On the Opportunities and Challenges of using Animals Videos in Reinforcement Learning

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Abstract—We investigate the use of animals videos to improve efficiency and performance in Reinforcement Learning (RL). Under a theoretical perspective, we motivate the use of weighted policy optimization for off-policy RL, describe the main challenges when learning from videos and propose solutions. We test our ideas in offline and online RL and show encouraging results on a series of 2D navigation tasks.

Index Terms—Learning from Data, Off-Policy Reinforcement Learning, Domain Adaptation

I. INTRODUCTION

Reinforcement Learning (RL) is a powerful tool to learn control policies from experience where the learning agent does not have explicit information about the task but is only allowed to interact with the environment and observe rewards [1]. Despite the trial-and-error nature is a peculiarity of RL, it is often a concern and an obstacle for its actual deployment in real-world scenarios [2]. A solution to this problem is offered by the offline-RL framework [3] where control policies are entirely learned from static datasets which make unnecessary any further interaction with the environment. However, collecting datasets of ready-to-use demonstrations (states, actions and rewards) represents another source of challenge and, even when both states and actions are available, domain and structural differences between source agent, i.e. the agent from which we collect data, and the target agent (the learner) could hinder the actual usefulness of the dataset. More commonly, offline datasets come in the form of videos and therefore methods for the extraction of usable states, actions and rewards from videos are needed.

In this paper, we want to leverage videos of animals navigating the environment as offline datasets. We propose an hybrid approach which leverages agent interactions to extract ready-to-use demonstrations from videos and uses the extracted data to improve RL efficiency and performance. In order to accomplish our goal we address three main problems throughout the paper: (i) dealing with domain adaptation (DA) issues, (ii) dealing with videos as offline datasets and (iii) theoretically motivating off-policy learning algorithms.

Contributions: We start by formulating an adversarial DA algorithm [4] which maps both the offline dataset and the online interactions of the learning agent into a common subspace, allowing for the use of data from different domains. Further, we show a simple method based on supervised learning to recover demonstrations (states, actions and rewards) from observations (states only) and finally, we re-derive weighted regression type of algorithms such as Relative Entropy Policy Search (REP) [5], Maximum a posteriori Policy Optimization (MPO) [6], Advantage Weighted Regression (AWR) [7] and Advantage Weighted Actor Critic (AWAC) in the light of a recent work on principled off-policy learning [9]. Note that, with respect to [9], we cannot use importance sampling (IS) in our formulation as the behavioral policy generating the data is unknown when learning from videos of animals. Our final algorithm Advantage Weighted Policy Optimization (AWPO) would indeed not require IS. We test our method in navigation tasks for both offline and online RL showing encouraging results.

Notation: Unless indicated, we use uppercase letters (e.g., $S_t$) for random variables, lowercase letters (e.g., $s_t$) for values of random variables, script letters (e.g., $S$) for sets, and bold lowercase letters (e.g., $\theta$) for vectors. Let $[t_1 : t_2]$ be the set of integers $t$ such that $t_1 \leq t \leq t_2$; we write $S_t$ such that $t_1 \leq t \leq t_2$ as $S_{t_1:t_2}$. We denote with $\mathbb{E}[^\cdot]$ probability and with $\Delta_{\text{KL}}[^\cdot][\cdot]$ the KL-divergence.

II. PRELIMINARIES

We consider an infinite-horizon discounted Markov Decision Process (MDP) defined by the tuple $(S,A,P,r,D,\gamma)$ where $S$ is the set of states and $A$ is the set of actions, both possibly infinite. $P : S \times A \rightarrow \Delta_S$ is the transition probability function and $\Delta_S$ denotes the space of probability distributions over $S$. The function $r : S \times A \rightarrow \mathbb{R}$ maps state-action pairs to rewards. $D \in \Delta_S$ is the initial state distribution and $\gamma \in [0,1)$ the discount factor. We model the decision agent as a stationary policy $\pi : S \rightarrow \Delta_A$, where $\pi(a|s)$ is the probability of taking action $a$ in state $s$. The goal is to choose a policy that maximizes the expected total discounted reward $J(\pi) = \mathbb{E}_\tau[\sum_{t=0}^{\infty} \gamma^t r(s_t,a_t)]$, where $\tau = (s_0,a_0,s_1,a_1,\ldots)$ is a trajectory sampled according to $s_0 \sim D$, $a_t \sim \pi(\cdot|s_t)$ and $s_{t+1} \sim P(\cdot|s_t,a_t)$. A policy $\pi$ induces a normalized discounted state visitation distribution $d^\pi$, where $d^\pi(s) = (1-\gamma) \sum_{t=0}^{\infty} \gamma^t \mathbb{P}(s_t = s|D,\pi,P)$. We define the corresponding normalized discounted state-action visitation distribution as $\mu^\pi(s,a) = d^\pi(s)\pi(a|s)$. We denote the state value function of $\pi$ as $V^\pi(s) = \mathbb{E}_{\tau \sim \pi}[\sum_{t=0}^{\infty} \gamma^t r(s_t,a_t) | S_0 = s]$, the state-action value function...
where a function is parameterized with parameters $\theta \in \Theta \subset \mathbb{R}^k$ we write $\pi_\theta$.

