IMITATION LEARNING FROM PIXEL OBSERVATIONS FOR CONTINUOUS CONTROL

Anonymous authors
Paper under double-blind review

ABSTRACT

We study imitation learning from visual observations only for controlling dynamical systems with continuous states and actions. This setting is attractive due to the large amount of video data available from which agents could learn from. However, it is challenging due to $i)$ not observing the actions and $ii)$ the high-dimensional visual space. In this setting, we explore recipes for imitation learning based on adversarial learning and optimal transport. These recipes enable us to scale these methods to attain expert-level performance on visual continuous control tasks in the DeepMind control suite. We investigate the tradeoffs of these approaches and present a comprehensive evaluation of the key design choices. To encourage reproducible research in this area, we provide an easy-to-use implementation for benchmarking visual imitation learning, including our methods and expert demonstrations.

1 INTRODUCTION

Learning continuous control policies directly from pixel observations is an important problem due to its potential impact on fields like robotics, autonomous driving and video games. These domains have rich resources of data available of humans performing expert-level demonstrations that our software agents do not leverage as they are often trained from scratch without any knowledge of how humans think about these problems. Using unlabeled video data is challenging as it $i)$ requires distilling a representation of the world into the policy of an agent, and $ii)$ we do not know the underlying actions and reasoning process of the expert. This renders common algorithms like canonical behavioral cloning (Pomerleau, 1988; 1991) useless in the no-action setting.

Recently the community has advanced our understanding in learning visual representations and learning to imitate demonstrations provided as proprioceptive states. Visual representation learning has been crucial in recent advancements for sample-efficient reinforcement learning (RL) directly from pixels in continuous spaces, *e.g.* with reconstruction (Finn et al., 2016; Yarats et al., 2019), contrastive learning (Srinivas et al., 2020; Stooke et al., 2020), unsupervised pre-training (Liu & Abbeel, 2021; Yarats et al., 2021b; Seo et al., 2021), world models (Hafner et al., 2018; 2019; 2020) and data augmentation (Yarats et al., 2021c; Raileanu et al., 2020; Laskin et al., 2020).

These approaches require known reward signals from the environment, which are not always available or well-defined. When expert demonstrations are available, imitation learning (IL) and inverse RL (IRL) methods overcome the issue of not having a reward signal and seek to recover the expert agent (Ng & Russell, 2000). These methods work exceptionally well when low-dimensional proprioceptive states and actions are available and typically consist in learning based on the mismatch between the expert and agent's state(-action) distributions.

In this paper, we combine the budding areas of model-free image-based reinforcement learning and state-action imitation learning to control non-trivial continuous dynamical systems from pixel demonstrations. We extend two leading proprioceptive-state approaches to comparing the pixel trajectories of the learner and expert – see fig. 2 for an illustration. The first approach, *pixel sinkhorn imitation learning*, P-SIL, extends optimal transport approaches for imitation learning to the image setting (Papagiannis & Li, 2020; Dadashi et al., 2021). A key component here is how we learn and compare latent representations using the cosine distance on a target encoder that we learn online. Our second approach, *pixel discriminator actor critic*, P-DAC, is a GAIL-based method for pixels (Ho & Ermon, 2016; Kostrikov et al., 2019; Torabi et al., 2018). We propose several key

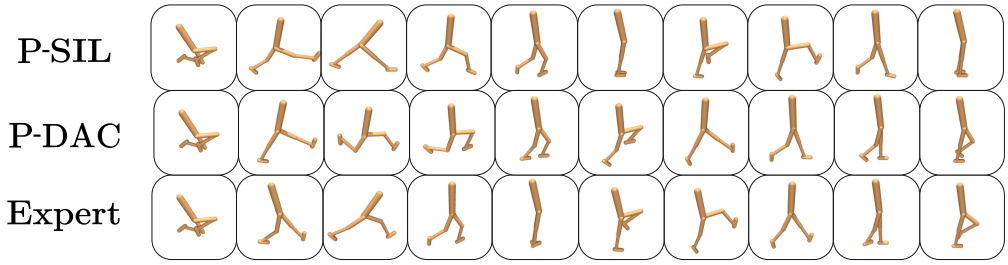

Figure 1: Our pixel-based imitation learning agents learn to recover non-trivial behaviors for continuous control tasks without access to expert actions.

modifications, including data augmentation and using the RL encoder for representations, that enable P-DAC to scale to non-trivial control tasks without the need of having access to expert actions. The imitation rewards from these methods are optimized with DrQ-v2 as an underlying image-based RL backbone (Yarats et al., 2021a). We demonstrate the versatility and strong performance of both approaches on DeepMind control suite tasks, and find that both P-DAC and P-SIL are able to recover expert performance while outperforming canonical extensions of corresponding state-based IL methods, such as SIL (Papagiannis & Li, 2020) and DAC (Kostrikov et al., 2019; Ho & Ermon, 2016) in terms of performance and sample efficiency. Furthermore our extensive ablation study reveals insights into the key design decisions for pixel imitation learning. Finally, we also provide an easy-to-use implementation of these methods and expert demonstrations with unified backbone to make it easy for practitioners to build upon in this under-explored area.

