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Techniques for Sample-Efficient Reinforcement Learning

by

William Fairclough Whitney

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Professor Kyunghyun Cho

To my dog Weierstraß, with affection.

add dedication

Acknowledgements

- all my collaborators
- housemates

Abstract

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1 Introduction

{sec:introduction}

Reinforcement learning (RL) provides a framework for systems which learn to make decisions under uncertainty about their environment. Such a system must simultaneously determine which of all possible environments it is interacting with and solve for an optimal strategy in that environment. This uncertainty is the core challenge of reinforcement learning, and one of the most fundamental questions of the field is how much experience a learning system requires to resolve its uncertainty and perform well. We call this the sample complexity of reinforcement learning.

Classically reinforcement learning was restricted to environments with small, countable state and action spaces.[1] In this setting a variety of algorithms were developed with robust guarantees on their performance relative to the ideal policy and on the amount of data required to approach perfect behavior. Bandit algorithms for environments without temporal dependence and dynamic programming for those with non-trivial dynamics both yielded practical success. However, the specter of exponentially-increasing sample complexity limited these approaches to low-dimensional settings.

The combination of deep learning with reinforcement learning in the last decade has given rise to the new subfield of "deep reinforcement learning", which leverages function approximation to scale reinforcement learning to tasks with large or uncountable state or action spaces. Deep reinforcement learning has led to dramatic results across a range of domains, from board games like Go to complex multiplayer computer games like StarCraft, from controlling automated balloons to manipulating Rubik's cubes, and even to abstract tasks like chip design.

A key unifying feature of these most impressive deep RL results is the availability of simulators. Each of these domains admits the construction of a simulation of sufficient fidelity that a policy may be trained in simulation and then deployed on the real task with little to no fine tuning. Furthermore, these simulations are inexpensive relative to collecting "real" data, reducing the cost of training a policy by orders of magnitude. By turning data collection into computation, simulation freed deep RL from paying attention to sample efficiency, as it was more important how computationally fast an algorithm was than how many hours or years of (virtual) experience it consumed.[2]

1.1 The Cost of Free Data

Our reliance on simulation comes with hidden costs. Simulation-based RL has generated spectacular results, and simulation should be a primary tool in any effort to solve a real-world task. However, the availability of cheap simulation has shaped what the deep RL community studies by reinforcing work on simulatable domains and the large-data regime. This has resulted in slower progress on questions in the sample-limited regime. Sample-efficient reinforcement learning is important due to the fundamental scientific importance of understanding sample complexity and the intractibility of simulating every domain of interest.

Sample complexity is foundational. The study of sample complexity in reinforcement learning addresses fundamental questions about what information is needed to reliably solve a problem. The observation that realistic, high-dimensional tasks are solvable with small sample sizes may be surprising, given that there are theoretical lower bounds requiring a number of samples which is linear in the number of states or exponential in the horizon [Du et al. 2020]. This disagreement requires explanation, and it suggests that real-world problems contain a significant amount of structure which makes them easier to solve. Understanding this structure in more

detail, as well as how it interacts with the inductive biases of the function approximators we use, could lead to significant breakthroughs.

Simulators are expensive. While many simulators already exist that are computationally inexpensive, many important systems of interest are computationally difficult to simulate with sufficient precision for transfer to the real world. Simulations of fluid dynamics, deformable materials, and large numbers of contacts (to name a few) can be significantly slower than real-time. Furthermore, the development of new realistic simulators is *financially* expensive not only because of the engineering of the simulator itself, but additionally due to the need to create and maintain a close correspondence between the simulation and the physical system of interest. These costs inhibit the use of simulators for domains which are too complex or too niche.

This thesis consists of work done in the last several years which makes deep RL somewhat more capable in the sample-limited regime. With this line of work I hope to unlock the wide range of environments which currently lack high-fidelity simulators. Beyond simply enabling RL in more complex environments, improvements to sample efficiency has the potential to allow agents to adapt on the fly to the specifics of the environment or objectives they interact with. A home robot might come to know the best way to pick up *your* cups, or an automated factory could produce more rapidly over the course of a production run as the networked assembly arms pool experience about manipulating each component part. In these settings learning more efficiently can be directly translated into consumer experience and dollars saved.

1.2 Elements of Sample-Efficient Learning

Reinforcement learning can be thought of as comprising two distinct processes: data collection and policy optimization. Data collection, also known as *exploration*, is when the agent interacts with the environment in order to gain more information about the optimal policy. Policy opti-

mization is the process of using data collected from the environment to produce a policy that achieves as much reward as possible. In order that an RL algorithm overall be sample efficient, both exploration and policy optimization must themselves be efficient.

Efficient exploration means rapidly acquiring information about the optimal policy. This means collecting data that is diverse, such that valuable states and actions will be quickly uncovered, but also biasing data collection towards states and actions which are more likely to be optimal. If done well exploration spans the environment and then collects evidence to allow the agent to discard poor policies and differentiate between actions which are optimal and those which are merely good.

Efficient policy optimization means squeezing as much performance as possible out of the data which is currently available. While this is often discussed in the narrow frame of model-free RL, this process might include building models, learning representations, or even meta-learning. In principle one might hope to feed some prior beliefs along with whatever data has been collected from the environment and get back the best policy which is supported by that data. Recent work in off-policy RL and the offline RL setting have made progress towards this vision, but it remains some way off.

1.3 Overview

This thesis consists of work on improving the sample efficiency of reinforcement learning through three main directions: (1) collecting more diverse data without confounding policy learning; (2) learning representations which capture structure in the environment; and (3) studying policy optimization in the batch setting to develop policy improvement operators that are robust to limited data. The motivating challenge through much of this work is robotic manipulation using low-dimensional positions or high-dimensional images as observations and with continuous-valued action spaces. However, the findings described here are applicable more widely across reinforce-

ment learning.

The rest of the thesis is organized as follows:

- Chapter 2 introduces background on the problem of sample-efficient RL and how it relates to the several settings under which RL has been studied.
- Part I describes the role of exploration in sample-efficient RL, with Chapter 3 illustrating how exploration techniques adapted from deep RL to the sample-limited robotic setting can improve sample efficiency and performance.
- Part II discusses the role of representation in reinforcement learning, with connections to representation learning more generally in Chapter 4 and work on representations for sample-efficient RL in Chapter 5.
- Part III studies policy optimization in the offline setting, first describing the impact of over-paraterized models in offline bandit problems in Chapter 6, then studying the repeated application of policy improvement operators in the full offline RL problem in Chapter 7.

Notes

1. Or more accurately, environments admitting assumptions that allow them to be treated as such. A 2-D continuous state space can be treated as a discrete grid of states with arbitrarily little waste under the assumption that the environment changes sufficiently slowly, for example.

2. Of course, not everyone in the deep RL community ignores sample efficiency. Notably many people working on robotics have maintained remarkable discipline in only running simulated benchmarks for physically plausible amounts of time, but there is also a small but vibrant community working on reaching human Atari performance with human-like amounts of experience.

2 | The Many Settings of Reinforcement Learning

{sec:rl-settings}

2.1 Notation

A Markov decision process (MDP) $\mathcal{M}$ consists of a tuple $(\mathcal{S}, \mathcal{A}, P, R, \gamma, s_0)$, where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, P is the transition function mapping $\mathcal{S} \times \mathcal{A}$ to distributions on $\mathcal{S}$, R is the scalar reward function on $\mathcal{S} \times \mathcal{A}$, γ is the discount factor, and s_0 is the starting state. Note that a single start state can be converted to a start distribution by letting $P(s_0, \cdot)$ be independent of the action taken. An *agent* interacts with an MDP by producing a policy π at each timestep and observing the transitions it visits.

The *value* of a state s for a policy π is the (discounted) sum of future rewards obtained by running that policy starting from the state s:

$$V^\pi(s) = \mathop{\mathbb{E}}_{\substack{a_t \sim \pi(\cdot|s_t) \\ s_{t+1} \sim P(s_t, a_t)}} \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \,\Big|\, s_0 = s \tag{2.1}$$

Similarly the value of a state-action pair (s, a) is written as

$$Q^\pi(s, a) = \mathop{\mathbb{E}}_{\substack{a_t \sim \pi(\cdot|s_t) \\ s_{t+1} \sim P(s_t, a_t)}} \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \,\Big|\, s_0 = s, a_0 = a \tag{2.2}$$

Any MDP admits a deterministic optimal policy π^* with corresponding value functions V^* and Q^* such that $V^*(s) \geqslant V^\pi(s)$ for all s and π [Sutton and Barto 2018].

2.2 Discounting and Resets

When $\gamma < 1$ we say that the setting is *discounted*, and for $\gamma = 1$ we say that it is *undiscounted*. An environment may have a time limit T such that after every T steps, the state is reset to s_0. In this case we call it *episodic*. To satisfy the Markov property, episodic environments should include the current timestep t in the state.

For episodic environments, it is natural to define a policy's quality in terms of the total reward earned (on average) in a single episode, with discounted environments preferring rewards obtained earlier in the episode. For non-episodic environments comparisons between policies are less clear-cut; see Section 2 of Strehl and Littman [2008] for a discussion.

Common practice in deep reinforcement learning is to train agents with discounting and resets, but not include the timestep in the state observations and simply ignore the transition from s_T to s_0. Policies are typically evaluated by the total undiscounted reward in an episode, despite the conflict with the training setup. In most cases the rewards are truncated to reflect the limited episode duration [Schulman et al. 2017; Fujimoto et al. 2018a; **?**]. Since the agent is unable to tell when an episode will end, this effectively introduces noise into value prediction targets, and this noise varies by state depending on how often the agent has ended an episode on that state. In other cases value targets may be bootstrapped from the state s_T as if the environment were not episodic. This has two issues: (1) it introduces bias by treating an estimate of $V(s_T)$ as the true value, when in some states and environments this estimate may never be updated; and (2) by pretending the environment has no resets, it introduces a mismatch between the training and test objectives.[3] However, it does not introduce noise.

More fundamentally, practically all discounted policy gradient algorithms drop the discount-

ing term from the state distribution. Nota and Thomas [2020] show that this results in following a direction which is not the gradient of any function, and which is not guaranteed to converge to a good solution with respect to the discounted or undiscounted objectives. While this is deeply worrying, these methods frequently work well in practice. This may be due to their usage with overparameterized neural network models, which are largely invariant to a reweighting of the data [Byrd and Lipton 2018; Brandfonbrener et al. 2021].

2.3 Defining Sample Complexity

We say that a policy π is ε-optimal if $V^*(s_0) \leqslant V^{\pi}(s_0) + \varepsilon$. Define $\boldsymbol{\pi} = A(\mathcal{M}, i)$ to be the policy obtained by running the agent (i.e. algorithm) A in the environment $\mathcal{M}$ for i timesteps, being careful to note that the policy $\boldsymbol{\pi}$ is itself a random variable due to the randomness in the experience collected in those i steps. Let the *sample complexity* of learning a ε-optimal policy on $\mathcal{M}$ with A be the expected number of steps (indexed as i) such that

$$V^{\pi_i}(s_0) < V^*(s_0) \leqslant -\varepsilon, \qquad \text{where } \pi_i = A(\mathcal{M}, i). \tag{2.3}$$

This definition is related to those proposed by Fiechter [1994] and Strehl and Littman [2008] for PAC learning. Sometimes it is also useful to consider the "anytime" performance of an algorithm A on an MDP $\mathcal{M}$. An algorithm A_1 would dominate A_2 if $\forall i$, $V^{A_1(\mathcal{M},i)}(s_0) \geqslant V^{A_2(\mathcal{M},i)}(s_0)$.

2.4 Online and Deployment Settings

{sec:regret-deploymen

While the overall MDP framework is largely shared in the community, several different objectives for a learning agent are commonly studied. The online and offline settings are perhaps the most studied in the theory community, but the "learn-and-deploy" setting has the most relevance for present applications of RL.

THE ONLINE SETTING. Here an RL agent learns by continually interacting with the environment with the goal of maximizing the total reward earned across all time. This gives rise to the explore-exploit tradeoff when acting: at each moment, the agent may choose to take an action which is uninformative but leads to greater short-term reward, or one which will yield more information at the cost of lower reward. The objective for this setting is to minimize the rate of accumulation of *regret*, which measures the difference between the total reward obtained by an optimal policy and the agent:

talk about sample complexity

$$L(A, \mathcal{M}, T) = \mathbb{E}\left[\sum_{i=1}^{T} R(s_i^*, a_i^*) - R(s_i, a_i)\right]. \tag{2.4}$$

This setting is appropriate when an agent is being trained "on the job," where mistakes early in learning have just as much deleterious effect as those made later.

THE LEARN-AND-DEPLOY SETTING. This setting consists of distinct learning and deployment phases. In the learning phase, the agent is not required to perform well and may collect whatever data is most informative. In the deployment phase, the policy is fixed and should be as close to optimal as possible. Note that the policy produced at the end of the training procedure need bear no resemblance to those used to collect data. For episodic environments, with a training period consisting of N steps we can write the this objective as

talk about sample complexity

$$L(A, \mathcal{M}, N) = V^*(s_0) - V^{\pi_N}(s_0), \qquad \text{where } \pi_N = A(\mathcal{M}, N) \tag{2.5}$$

Historically this setting has not been much discussed, though it is analagous to the task of best-arm identification in bandits [Russo 2016; Kaufmann et al. 2016]. It is also related to the iterative technique of fitted Q iteration [Ernst et al. 2005; Riedmiller 2005].

Crucially, this setting is the one used in practice in nearly every application of reinforcement learning. RL algorithms are not yet safe and reliable enough to allow them to update a policy on

the fly, especially with a physical system which may be damaged or cause injury. Furthermore, most works studying RL implicitly provide results in this setting by evaluating according to a different policy than the one used for training, for example showing learning curves with a deterministic policy [Mnih et al. 2015b; Lillicrap et al. 2016; Fujimoto et al. 2018a; **?**]. Comparisons of final, large-data performance similarly reflect this setting [Silver et al. 2016; Vinyals et al. 2019; OpenAI et al. 2019a,b].

talk about sample complexity

The offline setting. Also known as the *batch* setting, this consists only of pure policy optimization given a fixed dataset of environment interactions collected by an extrinsic behavior policy. After learning from this data in whatever way it sees fit, an algorithm produces a fixed policy with the objective of earning as much reward as possible. Though described as a reinforcement learning setting, it does not include any actual reinforcement as the agent never learns from its own interactions with the environment. However, this makes the offline RL setting uniquely valuable for isolating how much can be learned from particular data. This setting is also appealing as it would in principle allow an agent to be trained in a risk-free way by using data collected from a safe policy, and for free (in terms of samples) if data from one experiment can be repurposed as training data for another.[4]

Do I want a section on simulated versus physical envs?

Notes

3. This mismatch is decreased if the divergence between the distributions $P(s_T, \pi(\cdot \mid s_T))$ and s_0 is smaller. Like most problems in RL, it also becomes smaller if smaller discount factors are used. However in general there are actions which would provide more short-term reward, and thus perform better toward the end of an episode, than the infinite-horizon optimal actions.

4. While there are doubtless some settings where this cross-task data reuse is possible, it has quite clear limits. For a policy to be trained to solve task B using data collected from task A, the policy used for task A would have had to actually also solve task B. It could have been done piecewise rather than in a single good trajectory, but unless the tasks are extremely similar it is vanishingly unlikely. Perhaps a more practical application would be to start with a safe but poor policy for solving a task, then incrementally collect new data, refine the policy using offline RL, validate that the new policy is also safe, and then collect data once more.

Part I

Exploration and Sample Efficiency

{sec:exploration}

Introducing exploration for sample-efficient control.

3 Decoupled Exploration and Exploitation Policies

{sec:deep}

3.1 Introduction

Recent progress in reinforcement learning (RL) for continuous control has led to significant improvements in sample complexity and performance. While earlier on-policy algorithms required hundreds of millions of environment steps to learn, recent off-policy algorithms have brought the sample complexity of model-free RL in range of solving tasks on real robots [Haarnoja et al. 2018c].

In parallel, a rich literature has been developed for directed exploration in deep reinforcement learning, inspired in part by the theoretical impact of exploration on sample complexity. The bulk of these methods fall into the family of bonus-based exploration (BBE) methods, in which a policy receives a bonus for visiting states deemed to be interesting or novel. BBE algorithms have enabled RL to solve a variety of long-horizon, sparse-reward tasks, most notably the game Montezuma's Revenge from the Arcade Learning Environment (ALE) [Bellemare et al. 2015].

These two subfields both aim to minimize the sample complexity of model-free RL, and their methods are in principle perfectly complementary. Off-policy algorithms extract improved policies from data collected by (notionally) arbitrary behavior, and their performance is limited only by the coverage of the data; meanwhile exploration generates data with improved coverage. How-

ever, to date the impact of directed exploration techniques on sample-efficient control has been minimal, with state of the art algorithms using undirected exploration such as maximum-entropy objectives. In this paper we investigate the missing synergy between off-policy continuous control and directed exploration.

We find that BBE is poorly suited to the few-sample regime due to slowly-decaying bias in the learned policy and slow adaptation to the non-stationary exploration bonus. Bias due to optimizing a reward function other than the task reward leads a policy trained with BBE to exhibit poor performance until the bonus decays toward zero. Meanwhile, the non-stationary (continually decreasing) exploration bonus cannot necessarily be optimized by a fixed policy, violating one of the core assumptions of RL. This leads to slow exploration as the policy adapts only gradually, especially in the off-policy case where replay buffers will contain stale rewards. These observations underline research by Taiga et al. [2020] showing that across the ALE, no BBE algorithm outperforms undirected ε-greedy exploration.

We demonstrate that bias and slow coverage are the culprits of BBE's lackluster performance by proposing a new exploration algorithm, Decoupled Exploration and Exploitation Policies (DEEP), which addresses these limitations. DEEP decouples the learning of a *task policy*, which is trained to maximize the true task reward, and an *exploration policy*, which maximizes only the exploration bonus. Both policies are trained off-policy using data collected according to the product of the two policy distributions. Unlike the policy learned by BBE, DEEP's task policy is always unbiased in the sense that it reflects the current belief about the optimal action in each state. Furthermore, this decoupling allows DEEP to aggressively update the exploration policy without affecting the convergence of the task policy, thereby adapting more rapidly to the changing exploration bonus.

We perform experiments using policies based on Q-learning [Sutton and Barto 2018; Mnih et al. 2015a] on toy tasks and soft actor-critic (SAC) [Haarnoja et al. 2018c] on larger-scale tasks from the DeepMind Control Suite [Tassa et al. 2018]. Our results show that on tasks with dense

rewards and uniform resets, BBE often performs worse than the underlying policy-learning algorithm while DEEP incurs no cost for exploring. On tasks with more natural resets and sparse rewards, DEEP covers the state space more rapidly than BBE and reaches peak performance in a fraction of the samples required with undirected exploration. In total, DEEP strictly outperforms undirected exploration while solving many sparse environments just as fast as dense ones.

3.2 Background

3.2.1 Notation

A Markov decision process (MDP) $\mathcal{M}$ consists of a tuple $(\mathcal{S}, \mathcal{A}, P, R, \gamma)$, where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, P is the transition function mapping $\mathcal{S} \times \mathcal{A}$ to distributions on $\mathcal{S}$, R is the scalar reward function on $\mathcal{S} \times \mathcal{A}$, and γ is the discount factor. We use lower-case (s, a, r) to refer to concrete realizations of states, actions, and rewards. We use $\mathcal{M}_f$ to denote the MDP $\mathcal{M}$ with the original reward function R replaced by another function f. For convenience we assume exploration rewards are within $[0, 1]$, and we define $\bar{r} = 1/1-\gamma$, which is the maximum discounted value possible.