III. DOMAIN ADAPTATION AND ACTIONS-REWARDS ESTIMATION FROM VIDEOS

Given $s \in S$ a single or an aggregation of RGB frames, we can extract from videos in a source MDP the offline dataset $(s_S, s'_S)_{1:M}$ made only of observations. Further, we assume an isomorphism exists between the source MDP, from which collect the dataset, and the target MDP of the learner.

Assumption 1. Given a source MDP defined by the tuple $(S_S, A_S, P, r, D, \gamma)$ in which the source agent (an animal in our case) operates and a target MDP defined by $(S_T, A_T, P, r, D, \gamma)$, we assume there exist two invertible functions $i_o : S_S \rightarrow S_T$ and $i_a : A_S \rightarrow A_T$ such that $P(s'_T | s_T, a_T) = P(i_o(s'_S) | i_a(s_S), i_a(a_S))$.

Under assumption [1] we can build an algorithm which collects data from the source MDP and learns in the target. Moreover, we assume the dataset $(s_S, s'_S)_{1:M}$ depicts an optimal behavior with respect to the reward function $r$ which is shared by both the source and target MDPs.

A. Domain adaptation

In the following we focus on $i_o : S_S \rightarrow S_T$ in assumption [1] which provides a connection between the source state space $S_S$ and the target $S_T$. In order to leverage data collected in $S_S$ for learning in $S_T$, we have two main alternatives: either directly estimating $i_o$ or mapping both $S_S$ and $S_T$ in a common lower dimensional subspace $\mathcal{H}$. In the specific case of learning from videos, estimating $i_o$ can be accomplished using unpaired image-to-image translation as done in [10, 11, 12]. However, image-to-image translation is an expensive approach which requires large datasets and a conspicuous amount of iterations. As a result, we opt for mapping both $S_S$ and $S_T$ in a common encoding subspace $\mathcal{H}$ using the adversarial domain adaptation framework originally proposed in [4]. We define two different encoders $f_\delta^\text{enc} : S_T \rightarrow \mathcal{H}$ and $f_\psi^\text{enc} : S_S \rightarrow \mathcal{H}$ and sample from the source MDP $(s_S^{(i)}_{1:m})_{i=1}^m \sim (S_S, s'_S)_{1:M}$ and from the target MDP $(s_T^{(i)}_{1:m}) \sim \mathcal{D}^{\pi_k}$. Our adversarial DA step consists in the following min-max game

$$\min_{\psi} \max_{\phi} \frac{1}{m} \sum_{i=1}^m \left[ f_\phi^\text{disc}(f_\delta^\text{enc}(s_T^{(i)})) - f_\phi^\text{disc}(f_\psi^\text{enc}(s_S^{(i)})) \right],$$  

(1)

where $f_\phi^\text{disc} : \mathcal{H} \rightarrow \mathbb{R}$ is a discriminator function which classifies from which MDP (either target or source) the embedding $h \in \mathcal{H}$ has been generated and the source encoder $f_\psi^\text{enc} : S_S \rightarrow \mathcal{H}$ works on making the classification step harder for the discriminator. At optimality, the discriminator is no longer able to distinguish from which MDP the embedding $h$ has been generated meaning that both $S_S$ and $S_T$ have been mapped into the same common subspace $\mathcal{H}$. Note that, eq. [1] is the Wasserstein loss as introduced in [13]. We prefer this loss to the original binary cross-entropy in [14] for stability reasons.

B. Actions and Rewards estimation

Assume we have the following encoders $f_\psi^\text{enc} : S_T \rightarrow \mathcal{H}$ and $f_\phi^\text{enc} : S_S \rightarrow \mathcal{H}$ for the target and source MDPs respectively and a set of observations from the source MDP $(s_S, s'_S)_{1:M}$. Source actions $(s_S)_{1:M}$ and rewards $(r_S)_{1:M}$ can be estimated via supervised learning. Specifically, we define two inverse models $f_\psi^\text{enc} : \mathcal{H} \times \mathcal{H} \rightarrow \Delta_A$ and $f_\phi^\text{enc} : \mathcal{H} \times \mathcal{H} \rightarrow \mathbb{R}$ for actions and rewards respectively, collect learner interactions $(s_T, a_T, s'_T, r_T)_{1:N}$ in the target MDP and train the two inverse models in order to minimize the following losses

