Behavior From the Void: Unsupervised Active Pre-Training

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Abstract

We introduce a new unsupervised pre-training method for reinforcement learning called APT, which stands for Active Pre-Training. APT learns behaviors and representations by actively searching for novel states in reward-free environments. The key novel idea is to explore the environment by maximizing a non-parametric entropy computed in an abstract representation space, which avoids the challenging density modeling and consequently allows our approach to scale much better in environments that have high-dimensional observations (e.g., image observations). We empirically evaluate APT by exposing task-specific reward after a long unsupervised pre-training phase. On Atari games, APT achieves humanlevel performance on 12 games and obtains highly competitive performance compared to canonical fully supervised RL algorithms. On DMControl suite, APT beats all baselines in terms of asymptotic performance and data efficiency and dramatically improves performance on tasks that are extremely difficult to train from scratch.

1. Introduction

Deep reinforcement learning (RL) provides a general framework for solving challenging sequential decision-making problems, it has achieved remarkable success in advancing the frontier of AI technologies. These landmarks include outperforming humans in computer games (Mnih et al., 2015; Schrittwieser et al., 2019; Vinyals et al., 2019; Badia et al., 2020a) and solving complex robotic control tasks (Andrychowicz et al., 2017; Akkaya et al., 2019). Despite these successes, they have to train from scratch to maximize extrinsic reward for every encountered task. This is in sharp contrast with how intelligent creatures quickly adapt to new tasks by leveraging previously acquired behaviors.

Unsupervised pre-training, a framework that trains models without expert supervision, has obtained promising results

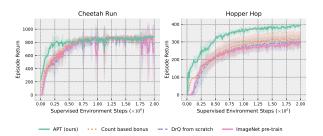


Figure 1: Comparison of RL with unsupervised pre-training from pixels. APT (ours) and count-based bonus are allowed to train for 5M environment steps without access to environment reward, and then got exposed to it reward during testing. APT significantly outperform training DrQ (Kostrikov et al., 2020) from scratch, count-based bonus, and ImageNet pre-trained model.

in computer vision (Oord et al., 2018; He et al., 2020; Chen et al., 2020) and natural language modeling (Vaswani et al., 2017; Devlin et al., 2019; Brown et al., 2020). The learned representation when fine-tuned on the downstream tasks can solve them efficiently in a few-shot manner. The key insight is that with the models and datasets growing, there is still no sign of saturating performance during pre-training.

Driven by the significance of massive unlabeled data, we consider an analogy setting of unsupervised pre-training in computer vision where labels are removed during training. In RL with unsupervised pre-training, the agent are allowed to train for a long period without access to environment reward, and then got exposed to it reward during testing. The goal of pre-training is to have data efficient adaptation for some downstream task defined in the form of rewards. In a first investigation towards better data for RL pre-training, we evaluated count-based bonus (Bellemare et al., 2016), which encourages the agent to visit novel states. We apply count-based bonus to DrQ (Kostrikov et al., 2020) which is current state-of-the-art RL for training from pixels. We also evaluated ImageNet pre-trained representations. The results are shown in Figure 1. We can see that count-based bonus fails to outperform train DrO from scratch. We hypothesis the ineffectiveness stems from density modeling at the pixel level being difficult. ImageNet pre-training does not outperform train from scratch either, which was also shown in previous research in real world robotics (Julian et al., 2020).

To address the issue of obtaining diverse data for RL with unsupervised pre-training, we propose to actively collect

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Table 1: Methods for pre-training RL in reward-free setting. DIAYN (Eysenbach et al., 2019), Count based bonus(CBB) (Bellemare et al., 2016), MEPOL (Mutti et al., 2020), VISR (Hansen et al., 2020), DADS (Sharma et al., 2020), EDL (Campos et al., 2020). Exploration: the method can explore efficiently. Visual: the method works well in visual RL. Off-policy: the method is off-policy RL.

Algorithm	Objective	Visual Domain	Exploration	Off-policy	Pre-Trained model
MaxEnt	$\max \mathrm{H}(s)$	Х	√ *	Х	$\pi(a s)$
CBB	$\max \mathbb{E}_s \left[c(s) \right]$	X	✓	✓	$\pi(a s)$
MEPOL	$\max \mathrm{H}(s)$	X	√ *	X	$\pi(a s)$
VISR	$\max - H(z s)$	✓	X	✓	$\psi(s,z),\phi(s)$
DIAYN	$\max -H(z s) + H(a z,s)$	X	√ *	1	$\pi(a s,z)$
EDL	$\max \mathrm{H}(s) - \mathrm{H}(s z)$	X	√ *	1	$\pi(a s,z)$
DADS	$\max \mathrm{H}(s) - \mathrm{H}(s z)$	X	×	✓	$\pi(a s,z), q(s' s,z)$
APT	$\max \mathrm{H}(s)$	✓	✓	✓	$\pi(a s), Q(s,a)$

 $\psi(s,a)$: successor feature, $\phi(s)$: state representation, c(s): count-based bonus. *: only in state-based RL.

novel data by exploring unknown areas in the task-agnostic environment. Concretely, our approach relies on the entropy maximization principle (Jaynes, 1957; Shannon, 1948). Our motivation is that by doing so, the learned behavior and representation can be trained on the whole environment while being as task agnostic as possible. Since entropy maximization in high dimensional state space is intractable as an oracle density model is not available, we resort to the particle-based entropy estimator (Singh et al., 2003; Beirlant, 1997). This estimator is nonparametric and asymptotically unbiased. The key idea is for a set of samples, computing the average of the Euclidean distance of each particle to its nearest neighbors. We consider an abstract representation space in order to make the distance meaningful. To do so, we adapt the idea of contrastive representation learning (Chen et al., 2020) to encode image observations to lower dimensional space. Since our method does active unsupervised exploration during the pre-training phase, the method is named Unsupervised Active Pre-Training (APT).