3.2.2 Bonus-based exploration: a recipe for exploration in deep RL

{sec:intrinsic_reward

Bonus-based exploration has emerged as the standard framework for exploration in the deep reinforcement learning community. In this framework, an agent learns in a sequence of MDPs $\widetilde{\mathcal{M}} = \{\mathcal{M}_{\widetilde{R}_n}\}_{n=1}^{N}$ where the reward function $\widetilde{R}_n$ changes as a function of each transition. A typical choice is $\widetilde{R}_n = R + R_n^+$, where R_n^+ is an exploration bonus which measures the "novelty" of a transition (s, a, s') given the history of all transitions up to n. After taking each transition (s, a, s'), the reward $\widetilde{r} = \widetilde{R}_n(s, a, s')$ is calculated and the tuple $(s, a, s', \widetilde{r})$ is added to a replay dataset D. The agent optimizes its reward in this (non-stationary) MDP $\widetilde{\mathcal{M}}$ via some model-free RL algorithm

operating on the replay dataset. The realization of a particular algorithm in this family amounts to defining a novelty function and picking a model-free RL algorithm [Stadie et al. 2015; Houthooft et al. 2016; Bellemare et al. 2016; Pathak et al. 2017; Tang et al. 2017; Burda et al. 2018; Machado et al. 2020]. We illustrate this recipe in Algorithm 1.

Pseudo-counts. Building upon theoretically-motivated exploration methods for discrete environments [Strehl and Littman 2008], Bellemare et al. [2016] proposed to give exploration bonuses based on a *pseudo-count* function $\hat{N}$. A pseudo-count has two key properties. Like a true count, a pseudo-count increases by 1 each time a state (or state-action pair) is visited. Unlike a true count, a pseudo-count generalizes across states and actions; that is, when a state s is visited, the pseudo-count for nearby states $s + \varepsilon$ may increase as well.

3.3 Limitations of bonus-based exploration

The bonus-based exploration algorithm, illustrated in Algorithm 1, has two weaknesses which limit its usefulness for sample-efficient policy learning.

Bias with finite samples. Because they estimate the optimal policy on the modified MDP $\mathcal{M}'$, bonus-based exploration algorithms learn biased policies as long as the exploration bonus is nonzero. According to theory, the exploration bonus should be scaled larger than is done in practice [Strehl and Littman 2008] and decay slower than $1/N(s)$ [Kolter and Ng 2009] in order to guarantee convergence to the optimal policy. This behavior, shown in Figure 3.2, can result in slow convergence to the optimal policy and substantially biased policies after a practically feasible number of samples.

Slow adaptation to changing rewards. Algorithms in this family update the policy according to the schedule of the underlying model-free RL algorithm – for example at the end of each

Algorithm 1 Bonus-based exploration {alg:bbe}

Require: replay dataset D, policy π, bonus R_n^+

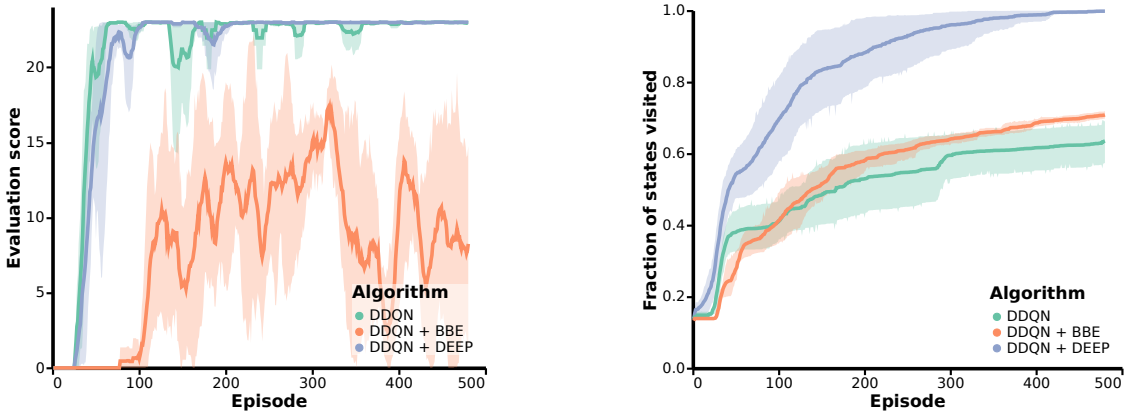
$n \leftarrow 0$
repeat
  for one episode **do**
    Collect $(s, a, s', r) \sim P(s, \pi(s))$
    $\widetilde{r} \leftarrow r + R_n^+(s, a, s')$
    $D \leftarrow D \cup (s, a, s', \widetilde{r})$
    $R_{n+1}^+ \leftarrow \text{Update}(R_n^+, (s, a, s'))$
    $n \leftarrow n + 1$
  Train π with samples from D
until $n = N$

Algorithm 2 Decoupled Exploration and Exploitation Policies {alg:deep}

Require: replay dataset D, temperature τ, task policy π_{task}, exploration policy π_{explore}, bonus R_n^+

$n \leftarrow 0$
repeat
  for one episode **do**
    Update π_{explore} on $\mathcal{M}_{R_n^+}$
    Set $\beta(a|s) \propto \pi_{\text{task}}(a|s) \cdot \pi_{\text{explore}}(a|s)$
    Collect $(s, a, s', r) \sim P(s, \beta(s))$
    $D \leftarrow D \cup (s, a, s', r)$
    $R_{n+1}^+ \leftarrow \text{Update}(R_n^+, (s, a, s'))$
    $n \leftarrow n + 1$
  Train π_{task} with samples from D
until $n = N$

Figure 3.1: Comparison of classic bonus-based exploration (BBE) with our method (DEEP). BBE computes exploration bonuses at the time of visiting a transition, adds them to the real rewards, and uses a replay buffer of experience to learn a policy. DEEP separates the exploration policy π_{explore} from the task policy π_{task}, allowing π_{task} to be an unbiased estimate of the optimal policy throughout training. It always uses the *current* exploration reward function R_n^+ when updating the exploration value function, and is fast-adapting to deal with the non-stationary bonus MDP.



(a) Reward **(b)** Coverage

Figure 3.2: Experiments in a 40×40 grid-world environment with one goal state, where learning algorithms were warm-started with 20 episodes of data from a skilled policy. **(a)** With enough signal to find the goal, DDQN (Double DQN, Hasselt et al. [2016]) alone rapidly converges to the optimal policy. BBE introduces bias, causing the policy to continually explore. Our method, DEEP, learns the task policy just as rapidly as DDQN alone. **(b)** Though it performs well, DDQN simply goes to the goal during each train episode and does not explore other options. BBE continues to seek out new states at a slow but steady rate. DEEP explores far more than BBE during data collection despite simultaneously performing just as well as DDQN at evaluation time.

{fig:gridworld_warmst

episode. This works well for the stationary MDPs that these algorithms were developed for, but the modified MDP $\mathcal{M}'$ which represents the exploration problem is non-stationary. This leads to an agent which determines the most novel state and then stays there for an entire episode. This degenerate behavior leads to potentially exploring only a single state per episode instead of visiting a sequence of new states as the reward function evolves.[5] The use of replay buffers compounds this effect, since algorithms in this family compute exploration rewards at the time the transition is collected, rather than when it is used. An algorithm which is unaware of the non-stationary nature of the MDP will maximize the return on this mixture of reward functions rather than the reward that incorporates the current bonus, resulting in slow coverage of the environment. Figure 3.3 shows uniform random actions, BBE, and BBE with the fast adaptation scheme we propose in Section 3.4.3 all exploring in a 40×40 grid-world without rewards. While BBE covers the state space much faster than undirected exploration, it is unnecessarily slow. See Appendix **??** for visualizations.

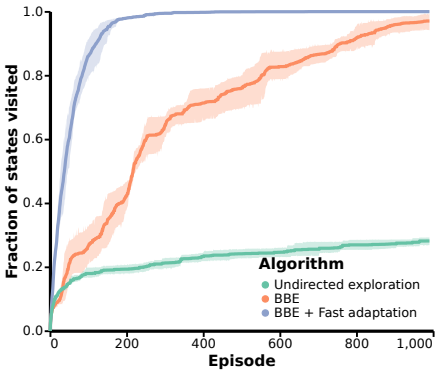


Figure 3.3: Pure exploration

{fig:gridworld_visits

3.4 Decoupled exploration for sample-efficient control

In this section, we describe a new algorithm called Decoupled Exploration and Exploitation Policies (DEEP) which addresses the limitations of BBE. The core insight is that by leveraging off-policy RL algorithms, DEEP can learn two policies from the same replay: a task policy π_{task}, which maximizes the reward on the original MDP $\mathcal{M}_R$, and an exploration policy π_{explore}, which maximizes only the reward on the bonus MDP $\mathcal{M}_{R_n^+}$. This decoupling serves two purposes. First, it enables good performance even before exploration is complete by using π_{task} at test time. Second, it allows π_{explore} to be updated aggressively in order to more closely match the non-stationary bonus MDP; unlike π_{task}, it is not important that π_{explore} converge exactly to an optimal policy.

Like BBE, DEEP is a family of algorithms related by their structure; a particular algorithm in this family consists of a choice of an exploration reward function and an off-policy RL algorithm for learning each policy. Throughout this work, we use a pseudo-count based exploration reward. For discrete tasks we use Double DQN (DDQN, Hasselt et al. [2016]) and Boltzmann policies. For tasks with continuous actions we use soft actor-critic (SAC) for π_{task} and a DDQN policy for π_{explore}.

3.4.1 Pseudo-count estimation

{sec:kernel_counts}

Following Bellemare et al. [2016], we use an exploration reward derived from pseudo-counts. Instead of the high-dimensional pixel observations of the ALE, Control Suite has low-dimensional (<100-D) observations corresponding to joint and object locations and velocities. This lower dimensionality renders extracting pseudo-counts from a density estimator unnecessary, and in our experiments we specify a pseudo-count function based on kernels. For a real-valued state-action pair $x = [s, a]$ and a set of previous observations $\{x_i\}_{i=1}^n$, define the pseudo-count of x and the exploration reward as

$$\hat{N}_n(x) = \sum_{i=1}^{n} k(x_i, x) \qquad\qquad R_n^+(s,a) = \hat{N}_n\big([s,a]\big)^{-1/2} \tag{3.1}$$

where k is a kernel function scaled to have a global maximum $k(x, x) = 1$. This satisfies the key requirement for a pseudo-count function, namely that a visit to a state x increases $\hat{N}(x)$ by 1 and $\hat{N}(x')$ by at most 1 for any other state x'. In our experiments we use a Gaussian kernel (scaled to have a maximum value of 1) with diagonal covariance. For implementation details see Appendix ??.

3.4.2 Separating task and exploration policies

DEEP uses two separate policies. Each is trained off-policy using transitions sampled from the replay buffer; π_{task} is updated using the rewards from R logged in the replay, while π_{explore} is updated using rewards from R_n^+. Since π_{task} is trained only on the rewards for the true task, it is unbiased in the sense that it reflects the current best estimate of the optimal policy. This stands in contrast to BBE policies, which optimize the sum of task and exploration rewards and thus represent a biased estimate of the optimal task policy until the exploration rewards go to zero. Our method is agnostic to the choice of algorithm and policy parameterization. However, it will

be most effective with policy learning algorithms that work well when trained far off-policy and produce high-entropy policies (e.g. policies which cover all optimal actions). For these reasons we use the state-of-the-art maximum-entropy algorithm SAC to learn π_{task} in environments with continuous actions. For experiments with discrete action spaces we forego explicitly learning the task policy π_{task}; instead we learn the task Q-function via DDQN [Hasselt et al. 2016] and define the task policy as $\pi_{\text{task}}(a|s;Q) \propto \exp(Q(s,a)/\tau)$, where $\tau > 0$ becomes a hyperparameter – we refer to the supplementary material for details.

3.4.3 Fast-adapting exploration policy

{sec:fast_adaptation}

The non-stationary nature of the exploration reward function poses a challenge to typical model-free RL algorithms, which assume a fixed reward function. BBE methods update a single policy using a replay buffer which, at a step n, contains rewards from a mixture of bonus reward functions $\{R_1^+, \ldots, R_n^+\}$, computed using different past novelty or count estimates.[6] This results in slow adaptation to the non-stationary objective of exploration. DEEP makes two changes to mitigate the impact of the non-stationarity in the exploration reward function.

First, DEEP leverages access to R_n^+ to compute exploration rewards when they are needed to update π_{explore} rather than when the transition is collected. We choose to use Q-learning rather than a more sophisticated algorithm in order to learn π_{explore} as rapidly as possible; with changing rewards, using a policy to amortize the maximization of a value function as in SAC or DDPG would slow down learning. We represent π_{explore} directly as a Boltzmann policy of this exploration Q-function Q_{explore}:

$$\pi_{\text{explore}}(a \mid s) \propto \exp\left\{\frac{Q_{\text{explore}}(s,a)}{\tau_{\text{explore}}}\right\}, \tag{3.2}$$

where τ_{explore} is a temperature hyperparameter.

Second, by decoupling π_{explore} from π_{task}, DEEP unlocks the ability to update π_{explore} more

aggressively without affecting π_{task}'s convergence to the optimal policy. This enables the exploration policy to more rapidly adapt to the non-stationary exploration reward. In our experiments we achieve this by using a larger learning rate and more updates per environment step than is usually done; future work might investigate more sophisticated schemes such as prioritized sweeping [Moore and Atkeson 1993] or prioritized experience replay [Schaul et al. 2016]. To improve stability we use DDQN updates and clip Q targets at $\bar{r}$, the maximum discounted exploration value.

{sec:optimistic}

Optimism. Further adapting π_{explore} to the unique properties of the exploration reward function, we propose to leverage optimism in its updates and actions. We propose to make Q_{explore} optimistic by leveraging the pseudo-count function in a manner similar to that proposed by Rashid et al. [2020]. We assume that the value function is trustworthy for transitions with very large counts, and very untrustworthy for transitions with near-zero counts. When the count is zero we impose an optimistic prior which assumes the transition will lead to a whole episode of novel transitions; as the count increases we interpolate between this prior and the learned value function using a weighting function:

$$Q^{+}_{\text{explore}}(s,a) = w(s,a)\cdot Q_{\text{explore}}(s,a) + (1-w(s,a))\cdot \bar{r}, \qquad w(s,a) = \frac{\sqrt{N(s,a)}}{\sqrt{N(s,a)+c}} \tag{3.3}$$

{{eq:optimism}}

where $\bar{r} = 1/1-\gamma$, is the maximum discounted return in the bonus MDP and c is a small constant representing how many counts' worth of confidence to ascribe to the optimistic prior. We use this optimistic Q^{+}_{explore} for computing targets for Bellman updates and for computing π_{explore} (Eq. 3.4). For details of the implementation of the fast-adapting π_{explore}, see Appendix **??**.

3.4.4 Product distribution behavior policy

A good behavior policy should attempt to explore all of the transitions which are relevant for learning the optimal policy. This entails a trade-off between taking actions which are more novel and ones which are more likely to be relevant to a high-performing policy. DEEP encodes this by representing the behavior policy as a product of the task policy π_{task} and the pure-exploration policy π_{explore}:

$$\beta(a \mid s) \propto \pi_{\text{task}}(a \mid s)\, \pi_{\text{explore}}(a \mid s). \tag{3.4}$$ {{eq:behavior_policy}}

The choice to parameterize β as a factored policy was made for its simplicity and ease of off-policy learning. Alternative formulations for making this trade-off while preserving the unbiased task policy are possible, and we view the form of our proposed behavior policy as just one option among many. One alternative would be interleaving the behavior of multiple policies within one episode, akin to e.g. Scheduled Auxiliary Control [Riedmiller et al. 2018].

In order to approximately sample from this behavior policy, we use self-normalized importance sampling with π_{task} as the proposal distribution:

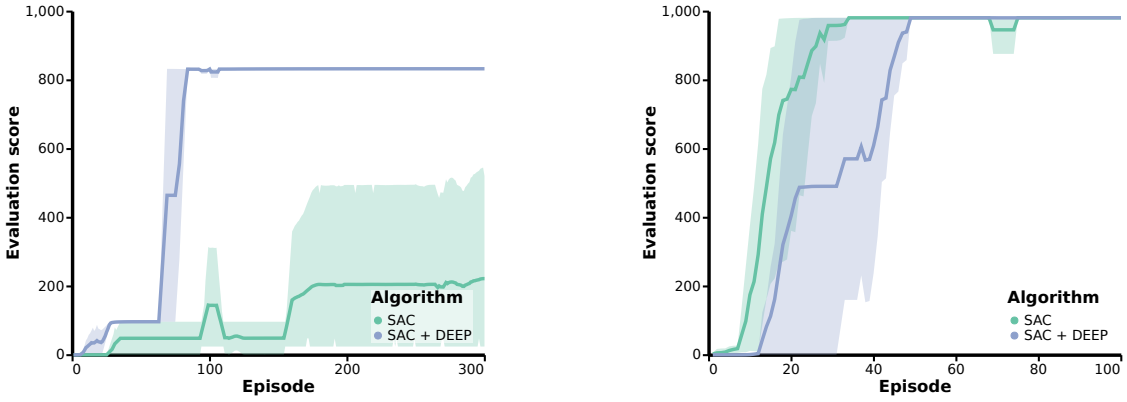
1. Draw k samples $a_1, \ldots, a_k$ from π_{task}
2. Evaluate $\pi_{\text{explore}}(a_i \mid s)$ for each $i \in 1 \ldots k$
3. Draw a sample from the discrete distribution $p(a_i) = \pi_{\text{explore}}(a_i \mid s) / \sum_{i'} \pi_{\text{explore}}(a_{i'} \mid s)$.

Note that since the proposal distribution is π_{task}, the π_{task} terms in computing weights cancel and only the π_{explore} terms remain. Importance weighting is consistent in the limit of $k \to \infty$ but introduces bias towards π_{task} [Vehtari et al. 2015]. With small k, this bias makes it unlikely that β will select actions that are very unlikely under π_{task}; roughly speaking, this procedure selects the "most exploratory" action in the support of the task policy. This may act as a backstop to prevent

the behavior from going too far outside the task policy to be useful. DEEP works best when π_{task} is trained in a way that preserves variance in the policy (e.g. SAC's target entropy), enabling the behavior policy to select exploratory actions. In discrete action spaces we additionally use self-normalized importance sampling – using a uniform proposal over actions – to obtain samples from π_{task} in step 1.

3.5 Experiments

In this section we perform experiments to give insight into the behavior of undirected exploration, BBE, and DEEP. First we perform a set of investigative experiments to probe how DEEP interacts with environments with different reward structures. Then we perform experiments on pairs of benchmark continuous control tasks with easy and hard exploration requirements.



(a) Local optimum environment **(b)** Adversarial environment

{sub:hallway_two_local_optimum} {sub:fingertip_dist

Figure 3.4: Two environments illustrating different reward structures. **(a)** An environment with a locally-optimal goal (reward 0.1) near the start state. SAC finds this nearby goal, but doesn't explore far enough to find the real goal (reward 1.0). When trained with DEEP, it finds the distractor goal but moves on to the real goal. **(b)** An adversarial environment for DEEP which has a very small goal state close to the start state, making it easy to find with random actions but hard with directed exploration.

{fig:hallway}

3.5.1 Investigative experiments

We construct a simple MuJoCo [Todorov et al. 2012] environment called Hallway to look more closely at how exploration interacts with reward structure. This environment consists of a long narrow 2D room with the agent controlling the velocity of a small sphere, which starts each episode at one end of this hallway. The following two experiments share dynamics and differ only in their rewards.

Local optima. A valuable role for exploration is enabling an agent to escape from locally optimal behavior. To test this, we add two goal states with shaped rewards to the Hallway environment. The first is close to the start state but only provides reward at most 0.1, while the second is at the far end of the hallway but provides reward 1.0. Figure 3.4(a) shows that exploration using DEEP allows the agent to quickly find its way to the faraway optimal reward while SAC gets stuck in the local optimum.

