Multi-Environment Pretraining Enables Transfer to Action Limited Datasets

David Venuto 1 2, Mengjiao Yang 3 4, Pieter Abbeel 4, Doina Precup 1 2 3, Igor Mordatch 3, Ofir Nachum 3

Abstract

Using massive datasets to train large-scale models has emerged as a dominant approach for broad generalization in natural language and vision applications. In reinforcement learning, however, a key challenge is that available data of sequential decision making is often not annotated with actions - for example, videos of game-play are much more available than sequences of frames paired with their logged game controls. We propose to circumvent this challenge by combining large but sparsely-annotated datasets from a target environment of interest with fully-annotated datasets from various other source environments. Our method, Action Limited PreTraining (ALPT), leverages the generalization capabilities of inverse dynamics modelling (IDM) to label missing action data in the target environment. We show that utilizing even one additional environment dataset of labelled data during IDM pretraining gives rise to substantial improvements in generating action labels for unannotated sequences. We evaluate our method on Atari game-playing environments and show that with target environment data equivalent to only 12 minutes of gameplay, we can significantly improve game performance and generalization capability compared to other approaches. Furthermore, we show that ALPT remains beneficial even when target and source environments share no common actions, highlighting the importance of pretraining on broad datasets even though they might seem irrelevant to the target task at hand.

1. Introduction

The training of large-scale models on large and diverse data has become a standard approach in natural language and computer vision applications (Devlin et al., 2019; Brown et al., 2020; Mahajan et al., 2018; Zhai et al., 2021). Recently, a number of works have shown that a similar approach can be applied to tasks more often tackled by reinforcement learning (RL), such as robotics and game-playing. For example, Reed et al. (2022) suggest combining large datasets of expert behavior from a variety of RL domains in order to train a single generalist agent, while Lee et al. (2022) demonstrate a similar result but using non-expert (offline RL) data from a suite of Atari game-playing environments and using a decision transformer (DT) sequence modeling objective.

Applying large-scale training necessarily relies on the ability to gather sufficiently large and diverse datasets. For RL domains, this can be a challenge, as the most easily available data – for example, videos of a human playing a video game or a human completing a predefined task – often does not contain labelled actions, i.e., game controls or robot joint controls. We call such datasets action limited, because little or none of the dataset is annotated with action information. Transferring the success of approaches like DT to such tasks is therefore bottlenecked by the ability to acquire action labels, which can be expensive and time-consuming (Zolna et al., 2020).

Some recent works have explored approaches to mitigate the issue of action limited datasets. For example, Video PreTraining (VPT) (Baker et al., 2022) proposes gathering a small amount (2k hours of video) of labeled data manually which is used to train an inverse dynamics model (IDM) (Nguyen-Tuong et al., 2008); the IDM is then used to provide action labels on a much larger video-only dataset (70k hours). This method is shown to achieve human level performance in Minecraft. It has also been demonstrated that some agents can learn directly from videos without any action labels (Seo et al., 2022).

While VPT shows promising results, it still requires over 2k hours of manually-labelled data; thus, a similar amount of expensive labelling is potentially necessary to extend VPT to other environments. In this paper, we propose an orthogonal but related approach to VPT: leveraging a large set of labeled data from various source domains to learn an agent policy on a limited action dataset of a target evaluation environment. To tackle this setting, we propose Action Lim-

---

Proceedings of the 40th International Conference on Machine Learning, Honolulu, Hawaii, USA. PMLR 202, 2023. Copyright 2023 by the author(s).
Multi-Environment Pretraining Enables Transfer to Action Limited Datasets

Multi-Environment Pretraining (ALPT), which relies on the hypothesis that shared structures between environments can be exploited by non-causal (i.e., bidirectional) transformer IDMs. This allows us to look at both past and future frames to infer actions. In many experimental settings, the dynamics are far simpler than multi-faceted human behavior in the same setting. It has been suggested that IDMs are therefore more data efficient and this has been empirically shown (Baker et al., 2022). ALPT thus uses the multi-environment source datasets as pretraining for an IDM, which is then finetuned on the action-limited data of the target environment in order to provide labels for the unlabelled target data, which is then used for training a DT agent.

Through various experiments and ablations, we demonstrate that leveraging the generalization capabilities of IDMs is critical to the success of ALPT, as opposed to, for example, pretraining the DT model alone on the multi-environment datasets or training the IDM only on the target environment. On a benchmark game-playing environment, we show that ALPT yields as much as 5x improvement in performance, with as little as 10k labelled samples required (i.e., 0.01% of the original labels), derived from only 12 minutes of labelled game play (Ye et al., 2021). We show that these benefits even hold when the source and target environments use distinct action spaces; i.e., the environments share similar states but no common actions, further demonstrating the power of IDM pretraining.

While ALPT is, algorithmically, a straightforward application of existing offline RL approaches, our results provide a new perspective on large-scale training for RL. Namely, our results suggest that the most efficient path to large-scale RL methods may be via generalist inverse dynamics modelling paired with specialized agent finetuning, instead of generalist agent training alone.

