QXplore: Q-learning Exploration by Maximizing Temporal Difference Error

Riley Simmons-Edler∗
Department of Computer Science
Princeton University
Princeton, NJ, 08540
rileys@cs.princeton.edu

Ben Eisner
Samsung AI Center New York
New York, NY, 10011
ben.eisner@samsung.com

Eric Mitchell
Samsung AI Center New York
New York, NY, 10011
eric.m1@samsung.com

Sebastian Seung
Samsung AI Center New York
New York, NY, 10011
s.seung@samsung.com

Daniel Lee
Samsung AI Center New York
New York, NY, 10011
daniel.d.lee@samsung.com

Abstract

A major challenge in reinforcement learning for continuous state-action spaces is exploration, especially when reward landscapes are very sparse. Several recent methods provide an intrinsic motivation to explore by directly encouraging RL agents to seek novel states. A potential disadvantage of pure state novelty-seeking behavior is that unknown states are treated equally regardless of their potential for future reward. In this paper, we propose that the temporal difference error of predicting primary reward can serve as a secondary reward signal for exploration. This leads to novelty-seeking in the absence of primary reward, and at the same time accelerates exploration of reward-rich regions in sparse (but nonzero) reward landscapes compared to state novelty-seeking. This objective draws inspiration from dopaminergic pathways in the brain that influence animal behavior. We implement this idea with an adversarial method in which $Q$ and $Q_x$ are the action-value functions for primary and secondary rewards, respectively. Secondary reward is given by the absolute value of the TD-error of $Q$. Training is off-policy, based on a replay buffer containing a mixture of trajectories induced by $Q$ and $Q_x$. We characterize performance on a suite of continuous control benchmark tasks against recent state of the art exploration methods and demonstrate comparable or better performance on all tasks, with much faster convergence for $Q$.

1 Introduction

Deep reinforcement learning (RL) has recently achieved impressive results across several challenging domains, such as playing games [1–3] and controlling robots [4, 5]. In many of these tasks, a well-shaped reward function is used to assist in learning good policies. On the other hand, deep RL still remains challenging for tasks where the reward function is very sparse. In these settings,
state-of-the-art RL methods often perform poorly and train very slowly, if at all, due to the low probability of observing improved rewards by following the current optimal policy or with a naive exploration policy such as \( \epsilon \)-greedy sampling.

The challenge of learning from sparse rewards is typically framed as a problem of *exploration*, inspired by the notion that a successful RL agent must efficiently explore the state space of its environment in order to find improved sources of reward. One common exploration paradigm is to directly determine the novelty of states and to encourage the agent to visit states with the highest novelty. In small, countable state spaces this can be achieved through counting how many times each state has been visited. Direct counting of states is challenging or impossible in high-dimensional or continuous state spaces, but recent work [6–8] using count-like statistics have shown success on benchmark tasks with complex state spaces. Another paradigm for exploration learns a dynamic model of the environment and computes a novelty measure proportional to the error of the model in predicting transitions in the environment. This exploration method relies on the core assumption that well-modeled regions of the state space are similar to previously visited states and thus are less interesting than other regions of state space. Predictions of the transition dynamics can be directly computed [9–12], or related to an information gain objective on the state space, as described in VIME [13] and EMI [14].

Several exploration methods have recently been proposed that capitalize on the function approximation properties of neural networks. Random network distillation (RND) trains a function to predict the output of a randomly-initialized neural network from an input state, and uses the approximation error as a reward bonus for a separately-trained RL agent [15]. Similarly, DORA [16] trains a network to predict zero on observed states and deviations from zero are used to indicate unexplored states. An important shortcoming of existing exploration methods is that they only incorporate information about states and therefore treat all unobserved states the same, regardless of their viability for future reward. This can be problematic in scenarios where there are sparse rewards and successful exploration requires finding unobserved states that actually lead to higher rewards. As a result, current state-based novelty exploration methods can be quite sample inefficient and can require very long training times to achieve good performance [15, 17, 18].

In this paper we propose QXplore, a new exploration formulation that seeks novelty in the predicted reward landscape instead of novelty in the state space. QXplore exploits the inherent reward-space signal from the computation of temporal difference error (TD-error) in value-based RL, and explicitly promotes visiting states where the current understanding of reward dynamics is poor. Our formulation draws inspiration from biological models of dopamine pathways in the brain where levels of dopamine correlate with TD-error in learning trials [19]. Dopamine-seeking behavior has previously been described in animals [20] and serves as a biologically plausible exploration objective in contrast to simple state novelty. In the following sections, we describe QXplore and demonstrate its utility for sample efficient learning on a variety of complex benchmark environments with continuous controls and sparse rewards.