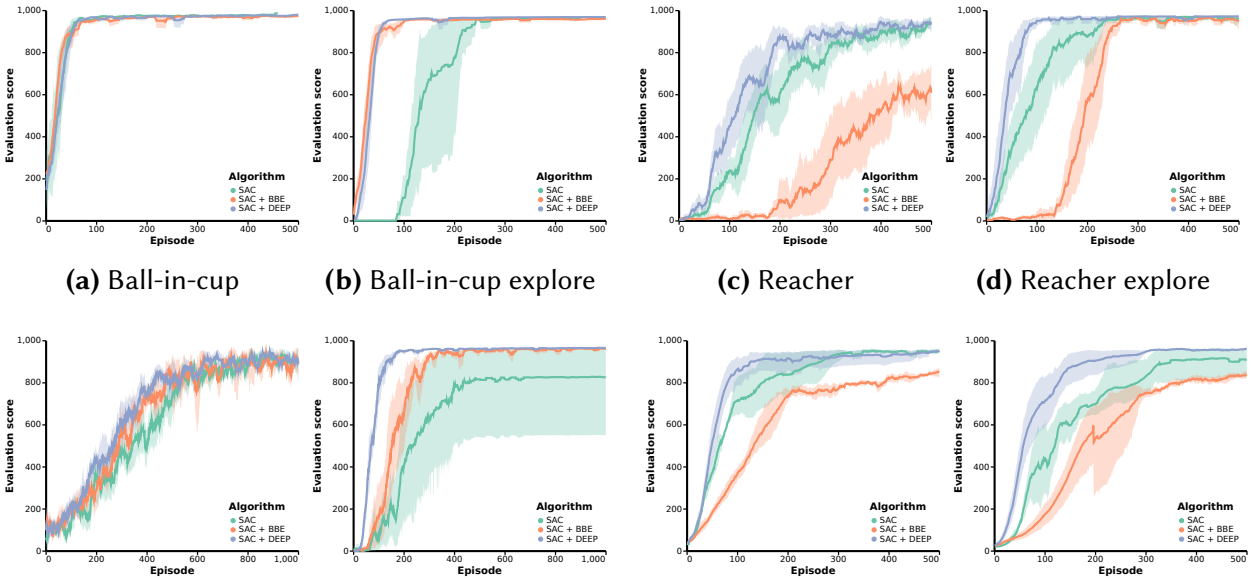
Limitations. DEEP covers states quickly, but there is no such thing as a universally optimal exploration strategy. For example, there exist environments for which the random walk dynamics of undirected exploration find the optimal strategy faster than uniform state coverage. Figure 3.4(b) provides one such example: a Hallway environment with a very small goal state close to the start state. SAC discovers this goal faster than SAC + DEEP, though DEEP does eventually find it as well.

3.5.2 Benchmark experiments

Next we provide experiments based on DeepMind Control Suite [Tassa et al. 2018], a standard benchmark for continuous control RL algorithms. We introduce versions of several environments which are modified to remove the accommodations that make them solvable without exploration,

then provide results of SAC, SAC + BBE, and SAC + DEEP on the original and modified environments.

3.5.2.1 Results



(a) Ball-in-cup **(b)** Ball-in-cup explore **(c)** Reacher **(d)** Reacher explore

(e) Finger **(f)** Finger explore **(g)** Walker **(h)** Walker explore

Figure 3.5: Results on original Control Suite environments (left in each pair) and modified versions without exploratory resets and rewards (right). Across the original environments, SAC + DEEP performs as well or better than SAC, while SAC + BBE performs much worse on some environments. On the exploration environments, DEEP + SAC learns much faster than SAC. BBE sometimes provides significant gains over SAC but sometimes performs worse even on exploration environments. {fig:control_suite}

3.5.2.2 Environments for evaluating exploration

While Control Suite has driven great progress in policy learning, it was not designed to evaluate an agent's exploration capabilities; in fact, the included environments were selected to be solvable by algorithms with only undirected exploration. From that work:

> We ran variety of learning agents (e.g. Lillicrap et al. 2015; Mnih et al. 2016) against all tasks, and iterated on each task's design until we were satisfied that [...] the task is solved correctly by at least one agent. [Tassa et al. 2018]

Control Suite avoids the need for directed exploration via two mechanisms. First, in many environments the start state distribution is sufficiently wide (e.g. uniform over reachable states) to guarantee that any policy will see high-value states.[7] Second, some environments have rewards shaped to guide the agent towards better performance (e.g. a linearly increasing reward for forward walking speed).

To construct a benchmark for continuous control with exploration, we selected four environments with different objectives (manipulation and locomotion, single-objective or goal-conditional) and observation dimensions (6-24). We then created "exploration" versions of these environments with restricted start state distributions and sparse rewards. The original environments and their exploration versions together form a benchmark which measures an algorithm's exploration ability and policy convergence. Environment details are in Appendix **??** and their implementation is in the supplement.

3.5.2.3 Algorithms

We include experiments on these eight benchmark tasks with three algorithms: SAC [Haarnoja et al. 2018c] with no additional exploration; BBE with SAC for the policy learner; and DEEP with SAC for π_{task} and DDQN for π_{explore}. BBE and DEEP use the pseudo-count reward described in Section 3.4.1 and the SAC implementation is that of Yarats and Kostrikov [2020] with no hyperparameter changes.

The kernel-based exploration bonus used for BBE and DEEP requires a scaling law to set the kernel variance as a function of the observation dimension. We adapt the scaling relationship from [Henderson and Parmeter 2012] (see Appendix **??**). BBE has an additional hyperparameter for the scale of the bonus. We performed a sweep with values in $\{10^{-2}, 10^{-1}, 1, 10\}$ and found that 1 performed best overall. This setting, which makes the maximum bonus equal to the maximum environment reward, ensures that visiting a new state remains the best option until the true goal state is discovered. Further implementation details are available in Appendix **??**. We additionally

performed an ablation which, like DEEP, learns separate Q functions for the two rewards, but which learns one policy to maximizes the sum of their Q values. In our experiments (available in Appendix ??) this ablation never outperforms BBE, so for clarity we exclude it here.

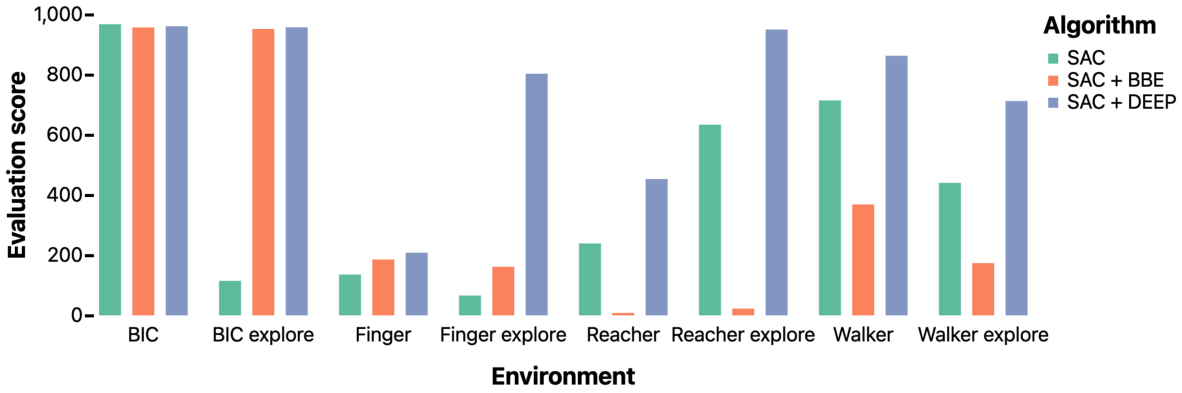


Figure 3.6: Results after 100 episodes. In this extremely sample-limited regime, exploration speed and fast policy convergence are both essential. In every environment, SAC with DEEP (blue, right column in each set of three) performs comparably to or better than SAC alone or SAC with BBE.

{fig:control_suite_su

We present experiments on the original versions of four Control Suite tasks and their exploration counterparts. The results are shown in Figure 3.5 with the means and 95% confidence intervals over 8 seeds. We find that across the original environments, DEEP gives similar or slightly better performance to SAC, while BBE significantly impairs SAC on two of the four environments and matches SAC on the other two. Across the exploration environments, DEEP gives the best performance and sample efficiency. BBE performs better than SAC alone on two exploration environments and worse than SAC on the other two. Figure 3.6 shows the performance of each algorithm after only 100 episodes, highlighting the substantial benefits from using DEEP in the few-sample regime.

Overall, SAC + DEEP never performs worse than SAC alone, while yielding substantial improvements in environments where rewarding states are harder to discover. BBE's more mixed performance provides a possible explanation for the limited influence that methods of that family have had on sample-efficient continuous control, and perhaps more generally on sample-efficient RL. Given that in this setting the addition of BBE is as likely to harm as to help, its lack of adoption

is unsurprising.

3.6 Related work

Sample-efficient continuous control. Our method leverages progress on sample efficient off-policy RL, as it can be combined with any off-policy algorithm. A strong line of work has brought the sample complexity of model-free control within range of solving tasks on real robots [Popov et al. 2017; Kalashnikov et al. 2018; Haarnoja et al. 2018b; Fujimoto et al. 2018c; Haarnoja et al. 2018c; Abdolmaleki et al. 2018].

Bonus-based exploration. There have been many bonuses proposed in the BBE framework. Several works [Stadie et al. 2015; Pathak et al. 2017; Burda et al. 2018] propose to use prediction error of a learned model to measure a transition's novelty, with the key differences being the state representation used for making predictions. Houthooft et al. [2016] propose a bonus based on the information gain of the policy. Bellemare et al. [2016] and others [Ostrovski et al. 2017; Tang et al. 2017] use continuous count analogues to calculate the count-based bonuses of Strehl and Littman [2008]. Machado et al. [2020] use the norm of learned successor features as a bonus, and show that it implicitly counts visits. Unlike previous work, our paper focuses on the updates and representation of the behavior policy, and DEEP can be used in conjunction with any of these bonuses. Never Give Up [Badia et al. 2020] uses an episodic exploration bonus and trains policies with different bonus scales including a task policy. However, it is designed to maximize asymptotic performance rather than sample efficiency and does not learn faster than a baseline early in training.

Optimism. Classic exploration methods [Kearns and Singh 1998; Brafman and Tennenholtz 2002; Strehl and Littman 2008; Jaksch et al. 2008], depend on an optimistically-defined model. Model-free methods with theoretical guarantees [Strehl et al. 2006; Jin et al. 2018] use Q functions

initialized optimistically. Similar to our Eq. (3.3), Rashid et al. [2020] propose a method for ensuring optimism in Q learning with function approximation by using a count function. However, DEEP leaves the task policy unbiased in the few-sample regime by separating the exploration policy from the task policy.

Temporally-extended actions. A variety of work proposes to speed up ϵ-greedy exploration via temporally-extended actions which reduce dithering. Some methods [Schoknecht and Riedmiller 2003; Neunert et al. 2020] propose to bias policies towards repeating primitive actions, resulting in faster exploration without limiting expressivity. Dabney et al. [2020] describe a temporally-extended version of ϵ-greedy exploration which samples a random action and a random *duration* for that action. Whitney et al. [2020] use a learned temporally-extended action space representing the reachable states within a fixed number of steps. While these methods improve over single-step ϵ-greedy, they are unable to perform directed exploration or discover faraway states.

Randomized value functions. Modern works [Osband et al. 2016, 2019] extend Thompson sampling [Thompson 1933] to neural networks and the full RL setting. Relatedly, [Fortunato et al. 2018; Plappert et al. 2018] learn noisy parameters and sample policies from them for exploration.

3.7 Discussion

In this paper we have investigated the potential for directed exploration to improve the sample efficiency of RL in continuous control. We found that BBE suffers from bias and slow state coverage, leading to performance which is often worse than undirected exploration. We introduced Decoupled Exploration and Exploitation Policies, which separately learns an unbiased task policy and an exploration policy and combines them to select actions at training time. DEEP pays no performance penalty even on dense-reward tasks and explores faster than BBE. In our ex-

periments, DEEP combined with SAC provides strictly better performance and sample efficiency than SAC alone. We believe that with its combination of reliable and efficient policy learning across dense and sparse environments, SAC + DEEP provides a compelling default algorithm for practitioners.

add appendices

Notes

5. Some implementations of bonus-based exploration may update the policy within an episode, for example via a single gradient step per environment step on transitions sampled i.i.d. from a replay. However, such a small update is typically not enough to change the qualitative behavior of the agent and adapting to the changing MDP has not been an emphasis in prior work.

6. See e.g. the code from Machado et al. [2020]: https://github.com/mcmachado/count_based_exploration_sr/blob/master/function_approximation/exp_eig_sr/train.py#L204

7. Some environments, such as Manipulator, additionally start a fraction of episodes at the goal state.

Part II

Representations and Auxiliary Tasks

{sec:representation}

Introduction to representation for RL.

4 Evaluating Learned Representations

{sec:representation-e

As it relates to regret, don't cover the whole paper

5 | Dynamics-Aware Embeddings

{sec:dyne}

5.1 Introduction

In recent years, there has been a lot of excitement around end-to-end model-free reinforcement learning for control, both in simulation [Lillicrap et al. 2015; Andrychowicz et al. 2018; Haarnoja et al. 2018b; Fujimoto et al. 2018c] and on real hardware [Kalashnikov et al. 2018; Haarnoja et al. 2018c]. In this paradigm, we simultaneously learn intermediate representations and policies by maximizing rewards provided by environment. End-to-end learning has one indisputable advantage: since every component of the system is optimized for the end objective, there are no sub-optimal modules that limit best-case performance by losing task-relevant information.

Learning only from the target task is however a double-edged sword. When the end objective provides only weak signal for learning, a policy with a poor representation may require many samples to learn a better one. By contrast, a policy with a good representation may be able to rapidly fit a simple function of that representation even with weak signal.

Consider the environment shown in Figure 5.1, and two representations of its state: coordinates and pixels. As a function of the agent's x coordinate, the value function is simple and smooth. The coordinate representation has structure which is useful for learning about the task; namely, points which are close in L^2 distance have similar values. By contrast, a pixel representation of the agent's state (below, blue) is practically a one-hot vector. Two states whose x coordinates differ by one unit have pixels exactly as different as states which differ by 100 units.

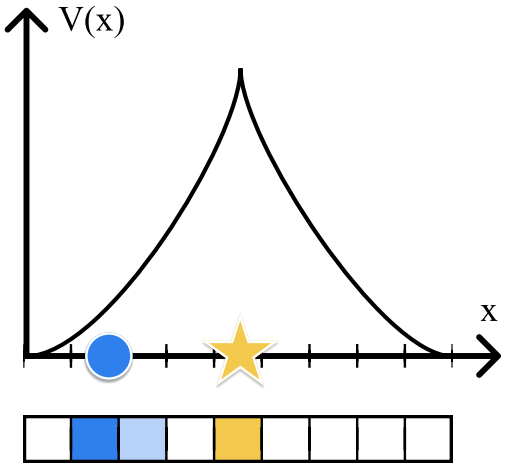


Figure 5.1: A 1D environment. The agent (blue dot) can move continuously left and right to reach the goal (gold star).

{fig:pixel_illustrati

This illustrates the importance of good representations and the potential of representation learning to aid RL.

We propose a self-supervised objective for learning embeddings of states and action sequences such that a pair of states or action sequences will be close together if they have similar outcomes. This objective simultaneously trains a smooth embedding space for states and a temporally abstract action space for control which is task-independent and generalizes across goals and objects.

We demonstrate the effectiveness of our representation learning objective by training the twin delayed deep deterministic policy gradient algorithm (TD3) [Fujimoto et al. 2018c] with learned action and state spaces. With a learned representation of temporally abstract actions, our method exhibits improved sample efficiency compared to state-of-the-art RL methods on control tasks, with larger gains on more complex environments. When additionally combined with our learned state representation, our method allows TD3 to scale to pixel observations. We demonstrate good performance on a simple family of goal-conditioned 2D control tasks within a few million environment steps without adjusting any TD3 hyperparameters. This stands in contrast to end-to-end model-free RL from pixels, which requires extensive tuning [Lillicrap et al. 2015] and on the order of 100 million environment steps[8] [Barth-Maron et al. 2018].

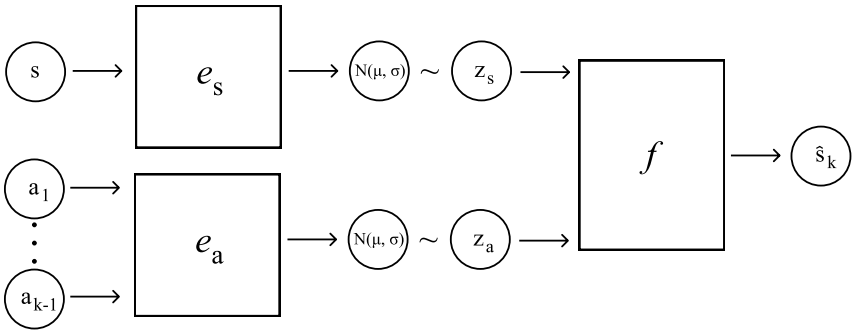


Figure 5.2: Computational architecture for training the DynE encoders e_a and e_s. The encoders are trained to minimize the information content of the learned embeddings while still allowing the predictor f to make accurate predictions.

{fig:model}

5.2 Dynamics-aware embeddings

5.2.1 Notation

We consider the framework of reinforcement learning in Markov decision processes (MDPs).[9] We denote the state of an environment (e.g. joint angles of a robot or pixels) by $s \in \mathcal{S}$, and we assume that the states given by the environment satisfy the Markov property. We refer to a sequence of actions $\{a_1, \ldots, a_k\} \in \mathcal{A}^k$ using the shorthand $\boldsymbol{a}^k$. We use $s' \sim \mathbf{T}(s, a)$ to refer to the environment's (stochastic) transition function, and overload it to accept sequences of actions: $s_{t+k} \sim \mathbf{T}(s_t, \boldsymbol{a}_t^k)$.

5.2.2 Model and learning objective

We propose that a good representation for reinforcement learning should represent states or actions close together if they have similar outcomes (resulting trajectories). This allows the agent to generalize from a small number of samples since each sample accurately reflects the value of all the states or actions in its neighborhood. In a Markov decision process the outcome of taking an action a in a state s is summarized by the distribution of resulting states $p(s'|s, a) = \mathbf{T}(s, a)$.

Therefore we construct a method which embeds states and actions such that nearby embeddings have similar distributions of next states.

Our method, which we call Dynamics-aware Embedding (DynE), learns encoders e_s and e_a which embed a state and action sequence into latent spaces $z_s \in \mathcal{Z}_s$ and $z_a \in \mathcal{Z}_a$ respectively. These encodings are optimized to form a maximally compressed representation of the sufficient statistics of $p(s'|s, \boldsymbol{a}^k)$ such that $p(s'|s, \boldsymbol{a}^k) \approx p(s'|z_s, z_a)$. We approximate this by maximizing the following objective:

$$\mathcal{L}(\phi_s, \phi_a, \theta) = \mathop{\mathbb{E}}_{s, \boldsymbol{a}^k, s' \sim \rho^\pi} \Big[-\log p(s'|z_s, z_a; \theta) \qquad \text{predict } s' \qquad (5.1) \quad \texttt{\{\{eq:logprob\}\}}$$

$$+ \beta D_{\mathrm{KL}}\big(e_s(s; \phi_s) \;||\; \mathcal{N}(0, \boldsymbol{I})\big) \qquad \text{compress } s \qquad (5.2) \quad \texttt{\{\{eq:skl\}\}}$$

$$+ \gamma D_{\mathrm{KL}}\big(e_a(\boldsymbol{a}^k; \phi_a) \;||\; \mathcal{N}(0, \boldsymbol{I})\big) \Big] \qquad \text{compress } \boldsymbol{a}^k \qquad (5.3) \quad \texttt{\{\{eq:akl\}\}}$$

where $z_s \sim e_s(s)$, $z_a \sim e_a(\boldsymbol{a}^k)$, and ρ^π is the distribution of transitions under a behavior policy π.

The DynE objective is similar to a β-VAE [Higgins et al. 2017a] for s' but with a different variational family; like a β-VAE, it forms a variational lower bound on $p(s')$ when $\beta = \gamma = 1$. Where a variational autoencoder [Kingma and Welling 2013; Rezende et al. 2014] or β-VAE chooses the variational family to be $\mathcal{Q} = \{q(z|s')\}$, we use a factored latent space $\{z_s, z_a\}$ and independent posterior approximations given the previous state and the action: $\mathcal{Q} = \{(q(z_s|s), q(z_a|\boldsymbol{a}^k))\}$. This factorization yields separate encoders for states and actions where the state encoder's output is valid for any action and vice versa.

The DynE objective can also be interpreted in the information bottleneck (IB) framework [Tishby et al. 2000]. In the IB framework term (5.1) is the prediction objective and terms (5.2) and (5.3) regularize the latent representation to remove all extraneous information. Our construction is nearly identical to the approximate information bottleneck proposed by Alemi et al. [2016], with the main difference being the factorization of the representation into separate state and action components.