2. Related Work

In this section, we briefly review relevant works in multi-task RL, meta-learning for RL, semi-supervised learning, and transfer learning.

Multi-Task RL. It is commonly assumed that similar tasks share similar structure and properties (Caruana, 1997; Rudor, 2017; Zhang et al., 2014; Radford et al., 2019a). Many multi-task RL works leverage this assumption by learning a shared low-dimensional representation across all tasks (Calandriello et al., 2014; Borsa et al., 2016; D’Eramo et al., 2020). These methods have also been extended to tasks where the action space does not align completely (Bram et al., 2020). Other methods assume a universal dynamics model when the reward structure is shared but dynamics are not (Zhang et al., 2021a). Multi-task RL has generally relied on a task identifier (ID) to provide contextual information, but recent methods have explored using additional side information available in the task meta-data to establish a richer context (Sodhani et al., 2021). ALPT can be seen as multi-task RL, given that we train both the sequence model and IDM using multiple different environments, but we do not explicitly model context information or have access to task IDs.

Meta RL. Meta-learning is a set of approaches for learning to learn which leverages a set of meta-training tasks (Schmidhuber, 1987; Bengio et al., 1991), from which an agent can learn either parts of the learning algorithms (e.g., how to tune the learning rate) or the entire algorithm (Lalombe et al., 2021; Kalousis, 2002). In this setting, meta-learning can be used to learn policies (Duan et al., 2017; Finn et al., 2017) or dynamics models (Clavera et al., 2019). A distribution of tasks is assumed to be available for sampling, in order to provide additional contextual information to the policy. One such method models contextual information as probabilistic context variables which condition the policy (Rakelly et al., 2019). This method has been shown to learn from only a handful of trajectories. Meta-training can be used to learn policies offline, while using online interaction to correct for distribution shift, without requiring any rewards in the online data (Pong et al., 2022). These methods are commonly used to train on a source set of tasks, like ALPT, but usually require task labels. Meta-training tasks need to be hand-selected, and the results are highly dependent on the quality of that process.

Semi-supervised learning. Semi-supervised learning uses both labelled and unlabelled data to improve supervised learning performance (Zhu et al., 2009). It is especially useful when a limited amount of labelles data is given and additional labels are difficult to acquire, unlabelled data is plentiful. Early methods of this type infer unknown labels using a classifier trained on the labelled data (Zhu & Ghahramani, 2002). Other methods rely on additional structural side information to regularize supervised objectives (Szummer & Jaakkola, 2001), such as the time scale of a Markov random walk over a representation of the data. Many methods, especially those using deep learning, combine supervised and unsupervised learning objectives (Rasmus et al., 2015). More recent methods use generative models and approximate Bayesian inference to fill in missing labels (Kingma et al., 2014). The problem of semi-supervised learning is especially relevant in RL, where large datasets of experience containing action descriptions or rewards may hard to acquire, e.g., through manual annotation of videos or running robotic experiments. By using an inverse dynamics model, ALPT applies semi-supervised learning to label actions in a large dataset of experience frames, given only limited labeled action data.

Transfer Learning and Zero-shot RL. Policies learned by
Multi-Environment Pretraining Enables Transfer to Action Limited Datasets

Figure 1: The dynamics model pretraining procedure of ALPT using the source set of environments along with the limited action target environment dataset.

RL in one domain can have limited capability to generalize to new settings (Oh et al., 2016). The most difficult problem is zero-shot RL, where the agent must generalize at evaluation time to a new environment that was not seen in training, without acquiring any new data. Transfer learning (Taylor & Stone, 2009) tackles a subset of generalization problems where the agent can access interactions from a related environment or task during training. This prior experience in other environments is leveraged to improve learning in novel environments. Transfer learning has been applied across both environments (Mordatch et al., 2016; Tzeng et al., 2020) and tasks (Rusu et al., 2016; Parisotto et al., 2016). It has also been examined in hard exploration games, using imitation learning from human-generated video data (Aytar et al., 2018). ALPT can be seen as tackling the transfer learning problem, with limited action data from the target environment and providing pseudo-labels for actions. Notably, we consider the under-explored scenario where the action space is not completely shared between the training and test environments.

3. Background

In this section, we review the standard offline RL setting and the use of decision transformers (DT) as a sequence modeling objective for offline RL. We then define the setting of multi-environment offline RL with action-limited data, which is our focus.

3.1. Offline Reinforcement Learning

We consider an agent acting within a Markov decision process (MDP) defined by \( \langle S, A, P, R \rangle \), where \( S \) is the set of states, \( A \) is the set of actions, \( P : S \times A \to \text{Dist}(S) \) is the transition probability kernel and \( R : S \times A \to [0, 1] \) is the scalar reward function.