$$L^o(\theta) = ||\phi_T - f_\psi(f_\delta(s_T), f_\delta(s'_T))||^2,$$$$

L^w(\theta) = ||\gamma_T - f_\phi(f_\delta(s_T), f_\delta(s'_T))||^2.$$

We then sample $\tilde{s}_S \sim f_\psi(f_\delta(s_S), f_\psi(s'_S))$ and compute $\hat{r}_S = f_\phi(f_\delta(s_S), f_\psi(s'_S))$ obtaining a set of demonstrations $(f_\psi(s_S), \tilde{s}_S, f_\psi(s'_S), \hat{r}_S)_{1:M}$ suitable for learning in the target MDP. Note that, the learning agent will end-up using the following set of joint offline data and online interactions

$$f_\psi(s_S), \hat{a}_S, f_\psi(s'_S), \tilde{r}_S) \cup (f_\psi(s_S), \hat{a}_S, f_\psi(s'_S), \hat{r}_S)$$

(3)

where both $s_S$ and $s'_T$, the RGB frames observations, are encoded in the embedding space $\mathcal{H}$ for domain adaptation purposes. Moreover, recall we assume the demonstrating agent in the source MDP to be a quasi-optimal expert, we add therefore a small constant bonus $r_1$ to $\hat{r}_S$ in order to encourage the learning agent to follow the demonstrating agent and to compensate for reward sparsity. This solution, based on inverse models, learner’s interactions and supervised learning, has been quite studied in the literature and we refer to [15, 16, 17] for more details.

IV. ADVANTAGE WEIGHTED POLICY OPTIMIZATION

After addressing domain adaptation and actions-rewards estimation, we obtain the set of data in [3] made of joint offline data and online interactions. The final challenge in order to successfully leverage videos of animals in RL is determining the proper algorithm able to learn from off-policy data. We start by stating some important results instrumental for our derivations.

Policy improvement lower bound: Our starting point is the policy improvement lower bound originally developed in [18] and refined in [19].

Theorem 1 (19). Consider the current policy $\pi_k$. For any future policy $\pi$ we have

$$J(\pi) - J(\pi_k) \geq \frac{1}{1 - \gamma} \mathbb{E}_{(s,a) \sim D_k} \left[ \frac{\pi(a | s)}{\pi_k(a | s)} A^{\pi_k}(s, a) \right]$$

$$- 2 \gamma C^{\pi, \pi_k} \mathbb{E}_{a \sim \pi_k(a)} [TV(\pi_k(a), \pi)]$$

(4)

where $C^{\pi, \pi_k} = \max_{a \in A} \mathbb{E}_{s \sim \pi_k(s)} [A^{\pi_k}(s, a)]$ and $TV(\pi_k, \pi) = \frac{1}{2} \int_{a \in A} |\pi_k(a | s) - \pi(a | s)| da$ is the total
variation distance between the distributions $\pi_k(\cdot|s)$ and $\pi(\cdot|s)$.

Theorem 1 has been further generalized for the off-policy setting in [9] in order to allow for expectations with respect to any behavioral policy.

**Theorem 2 ([9]).** Consider the current policy $\pi_k$ and the behavioral policy $\beta$. For any future policy $\pi$ we have

$$J(\pi) - J(\pi_k) \geq \frac{1}{1-\gamma} \mathbb{E}_{(s,a)\sim\mu^\beta} \left[ \frac{\pi(a|s)}{\beta(a|s)} A^\pi_k(s,a) \right] - 2\gamma C^\pi,\pi_k \left( \mathbb{E}_{s\sim d^\pi} [TV(\beta,\pi)(s)] \right)$$

(5)

where $C^\pi,\pi_k$ and $TV(\beta,\pi)$ are defined as in Theorem 7.

The first term on the right-hand side in both (4) and (5) is referred to as the surrogate objective, while the second is a penalty term or a soft constraint. Note that both Theorem 1 and Theorem 2 show that, enforcing any future policy $\pi$ to stay close to the behavioral policy $\pi_k$ or $\beta$, a monotonic policy improvement is guaranteed. For practical purposes, the following surrogate optimization problem for Theorem 1 is derived in [20]

$$\max_{\pi} \mathbb{E}_{(s,a)\sim\mu^\pi} \left[ \frac{\pi(a|s)}{\pi_k(a|s)} A^\pi_k(s,a) \right]$$

(6)

$$\mathbb{E}_{s\sim d^\pi} \left[ TV(\pi_k,\pi)(s) \right] \leq \epsilon.$$

Based on (6), the popular on-policy Proximal Policy Optimization (PPO) [21] and its off-policy version Generalized PPO (GePPO) in [9] are formalized. We provide a thorough review on the state-of-art algorithms commonly adopted in deep RL and of their connections with Theorems 1 and 2 in the appendix.

