UNSUPERVISED ACTIVE PRE-TRAINING FOR REINFORCEMENT LEARNING

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ABSTRACT

We introduce a new unsupervised pre-training method for reinforcement learning called **APT**, which stands for **A**ctive**P**re-**T**raining. APT learns a representation and a policy initialization by actively searching for novel states in reward-free environments. We use the contrastive learning framework for learning the representation from collected transitions. The key novel idea is to collect data during pre-training by maximizing a particle based entropy computed in the learned latent representation space. By doing particle based entropy maximization, we alleviate the need for challenging density modeling and are thus able to scale our approach to image observations. APT successfully learns meaningful representations as well as policy initializations without using any reward. APT is conceptually simple to implement, scalable, and empirically powerful. We empirically evaluate APT on the Atari game suite and DMControl suite by exposing task-specific reward to agent after a long unsupervised pre-training phase. 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 for training from scratch. On Atari games, APT achieves human-level performance on 12 games and obtains highly competitive performance compared to canonical RL algorithms.

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 thanks to scalable and efficient learning algorithms (Mnih et al., 2015; Lillicrap et al., 2015; Schulman et al., 2015; 2017). These landmarks include outperforming humans in board (Silver et al., 2016; 2018; Schrittwieser et al., 2019) and computer games (Mnih et al., 2015; Berner et al., 2019; Schrittwieser et al., 2019; Vinyals et al., 2019; Badia et al., 2020), and solving complex robotic control tasks (Andrychowicz et al., 2017; Akkaya et al., 2019). Despite these successes, a key challenge with Deep RL is that it requires a huge amount of interactions with the environment before it learns effective policies, and needs to do so for each encountered task. Environments are required to have carefully designed task-specific reward functions to guide the RL algorithms (Andrychowicz et al., 2017; Ng et al., 1999), which further limits the wide applications of Deep RL. This is in contrast to how intelligent creatures learn in the absence of external supervisory signals, acquiring abilities in a task-agnostic manner by exploring the environment.

Unsupervised pre-training is a framework that trains models without expert supervision has obtained promising results in computer vision (Oord et al., 2018; He et al., 2019; Chen et al., 2020b; Grill et al., 2020) and natural language modeling (Vaswani et al., 2017; Devlin et al., 2018; Peters et al., 2018; Brown et al., 2020). The key insight of unsupervised pre-training techniques is learning a good representation or initialization from a massive amount of unlabeled data such as ImageNet (Deng et al., 2009), Instagram image set (He et al., 2019), Wikipedia, and WebText (Radford et al., 2019) which are easier to collect and scales to millions or trillions of data points. As a result, The learned representation when fine-tuned on the downstream tasks can solve them efficiently without needing any supervision or in a few-shot manner.

Driven by the significance of massive abundance of unlabeled data relative to labeled data, we pose the following question: *is enabling efficient unsupervised pre-training for deep RL as easy as increasing the amount of unlabeled data?* Unlike the computer vision or language domains, in

reinforcement learning it's not obvious where to extract large pools of unlabeled data. A natural choice is pre-training on ImageNet and transfer the encoder to reinforcement learning tasks. We experimented with using ImageNet data for unsupervised representation learning as initialization of the encoder in deep RL agent, specifically, we used the momentum contrast (He et al., 2019; Chen et al., 2020c) method which is one of the state-of-the-art methods for representation learning. We used DrQ (Kostrikov et al., 2020) as the RL optimization algorithm. The results on DMControl are shown in Figure 1. We can see that using ImageNet pre-trained representations does not lead to any significant improvement over training from scratch. We also experimented with using supervised pre-trained ResNet features as initialization similar to Levine et al. (2016) (details in Appendix) but the results are no different. This seems in contrast to the preeminent successes of ImageNet pre-trained models in various computer vision downstream tasks (see $e.g.$ Krizhevsky et al., 2012; Zeiler & Fergus, 2014; Hendrycks et al., 2019; Chen et al., 2020a). On the other hand, previous research in robotics also found that ImageNet pre-training did not help (Julian et al., 2020). We hypothesize that the reason for the discrepancy is that the ImageNet data distribution is far from the induced sample distribution encountered during RL training. It is therefore necessary to collect data from the RL agent induced distribution.

To investigate this hypothesis, we also experimented with training RL agents by 'exhaustively' collecting data during the reward-free interaction. Specifically, during pre-training phase, the only reward signal is defined by the count-based exploration (Bellemare et al., 2016; Ostrovski et al., 2017) which is one of the state-of-the-art methods for exploration (Taïga et al., 2019), and the density estimation model is PixelCNN (Van den Oord et al., 2016). The results of using the resulting pre-trained policy as initialization are shown in Figure 1. We can see that pre-trained initialization in Cheetah environment does not improve significantly over random initialization on Cheetah Run task. Similarly, pre-trained initialization in Hopper environment only leads to a small improvement over baseline. The reason for this ineffectiveness is that density modeling at pixel level is difficult especially in the low-data and non-stationary regime. The results on DMControl demonstrate that simply increasing the amount of unlabeled data does not work well, therefore we need a more systematical strategy that caters to RL.