2 Background and Related Work

2.1 Reinforcement Learning (RL) with Pixel Observations

Pixel reinforcement learning can be instantiated as an infinite-horizon Markov decision process (MDP) (Bellman, 1957; Sutton & Barto, 2018), where the agent's state is approximated by a stack of consecutive RGB frames (Mnih et al., 2015). The MDP is of the form $(\mathcal{O}, \mathcal{A}, P, R, \gamma, d_0)$ where $\mathcal{O}$ is the observation space, $\mathcal{A}$ is the action space, $P : \mathcal{O} \times \mathcal{A} \to \Delta(\mathcal{O})$ is the transition function ($\Delta(\mathcal{O})$ is a probability distribution over $\mathcal{O}$), $R : \mathcal{O} \times \mathcal{A} \to \mathbb{R}$ is the reward function, $\gamma \in [0, 1)$ is the discount factor and d_0 is the initial state distribution. The RL problem consists of finding an optimal policy $\pi : \mathcal{O} \to \Delta(\mathcal{A})$ that maximizes the expected long-term reward $\mathbb{E}_\pi[\sum_{t=0}^{\infty} \gamma^t R(\boldsymbol{o}_t, \boldsymbol{a}_t)]$, where $\boldsymbol{o}_0 \sim d_0, a_t \sim \pi(\cdot|\boldsymbol{o}_t)$ and $\boldsymbol{o}_{t+1} \sim P(\cdot|\boldsymbol{o}_t, \boldsymbol{a}_t)$.

2.2 Imitation Learning

In imitation learning, agents do not have access to environment reward R. Instead, they are provided with a dataset of multiple expert trajectories which the agent aims to imitate, where each trajectory is of the form $\boldsymbol{o}^e = (\boldsymbol{o}^e_0, \ldots, \boldsymbol{o}^e_T) \in \mathcal{O}^T$. More formally, agent trajectories $\boldsymbol{o}^a = (\boldsymbol{o}^a_0, \ldots, \boldsymbol{o}^a_T)$ under the policy π have to be close to expert trajectories $\boldsymbol{o}^e$ under some metric between trajectories. We note these trajectories are empirical proxies for the occupancy distributions under the learner and expert policies (Ho & Ermon, 2016; Dadashi et al., 2021). This paper follows the line of research in imitation learning via agent-expert density matching, initially studied by Ng & Russell (2000); Boularias et al. (2011); Englert et al. (2013). Here, imitation-reward signals are derived from trajectories obtained by an expert policy; the agent is then trained using RL methods, which use these imitation rewards as learning signals.

Generative Adversarial Learning for IL P-DAC builds on the budding area of state(-action)-based generative adversarial imitation learning, originally initiated by Ho & Ermon (2016) with the GAIL method, which uses adversarial learning (Goodfellow et al., 2014). A significant body of work built upon GAIL, notably AIRL and WGAIL (Fu et al., 2018; Xiao et al., 2019; Kostrikov et al., 2020), which propose alternative losses relying on other probabilistic divergences. Also, Torabi et al.

(2018) extend GAIL to the no-action setting, a setting which we consider in this paper as well. DAC (Kostrikov et al., 2019) significantly improves upon GAIL by turning it into an offline algorithm, and adding a gradient penalty. One of our approaches, P-DAC, directly builds upon DAC, extending it to the visual setting. A key difference, which allowed us to stabilize visual DAC, was to store imitation rewards in the replay buffer and to not recompute them with up-to-date discriminators and encoders. Also, while DAC parameterizes the discriminator directly on the (proprioceptive) observation space, we compose the discriminator with the RL encoder to leverage representations learned in the RL pipeline. GAIL-based methods in visual spaces are still nascent, and contain works leveraging auxiliary losses (Cetin & Celiktutan, 2021). Toyer et al. (2020) propose a robust visual IL benchmark in which they evaluate mainly adversarial approaches in the discrete action setting. Finally, Rafailov et al. (2021) concurrently propose a model-based extension of GAIL, which can be understood as adversarial learning in the latent space of a world model. They use as baseline a direct extension of DAC to visual spaces by parameterizing a discriminator in image space, which does not perform well on nearly all tasks they consider, while our P-DAC extension achieves expert performance on all considered tasks (including tasks considered by Rafailov et al. (2021), such as walker walk and cheetah run).

Optimal Transport for IL P-SIL extends to the visual case recent SOTA works on imitation learning via optimal transport, namely Dadashi et al. (2021) and Papagiannis & Li (2020). They both leverage optimal transport matching to define rewards. The former uses a greedy approximation of the Wasserstein while the latter leverages the entropic Wasserstein with cosine cost. However, the latter also learns an embedding for states adversarially, while we leverage the encoder of the RL algorithm, avoiding the need for minimax optimization, and allowing to avoid any computational slowdown. Finally, most of the adversarial algorithms in the GAIL line (Ho & Ermon, 2016; Fu et al., 2018) can also be interpreted from the stand-point of the minimization of an OT functional between the state(-action) occupancy distribution of the agent and expert (Xiao et al., 2019). App. A reviews relevant background on optimal transport.

3 Recipes for Visual Imitation Learning

We now describe our IL approaches, which consist of alternative ways to define imitation rewards that an RL backbone algorithm can learn from. In this paper, we leverage DrQ-v2 as RL algorithm (Yarats et al., 2021a). For all methods, we gather episodes under the current policy, evaluate reward trajectories, and update the replay buffer with such episodes, replacing environment rewards by imitation rewards. We summarize the overall process in algorithm 1.

3.1 Pixel Sinkhorn Imitation Learning (P-SIL)

Our first approach extends imitation learning algorithms based on optimal transport to a setting where only pixel observations are available. We define imitation-reward signals via the negative entropic Wasserstein distance between embedded agent and experts' image trajectories.