## 2 QXplore: TD-Error as Adversarial Reward Signal

### 2.1 Method Overview

We first provide an overview of the method - a visual representation is depicted in Figure 1. At a high level, QXplore is a Q-Learning method that jointly trains two independent agents equipped with their own Q-functions and reward functions:

1. \( Q \): A standard Q-function, that learns a value function on reward provided by the external environment.

2. \( Q_x \): A Q-function that learns a value function directly on the TD-error of \( Q \).

Together, \( Q \) and \( Q_x \) form an adversarial pair, where a policy \( \pi_{Q_x} \) that samples \( Q_x \) achieves reward when the agent ventures into states whose reward dynamics are foreign to \( Q \) (i.e. \( Q \) under/overestimates reward achieved). Separate replay buffers are maintained for each agent, but each agent receives samples from both buffers at train time.
Figure 1: Method diagram for QXplore. We define two Q-functions, each of which samples trajectories from the environment, which share replay buffer contents. $Q_x$’s reward function is the unsigned temporal difference error of the current $Q$ on data sampled from both replay $Q$ and replay $Q_x$. $\pi_{Q_x}$ is defined by $Q_x$ and maximizes the TD-error of $Q$, while $\pi_Q$ is defined by $Q$ and maximizes reward.

QXplore’s formulation is independent of the Q-learning method used, and is therefore a general exploration technique that can be applied to any Q-learning setting, and can easily be combined with other exploration schemes.

2.2 Preliminaries

We consider RL in the terminology of Sutton and Barto [21], in which an agent seeks to maximize reward in a Markov Decision Process (MDP). An MDP consists of states $s \in S$, actions $a \in A$, a state transition function $S : S \times A \times S \rightarrow [0, 1]$ giving the probability of moving to state $s_{t+1}$ after taking action $a_t$ from state $s_t$ for discrete timesteps $t \in 0, \ldots, T$. Rewards are sampled from reward function $r : S \times A \rightarrow \mathbb{R}$. An RL agent has a policy $\pi(s_t, a_t) = p(a_t | s_t)$ that gives the probability of taking action $a_t$ when in state $s_t$. The agent aims to learn a policy to maximize the expectation of the time-decayed sum of reward $R_\pi(s_0) = \sum_{t=0}^T \gamma^t r(s_t, a_t)$ where $a_t \sim \pi(s_t, a_t)$.

A value function $V_\theta(s_t)$ with parameters $\theta$ is a function which computes $V_\theta(s_t) = r(s_t, a_t) + \gamma \cdot \text{argmax}_{a'} Q_\theta(s_{t+1}, a')$, the expected future reward assuming the optimal action is taken at each future timestep. An approximation to this optimal Q-function $Q_\theta$ with some parameters $\theta$ may be trained using a mean squared TD-error objective $L_{Q_\theta} = \|Q_\theta(s_t, a_t) - (r(s_t, a_t) + \gamma \cdot \text{argmax}_{a'} Q_\theta'(s_{t+1}, a'))\|^2$ given some target Q-function $Q'_\theta$, commonly a time-delayed version of $Q_\theta$ [22]. Extracting a policy $\pi$ given $Q_\theta$ amounts to approximating $\text{argmax}_{a} Q_\theta(s_t, a)$. Many methods exist for approximating the $\text{argmax}_{a}$ operation in both discrete and continuous action spaces [23, 24]. Following the convention of Mnih et al. [1], we train $Q_\theta$ using an off-policy replay buffer of previously visited $(s, a, r, s')$ tuples, which we sample uniformly.

2.3 TD-error objective

First we will describe our TD-error exploration objective. The core concept of using TD-error as part of a reward function was first described as a count-based exploration weighting function in work by Schmidhuber, Thrun, and Moller [25–27]. The operative notion being that, state visitation frequencies being equivalent, it is better to visit states which have high TD-error associated with them to learn more efficiently about the environment. Later, Gehring and Precup used TD-error as
Algorithm 1 QXplore Algorithm