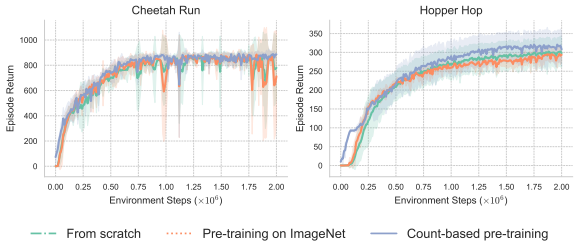

Figure 1: Unsupervised pre-training for deep RL on DMControl. After pre-training ($e.g.$ on ImageNet or in Cheetah reward free environment), the agent fine-tunes the pre-trained representation or initialization to achieve higher task-specific rewards ($e.g.$ let the Cheetah run faster). ImageNet pre-training denotes training MoCo on downsampled ImageNet. Count-based pre-training means training RL agent with only count-based exploration signal. The training details are in Appendix Section C.1. The results show none of the two methods outperforms training from scratch.

In this paper, we address the issue by proposing to actively collect novel data by exploring unknown areas in the task agnostic environment. Our means is maximizing the the entropy of visited state distribution subject to some prior constraints. The entropy maximization principle (Jaynes, 1957) originated in statistical mechanics, where Jaynes showed that entropy in statistical mechanics and information theory were equivalent. Our motivation is that the resulting representation and initialization will encode both prior information while be as agnostic possible, and can be adapted to various downstream tasks. While the entropy maximization principle seems simple, it is practically difficult to calculate the Shannon entropy (Shannon, 2001) as a density model is needed. To remedy this, we resort to the particle-based entropy estimator (Singh et al., 2003; Beirlant, 1997) which has wide applications in various machine learning areas (Sricharan et al., 2013; Pál et al., 2010; Jiao et al., 2018). The particle based entropy estimator is known to be asymptotically unbiased and consistent. Specifically, it computes the average of the Euclidean distance of each sample to its nearest neighbors. We compute the entropy in the latent representation space, for this we adapt the idea of contrastive learning (Hadsell et al., 2006; Gutmann & Hyvärinen, 2010; Mnih & Kavukcuoglu, 2013; He et al., 2019; Chen et al., 2020b) to encode image observations to representation space.

Our approach alternates between training the encoder via contrastive learning and RL style optimization of maximizing expected reward where reward is defined by the particle based entropy. After the pre-training phase, we can either fine-tune the encoder representation for test tasks that

have different action space dimension or fine-tune the policy initialization for tasks with the same action space dimension. Since our method actively collects data during the pre-training phase, the method is named as **A**ctive **P**re-**T**raining (**APT**). We empirically evaluate APT on the Atari game suite and DMControl suite by exposing task-specific reward to the agent after a long unsupervised pre-training phase. On the full suite of Atari games, fine-tuning APT pre-trained models achieves human-level performance on 12 games. On the Atari $100k$ benchmark (Kaiser et al., 2019), our fine-tuning achieves $1.3\times$ higher human median scores than state-of-the-art training from scratch and $4\times$ higher scores than state-of-the-art pre-training RL. On DMControl suite, fine-tuning APT pre-trained models beating all baselines in terms of asymptotic performance and data efficiency and solving tasks that are extremely difficult for training from scratch.

The contributions of our paper can be summarized as: (i) We propose a new approach for pre-training in RL. (ii) We show that our pre-training method significantly improves data efficiency of solving downstream tasks on DMControl and Atari suite. (iii) We demonstrate that pre-training with particle based entropy maximization in contrastive representation space significantly outperforms prior count-based approaches that rely on density modeling.

2 Related Work

2.1 Intrinsic Motivation and Exploration

The learning process of RL agents becomes highly inefficient in sparse supervision tasks when relying on standard exploration techniques. This issue can be alleviated by introducing intrinsic motivation, $i.e.$, denser reward signals that can be automatically computed. These rewards are generally task-agnostic and might come from state visitation count bonus (Bellemare et al., 2016; Tang et al., 2017; Ostrovski et al., 2017; Zhao & Tresp, 2019), learning to predict environment dynamics (Meyer & Wilson, 1991; Pathak et al., 2017; Burda et al., 2018a; Sekar et al., 2020), distilling random neural networks (Burda et al., 2018b; Choi et al., 2018), hindsight relabeling (Andrychowicz et al., 2017), learning options (Sutton et al., 1999) through mutual information (Jung et al., 2011; Mohamed & Rezende, 2015), information gain (Lindley, 1956; Sun et al., 2011; Houthooft et al., 2016), successor features (Kulkarni et al., 2016; Machado et al., 2018), maximizing mutual information between behaviors and some aspect of the corresponding trajectory (Gregor et al., 2016; Florensa et al., 2017; Warde-Farley et al., 2018; Hausman et al., 2018; Eysenbach et al., 2018; Shyam et al., 2019; Hansen et al., 2020), using imitation learning to return to the furthest discovered states (Ecoffet et al., 2019), self-play curriculum (Schmidhuber, 2013; Sukhbaatar et al., 2017; Liu et al., 2019), exploration in latent space (Vezzani et al., 2019), temporal ϵ-greedy (Dabney et al., 2020), injecting noise in parameter space (Fortunato et al., 2017; Plappert et al., 2017), learning to schedule a set of polices (Riedmiller et al., 2018), learning to imitate self (Oh et al., 2018), predicting improvement measure (Schmidhuber, 1991; Oudeyer et al., 2007; Lopes et al., 2012; Achiam & Sastry, 2017), and unsupervised auxiliary task (Jaderberg et al., 2016). The work closest to ours is Hazan et al. (2019) which presents provably efficient exploration algorithms under certain conditions. However, their method directly estimates state visitations through a density model which is difficult to scale. In contrast, our work turns to particle based entropy maximization in contrastive representation space.