Our approach can be applied to a wide-range of existing RL algorithms. In this paper we consider applying our approach to DrQ (Kostrikov et al., 2020) which is a state-of-the-art visual RL algorithm. On the Atari 26 games subset, APT significantly improves DrQ's data-efficiency, achieving 54% relative improvement. On the full suite of Atari 57 games (Mnih et al., 2015), APT significantly outperforms prior state-of-the-art, achieving a median human-normalized score $3\times$ higher than the highest score achieved by prior unsupervised RL methods and DQN. On DeepMind control suite, APT beats DrQ and unsupervised RL in terms of asymptotic performance and data efficiency and solving tasks that are extremely difficult to train from scratch.

The contributions of our paper can be summarized as: (i) We propose a new approach for unsupervised pre-training for visual RL. (ii) We show that our pre-training method significantly improves data efficiency of solving downstream tasks on DMControl and Atari suite.

2. Related Work

2.1. Entropy Maximization

Entropy maximization has been used in many contexts of reinforcement learning, from inverse RL (Ziebart et al., 2008) to optimal control (Todorov, 2008; Toussaint, 2009; Rawlik et al., 2012) and actor-critic (Haarnoja et al., 2018). However, most applications only consider action space entropy and maximize both the expected return and the expected entropy of the policy.

State space entropy maximization has been recently used as an exploration method (Hazan et al., 2019; Lee et al., 2019). In Hazan et al. (2019) they present provably efficient exploration algorithms under certain conditions. However, their method directly estimates state visitations through a density model, which is difficult to scale to pixels. In contrast, our work turns to particle based entropy maximization in a contrastive representation space.

Recently Mutti et al. (2020) shows maximizing particle-based entropy can improve data efficiency in solving down-stream continuous control tasks. Their method relies on importance sampling and on-policy RL which suffer from high variance. Their work also only considers learning with access to underlying state, and it is not obvious how to modify it to work from pixels. In contrast, our work introduces several important design choices to make it applicable to visual RL domains.

The work by Badia et al. (2020b) also considers k-nearest neighbor based count bonus to encourage exploration, yielding improved performance on Atari games. K-nearest neighbor based exploration is shown to improve exploration and data efficiency in model-based RL (Tao et al., 2020). Concurrently, this count-based intrinsic reward has been shown to be an effective unsupervised pre-training objective for transferring learning in RL (Campos et al., 2021). In addition to entropy based unsupervised exploration, they also introduce a Lévy flight (Viswanathan et al., 1996) inspired

exploration strategy for fine-tuning, their large scale experiments show the effectiveness of unsupervised pre-training. A key distinction is that the objective of our intrinsic reward is based on particle-based entropy instead of a heuristically defined count-based intrinsic reward.

2.2. Data Efficiency in RL

Deep RL algorithms are sample inefficient compared to intelligent biological creatures, which can quickly learn to complete new tasks. To close this data efficiency gap, various methods have been proposed: Kaiser et al. (2020) introduce a model-based agent (SimPLe) and show that it compares favorably to standard RL algorithms when data is limited. Hessel et al. (2018); Kielak (2020); van Hasselt et al. (2019) show combining existing RL algorithms (Rainbow) can boost data efficiency. Laskin et al. (2020b) show combing combining contrastive loss with RL improves data-efficiency while follow-up results from Kostrikov et al. (2020) suggest that most of the benefits come from its use of image augmentation. Data augmentation has also been shown effective for improving data efficiency in visionbased RL (Laskin et al., 2020a; Kostrikov et al., 2020). Temporal contrastive learning combined with model-based learning has been shown to boost data efficiency (Schwarzer et al., 2021). Our work improves data efficiency of RL in an orthogonal direction by unsupervised pre-training, the above advances can be used along with APT to obtain better RL optimization.

3. Preliminaries

Reinforcement Learning Reinforcement learning (RL) considers the problem of finding an optimal policy for an agent that interacts with an uncertain environment and collects reward per action. The goal of the agent is to maximize its cumulative reward.

Formally, this problem can be viewed as a Markov decision process (MDP) defined by $(\mathcal{S}, \mathcal{A}, \mathcal{T}, \rho_0, r, \gamma)$ where $\mathcal{S} \subseteq \mathbb{R}^{n_s}$ is a set of n_s -dimensional states, $\mathcal{A} \subseteq \mathbb{R}^{n_a}$ is a set of n_a -dimensional actions, $\mathcal{T}: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0,1]$ is the state transition probability distribution. $\rho_0: \mathcal{S} \to [0,1]$ is the distribution over initial states, $r: \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ is the reward function, and $\gamma \in [0,1)$ is the discount factor. At environment states $s \in \mathcal{S}$, the agent take actions $s \in \mathcal{A}$, in the (unknown) environment dynamics defined by the transition probability $s \in \mathcal{S}$ 0, and the reward function yields a reward immediately following the action $s \in \mathcal{S}$ 1 we define the discounted return $s \in \mathcal{S}$ 2 we define the discounted sum of future rewards collected by the agent. In value-based reinforcement learning, the agent learns learns an estimate of the expected discounted return, a.k.a, state-action value

function.

$$Q^{\pi}(s_t, a_t) = \mathbb{E}_{s_{t+1}, a_{t+1}, \dots} \left[\sum_{l=0}^{\infty} \gamma^l r(s_{t+l}, a_{t+l}) \right]. \quad (1)$$

A common way of deriving a new policy from a state-action value function is to act ϵ -greedily with respect to the action values (discrete) or to use policy gradient to maximize the value function (continuous).