We interpret an image trajectory $\boldsymbol{o} = (\boldsymbol{o}_1, \dots, \boldsymbol{o}_T)$ as a discrete probability measure of the form $\mu_{\boldsymbol{o}} = \frac{1}{T}\sum_{t=1}^{T} \delta_{\boldsymbol{o}_t}$, where images $\boldsymbol{o}_t \in \mathbb{R}^{3\times84\times84}$ are atoms, each weighted uniformly over time. Optimal transport distances directly on image observations provide weak signal given that $i)$ the metric between individual images does not take into account spatial relationships between individual pixels, and $ii)$ the sample complexity of OT grows exponentially with the dimensions (the number of samples in each trajectory necessary for a good estimate of the OT plan π) (Genevay et al., 2019).

To alleviate these challenges, we embed image trajectories using DrQ-v2's encoder:

$$\boldsymbol{o}^{a,\phi} = \Big[f_\phi(\boldsymbol{o}_1^a), \dots, f_\phi(\boldsymbol{o}_T^a)\Big], \qquad \boldsymbol{o}^{e,\phi} = \Big[f_\phi(\boldsymbol{o}_1^e), \dots, f_\phi(\boldsymbol{o}_T^e)\Big]. \tag{1}$$

In order to be agnostic to the scale of the encoded states, we consider the cosine distance as metric d_c between encoded visual observations, similarly to Papagiannis & Li (2020),

$$C_{t,t'} = d_c(\boldsymbol{o}_t^{a,\phi}, \boldsymbol{o}_{t'}^{e,\phi}) = 1 - \frac{\langle \boldsymbol{o}_t^{a,\phi}, \boldsymbol{o}_{t'}^{e,\phi} \rangle}{||\boldsymbol{o}_t^{a,\phi}||\ ||\boldsymbol{o}_{t'}^{e,\phi}||}. \tag{2}$$

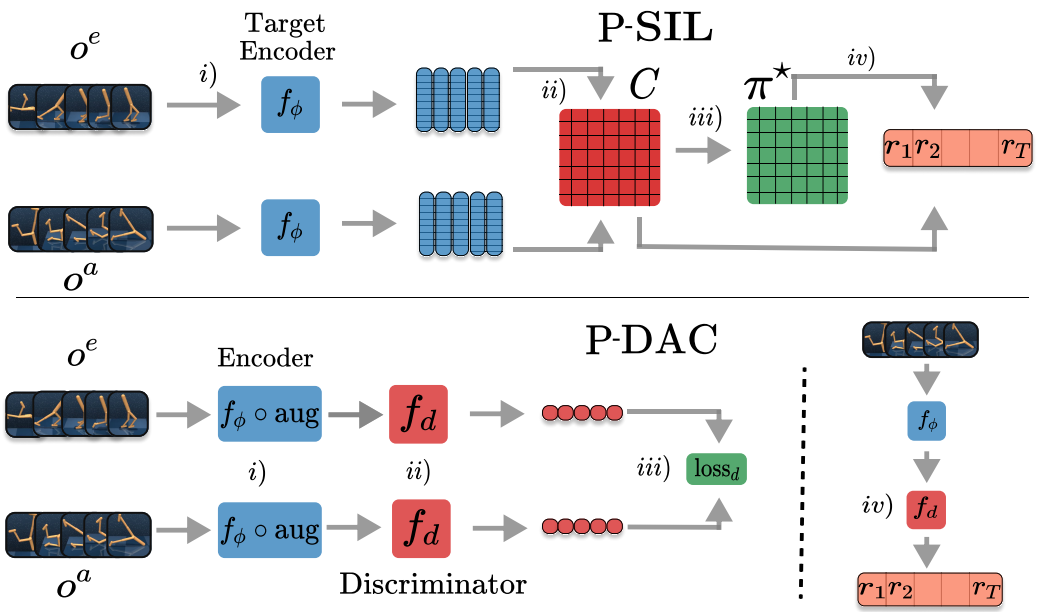

Figure 2: Summary of P-SIL and P-DAC. Top: P-SIL, $i)$ encodes the agent o^a and expert o^e trajectories into a latent space, $ii)$ computes a cost matrix C and $iii)$ transport map $\pi^\star$ between these to $iv)$ produce imitation rewards $r_{1:T}$. Bottom: P-DAC, $i)$ encodes the (data-augmented) agent o^a and expert o^e trajectories into a latent space, $ii)$ passes them through the discriminator, and $iii)$ evaluates the DAC loss. $iv)$ Rewards $r_{1:T}$ can then be produced with the discriminator.

We estimate the entropic Wasserstein distance with the cosine cost between embedded trajectories

$$\mathcal{W}_\epsilon^2(\mu_{\boldsymbol{o}^{a,\phi}}, \mu_{\boldsymbol{o}^{e,\phi}}) = \min_{\gamma \in \Pi} \sum_{t,t'=1}^{T} C_{t,t'} \gamma_{t,t'} - H(\gamma) \tag{3}$$

to obtain an optimal alignment $\pi^\star$. Finally, we extract rewards for each of the agent's states as

$$r(\boldsymbol{o}_t^{a,\phi}) = -\sum_{t'=1}^{T} C_{t,t'} \gamma^\star_{t,t'}. \tag{4}$$