**AWPO derivations:** In the following, we focus on deriving from Theorem 2 an off-policy algorithm which we call Advantage Weighted Policy Optimization (AWPO). This belongs to the family of weighted regression algorithms and have strong similarities with REPS, MPO, AWR and AWAC to mention some of them. The main source of difference lies in the way the algorithm is derived and in the need for an off-policy Advantage Estimation. We start from the lower bound in Theorem 2 and proceed analogously to [19]. Note that, the total variation distance is a metric [22], hence $TV(\beta,\pi)(s) = TV(\pi,\beta)(s)$. Through Pinsker’s inequality [23] we get $TV(\pi,\beta)(s) \leq \sqrt{\mathbb{D}_{KL}(\pi||\beta)(s)/2}$ and combined with Jensen’s inequality yields

$$\mathbb{E}_{s\sim d^\beta} \left[ TV(\pi,\beta)(s) \right] \leq \mathbb{E}_{s\sim d^\beta} \left[ \frac{1}{2} \mathbb{D}_{KL}(\pi||\beta)(s) \right]$$

$$\leq \sqrt{\frac{1}{2} \mathbb{E}_{s\sim d^\beta} \left[ \mathbb{D}_{KL}(\pi||\beta)(s) \right],}$$

from which we get the surrogate problem in (7) where $\beta$ is any behavioral policy.

$$\max_{\pi} \mathbb{E}_{s\sim d^\beta} \left[ \mathbb{E}_{a\sim\pi(s)} \left[ A^\pi(s,a) \right] \right],$$

$$\mathbb{E}_{s\sim d^\beta} \left[ \mathbb{D}_{KL}(\pi(\cdot|s)||\beta(\cdot|s)) \right] \leq \epsilon.$$  

(7)

By converting the KL-divergence in (7) as a soft constraint and solving the Lagrangian problem in closed form, we obtain the following optimal solution

$$\pi^*(a|s) = \beta(a|s) \exp \left( \frac{A^{\pi_k}(s,a)}{\lambda} \right) \frac{1}{Z(s)}$$

where $Z(s)$ is a normalizing factor ensuring $\pi^*(\cdot|s)$ is a probability distribution. Further, we project $\pi^*$ on the manifold of function approximations parameterized by $\theta$. Given $\pi_{\theta_k}$, the policy parameterized by $\theta_k$ at step $k$, for $k+1$ we obtain

$$\theta_{k+1} = \arg \max_\theta \mathbb{E}_{(s,a)\sim\mu^\beta} \left[ \log \pi_{\theta}(a|s) \exp \left( \frac{A^{\pi_k}(s,a)}{\lambda} \right) \right].$$

(8)

We defer to the appendix more details on this derivation.

**Remark 1 (Novelty).** We show direct connection with the generalized policy improvement in Theorem 2 which is a missing piece in all the aforementioned literature [3, 6, 7, 8]. Moreover, a novel small nuance of our formulation is the need for off-policy policy evaluation since we make use of samples from $\beta$ to compute $A^{\pi_k}$ for the current policy $\pi_{\theta_k}$.

**Remark 2 (Off-policy policy evaluation).** Off-policy evaluation is defined as leveraging data generated by a behavioral policy $\beta$ to evaluate the performance metric of the evaluation policy $\pi_{\theta_k}$ (cf. [23]). Well known algorithms for off-policy policy evaluation are Retrace in [24], V-trace in [25] and UnO in [23]. All of these require however importance sampling (IS) correction, which implies knowledge of $\beta$. When learning from videos of animals, $\beta$ is unknown and cannot be estimated using Imitation Learning as in [26, 27] given the absence of actions. A preferable alternative is to avoid IS correction. Thus, we identify and test three main algorithms for off-policy evaluation which do not perform IS correction, these are: Tree-Backup Lambda (TBL) [28], Harutyunyan Q-Lambda (HQL) [29] and Peng Q-Lambda (PQL) [30]. We refer to [23, 24, 31] for additional details on policy evaluation with off-policy correction.

The full algorithm, consisting in: DA step, source actions-rewards estimation and off-policy RL is summarized in Algorithm 1.