In our experiments we use an isotropic Normal distribution for $p(s'|z_s, z_a; \theta)$ such that term (5.1) reduces to $\|f(z_s, z_a; \theta) - s'\|_2^2$ where f computes the mean. We use diagonal-covariance Normal distributions for e_s and e_a such that $\{\mu_s, \sigma_s^2\} = e_s(s)$, $\{\mu_a, \sigma_a^2\} = e_a(\boldsymbol{a}^k)$, $z_s \sim \mathcal{N}(\mu_s, \sigma_s^2)$, and $z_a \sim \mathcal{N}(\mu_a, \sigma_a^2)$. The behavior policy we use for data collection is $\pi = Unif(\mathcal{A})$.

5.3 Using learned embeddings for reinforcement learning

5.3.1 Decoding to raw actions

In order to be useful for RL, the abstract action space produced by the encoder must be decodeable to raw actions in the environment. Since the mapping from action sequences to high-level actions is many-to-one, inverting it is nontrivial. We simplify this ill-posed problem by defining an objective with a single optimum.

Once the action encoder e_a is fully trained, we hold it fixed and train an action decoder d_a to minimize

$$\mathcal{L}(d_a) = \mathop{\mathbb{E}}_{z_a \sim \mathcal{N}(0, I)} \left[||e_a(d_a(z_a)) - z_a||_2^2 + \lambda ||d_a(z_a)||_2^2 \right] \tag{5.4}$$ {{eq:decoder}}

The first term of this objective ensures that the action decoder d is a one-sided inverse of e_a; that is, $e_a(d_a(z_a)) = z_a$ but $d_a(e_a(a_1, \ldots, a_k)) \neq a_1, \ldots, a_k$. The second term of the loss ensures that d_a is in particular the minimum-norm one-sided inverse of e_a and gives the objective for the output of d_a a single minimum. Out of all the action sequences which have the same outcome, the minimum-norm sequence is desireable as it leads to trajectories which are smooth and consume less energy. We choose λ to be small (e.g. 10^{-2}) to ensure that the reconstruction criterion dominates the optimization.

5.3.2 Efficient RL with temporal abstraction

Once equipped with a decoder which maps from high-level actions to sequences of raw actions, we train a high-level policy that solves a task by selecting high-level actions. In this section we extend the deterministic policy gradient [Silver et al. 2014] family of algorithms to work with temporally-extended actions while maintaining off-policy updates and learning from every environment step. This allows our method to achieve superior sample efficiency when working with high-level actions. In particular, we extend the twin delayed deep deterministic policy gradient (TD3) algorithm [Fujimoto et al. 2018c] to work with the DynE representation of actions to form an algorithm we call DynE-TD3.

We first describe why DPG requires modifications to accommodate temporally-abstracted actions. One simple approach to combining DynE with DPG would be to incorporate the k-step DynE action space into the environment to form a new MDP. This MDP allows the use of DPG without modification; however, it only emits observations once every k timesteps. As a result, after N steps in the original environment, the deterministic policy μ and critic function Q can only be trained on N/k observations. This has a substantial impact on sample efficiency when measured in the original environment.

Instead we require an algorithm which can perform updates to the policy μ and critic Q for every environment step. To do this, we train both μ and Q in the abstract action space with minor changes to their updates. We distinguish these functions which use DynE actions from their raw equivalents by adding a superscript DynE, i.e. μ^{DynE} and Q^{DynE}. We augment the critic function with an additional input, i, which represents the number of steps $0 \leqslant i < k$ of the current embedded action z that have already been executed. This forms the DynE-TD3 critic:

$$Q^{\text{DynE}}(e_s(s_t), z_t, i) = \sum_{j=0}^{k-i-1} \left(\gamma^j r_{t+j}\right) + \gamma^{k-i} Q^{\text{DynE}}\Big(e_s(s_{t+k-i}), \mu^{\text{DynE}}(e_s(s_{t+k-i})), 0\Big) \qquad (5.5) \quad \texttt{\{\{eq:critic\}\}}$$

In plain language, the value of being on step i of abstract action e_t is the value of finishing the remaining $(k - i)$ steps of z_t and then continuing on following the policy. This is similar to the idea of k-step returns [Sutton and Barto 2018], but with a variable k which depends on the step within the current plan. Whereas k-step returns would typically require an off-policy correction such as Retrace [Munos et al. 2016], conditioning on z_t and i determines all $k - i$ actions in the return. In effect, they remain a single action, making the update valid off policy. The DynE critic is trained by minimizing the Bellman error implied by Eq. (5.5).

To update the policy we follow the standard DPG technique of using the gradient of the critic. We modify the algorithm to take into account that $i = 0$ at the time of issuing a new high-level action. The gradient of the return with respect to the policy parameters is then

$$\nabla_\theta J_\pi(\mu_\theta^{\text{DynE}}) \approx \mathop{\mathbb{E}}_{s\sim\rho^\pi}\left[\nabla_\theta \mu_\theta^{\text{DynE}}(e_s(s))\ \nabla_z Q^{\text{DynE}}(e_s(s), z, 0)|_{z=\mu_\theta^{\text{DynE}}(e_s(s))}\right] \tag{5.6}$$

given that data was collected according to a behavior policy π.

5.4 Related work

Successor representations, an inspiration for this work, represent a state by the expected rate of future visits to other states [Dayan 1993; Kulkarni et al. 2016b; Barreto et al. 2017]. Successor representations have been demonstrated to be an effective model of animal and human learning [Momennejad et al. 2017; Stachenfeld et al. 2017]. They are also one of the earliest realizations of the idea of representing each state by its future. Whereas successor representations learn future occupancy maps for a particular policy, we learn an embedding space where states are close together if they have similar outcomes for any policy.

Several papers have proposed using (variational) auto-encoders to learn embeddings for ob-

servations [Lange and Riedmiller 2010; Van Hoof et al. 2016; Higgins et al. 2017b; Caselles-Dupré et al. 2018]; unlike our work, these models operate on a single observation at a time and do not depend on the environment dynamics. Forward prediction has also been used as an auxiliary task to speed RL training [Jaderberg et al. 2016], and Jonschkowski et al. [2017] learn representations which adhere to physical constraints. Ghosh et al. [2018] propose to learn state embeddings using the action distribution of a goal-conditioned policy; however, their technique depends on already having a successful policy. Other work has proposed to use mutual information maximization to learn embeddings which facilitate exploration via intrinsic motivation [Kim et al. 2018].

Similarly to this work, hierarchical reinforcement learning seeks to learn temporal abstractions. These abstractions are variously defined as skills [Florensa et al. 2017; Hausman et al. 2018], options [Sutton et al. 1999; Bacon et al. 2017], or goal-directed sub-policies [Kulkarni et al. 2016a; Vezhnevets et al. 2017]. Most closely related are SeCTAR [Co-Reyes et al. 2018] and HIRO [Nachum et al. 2018]. SeCTAR simultaneously learns a generative model of future states and a low-level policy which can reach those states. HIRO learns a representation of goals such that a high-level policy can induce any action in a low-level policy. Unlike this work, both SeCTAR and HIRO learn state-dependent low-level policies, not action representations. Furthermore SeCTAR assumes the reward function is given ahead of time, and HIRO's off-policy performance depends on an approximate re-labeling of action sequences to train the high-level policy.

Also related are methods which attempt to learn embeddings of single actions to enable efficient learning in very large action spaces [Dulac-Arnold et al. 2015; Chandak et al. 2019]. In particular, Chandak et al. [2019] learns a latent space of actions based on the effects of an action on the environment. However, their latent spaces are for a single action and they do not consider learned state representations. Another related direction is learning embeddings of one or more actions from demonstrations [Tennenholtz and Mannor 2019]; this embedded action space builds in prior knowledge from the demonstrator and can allow faster learning.

5.5 Representation Experiments

In this section we empirically investigate how the learned DynE representations reshape the problem of reinforcement learning. First we make a connection between temporal abstraction and exploration, revealing that DynE actions result in better state coverage. Then we probe the relationship between DynE state embeddings and the task value function.

5.5.1 Temporal abstraction and exploration

When embedding an action sequence, the DynE objective seeks to preserve information about the outcome of that action sequence (i.e. the change in state), but minimize information about the original action sequence. As shown in Appendix **??**, this leads to a representation where all action sequences which have similar outcomes embed close together. We propose that this temporally abstract action space, where actions correspond to multi-step outcomes, allows random actions to explore the environment more efficiently.

We empirically validate the exploration benefits of the temporally abstract DynE actions. Figure 5.3 shows that uniformly sampling a DynE action results in a nearly uniform distribution over the states reachable within k steps. Over the course of an entire episode, selecting DynE actions uniformly at random reaches faraway states more often than random exploration with raw actions. Appendix **??** shows the qualitative difference between random trajectories in the raw and DynE action spaces, and Appendix **??** studies the impact of varying k on the performance of a learned policy.

5.5.2 State representations

The DynE objective compresses states while preserving information about the outcome of taking any action in that state. If this compression is successful, states which have similar outcomes

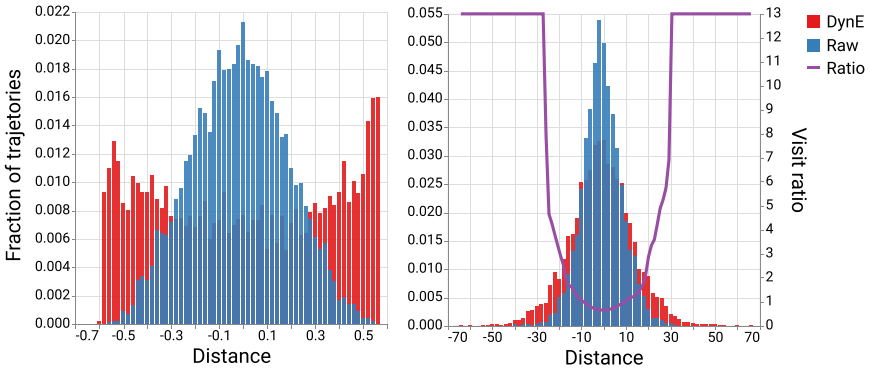


Figure 5.3: The distribution of state distances reached by uniform random exploration using DynE actions ($k = 4$) or raw actions in Reacher Vertical. **Left:** Randomly selecting a 4-step DynE action reaches a state uniformly sampled from those reachable in 4 environment timesteps. **Right:** Over the length of an episode (100 steps), random exploration with DynE actions reaches faraway states very much more often than exploration with raw actions. The visit ratio shows how frequently DynE exploration reaches a certain distance compared to raw exploration.

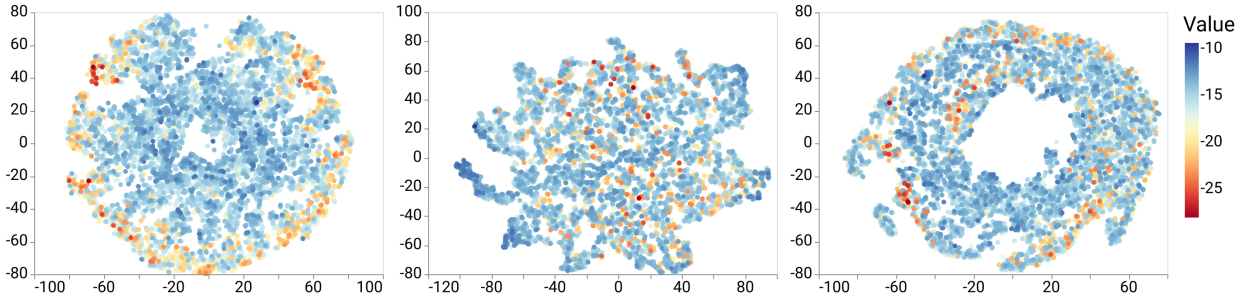
{fig:exploration_hist

will be close together in embedding space. In an MDP, two states which have identical successor states have values which differ by at most the range of the reward function $r_{\max} - r_{\min}$. While in general states which lead to merely similar successors may have arbitrarily different value, we suggest that in many tasks of interest, similar successors may entail similar value.

We investigate whether the DynE state embedding leads to neighborhoods with similar value in the Reacher Vertical environment. We collect 10K states from a random policy in the environment and perform dimensionality reduction on three representations of those states: the DynE embedding of state images, low-dimensional joint states, and pixels. Figure 5.4 shows the results of this dimensionality reduction, in which every point is colored by its value under a fully-trained TD3 policy on the low-d states. DynE embeddings have neighborhoods with more similar values than states or pixels.

5.6 Reinforcement learning experiments

In this section we assess the effectiveness of the DynE representations for deep RL, individually analyzing the contributions of the action and state representations before combining them. First



(a) DynE (pixels) (b) States (c) Pixels

Figure 5.4: The relationship between state representations and task value. Each plot shows the t-SNE dimensionality reduction of a state representation, where each point is colored by its value under a near-optimal policy. (a) The DynE embedding from pixels places states with similar values close together. (b) The low-dimensional states, which consist of joint angles, relative positions, and velocities, have some neighborhoods of similar value, but also many regions of mixed value. (c) The relationship between the pixel representation and the task value is very complex.

{fig:state_tsne}

we evaluate the DynE action space on a set of six tasks with low-dimensional state observations, testing its usefulness across a set of tasks and object interactions. Then, we test the DynE state space on a set of three tasks with pixel observations. Finally, we combine DynE actions with DynE observations, verifying that the two learned representations are complementary.

Appendix **??** provides a full description of hyperparameters and model architectures, and all of the code for DynE is available on GitHub at `https://github.com/dyne-submission/dynamics-aware-embeddings`.

Environments We use six continuous control tasks from two families implemented in the MuJoCo simulator [Todorov et al. 2012] to evaluate our method. Within each family, the task and observation space change but the robot being controlled stays roughly the same, allowing us to test the transferrability of the DynE action space between tasks. The Reacher family consists of three of tasks which involve controlling a 2D, 2DoF arm to interact with various objects. The 7DoF family of tasks from OpenAI Gym [Brockman et al. 2016a] is quite difficult, featuring three tasks in which a 3D, 7DoF arm must use different end effectors to push or throw various objects to randomly-generated goal positions. Images and detailed descriptions of both families of tasks

are available in Appendix ??.

5.6.1 Low-dimensional states

{sec:action_experimen

For training the DynE action representation we use 100K steps with a uniformly random behavior policy in the simplest environment in each family with no reward or other supervisory signal. As this DynE pretraining is unsupervised and only occurs once for each family of environments, the x axis on these training curves refers only to the samples used to train the policy.[10] We then transfer this action representation to all three environments in the family. When training DynE-TD3 we use all of the default hyperparameters from the TD3 implementation across all environments.

We directly test the impact of switching from raw to DynE actions by comparing TD3 to DynE-TD3. For completeness we compare with two additional state-of-the-art model-free methods: soft actor-critic (SAC) [Haarnoja et al. 2018b,c] and proximal policy optimization (PPO) [Schulman et al. 2017]. We also compare with soft actor-critic with latent space policies (SAC-LSP) [Haarnoja et al. 2018a], an innovative hierarchical method which transforms a low-level action space into an abstract one by training an invertible low-level policy. In all cases we use the official implementations[11][12][13] and the MuJoCo hyperparameters used by the authors. We also attempted to compare with the hierarchical method by Nachum et al. [2018], but after several emails with the authors and dozens of experiments we were unable to get it to converge on tasks other than those in their paper.

Results Figure 5.5 shows the results of these experiments. Most significantly, they show that switching from the raw action space (TD3 curve) to the DynE action space results in faster training and allows TD3 to solve the difficult 7DoF suite of tasks. We see that the DynE action space generalizes across several tasks with the same robot, even when interacting with objects unseen during training. It is especially worth noting that the gains from DynE increase as the tasks be-

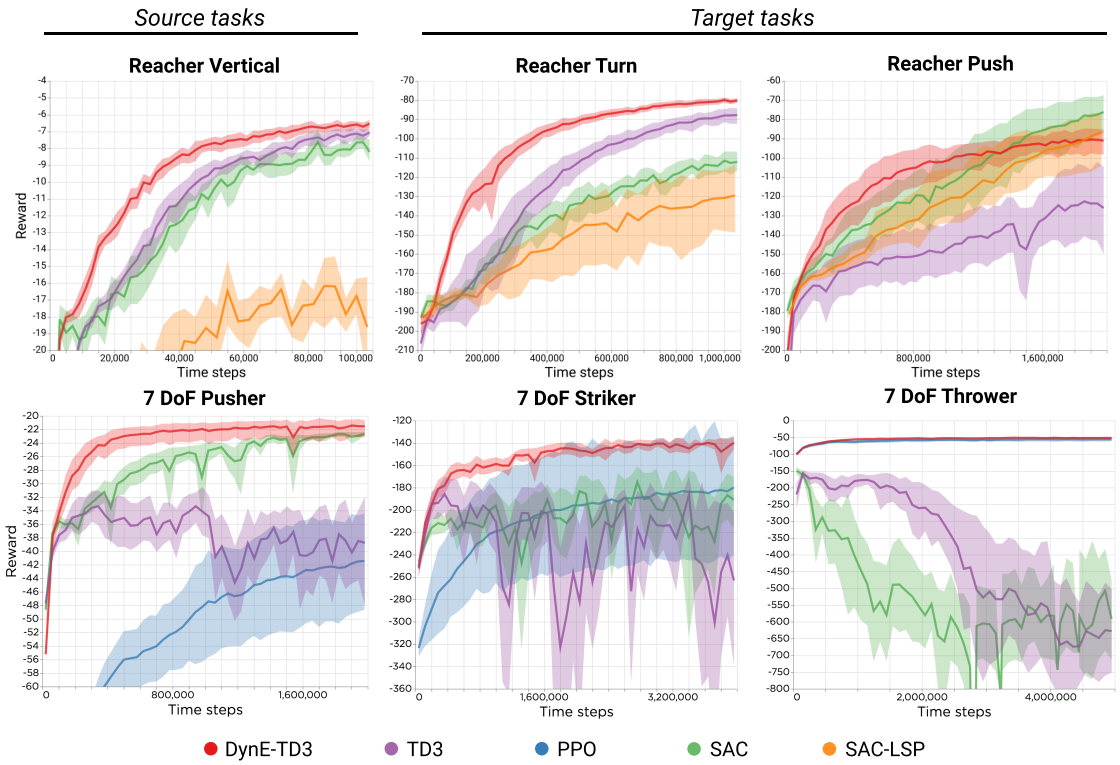


Figure 5.5: Performance of DynE-TD3 and baselines on two families of environments with low-dimensional observations. Dark lines are mean reward over 8 seeds and shaded areas are bootstrapped 95% confidence intervals. Across all the environments, TD3 learns faster with the DynE action space than with the raw actions. Within each family of environments, the DynE action space was trained only on the simplest task (left).

{fig:lowd_results}

come harder, maintaining convergence, stability, and low variance in the face of high-dimensional control with difficult exploration. Since SAC-LSP [Haarnoja et al. 2018a] performs similarly but worse than SAC we test it only on the simpler Reacher family of tasks; meanwhile, the PPO curves do not enter the frame on the Reacher family of tasks due to its poor sample efficiency.

5.6.2 Pixels

Using the Reacher family of environments we evaluate several state representations by their effectiveness for policy learning with TD3.

We evaluate two established methods for learning representations from single images. "DARLA" is the Disentangled Representation Learning Agent proposed by Higgins et al. [2017b] with the

denoising autoencoder loss, which is referred to in that work as β-VAE$_{DAE}$. "VAE" is a standard variational autoencoder [Kingma and Welling 2013; Rezende et al. 2014], which has previously been found to learn effective representations for control [Van Hoof et al. 2016]; it is equivalent to DARLA with the pixel-space loss and $\beta = 1$. Since these representations operate on a single frame at a time, we apply them to the most recent four frames independently and then concatenate the embeddings before feeding them to the policy. These representations have compressed latent spaces, but they encode no knowledge of the environment's dynamics, allowing us to evaluate the importance of incorporating the dynamics into our embeddings.

Next we evaluate representation learning methods whose objectives incorporate the dynamics. "S-DynE," for State DynE, is the DynE state embedding e_s, and "SA-DynE" combines the DynE state and action representations. "S-Deterministic" and "SA-Deterministic" are ablations of the corresponding DynE methods which have the same forward-prediction objective but no KL or noise on the latent representations. Comparing the DynE methods to their respective ablations reveals the contribution of explicitly introducing a compression objective to the latent space.