In the context of unsupervised pre-training for RL, usually the setting is training the agent for a long period with environment rewards removed followed by a short testing period with environment rewards provided (Mohamed & Rezende, 2015; Gregor et al., 2016). The goal is to learn a pre-trained agent that can quickly adapt to testing tasks defined by rewards.

RL with Unsupervised Pre-Training The current state-of-the-art for RL with unsupervised pre-training maximizes the mutual information (I) between policy-conditioning variable (z) and the behavior induced by the policy in terms of state visitation (s).

$$\max I(s; z) = \max H(z) - H(z|s). \tag{2}$$

The task variable z is usually sampled from a fixed distribution. The objective can then be simplified as $\max -H(z|s)$. Since maximizing this conditional entropy is intractable, existing approaches Gregor et al. (2016); Eysenbach et al. (2019); Hansen et al. (2020) maximize its variational lower bound (Barber & Agakov, 2003).

$$J(\theta) = \sum_{s,z} p(s,z) \log q_{\theta}(z|s) = \mathbb{E}_{s,z} \left[\log q_{\theta}(z|s) \right]. \quad (3)$$

However, these methods suffer from insufficient exploration.

Another line of work considers the alternative direction of maximizing the mutual information (Sharma et al., 2020; Campos et al., 2020).

$$\max I(s; z) = \max H(s) - H(s|z). \tag{4}$$

This intractable quantity can be similarly lowered bound by a variational approximation.

$$I(s;z) \ge \mathbb{E}_{s,z} \left[q_{\theta}(s|z) \right] - \mathbb{E}_s \left[\log p(s) \right]. \tag{5}$$

The last entropy has to be approximated.

$$\mathbb{E}_s \left[\log p(s) \right] \approx \mathbb{E}_{s,z} \left[\log q(s|z) \right]. \tag{6}$$

Similarly, this approach suffers from insufficient exploration as theoretically and empirically evidenced in Campos et al. (2020). These approaches have only been shown to work from explicit state-representations and it remains unclear how to modify to learning from pixels.

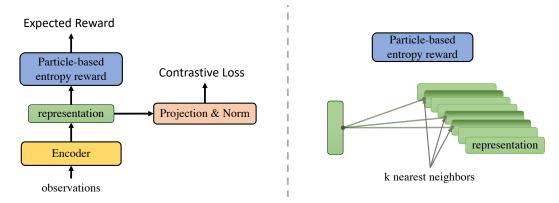


Figure 2: APT model diagram. APT maximizes a particle-based entropy of the states induced by the policy. This particle-based entropy is based on k nearest neighbors in an abstract representation space. The representation is learned by contrastive representation learning on explored states. After pre-training, the learned task-agnostic policy is fine-tuned for downstream task defined by reward.

The fundamental problem faced by these methods is no principled structured exploration. In the next section, we introduce a new nonparametric unsupervised pre-training method for RL which addresses these issues and outperforms the state-of-the-art on visual RL benchmarks.

4. Unsupervised Active Pre-Training for RL

We want to incentivize the agent with a reward r_t to maximize entropy in an abstract representation space. Entropy maximization in high dimensional state space is non-trivial, since density estimation is challenging. We resort to learning a mapping $f_{\theta}: R^{n_s} \to R^{n_z}$ that maps our high-dimensional state space into lower-dimensional abstract representations. Our approach estimates the entropy via the nonparametric particle-based approximation, which forms the basis for an intrinsic reward r_t .

4.1. Particle-based Entropy Maximization Reward

To estimate the entropy in the lower dimensional abstract representation space, we resort to the nonparametric particle-based entropy estimator (Singh et al., 2003; Beirlant, 1997) which has been well studied in statistics (see e.g. Jiao et al., 2018). This particle-based entropy is based on measuring the distance between each particle and its k nearest neighbors.

$$H_{\text{APT}}(z) = -\frac{1}{n} \sum_{i=1}^{n} \log \frac{k}{n v_i^k} + b(k) \propto \sum_{i=1}^{n} \log v_i^k,$$
 (7)

where b(k) is a bias correction term that only depends on k, v_i^k is the volume of the hyper-sphere of radius $\|z_i - z_i^{(k)}\|_{n_z}$, which is the Euclidean distance between z_i and its k-th nearest neighbor $z_i^{(k)}$. The intuition is that the entropy is roughly proportional to the average of the volumes around each particle. The volume measures reflects the sparsity

around each particle.

$$\mathbf{v}_{i}^{k} = \frac{\|z_{i} - z_{i}^{(k)}\|_{n_{z}}^{n_{z}} \cdot \pi^{n_{z}/2}}{\Gamma(n_{z}/2 + 1)}.$$
 (8)

Substitute equation (8) into equation (7), the entropy is simplified to a sum of the log of the distance between each particle and its k-th nearest neighbor.

$$H_k(z) \propto \sum_{i=1}^n \log \|z_i - z_i^{(k)}\|_{n_z}^{n_z}.$$
 (9)

In practice, we find averaging over all k nearest neighbors leads to a more robust and stable results.

$$\hat{H}_{APT}(z) = \sum_{i=1}^{n} \log \left(c + \frac{1}{k} \sum_{z_i^{(j)} \in N_k(z_i)} \|z_i - z_i^{(j)}\|_{n_z}^{n_z} \right),$$
(10)

where $N_k(\cdot)$ denotes the k nearest neighbors around a particle, c is a constant for numerical stability (fixed to 1 in all our experiments).

For a batch of transitions $\{(s, a, s')\}$ sampled from the replay buffer, each s' is treated as a particle and we associate each transition with a intrinsic reward given by

$$r(s, a, s') = \log \left(c + \frac{1}{k} \sum_{z^{(j)} \in \mathcal{N}_k(z)} \|z - z^{(j)}\|_{n_z}^{n_z} \right)$$
 (11) where $z = f_{\theta}(s)$ (12)

In order to keep the rewards on a consistent scale, we normalized the intrinsic reward by dividing it by a running estimate of the mean of the intrinsic reward.