In offline RL, the agent is given a dataset of episodes, i.e., sequences of states, actions, and rewards collected by unknown policies interacting with the environment:

\[
\langle \ldots, s_t, a_t, r_t, \ldots \rangle.
\]

The objective is typically to use this dataset in order to learn a conditional action distribution, \( P_b(a_t|s_{\leq t}, a_{<t}, r_{<t}) \), that maximizes the expectation of the total return, \( G_t = \sum_{k \geq 0} r_{t+k} \) when used to interact with the environment from which the training episodes were generated.

3.2. Offline RL as Sequence Modeling

Decision transformer (DT) (Chen et al., 2021a) is an approach to offline RL which formulates this problem as se-
We now describe our proposed approach to offline RL in multi-environment and action limited settings. ALPT relies on an inverse dynamics model (IDM) which uses the combined labelled data in order to learn a representation that generalizes well to the limited action data from the target environment. The predicted labels of the IDM on the unlabelled portion of the target environment dataset are then used for training a sequence model parameterized as a decision transformer (DT). We elaborate on this procedure below and summarize the full algorithm in Table 1.

4.1. Inverse Dynamics Modeling

Our inverse dynamics model (IDM) is a bidirectional transformer trained to predict actions from an action-unlabelled sub-trajectory of an episode. The training objective for learning an IDM $P_\theta$ is

$$J(\theta) = \mathbb{E}_\tau \left[ \sum_{t} - \log P_\theta(G_t | s_{\leq t}, a_{\leq t}, r_{<t}) \right]$$

(3)

During inference, at each timestep $t$, after observing $s_t$, DT uses the predicted return distribution $P_\theta(G_t | s_{\leq t}, a_{\leq t}, r_{<t})$ to choose an optimistic estimate $G_t$ of return, before using $P_\theta(a_t | s_{\leq t}, a_{<t}, r_{<t}, G_t)$ to select an action $a_t$ (see Lee et al. (2022) for details).

3.3. Multi-Environment and Action Limited Datasets

Our goal is to use pretraining on a set of environments where labelled data is plentiful, in order to do well on a target environment where only limited action-labelled data is available. Therefore, the offline RL setting we consider includes multiple environments and action-limited datasets, as we detail below.

We consider a set of $n$ source environments, defined by a set of MDPs: $E = \{M_1, \ldots, M_n\}$, and a single target environment $M_*$. For each source environment $M_d$, we have an offline dataset of episodes generated from $M_d$, denoted by $D_d = \{\tau := \{s_t, a_t, r_t, \ldots\}\}$, fully labelled with actions. For the target environment, the agent has access to a small labelled dataset from $M_*$, denoted as $D_+^* = \{\tau := \{s_t, a_t, r_t, \ldots\}\}$, and a large dataset without action labels, $D_-^* = \{\tau := \{s_t, r_t, \ldots\}\}$.

4. Action Limited Pretraining (ALPT)

4.2. Multi-Environment Pretraining and Finetuning

ALPT is composed of a two-stage pretraining and finetuning process.

During pretraining, we use the combined labelled datasets for all source environments combined with the labelled portion of the target environment dataset: $(\bigcup_{d=1}^n D_d) \cup D_+^*$, to train the IDM $P_\theta$. Concurrently, we also train the DT $P_\theta$ on the combined labelled and unlabelled datasets for all source environments combined with the target environment datasets, by using the IDM to provide action labels on the unlabelled portion $D_-^*$. The DT training dataset is therefore: $(\bigcup_{d=1}^n D_d) \cup D_+^* \cup D_-^*$.

During finetuning, we simultaneously train both the IDM and DT exclusively on the target environment dataset. We train the IDM on the labelled portion $D_+^*$. We train DT on the full action limited dataset $D_+^* \cup D_-^*$ by using the IDM to provide action labels on the unlabelled portion $D_-^*$.

Finally, during evaluation we use the trained DT agent to select actions in the target environment $M_*$, following the same protocol described in Section 3.2.

5. Experiments

We evaluate ALPT on a multi-game Atari setup similar to Lee et al. (2022). Our findings are three-fold: (1) ALPT, when pretrained on multiple source games, demonstrates significant benefits on the target game with limited action labels; (2) ALPT maintains its significant benefits even when pretrained on just a single source game with a disjoint action space, (3) we demonstrate similar benefits on maze navigation tasks.

5.1. Experimental Procedure

Architecture and Training. Our architecture and training protocol follow the multi-game Atari setting outlined in Lee et al. (2022). Specifically, we use a transformer with 6 layers of 8 heads each and hidden size 512. The rest of the architecture and training hyperparameters remain unchanged for experiments on Atari. For the Maze navigation experiments, we modify the original hyperparameters to use a batch size of 256 and a weight decay of $5 \times 10^{-5}$. During
Table 1: A summary of ALPT.