For training all of the learned representations we use a dataset of 100K steps in each environment from a uniformly random policy. In every case we train TD3 with the learned representations using all of the default hyperparameters from the official TD3 implementation.

We compare these representation learning methods with TD3 trained from pixels. As there are no experiments on pixels in the TD3 paper, we performed extensive search over network architectures and hyperparameters. We included in our search the configurations used in the pixel experiments of DDPG [Lillicrap et al. 2015] as well as those used in successful discrete-action RL works from pixels [Schulman et al. 2017; Kostrikov 2018; Espeholt et al. 2018].

Results Figure 5.6 shows the results of these experiments. We find that the single-image methods are unable to solve any of the three tasks from pixels; TD3 from pixels diverges in all cases, while VAE and DARLA learn gradually at best. If simply reducing the dimension of the states

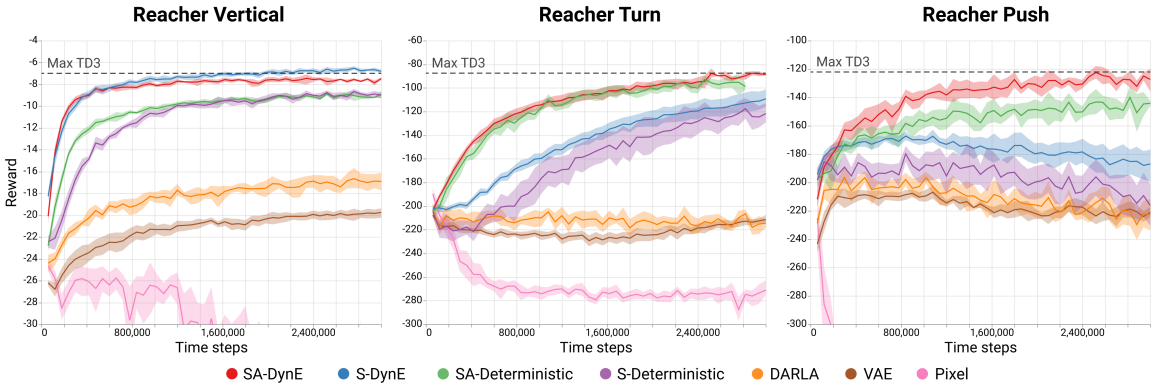


Figure 5.6: Performance of TD3 trained with various representations. Learned representations for state which incorporate the dynamics make a dramatic difference. SA-DynE converges stably and rapidly and achieves performance from pixels that nearly equals TD3's performance from states. Dark lines are mean reward over 8 seeds and shaded areas are bootstrapped 95% confidence intervals. {fig:pixel_results}

were sufficient to enable effective policy training, we would expect good performance from these methods. S-DynE and S-Deterministic, which incorporate the dynamics into their representation learning objectives, perform far better. The minimality imposed by the DynE objective allows S-DynE and SA-Dyne to outperform their deterministic ablations. SA-DynE learns rapidly and reliably, finding behaviors which qualitatively solve all three tasks. The improvement of SA-DynE over S-DynE shows that the state and action representations are complementary.

5.7 Discussion

In this work we proposed a method, Dynamics-aware Embedding (DynE), that jointly learns embedded representations of states and actions for reinforcement learning. Our experiments reveal that DynE action embeddings lead to more efficient exploration, resulting in more sample efficient learning on complex tasks, while DynE state embeddings allow unmodified model-free RL algorithms to scale to pixel observations. When combined, the DynE state and action embeddings result in stable, sample-efficient learning of high-quality policies from pixels.

add appendices

Notes

8. Number of steps required to train D4PG taken from Hafner et al. [2018], as Barth-Maron et al. [2018] does not include this information.

9. In the interest of space we omit the usual recap of Markov decision processes and reinforcement learning. We refer the reader to Section 2 of Silver et al. [2014] for notation and background on MDPs.

10. On all environments except the simplest (Reacher Vertical) shifting the DynE-TD3 plot by 100K steps does not affect the ordering of the results.

11. TD3: https://github.com/sfujim/TD3/

12. SAC and SAC-LSP: https://github.com/haarnoja/sac

13. PPO: https://github.com/openai/baselines/tree/master/baselines/ppo2

Part III

Improving Performance with Batched Data

{sec:offline}

Introduction to offline RL.

6 Offline Contextual Bandits with Overparameterized Models

{sec:offline-bandits}

6.1 Introduction

The offline contextual bandit problem can be used to model decision making from logged data in domains as diverse as recommender systems [Li et al. 2010; Bottou et al. 2013], healthcare [Prasad et al. 2017; Raghu et al. 2017], and robotics [Pinto and Gupta 2016]. Prior work on the problem has primarily focused on underparameterized models with finite and small VC dimensions. This work has come from the bandit literature [Strehl et al. 2010; Swaminathan and Joachims 2015a,b], the reinforcement learning literature [Munos and Szepesvári 2008; Chen and Jiang 2019], and the causal inference literature [Bottou et al. 2013; Athey and Wager 2017; Kallus 2018; Zhou et al. 2018].

In contrast, the best performance in modern supervised learning is often achieved by massively overparameterized models that are capable of fitting random labels [Zhang et al. 2016]. Use of such large models renders vacuous the bounds that require a small model class. But, the massive capacity of popular neural network models is now often viewed as a feature rather than a bug. Large models reduce approximation error and allow for easier optimization [Du et al. 2018] while still being able to generalize in regression and classification problems [Belkin et al. 2018, 2019]. In this paper, we investigate whether the strong performance of overparameterized

models in supervised learning translates to the offline contextual bandit setting. The main prior work that considers this setup is [Joachims et al. 2018], which we discuss in detail in Section 6.7.

To formalize the differences between the supervised learning and contextual bandit settings, we introduce a novel regret decomposition. This decomposition shares the approximation and estimation terms from classic work in supervised learning [Vapnik 1982; Bottou and Bousquet 2008], but adds a term for "bandit" error which captures the excess risk due to only receiving partial feedback.

We use this framework to address the question: can we use overparameterized models for offline contextual bandits? Or is the bandit error a fundamental problem when we use large models? We find mixed results. Value-based algorithms benefit from the same generalization behavior as overparameterized supervised learning, but policy-based algorithms do not. We show that this difference is explained by a property of their objectives called *action-stability*. An objective is action-stable if there exists a single prediction which is simultaneously optimal for any observed action (where a "prediction" is a vector of state-action values for a value-based objective or an action distribution for a policy-based objective). Action-stable objectives perform well when combined with overparameterized models since the random actions taken by the behavior policy do not change the optimal prediction. However, interpolating an unstable objective results in learning a different function for every sample of actions, even though the true optimal policy remains unchanged.

On the theory side, we prove that overparameterized value-based algorithms are action stable and have small bandit error via reduction to overparameterized regression. Meanwhile we prove that policy-based algorithms are not action-stable which allows us to prove lower bounds on the "in-sample" regret and lower bounds on the regret for simple nonparametric models.

Empirically, we demonstrate the gap in both action stability and bandit error between policy-based and value-based algorithms when using large neural network models on synthetic and image-based datasets.

In summary, our main contributions are:

- We introduce the concept of bandit error, which separates contextual bandits from supervised learning.
- We introduce action-stability and show that a lack of action-stability causes bandit error.
- We show a gap between policy-based and value-based algorithms based on action-stability and bandit error both in theory and experiments.

6.2 Setup

{sec:setup}

6.2.1 Offline contextual bandit problem

First we will define the contextual bandit problem [Langford and Zhang 2008]. Let the context space $\mathcal{X}$ be infinite and the action space $\mathcal{A}$ be finite with $|\mathcal{A}| = K < \infty$. At each round, a context $x \in \mathcal{X}$ and a full feedback reward vector $r \in [r_{\min}, r_{\max}]^K$ are drawn from a joint distribution $\mathcal{D}$. Note that r can depend on x since they are jointly distributed. A policy $\pi : \mathcal{X} \to \mathcal{P}(\mathcal{A})$ maps contexts to distributions over actions. An action a is sampled according to $\pi(a|x)$ and the reward is $r(a)$, the component of the vector r corresponding to a. We use "bandit feedback" to refer to only observing $r(a)$. This contrasts with the "full feedback" problem where at each round the full vector of rewards r is revealed, independent of the action.

In the offline setting there is a finite dataset of N rounds with a fixed behavior policy β. Then we denote the dataset as $S = \{x_i, r_i, a_i, p_i\}_{i=1}^N$ where p_i is the observed propensity $p_i = \beta(a_i|x_i)$. The tuples in the datasets lie in $\mathcal{X} \times [r_{min}, r_{max}]^K \times \mathcal{A} \times [0, 1]$ and are drawn i.i.d from the joint distribution induced by $\mathcal{D}$ and β. From S we define the datasets S_B for bandit feedback and S_F for

full feedback:

$$S_B = \{(x_i, r_i(a_i), a_i, p_i)\}_{i=1}^N, \quad S_F = \{(x_i, r_i)\}_{i=1}^N.$$

Note that we are assuming access to the behavior probabilities $p_i = \beta(a_i|x_i)$, so the issues that we raise do not have to do with estimating propensities. We will further make the following assumption about the behavior.

{ass:positivity}

Assumption 1 (Strict positivity)**.** *We have strict positivity of τ if $\beta(a|x) \geq \tau > 0$ for all a, x. Thus, in any dataset we will have $p_i = \beta(a_i|x_i) \geq \tau > 0$.*

There is important work that focuses learning without strict positivity by making algorithmic modifications like clipping [Bottou et al. 2013; Strehl et al. 2010; Swaminathan and Joachims 2015a] and behavior constraints [Fujimoto et al. 2018b; Laroche et al. 2019]. However, these issues are orthogonal to the main contribution of our paper, so we focus on the setting with strict positivity.

The goal of an offline contextual bandit algorithm is to take in a dataset and produce a policy π so as to maximize the value $V(\pi)$ defined as

$$V(\pi) := \mathop{\mathbb{E}}_{x,r\sim\mathcal{D}} \mathop{\mathbb{E}}_{a\sim\pi(\cdot|x)} [r(a)].$$

We will use π^* to denote the deterministic policy that maximizes V. Finally, define the Q function at a particular context, action pair as

$$Q(x, a) := \mathop{\mathbb{E}}_{r|x} [r(a)].$$

6.2.2 Model classes

The novelty of our setting comes from the use of overparameterized model classes that are capable of interpolating the training objective. To define this more formally, all of the algorithms we consider take a model class of either policies Π or Q functions $\mathcal{Q}$ and optimize some objective over the data with respect to the model class. Following the empirical work of [Zhang et al. 2016] and theoretical work of [Belkin et al. 2018] we will call a model class "overparameterized" or "interpolating" if the model class contains a model that exactly optimizes the training objective. Formally, if we have data $\{x_i\}_{i=1}^N$ and a pointwise loss function $\ell(x, y)$, then a model class Π can interpolate the data if

$$\inf_{\pi \in \Pi} \sum_{i=1}^{N} \ell(x_i, \pi(x_i)) = \sum_{i=1}^{N} \inf_{y} \ell(x_i, y).$$

This contrasts with traditional statistical learning settings where we assume that the model class is finite or has low complexity as measured by something like VC dimension [Strehl et al. 2010; Swaminathan and Joachims 2015a].

6.2.3 Algorithms

{sec:basic-algs}

Now that we have defined the problem setting, we can define the algorithms that we will analyze. This is not meant to be a comprehensive account of all algorithms, but a broad picture of the "vanilla" versions of the main families of algorithms. Since we are focusing on statistical issues we do not consider how the objectives are optimized.

Supervised learning with full feedback. In a full feedback problem, empirical value maximization (the analog to standard empirical risk minimization) is defined by maximizing the em-

pirical value $\hat{V}_F$:

$$\hat{V}_F(\pi; S_F) := \frac{1}{N}\sum_{i=1}^{N}\langle r_i, \pi(\cdot|x_i)\rangle \tag{6.1}$$

$$\pi_F := \arg\max_{\pi\in\Pi} \hat{V}_F(\pi; S_F). \tag{6.2}$$

Policy-based learning. Importance weighted or "inverse propensity weighted" policy optimization directly optimizes the policy to maximize an estimate of its value. Since we only observe the rewards of the behavior policy, we use importance weighting to get an unbiased value estimate to maximize. Explicitly:

$$\hat{V}_B(\pi; S_B) := \frac{1}{N}\sum_{i=1}^{N} r_i(a_i)\frac{\pi(a_i|x_i)}{p_i} \tag{6.3}$$

$$\pi_B := \arg\max_{\pi\in\Pi} \hat{V}_B(\pi; S_B). \tag{6.4}$$ {{eq:pi}}

Note that this is the "vanilla" version of the policy-based algorithm and modifications like regularizers, baselines/control variates, clipped importance weights, and self-normalized importance weights have been proposed [Bottou et al. 2013; Joachims et al. 2018; Strehl et al. 2010; Swaminathan and Joachims 2015a,b]. For our purposes considering this vanilla version is sufficient since as we show in Section 6.4, any objective that takes the form $\pi(a_i|x_i)f(x_i, a_i, r_i, p_i)$ at each datapoint will have the same sort of problem with action-stability.

It is important to note that with underparameterized model classes, this algorithm is guaranteed to return nearly the best policy in the class. Explicilty, Strehl et al. [2010] prove that for a finite policy class Π, with high probability the regret of the learned policy π_B is bounded as $O(\frac{1}{\tau}\sqrt{\frac{\log|\Pi|}{N}})$. This is elaborated in Appendix **??**. However, these guarantees no longer hold in our overparameterized setting.

Value-based learning. Another simple algorithm is to first learn the Q function and then use a greedy policy with respect to this estimated Q function. Explicitly:

$$\hat{Q}_{S_B} := \arg\min_{f \in \mathcal{Q}} \sum_{i=1}^{N} (f(x_i, a_i) - r_i(a_i))^2 \tag{6.5}$$ {{eqn:hatQ}}

$$\pi_{\hat{Q}_{S_B}}(a|x) := \mathbb{1}\left[a = \arg\max_{a'} \hat{Q}_{S_B}(x, a')\right]. \tag{6.6}$$

This algorithm is sometimes called the "direct method" [Dudík et al. 2011]. The RL literature also often defines a class of model-based algorithms, but in the contextual bandit problem there are no state transitions so model-based algorithms are equivalent to value-based algorithms.

This algorithm also has a guarantee with small model classes. Explicilty, Chen and Jiang [2019] prove that for a finite *and well specified* model class $\mathcal{Q}$, with high probability the regret of the learned policy $\pi_{\hat{Q}_{S_B}}$ is bounded as $O(\frac{1}{\sqrt{\tau}}\sqrt{\frac{\log|\mathcal{Q}|}{N}})$. This is elaborated in Appendix **??**. Again, these guarantees no longer hold in our overparameterized setting.

Doubly robust policy optimization. The class of doubly robust algorithms [Dudík et al. 2011] does not fall cleanly into the value-based or policy-based bins since it requires first learning a value function and using that to optimize a policy. However, with overparamterized models, doubly robust learning becomes exactly equivalent to our vanilla value-based algorithm unless we use crossfitting since the estimated Q values will coincide with the rewards. We prove this formally in Appendix **??** where we also show some issues that the doubly robust policy objective can have with overparameterized models and highly stochastic rewards. For our purposes, we will only consider the policy-based and value-based approaches since the doubly robust approach collapses to the value-based approach with overparameterized models.

6.3 Bandit error

{sec:decomp}

In supervised learning, the standard decomposition of the excess risk separates the approximation and estimation error [Bottou and Bousquet 2008]. The approximation error is due to the limited function class and the estimation error is due to minimizing the empirical risk rather than the true risk. Since the full feedback policy learning problem is equivalent to supervised learning, the same decomposition applies. Formally, consider a full feedback algorithm $\mathcal{A}_F$ which takes the dataset S_F and produces a policy π_F. Then

$$\underbrace{\mathop{\mathbb{E}}_{S}[V(\pi^*) - V(\pi_F)]}_{\text{regret}} = \underbrace{V(\pi^*) - \sup_{\pi \in \Pi} V(\pi)}_{\text{approximation error}} + \underbrace{\mathop{\mathbb{E}}_{S}[\sup_{\pi \in \Pi} V(\pi) - V(\pi_F)]}_{\text{estimation error}}.$$

We can instead consider a bandit feedback algorithm $\mathcal{A}_B$ which takes the dataset S_B and produces a policy π_B. To extend the above decomposition to the bandit problem we add a new term, the bandit error, that results from having access to S_B rather than S_F. Now we have:

$$\underbrace{\mathop{\mathbb{E}}_{S}[V(\pi^*) - V(\pi_B)]}_{\text{regret}} = \underbrace{V(\pi^*) - \sup_{\pi \in \Pi} V(\pi)}_{\text{approximation error}} + \underbrace{\mathop{\mathbb{E}}_{S}[\sup_{\pi \in \Pi} V(\pi) - V(\pi_F)]}_{\text{estimation error}} + \underbrace{\mathop{\mathbb{E}}_{S}[V(\pi_F) - V(\pi_B)]}_{\text{bandit error}}.$$

Disentangling sources of error. The approximation error is the same quantity that we encounter in the supervised learning problem, measuring how well our function class can do. The estimation error measures the error due to overfitting on finite contexts and noisy rewards. The bandit error accounts for the error due to only observing the actions chosen by the behavior policy. This is not quite analogous to overfitting to noise in the rewards since stochasticity in the actions is actually required to have the coverage of context-action pairs needed to learn a policy. While the standard approximation-estimation decomposition could be directly extended to the bandit problem, our approximation-estimation-bandit decomposition is more conceptually useful

since it disentangles these two types of error.

Can bandit error be negative? Usually, we think about an error decomposition as a sum of positive terms. This is not necessarily the case with our decomposition, but we view this as a feature rather than a bug. Intuitively, the bandit error term captures the contribution of the actions selected by the behavior policy. If the behavior policy is nearly optimal and the rewards are highly stochastic, there may be more signal in the actions selected by the behavior policy than the observed rewards. Thus overfitting the actions chosen by behavior policy can sometimes be beneficial, causing the bandit error to be negative. The two terms disentangle the approximation error (due to reward noise) from bandit error (due to behavior actions).

6.4 Action-stable objective functions

{sec:stable}

Consider a simple thought experiment. We collect a contextual bandit dataset S_B from a two-action environment using a uniformly random behavior policy. Then we construct a second dataset $\widetilde{S}_B$ by evaluating the outcome of taking the opposite action at each observed context. Since nothing about the environment has changed, we know that the optimal policy remains the same. Therefore we desire the following property from a bandit objective: there exists a single model which is optimal (with respect to that objective) on both S_B and $\widetilde{S}_B$. We say that such an objective is *action-stable* because it has an optimal policy which is stable to re-sampling of the actions in the dataset.

More formally, we define action stability pointwise at a datapoint $z = (x, r, p)$ where $r \in [r_{\min}, r_{\max}]^K$ and $p \in \Delta^K$ is the behavior probability vector in the K-dimensional simplex (recall that K is the number of the actions). Let $z(a)$ denote the datapoint when action a is sampled so that $z(a) = (x, r(a), p(a), a)$. The objectives for both policy and value-based algorithms decompose into sums over the data of some loss $\ell(z(a), \pi(a|x))$ or $\ell(z(a), Q(x, a))$.

Note that the output space of a policy is the simplex so that $\pi(\cdot|x) \in \Delta^K$, while the output of a Q function[14] is $Q(x, \cdot) \in \mathbb{R}^K$. To allow for this difference in our definition, we will define a generic K-dimensional output space $\mathcal{Y}^K$ and its corresponding restriction to one dimension as $\mathcal{Y}$. So for a policy-based algorithm $\mathcal{Y}^K = \Delta^K$ and $\mathcal{Y} = [0, 1]$, while for a value-based algorithm $\mathcal{Y}^K = \mathbb{R}^K$ and $\mathcal{Y} = \mathbb{R}$. Now we can define action-stability.

Definition 6.1 (Action-stable objective)**.** An objective function ℓ is action-stable at a datapoint z if there exists $y^* \in \mathcal{Y}^K$ such that for all $a \in \mathcal{A}$:

$$\ell(z(a), y^*(a)) = \min_{y \in \mathcal{Y}} \ell(z(a), y).$$

If an objective is not action-stable, a function which minimizes that objective exactly at every datapoint $(x, r(a), p(a), a)$ does *not* minimize it for a different choice of a. As a direct consequence, interpolating an unstable objective results in learning a different function for every sample of actions, even though the true optimal policy remains unchanged.