With the intrinsic reward defined in equation (12), we can derive that the intrinsic reward decreases to 0 as most of

Algorithm 1: Training APT

```
Randomly Initialize f encoder
Randomly Initialize \pi and Q networks
for t := 1, T do
    Receive observation s_t from environment
    Take action a_t \sim \pi(\cdot|s_t), receive observation s_{t+1} and \kappa from environment
    \mathcal{D} \leftarrow \mathcal{D} \cup (s_t, a_t, \gamma_t, s_t')\{(s_i, a_i, \gamma_i, s_i')\}_{i=1}^N \sim \mathcal{D}
                                                                                                          // sample a mini batch
    Train neural encoder f on mini batch with equation (14)
                                                                                                   // representation learning
    for each i=1..N do
         a_i' \sim \pi(\cdot|s_i')
        \hat{Q}_i = Q_{\theta'}(s_i', a_i')
Compute r_{\text{APT}} with equation (12)
                                                                                       // particle-based entropy reward
        y_i \leftarrow r_{\text{APT}} + \gamma \hat{Q}_i
    loss_Q = \sum_i (Q(s_i, a_i) - y_i)^2
    Gradient descent step on Q and \pi
                                                                                                          // standard Q-learning
end
```

the state space is visited, which is a favorable property for pre-training.

Proposition 1. Assume the MDP is episodic and its state space is finite $S \subseteq \mathbb{R}^{n_s}$, the representation encoder f_{θ} : $\mathbb{R}^{n_s} \to \mathbb{R}^{n_z}$ is deterministic, and we have a buffer of observed states (s_1, \ldots, s_T) with total sample size T. For an optimal policy that maximizes the intrinsic rewards defined as in equation (12) with $k \in \mathbb{N}$, we can derive the intrinsic reward is 0 in the limit of sample size T.

$$\lim_{T \to \infty} r(s, a, s') = 0, \ \forall s \in \mathcal{S}.$$
 (13)

Proof. Since the intrinsic reward r(s,a,s') defined in equation (12) depends on the k nearest neighbors in latent space and the encoder f_{θ} is deterministic, we just need to prove the visitation count c(s) of s is larger than k as T goes infinity. We know the MDP is episodic, therefore as $T \to \infty$, all states communicate and $c(s) \to \infty$, thus we have $\lim_{T \to \infty} c(s) \geq k, \forall k \in \mathbb{N}, \forall s \in \mathcal{S}$.

4.2. Learning Contrastive Representations

The fore-mentioned part is independent of the representation learning method. We choose contrastive representation learning since it maximally distinguishes an input s_i from alternative inputs s_j , which we hypothesize is helpful for entropy maximization. Recent work, CURL (Laskin et al., 2020b) and SPR (Schwarzer et al., 2021), shows contrastive learning (with data augmentation) helps learn meaningful representations in RL. Within each batch of transitions sampled from the replay buffer, we apply data augmentation to each data point and the augmented observations are encoded into a small latent space z followed by a deterministic

projection $h_{\phi}(\cdot)$ where a contrastive loss is applied. Our contrastive learning is based on SimCLR (Chen et al., 2020), chosen for its simplicity.

$$\min_{\theta,\phi} - \mathbb{E} \left[\log \frac{\exp(h_{\phi}(f_{\theta}(s_i))^T h_{\phi}(f_{\theta}(s_j)))}{\sum_{i=1}^{2N} \mathbb{I}_{[k \neq i]} \exp(h_{\phi}(f_{\theta}(s_i))^T h_{\phi}(f_{\theta}(s_k)))} \right].$$
(14)

We use the same set of image augmentations as in DrQ from Kostrikov et al. (2020) consisting of small random shifts and color jitter. Following DrQ (Kostrikov et al., 2020), the mapping f is represented by the convolutional residual network followed by a fully-connected layer, a LayerNorm and a Tanh non-linearity. We decrease the output dimension of the fully-connected layer after the convnet from 50 to 15. We find it helps to use spectral normalization (Miyato et al., 2018) to normalize the weights and use ELU (Clevert et al., 2016) as the non-linearity in between convolutional layers.

Table 1 positions our new approach with respect to existing ones. Figure 2 shows the resulting model. Training proceeds as in other algorithms maximizing extrinsic reward: by learning neural encoder f and computing intrinsic reward r and then trying to maximize this intrinsic return by training the policy. Algorithm 1 shows the pseudo-code of APT, we highlight the changes from DrQ to APT in color.

4.3. Implementation Details

For our DeepMind control suite and Atari games experiments, we largely follow DrQ (Kostrikov et al., 2020), except we perform two gradient steps per environment step instead of one. Our ablation studies in experiment section

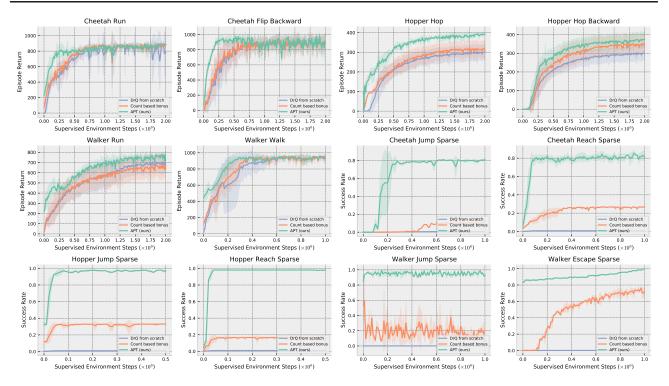


Figure 3: Results on standard (dense reward) tasks and sparse reward tasks from DeepMind Control suite. All curves are the average of three runs with different seeds, and the shaded areas are standard errors of the mean. The sparse reward tasks are challenging for even training state-of-the-art (DrQ) from scratch. APT significantly outperforms all baselines on every task.

confirm that these changes are not themselves responsible for our performance. Kornia (Riba et al., 2020) is used for efficient GPU-based data augmentations. Our model is implemented in PyTorch (Paszke et al., 2019).