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. (2019) introduce a model-based agent (SimPLe) and show that it compares favorably to standard RL algorithms when data is limited. Planing with model learned from experience has been shown successful in vision-based RL (Ha & Schmidhuber, 2018; Hafner et al., 2019; Schrittwieser et al., 2019), Hessel et al. (2018); Kielak (2020); van Hasselt et al. (2019) shows combining existing RL algorithms (Rainbow) can boost data efficiency. Laskin et al. (2020); Kostrikov et al. (2020) have found that applying modest image augmentation can substantially improve data efficiency in vision-based environments, yielding better results than prior model-based methods. Cobbe et al. (2020) demonstrate separating policy gradient and auxiliary optimization can significantly improve data efficiency in vision-based tasks. Our work improves data efficiency of RL in an orthogonal direction by unsupervised pre-training, the above advances can be used inside of APT to obtain better RL optimization.

3 METHOD

Our method shown in Figure 2 consists of contrastive representation learning and particle based entropy maximization in the learned representation space. Consider an agent that sees an observation x_t, takes an action a_t and transitions to the next state with observation x_{t+1} following unknown environmental dynamics. We want to incentivize this agent with a reward r_t relating to how informative the transition was. The goal of the agent is to learn a good representation $f_\theta(x)$ of the observation x, or a good initialization of policy $\pi(a|x)$ by interacting with the environment in a reward-free manner, such that fine-tuning on downstream tasks achieves higher long-term cumulative task specific reward than training from scratch.

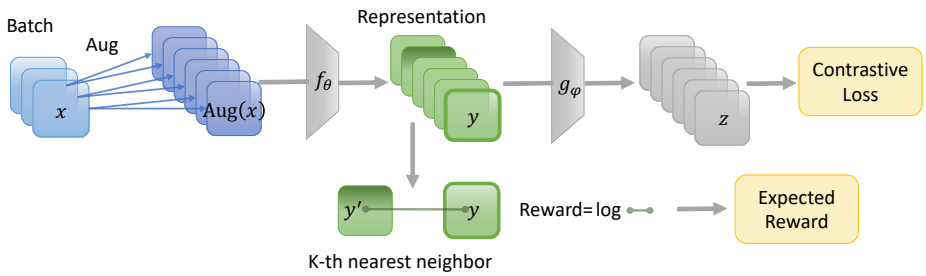

Figure 2: Diagram of the proposed method Unsupervised Active Pre-Training: it consists of contrastive representation learning on data collected by the agent (equation (1)) and RL optimization to maximize particle based entropy (equation (5)). After pre-training, the task-agnostic encoder f_θ and the RL policy initialization can be fine-tuned for different downstream tasks to maximize task-specific reward.

Self-supervised contrastive learning. 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 where a contrastive loss is applied. Our contrastive learning is based on SimCLR (Chen et al., 2020b), chosen for its simplicity.

$$\min_{\theta,\phi} -\mathbb{E}\left[\log \frac{\exp(z_i^T z_j)}{\sum_{i=1}^{2N} \mathbb{I}_{[k\neq i]} \exp(z_i^T z_k)}\right], \tag{1}$$

where z_i, z_j are normalized representations of two random augmentations x_i and x_j of the data point x followed by $g_\phi(f_\theta(x_i)(\cdot))$, and N is the batch size. This objective tries to maximally distinguish an input x_i from alternative inputs x_j. The intuition is that by doing so, the representation captures important information between similar data points, and therefore improve performance on downstream tasks.

Particle based entropy maximization. Let the distribution of observations be $p(x)$. The entropy of the observations is given by $H(x) = -\mathbb{E}_{x\sim p(x)}\left[\log p(x)\right]$. However, in high-dimensional spaces it is challenging to estimate the density, preventing us from directly maximizing the exact entropy.

To remedy this issue, we resort to the particle-based entropy estimator (Singh et al., 2003; Beirlant, 1997) which is based on k-Nearest Neighbors (kNN). The particle based entropy estimate is given by

$$\widehat{H}_k(p) = -\frac{1}{N}\sum_{i=1}^{N} \log \frac{k}{N\mathrm{Vol}_i^k} + \log k - \Psi(k) \propto \sum_{i=1}^{N} \log \mathrm{Vol}_i^k, \tag{2}$$

where Ψ is the digamma function, $\log k - \Psi(k)$ is a bias correction term, Vol_i^k is the volume of the hyper-sphere of radius $R_i = \|x_i - x_i^{k\mathrm{NN}}\|$, which is the Euclidean distance between x_i and its k-th nearest neighbor $x_i^{k\mathrm{NN}}$. The volume is given by:

$$\mathrm{Vol}_i^k = \frac{\|x_i - x_i^{k\mathrm{NN}}\|_n^n \cdot \pi^{n/2}}{\Gamma\left(\frac{p}{2}+1\right)}, \tag{3}$$

where Γ is the gamma function, and n the dimensions of $\boldsymbol{X}$. Put equation (2) and equation (3) together, we simplify the entropy:

$$\widehat{H}_k(p) \propto \sum_{i=1}^{N} \log \|x_i - x_i^{k\mathrm{NN}}\|_n^n. \tag{4}$$

When the target data distribution $p'(x)$ (as in the case of off-policy RL, which we use for sample efficiency) is different from the sampling distribution $p(x)$, in principle importance sampling is needed to correct bias (Ajgl & Šimandl, 2011). However, empirically we find the biased approximation in equation (2) works fine and does not need to estimate the importance ratios.