We find that policy-based objectives are not action-stable, while value-based objectives are. In the next section we will use the instability of policy-based objectives to show that policy-based algorithms exhibit large bandit error when used with overparameterized models. Our stability results are stated in the following two Lemmas, whose proofs can be found in Appendix **??**.

{thmt@@vbstable@data}
{thmt@@vbstable}

Lemma 6.2 (Value-based stability)**.** *Value-based objectives are action stable since we can let $y^* = r$ and this minimizes the square loss at every action.*

{thmt@@pbstable@data}
{thmt@@pbstable}

Lemma 6.3 (Policy-based instability)**.** *All policy-based objectives which take the form $\ell(z(a), \pi(a|x)) = f(z(a))\pi(a|x)$ are not action-stable at z unless $f(z(a)) > 0$ for exactly one action a.*

These Lemmas tell us that the stochasticity of the behavior policy can cause instability for policy-based objectives. This is worrisome since one would hope that more stochastic behavior

policies give us more information about all the actions and should thus yield better policies. Indeed, this is the case for value-based algorithms as we will see in the next section. But for policy-based algorithms, stochastic behavior can itself be a cause of overfitting due to the instability of the objective function.

Stabilizing policy-based algorithms. To avoid this problem in a policy-based algorithm, the sign of the function $f(z(a))$ must indicate the optimal action. This essentially requires having access to a *baseline* function $b(s)$ that separates the optimal action from all the others so that $r(a) > b(s)$ if and only if a is the optimal action. And then $f(z(a)) = \frac{r(a)-b(s)}{\beta(a|s)}$ yields an action-stable algorithm. This is in general as difficult as learning the full value function Q. One notable special case is when the bandit problem is induced by an underlying classification problem, so that only one action has reward 1 and all others have 0. In this case, any constant baseline between 0 and 1 will lead to action stability. This case has often been considered in the literature, e.g. by Joachims et al. [2018] as we discuss in Section 6.7.

Now that we have built up an understanding of the problem we can prove some formal results that show how value-based algorithms more effectively leverage overparameterized models by being action-stable.

6.5 Regret bounds

Recall that as explained in Section 6.2, both policy-based and value-based algorithms have regret guarantees when we use small model classes [Strehl et al. 2010; Chen and Jiang 2019]. But, when we move to the overparameterized setting, this is no longer the case. In this section we prove regret upper bounds for value-based learning by using recent results in overparameterized regression. Then we prove lower bounds on the regret of policy-based algorithms due to their action-instability.

6.5.1 Value-based learning

In this section we show that value-based algorithms can provably compete with the optimal policy. The key insight is to reduce the problem to regression and then leverage the guarantees on overparameterized regression from the supervised learning literature. This is formalized by the following theorem.

{thmt@@reduction@data
{thmt@@reduction}

Theorem 6.4 (Reduction to regression)**.** *By Assumption 1 we have $\beta(a|x) \geq \tau$ for all x, a. Then with $\hat{Q}_{S_B}$ as defined in (6.5) we have*

$$V(\pi^*) - V(\pi_{\hat{Q}_{S_B}}) \leq \frac{2}{\sqrt{\tau}} \sqrt{\mathop{\mathbb{E}}_{x,a\sim\beta}[(Q(x,a) - \hat{Q}_{S_B}(x,a))^2]}.$$

A proof can be found in Appendix **??**. Similar results are presented as intermediate results in Chen and Jiang [2019]; Munos and Szepesvári [2008]. The implication of this result that we want to emphasize is that any generalization guarantees for overparameterized regression immediately become guarantees for value-based learning in offline contextual bandits. Essentially, Theorem 6.4 gives us a regret bound in any problem where overparameterized regression works. The following results from the overparameterized regression literature demonstrate a few of these guarantees, which all require some sort of regularity assumption on the true Q function to bound the regression error:

- The results of [Bartlett et al. 2020] give finite sample rates for overparameterized linear regression by the minimum norm interpolator depending on the covariance matrix of the data and assuming that the true function is realizable.
- The results of [Belkin et al. 2019] imply that under smoothness assumptions on Q, a particular singular kernel will interpolate the data and have optimal non-parametric rates. After applying our reduction, the rates are no longer optimal for the policy learning problem due to the square root.

- The results of [Bach 2017] show how choosing the minimum norm infinite width neural network in a particular function space can yield adaptive finite sample guarantees for many types of underlying structure in the Q function.
- The results of [Cover 1968] imply the consistency of a one nearest neighbor regressor when the rewards are noiseless and Q is piecewise continuous. This will contrast nicely with Theorem 6.6 below.

Each of these guarantees implies a corresponding corollary to Theorem 6.4 resulting in a regret bound for that particular combination of model and assumptions on Q.

6.5.2 Policy-based learning

Now we will show how the policy-based learning algorithms can provably fail because they lack action-stability. We will do this in a few ways. First, we will show that on the contexts in the dataset an action-unstable algorithm must suffer regret. This means that we cannot even learn the optimal policy at the contexts seen during training. Then to deal with generalization beyond the dataset we will prove a regret lower bound for a specific overparameterized model, namely one nearest neighbor. Finally, we discuss a conjecture that such lower bounds can be extended to richer model classes like neural networks.

Since we are proving lower bounds, making any more simplifying assumptions only makes the bound stronger. As such, all of our problem instances that create the lower bounds have only two actions ($K = 2$).

Regret on the observed contexts. Before considering how a policy generalizes off of the data, it is useful to consider what happens at the contexts in the dataset. This is especially true for overparameterized models which can exactly optimize the objective on the dataset. To do this, we will define the value of a policy π on the contexts in a dataset S (which we will call the

"in-sample" value) by

$$V(\pi; S) := \frac{1}{N} \sum_{i=1}^{N} \mathop{\mathbb{E}}_{r|x_i} \mathop{\mathbb{E}}_{a \sim \pi(\cdot|x_i)} [r(a)]. \tag{6.7}$$

Then the following Theorem shows that the policy π_B learned by the simple policy-based algorithm in Equation (6.4) must suffer substantial regret on S.

{thmt@@vsthm@data}
{thmt@@vsthm}

Theorem 6.5 (In-sample regret lower bound)**.** *Let $K = 2$ and the policy class be overparameterized. Define $\Delta_r(x) = \left|\mathbb{E}_{r|x}[r(1) - r(2)]\right|$ as the absolute expected gap in rewards at x. Define $p_u(x)$ to be the probability that the policy-based objective is action-unstable at x. Recall that $\beta(a|x) \geq \tau$ by Assumption 1. Then*

$$\mathop{\mathbb{E}}_{S}[V(\pi^*; S) - V(\pi_B; S)] \geq \tau \mathop{\mathbb{E}}_{x} \left[p_u(x)\Delta_r(x)\right].$$

The full proof is in Appendix **??**. This Theorem tells us that as often as the objective is action-unstable, we can suffer substantial regret even *on the contexts in the dataset.* We now offer some brief intuition of the proof. When we have two actions and an algorithm is not action-stable at x, then action chosen by the learned policy π_B at x_i is directly dependent on the observed action a_i. Since the behavior β will choose each action with probability at least τ by Assumption 1, the learned policy π_B must choose the suboptimal action with probability at least τ at x_i. This causes unavoidable regret for unstable algorithms, as formally stated in Theorem 6.5.

Note that Theorem 6.5 essentially says that action-unstable algorithms convert noise in the behavior into regret. This is the essential problem with unstable algorithms. Rather than using stochasticity in the behavior policy to get estimates of counterfactual actions, an action-unstable algorithm is sensitive to this stochasticity like it is label noise in supervised learning.

In Appendix **??** we present a result that makes this connection between behavior policy noise and action-instability more direct. Specifically we show a reduction that takes any classification

problem and turns it into a bandit problem such that optimizing the policy-based objective is equivalent to solving a noisy variant of the classification problem. On the contrary, optimizing the full-feedback objective is equivalent to the noiseless classification problem.

The limitation of this result is that it only applies in-sample and does not rule out that the model class could leverage its inductive bias to perform well away from the training data. Next we convert this in-sample regret lower bound into a standard regret lower bound for a particular simple interpolating model class, the nearest neighbor policy.

Regret with generalization: nearest neighbor models. The above result shows what happens at the contexts *in the dataset* S. It seems that only pathological combinations of model class and problem instance could perform poorly on S but recover strong performance off of the data. However, it cannot be ruled out a priori if the model class has strong inductive biases to generalize well. In this section we will show that at least for a very simple overparameterized model class, the generalization of the model does not improve performance.

The following theorem shows that the simplest interpolating model class, a one nearest neighbor rule, fails to recover the optimal policy even in the limit of infinite data.

{thmt@@nn@data}
{thmt@@nn}

Theorem 6.6 (Regret lower bound for one nearest neighbor)**.** *Let* $\Delta_r = r_{\max} - r_{\min}$. *Then there exist problem instances with noiseless rewards where*

$$\limsup_{N\to\infty} \mathop{\mathbb{E}}_{S}[V(\pi_F) - V(\pi_B)] = \frac{\Delta_r}{2},$$

but

$$\limsup_{N\to\infty} \mathop{\mathbb{E}}_{S}[V(\pi^*) - V(\pi_F)] = 0.$$

The proof is in Appendix **??**. This result shows that using a nearest neighbor scheme to generalize based on the signal provided by the policy-based objective is not sufficient to learn

an optimal policy. Importantly, note that since the rewards are noiseless, a nearest neighbor policy does recover the optimal policy with full feedback and Theorem 6.4 shows that value-based algorithms also recover the optimal policy in this setting. So, the model class is capable of solving the problem, it is the action-unstable algorithm that is causing irreducible error.

More complicated model classes. The above result for nearest neighbor models is illustrative, but does not apply to richer model classes like neural networks. While we were not able to construct such lower bounds, we conjecture that they do exist and hope that future work can prove them. We have two reasons to believe that such lower bounds exist. First, Theorem 6.5 is agnostic to model class. For a policy to perform well despite poor performance in-sample would require strong inductive biases from the model class. Proving lower bounds requires ruling out such inductive biases as we have shown for nearest neighbor rules. Second, our empirical results presented in the next section show that policy-based algorithms have action-instability and high bandit error with neural networks. The inductive biases are not enough to overcome the poor in-sample performance.

6.6 Experiments

{sec:exp}

In this section we experimentally verify that the phenomena described by the theory above extend to practical settings that go slightly beyond the assumptions of the theory.[15] Specifically we want to verify the following with overparameterized neural network models:

1. Policy-based algorithms are action-unstable while value-based algorithms are action-stable.
2. This causes high bandit error for policy-based algorithms, but not value-based algorithms.

We will break the section into two parts. First we consider a synthetic problem using simple feed-forward neural nets and then we show similar phenomena when the contexts are high-dimensional images and the models are Resnets [He et al. 2016].

6.6.1 Synthetic data

First, we will clearly demonstrate action-stability and bandit error in a synthetic problem with a linear reward function. Specifically, we sample some hidden reward matrix θ and then sample contexts and rewards from isotropic Gaussians:

$$\theta \sim U([0,1]^{K\times d}), \quad x \sim \mathcal{N}(0, I_d), \quad r \sim \mathcal{N}(\theta x, \epsilon I_d).$$

Actions are sampled according to a uniform behavior:

$$a \sim \beta(\cdot|x) = U(\{1, \dots, K\}).$$

For these experiments we set $K = 2, d = 10, \epsilon = 0.1$. We take $N = 100$ training points and sample an independent test set of 500 points. As our models we use MLPs with one hidden layer of width 512. In our experience, the findings are robust to all these hyperparameters of the problem so long as the model is overparameterized. Full details about the training procedure along with learning curves and further results are in Appendix **??**.

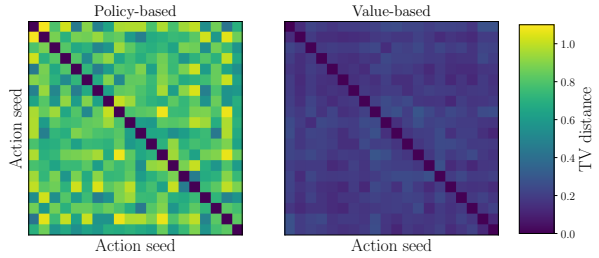


Figure 6.1: We test action-stability by resampling the actions 20 times for a single dataset of contexts. Each pixel corresponds to the pair of action seeds i, j and the color shows the TV distance between $\pi_i(\cdot|x)$ and $\pi_j(\cdot|x)$ on a held-out test set sampled from the data generating distribution. The policy-based algorithms are highly sensitive to the randomly sampled actions. {fig:toy_stability}

To confirm (1) and (2) listed above we conduct two experiments. First, to test the action-stability of an algorithm with a neural network model, we train 20 different policies on the same

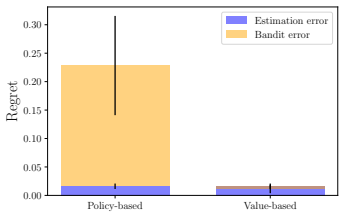


Figure 6.2: Estimated bandit error by averaging the values calculated on the held-out test sets for 50 independently sampled datasets. Error bars show one standard deviation. While policy-based learning has high bandit error, value-based learning has essentially zero bandit error.

{fig:toy_regret}

dataset of contexts and rewards, but with resampled actions. Formally, we sample $\{x_i, r_i\}_{i=1}^N$ from the Gaussian distributions described above and then sample $a_i \sim \beta(\cdot|x_i)$ with 20 different seeds. We then train each algorithm to convergence and compare the resulting policies by total variation (TV) distance. Results are shown in Figure 6.1. We find that our results from Section 6.4 are confirmed: policy-based algorithms are unstable leading to high TV distance between policies trained on different seeds while value-based algorithms are stable.

Second, we estimate the bandit error of each algorithm. To do this we train policies to convergence for the policy-based, value-based, and full-feedback objectives 50 independently sampled datasets (where now we also resample the contexts and rewards). For this estimate, we assume perfect optimization and no approximation error. Each estimate is calculated on a held out test set. Explicitly, let $\pi_B^j, \pi_Q^j, \pi_F^j$ are the policy-based, value-based, and full-feedback policies trained on dataset S^j with seed j and corresponding test set T^j. Then we estimate bandit error as $\frac{1}{J}\sum_{j=1}^J V(\pi_F^j; T^j) - V(\pi_B^j; T^j)$. Similarly, since we know θ we can compute π^* and use this to estimate the estimation error. The results shown in Figure 6.2 demonstrate that the policy-based algorithm suffers from substantially more bandit error and thus more regret.

6.6.2 Classification data

Most prior work on offline contextual bandits conducts experiments on classification datasets that are transformed into bandit problems [Beygelzimer and Langford 2009; Dudík et al. 2011;

Swaminathan and Joachims 2015a,b; Joachims et al. 2018; Chen et al. 2019]. This methodology obscures issues of action-stability because the very particular reward function used (namely 1 for a correct label and 0 for incorrect) makes the policy-based objective action-stable. However, even minor changes to this reward function can dramatically change the performance of policy-based algorithms by rendering the objective action-unstable.

To make a clear comparison to prior work that uses deep neural networks for offline contextual bandits like Joachims et al. [2018], we will consider the same image based bandit problem that they do in their work. Namely, we will use the a bandit version of CIFAR-10 [Krizhevsky 2009].

To turn CIFAR into an offline bandit problem we view each possible label as an action and assign reward of 1 for a correct label/action and 0 for an incorrect label/action. We use two different behavior policies to generate training data: (1) a uniformly random behavior policy and (2) the hand-crafted policy used in [Joachims et al. 2018]. We train Resnet-18 [He et al. 2016] models using Pytorch [Paszke et al. 2019]. Again full details about the training procedure are in Appendix **??**.

As explained in Section 6.4, the policy-based objective is stable if and only if the sign of the reward minus baseline is an indicator of the optimal action. To test this insight we consider two variants of policy-based learning: "unstable" where we use a baseline of -0.1 so that the effective rewards are 1.1 for a correct label and 0.1 for incorrect and "stable" where we use a baseline of 0.1 so that the effective rewards are of 0.9 and -0.1 to make the objective stable[16]. Note that this "stable" variant of the algorithm *only* exists because we are considering a classification problem. In settings with more rich structure in the rewards, defining such an algorithm is not possible and only versions of the unstable algorithm would exist.

We again estimate the regret decomposition as we did with the synthetic data. The difference is that this time we only use one seed since we only have one CIFAR-10 dataset. The results in Figure 6.3 confirm the results from the synthetic data. The standard (unstable) policy-based

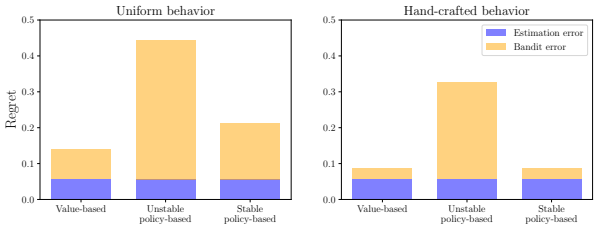


Figure 6.3: Estimated regret decomposition on CIFAR with uniform behavior (left) and the hand-crafted behavior of Joachims et al. [2018] (right). We see that the value-based learning has lowest bandit error and unstable policy-based learning the most. On the hand-crafted dataset the stable policy-based algorithm performs as well as value-based learning. {fig:cifar_regret}

algorithm suffers from large bandit error. The value-based algorithm has the best performance across both datasets although the "stable" policy-based algorithm performs about as well for the hand-crafted behavior policy.

6.7 Related work

{sec:related}

Now that we have presented our results, we will contrast them with some related work to clarify our contribution.

6.7.1 Relation to propensity overfitting

Swaminathan and Joachims [2015b] introduce what they call "propensity overfitting". By providing an example, they show that policy-based algorithms overfit to maximize the sum of propensities ($\sum_i \frac{\pi(a_i|x_i)}{p_i}$) rather than the value when the rewards are strictly positive. They provide a motivating example, but no formal definition of propensity overfitting and argue that it helps to describe the gap between supervised learning and bandit learning. In contrast, we introduce and formally define bandit error, which makes this gap between supervised learning and bandit learning precise and does not rely on the specific algorithm being used. Then we introduce and formally define action-instability, which explains an important cause of bandit error for policy-based algorithms when using large models. By mathematically formalizing these ideas we provide

a more rigorous foundation for future work.

6.7.2 Relation to [Joachims et al. 2018]

The main related work that considers offline contextual bandits with large neural network models is Joachims et al. [2018]. Specifically, that paper proposes a policy-based algorithm with an objective of the form: $\frac{r_i(a_i)-\lambda}{\beta(a_i|x_i)}\pi(a_i|x_i)$ for some constant baseline λ determined by a hyperparameter sweep, but motivated by a connection to self-normalized importance sampling.

Our work contrasts with this prior work in two key ways. First, we show that the algorithm proposed in Joachims et al. [2018] is action-unstable. Specifically, our Lemma 6.3 shows that any policy-based algorithm with an objective of the form $\sum_i f(z_i(a_i))\pi(a_i|x_i)$ cannot be action-stable unless the sign of $f(z(a))$ is the indicator of the optimal action. However, since that paper only tests the algorithm on classification problems where the rewards are in $\{0, 1\}$, any setting of λ between 0 and 1 causes the sign of f to indicate the optimal action. The action-stability analysis shows how this algorithm will struggle beyond the classification setting.

Second, we show that value-based methods provably and empirically work in the overparameterized setting. In contrast, Joachims et al. [2018] does not consider value-based methods. We show that value-based methods are not affected by action-stability issues (Lemma 6.2) and have vanishing bandit error (Theorem 6.4). We empirically test this conclusion on the same CIFAR-10 bandit problem as Joachims et al. [2018] and find that a value-based approach outperforms the policy-based approach proposed in that paper (Figure 6.3).