5. Experiments

We test APT on DeepMind Control Suite (DMControl; Tassa et al., 2020) and the full suite of 57 Atari games (Bellemare et al., 2013) from OpenAI Gym (Brockman et al., 2016).

Following the setting of the state-of-the-art unsupervised RL, the agents are allowed a long unsupervised pre-training phase, followed by a short test phase exposing to downstream reward, during which the pre-trained model is fine-tuned. Specially, all considered unsupervised pre-training RL are allowed to train 250M steps on Atari games and 5M steps on DMControl environment.

On DMControl, we evaluate the performance of different methods by computing the average success rate and episodic return at the end of training. On Atari, we normalize the episodic return with respect to expert human scores to account for different scales of scores in each game, as done in previous works. The human-normalized performance of an agent on a game is calculated as agent score—random score and aggregated across games by mean or median.

We aim to answer the following questions in the evaluation.

Question 1. How does APT compare to supervised baselines e.q. DrO on DMControl?

Results shown in Figure 3 show that APT beats prior state-of-the-art training DrQ from scratch across different environments. Notably, on the sparse reward tasks that are extremely difficult for training from scratch, APT yields significantly higher data efficiency and asymptotic performance.

Question 2. How does APT compare to supervised RL e.g DQN on Atari?

We investigate APT on the Atari 26 games subset considered in Kaiser et al. (2020) and the full suite 57 Atari games (Mnih et al., 2015). Comparison with supervised RL are shown in Table 3 (top).

APT significantly outperforms DrQ, showing the benefit of unsupervised pre-training. Importantly, the adding of unsupervised pre-training on top of DrQ leads a significant increase in performance(a 54% increase in median score, a 73% increase in mean score, and 5 more games with human-level performance), surpassing DQN which trained on hundreds of millions of sampling steps.

Compared with SPR (Schwarzer et al., 2021) which is a recent state-of-the-art model-based data-efficient algorithm, APT achieves comparable mean and median scores. The SPR is based on Rainbow which combines more advances

Table 2: Results of different methods on DMControl environments. CBB and APT use DrQ as RL optimization algorithm. *: controlled baselines with the same encoder as in APT. Supervised RL training from scratch: DrQ (Kostrikov et al., 2020), CURL (Laskin et al., 2020b) and SAC(state). Mutual information maximization based unsupervised RL: DIAYN (Eysenbach et al., 2019). Entropy maximization based unsupervised RL: MEPOL (Mutti et al., 2020) which is a TRPO (Schulman et al., 2015) like on-policy algorithm.

Methods	DrQ	CURL	CBB	DIAYN*	MEPOL*	APT (ours)	SAC (state)
Cheetah Run Hopper Hop Walker Run	$ \begin{vmatrix} 660 \pm 96 \\ 315 \pm 103 \\ 713 \pm 139 \end{vmatrix} $	641 ± 51 289 ± 87 676 ± 127	113 ± 69 327 ± 121 381 ± 171	81 ± 29 171 ± 45 137 ± 43	156 ± 128 61 ± 29 275 ± 71	671 ± 89 398 ± 45 789 ± 58	$ \begin{vmatrix} 772 \pm 60 \\ 285 \pm 95 \\ 801 \pm 76 \end{vmatrix} $
Cheetah Jump Sparse Hopper Reach Sparse Walker Turnover Sparse	$\begin{array}{c c} .0 \pm .0 \\ .13 \pm .05 \\ .0 \pm .0 \end{array}$	$.0 \pm .0$ $.0 \pm .0$ $.0 \pm .0$	$.18 \pm .08$ $.17 \pm .31$ $.67 \pm .14$	$.21 \pm .09$ $.12 \pm .08$ $.58 \pm .22$	$.05 \pm .02$ $.13 \pm .06$ $.43 \pm .12$	$.79 \pm .13$ $.94 \pm .04$ $.97 \pm .03$	$ \begin{array}{c c} .56 \pm .23 \\ .71 \pm .18 \\ .69 \pm .16 \end{array} $

than DrQ which is significantly simpler. We believe combining APT with SPR will lead to further improvement which is an interesting future direction.

Table 3: Evaluation on Atari games. @N represents the amount of RL interaction utilized. Mdn is the median of human-normalized scores, M is the mean and >H is the number of games with human-level performance. On each subset, we mark as bold the highest score.

	26 Game Subset					Full 57 Games		
Algorithm	Mdn	M	>H	Mdn	M	>H		
// Fully-Supervised Training								
SimPLe @100K	14.39	44.30	2	_	_	_		
OTR @100K	20.40	26.42	1	_	_	_		
PPO $@500K$	20.93	43.74	7	_	_	_		
DQN @10M	27.80	52.95	7	8.61	27.55	7		
SPR @100K	41.50	70.40	7	_	_	_		
CURL @100K	17.50	38.10	2	_	_	_		
DrQ @100K	28.42	35.70	2	_	_	_		
// Unsupervised Pre	e-Train	ing w/ S	upervis	sed Fir	ne-Tuning	?		
DIAYN @100 <i>K</i>	1.34	25.39	2	2.95	23.90	6		
VISR @100K	9.50	128.07	7	6.81	102.31	11		
GPI VISR $@100K$	6.59	111.23	7	8.99	109.16	12		
CBB@100K	1.23	21.94	3	_	_	_		
MEPOL@100K	0.34	17.94	2	_	_	_		
APT(ours)@100 <i>K</i>	47.50	69.55	7	33.41	47.73	12		
↑ w.r.t DrQ	15.38	26.36	5	_	_	_		
↑ w.r.t DrQ in %	54%	73%	250%	_	_	_		

[↑] w.r.t DrQ: improvement over DrQ.