| Step       | Procedure                                                                 |
|------------|---------------------------------------------------------------------------|
| Pretraining| Train IDM on all labelled data: $\bigcup_{d=1}^{D_d} D_d \cup D_d^+$. Train DT on all data: $\bigcup_{d=1}^{D_d} D_d \cup D_d^+ \cup D_d^-$, with IDM providing action labels on $D_d^-$ |
| Finetuning | Train IDM on labelled data in target environment dataset: $D_d^+$. Train DT on all data in target environment dataset: $D_d^+ \cup D_d^-$, with IDM providing action labels on $D_d^-$ |
| Evaluation | Use trained DT agent to interact with target environment $M_r$. |

Datasets. As in Lee et al. (2022), we use the standard offline RL Atari datasets from RL Unplugged (Gulcehre et al., 2020). Each game’s dataset consists of 100M environment steps of training a DQN agent (Agarwal et al., 2020b). Since we use data from the full run of the DQN agent, the dataset contains a mix of optimal and sub-optimal data. For the source games, we use this dataset in its entirety. For the target game, we derive an action-limited dataset by keeping the action labels for randomly sampled sequences consisting of a total 10k transitions (0.01% of the original dataset, equivalent to 12 minutes of gameplay) and removing action labels in the remainder of the dataset. For the maze navigation experiments, we generate the data ourselves. The offline datasets for each maze configuration contain 500 trajectories with a length of 500 steps or until the goal state is reached. They are generated using an optimal policy for each maze, with an $\epsilon$-greedy exploration rate of 0.5 to increase data diversity.

5.2. Baseline Methods

We detail the methods that we compare ALPT to below.

Single-game variants. To evaluate the benefit of multi- versus single-environment training, we assess the performance of training either DT alone or DT and IDM simultaneously on the target game. When training DT alone (DT1), we train it only on the 10k subset of data that is labelled, while when training DT and IDM simultaneously (DT1-IDM) we use the IDM to provide action labels on the unlabelled portion of the data.

Multi-game DT variants. To assess the need for IDM versus training on DT alone, we evaluate a multi-game baseline (DT5) composed of DT alone. For this baseline, we pretrain DT on all labelled datasets combined from both the source and target environments before finetuning the DT model on the 10k labelled portion of the target game.

Table 2: A summary of the baseline methods.

| Method     | Training Games | IDM |
|------------|----------------|-----|
| DT-1       | 1              | $\times$ |
| DT-5       | 5              | $\times$ |
| DT1-IDM    | 1              | $\checkmark$ |
| DT5-RET    | 1              | $\times$ |
| ALPT-X     | $X$ if specified, otherwise 5 | $\checkmark$ |

Return prediction DT variants. As an alternative way for DT to leverage the unlabelled portion of the target environment dataset, we evaluate a baseline (DT5-RET) that uses the unlabelled portion for training its return prediction. The model still undergoes a pretraining and finetuning stage, first pretraining on all available data and then finetuning only on data from the target game.

We give a summary of the baseline methods as well as ALPT in Table 2. We also present results of an additional variant of ALPT in which only the IDM is pretrained (rather than both the IDM and DT) in Appendix A.

5.3. How does ALPT perform compared to the baselines?

We focus our first set of multi-game pretraining experiments on 5 Atari games: \{Asterix, Breakout, SpaceInvaders, Freeway, Seaquest\}. This subset of games is selected due to having a similar shared game structure and access to high-quality and diverse pretraining data. We evaluate each choice of target game in this setting, i.e., for each game we evaluate using it as the target game while the remaining 4 games comprise the source environments. We compare our pretraining regime (ALPT) with the single-game variant and standard DT baselines in Figure 2. We see that pretraining ALPT on the source games results in substantial downstream performance improvements. We show that there are relatively minimal performance improvements when pretraining on datasets that do not include any non-target environments (DT1-IDM). Utilizing ALPT results in improvements up to...
Multi-Environment Pretraining Enables Transfer to Action Limited Datasets

Figure 2: Game performance across the ALE environments for the baseline and ALPT. The figure shows the evaluation game performance (Episodic Return) of our DT policies during finetuning on the limited action target dataset. Higher score is better. The shaded area represents the standard deviation over 3 random seeds. The x-axis shows the number of finetuning steps. We evaluate ALPT on 16 episodes of length 2500 each following (Lee et al., 2022).

Figure 3: We evaluate performance of ALPT with a higher number of source games. We show performance of ALPT trained on 36 Atari source games (ALPT-36) and ALPT trained on 9 Atari source games (ALPT-9). We find that performance generally improves with more source games.

≈ 500% higher than the single-game training regime. The performance difference is especially stark in Breakout and Seaquest. Additionally, we show that performance is not recovered under pretraining only the sequence model (DT5) on the action rich environments, indicating that most generalization benefits are occurring due to the IDM pretraining. We also show that performance using DT1 and DT5-RET is poor, highlighting the need for explicit re-labelling to achieve good performance during sequence model finetuning.

We also encourage the reader to look to Appendix A for a comparison to a variant of ALPT for which only the IDM is pretrained, while the DT is initialized from scratch during finetuning. We find that this variant maintains strong performance compared to DT1-IDM, suggesting that the main benefit of pretraining is the IDM.