Given a batch of transitions sampled from the replay buffer, we associate the particle based entropy estimation with the intrinsic reward, and use off-policy RL algorithm to maximize the expected reward. For a batch of transitions $\{(x_t, a_t, x_{t+1})\}$ sampled from the replay buffer, each x_{t+1} is treated as a particle and we associate each transition with a intrinsic reward given by

$$r(x_t, a_t, x_{t+1}) := \log \|y_{t+1} - y_{t+1}^{k\mathrm{NN}}\|_n^n, \tag{5}$$

where $y = f_\theta(x)$ is the representation (i.e. we estimate the entropy in the latent space), we use $n = 2$ in our implementation. The nearest neighbor is computed over the current batch, we use $k = 3$ in practice but the robustness study shows that the performance is not sensitive to the choice of k.

Algorithm. APT alternates between minimizing contrastive loss in equation (1) and maximizing expected intrinsic reward in equation (5). The pseudocode of APT is shown in Algorithm 1 and the full pseudocode of the algorithm is summarized in Algorithm 2 in Appendix. The diagram of APT is shown in Figure 2.

Algorithm 1 Unsupervised Active Pre-Training

f: encoder network shared between actor & critic
g: projection network for contrastive learning
k: hyperparameter of kth-nearest neighbor
while iterations so far $<$ max pre-training iterations **do**
  Interact with a *reward-free* environment
  // sample a batch of transitions from replay buffer
  Compute contrastive_loss using equation (1)
  // update f and g to minimize contrastive loss
  Update(f.param, g.param)
  // compute intrinsic reward for each transition
  Compute y_{t+1} for each transition
  Set $r(x_t, a_t, x_{t+1}) = \log \|y_{t+1} - y_{t+1}^{k\mathrm{NN}}\|_2^2$
  // update RL agent to maximize expected reward
  Update(actor.param, critic.param)
end while

Implementation. The encoder network f is a `ReLU` convolution neural network 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. In order to keep the rewards on a consistent scale we normalized the intrinsic reward by dividing it by a running estimate of the standard deviation of the intrinsic reward. 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., 2020). 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. 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. We incorporate the memory mechanism (with a moving average of weights for stabilization) from He et al. (2019); Chen et al. (2020c). We use DrQ as the RL optimization algorithm at both pre-training phase and fine-tuning phase. The batch size of contrastive learning is 1024, the batch size of RL optimization is 512. The pre-training phase consists of $5M$ environment steps on DMControl and $250M$ environment steps on Atari games. The replay buffer size is $100K$. The projection network is a two-layer MLP with hidden size of 128 and output size of 64. All hyperparameters are included in Table 4 and Table 3 in Appendix.

4 EXPERIMENTS

The purpose of our evaluation is to study the following questions:

- Can APT enable faster learning (higher data efficiency) and higher asymptotic reward than data efficient RL algorithms training from scratch ? (See Section 4.2, Figure 3, and Table 1)
- Are there differences in performance between fine-tuning only the representation (encoder) and fine-tuning both representation and RL agent initialization? (See Section 4.3 and Figure 4)

4.1 EXPERIMENTAL SETUP

The evaluation benchmarks are DeepMind Control Suite (DMControl; Tassa et al., 2020) and Atari suite (Bellemare et al., 2013) from OpenAI Gym (Brockman et al., 2016). For DMControl, we use