Question 3. How does APT compare to unsupervised pretraining e.g DIYAN on DMControl?

DIAYN is a mutual information maximization based unsupervised RL method which has been shown effective in learning meaningful behaviors for fine-tuning in state-based RL (Eysenbach et al., 2019).

MEPOL is a TRPO (Schulman et al., 2015) based pretraining RL method which also maximizes particle-based entropy (Mutti et al., 2020). MEPOL has only been shown to work with explicit state representation. We adapt DIAYN and MEPOL to train from pixels using the same encoder as in APT.

The results on six representative tasks are shown in Table 2, we can see that APT significantly outperforms baselines by a large margin. Importantly, APT achieves significantly higher success rates than baselines in sparse reward environments, confirming the advantage of learning a task-agnostic exploratory policy.

Table 4: Scores on the 26 Atari games for variants of APT, VISR, and APT. Scores are averaged over 3 random seeds.

Variant	Human-Norm	nalized Score
	median	mean
APT	47.50	69.55
DrQ	28.42	35.70
APT w/o optim change	41.50	60.10
APT w/o data aug	43.18	57.85
APT w/ random neighbors	20.80	24.97
APT w/ random encoder	33.24	41.08
DIAYN w/o data aug	0.96	14.30

Question 4. How does APT compare to unsupervised RL e.g VISR on Atari?

Comparison with unsupervised pre-trained RL are shown in Table 3 (bottom). In term of median score, APT beats unsupervised RL baselines significantly, achieving nearly four times higher score than the second highest score. In terms of mean score, APT outperforms all baselines significantly, except VISR, which achieves higher score than APT. We hypothesis the reason is because the successor features (Dayan, 1993; Barreto et al., 2017) of VISR allows fast task inference for some games.

Question 5. How does APT behave differently from unsupervised RL on Atari?

We investigate the difference of learned behaviors on the full suite of Atari games. Table 5 shows the breakdown of scores on each game. We can see VISR performs slighter better in dense reward games (which consist of most of the

Table 5: Performance of different methods on the 26 Atari games considered by (Kaiser et al., 2020) after 100K environment steps. The results are recorded at the end of training and averaged over 10 random seeds for APT. APT outperforms prior methods on all aggregate metrics, and exceeds expert human performance on 7 out of 26 games while using a similar amount of experience. Prior work has reported different numbers for some of the baselines, particularly SimPLe and DQN. To be rigorous, we pick the best number for each game across the tables reported in van Hasselt et al. (2019) and Kielak (2020).

Game	Random	Human	SimPLe	DER	CURL	DrQ	SPR	VISR	APT (ours)
Alien	227.8	7127.7	616,9	739.9	558.2	771.2	801.5	364.4	2614.8
Amidar	5.8	1719.5	88.0	188.6	142.1	102.8	176.3	186.0	211.5
Assault	222.4	742.0	527.2	431.2	600.6	452.4	571.0	12091.1	891.5
Asterix	210.0	8503.3	1128.3	470.8	734.5	603.5	977.8	6216.7	185.5
Bank Heist	14.2	753.1	34.2	51.0	131.6	168.9	380.9	71.3	416.7
BattleZone	2360.0	37187.5	5184.4	10124.6	14870.0	12954.0	16651.0	7072.7	7065.1
Boxing	0.1	12.1	9.1	0.2	1.2	6.0	35.8	13.4	21.3
Breakout	1.7	30.5	16.4	1.9	4.9	16.1	17.1	17.9	10.9
ChopperCommand	811.0	7387.8	1246.9	861.8	1058.5	780.3	974.8	800.8	317.0
Crazy Climber	10780.5	23829.4	62583.6	16185.2	12146.5	20516.5	42923.6	49373.9	44128.0
Demon Attack	107805	35829.4	62583.6	16185.3	12146.5	20516.5	42923.6	8994.9	5071.8
Freeway	0.0	29.6	20.3	27.9	26.7	9.8	24.4	-12.1	29.9
Frostbite	65.2	4334.7	254.7	866.8	1181.3	331.1	1821.5	230.9	1796.1
Gopher	257.6	2412.5	771.0	349.5	669.3	636.3	715.2	498.6	2590.4
Hero	1027.0	30826.4	2656.6	6857.0	6279.3	3736.3	7019.2	663.5	6789.1
Jamesbond	29.0	302.8	125.3	301.6	471.0	236.0	365.4	484.4	356.1
Kangaroo	52.0	3035.0	323.1	779.3	872.5	940.6	3276.4	1761.9	412.0
Krull	1598.0	2665.5	4539.9	2851.5	4229.6	4018.1	2688.9	3142.5	2312.0
Kung Fu Master	258.5	22736.3	17257.2	14346.1	14307.8	9111.0	13192.7	16754.9	17357.0
Ms Pacman	307.3	6951.6	1480.0	1204.1	1465.5	960.5	1313.2	558.5	2827.1
Pong	-20.7	14.6	12.8	-19.3	-16.5	-8.5	-5.9	-26.2	-8.0
Private Eye	24.9	69571.3	58.3	97.8	218.4	-13.6	124.0	98.3	96.1
Qbert	163.9	13455.0	1288.8	1152.9	1042.4	854.4	669.1	666.3	17671.2
Road Runner	11.5	7845.0	5640.6	9600.0	5661.0	8895.1	14220.5	6146.7	4782.1
Seaquest	68.4	42054.7	683.3	354.1	384.5	301.2	583.1	706.6	2116.7
Up N Down	533.4	11693.2	3350.3	2877.4	2955.2	3180.8	28138.5	10037.6	8289.4
Mean Human-Norm'd	0.000	1.000	44.3	28.5	38.1	35.7	70.4	64.31	69.55
Median Human-Norm'd	0.000	1.000	14.4	16.1	17.5	26.8	41.5	12.36	47.50
# Superhuman	0	N/A	2	2	2	2	7	6	7

full game suite) while APT outperforms VISR on harder exploration games.