**V. EXPERIMENTS**

We conduct a series of experiments in order to gradually evaluate all the single pieces of our algorithm. We focus on 2D navigation tasks with sparse rewards and run tests on offline RL in order to assess the offline performance of AWPO with different Advantage Estimation algorithms. Then, we continue testing Algorithm 1 in RL with offline observations without DA, with simplified DA (environment in Fig. 1a as target and Fig. 1b as source for both these experiments) and finally with hard DA where the rodent video in Fig. 2 is used as offline dataset (Fig. 1a for target and Fig. 1c for source). For all the implementations details for both the offline1
Algorithm 1: AWPO from Videos w/ Adv Domain Adaptation

Input: \((s_S, s_T, s_T')\): samples, \(\pi_\theta, f_{\psi}, f_{\phi}, f_{\chi}, f_{\pi}, r, r_i, \alpha, \lambda, K, N\).

for \(k = 1, K - 1\) do
\[
\begin{align*}
&(s_T, a_T, s_T', r_T) \sim \pi_{\theta_k} \\
&\text{Adv DA in (1),} \\
&a_S \text{ and } r_S \text{ estimation as in (2),} \\
&\text{set } \hat{r}_i = f_{\pi}^\nu(f_{\psi}(s_i), f_{\phi}(s_i)) + r_i \\
&\text{Given the data } D \text{ in (3) where } h \leftarrow f_{\psi}(s): \\
&\text{Perform } A^\pi_{\theta_k}(h, a) \text{ estimation,} \\
&\theta_{k+1} = \theta_k + \alpha \nabla_{\theta} \mathbb{E}_D \left[ \log \pi_\theta(a|h) \exp \left( \frac{A^\pi_{\theta_k}(h, a)}{\lambda} \right) \right] \\
&\theta \leftarrow \theta_{k+1}
\end{align*}
\]

return \(\pi_{\theta}\)

online experiments we defer to the code. In a nutshell, the encoders are 3 layers Convolutional Neural Networks (CNN) and discriminator, policy network, critic network and inverse models are MultiLayer Perceptrons (MLP) with a single hidden layer.

A. Offline RL

In the following we test AWPO with different advantage estimation techniques. In addition to the aforementioned HQL \(^{(29)}\), PQL \(^{(30)}\) and TBL \(^{(28)}\), which perform IS free off-policy correction to compensate for the use of off-policy data without knowing \(\beta\), we also test Generalized Advantage Estimation (GAE) \(^{(33)}\), which does not perform off-policy correction. Moreover, we compare AWPO against the offline RL baselines Soft-Actor Critic (SAC) \(^{(34)}\), Behavioral Cloning (BC) \(^{(35)}\), AWAC \(^{(8)}\) and the state-of-the-art TD3+BC \(^{(36)}\). We focus on the navigation tasks available in the popular library "Datasets for Deep Data-Driven RL" \(^{(3)}\). The full results are in Table I and show all the different versions of AWPO matching SOTA performance. Note that, in these experiments, the datasets are made of demonstrations (state, actions and rewards) and do not require any DA step.

B. Online RL

We focus on the 2D navigation task in Fig. 1a as target MDP, where the state \(s_T \in S_T\) is the \(128 \times 128\) RGB image showing the full grid and the goal is to reach the bottom right corner labelled by the green square. We run all the experiments for \(400k\) training steps and evaluate the policy every \(4k\) steps for 10 episodes. This procedure is repeated for 10 different random seeds. Table II summarizes the final results where we report the reward obtained at the end of the training process and averaged over episodes and seeds. Note that, almost all the different versions of AWPO benefit from the introduction of videos as offline dataset when associated with DA. In particular, Algorithm 1 combined with AWPO+HQL, AWPO+PQL and AWPO+TBL always outperforms its RL only counterpart. However, when we turn the DA step off, as in the 2nd row in Table II we observe limited benefit in leveraging offline videos. The only exception is given by AWPO+GAE which shows great stability in its RL only version (only .09 of standard deviation) and higher instability when associated with offline datasets which leads to lower average performance. We include plots of the training curves for each experiment in the appendix.

VI. CONCLUSIONS

This paper analyzes the challenges of using videos in RL as offline datasets in order to increase learning efficiency and performance. The main problems we identify consist in dealing with domain discrepancies between source and target domains, learning from offline observations rather than demonstrations and being able to opportunely accomplish off-policy learning. For domain discrepancies we mean using data collected in conditions which are not necessarily the one encountered by the learning agent. As described in Assumption II we allow for structural differences in \(S\) and \(A\) and our DA step works on

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**TABLE I: Offline RL experiments.** The reported reward is averaged over the final 10 evaluations and 10 seeds. Each trial consists of 200 iterations and during each iteration 30k offline samples are used for training.