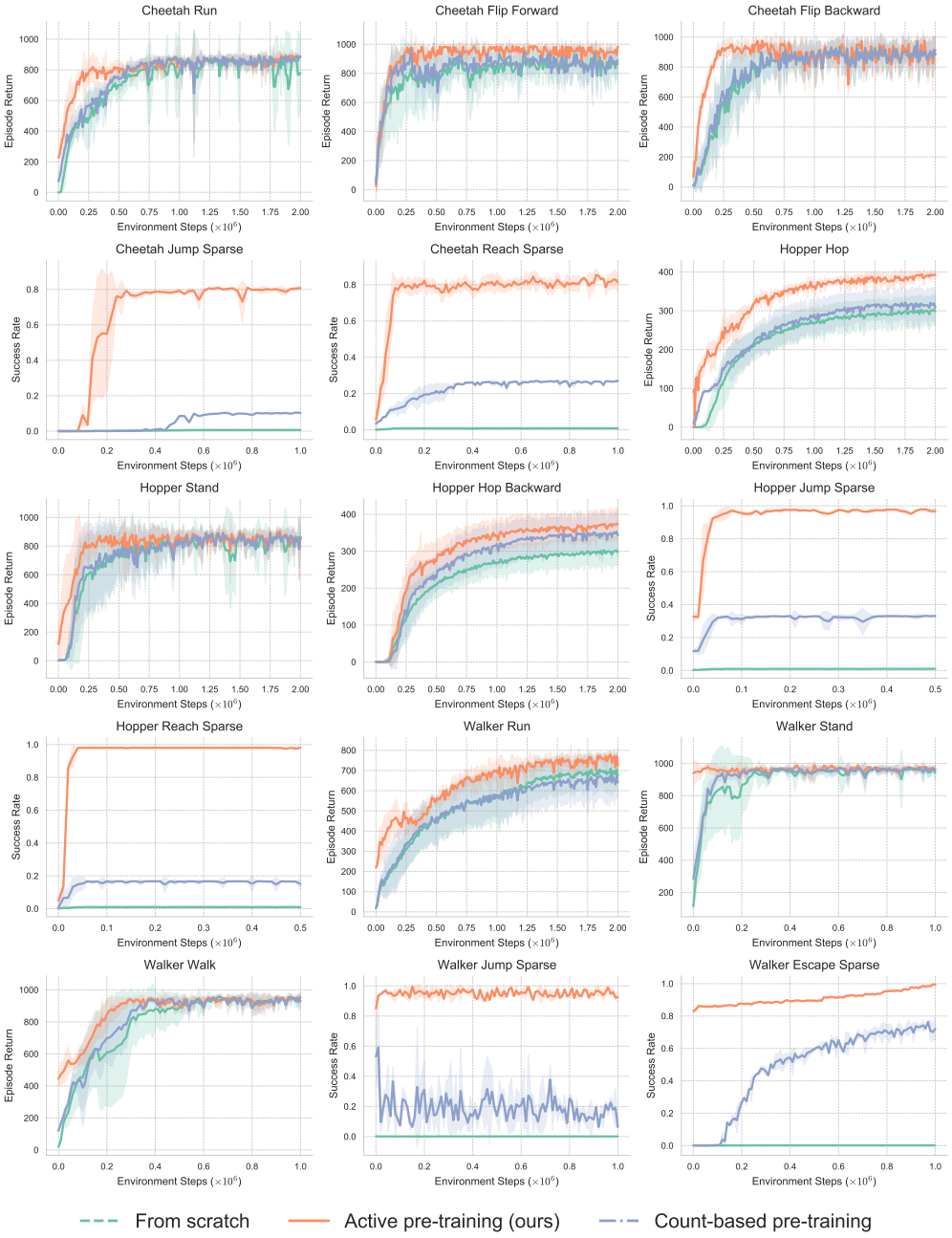

Figure 3: Evaluation on DeepMind Control suite. Models are pre-trained on Cheetah, Hopper, and Walker, and subsequently fine-tuned on respective downstream tasks. The 'sparse' denotes reward is sparse.

pixel observation instead of state as input. For all of the experiments, we use DrQ as the underlying RL optimization algorithm. Unless stated otherwise, all curves are the average of three runs with different seeds, and the shaded areas are standard errors of the mean. In addition to the existing tasks in DMControl, we also design several new sparse reward tasks: (1) *{HalfCheetah, Hopper, Walker} Jump Sparse*: the agent receives 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 to a given target location otherwise reward is 0. (3) *Walker Escape 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.

Table 1: Evaluation on Atari games. $@N$ represents the amount of RL interaction utilized. Mdn is median of human-normalized scores, M is mean, > 0 is the number of games with better than random performance, and $> H$ is the number of games with human-level performance. On each subset we mark as bold the highest score. The reported results of supervised RL $e.g.$ SimPLe in VISR are significantly weaker than reported in Kostrikov et al. (2020); Laskin et al. (2020). We report the best available results and contrast them to APT's results. The results of VISR are cited from Hansen et al. (2020) as the source code is not publicly available. **Top**: data-limited RL. **Bottom**: RL with unsupervised Pre-Training.

	26 Game Subset				47 Game Subset				Full 57 Games			
Algorithm	Mdn	M	>0	$>H$	Mdn	M	>0	$>H$	Mdn	M	>0	$>H$
// Supervised training $@100k$												
SimPLe	14.39	44.30	**26**	2	–	–	–	–	–	–	–	–
OTRainbow	20.40	26.42	**26**	1	–	–	–	–	–	–	–	–
DrQ	28.42	35.70	24	2	–	–	–	–	–	–	–	–
PPO $@500k$	20.93	43.74	25	**7**	–	–	–	–	–	–	–	–
DQN $@10M$	27.80	52.95	25	**7**	9.91	28.07	**41**	7	8.61	27.55	**48**	7
// Unsupervised Pre-Training $@0$ *with supervised fine-tuning* $@100k$												
DIAYN	0.01	16.94	13	2	1.31	19.64	28	6	1.55	16.65	33	6
VISR	9.50	**128.07**	21	**7**	9.42	121.08	35	11	6.81	102.31	40	11
GPI VISR	6.59	111.23	22	**7**	11.70	**129.76**	38	**12**	8.99	**109.16**	44	**12**
Count-based	1.23	21.94	16	3	–	–	–	–	–	–	–	–
APT (ours)	**38.23**	59.89	**26**	**7**	**34.22**	61.78	36	**12**	**41.25**	87.33	43	**12**

4.2 Evaluation of single environment Pre-Training on DMControl and Atari

We conduct a full evaluation of APT on a diverse set of tasks in the single environment setting, the models are pre-trained on Cheetah, Hopper, and Walker for a long period of interacting without reward supervision ($5M$ steps), then fine-tuned for 15 downstream RL tasks such as controlling the Walker to turn itself over. Fine-tuning representation is a common practice in deep learning (Krizhevsky et al., 2012; He et al., 2016). In our RL experiments APT stands for fine-tuning both representation and RL agent initialization. The main baseline is count-based exploration (Bellemare et al., 2014; 2016; Ostrovski et al., 2017), which was proposed as a way to estimate counts in high dimensional states spaces by estimating density; the agent is then encouraged to visit states with a low visit count. We followed Ostrovski et al. (2017) to use PixelCNN (Van den Oord et al., 2016) as a density model. Count-based exploration with PixelCNN is an efficient exploration method in sparse reward environments (Taïga et al., 2019), we will refer this baseline as count-based exploration or count-based throughout the rest of the paper.