6.7.3 Variance of importance weighting

The importance weighted value estimates used by policy-based algorithms suffer from high variance due to low probability actions that have very large importance weights. Much prior work focuses on reducing this variance [Strehl et al. 2010; Bottou et al. 2013; Swaminathan and Joachims

2015a]. In contrast, the issue we consider, action-instability in the overparameterized setting, is distinct from this variance issue. When the policy class is flexible enough to optimize the objective at each datapoint, the optimal predictor in that class does not depend on the importance weights. Meanwhile action-unstable objectives translate stochasticity in the behavior policy into noise in the objective, causing the overfitting issues that we see in policy-based algorithms. In fact, our Theorem 6.5 suggests that regret will be worse for more uniform behavior policies when using an action-unstable objective, even though these may be beneficial in terms of variance. This is born out in our experiments where the behavior is usually *uniform* and *known*, which is a favorable setup in terms of the variance of the value estimates, but an unfavorable setup for action-unstable policy learning algorithms.

6.8 Discussion

We have examined the offline contextual bandit problem with overparameterized models. We introduced a new regret decomposition to separate the effects of estimation error and bandit error. We showed that policy-based algorithms are not action-stable and thus suffer from high bandit error with stochastic behavior policies. This is borne out both in the theory and experiments.

It is important to emphasize that our results may not apply beyond the setting we consider in this paper. When there is no strict positivity, there is unobserved confounding, there are continuous actions, or the model classes are small and misspecified then policy-based learning may have lower regret and lower bandit error than value-based learning.

In future work we hope to extend the ideas from the bandit setting to the full RL problem with longer horizon that requires temporal credit assignment. We predict that action-stability and bandit error remain significant issues there. We also hope to investigate action-stable algorithms beyond the simple value-based algorithms we consider here.

add appendices

Notes

14. When using neural networks Q is usually implemented as a function of x with K outputs [Mnih et al. 2015a].

15. Code can be found at `https://github.com/davidbrandfonbrener/deep-offline-bandits`.

16. This corresponds to the optimal value of λ in the experiments of Joachims et al. [2018]. Our "stable" model slightly outperforms theirs, likely due to a slightly better implementation.

7 | Offline RL Without Off-Policy Evaluation

{sec:offline-rl}

7.1 Introduction

An important step towards effective real-world RL is to improve sample efficiency. One avenue towards this goal is offline RL (also known as batch RL) where we attempt to learn a new policy from data collected by some other behavior policy without interacting with the environment. Recent work in offline RL is well summarized by Levine et al. [2020].

In this paper, we challenge the dominant paradigm in the deep offline RL literature that primarily relies on actor-critic style algorithms that alternate between policy evaluation and policy improvement [Fujimoto et al. 2018b, 2019; Peng et al. 2019; Kumar et al. 2019, 2020; Wang et al. 2020b; Wu et al. 2019; Kostrikov et al. 2021; Jaques et al. 2019; Siegel et al. 2020; Nachum et al. 2019]. All these algorithms rely heavily on off-policy evaluation to learn the critic. Instead, we find that a simple baseline which only performs one step of policy improvement using the behavior Q function often outperforms the more complicated iterative algorithms. Explicitly, we find that our one-step algorithm beats prior results of iterative algorithms on most of the gym-mujoco [Brockman et al. 2016b] and Adroit [Rajeswaran et al. 2017] tasks in the the D4RL benchmark suite [Fu et al. 2020].

We then dive deeper to understand why such a simple baseline is effective. First, we examine

what goes wrong for the iterative algorithms. When these algorithms struggle, it is often due to poor off-policy evaluation leading to inaccurate Q values. We attribute this to two causes: (1) distribution shift between the behavior policy and the policy to be evaluated, and (2) iterative error exploitation whereby policy optimization introduces bias and dynamic programming propagates this bias across the state space. We show that empirically both issues exist in the benchmark tasks and that one way to avoid these issues is to simply avoid off-policy evaluation entirely.

Finally, we recognize that while the the one-step algorithm is a strong baseline, it is not always the best choice. In the final section we provide some guidance about when iterative algorithms can perform better than the simple one-step baseline. Namely, when the dataset is large and behavior policy has good coverage of the state-action space, then off-policy evaluation can succeed and iterative algorithms can be effective. In contrast, if the behavior policy is already fairly good, but as a result does not have full coverage, then one-step algorithms are often preferable.

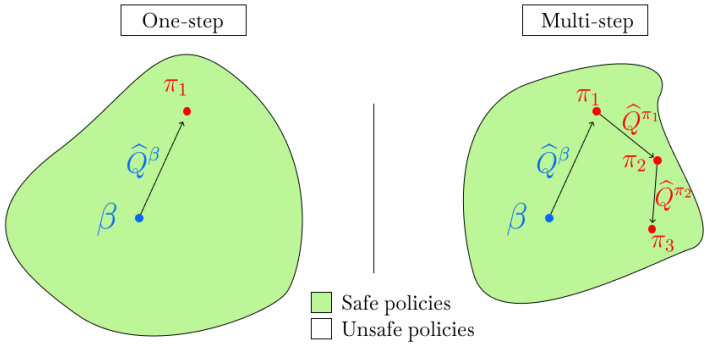


Figure 7.1: A cartoon illustration of the difference between one-step and multi-step methods. All algorithms constrain themselves to a neighborhood of "safe" policies around β. A one-step approach (left) only uses the on-policy $\widehat{Q}^\beta$, while a multi-step approach (right) repeatedly uses off-policy $\widehat{Q}^{\pi_i}$. {fig:cartoon}

Our main contributions are:

- A demonstration that a simple baseline of one step of policy improvement outperforms more complicated iterative algorithms on a broad set of offline RL problems.
- An examination of failure modes of off-policy evaluation in iterative offline RL algorithms.

- A description of when one-step algorithms are likely to outperform iterative approaches.

7.2 Setting and notation

We will consider an offline RL setup as follows. Let $\mathcal{M} = \{\mathcal{S}, \mathcal{A}, \rho, P, R, \gamma\}$ be a discounted infinite-horizon MDP. In this work we focus on applications in continuous control, so we will generally assume that both $\mathcal{S}$ and $\mathcal{A}$ are continuous and bounded. We consider the offline setting where rather than interacting with $\mathcal{M}$, we only have access to a dataset D_N of N tuples of (s_i, a_i, r_i) collected by some behavior policy β with initial state distribution ρ. Let $r(s,a) = \mathbb{E}_{r|s,a}[r]$ be the expected reward. Define the state-action value function for any policy π by $Q^\pi(s,a) := \mathbb{E}_{P,\pi|s_0=s,\ a_0=a}[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)]$. The objective is to maximize the expected return J of the learned policy:

$$J(\pi) := \mathop{\mathbb{E}}_{\rho,P,\pi}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)\right] = \mathop{\mathbb{E}}_{\substack{s\sim\rho \\ a\sim\pi|s}}[Q^\pi(s,a)]. \tag{7.1}$$

Following Fu et al. [2020] and others in this line of work, we allow access to the environment to tune a small (< 10) set of hyperparameters. See Paine et al. [2020] for a discussion of the active area of research on hyperparameter tuning for offline RL. We also discuss this further in Appendix ??.

7.3 Related work

Most prior work on deep offline RL consists of iterative actor-critic algorithms. The primary innovation of each paper is to propose a different mechanism to ensure that he learned policy does not stray too far from the data generated by the behavior policy. Broadly, we group these methods into three camps: policy constraints/regularization, modified of imitation learning, and

Q regularization:

1. The majority of prior work acts directly on the policy. Some authors have proposed explicit constraints on the learned policy to only select actions where (s, a) has sufficient support under the data generating distribution [Fujimoto et al. 2018b, 2019; Laroche et al. 2019]. Another proposal is to regularize the learned policy towards the behavior policy [Wu et al. 2019] usually either with a KL divergence [Jaques et al. 2019] or MMD [Kumar et al. 2019]. This is a very straighforward way to stay close to the behavior with a hyperparameter that determines just how close. All of these algorithms are iterative and rely on off-policy evaluation.

2. [Siegel et al. 2020; Wang et al. 2020b; Chen et al. 2020] all use algorithms that filter out datapoints with low Q values and then perform imitation learning. [Wang et al. 2018; Peng et al. 2019] use a weighted imitation learning algorithm where the weights are determined by exponentiated Q values. These algorithms are iterative.

3. Another way to prevent the learned policy from choosing unknown actions is to incorporate some form of regularization to encourage staying near the behavior and being pessimistic about unknown state, action pairs [Wu et al. 2019; Nachum et al. 2019; Kumar et al. 2020; Kostrikov et al. 2021]. However, properly being able to quantify uncertainty about unknown states is notoriously difficult when dealing with neural network value functions [Buckman et al. 2020]. Again all of these algorithms are iterative.

Some recent work has also noted that optimizing policies based on the behavior value function can perform surprisingly well [Gulcehre et al. 2020; Goo and Niekum 2020]. However, these papers propose complicated variants of the one-step approach involving ensembles, non-standard regularizers and paraterizations or ensembles and distributional Q functions. In contrast, we implement the simplest possible one-step algorithms without any modifications to the network architecture or standard regularizers/constraints. Moreover, we focus on providing an analysis of when and why this simple baseline works.

There are also important connections between the one-step algorithm and the literature on conservative policy improvement [Kakade and Langford 2002; Schulman et al. 2015; Achiam et al. 2017], which we discuss in more detail in Appendix **??**.

7.4 Defining the algorithms

In this section we provide a unified algorithmic template for offline RL algorithms as offline approximate modified policy iteration. We show how this template captures our one-step algorithm as well as a multi-step policy iteration algorithm and an iterative actor-critic algorithm. Then any choice of policy evaluation and policy improvement operators defines one-step, multi-step, and iterative algorithms.

7.4.1 Algorithmic template

We consider a generic offline approximate modified policy iteration (OAMPI) scheme, shown in Algorithm 3. Essentially the algorithm alternates between two steps. First, there is a policy evaluation step where we estimate the Q function of the current policy π_{k-1} by $\widehat{Q}^{\pi_{k-1}}$ using only the dataset D_N. Implementations also often use the prior Q estimate $\widehat{Q}^{\pi_{k-2}}$ to warm-start the approximation process. Second, there is a policy improvement step. This step takes in the estimated Q function $\widehat{Q}^{\pi_{k-1}}$, the estimated behavior $\hat{\beta}$, and the dataset D_N and produces a new policy π_k. Again an algorithm may use π_{k-1} to warm-start the optimization. Moreover, we expect this improvement step to be regularized or constrained to ensure that π_k remains in the support of β and D_N. Choices for this regularization/constraint are discussed below. Now we discuss a few ways to instantiate the template.

One-step. The simplest algorithm sets the number of iterations $K = 1$. We train the policy evaluation to estimate Q^β, and then use one of the policy improvement operators discussed below

Algorithm 3 OAMPI

{alg:oapi}

Require: K, dataset D_N, estimated behavior $\hat{\beta}$

1: Set $\pi_0 = \hat{\beta}$. Initialize $\widehat{Q}^{\pi_{-1}}$ randomly.
2: **for** k = 1, …, K **do**
3: Policy evaluation: $\widehat{Q}^{\pi_{k-1}} = \boldsymbol{Q}(\pi_{k-1}, D_N, \widehat{Q}^{\pi_{k-2}})$
4: Policy improvement: $\pi_k = \mathcal{I}(\widehat{Q}^{\pi_{k-1}}, \hat{\beta}, D_N, \pi_{k-1})$

to find the resulting π_1.

Multi-step. The multi-step algorithm now sets $K > 1$. The evaluation operator must evaluate off-policy since D_N is collected by β, but evaluation steps for $K \geq 2$ require evaluating policies $\pi_{k-1} \neq \beta$. Each iteration is trained to convergence in both the estimation and improvement steps.

Iterative actor-critic. An actor critic approach looks somewhat like multistep policy iteration, but does not attempt to train to convergence at each iteration. Instead, each iteration consists of one gradient step to update the Q estimate and one gradient step to improve the policy. Since all of the evaluation and improvement operators that we consider are gradient-based, this algorithm can adapt the same evaluation and improvement operators used by the multi-step algorithm. Most algorithms from the literature fall into this category [Fujimoto et al. 2018b; Kumar et al. 2019, 2020; Wu et al. 2019; Wang et al. 2020b; Siegel et al. 2020].

7.4.2 Policy evaluation operators

Following prior work on continuous state and action problems, we always evaluate by simple fitted Q evaluation [Fujimoto et al. 2018b; Kumar et al. 2019; Siegel et al. 2020; Wang et al. 2020b; Paine et al. 2020; Wang et al. 2021]. Explicitly the evaluation step for the one-step or multi-step

algorithms looks like

$$Q(\pi_{k-1}, D_N, \widehat{Q}^{\pi_{k-2}}) = \arg\min_Q \sum_{i=1}^{N} \left(r(s_i, a_i) + \gamma \mathop{\mathbb{E}}_{a' \sim \pi_{k-1}|s'_i} Q(s'_i, a') - Q(s_i, a_i) \right)^2, \tag{7.2}$$

where the right hand side may depend on $\widehat{Q}^{\pi_{k-2}}$ to warm-start optimization. In practice this is optimized by stochastic gradient descent with the use of a target network [Mnih et al. 2015a]. For the iterative algorithm the arg min is replaced by a single stochastic gradient step. We estimate the expectation over next state by a single sample from π_{k-1} (or from the dataset in the case when $\pi_{k-1} = \hat{\beta}$). See [Voloshin et al. 2019; Wang et al. 2021] for more comprehensive examinations of this evaluation step.

7.4.3 Policy improvement operators

To instantiate the template, we also need to choose a specific policy improvement operator $\mathcal{I}$. We consider the following improvement operators selected from those discussed in the related work section. Each operator has a hyperparameter controlling deviation from the behavior policy.

Behavior cloning. The simplest baseline worth including is to just return $\hat{\beta}$ as the new policy π. Any policy improvement operator ought to perform at least as well as this baseline.

Constrained policy updates. Algorithms like BCQ [Fujimoto et al. 2018b] and SPIBB [Laroche et al. 2019] constrain the policy updates to be within the support of the data/behavior. In favor of simplicity, we implement a simplified version of the BCQ algorithm that removes the policy correction network which we call Easy BCQ. We define a new policy $\hat{\pi}_k^M$ by drawing M samples from $\hat{\beta}$ and then executing the one with the highest value according to $\widehat{Q}^{\beta}$. Explicitly:

$$\hat{\pi}_k^M(a|s) = \mathbb{1}[a = \arg\max_{a_j} \{\widehat{Q}^{\pi_{k-1}}(s, a_j) : a_j \sim \pi_{k-1}(\cdot|s),\ 1 \le j \le M\}]. \tag{7.3}$$

Regularized policy updates. Another common idea proposed in the literature is to regularize towards the behavior policy [Wu et al. 2019; Jaques et al. 2019; Kumar et al. 2019; Ma et al. 2019]. For a general divergence D we can define an algorithm that maximizes a regularized objective:

$$\hat{\pi}_k^{\alpha} = \arg\max_{\pi} \sum_i \mathop{\mathbb{E}}_{a\sim\pi|s} [\widehat{Q}^{\pi_{k-1}}(s_i, a)] - \alpha D(\hat{\beta}(\cdot|s_i), \pi(\cdot|s_i)) \tag{7.4}$$

A comprehensive review of different variants of this method can be found in [Wu et al. 2019] which does not find dramatic differences across regularization techniques. In practice, we will use reverse KL divergence, i.e. $KL(\pi(\cdot|s_i)\|\hat{\beta}(\cdot|s_i))$. To compute the reverse KL, we draw samples from $\pi(\cdot|s_i)$ and use the density estimate $\hat{\beta}$ to compute the divergence. Intuitively, this regularization forces π to remain within the support of β rather than incentivizing π to cover beta.

Variants of imitation learning. Another idea, proposed by [Wang et al. 2018; Siegel et al. 2020; Wang et al. 2020b; Chen et al. 2020] is to modify an imitation learning algorithm either by filtering or weighting the observed actions so as to get a policy improvement. The weighted version that we implement uses exponentiated advantage estimates to weight the observed actions:

$$\hat{\pi}_k^{\tau} = \arg\max_{\pi} \sum_i \exp(\tau(\widehat{Q}^{\pi_{k-1}}(s_i, a_i) - \widehat{V}(s_i))) \log \pi(a_i|s_i). \tag{7.5}$$

7.5 Benchmark Results

{sec:bench}

Our main empirical finding is that one step of policy improvement is sufficient to beat state of the art results on much of the D4RL benchmark suite [Fu et al. 2020]. This is striking since prior work focuses on iteratively estimating the Q function of the current policy iterate, but we only use one-step derived from $\widehat{Q}^{\beta}$. Results are shown in Table 7.1. Full experimental details are in Appendix **??**.

As we can see in the table, all of the one-step algorithms usually outperform the best itera-

Table 7.1: Results of one-step algorithms on the D4RL benchmark. The first column gives the best results across several iterative algorithms considered in [Fu et al. 2020]. We run 3 seeds and each algorithm is tuned over 6 values of their respective hyperparameter. We report the mean and standard deviation over seeds on 100 evaluation episodes per seed. We **bold** the best result on each dataset and blue any result where a one-step algorithm beat the best reported iterative result from [Fu et al. 2020]. We use m for medium, m-e for medium-expert, m-re for medium-replay, r for random, and c for cloned.

	Iterative	One-step			
	[Fu et al. 2020]	BC	Easy BCQ	Rev. KL Reg	Exp. Weight
halfcheetah-m	46.3	41.9 ± 0.1	52.6 ± 0.2	**55.2 ± 0.4**	48.4 ± 0.1
walker2d-m	81.1	68.6 ± 6.3	**87.2 ± 1.3**	85.9 ± 1.4	81.8 ± 2.2
hopper-m	58.8	49.9 ± 3.1	74.5 ± 6.2	**83.7 ± 4.5**	59.6 ± 2.5
halfcheetah-m-e	64.7	61.1 ± 2.7	78.2 ± 1.6	**93.8 ± 0.5**	93.4 ± 1.6
walker2d-m-e	111.0	78.5 ± 22.4	112.2 ± 0.3	111.2 ± 0.2	**113.0 ± 0.4**
hopper-m-e	**111.9**	49.1 ± 4.3	85.1 ± 2.2	98.7 ± 7.5	103.3 ± 9.1
halfcheetah-m-re	**47.7**	34.6 ± 0.9	38.3 ± 0.3	41.9 ± 0.5	38.1 ± 1.3
walker2d-m-re	26.7	26.6 ± 3.4	69.1 ± 4.2	**74.9 ± 6.6**	49.5 ± 12.0
hopper-m-re	48.6	23.1 ± 2.7	78.4 ± 7.2	92.3 ± 1.1	**97.5 ± 0.7**
halfcheetah-r	**35.4**	2.2 ± 0.0	5.4 ± 0.3	8.8 ± 3.8	3.2 ± 0.1
walker2d-r	**7.3**	0.9 ± 0.1	3.7 ± 0.1	6.2 ± 0.7	5.6 ± 0.8
hopper-r	**12.2**	2.0 ± 0.1	6.6 ± 0.1	7.9 ± 0.7	7.5 ± 0.4
pen-c	56.9	46.9 ± 11.0	**65.9 ± 3.6**	57.4 ± 3.5	60.0 ± 4.1
hammer-c	2.1	0.4 ± 0.1	**2.9 ± 0.5**	0.2 ± 0.1	2.1 ± 0.7
relocate-c	-0.1	-0.1 ± 0.0	**0.3 ± 0.2**	0.2 ± 0.1	0.2 ± 0.1
door-c	0.4	0.0 ± 0.1	**0.6 ± 0.6**	0.2 ± 0.7	0.2 ± 0.3

{tab:d4rl}

tive algorithms tested by Fu et al. [2020]. The one notable exception is the case of random data (especially on halfcheetah), where iterative algorithms have a clear advantage. We will discuss potential causes of this further in Section 7.7.

To give a more direct comparison that controls for any potential implementation details, we use our implementation of reverse KL regularization to create multi-step and iterative algorithms. We are not using algorithmic modifications like Q ensembles, regularized Q values, or early stopping that have been used in prior work. But, our iterative algorithm recovers similar performance to prior regularized actor-critic approaches. These results are shown in Table 7.2.

Put together, these results immediately suggest some guidance to the practitioner: it is worth-

Table 7.2: Results of reverse KL regularization on the D4RL benchmark across one-step, multi-step, and iterative algorithms. Again we run 3 seeds and 6 hyperparameters and report the mean and standard deviation across seeds using 100 evaluation episodes.