| Algorithm 1 QXplore Algorithm |
|--------------------------------|
| **Input:** MDP S, Q-function $Q_\theta$ with target $Q'_\theta$, $Q_x$ function $Q_{x,\theta}$ with target $Q'_{x,\phi}$, replay buffers $B_Q$ and $B_{Q_x}$, batch size $B$ and sampling ratios $R_Q$ and $R_{Q_x}$, CEM policies $\pi_Q$ and $\pi_{Q_x}$, time decay parameter $\gamma$, soft target update rate $\tau$, and environments $E_Q$, $E_{Q_x}$ |
| while not converged do |
| Reset $E_Q$, $E_{Q_x}$ |
| while $E_Q$ and $E_{Q_x}$ are not done do |
| **Sample environments** |
| $B_Q \leftarrow (s, a, r, s') \sim \pi_Q | E_Q$ |
| $B_{Q_x} \leftarrow (s, a, r, s') \sim \pi_{x} | E_{Q_x}$ |
| **Sample minibatches** |
| $(s_Q, a_Q, r_Q, s'_Q) \leftarrow B \ast R_Q \text{ elements from } B_Q \text{ and } B \ast (1 - R_Q) \text{ from } B_Q$ |
| $(s_{Q_x}, a_{Q_x}, r_{Q_x}, s'_{Q_x}) \leftarrow B \ast R_{Q_x} \text{ elements from } B_{Q_x} \text{ and } B \ast (1 - R_{Q_x}) \text{ from } B_Q$ |
| **Train** |
| $r_x \leftarrow |Q_{\theta}(s_{Q_x}, a_{Q_x}) - (r_{Q_x} + \gamma Q'_\theta(s'_{Q_x}, \pi_Q(s'_{Q_x})))||$ |
| $L_Q \leftarrow ||Q_{\theta}(s_{Q_x}, a_{Q_x}) - (r_{Q_x} + \gamma Q'_\theta(s'_{Q_x}, \pi_Q(s'_{Q_x})))||^2$ |
| $L_{Q_x} \leftarrow ||Q_{x,\phi}(s_{Q_x}, a_{Q_x}) - (r_x + \gamma Q'_{x,\phi}(s'_{Q_x}, \pi_{Q_x}(s'_{Q_x})))||^2$ |
| Update $\theta \propto L_Q$ |
| Update $\phi \propto L_{Q_x}$ |
| $\theta' \leftarrow (1 - \tau)\theta + \tau \phi$ |
| $\phi' \leftarrow (1 - \tau)\phi + \tau \phi$ |
| end while |
| end while |

...a negative signal to constrain exploration to focus on states that are well understood by the value function to avoid common failure modes [28].

In contrast to these previous works, we treat TD-error as a reward signal and use a Q-function trained on this signal to imply an exploration policy directly, rather than as a supplementary objective or to compute a confidence bound. Crucially, when combined with neural network function approximators, this signal provides meaningful exploration information everywhere as discussed in Section 2.5. For a given value function with parameters $\theta$, and TD-error $\delta$, we define our exploration reward function as

$$r_{x,\theta}(s_t, a_t, s_{t+1}) = |\delta_t| = |Q_\theta(s_t, a_t) - (r_E(s_t, a_t) + \gamma \max_{a'}Q'_{\theta'}(s_{t+1}, a'))|$$

(2)

for some extrinsic reward function $r_E$ and target Q-function $Q'_\theta$. Notably, we use the absolute value of the temporal difference, rather than the squared error used to compute updates for $Q_\theta$ to keep the magnitudes of $r_E$ and $r_x$ comparable and reduce the influence of outlier temporal differences on the gradients of $Q_x$, which we describe below.

Intuitively, a policy maximizing the expected sum of $r_x$ will sample trajectories where $Q_\theta$ does not have a good estimate of the future rewards it will experience. This is useful for exploration because $r_x$ will be large not only for state-action pairs producing unexpected reward, but for all state-action pairs leading to such states. In addition, a policy maximizing TD error can be seen as an adversarial teacher for training $Q_\theta$. Further, TD-error-based exploration with a dedicated exploration policy removes the exploitation-versus-exploration tradeoff that state-novelty methods must contend with, as maximizing TD-error will definitively produce trajectories that provide information about the task for $Q_\theta$ to train on.

2.4 $Q_x$: Learning an adversarial Q-function to maximize TD-error

Next, we will describe how we use the TD-error signal defined in Section 2.3 to define an exploration policy. $r_x$ itself is a generic reward objective, which can be combined with many RL algorithms, but given its derivation from a Q-function trained off-policy via bootstrapped target function training a second Q-function to maximize $r_x$ allows the entire algorithm to be trained off-policy with a replay buffer shared between $Q_\theta$ and the Q-function maximizing $r_x$, which we term $Q_x$. This approach is beneficial for exploration, as trajectories producing improved reward may be sampled only very rarely, and a shared replay buffer improves data efficiency for training both Q-functions. Extensions using
on-policy training with actor-critic methods \cite{29} and/or substituting $Q_\theta(s, a)$ for a value function $V_\theta(s)$ are also possible, though we do not explore them here.