Results on DMControl shown in Figure 3 demonstrate that APT beats all baselines on all the tasks across different environments, while the sparse reward tasks are extremely difficult for training from scratch. In some cases, APT allows for very rapid fine-tuning, indicating APT learns task-agnostic representation and meaningful RL initialization. The significantly superior performance of APT empirically shows that maximizing particle-based entropy can drive the RL agent to collect diverse samples and learn task-agnostic initializations that are effective for downstream tasks.

The evaluation on the full suite of 57 Atari games (Bellemare et al., 2013) follows the setting of VISR (Hansen et al., 2020). Firstly, we evaluate APT in a two-phase setup. Agents are allowed a long unsupervised pre-training phase(250M steps) without access to rewards, followed by a short test phase(100k steps). DIAYN (Eysenbach et al., 2018) is a skill-discovery method that maximizes the mutual information between latent variable polices and their behavior in terms of state visitation. The main baseline is VISR (and its variant GPI VISR), which combines skill discovery with universal successor approximators (Borsa et al., 2018) to enable fast task inference at both training and test phases (Barreto et al., 2017; 2018). Due to the high computational cost, the count-based baseline is not evaluated on the entire 57 games suite but on the $100k$ subset (Kaiser et al., 2019). Secondly, we contrast APT with canonical RL algorithms in low-data regime, following the setting of Kaiser et al. (2019). The compared algorithms include DrQ, SimPLe (Kaiser et al., 2019), proximal policy optimization (PPO) (Schulman et al., 2017), and OTRainbow (Kielak, 2020).

Results shown in Table 1 demonstrate that APT significantly outperforms all baselines and buying performance equivalent to hundreds of millions of sampling steps. 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, we leave it for future direction. A further discussion of the connections and differences between APT and VISR can be found in Section A in Appendix which gives more intuitions.

4.3 Representation and RL agent initialization fine-tune

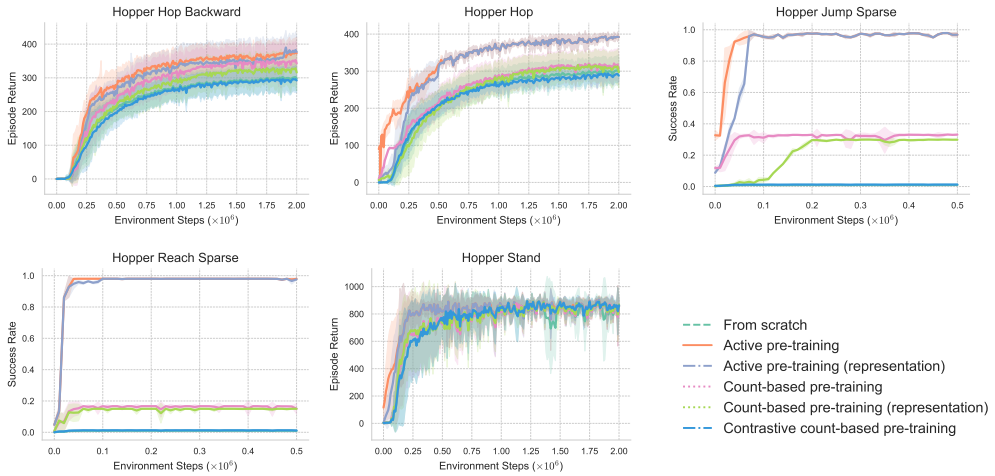

Figure 4: Comparison of fine-tuning representation, fine-tuning both representation and RL agent, and ablated baselines. Models are pre-trained on Hopper, and subsequently fine-tuned on downstream tasks. The 'sparse' denote reward is sparse. Both variants of APT outperform training from scratch and other baselines.

We investigated the difference between fine-tuning only the representation and fine-tuning both representation and policy initialization. APT denotes fine-tuning both representation and RL policy initialization while APT (representation) stands for fine-tuning encoder from pre-trained models and randomly initializing policy. The notable difference is that APT (representation) decouples the action space dimension from pre-trained models. We applied count-based exploration on top of contrastive learning representations to eliminate potential effect of representation learning difference, this baseline is shown as contrastive count-based pre-training, where we train VAE (Kingma & Welling, 2013) on the learned contrastive representations to estimate state visitation.

As we show in Figure 4, APT (representation) beats all of the supervised RL and pre-training RL baselines, fine-tuning both representation and RL initialization further improves performance. In some cases, APT allows for more rapid performance improvement than APT (representation) in a small fraction of total number of samples, indicating APT learns meaningful task-agnostic behavior. Both APT and APT (representation) significantly outperform the ablated contrastive count-based pre-training baseline, confirming the particle based entropy maximization is a crucial component.