If we are provided with multiple expert trajectories $\boldsymbol{o}^{e_1}, \ldots, \boldsymbol{o}^{e_N}$, we infer the nearest-neighbor expert by computing the embedded entropic Wasserstein distance with cosine cost between each expert trajectory and the agent's rollout. We then set rewards with the alignment to the closest expert:

$$e_\star = \underset{n \in \{1,\ldots,N\}}{\arg\min}\ \mathcal{W}_\epsilon^2(\mu_{\boldsymbol{o}^{a,\phi}}, \mu_{\boldsymbol{o}^{e_n,\phi}}) \qquad r(\boldsymbol{o}_t^{a,\phi}) = -\sum_{t'=1}^{T} d_c(\boldsymbol{o}_t^{a,\phi}, \boldsymbol{o}_{t'}^{e_\star,\phi}) \gamma^\star_{t,t'}. \tag{5}$$

The rewards computed in (5) are non-stationary as the encoder f_ϕ is updated to optimize the critic loss. To increase the stability of P-SIL, we use a target network $f_{\phi'}$, which is updated every T_{update} environment steps with the weights of DrQ-v2's encoder. We use $f_{\phi'}$ to estimate rewards via (5).

An important benefit of P-SIL is that computing imitation rewards does not add any computational burden as the cost of (5) is negligible, and we use the encoder of the RL agent. This is in contrast to adversarial approaches (Papagiannis & Li, 2020; Ho & Ermon, 2016), which require training a discriminator by solving an inner-loop maximization problem and then infer rewards using the discriminator. We therefore preserve the attractive computational efficiency of the base algorithm DrQ-v2.

In summary, we compute imitation rewards as the entropic Wasserstein discrepancy between the agent's and expert's encoded states for the single-demonstration case. For multiple expert demonstrations, we use the transport cost from the closest expert demonstration in the OT sense.

3.2 PIXEL DISCRIMINATOR ACTOR CRITIC (P-DAC)

We now propose and study P-DAC as a GAIL-based method for pixels that builds on the work by Ho & Ermon (2016); Torabi et al. (2018); Kostrikov et al. (2019). The key differences to previous works are $i)$ that we compose the discriminator with the RL encoder to leverage its representations, $ii)$ that we apply data augmentation to discriminator inputs and $iii)$ that we store imitation rewards in the buffer rather than recomputing them at each iteration. We now describe the main components of P-DAC in more details.

In contrast to P-SIL, it is necessary to train a discriminator, along with DrQ-v2's other networks (actor, critic and encoder). To train the discriminator, we sample batches $\boldsymbol{o}^e_{1:N}$ and $\boldsymbol{o}^a_{1:N}$ of size N from both the expert buffer and the policy buffer, respectively, apply data augmentation, and encode augmented observations using DrQ-v2's encoder, which then yields

$$\boldsymbol{o}^{a,\phi} = \Big[f_\phi \circ \text{aug}(\boldsymbol{o}^a_1), \dots, f_\phi \circ \text{aug}(\boldsymbol{o}^a_N)\Big], \qquad \boldsymbol{o}^{e,\phi} = \Big[f_\phi \circ \text{aug}(\boldsymbol{o}^e_1), \dots, f_\phi \circ \text{aug}(\boldsymbol{o}^e_N)\Big]. \quad (6)$$

Per common practice (Kostrikov et al., 2019), we omit importance sampling when estimating the policy state occupancy via replay buffer. We then maximize

$$\max_D \sum_{n=1}^N \log D(\boldsymbol{o}^{a,\phi}_n) + \sum_{n=1}^N \log(1 - D(\boldsymbol{o}^{e,\phi}_n)) + E_{\bar{\boldsymbol{o}}^\phi}[\big\|\nabla D(\bar{\boldsymbol{o}}^\phi)\big\| - 1]^2, \quad (7)$$

with respect to the discriminator's weights and add a gradient penalty as recommended by Kostrikov et al. (2019). Here, $\bar{\boldsymbol{o}}^\phi$s are sampled along straight lines between agent and expert's encoded observations.

To compute rewards at the end of episodic rollouts, we first embed the observation trajectory with DrQ-v2's encoder. We then apply the discriminator to the encoded observations, and compute rewards

$$r(\boldsymbol{o}^a_t) = \log\Big(\sigma \circ D(\boldsymbol{o}^{a,\phi}_t)\Big) - \log\Big(1 - \sigma \circ D(\boldsymbol{o}^{a,\phi}_t)\Big), \quad (8)$$

where σ is the sigmoid function. We then add the episode with imitation rewards computed in (8) to the replay buffer. This differs from the original GAIL implementation (Ho & Ermon, 2016), where training is online, and from its follow-up offline extension DAC (Kostrikov et al., 2019) that recomputes rewards at each training iteration. We will show in the experiment section that data augmentation is a key component to scaling to challenging environments. Finally, in contrast with previous works that parameterize the discriminator directly in observation space (Ho & Ermon, 2016; Torabi et al., 2018; Kostrikov et al., 2019), we compose it with the RL encoder, which allows us to leverage its representations.

4 EXPERIMENTS

In this section, we empirically evaluate the proposed algorithms on tasks from the DeepMind control suite, aiming to contrast their strengths and weaknesses. We also provide an extensive ablation study highlighting the key design choices that enabled solving challenging tasks with imitation learning from visual observations only.

Our set of experiments was designed with the aim of answering the following questions.

1. *Are* P-DAC *and* P-SIL *able to achieve expert performance and how do they compare in terms of sample efficiency (number of interactions with the environment required to solve a task) and computational efficiency?*

   Yes. P-DAC is more sample efficient than P-SIL, see fig. 3. Furthermore, our methods allow to learn policies that are closer to expert policies than baselines under the embedded Wasserstein metric, see fig. 4.