For completeness, we examine the performance of a standard offline RL algorithm (Conservative Q-Learning) (Kumar et al., 2020) against ALPT in Appendix C.

5.4. Is dynamics modelling improved under more or less source datasets?

In this set of experiments, we expand the set of source and target games. As in the previous experiments, each source game provides a fully-labelled dataset of size 100M, while each target game has a dataset of size 100M with only 10k action labels. We evaluate performance using 5 target games (‘Pong’, ‘SpaceInvaders’, ‘StarGunner’, ‘MsPacman’, ‘Alien’) and using either 36 source games (ALPT-36, trained on all 41 game datasets available in Agarwal et al. (2020b) minus the 5 target games) and using 9 source games (ALPT-9, trained on {‘Asterix’, ‘Breakout’, ‘Freeway’, ‘Seaquest’, ‘Atlantis’, ‘DemonAttack’, ‘Frostbite’, ‘Gopher’, ‘TimePilot’}). Note that for each of these ALPT variants, we perform a single pretraining phase and then multiple finetuning phases (one for each target game), thus showing that a single pretrained model can be transferred to various target games.

We compare pretraining with ALPT to training DT1-IDM on each target game alone. Results are presented in Figure 3, and show that target game performance improves with more source games.

5.5. Can ALPT help when source and target have disjoint action spaces?

The previous experiments have included at least one source game during pretraining whose the action space overlaps with that of the target environment. The next set of experiments aims to explore pretraining on source environments where the action space \(A_d\) is disjoint with the target environment action space \(A_s\), that is, \(A_d \cap A_s = \emptyset\). To do so,
Multi-Environment Pretraining Enables Transfer to Action Limited Datasets

Figure 4: We evaluate performance of ALPT when source and target games have disjoint action spaces. In each of these plots we pretrain using a single source game Freeway. Despite the disjoint action space, we still see benefits of pretraining.

we use Freeway as our single source environment dataset. In Freeway, the action space consists of \{Up, Down\}. In contrast, a game such as Breakout has an action space consisting of \{Left, Right\}. Surprisingly, using Freeway as a source environment and Breakout as a target environment still yields significant benefits for ALPT. We present this result in Figure 4, as well as a variety of other choices for the target environment, none of which share any actions with the source environment Freeway.

We hypothesize that performance improvements are not unexpected due to the already known broad generalization capabilities of transformer architectures. It may also be the case that, despite the action spaces being disjoint, they still exhibit similar structure. For example, a top-down action space and a left-right action space are structurally opposite to each other in terms of movement, differing only in orientation. This similar structure is potentially learned and leveraged during finetuning.

5.6. Do ALPT’s benefits persist in other domains?

We now demonstrate ALPT’s benefits on an action-limited navigation task. This corresponds to a scenario where we have densely annotated navigation maps for a set of source regions but only a sparsely annotated navigation map for a target region. We would like to evaluate whether ALPT, pretrained on source regions with abundant action labels, can generalize to navigating in a target region (of a different layout) with limited action labels.

Maze Navigation Environments. To answer the above question, we consider a gridworld navigation task where an agent seeks to navigate to a goal location in a 20 × 20 2D maze from a random starting location to a random goal location using 4 discrete actions: \{Up, Down, Left, Right\}. The agent receives a reward of 1 at the goal state and \(r = 0\) otherwise. To collect the offline training datasets, we follow Yang et al. (2022); Zhang et al. (2018) to algorithmically generate maze layouts with random internal walls that form blocked or tunneled obstacles as shown in Figure 5. We start with blocked obstacles, and generate one source maze from which we collect 500 trajectories with full action labels. We then use a different random seed to generate the target maze, from which we collect 500 trajectories with only 250 action labels (0.5% of the full action labels). We then train the IDM of ALPT-Blocked on both the source and target datasets, labeling the missing actions from the target game, and train DT all at the same time (no separate finetuning stage). ALPT-Blocked and other baselines are evaluated in the target maze only.

Results. Performance in the target maze environment with limited action labels is presented in Figure 5 (b). ALPT-Blocked trained on both source and target mazes allows us to solve the target task twice as fast compared to only training on the target maze without access to another source maze. To further illustrate the benefit of multi-environment training on more diverse data, we introduce the tunneled maze, and train ALPT-Blocked+Tunnelled on 500 trajectories with full actions from a source blocked maze and a source tunneled maze, respectively, as well as 250 action samples of the target blocked maze. Training on both tunneled and blocked mazes enables greater dataset diversity, which further improves generalization, leading to even faster
convergence on the target task. These preliminary results on navigation suggest that multi-environment pretraining can benefit a broad set of tasks.

![Figure 5](image)

Figure 5: (a) An example diagram of the Blocked (above) and Tunneled (below) mazes. The green cell is the goal state. (b) Evaluation performance while training on the 20x20 Maze dataset. Higher score is better. The shaded area represents the standard deviation over 3 random seeds. The action limited target dataset contains 250 labelled actions in these experiments.

