presented the first reconstruction-free MBRL agent based on the prototypical representation and its temporal dynamics. In experiments, we demonstrated the consistently improved accuracy and robustness of the proposed model in comparison to the Temporal Predictive Control (TPC) agent and the Dreamer agent for both standard and natural background DMC tasks. Our results suggest that there are unexplored broad areas in reconstruction-free MBRL. Interesting future directions are to apply this model on Atari games and to investigate the possibility of learning hierarchical structures such as skills without reconstruction.

REFERENCES

Rishabh Agarwal, Marlos C. Machado, Pablo Samuel Castro, and Marc G Bellemare. Contrastive behavioral similarity embeddings for generalization in reinforcement learning. In *International Conference on Learning Representations*, 2021.

Yuri Burda, Harrison Edwards, Amos Storkey, and Oleg Klimov. Exploration by random network distillation. *arXiv preprint arXiv:1810.12894*, 2018.

Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, and Armand Joulin. Unsupervised learning of visual features by contrasting cluster assignments. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin (eds.), *Advances in Neural Information Processing Systems*, volume 33, pp. 9912–9924. Curran Associates, Inc., 2020.

Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers, 2021.

Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In Hal Daumé III and Aarti Singh (eds.), *Proceedings of the 37th International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pp. 1597–1607. PMLR, 13–18 Jul 2020.

Marco Cuturi. Sinkhorn distances: Lightspeed computation of optimal transport. In C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger (eds.), *Advances in Neural Information Processing Systems*, volume 26. Curran Associates, Inc., 2013.

Carles Gelada, Saurabh Kumar, Jacob Buckman, Ofir Nachum, and Marc G. Bellemare. DeepMDP: Learning continuous latent space models for representation learning. In Kamalika Chaudhuri and Ruslan Salakhutdinov (eds.), *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pp. 2170–2179. PMLR, 09–15 Jun 2019.

Karol Gregor, Danilo Jimenez Rezende, Frederic Besse, Yan Wu, Hamza Merzic, and Aaron van den Oord. Shaping belief states with generative environment models for rl. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett (eds.), *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires, Zhaohan Guo, Mohammad Gheshlaghi Azar, Bilal Piot, koray kavukcuoglu, Remi Munos, and Michal Valko. Bootstrap your own latent - a new approach to self-supervised learning. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin (eds.), *Advances in Neural Information Processing Systems*, volume 33, pp. 21271–21284. Curran Associates, Inc., 2020.

Zhaohan Daniel Guo, Bernardo Avila Pires, Bilal Piot, Jean-Bastien Grill, Florent Altché, Remi Munos, and Mohammad Gheshlaghi Azar. Bootstrap latent-predictive representations for multitask reinforcement learning. In Hal Daumé III and Aarti Singh (eds.), *Proceedings of the 37th International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pp. 3875–3886. PMLR, 13–18 Jul 2020.

D. Ha and J. Schmidhuber. World models.

Danijar Hafner, Timothy Lillicrap, Ian Fischer, Ruben Villegas, David Ha, Honglak Lee, and James Davidson. Learning latent dynamics for planning from pixels. In Kamalika Chaudhuri and Ruslan Salakhutdinov (eds.), *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pp. 2555–2565. PMLR, 09–15 Jun 2019.

Danijar Hafner, Timothy Lillicrap, Jimmy Ba, and Mohammad Norouzi. Dream to control: Learning behaviors by latent imagination. In *International Conference on Learning Representations*, 2020.

Danijar Hafner, Timothy P Lillicrap, Mohammad Norouzi, and Jimmy Ba. Mastering atari with discrete world models. In *International Conference on Learning Representations*, 2021.

Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.

Max Jaderberg, Volodymyr Mnih, Wojciech Marian Czarnecki, Tom Schaul, Joel Z Leibo, David Silver, and Koray Kavukcuoglu. Reinforcement learning with unsupervised auxiliary tasks. *arXiv preprint arXiv:1611.05397*, 2016.

Lukasz Kaiser, Mohammad Babaeizadeh, Piotr Milos, Blazej Osinski, Roy H Campbell, Konrad Czechowski, Dumitru Erhan, Chelsea Finn, Piotr Kozakowski, Sergey Levine, et al. Model-based reinforcement learning for atari. *arXiv preprint arXiv:1903.00374*, 2019.

Will Kay, Joao Carreira, Karen Simonyan, Brian Zhang, Chloe Hillier, Sudheendra Vijayanarasimhan, Fabio Viola, Tim Green, Trevor Back, Paul Natsev, Mustafa Suleyman, and Andrew Zisserman. The kinetics human action video dataset, 2017.

Michael Laskin, Aravind Srinivas, and Pieter Abbeel. CURL: Contrastive unsupervised representations for reinforcement learning. In Hal Daumé III and Aarti Singh (eds.), *Proceedings of the 37th International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pp. 5639–5650. PMLR, 13–18 Jul 2020a.