2. *Are* P-DAC *and* P-SIL *robust to the number of expert demonstrations they are provided?*

   Yes, see fig. 5.

3. *Is data augmentation as essential and effective as in pixel-based reinforcement learning?*

   Yes, agents can not approach expert performance on nearly all task without data augmentation, see fig. 6.

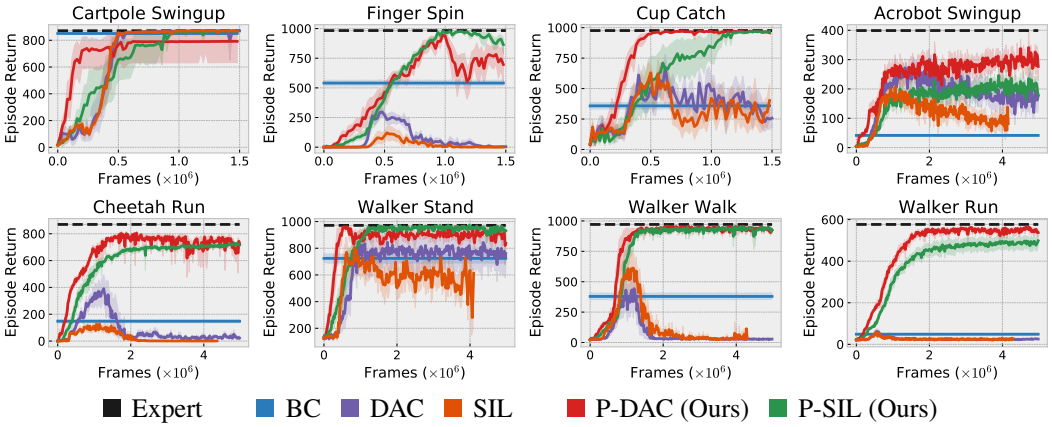

Figure 3: Our agents P-DAC and P-SIL demonstrate superior performance over vanilla instantiations of DAC and SIL, as well as BC over a set of challenging image-based tasks from DMC. In many cases P-DAC and P-SIL are able to recover the expert performance by using only 10 expert trajectories. Note, DAC and BC have privileged access to expert actions, while other methods do not.

4. *Is optimal transport providing a gain over simpler metrics without alignment (e.g., cosine distance between trajectories)?*
   Yes, there is a significant performance gain when leveraging OT alignments, see fig. 7
5. *Are expert actions required to solve challenging tasks or are pixel observations enough?*
   No, P-DAC without actions performs on par or better than P-DAC with actions on all environments, see fig. 8.

4.1 Experimental Setup

Environments We consider 8 Mujoco (Todorov et al., 2012) tasks in the DeepMind control suite (Tassa et al., 2018). The selected tasks are distinct enough to demonstrate the versatility and robustness of P-DAC and P-SIL. Environment observations are stacks of three consecutive 84×84 RGB images. Environment rewards are used to evaluate the performance of agents, but they are not provided to the agents during training. For the simplest tasks, we allow a budget of 1.5M environment frames, while for hard tasks we allow 5M environment frame in main results. In ablations, we allow 3M for hard tasks.

Expert Demonstrations We gather expert demonstrations by training DrQ-v2 in reinforcement learning mode (training is on environment rewards). We run 10 seeds and pick the seed that achieves highest episodic reward to generate expert trajectories (sequences of image observations).

Baselines As baselines, we consider our two proposed approaches, P-DAC and P-SIL, along with a behavioral cloning (BC) baseline that we strengthen by leveraging the same data augmentation as in our approaches. We also consider canonical extensions of DAC (Kostrikov et al., 2019) and SIL (Papagiannis & Li, 2020), in which the discriminator is directly defined on pixel-space, and without the tricks proposed in this paper (e.g., no data-augmentation applied to discriminator inputs, no target encoder for SIL,...). We note that the BC and DAC baselines are privileged as they access expert actions while our baselines do not.

Setup In all experiments, we run 10 seeds under each configuration and average results, while providing a 90% confidence interval. We compare agents with respect to two distinct scores. Firstly, we use the episodic return as a metric to verify whether the agent solves the task; secondly, we average the entropic Wasserstein distance with cosine cost between agent rollouts and expert demonstrations, both embedded via a common random encoder. This aims to show that agent rollouts are close to the expert demonstrations they are trained on. Finally, in ablation bar-plots, we show episodic reward averaged over the final 10 environment interactions. We provide a description of all hyperparameters in the appendix.

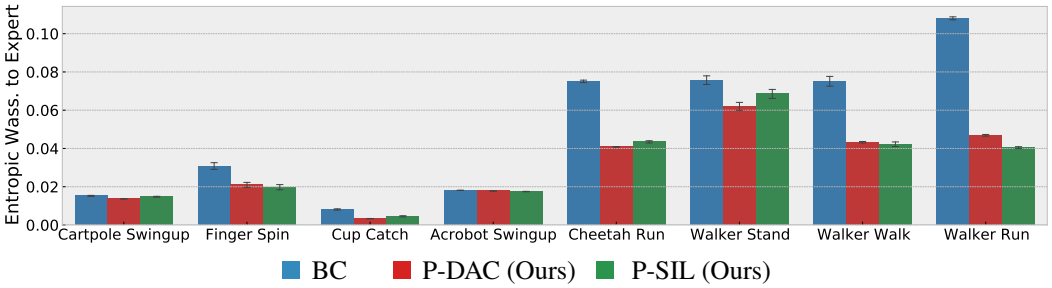

Figure 4: Entropic Wasserstein distance to the expert demonstrations (*the lower the better*) for P-DAC, P-SIL, DAC, and data-augmented BC on DeepMind control suite tasks from pixel observations only. We notice P-SIL and P-DAC are on par in terms of closeness to expert demonstrations while BC is significantly worse. This is due to the issue of distributional shift that BC suffers from in the low number of demonstrations regime.