We define a Q-function, $Q_{x, \phi}(s, a)$ with parameters $\phi$, whose reward objective is $r_x$. We train $Q_{x, \phi}$ using the standard bootstrapped loss function

$$L_{Q_x, \phi} = \left| Q_{x, \phi}(s_t, a_t) - (r_x(s_t, a_t, s_{t+1}) + \gamma \max_{a'} Q'_{x, \phi}(s_{t+1}, a')) \right|^2$$

(3)

The two Q-functions, $Q_\theta$ and $Q_x$, are trained off-policy in parallel, sharing replay data so that $Q_\theta$ can train on sources of reward discovered by $Q_x$ and so that $Q_x$ can better predict the TD-errors of $Q_\theta$. Since the two share data, $Q_x$ acts as an adversarial teacher for $Q_\theta$, sampling trajectories that produce high TD-error under $Q_\theta$ and thus provide novel information about the reward landscape. To avoid off-policy divergence issues due to the two Q-functions’ different reward objectives, we perform rollouts of both Q-functions in parallel, using a cross-entropy method policy inspired by Kalashnikov et al. \cite{5}, and sample a fixed ratio of experiences collected by each policy for each training batch. We find that the ratio of training experiences collected by each policy was critical for stable training, as described in Section 3.3. Our full method is shown in Figure 1 and pseudocode in Algorithm 1.

2.5 State Novelty from Neural Network Function Approximation Error

A key question in using TD-error for exploration is: What happens when the reward landscape is flat? Theoretically, in the case that $\forall (s, a), r(s, a) = C$ for some constant $C \in \mathbb{R}$, an optimal Q-function which generalizes perfectly to unseen states will, in the infinite time horizon case, simply output $\forall (s, a), Q^*(s, a) = \sum_{t=0}^{\infty} C\gamma^t$. This results in a TD-error of 0 everywhere and thus no exploration signal. However, using neural network function approximation, we find that perfect generalization to unseen states-action pairs does not occur, and in fact observe in Figure 2 that the distance of a new datapoint from the training data manifold correlates with the magnitude of the network output’s deviation from $\sum_{t=1}^{\infty} C\gamma^t$ and thus with TD-error. As a result, in the case where the reward landscape is flat TD-error exploration converges to a form of state novelty exploration. This property of neural network function approximation has been used by several previous exploration methods to good effect, including RND \cite{15} and DORA \cite{16}.

![Figure 2](image_url)

Figure 2: Predictions of 3-layer MLPs of 256 hidden units per layer trained to imitate $f(x) = 0$ on $\mathbb{R} \rightarrow \mathbb{R}$ with training data sampled uniformly from the range $[-0.75, -0.25] \cup [0.25, 0.75]$ (the dark shaded regions in the figure). Each line is the final response curve of an independently trained network once its training error has converged (MSE < 1e-7). The networks consistently fail to either extrapolate outside of the training regions or interpolate between the two training regions.

3 Experiments

We performed a number of experiments to demonstrate the effectiveness of $Q_x$ on continuous control benchmark tasks. We benchmark on five continuous control tasks using the MuJoCo physics
simulator that each require exploration due to sparse rewards. We limit our investigation in this work to continuous control exploration tasks for two reasons. First, the exploration problem is more isolated in such tasks compared to Atari games and other visual tasks, while still remaining highly non-trivial to solve. Second, due to the smaller state observations (length 20 vectors for most tasks) compared to images, state novelty methods have relatively less information to guide exploration, and have been reported to perform worse \[14\], making non-image-based RL tasks a more compelling use-case for $Q_x$, as TD-error prediction should be unaffected by the observation dimensionality.

We first compare with a state of the art state novelty-based method, RND \[15\], as well as $\epsilon$-greedy sampling as a simple baseline. We then present several ablations to QXplore, as well as some analysis of its robustness in response to key hyperparameters.

### 3.1 Experimental Setup

![Figure 3: Illustration of our CheckpointCheetah task versus the SparseHalfCheetah task. CheckpointCheetah receives 1 reward when crossing through each checkpoint for the first time and 0 otherwise, with optimal behaviour similar to the original HalfCheetah task from OpenAI Gym \[30\] (run as fast as you can), while the SparseHalfCheetah task receives 0 reward during any step it is in the goal zone and -1 otherwise.](image)

We describe here the details of our implementation and training parameters. We held these factors constant for both QXplore and RND/$\epsilon$-greedy to enable a fair comparison. We used an off-policy Q-learning method based off of TD3 \[31\] and CGP \[32\] with twin Q-functions and a cross-entropy method policy for better hyperparameter robustness. Each network ($Q_0, Q_x, \phi$, RND’s random and predictor networks) consisted of a 3-layer MLP of 256 neurons per hidden layer, with ReLU non-linearities. We used a batch size of 128 and learning rate of 0.001, and for QXplore sampled training batches for $Q$ and $Q_x$ of 75% self-collected data and 25% data collected by the other Q-function’s policy.