6. Conclusion

We explored the problem of learning agent policies from action limited datasets. Inspired by the paradigm of large-scale, multi-environment training, we proposed ALPT, which pretrains an inverse dynamics model (IDM) on multiple environments to provide accurate action labels for a decision transformer (DT) agent on an action limited target environment dataset. Our experiments and ablations highlight the importance of pretraining the IDM, as opposed to pretraining the DT agent alone. Our results support the importance of generalist inverse dynamics models as an efficient way to implement large-scale RL. As more labelled data becomes available for training offline RL agents, ALPT provides an efficient way of bootstrapping performance on new tasks with action limited data.

6.1. Limitations

The largest limitation of ALPT is the assumption that we would have plentiful labelled data from related environments. One interesting fact we uncover is that this data does not have to be based on the same action space as the desired target environment, indicating the versatility of ALPT and its ability to ingest diverse source environment training data. We also caution that we have only evaluated ALPT so far on limited, self-contained video game tasks and simple navigation environments. We hope that as more labelled data becomes available in RL domains, ALPT will have wider applicability, allowing RL agents to scale and bootstrap to new environments. It would also be useful to investigate further how much labelled data from a limited set of source environments is required to be able to handle a much larger set of unlabelled datasets.

References

Rishabh Agarwal, Dale Schuurmans, and Mohammad Norouzi. An optimistic perspective on offline reinforcement learning. In *Proceedings of the 37th International Conference on Machine Learning*, ICML’20, 2020a.

Rishabh Agarwal, Dale Schuurmans, and Mohammad Norouzi. An optimistic perspective on offline reinforcement learning. In *International Conference on Machine Learning*, pp. 104–114. PMLR, 2020b.

Yusuf Aytar, Tobias Pfaff, David Budden, Tom Le Paine, Ziyu Wang, and Nando de Freitas. Playing hard exploration games by watching youtube. NIPS’18, 2018.

Bowen Baker, Ilge Akkaya, Peter Zhokhov, Joost Huizinga, Jie Tang, Adrien Ecoffet, Brandon Houghton, Raul Sampedro, and Jeff Clune. Video pretraining (vpt): Learning to act by watching unlabeled online videos, 2022.

Y. Bengio, S. Bengio, and J. Cloutier. Learning a synaptic learning rule. In *IJCNN-91-Seattle International Joint Conference on Neural Networks*, 1991.

Diana Borsa, Thore Graepel, and John Shawe-Taylor. Learning shared representations in multi-task reinforcement learning, 2016.

Timo Bräm, Gino Brunner, Oliver Richter, and Roger Wattenhofer. Attentive multi-task deep reinforcement learning. In *Machine Learning and Knowledge Discovery in Databases*, 2020.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, 2020.

Daniele Calandriello, Alessandro Lazaric, and Marcello Restelli. Sparse multi-task reinforcement learning. In *Advances in Neural Information Processing Systems*, 2014.

Rich Caruana. Multitask learning. 1997.
Multi-Environment Pretraining Enables Transfer to Action Limited Datasets

Lili Chen, Kevin Lu, Aravind Rajeswaran, Kimin Lee, Aditya Grover, Michael Laskin, Pieter Abbeel, Aravind Srinivas, and Igor Mordatch. Decision transformer: Reinforcement learning via sequence modeling, 2021a.

Lili Chen, Kevin Lu, Aravind Rajeswaran, Kimin Lee, Aditya Grover, Misha Laskin, Pieter Abbeel, Aravind Srinivas, and Igor Mordatch. Decision transformer: Reinforcement learning via sequence modeling. In Advances in Neural Information Processing Systems, 2021b.

Ignasi Clavera, Anusha Nagabandi, Simin Liu, Ronald S. Fearing, Pieter Abbeel, Sergey Levine, and Chelsea Finn. Learning to adapt in dynamic, real-world environments through meta-reinforcement learning. In International Conference on Learning Representations, 2019.

Carlo D’Eramo, Davide Tateo, Andrea Bonarini, Marcello Restelli, and Jan Peters. Sharing knowledge in multi-task deep reinforcement learning. In International Conference on Learning Representations, 2020.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. Association for Computational Linguistics, 2019.

Yan Duan, John Schulman, Xi Chen, Peter L. Bartlett, Ilya Sutskever, and Pieter Abbeel. RL’2: Fast reinforcement learning via slow reinforcement learning, 2017.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning, 2017.

Scott Fujimoto, David Meger, and Doina Precup. Off-policy deep reinforcement learning without exploration. In International Conference on Machine Learning, pp. 2052–2062, 2019.

Caglar Gulcehre, Ziyu Wang, Alexander Novikov, Thomas Paine, Sergio Gómez, Konrad Zolna, Rishabh Agarwal, Josh S Merel, Daniel J Mankowitz, Cosmin Paduraru, et al. RL unplugged: A suite of benchmarks for offline reinforcement learning. Advances in Neural Information Processing Systems, 33:7248–7259, 2020.

Alexandros Kalousis. Algorithm selection via meta-learning. PhD thesis, University of Geneva, 2002.