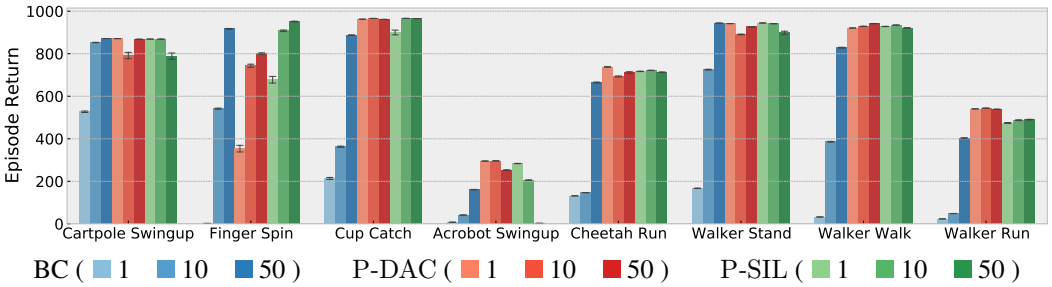

Figure 5: Ablation study on the number of demonstration. We train all P-DAC, P-SIL and BC on $1, 10$ and 50 demonstrations. We observe P-DAC and P-SIL are robust to the number of demonstrations, while BC is not, and fails on most tasks for the 1-demonstration setting.

4.2 Main Results

Sample efficiency We begin by comparing baselines with respect to sample efficiency, i.e., the number of environment interactions required to solve a task. We observe in fig. 3 that both P-DAC and P-SIL achieve expert performance on all environments besides Acrobot swingup, which is a hard exploration task. However, both approaches significantly surpass the performance of SIL, DAC and data-augmented behavioral cloning even though the latter two are privileged by knowing expert actions. We also note that P-DAC is more sample efficient than P-SIL.

In fig. 4, we show the entropic Wasserstein between embeddings of agent rollouts and expert trajectories; results correlate well with those under episodic return (see fig. 3). Again, P-SIL and P-DAC outperform data-augmented BC under this alternative metric, i.e., trajectories under these are closer in the embedded entropic Wasserstein sense than those of BC.

4.3 Ablations

We now provide an extensive ablation contrasting the approaches and key design choices.

Number of demonstrations We first evaluate the robustness of baselines to the number of expert demonstrations provided to the learner. We train all agents on $1, 10$ and 50 demonstrations, on all tasks, and plot episodic return averaged across seeds in fig. 5. We observe that our approaches are robust to the number of demonstrations, with comparable performance for $1, 10$ and 50 demonstrations across tasks (besides finger spin). By contrast, the data-augmented BC baseline is non-robust, and requires a large number of demonstrations (typically 50) to approach expert performance.

Data augmentation Next, we evaluate whether data augmentation is necessary to achieve expert performance. We observe that without augmentation, both P-DAC and P-SIL are not able to

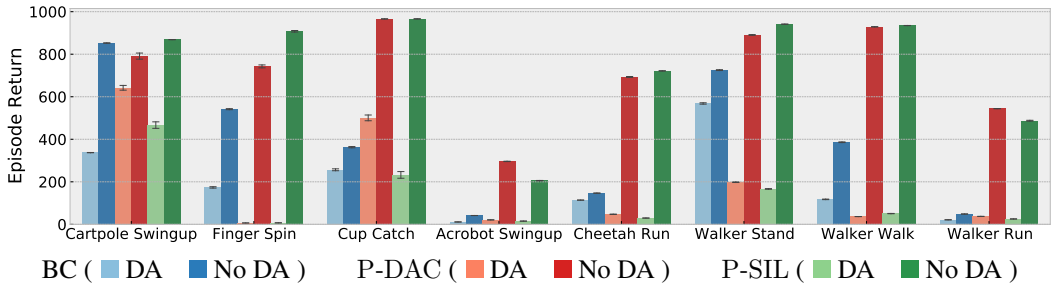

Figure 6: Ablation study on data augmentation (DA). We compare P-DAC, P-SIL and BC with and without data augmentation. We observe the gap in performance to be significantly larger for P-DAC and P-SIL, showing that DA is a crucial component of our methods.