We evaluate on several benchmark tasks. First, the SparseHalfCheetah task originally proposed by VIME \[13\], in which a simulated cheetah receives a reward of 0 if it is at least 5 units forward from the initial position and otherwise receives a reward of -1. Second, we trained on a variant of the halfcheetah task from the OpenAI gym \[30\] that we refer to as CheckpointCheetah, in which reward is 0 except when the cheetah passes through a checkpoint, which are spaced 5 units apart. The simulation step size is larger than in SparseHalfCheetah, making reaching the first checkpoint easier, but the small number of states that provide reward means that state novelty is less efficient at reaching high performance. We illustrate the difference between them in Figure 3.

Finally we benchmark on three OpenAI gym tasks, FetchPush, FetchSlide, and FetchPickAndPlace, originally developed for goal-directed exploration methods such as HER \[18\]. In each of the three the objective is to move a block to a target position, with a reward function returning -1 if the block is not at the target and 0 if it is. We trained each method with 5 random seeds for 500,000 timesteps on cheetah tasks and 1,000,000 timesteps on Fetch tasks (20,000 episodes for the Fetch tasks, 1000 episodes for cheetahs). For consistency, we structured the reward function of the SparseHalfCheetah task to match the Fetch tasks, such that the baseline reward level is -1 while a successful state provides 0 reward.
Figure 4: Performance of QXplore on various benchmarks, compared with RND and $\epsilon$-greedy sampling. Note that due to parallel rollouts of $Q$ and $Q_x$, QXplore samples twice as many trajectories compared to the other methods, but does the same number of training iterations. QXplore performs consistently better due to faster exploration and the separation of exploration and reward maximization objectives.

3.2 Exploration Benchmark Performance

We show the performance of each method on each task in Figure 4. QXplore outperforms RND and $\epsilon$-greedy on both cheetah tasks. This is consistent with our belief that TD-error allows exploration to focus on reward-relevant regions of the state space, leading to faster convergence. QXplore also manages to achieve improved performance in only 20,000 episodes on the Fetch tasks, which took 30,000-50,000 episodes with HER [18], while RND and $\epsilon$-greedy both fail to make progress. While the comparison is not apples-to-apples due to differing baseline methods (TRPO [33] versus Q-Learning), the results reported by EMI on the SparseHalfCheetah task for both their method and EX2 [8] are similar to QXplore’s performance, but require 10 times more iterations [14].

Qualitatively, on SparseHalfCheetah we observe some interesting behaviour from $Q_x$ late in training. After initially converging to obtain reward consistently, $Q_x$ appears to get “bored” during the last 200 episodes and will try to move closer to the 5-unit reward threshold, often jumping back and forth across it during an episode, which results in reduced reward but higher TD-error. This behaviour is distinctive of TD-error seeking over state novelty seeking, as such states are not novel compared to moving further past the threshold but do result in higher TD-error.

3.3 Robustness

As RL tasks are highly heterogeneous, and good parameterization/performance can be hard to obtain in practice for many methods [34], we provide some sweeps over core hyperparameters of QXplore on SparseHalfCheetah to demonstrate some degree of robustness and thus a hope for good behaviour.
on other tasks without extensive parameter tuning. The parameters we consider are the learning rates of Q and Q_x, as well as the ratio of experiences collected using each Q-function used to train each Q-function (self-data versus other-data). We found that while QXplore is fairly sensitive to learning rate, keeping learning rates for Q and Q_x the same works well. We also found that performance is surprisingly invariant to the on/off-policy data ratio, including when Q is trained entirely off-policy on data collected by Q_x, suggesting that the data collected by Q_x is sufficient to train a policy to maximize reward decently well even without directly observing the reward function. Figures and further details can be found in the supplement.

3.4 TD-Error Versus Reward Prediction Error

While Q_x is described for TD-error reward, we ran several tests with γ_Q set to 0 such that Q_θ(s, a) simply predicts r(s, a) for the current step instead of acting as a Q-function, shown in Figure 5. Reward error reward for Q_x still produces the same state novelty fallback behaviour in the absence of reward, but provides less information than TD-errors do and does not allow us to use Q_θ as an optimal Q-function once trained. We tested this variant on SparseHalfCheetah and FetchPush (where Q_x does not consistently find reward but does provide data to train Q), and observe that while Q_x still finds reward in the case of SparseHalfCheetah, it takes consistently longer to converge for all runs, demonstrating that TD-error makes learning easier in sparse reward environments.