This is not surprising since the pre-trained policy in VISR conditions on latent task variables and VISR can identity task by successor features (Dayan, 1993; Barreto et al., 2017). As shown before, VISR suffers from insufficient exploration which explains its inferior performance in harder games.

Note that it is possible we can further improve the performance by directly applying VISR on top of the pre-trained models learned by APT, which we leave as an interesting future work.

Question 6. What is the contribution of each component?

We conduct several ablation studies to measure the contributions of components in our method. Table 4 shows the performance of each variant of APT and controlled baseline.

We find that changing gradient step from 1 to 2 and using data augmentation improves performance. We test a variant

of APT that uses randomly selected neighbors to compute intrinsic reward, we find that the k nearest neighbors based is crucial to encourage efficient exploration. We also test a variant of APT that uses a fixed randomly initialized encoder, this variant works significantly worse than APT but still better than DrQ, indicating the particle-based entropy maximization is key to the superior performance of APT.

6. Conclusion

A new unsupervised pre-training method for RL is introduced to address reward-free pre-training for visual RL, allowing the same task-agnostic pre-trained model to successfully tackle a broad set of RL tasks. Our major contribution is introducing a practical intrinsic reward derived from particle-based entropy maximization in abstract representation space. Empirical study on DMControl suite and Atari games show our method dramatically improves performance on tasks that are extremely difficult for training from scratch. Our method achieves the results of fully supervised canonical RL algorithms using a small fraction of total samples and outperforms data-efficient supervised RL

methods.

7. Limitations and Future Work

The long pre-training phrase in our work is computational intensive, since the exhaustive search and exploration is of high sample complexity, one way to remedy this is by combining our method with successful model-based RL and search approaches (see e.g. Schrittwieser et al., 2019; Sekar et al., 2020; Hafner et al., 2020) to reduce sample complexity.

Our strategy of using the pre-trained model is simply finetuning it with task specific reward, making it prone to catastrophic forgetting (Ratcliff, 1990; Goodfellow et al., 2013) and adversarial rewards, it worth investigating introducing additional neural networks at fine-tuning stage.

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A. General Implementation Details

For our Atari games and DeepMind Control Suite experiments, we largely follow DrQ (Kostrikov et al., 2020), with the following exceptions. We use three layer convolutional neural network from (Mnih et al., 2015) for policy network, and the Impala architecture for neural encoder with LSTM module removed. We use the ELU nonlinearity (Clevert et al., 2016) in between layers of the encoder. The number of power iterations is 5 in spectral normalization.

The convolution neural network is followed by a full-connected layer normalized by LayerNorm (Ba et al., 2016) and a tanh nonlinearity applied to the output of fully-connected layer.

The data augmentation is a simple random shift which has been shown effective in visual domain RL in DrQ (Kostrikov et al., 2020) and RAD (Laskin et al., 2020a). Specifically, the images are padded each side by 4 pixels (by repeating boundary pixels) and then select a random 84×84 crop, yielding the original image. The replay buffer size is 100K. This procedure is repeated every time an image is sampled from the replay buffer. The learning rate of contrastive learning is 0.001, the temperature is 0.1. The projection network is a two-layer MLP with hidden size of 128 and output size of 64. Batch size used in both RL and representation learning is 512. The pre-training phase consists of 5M environment steps on DMControl and 250M environment steps on Atari games. The evaluation is done for 125K environment steps at the end of training for 100K environment steps.

B. Atari Details

The corresponding hyperparameters used in Atari experiments are shown in Table 7 and Table 8.

C. DeepMind Control Suite Details

The action repeat hyperparameters are show in Table 6. The corresponding hyperparameters used in DMControl experiments are shown in Table 9 and Table 8.

Table 6: The action repeat hyper-parameter used for each environment.

Environment name	Action repeat
Cheetah	4
Walker	2
Hopper	2

D. DeepMind Control Suite Sparse Environments

In addition to the existing tasks in DMControl, we tested different methods on three set customized sparse reward tasks: (1) [HalfCheetah, Hopper, Walker] Jump Sparse: the agent receives a positive reward 1 for jumping above a given height otherwise reward is 0. (2) [HalfCheetah, Hopper, Walker] Reach Sparse: the agent receives positive reward 1 for reaching a given target location otherwise reward is 0. (3) Walker Turnover Sparse: the initial position of Walker is turned upside down, and receives reward 1 for successfully turning itself over otherwise 0. In all the considered tasks, the episode ends when the goal is reached.

E. Scores on the full 57 Atari games

A comparison between APT and baselines on each individual Atari game is shown in Table 10. Prior work has reported different numbers for some of the baselines, particularly SimPLe and DQN. To be rigorous, we pick the best number for each game across the tables reported in van Hasselt et al. (2019) and Kielak (2020). APT achieves superhuman performance on 12 games, compared to a maximum of 11 for any previous methods and achieves scores significantly higher than any previous methods.

Table 7: Hyper-parameters in the Atari suite experiments.