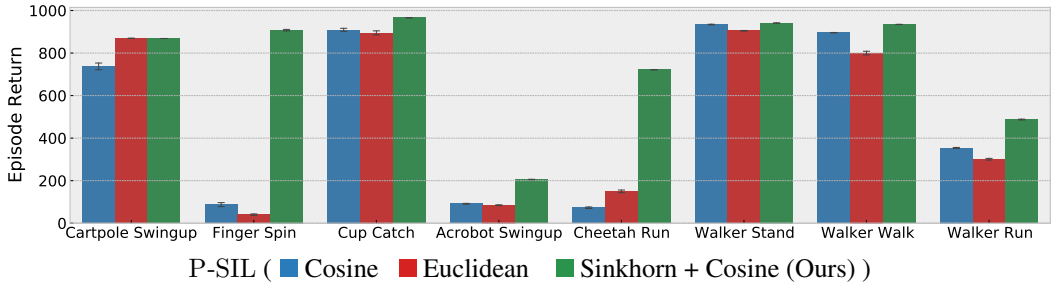

Figure 7: Ablation study on the distance between trajectories for P-SIL. We compare our approach (OT alignment with cosine cost), to the cosine distance and the Euclidean distance between trajectories (without OT). We observe that OT significantly outperform non-OT approaches. Hence, OT alignment is also an essential component of P-SIL.

recover solid performance on nearly all tasks, especially locomotion ones. We note that behavioral cloning is less sensible to it. This may be explained by the fact that augmentation is necessary to obtain good representations as seen in Laskin et al. (2020); Yarats et al. (2019; 2021a), and that our imitation approaches leverage such representations to design reward signals. As a result, without good representations the agents can not recover any meaningful behaviors.

Metrics We continue with analyzing one of the key design choices behind P-SIL, i.e., whether an optimal transport alignment of the agent and expert trajectories is required over simply leveraging an l_2 or cosine distance (no alignment). We observe in fig. 7 that OT is essential to achieving expert performance on most tasks. We believe this is due to the high variance in the initial state distribution of agent and expert, which leads to unaligned trajectories, and hence uninformative rewards in the absence of OT alignment.

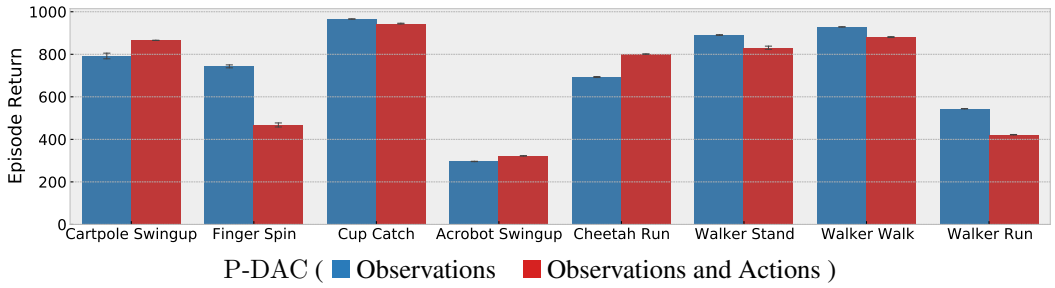

Figure 8: Ablation study on the need for expert actions. We train P-DAC with and without actions concatenated to observations (the former is privileged). We observe the performance gap to be marginal, hence actions are not necessary in the considered environments, contrarily to popular beliefs on GAIL-like algorithms.

Observations vs Observations-actions GAIL-like methods are often assumed to require expert actions to recover non-trivial performance. We hence compare our implementation of P-DAC with a privileged implementation of P-DAC which accesses expert actions. In the latter case, we concatenate embedded image observations, and actions before passing these to the discriminator. We observe in fig. 8 that our approach without expert actions performs on par with the action-baseline, highlighting that on the considered environments, actions are not required to achieve strong performance. This is encouraging given that there are massive amounts of unlabeled video data that these agents could potentially learn from.

5 Conclusion

We propose effective methods for imitation learning directly from pixels without expert actions, extending state-based adversarial and optimal transport approaches, and significantly outperforming canonical extensions of these. This steps us closer toward leveraging the rich amount of expert-level data on non-trivial environments for the control of continuous systems. We envision that continuing to scale in this space will involve further understanding how to recover a representation of the high-dimensional data, *e.g.* with unsupervised pretraining, and how to go beyond settings where the expert and learner live in the same space.

References

Richard Bellman. A markovian decision process. *Indiana Univ. Math. J.*, 1957.

Abdeslam Boularias, Jens Kober, and Jan Peters. Relative entropy inverse reinforcement learning. In *Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics*, pp. 182–189. JMLR Workshop and Conference Proceedings, 2011.

Edoardo Cetin and Oya Celiktutan. Domain-robust visual imitation learning with mutual information constraints. In *International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=QubpWYfdNry.

Robert Dadashi, Leonard Hussenot, Matthieu Geist, and Olivier Pietquin. Primal wasserstein imitation learning. In *International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=TtYSU29zgR.

Peter Englert, Alexandros Paraschos, Jan Peters, and Marc Peter Deisenroth. Model-based imitation learning by probabilistic trajectory matching. In *2013 IEEE International Conference on Robotics and Automation*, pp. 1922–1927, 2013. doi: 10.1109/ICRA.2013.6630832.

Chelsea Finn, X. Tan, Yan Duan, Trevor Darrell, Sergey Levine, and P. Abbeel. Deep spatial autoencoders for visuomotor learning. *2016 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 512–519, 2016.

Justin Fu, Katie Luo, and Sergey Levine. Learning robust rewards with adverserial inverse reinforcement learning. In *International Conference on Learning Representations*, 2018. URL https://openreview.net/forum?id=rkHywl-A-.

Aude Genevay, Lénaic Chizat, Francis Bach, Marco Cuturi, and Gabriel Peyré. Sample complexity of sinkhorn divergences. In *The 22nd International Conference on Artificial Intelligence and Statistics*, pp. 1574–1583. PMLR, 2019.

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. *Advances in neural information processing systems*, 27, 2014.