Misha Laskin, Kimin Lee, Adam Stooke, Lerrel Pinto, Pieter Abbeel, and Aravind Srinivas. Reinforcement learning with augmented data. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin (eds.), *Advances in Neural Information Processing Systems*, volume 33, pp. 19884–19895. Curran Associates, Inc., 2020b.

L. Smith P. Abbeel M. Johnson M. Zhang, S. Vikram and S. Levine. Solar: deep structured representations for model-based reinforcement learning. In *In International Conference on Machine Learning*, 2019.

Xiao Ma, Siwei Chen, David Hsu, and Wee Sun Lee. Contrastive variational reinforcement learning for complex observations, 2020.

Tung D Nguyen, Rui Shu, Tuan Pham, Hung Bui, and Stefano Ermon. Temporal predictive coding for model-based planning in latent space. In Marina Meila and Tong Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 8130–8139. PMLR, 18–24 Jul 2021.

Masashi Okada and Tadahiro Taniguchi. Dreaming: Model-based reinforcement learning by latent imagination without reconstruction, 2021.

Julian Schrittwieser, Ioannis Antonoglou, Thomas Hubert, Karen Simonyan, Laurent Sifre, Simon Schmitt, Arthur Guez, Edward Lockhart, Demis Hassabis, Thore Graepel, et al. Mastering atari, go, chess and shogi by planning with a learned model. *Nature*, 588(7839):604–609, 2020.

John Schulman, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. High-dimensional continuous control using generalized advantage estimation, 2018.

Max Schwarzer, Ankesh Anand, Rishab Goel, R Devon Hjelm, Aaron Courville, and Philip Bachman. Data-efficient reinforcement learning with self-predictive representations. In *International Conference on Learning Representations*, 2021a.

Max Schwarzer, Nitarshan Rajkumar, Michael Noukhovitch, Ankesh Anand, Laurent Charlin, Devon Hjelm, Philip Bachman, and Aaron Courville. Pretraining representations for data-efficient reinforcement learning, 2021b.

Austin Stone, Oscar Ramirez, Kurt Konolige, and Rico Jonschkowski. The distracting control suite – a challenging benchmark for reinforcement learning from pixels, 2021.

Adam Stooke, Kimin Lee, Pieter Abbeel, and Michael Laskin. Decoupling representation learning from reinforcement learning. In Marina Meila and Tong Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 9870–9879. PMLR, 18–24 Jul 2021.

Richard S Sutton. Dyna, an integrated architecture for learning, planning, and reacting. *ACM Sigart Bulletin*, 2(4):160–163, 1991.

Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

Richard S Sutton, Joseph Modayil, Michael Delp, Thomas Degris, Patrick M Pilarski, Adam White, and Doina Precup. Horde: A scalable real-time architecture for learning knowledge from unsupervised sensorimotor interaction. In *The 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 2*, pp. 761–768, 2011.

Yuval Tassa, Yotam Doron, Alistair Muldal, Tom Erez, Yazhe Li, Diego de Las Casas, David Budden, Abbas Abdolmaleki, Josh Merel, Andrew Lefrancq, Timothy Lillicrap, and Martin Riedmiller. Deepmind control suite, 2018.

Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding, 2019.

Denis Yarats, Rob Fergus, Alessandro Lazaric, and Lerrel Pinto. Mastering visual continuous control: Improved data-augmented reinforcement learning, 2021a.

Denis Yarats, Rob Fergus, Alessandro Lazaric, and Lerrel Pinto. Reinforcement learning with prototypical representations. In Marina Meila and Tong Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 11920–11931. PMLR, 18–24 Jul 2021b.

Denis Yarats, Ilya Kostrikov, and Rob Fergus. Image augmentation is all you need: Regularizing deep reinforcement learning from pixels. In *International Conference on Learning Representations*, 2021c.

Amy Zhang, Rowan Thomas McAllister, Roberto Calandra, Yarin Gal, and Sergey Levine. Learning invariant representations for reinforcement learning without reconstruction. In *International Conference on Learning Representations*, 2021.

A HYPERPARAMETERS

For hyperparameters that are shared with DREAMER, we use the default values suggested in the config file in the official implementation of DREAMER, with the following two exceptions. We set `discrete = False` and `actor.dist = tanh_normal`, as we find these changes improve performance over the default setting. The additional hyperparameters introduced in DREAMERPRO are listed in Table 3.

Table 3: Additional hyperparameters in DREAMERPRO.

Hyperparameter	Value
Number of prototypes K	2500
Prototype dimension	32
Softmax temperature τ	0.1
Sinkhorn iterations	3
Sinkhorn epsilon	0.0125
Momentum update fraction η	0.05