Parameter	Setting
Data augmentation	Random shifts and Intensity
Grey-scaling	True
Observation down-sampling	84×84
Frames stacked	4
Action repetitions	4
Reward clipping	[-1,1]
Terminal on loss of life	True
Max frames per episode	108k
Update	Double Q
Dueling	True
Target network: update period	1
Discount factor	0.99
Minibatch size	32
RL optimizer	Adam
RL optimizer (pre-training): learning rate	0.0001
RL optimizer (fine-tuning): learning rate	0.001
RL optimizer: β_1	0.9
RL optimizer: β_2	0.999
RL optimizer: ϵ	0.00015
Max gradient norm	10
Training steps	100k
Evaluation steps	125k
Min replay size for sampling	1600
Memory size	Unbounded
Replay period every	1 step
Multi-step return length	10
Q network: channels	32, 64, 64
Q network: filter size	$8 \times 8, 4 \times 4, 3 \times 3$
Q network: stride	4, 2, 1
Q network: hidden units	512
Non-linearity	ReLU
Exploration	ϵ -greedy
ϵ -decay	2500

Table 8: Hyper-parameters for Learning the Neural Encoder.

Parameter	Setting					
Value of k	search in $\{3, 5, 10\}$					
Temperature	0.1					
Non-linearity	ELU					
Network architecture	same as the Q network encoder (Atari) or the shared encoder (DMControl)					
FC hidden size	1024					
Output size	5					

Table 9: Hyper-parameters in the DeepMind control suite experiments.

Parameter	Setting		
Data augmentation	Random shifts		
Frames stacked	3		
Action repetitions	Table 6		
Replay buffer capacity	100000		
Random steps (fine-tuning phase)	1000		
RL minibatch size	512		
Discount γ	0.99		
RL optimizer	Adam		
RL learning rate	10^{-3}		
Contrastive Learning Temperature	0.1		
Shared encoder: channels	32, 32, 32		
Shared encoder: filter size	$3 \times 3, 3 \times 3, 3 \times 3$		
Shared encoder: stride	2, 2, 2, 1		
Actor update frequency	2		
Actor log stddev bounds	[-10, 2]		
Actor: hidden units	1024		
Actor: layers	3		
Critic Q-function: hidden units	1024		
Critic target update frequency	2		
Critic Q-function soft-update rate τ	0.01		
Non-linearity	ReLU		

Table 10: Comparison of raw scores of each method on Atari games. On each subset, we mark as bold the highest score. For VISR, due to the lack of available source code, we made a best effort attempt to reproduce the algorithm.

Game	Random	Human	VISR	APT
Alien	227.8	7127.7	364.4	2614.8
Amidar	5.8	1719.5	186.0	211.5
Assault	222.4	742.0	1209.1	891.5
Asterix	210.0	8503.3	6216.7	185.5
Asteroids	7191	47388.7	4443.3	678.7
Atlantis	12850.0	29028.1	140542.8	40231.0
Bank Heist	14.2	753.1	71.3	416.7
Battle Zone	2360.0	37187.5	7072.7	7065.1
Beam Rider	363.9	16826.5	1741.9	3487.2
Berzerk	123.7	2630.4	490.0	493.4
Bowling	23.1	160.7	21.2	-56.5
Boxing	0.1	12.1	13.4	21.3
Breakout	1.7	30.5	17.9	10.9
Centipede	2090.9	12017.1	7184.9	6233.9
Chopper Command	811.0	7387.8	800.8	317.0
Crazy Climber	10780.5	23829.4	49373.9	44128.0
Defender	2874.5	18688.9	15876.1	5927.9
Demon Attack	107805	35829.4	8994.9	6871.8
Double Dunk	-18.6	-16.4	-22.6	-17.2
Enduro	0.0	860.5	-3.1	-0.3
Fishing Derby	-91.7	-38.7	-93.9	-5.6
Freeway	0.0	29.6	-12.1	29.9
Frostbite	65.2	4334.7	230.9	1796.1
Gopher	257.6	2412.5	498.6	2190.4
Gravitar	173.0	3351.4	328.1	542.0
Hero	1027.0	30826.4	663.5	6789.1
Ice Hockey	-11.2	0.9	-18.1	-30.1
Jamesbond	29.0	302.8	484.4	356.1
Kangaroo	52.0	3035.0	1761.9	412.0
Krull	1598.0	2665.5	3142.5	2312.0
Kung Fu Master	258.5	22736.3	16754.9	17357.0
Montezuma Revenge	0.0	4753.3	0.0	0.2
Ms Pacman	307.3	6951.6	558.5	2527.1
Name This Game	2292.3	8049.0	2605.8	1387.2
Phoenix	761.4	7242.6	7162.2	3874.2
Pitfall	-229.4	6463.7	-370.8	-12.8
Pong	-20.7	14.6	-26.2	-8.0
Private Eye	24.9	69571.3	98.3	96.1
Qbert	163.9	13455.0	666.3	17671.2
Riverraid	1338.5	17118.0	5422.2	4671.0
Road Runner	11.5	7845.0	6146.7	4782.1
Robotank	2.2	11.9	10.0	13.7
Seaquest	68.4	42054.7	706.6	2116.7
Skiing	-17098.1	-4336.9	-19692.5	-38434.1
Solaris	1236.3	12326.7	1921.5	841.8
Space Invaders	148.0	1668.7	9741.0	3687.2
Star Gunner	664.0	10250.0	25827.5	8717.0
Surround	-10.0	6.5	-15.5	-2.5
Tennis	-23.8	-8.3	0.7	1.2
Time Pilot	3568.0	5229.2	4503.6	2567.0
Tutankham	11.4	167.6	50.7	124.6
Up N Down	533.4	11693.2	10037.6	8289.4
Venture	0.0	1187.5	-1.7	231.0
Video Pinball	0.0	17667.9	35120.3	2817.1
Wizard Of Wor	563.5	4756.5	853.3	1265.0
Yars Revenge	3092.9	54576.9	5543.5	1871.5
Zaxxon	32.5	9173.3	897.5	3231.0
Mean Human-Norm'd	0.000	1.000	68.42	47.73
Median Human-Norm'd	0.000	1.000	9.41	33.41
#Superhuman	0	N/A	11	12
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