Danijar Hafner, Timothy Lillicrap, Ian Fischer, Ruben Villegas, David Ha, Honglak Lee, and James Davidson. Learning latent dynamics for planning from pixels. *arXiv preprint arXiv:1811.04551*, 2018.

Danijar Hafner, Timothy Lillicrap, Jimmy Ba, and Mohammad Norouzi. Dream to control: Learning behaviors by latent imagination. *arXiv preprint arXiv:1912.01603*, 2019.

Danijar Hafner, Timothy P. Lillicrap, Mohammad Norouzi, and Jimmy Ba. Mastering atari with discrete world models. *CoRR*, 2020.

Jonathan Ho and S. Ermon. Generative adversarial imitation learning. In *NIPS*, 2016.

Ilya Kostrikov, Kumar Krishna Agrawal, Debidatta Dwibedi, Sergey Levine, and Jonathan Tompson. Discriminator-actor-critic: Addressing sample inefficiency and reward bias in adversarial imitation learning. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=Hk4fpoA5Km.

Ilya Kostrikov, Ofir Nachum, and Jonathan Tompson. Imitation learning via off-policy distribution matching. In *International Conference on Learning Representations*, 2020. URL https://openreview.net/forum?id=Hyg-JC4FDr.

Michael Laskin, Kimin Lee, Adam Stooke, Lerrel Pinto, Pieter Abbeel, and Aravind Srinivas. Reinforcement learning with augmented data, 2020.

Hao Liu and Pieter Abbeel. Unsupervised active pre-training for reinforcement learning. *openreview*, 2021. URL https://openreview.net/forum?id=cvNYovr16SB.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *nature*, 518(7540):529–533, 2015.

Andrew Y. Ng and Stuart J. Russell. Algorithms for inverse reinforcement learning. In *Proceedings of the Seventeenth International Conference on Machine Learning*, ICML '00, pp. 663–670, San Francisco, CA, USA, 2000. Morgan Kaufmann Publishers Inc. ISBN 1558607072.

Georgios Papagiannis and Yunpeng Li. Imitation learning with sinkhorn distances. *ArXiv*, abs/2008.09167, 2020.

G. Peyré and Marco Cuturi. Computational optimal transport. *Found. Trends Mach. Learn.*, 11: 355–607, 2019.

D. Pomerleau. Alvinn: An autonomous land vehicle in a neural network. In *NIPS*, 1988.

D. Pomerleau. Efficient training of artificial neural networks for autonomous navigation. *Neural Computation*, 3:88–97, 1991.

Rafael Rafailov, Tianhe Yu, Aravind Rajeswaran, and Chelsea Finn. Visual adversarial imitation learning using variational models. In *ICML 2021 Workshop on Unsupervised Reinforcement Learning*, 2021. URL https://openreview.net/forum?id=z-Z3l6667Mz.

Roberta Raileanu, Max Goldstein, Denis Yarats, Ilya Kostrikov, and Rob Fergus. Automatic data augmentation for generalization in deep reinforcement learning. *CoRR*, 2020.

Younggyo Seo, Lili Chen, Jinwoo Shin, Honglak Lee, P. Abbeel, and Kimin Lee. State entropy maximization with random encoders for efficient exploration. In *ICML*, 2021.

Richard Sinkhorn and Paul Knopp. Concerning nonnegative matrices and doubly stochastic matrices. *Pacific Journal of Mathematics*, 21:343–348, 1967.

Aravind Srinivas, Michael Laskin, and Pieter Abbeel. Curl: Contrastive unsupervised representations for reinforcement learning. *arXiv preprint arXiv:2004.04136*, 2020.

Adam Stooke, Kimin Lee, Pieter Abbeel, and Michael Laskin. Decoupling representation learning from reinforcement learning. *arXiv preprint arXiv*, 2020.

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

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. Technical report, DeepMind, January 2018.

Emanuel Todorov, Tom Erez, and Yuval Tassa. Mujoco: A physics engine for model-based control. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2012.

Faraz Torabi, Garrett Warnell, and Peter Stone. Generative adversarial imitation from observation. *arXiv preprint arXiv:1807.06158*, 2018.

Sam Toyer, Rohin Shah, Andrew Critch, and Stuart Russell. The MAGICAL benchmark for robust imitation. In *Advances in Neural Information Processing Systems*, 2020.

Cédric Villani. *Optimal transport: old and new*, volume 338. Springer, 2009.

Huang Xiao, Michael Herman, Joerg Wagner, Sebastian Ziesche, Jalal Etesami, and T. H. Linh. Wasserstein adversarial imitation learning. *ArXiv*, abs/1906.08113, 2019.

Denis Yarats, Amy Zhang, Ilya Kostrikov, Brandon Amos, Joelle Pineau, and Rob Fergus. Improving sample efficiency in model-free reinforcement learning from images. *arXiv preprint arXiv:1910.01741*, 2019.

Denis Yarats, Rob Fergus, Alessandro Lazaric, and Lerrel Pinto. Mastering visual continuous control: Improved data-augmented reinforcement learning. *arXiv preprint arXiv:2107.09645*, 2021a.

Denis Yarats, Rob Fergus, Alessandro Lazaric, and Lerrel Pinto. Reinforcement learning with prototypical representations. *CoRR*, 2021b.

Denis Yarats, Ilya Kostrikov, and Rob Fergus. Image augmentation is all you need: Regularizing deep reinforcement learning from pixels. In *9th International Conference on Learning Representations, ICLR 2021*, 2021c.