5 Discussion and Conclusion

A new unsupervised pre-training method for reinforcement learning is introduced to address task-agnostic pre-training. APT is conceptually simple to implement, scalable, and empirically powerful. We empirically validated APT on Atari and DMControl benchmarks and found it substantially improves data efficiency in a setting of few-step RL with unsupervised pre-training.

While empirically APT obtains better results than APT (representation), fine-tuning representation decouples the action space dimension, making it promising for learning *environment-agnostic* representations. We completed an initial exploration of APT (representation) in multi-environment setting, results shown in Appendix Section B demonstrate mixed results, indicating conflict exists in learning representations. This brings up an interesting future direction that is to apply APT to pre-train in a large number of reward-free environments. It would be interesting to fine-tune pre-trained models in real-world robotic learning and autonomous driving. Another possible direction for future work would be to apply APT to Procgen Benchmark (Cobbe et al., 2019) to study generalization.

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A ANALYSIS VARIATIONAL UNSUPERVISED RL METHODS

We contrast APT with variational unsupervised RL algorithms to give more intuitions besides the empirical evaluation in Table 1.

Utilizing a strong inductive bias that is likely to yield features relevant to rewards of possible downstream tasks has been the central goal of unsupervised RL research. One of the widely used such bias is proposed by Achiam & Sastry (2017); Gregor et al. (2016) that is to only represent the subset of observation space that the agent can control. This can be accomplished by maximizing the mutual information between a policy conditioning variable and the agent's behavior. Formally, the goal is to learn latent-conditioned policies $\pi_\theta(a|s, z)$ and define *skills* as the policies obtained when conditioning π on a fixed value of $z \in \mathrm{Z}$. There exist many algorithms that optimize policy parameter θ maximize the mutual information through various means (see $e.g.$ Eysenbach et al., 2018; Hansen et al., 2020; Warde-Farley et al., 2018; Sharma et al., 2019). The quantity can be derived by expanding the definition and derive a variational lower bound (Barber & Agakov, 2003).

$$
\begin{aligned}
J(\theta) &= I(z; s) && (6)\\
&= H(z) - H(z|s) && (7)\\
&= \mathbb{E}_{\pi,z}\left[\log q(z|s)\right] + \mathbb{E}_s\left[KL(p(\cdot|s)||q_\phi(\cdot|s))\right] + H(z) && (8)\\
&\geq \mathbb{E}_{\pi,z}[\log q_\phi(z|s)] + H(z), && (9)\\
& && (10)
\end{aligned}
$$

where $q_\phi(z|s)$ is a variational approximation. In practice, sampling z from a fixed distribution yields better and more stable results (Eysenbach et al., 2018; Hansen et al., 2020), which simplifies the objective to maximizing the conditional entropy,

$$L(\theta, \phi) = \mathbb{E}_{\pi,z}[\log q_\phi(z|s)]. \tag{11}$$

The optimization of equation (11) is then accomplished by RL algorithm by defining reward

$$r(s, a, s') = \log q_\phi(z|s) \tag{12}$$

equation (11) has been shown effective in RL, from learning skills in state based control in DIAYN (Eysenbach et al., 2018) and EDL (Campos et al., 2020) to combining successor features with skill discovery in VISR (Hansen et al., 2020).

Comparing the variational based intrinsic reward equation (12) with the intrinsic reward used in APT(equation (5)), we can see that the particle based reward does not need to learn a parametric probabilistic density and thus gracefully scales to high dimensional vision-based RL. We see that APT performs considerably better on downstream RL tasks as shown in Table 1.

B DISCUSSION OF MULTI-ENVIRONMENT PRE-TRAINING

Although APT is empirically shown to be highly competitive with the other supervised and unsupervised RL algorithms, validating its effectiveness in learning general task-agnostic pre-trained models, there is at least one limitation that hinders applying it to massive number of reward-free environments. The current algorithmic procedure of APT includes encoding observations to representation space, which may incur conflict between different environments.

To see this, we conduct initial exploration on simultaneously learning pre-trained representation from Hopper, Cheetah, and Walker. In Figure 5 we show how multi-environment learned representation tend to have mixed results, indicating there exists intervention between representation learning in different environments. In order to further close the gap between how intelligent creatures learning without supervisions and how current RL algorithms rely on task-specific supervisions, one promising direction is to scale up reward-free environments which is easier and cheaper to build than shaped tasks, then apply unsupervised reinforcement learning $e.g.$ APT to learn general task-agnostic and environment-agnostic models.