4 Discussion and Conclusions

Here, we have described a new source of exploration signal in reinforcement learning, inspired by animal behaviour in response to dopamine signals in the brain which are correlated with TD-error of the value function. We instantiate a reward function using TD-error, and show that when combined with neural network approximation, it is sufficient to discover solutions to challenging exploration tasks in much less time than recent state novelty-based exploration methods. TD-error has different advantages and disadvantages for exploration compared to state prediction, and we hope that our results can spur further work on diverse exploration signals in RL.

It is worth noting that there may be additional benefits provided by Q_x for training Q_θ in non-exploration contexts. Maximizing TD-error can be seen as a form of hard example mining, and for complex tasks could result in better generalization behaviour. In contrast to our work, minimizing TD-error has previously been used to constrain exploration in environments such as helicopter control where the cost of risky behavior can be high [28].

Stochastic reward sources serve as attractors for Q_x, due to unpredictable noise placing a lower bound on TD-error for that state, similar to the "Noisy-TV" problem described for state prediction methods [15]. In adversarial environments, it can prevent exploration depending on the variance of the reward.
relative to the total TD-error. Stochastic policies also introduce some measure of unpredictable noise in the target Q-values, resulting in higher TD-error. Empirically, these factors do not prevent learning for the tasks tested here, and tasks that are adversarial in this way might be uncommon in practice (as highly noisy reward sources are undesirable for practical reasons), but we hope to rectify this issue in future work through variance estimation and \( r_x \) rescaling, or signed TD-error which preserves the mean TD-error at zero.

We emphasize that we have only scratched the surface in terms of TD-error exploration here. Our instantiation makes several assumptions, such as the use of off-policy Q-learning, the use of two sampling policies, and the use of unsigned TD-error which is positive for both under-prediction and over-prediction of future rewards. We experimented briefly with a signed TD-error but more work remains to be done in this direction. In addition, explicitly combining TD-error rewards with extrinsic rewards is also worth investigating, as the two objectives are partially correlated for most tasks.

References

[1] Martin Riedmiller Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Ioannis Antonoglou, Daan Wierstra. Playing Atari with Deep Reinforcement Learning. *IJCAI International Joint Conference on Artificial Intelligence*, 2016. ISSN 10450823. doi: 10.1038/nature14236.

[2] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, Yutian Chen, Timothy Lillicrap, Fan Hu, Laurent Sifre, George van den Driessche, Thore Graepel, and Demis Hassabis. Mastering the game of Go without human knowledge. *Nature*, 2017. ISSN 1476-4687. doi: 10.1038/nature24270.

[3] OpenAI. OpenAI Five Benchmark: Results, 2018. URL https://blog.openai.com/openai-five-benchmark-results/.

[4] OpenAI, Marcin Andrychowicz, Bowen Baker, Maciek Chociej, Rafal Józefowicz, Bob McGrew, Jakub Pachocki, Arthur Petron, Matthias Plappert, Glenn Powell, Alex Ray, Jonas Schneider, Szymon Sidor, Josh Tobin, Peter Welinder, Lilian Weng, and Wojciech Zaremba. Learning Dexterous In-Hand Manipulation. *CoRR*, 2018. URL http://arxiv.org/abs/1808.00177.

[5] Dmitry Kalashnikov, Alex Irpan, Peter Pastor, Julian Ibarz, Alexander Herzog, Eric Jang, Deirdre Quillen, Ethan Holly, Mrinal Kalakrishnan, Vincent Vanhoucke, and Sergey Levine. QT-Opt: Scalable Deep Reinforcement Learning for Vision-Based Robotic Manipulation. In Aude Billard, Anca Dragan, Jan Peters, and Jun Morimoto, editors, *Proceedings of The 2nd Conference on Robot Learning*, volume 87 of *Proceedings of Machine Learning Research*, pages 651–673. PMLR, 2018. ISBN 012492543X. doi: arXiv:1806.10293v2. URL http://arxiv.org/abs/1806.10293.

[6] Haoran Tang, Rein Houthooft, Davis Foote, Adam Stooke, OpenAI Xi Chen, Yan Duan, John Schulman, Filip DeTurck, and Pieter Abbeel. #Exploration: A Study of Count-Based Exploration for Deep Reinforcement Learning. In I Guyon, U V Luxburg, S Bengio, H Wallach, R Fergus, S Vishwanathan, and R Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 2753–2762. Curran Associates, Inc., 2017. URL https://arxiv.org/abs/1611.04717.