	One-step	Multi-step	Iterative
halfcheetah-m	55.2 ± 0.4	**59.3 ± 0.7**	51.2 ± 0.2
walker2d-m	**85.9 ± 1.4**	74.5 ± 2.8	74.8 ± 0.7
hopper-m	**83.7 ± 4.5**	54.8 ± 4.3	54.7 ± 1.9
halfcheetah-m-e	93.8 ± 0.5	**94.2 ± 0.5**	93.7 ± 0.6
walker2d-m-e	**111.2 ± 0.2**	109.8 ± 0.3	108.7 ± 0.6
hopper-m-e	**98.7 ± 7.5**	90.6 ± 18.8	94.5 ± 11.9
halfcheetah-r	8.8 ± 3.8	18.3 ± 6.5	**21.2 ± 5.2**
walker2d-r	**6.2 ± 0.7**	5.4 ± 0.2	5.4 ± 0.4
hopper-r	7.9 ± 0.7	**21.9 ± 8.9**	9.7 ± 0.4

{tab:multi}

while to run the one-step algorithm as a baseline before trying something more elaborate. The one-step algorithm is substantially simpler than prior work, but usually achieves better performance.

7.6 What goes wrong for iterative algorithms?

{sec:why}

The benchmark experiments show that one step of policy improvement often beats iterative and multi-step algorithms. In this section we dive deeper to understand why this happens. First, by examining the learning curves of each of the algorithms we note that iterative algorithms require stronger regularization to avoid instability. Then we identify two causes of this instability: *distribution shift* and *iterative error exploitation*.

Distribution shift causes evaluation error by reducing the effective sample size in the fixed dataset for evaluating the current policy and has been extensively considered in prior work as discussed below. Iterative error exploitation occurs when we repeatedly optimize policies against our Q estimates and exploit their errors. This introduces a bias towards overestimation at each step (much like the training error in supervised learning is biased to be lower than the test error). Moreover, by iteratively re-using the data and using prior Q estimates to warmstart training at

each step, the errors from one step are amplified at the next. This type of error is particular to multi-step and iterative algorithms.

7.6.1 Learning curves and hyperparameter sensitivity

To begin to understand why iterative and multi-step algorithms can fail it is instructive to look at the learning curves. As shown in Figure 7.2, we often observe that the iterative algorithm will begin to learn and then crash. Regularization can help to prevent this crash since strong enough regularization towards the behavior policy ensures that the evaluation is nearly on-policy.

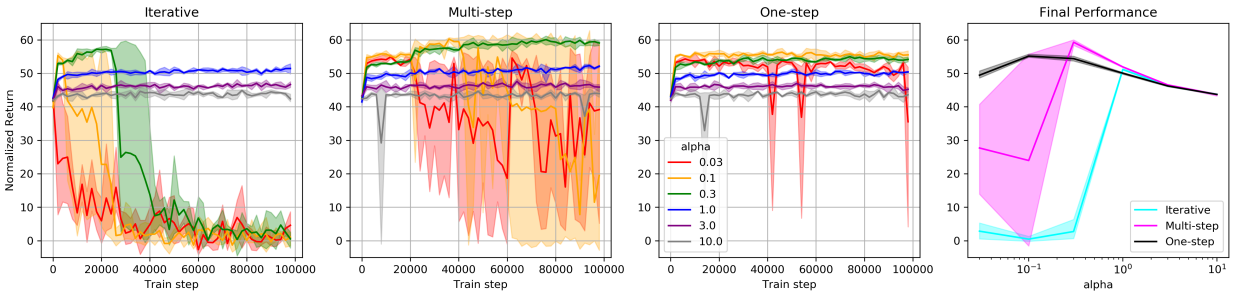


Figure 7.2: Learning curves and final performance on halfcheetah-medium across different algorithms and regularization hyperparameters. Error bars show min and max over 3 seeds. Similar figures for other datasets from D4RL can be found in Appendix **??**.

{fig:learning_curves}

In contrast, the one-step algorithm is more robust to the regularization hyperparameter. The rightmost panel of the figure shows this clearly. While iterative and multi-step algorithms can have their performance degrade very rapidly with the wrong setting of the hyperparameter, the one-step approach is more stable. Moreover, we usually find that the optimal setting of the regularization hyperparameter is lower for the one-step algorithm than the iterative or multi-step approaches.

7.6.2 Distribution shift

Any algorithm that relies on off-policy evaluation will struggle with distribution shift in the evaluation step. Trying to evaluate a policy that is substantially different from the behavior reduces

the effective sample size and increases the variance of the estimates. Explicitly, by distribution shift we mean the shift between the behavior distribution (the distribution over state-action pairs in the dataset) and the evaluation distribution (the distribution that would be induced by the policy π we want to evaluate).

Prior work. There is a substantial body of prior theoretical work that suggests that off-policy evaluation can be difficult and this difficulty scales with some measure of distribution shift. Wang et al. [2020a]; Amortila et al. [2020]; Zanette [2021] give exponential (in horizon) lower bounds on sample complexity in the linear setting even with good feature representations that can represent the desired Q function and assuming good data coverage. Upper bounds generally require very strong assumptions on both the representation and limits on the distribution shift [Wang et al. 2021; Duan et al. 2020; Chen and Jiang 2019]. Moreover, the assumed bounds on distribution shift can be exponential in horizon in the worst case. On the empirical side, Wang et al. [2021] demonstrates issues with distribution shift when learning from pre-trained features and provides a nice discussion of why distribution shift causes error amplification. Fujimoto et al. [2018b] raises a similar issue under the name "extrapolation error". Regularization and constraints are meant to reduce issues stemming from distribution shift, but also reduce the potential for improvement over the behavior.

Empirical evidence. Both the multi-step and iterative algorithms in our experiments rely on off-policy evaluation as a key subroutine. We examine how easy it is to evaluate the policies encountered along the learning trajectory. To control for issues of iterative error exploitation (discussed in the next subsection), we train Q estimators from scratch on a heldout evaluation dataset sampled from the behavior policy. We then evaluate these trained Q function on rollouts from 1000 datapoints sampled from the replay buffer. Results are shown in Figure 7.3.

The results show a correlation betweed KL and MSE. Moreover, we see that the MSE generally increases over training. One way to mitigate this, as seen in the figure, is to use a large value of

α. We just cannot take a very large step before running into problems with distribution shift. But, when we take such a small step, the information from the on-policy $\widehat{Q}^{\beta}$ is about as useful as the newly estimated $\widehat{Q}^{\pi}$. This is seen, for example, in Figure 7.2 where we get very similar performance across algorithms at high levels of regularization.

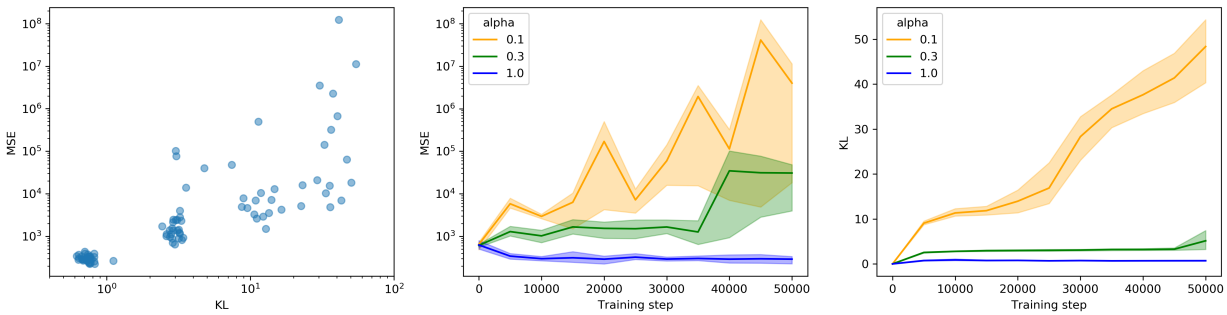


Figure 7.3: Results of running the iterative algorithm on halfcheetah-medium. Each checkpointed policy is evaluated by a Q function trained from scratch on heldout data. MSE refers to $\mathbb{E}_{s,a\sim\beta}[\hat{Q}^{\pi_i}(s,a) - Q^{\pi_i}(s,a)]$ and KL refers to $\mathbb{E}_{s\sim\beta}[KL(\pi(\cdot|s)\|\beta(\cdot|s)]$. Left: 90 policies taken from various points in training with various hyperaparmeters and random seeds. Center: MSE learning curves. Right: KL learning curves. Error bars show min and max over 3 random seeds. {fig:mse}

7.6.3 Iterative error exploitation

The previous subsection identifies how any algorithm that uses off-policy evaluation is fundamentally limited by distribution shift, even if we were given fresh data and trained Q functions from scratch at every iteration. But, in practice, iterative algorithms repeatedly iterate between optimizing policies against estimated Q functions and re-estimating the Q functions using the *same data* and using the Q function from the previous step to warm-start the re-estimation. This induces dependence between steps that causes a problem that we call iterative error exploitation.

Intuition about the problem. In short, iterative error exploitation happens because π_i tends to choose overestimated actions in the policy improvement step, and then this overestimation propagates via dynamic programming in the policy evaluation step. To illustrate this issue more

formally, consider the following: at each s, a we suffer some Bellman error $\varepsilon_\beta^\pi(s,a)$ based on our fixed dataset collected by β. Formally,

$$\widehat{Q}^\pi(s,a) = r(s,a) + \gamma \mathop{\mathbb{E}}_{\substack{s'|s,a \\ a'\sim\pi|s'}} [\widehat{Q}^\pi(s',a')] + \varepsilon_\beta^\pi(s,a). \tag{7.6}$$

Intuitively, ε_β^π will be larger at state-actions with less coverage in the dataset collected by β. Note that ε_β^π can absorb all noise due to our finite dataset as well as function approximation error.

All that is needed to cause iterative error exploitation is that the ϵ_β^π are highly correlated across different π, but for simplicity, we will assume that ε_β^π is *the same* for all policies π estimated from our fixed offline dataset and instead write ε_β. Now that the errors do not depend on the policy we can treat the errors as auxiliary rewards that obscure the true rewards and see that

$$\widehat{Q}^\pi(s,a) = Q^\pi(s,a) + \widetilde{Q}_\beta^\pi(s,a), \qquad \widetilde{Q}_\beta^\pi(s,a) := \mathop{\mathbb{E}}_{\pi|s_0,a_0=s,a}\left[\sum_{t=0}^{\infty} \gamma^t \varepsilon_\beta(s_t,a_t)\right]. \tag{7.7}$$

This assumption is somewhat reasonable since we expect the error to primarily depend on the data. And, when the prior Q function is used to warm-start the current one (as is generally the case in practice), the approximation errors are automatically passed between steps.

Now we can explain the problem. Recall that under our assumption the ε_β are fixed once we have a dataset and likely to have larger magnitude the further we go from the support of the dataset. So, with each step π_i is able to better maximize ε_β, thus moving further from β and increasing the magnitude of $\widetilde{Q}_\beta^{\pi_i}$ relative to Q^{π_i}. Even though Q^{π_i} may provide better signal than Q^β, it can easily be drowned out by $\widetilde{Q}_\beta^{\pi_i}$. In contrast, $\widetilde{Q}_\beta^\beta$ has small magnitude, so the one-step algorithm is robust to errors[17].

An example. Now we consider a simple gridworld example to illustrate iterative error exploitation. This example fits exactly into the setup outlined above since all errors are due to reward estimation so the ε_β is indeed constant over all π. The gridworld we consider has one determin-

istic good state with reward 1 and many stochastic bad states that have rewards distributed as $\mathcal{N}(-0.5, 1)$. We collect a dataset of 100 trajectories, each of length 100. One run of the multi-step offline regularized policy iteration algorithm is illustrated in Figure 7.4.

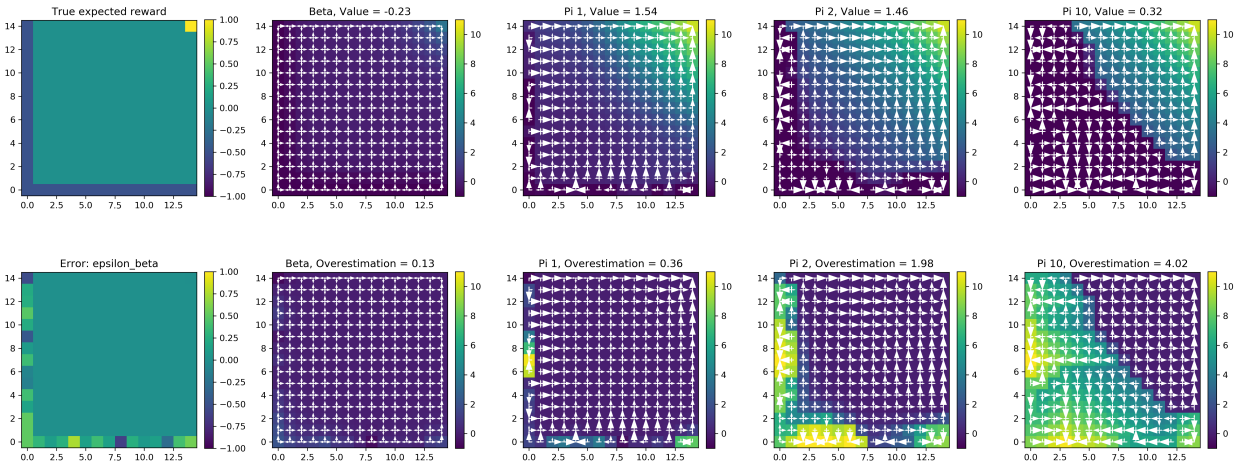


Figure 7.4: An illustration of multi-step offline regularized policy iteration. The leftmost panel in each row shows the true reward (top) or error ε_β (bottom). Then each subsequent panel plots π_i (with arrow size proportional to $\pi_i(a|s)$) over either Q^{π_i} (top) or $\widetilde{Q}^{\pi}_{\beta}$ (bottom), averaged over actions at each state. The one-step policy (π_1) has the highest value. The behavior policy here is a mixture of optimal π^* and uniform u with coefficient 0.2 so that $\beta = 0.2 \cdot \pi^* + 0.8 \cdot u$. We set $\alpha = 0.1$ as the regularization parameter for reverse KL regularization.

{fig:gridworld}

In the example, like in the D4RL benchmark, we see that one step outperforms multiple steps of improvement. Intuitively, when there are so many noisy states, it is likely that a few of them will be overestimated. Since the data is re-used for each step, these overestimations persist and propagate across the state space due to iterative error exploitation. This property of having many bad, but poorly estimated states likely also exists in the high-dimensional control problems encountered in the benchmark where there are many ways for the robots to fall down that are not observed in the data for non-random behavior. Moreover, both settings have larger errors in areas where we have less data. So even though the errors in the gridworld are caused by noise in the rewards, while errors in D4RL are caused by function approximation, we think this is a useful mental model of the problem.

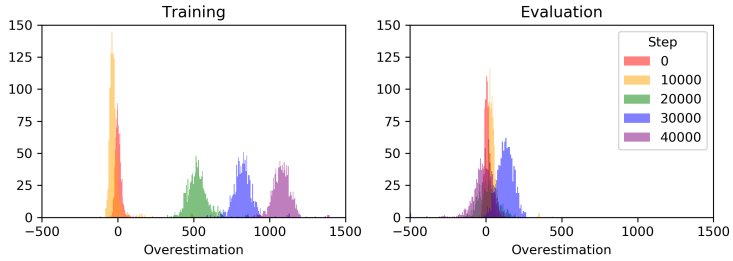


Figure 7.5: Histograms of overestimation error ($\widehat{Q}^{\pi_i}(s,a) - Q^{\pi_i}(s,a)$) on halfcheetah-medium with the iterative algorithm. Left: errors from the training Q function. Right: errors from an independently trained Q function. {fig:over}

Empirical evidence. In practice we cannot easily visualize the progression of errors. However, the dependence between steps still arises as overestimation of the Q values. We can track the overestimation of the Q values over training as a way to measure how much bias is being induced by optimizing against our dependent Q estimators. As a control we can also train Q estimators from scratch on independently sampled evaluation data. These independently trained Q functions do not have the same overestimation bias even though the squared error does tend to increase as the policy moves further from the behavior (as seen in Figure 7.3). Explicitly, we track 1000 state, action pairs from the replay buffer over training. For each checkpointed policy we perform 3 rollouts at each state to get an estimate of the true Q value and compare this to the estimated Q value. Results are shown in Figure 7.5.

7.7 When are multiple steps useful? {sec:when}

So far we have focused on why the one-step algorithm often works better than the multi-step and iterative algorithms. However, we do not want to give the impression that one-step is always better. Indeed, our own experiments in Section 7.5 show a clear advantage for the multi-step and iterative approaches when we have randomly collected data. While we cannot offer a precise delineation of when one-step will outperform multi-step, in this section we offer some intuition as to when we can expect to see benefits from multiple steps of policy improvement.

As seen in Section 7.6, multi-step and iterative algorithms have problems when they propagate estimation errors. This is especially problematic in noisy and/or high dimensional environments. While the multi-step algorithms propagate this noise more widely than the one-step algorithm, they also propagate the signal. So, when we have sufficient coverage to reduce the magnitude of the noise, this increased propagation of signal can be beneficial. The D4RL experiments suggest that we are usually on the side of the tradeoff where the errors are large enough to make one-step preferable.

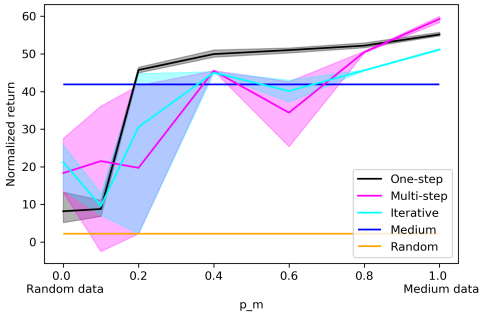


Figure 7.6: Performance of all three algorithms with reverse KL regularization across mixtures between halfcheetah-random and halfcheetah-medium. Error bars indicate min and max over 3 seeds.

{fig:interp}

In Appendix **??** we illustrate a simple gridworld example where a slight modification of the behavior policy from Figure 7.4 makes multi-step dramatically outperform one-step. This modified behavior policy (1) has better coverage of the noisy states (which reduces error, helping multi-step), and (2) does a worse job propagating the reward from the good state (hurting one-step).

We can also test empirically how the behavior policy effects the tradeoff between error and signal propagation. To do this we construct a simple experiment where we mix data from the random behavior policy with data from the medium behavior policy. Explicitly we construct a dataset D out of the datasets D_r for random and D_m for medium such that each trajectory in D comes from the medium dataset with probability p_m. So for $p_m = 0$ we have the random dataset and $p_m = 1$ we have the medium dataset, and in between we have various mixtures. Results are shown in Figure 7.6. It takes surprisingly little data from the medium policy for one-step to

outperform the iterative algorithm.

7.8 Discussion, limitations, and future work

This paper presents the surprising effectiveness of a simple one-step baseline for offline RL. We examine the failure modes of iterative algorithms and the conditions where we might expect them to outperform the simple one-step baseline. This provides guidance to a practitioner that the simple one-step baseline is a good place to start when approaching an offline RL problem.

But, we leave many questions unanswered. One main limitation is that we lack a clear theoretical characterization of which environments and behaviors can guarantee that one-step outperforms multi-step or visa versa. Such results will likely require strong assumptions, but could provide useful insight. We don't expect this to be easy as it requires understanding policy iteration which has been notoriously difficult to analyze, often converging much faster than the theory would suggest [Sutton and Barto 2018; Agarwal et al. 2019]. Another limitation is that while only using one step is perhaps the simplest way to avoid the problems of off-policy evaluation, there are possibly other more elaborate algorithmic solutions that we did not consider here. However, our strong empirical results suggest that the one-step algorithm is at least a strong baseline.

add appendices

Notes

17. We should note that iterative error exploitation is similar to the overestimation addressed by double Q learning [Van Hasselt et al. 2016; Fujimoto et al. 2018c], but distinct. Since we are in the offline setting, the errors due to our finite dataset can be iteratively exploited more and more, while in the online setting considered by double Q learning, fresh data prevents this issue. We are also considering an algorithm based on policy iteration rather than value iteration.

8 Conclusion

{sec:conclusion}

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