|                         | maze2d-large | antmaze-diverse | antmaze-play |
|-------------------------|--------------|-----------------|--------------|
| BC                      | 277.3 ± 134.8| 0.35 ± 0.33     | 0.46 ± 0.28  |
| AWPO+GAE                | 214.7 ± 126.5| 0.43 ± 0.29     | 0.48 ± 0.18  |
| AWAC                    | 270.6 ± 144.6| 0.44 ± 0.16     | 0.43 ± 0.2   |
| AWPO+HQL                | 262.8 ± 109.8| 0.43 ± 0.27     | 0.63 ± 0.26  |
| AWPO+PQL                | 300.3 ± 74.2 | 0.36 ± 0.21     | 0.46 ± 0.24  |
| AWPO+TBL                | 204.2 ± 98.3 | -               | -            |
| SAC                     | 186.02 ± 105.5| -              | -            |
| TD3+BC                  | 321.1 ± 157.7| 0.16 ± 0.2      | 0.43 ± 0.35  |

**TABLE II: Online RL experiments.** The reported reward is averaged over the final 10 evaluations and 10 seeds. Each experiment consists of 400k training steps. In RL only we focus on simple RL where we make no use of off-policy data or offline datasets. In RL+1b we collect an expert video in Fig. 1b and leverage this dataset without explicit DA step. Similarly in RL+1b+DA where however we use a DA step and set \(r_i = 0.01\). Finally, in RL+1c+DA (1) and RL+1c+DA (2) we use the video in Fig. 1b as offline dataset and we set \(r_i = 0.01\) for the former and \(r_i = 0.005\) for the latter.

|                         | GAPE | HQL | PQL | TBL |
|-------------------------|------|-----|-----|-----|
| RL only                 | .71 ± .09 | .02 ± .04 | .01 ± .03 | 0   |
| RL+1b                   | .04 ± .07 | .08 ± .16 | .13 ± .20 | .03 ± .06 |
| RL+1b+DA                | .44 ± .29 | .36 ± .27 | .35 ± .26 | .26 ± .23 |
| RL+1c+DA (1)            | .27 ± .26 | .28 ± .24 | .39 ± .24 | .25 ± .16 |
| RL+1c+DA (2)            | .42 ± .32 | .26 ± .23 | .21 ± .18 | .27 ± .26 |
Fig. 1: Environments used for our online RL experiments. Fig. 1a shows the target MDP. Fig 1b and Fig. 1c show two different source MDP from which we collect videos used as offline datasets in Algorithm 1. For both the environments in 1a and Fig 1b we rely on the open-source library minigrid [32].

Fig. 2: Frames from the video used as offline dataset. The video consists in a top view of a rodent foraging in an empty maze.

smoothing these discrepancies transforming the offline dataset in order to make it exploitable by the learning agent. The importance of this step is evident in Table II for the Fig. 1b experiments. Furthermore, learning from offline observations deals with the problem of estimating actions and rewards from static dataset made of observations only. Our solutions is based on inverse models trained using supervised learning and learner’s interactions. Finally, considering recent works on principled off-policy learning, we re-derive the AWPO algorithm and test it with and without offline videos on a series of challenging scenarios. Future works will focus on improving each individual step and test our solutions not only in navigation but also for learning locomotion and manipulation.

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C. On-policy methods

We consider Proximal Policy Optimization (PPO) in [21].

Given a current policy \( \pi_k \), as showed in [18], for any future policy \( \pi \) we have

\[
J(\pi) - J(\pi_k) = \frac{1}{1 - \gamma} \mathbb{E}_{s \sim d^s} \left[ E_{a \sim \pi(\cdot|s)}[A^{\pi_k}(s, a)] \right], \tag{11}
\]

From which follows the result in Theorem 1

\[
J(\pi) - J(\pi_k) \geq \frac{1}{1 - \gamma} \mathbb{E}_{s, (a, \mu_k) \sim \mu_k} \left[ \frac{\pi(a|s)}{\pi_k(a|s)} A^{\pi_k}(s, a) \right] - \frac{2\gamma C_{\pi, \pi_k}}{(1 - \gamma)^2} \mathbb{E}_{s \sim d^s} \left[ TV(\pi_k, \pi)(s) \right], \tag{12}
\]

where \( TV \) is the total variation distance defined as

\[
TV(\pi_k, \pi)(s) = \frac{1}{2} \int_{a \in A} |\pi_k(a|s) - \pi(a|s)| da. \tag{13}
\]

The inequality in (12) shows that, provided a small \( TV \) between the current and future policies, the difference in expected return (aka expected improvement) is lower bounded by a positive value, which means we can guarantee a monotonic improvement throughout policy gradient iterations. By further combining Pinsker’s inequality with Jensen’s inequality the following holds

\[
\mathbb{E}_{s \sim d^{\pi_k}} \left[ TV(\pi_k, \pi)(s) \right] \leq \mathbb{E}_{s \sim d^{\pi_k}} \left[ 2 \mathbb{D}_{KL}(\pi_k||\pi) \right] \leq \frac{1}{2} \mathbb{E}_{s \sim d^{\pi_k}} \left[ 2 \mathbb{D}_{KL}(\pi_k||\pi) \right].
\]