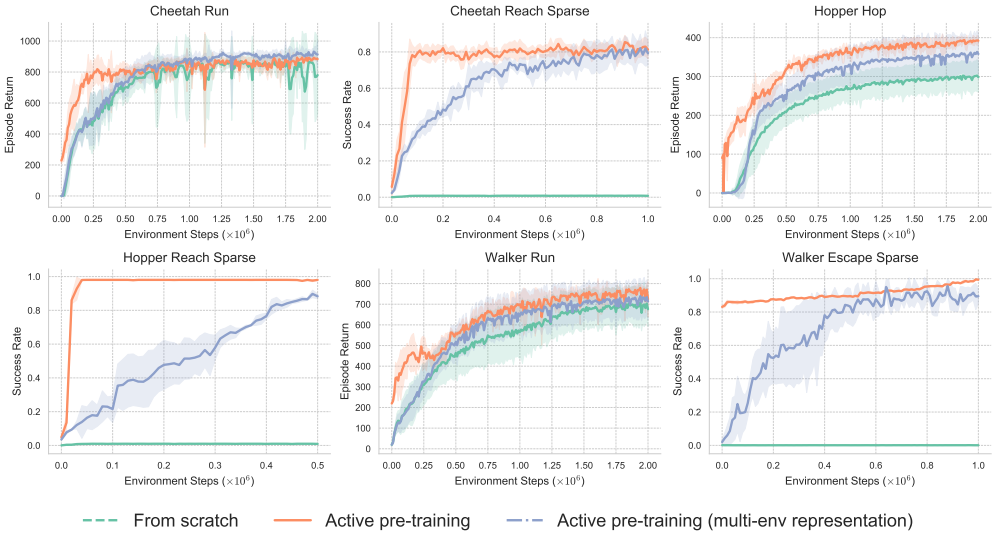

Figure 5: Comparison between fine-tuning representations learned on single environment and multiple environments. We apply APT to all the three environments.

C EXPERIMENT DETAILS

C.1 IMAGENET BASED PRE-TRAINING

In Figure 1, the ImageNet (Deng et al., 2009) pre-trained model is based on MoCo (He et al., 2019). The policies are represented by the Impala convolutional residual network as in (Espeholt et al., 2018), with the LSTM (Hochreiter & Schmidhuber, 1997) part excluded. Images sampled from ImageNet are downsampled to 84×84, followed by frame-stacking and data augmentation. We experiment the data augmentation methods used in He et al. (2019); Chen et al. (2020c) and the simpler random crop used in RL (Kostrikov et al., 2020). Results on DMControl shown no benefit comes from ImageNet unsupervised pre-trained models. In improve the quality of pre-trained representations, we consider initializing the filters in the first layer with weights from the model of He et al. (2016) which is trained on ImageNet classification. Similarly to fine-tuning MoCo trained models, we observe no difference in performance between fine-tuning supervised pre-trained models observed and training from scratch.

C.2 DMCONTROL HYPERPARAMETERS

Environment name	Action repeat
Cheetah	4
Walker	2
Hopper	2

Table 2: The action repeat hyper-parameter used for each environment.

C.3 ATARI HYPERPARAMETERS

For the experiments in Atari 100k experiments, we largely reuse the hyper-parameters from DrQ (Kostrikov et al., 2020). The evaluation is done for $125k$ environment steps at the end of training for $100k$ environment steps.

D APT PSEUDO-CODE

Algorithm 2 Pseudo-code of Unsupervised Active Pre-Training.

f: encoder network shared between actor & critic
g: projection network for contrastive learning
k: hyperparameter of kth-nearest neighbor

// Unsupervised pre-training phase
while iterations so far $<$ max pre-training iterations **do**
  Interact with a *reward-free* environment and collect transitions and save to replay buffer
  // sample a batch of transitions from replay buffer and compute contrastive loss
  Compute contrastive_loss using equation (1)
  // update f and g to minimize contrastive loss
  Contrastive_loss.backward()
  Update(f.param, g.param)
  // compute intrinsic reward for each transition
  $r(x_t, a_t, x_{t+1}) = \log \|y_{t+1} - y_{t+1}^{k\mathrm{NN}}\|_2^2$ (equation (5))
  // optimize reward via off-policy RL
  Compute expected_reward
  // update RL agent to maximize expected reward
  Update(actor.param, critic.param)
end while

// Supervised fine-tune phase
If fine-tune both representation and RL policy, initialize encoder and policy from pre-trained models. If fine-tune representation only, initialize encoder from pre-trained models and randomly initialize RL policy.
while iteration number $\leq$ max fine-tune iterations **do**
  Interact with a *task-specific* environment and collect transitions and save to replay buffer
  Sample a batch of transitions
  // fine-tune representation or fine-tune both representation and RL agent initialization
  Update(f.param, actor.param, critic.param)
end while

Parameter	Setting
Data augmentation	Random shifts
Frames stacked	3
Action repetitions	Table 2
Replay buffer capacity	100000
Random steps (fine-tuning phase)	1000
RL minibatch size	512
Contrastive learning minibatch size	512
K-Nearest Neighbors K value	3
Discount γ	0.99
RL/contrastive learning optimizer	Adam
RL learning rate	10^{-3}
Contrastive learning rate	10^{-3}
Learning rate schedule	`cosine`
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
Init temperature	0.1
Critic Q-function: hidden units	1024
Critic target update frequency	2
Critic Q-function soft-update rate τ	0.01
Non-linearity	`ReLU`

Table 3: Hyper-parameters in the DeepMind control 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
K-Nearest Neighbors K value	3
Contrastive learning optimizer	Adam
Contrastive learning rate	10^{-3}
Learning rate schedule	`cosine`
Temperature	0.1
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	8×8, 4×4, 3×3
Q network: stride	$4, 2, 1$
Q network: hidden units	512
Non-linearity	`ReLU`
Exploration	ϵ-greedy
ϵ-decay	2500

Table 4: Hyper-parameters in the Atari suite experiments.