Diederik P. Kingma, Danilo J. Rezende, Shakir Mohamed, and Max Welling. Semi-supervised learning with deep generative models. In Proceedings of the 27th International Conference on Neural Information Processing Systems, 2014.

Aviral Kumar, Justin Fu, Matthew Soh, George Tucker, and Sergey Levine. Stabilizing off-policy q-learning via bootstrapping error reduction. In Advances in Neural Information Processing Systems, 2019.

Aviral Kumar, Aurick Zhou, George Tucker, and Sergey Levine. Conservative q-learning for offline reinforcement learning. In Proceedings of the 34th International Conference on Neural Information Processing Systems, NIPS’20, 2020.

Thomas Lacombe, Yun Sing Koh, Gillian Dobbie, and Ocean Wu. A meta-learning approach for automated hyperparameter tuning in evolving data streams. In 2021 International Joint Conference on Neural Networks (IJCNN), 2021.

Kuang-Huei Lee, Ofir Nachum, Mengjiao Yang, Lisa Lee, Daniel Freeman, Winnie Xu, Sergio Guadarrama, Ian Fischer, Eric Jang, Henryk Michalewski, and Igor Mordatch. Multi-game decision transformers, 2022.

Dhruv Mahajan, Ross B. Girshick, Vignesh Ramanathan, Kaiming He, Manohar Paluri, Yixuan Li, Ashwin Bharambe, and Laurens van der Maaten. Exploring the limits of weakly supervised pretraining. In Computer Vision - ECCV 2018 - 15th European Conference, Proceedings, Part II, 2018.

Igor Mordatch, Nikhil Mishra, Clemens Eppner, and Pieter Abbeel. Combining model-based policy search with online model learning for control of physical humanoids. In 2016 IEEE International Conference on Robotics and Automation (ICRA), 2016.

Ofir Nachum, Bo Dai, Ilya Kostrikov, Yinlam Chow, Lihong Li, and Dale Schuurmans. Algaedice: Policy gradient from arbitrary experience, 2019.

D. Nguyen-Tuong, J. Peters, M. Seeger, and B. Schölkopf. Learning inverse dynamics: A comparison. In Advances in Computational Intelligence and Learning: Proceedings of the European Symposium on Artificial Neural Networks, 2008.

Junhyuk Oh, Valliappa Chockalingam, Satinder Singh, and Honglak Lee. Control of memory, active perception, and action in minecraft. In Proceedings of the 33rd International Conference on International Conference on Machine Learning, 2016.

Emilio Parisotto, Lei Jimmy Ba, and Ruslan Salakhudinov. Actor-mimic: Deep multitask and transfer reinforcement learning. In ICLR (Poster), 2016.

Vitchyr H Pong, Ashvin V Nair, Laura M Smith, Catherine Huang, and Sergey Levine. Offline meta-reinforcement learning with online self-supervision. In Proceedings of
the 39th International Conference on Machine Learning, Proceedings of Machine Learning Research, 2022.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. 2019a.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. 2019b.

Kate Rakelly, Aurick Zhou, Chelsea Finn, Sergey Levine, and Deirdre Quillen. Efficient off-policy meta-reinforcement learning via probabilistic context variables. In Proceedings of the 36th International Conference on Machine Learning, Proceedings of Machine Learning Research, 2019.

Antti Rasmus, Harri Valpola, Mikko Honkala, Mathias Berglund, and Tapani Raiko. Semi-supervised learning with ladder networks. In Proceedings of the 28th International Conference on Neural Information Processing Systems, 2015.

Scott Reed, Konrad Zolna, Emilio Parisotto, Sergio Gomez Colmenarejo, Alexander Novikov, Gabriel Barth-Maron, Mai Gimenez, Yury Sulsky, Jackie Kay, Jost Tobias Springenberg, Tom Eccles, Jake Bruce, Ali Razavi, Ashley Edwards, Nicolas Heess, Yutian Chen, Raia Hadsell, Oriol Vinyals, Mahyar Bordbar, and Nando de Freitas. A generalist agent, 2022.

Sebastian Ruder. An overview of multi-task learning in deep neural networks, 2017.

Andrei A. Rusu, Sergio Gomez Colmenarejo, Çağlar Güçlü, Guillaume Desjardins, James Kirkpatrick, Razvan Pascanu, Volodymyr Mnih, Koray Kavukcuoglu, and Raia Hadsell. Policy distillation. In ICLR (Poster), 2016.

Jürgen Schmidhuber. Evolutionary principles in self-referential learning. (on learning how to learn: The meta-meta-... hook. Technical report, PhD Thesis, 1987.

Younggyo Seo, Kimin Lee, Stephen L James, and Pieter Abbeel. Reinforcement learning with action-free pretraining from videos. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and Sivan Sabato (eds.), Proceedings of the 39th International Conference on Machine Learning, 2022.