The following problem is therefore proposed in [20] to maximize the lower bound in (12):

\[
\max_{\pi} \mathbb{E}_{(s, a) \sim \pi_k} \left[ \frac{\pi(a|s)}{\pi_k(a|s)} A^{\pi_k}(s, a) \right], \tag{14}
\]

Furthermore, converting the hard KL constraint in a soft

\[
\mathbb{E}_{s \sim d^{\pi_k}} \left[ \mathbb{D}_{KL}(\pi_k(\cdot|s)||\pi(\cdot|s)) \right] \leq \epsilon.
\]
We start again from the bound in Theorem 1. PPO [21] converts the previous into the following:

\[
J(\pi) - J(\pi_k) \geq \frac{1}{1 - \gamma} \mathbb{E}_{(s,a) \sim \mu^\pi_k} \left[ \frac{\pi(a|s)}{\pi_k(a|s)} A^\pi_k(s, a) \right] - 2\gamma C^\pi,\pi_k \mathbb{E}_{s \sim d^\pi_k} \left[ TV(\pi, \pi_k)(s) \right]
\]

and the following holds as well:

\[
E_{s \sim d^\pi_k} [TV(\pi, \pi_k)(s)] \leq \mathbb{E}_{s \sim d^\pi_k} \left[ \frac{1}{2D_KL(\pi||\pi_k)} \right] \leq \frac{1}{2} \mathbb{E}_{s \sim d^\pi_k} [D_KL(\pi||\pi_k)].
\]

These passages yield the following surrogate problem:

\[
\max_{\pi} \mathbb{E}_{s \sim d^\pi_k} \left[ E_{(s,a) \sim \mu^\pi_k} \left[ \frac{\pi(a|s)}{\pi_k(a|s)} A^\pi_k(s, a) \right] + \lambda \log \pi_k(a|s) \right].
\]

Note that, given the use of importance sampling in the derivation, PPO is an algorithm which necessarily requires knowledge of the policy generating the data \( \pi_k \).

### D. AWPO derivations

In the following we derive AWPO. Similar steps lead to AWR [7], AWAC [8] and Generalized Proximal Policy Optimization (GePPO) [9]. We start again from the bound in Theorem 1.

Note that, The total variation distance is a metric \([22]\), which means:

- \( TV(\pi, \pi_k)(s) = 0 \iff \pi = \pi_k \ \forall a \in A \),
- \( TV(\pi, \pi_k)(s) = TV(\pi_k, \pi)(s) \),
- \( TV(\pi, \pi_k)(s) \leq TV(\pi, \pi')(s) + TV(\pi', \pi_k)(s) \).

Considering the symmetric property (second bullet in the previous) eq. (12) can be rewritten as:

\[
TV(\pi, \pi_k)(s) = d^\pi_k(s) A^\pi_k(s, a) - \lambda d^\pi_k(s) \log \pi(a|s) + \lambda d^\pi_k(s) \log \pi_k(a|s) - \lambda d^\pi_k(s).
\]

We look for a stationary point by setting the differentiation equal to zero and we obtain:

\[
\log \pi(a|s) = \frac{A^\pi_k(s, a)}{\lambda} + \log \pi_k(a|s) - Z(s),
\]

\[
\pi^*(a|s) = \pi_k(a|s) \exp \left( \frac{A^\pi_k(s, a)}{\lambda} \right) \frac{1}{Z(s)}.
\]
Using a function approximation we need to project \( \pi^* \) on the function manifold as follows

\[
\theta^* = \arg \min_{\theta} \mathbb{E}_{s \sim d^\pi_k} \left[ \mathbb{D}_{KL}(\pi^* || \pi_\theta) \right] \\
= \arg \min_{\theta} \mathbb{E}_{s \sim d^\pi_k} \left[ \mathbb{D}_{KL} \left( \frac{\pi_k(a|s)}{\pi_\theta(a|s)} \right) \right] \\
= \arg \min_{\theta} \mathbb{E}_{s \sim d^\pi_k} \left[ \exp \left( \frac{A^\pi_k(s, a)}{\lambda} \right) \log \frac{\pi_\theta(a|s)}{\pi_k(a|s)} \right] \\
= \arg \max_{\theta} \mathbb{E}_{s \sim d^\pi_k, a \sim \pi_k} \left[ \log \pi_\theta(a|s) \exp \left( \frac{A^\pi_k(s, a)}{\lambda} \right) \right].
\]

This last formulation is interesting since the only dependence on \( \pi_k \) is through the samples in the expectation.