[7] Marc Bellemare, Srijan Srinivasan, Georg Ostrovski, Tom Schaul, David Saxton, and Remi Munos. Unifying count-based exploration and intrinsic motivation. In *Advances in Neural Information Processing Systems*, pages 1471–1479, 2016.

[8] Justin Fu, John Co-Reyes, and Sergey Levine. EX2: Exploration with Exemplar Models for Deep Reinforcement Learning. In I Guyon, U V Luxburg, S Bengio, H Wallach, R Fergus, S Vishwanathan, and R Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 2577–2587. Curran Associates, Inc., 2017. URL https://arxiv.org/abs/1703.01260.

[9] Deepak Pathak, Pulkit Agrawal, Alexei A. Efros, and Trevor Darrell. Curiosity-Driven Exploration by Self-Supervised Prediction. In *IEEE Computer Society Conference on
[10] Bradly C Stadie, Sergey Levine, and Pieter Abbeel. Incentivizing Exploration In Reinforcement Learning With Deep Predictive Models. CoRR, abs/1507.0, 2015.

[11] Nikolay Savinov, Anton Raichuk, Damien Vincent, Raphael Marinier, Marc Pollefeys, Timothy Lillicrap, and Sylvain Gelly. Episodic Curiosity through Reachability, 2019. URL https://openreview.net/forum?id=SkeK3s0qKQ.

[12] Yuri Burda, Harri Edwards, Deepak Pathak, Amos Storkey, Trevor Darrell, and Alexei A Efros. Large-Scale Study of Curiosity-Driven Learning. In International Conference on Learning Representations, 2019. URL https://openreview.net/forum?id=rJNwDjAqYX.

[13] Rein Houthooft, Xi Chen, Xi Chen, Yan Duan, John Schulman, Filip De Turck, and Pieter Abbeel. VIME: Variational Information Maximizing Exploration. In D D Lee, M Sugiyama, U V Luxburg, I Guyon, and R Garnett, editors, Advances in Neural Information Processing Systems 29, pages 1109–1117. Curran Associates, Inc., 2016. URL http://papers.nips.cc/paper/6591-vime-variational-information-maximizing-exploration.pdf.

[14] Hyoungseok Kim, Jaekyeom Kim, Yeonwoo Jeong, Sergey Levine, and Hyun Oh Song. EMI: Exploration with Mutual Information, 2018.

[15] Yuri Burda, Harrison Edwards, Amos Storkey, and Oleg Klimov. Exploration by random network distillation. In International Conference on Learning Representations, 2019. URL https://openreview.net/forum?id=H1JJnR5Ym.

[16] Lior Fox, Leshem Choshen, and Yonatan Loewenstein. {DORA} The Explorer: Directed Outreach Reinforcement Action-Selection. In International Conference on Learning Representations, 2018. URL https://openreview.net/forum?id=rylar0gCw.

[17] Adrien Ecoffet, Joost Huizinga, Joel Lehman, Kenneth O Stanley, and Jeff Clune. Go-Explore: a New Approach for Hard-Exploration Problems, 2019.

[18] Marcin Andrychowicz, Filip Wolski, Alex Ray, Jonas Schneider, Rachel Fong, Peter Welinder, Bob McGrew, Josh Tobin, OpenAI Pieter Abbeel, and Wojciech Zaremba. Hindsight Experience Replay. In I Guyon, U V Luxburg, S Bengio, H Wallach, R Fergus, S Vishwanathan, and R Garnett, editors, Advances in Neural Information Processing Systems 30, pages 5048–5058. Curran Associates, Inc., 2017. URL http://papers.nips.cc/paper/7090-hindsight-experience-replay.pdf.

[19] Yael Niv, Michael O Duff, and Peter Dayan. Dopamine, uncertainty and TD learning. Behavioral and brain functions : BBF, 1:6, may 2005. ISSN 1744-9081. doi: 10.1186/1744-9081-1-6. URL https://www.ncbi.nlm.nih.gov/pubmed/15953384https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1171969/.

[20] Óscar Arias-Carrión and Ernst Pöppel. Dopamine, learning, and reward-seeking behavior. Acta neurobiologicae experimentalis, 2007.

[21] Richard S Sutton and Andrew G Barto. Reinforcement Learning: An Introduction. (IEEE) Trans. Neural Networks, 9(5):1054, 1998. doi: 10.1109/TNN.1998.712192. URL https://doi.org/10.1109/TNN.1998.712192.