Shagun Sodhani, Amy Zhang, and Joelle Pineau. Multi-task reinforcement learning with context-based representations. In Proceedings of the 38th International Conference on Machine Learning, Proceedings of Machine Learning Research, 2021.

Martin Szummer and Tommi Jaakkola. Partially labeled classification with markov random walks. In Advances in Neural Information Processing Systems, 2001.

Matthew E. Taylor and Peter Stone. Transfer learning for reinforcement learning domains: A survey. Journal of Machine Learning Research, 2009.

Eric Tzeng, Coline Devin, Judy Hoffman, Chelsea Finn, Pieter Abbeel, Sergey Levine, Kate Saenko, Trevor Darrell, Pieter Abbeel, Kostas Bekris, and Lauren Miller. Adapting Deep Visuomotor Representations with Weak Pairwise Constraints. 2020.

Yifan Wu, George Tucker, and Ofir Nachum. Behavior regularized offline reinforcement learning, 2020. URL https://openreview.net/forum?id=BJg9hTNKPH.

Mengjiao Yang, Dale Schuurmans, Pieter Abbeel, and Ofir Nachum. Chain of thought imitation with procedure cloning. arXiv preprint arXiv:2205.10816, 2022.

Weirui Ye, Shaohuai Liu, Thanhard Kurutach, Pieter Abbeel, and Yang Gao. Mastering atari games with limited data. In Advances in Neural Information Processing Systems, 2021.

Xiaohua Zhai, Alexander Kolesnikov, Neil Houlsby, and Lucas Beyer. Scaling vision transformers, 2021.

Chi Zhang, Sanmukh Rao Kuppannagari, and Viktor Prasanna. {BRAC}+: Going deeper with behavior regularized offline reinforcement learning, 2021b. URL https://openreview.net/forum?id=bMCfFepJXM.

Chiyuan Zhang, Oriol Vinyals, Remi Munos, and Samy Bengio. A study on overfitting in deep reinforcement learning. arXiv preprint arXiv:1804.06893, 2018.

Zhanpeng Zhang, Ping Luo, Chen Change Loy, and Xiaoou Tang. Facial landmark detection by deep multi-task learning. In Computer Vision — ECCV 2014, 2014.

Xiaojun Zhu and Zoubin Ghahramani. Learning from labeled and unlabeled data with label propagation. Technical report, 2002.

Xiaojun Zhu, Andrew B. Goldberg, Ronald Brachman, and Thomas Dietterich. Introduction to Semi-Supervised Learning. 2009.
Konrad Zolna, Alexander Novikov, Ksenia Konyushkova, Caglar Gulcehre, Ziyu Wang, Yusuf Aytar, Misha Denil, Nando de Freitas, and Scott Reed. Offline learning from demonstrations and unlabeled experience, 2020.
Multi-Environment Pretraining Enables Transfer to Action Limited Datasets

A. Experiments with no DT pretraining

In the following set of experiments, we pretrain only the IDM component of ALPT and not the DT. We show the finetuning performance results for the Narrow set of Atari games in Figure 6. Note that the axis here is up to 100k steps as opposed to 1M for the figures in the main text.

B. Implementation Details

In Table 3 we give the implementation details of our IDM and DT transformer architectures.

The IDM model is the same as the DT model, except that it is non-causal. This is enforced by changing the attention mask to a matrix of all 1 values in the IDM.

Table 3: A summary of the transformer model parameters.

| Parameter       | Value       |
|-----------------|-------------|
| Layers          | 6           |
| Hidden Size     | 512         |
| Heads           | 8           |
| Batch Size      | 256         |
| Weight Decay    | $5 \times 10^{-5}$ |
| Learning Rate   | $3 \times 10^{-4}$ |
| Gradient Clipping| 1.0        |
| $\beta_1, \beta_2$ | 0.9, 0.999 |
| Warm-up Steps   | 4000        |
| Optimizer       | LAMB        |

C. Experiments with Conservative Q-Learning (CQL)

In this set of experiments, we examine the performance of Conservative Q-Learning (CQL) (Kumar et al., 2020) trained on a dataset of 10,000 frames, as opposed to 500,000 in the original work (Table 3 of CQL, 1% dataset size), from various Atari games utilized in our experiments. In Table 4 we report the final evaluation performance on the game after training for 100 iterations. All implementation details are consistent with the original implementation in the cited work. We utilize the CQL($\mathcal{H}$) method.

Figure 6: Evaluation game performance during finetuning of ALPT and DT1-IDM. In these experiments we do not pretrain the DT. 100k steps are shown.
Table 4: The final evaluation game performance after training CQL for 100 iterations on a dataset of 10,000 labelled frames from each Atari game.

| Game Name | Final Performance |
|-----------|-------------------|
| Asterix   | 227.5             |
| Breakout  | 12.3              |
| Freeway   | 10.2              |
| Seaquest  | 236.0             |
| SpaceInvaders | 250.9         |

D. Source Code

We make the source code publicly available for our Maze experiment only at this time. The details can be found at: https://anonymous.4open.science/r/alpt_maze-5927/README.md.