According to how we estimate \( A^\pi \) either AWR, AWAC or AWPO are recovered which can allow for both on-policy and off-policy data. AWAC leverages the same structure as the presented off-policy algorithms where transitions are stored in a replay buffer, the critic \( Q_{\theta_2} \) is updated as in \( \theta_{k+1} \) and the actor updated via

\[
\theta_{k+1} = \arg \max_{\theta} \mathbb{E}_{(s, a) \sim D} \left[ \log \pi_\theta(a|s) \right. \\
\left. \exp \left( \frac{Q_{\theta_2}(s, a) - \mathbb{E}_{\pi \sim \pi_k} [Q_{\theta_2}(s, a)]}{\lambda} \right) \right].
\] (16)

On the other hand, AWR starts from the observation that the replay buffer \( D \) contains data collected from \( N \) previous policies \( \{\pi_1, \ldots, \pi_N\} \). Sampling from \( D \) is then analogous to modeling the sampling policy as \( \mu(a|s) = \sum_{i=1}^N w_i \delta_{\pi_i}(a|s) \sum_{k=1}^N w_i d_{\pi_k}(s) \) where the weights \( \sum_i w_i = 1 \) specify the probabilities of selecting each policy \( \pi_i \). The following surrogate problem is then proposed

\[
\max_{\pi} \mathbb{E}_{s \sim d^\mu} \left[ \mathbb{E}_{\pi \sim \pi(s)} \left[ A^\pi(s, a) \right] \right], \\
\mathbb{E}_{s \sim d^\mu} \left[ \mathbb{D}_{KL} \left( \pi(s) || \mu(s) \right) \right] \leq \epsilon,
\] (17)

where \( d^\mu = \sum_{i=1}^N w_i d_{\pi_i} \). The resolution of this problem via the Lagrangian turns similar to \( \theta_{k+1} \). However, in \( \theta_{k+1} \) the advantage is computed as

\[
A^\pi(s, a) = R^\pi_{s,a} - V, \\
V = \arg \min \sum_i w_i \mathbb{E}_{s \sim d^\pi_i, a \sim \pi_i} \left[ ||R^\pi_{s,a} - V(s)||^2 \right],
\] (18)

where \( R^\pi_{s,a} \) is a k-steps Monte Carlo estimate of the discounted expected reward following \( \pi_i \). We notice that by averaging the previous k-steps advantage estimators we recover GAE in \( \theta_{k+1} \).

Finally, GePPO in \( \theta_{k+1} \) formalizes a principled way to use a replay buffer containing \( N \) previous policies \( \{\pi_1, \ldots, \pi_N\} \). Theorem 2 is proved in \( \theta_{k+1} \) and states that

\[
J(\pi) - J(\pi_k) \geq \frac{1}{1 - \gamma} \mathbb{E}_{(s, a) \sim d^\mu} \left[ \frac{\pi(a|s)}{\pi_k(a|s)} A^\pi(s, a) \right] \\
- \frac{2\gamma C_{\pi_k}}{(1 - \gamma)^2} \mathbb{E}_{s \sim d^\mu} \left[ TV(\pi, \pi_k)(s) \right],
\]

In the previous we distinguish 3 policies: \( \pi \) which is any future policy, \( \pi_k \) which is the current policy and \( \pi_{ref} \) which is the actual behavioral policy. This result can be generalized for the case in which \( \pi_{ref} \) is a mixture of policies from previous iterations yielding

\[
J(\pi) - J(\pi_k) \geq \frac{1}{1 - \gamma} \sum_{i=1}^N w_i \mathbb{E}_{s \sim d^\pi_i, a \sim \pi_i} \left[ \frac{\pi(a|s)}{\pi_i(a|s)} A^\pi(s, a) \right] \\
- \frac{2\gamma C_{\pi_k}}{(1 - \gamma)^2} \sum_{i=1}^N w_i \mathbb{E}_{s \sim d^\pi_i, a \sim \pi_i} \left[ TV(\pi, \pi_i)(s) \right].
\] (19)

Theorem 2 justifies the use of a replay buffer storing previous experience and shows a difference in the formulation of the advantage function with respect to \( \theta_{k+1} \). The GePPO formulation shows \( A^\pi_k \) rather than \( A^\pi_k \) and uses an Advantage version of \( V \)-Trace \( 25 \) for off-policy policy evaluation. Note that both \( V \)-Trace and GePPO use importance sampling and therefore require knowledge of the behavioral policies \( \{\pi_1, \ldots, \pi_N\} \) used to generate the data stored in the buffer.

E. Experiments training curves

In the following we show the training curves for the experiments in Table II

![Fig. 3: Table II RL only](image-url)
Fig. 4: Table II