[22] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, Stig Petersen, Charles Beattie, Amir Sadik, Ioannis Antonoglou, Helen King, Dharnesh Kurman, Daan Wierstra, Shane Legg, and Demis Hassabis. Human-level control through deep reinforcement learning. Nature, 518(7540):529–33, 2015. ISSN 1476-4687. doi: 10.1038/nature14236. URL http://www.ncbi.nlm.nih.gov/pubmed/25719670.

[23] Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning: Deep Deterministic Policy Gradients (DDPG). ICLR, 2015.
[24] Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor. In Jennifer Dy and Andreas Krause, editors, Proceedings of the 35th International Conference on Machine Learning, volume 80 of Proceedings of Machine Learning Research, pages 1861–1870, Stockholmsmässan, Stockholm Sweden, 2018. PMLR. URL https://proceedings.mlr.press/v80/haarnoja18b.html.

[25] Jürgen Schmidhuber. Adaptive confidence and adaptive curiosity. In Institut fur Informatik, Technische Universitat Munchen, Arcisstr. 21, 800 Munchen 2. Citeseer, 1991.

[26] Sebastian B Thrun and Knut Möller. On planning and exploration in non-discrete environments. GMD Sankt Augustin, Germany, 1991.

[27] Sebastian B Thrun and Knut Möller. Active exploration in dynamic environments. In Advances in neural information processing systems, pages 531–538, 1992.

[28] Clement Gehring and Doina Precup. Smart Exploration in Reinforcement Learning using Absolute Temporal Difference Errors. In Autonomous Agents and Multiagent Systems (AAMAS), 2013. ISBN 978-1-4503-1993-5.

[29] Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous Methods for Deep Reinforcement Learning. In Maria Florina Balcan and Kilian Q Weinberger, editors, Proceedings of The 33rd International Conference on Machine Learning, volume 48 of Proceedings of Machine Learning Research, pages 1928–1937, New York, New York, USA, 2016. PMLR. URL http://proceedings.mlr.press/v48/mniha16.html.

[30] Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. OpenAI Gym, 2016.

[31] Scott Fujimoto, Herke van Hoof, and David Meger. Addressing Function Approximation Error in Actor-Critic Methods. In Jennifer Dy and Andreas Krause, editors, Proceedings of the 35th International Conference on Machine Learning, volume 80 of Proceedings of Machine Learning Research, pages 1587–1596, Stockholmsmässan, Stockholm Sweden, 2018. PMLR. URL http://proceedings.mlr.press/v80/fujimoto18a.html.

[32] Riley Simmons-Edler, Ben Eisner, Eric Mitchell, Sebastian Seung, and Daniel Lee. Q-learning for continuous actions with cross-entropy guided policies. arXiv preprint arXiv:1903.10605, 2019.

[33] John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. Trust region policy optimization. In International Conference on Machine Learning, pages 1889–1897, 2015.

[34] Peter Henderson, Riashat Islam, Philip Bachman, Joelle Pineau, Doina Precup, and David Meger. Deep reinforcement learning that matters. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018.
Table 1: Parameters used for benchmark runs.

| DEFAULT PARAMETERS                                      |
|----------------------------------------------------------|
| CEM                                                      |
| ITERATIONS                                              | 4 |
| NUMBER OF SAMPLES                                       | 64 |
| TOP K                                                   | 6 |
| ALL NETWORKS                                             |
| NEURONS PER LAYER                                       | 256 |
| NUMBER OF LAYERS                                        | 3 |
| NON-LINEARITIES                                         | ReLU |
| OPTIMIZER                                               | ADAM |
| ADAM MOMENTUM TERMS                                     | $\beta_1 = 0.9, \beta_2 = 0.99$ |
| TRAINING                                                |
| Q LEARNING RATE                                          | 0.001 |
| BATCH SIZE                                              | 128 |
| TIME DECAY $\gamma$                                     | 0.99 |
| TARGET Q-FUNCTION UPDATE $\tau$                        | 0.005 |
| TARGET UPDATE FREQUENCY                                 | 2 |
| TD3 POLICY NOISE                                        | 0.2 |
| TD3 NOISE CLIP                                          | 0.5 |
| TRAINING STEPS PER ENV Timestep                         | 1 |
| QXPLORE-SPECIFIC                                        |
| $Q_x$ LEARNING RATE                                      | 0.001 |
| $Q$ BATCH DATA RATIO                                    | 0.75 |
| $Q_x$ BATCH DATA RATIO                                   | 0.75 |
| RND-SPECIFIC                                             |
|predictor network learning rate                          | 0.001 |
| $\epsilon$-GREEDY-SPECIFIC                              | 0.1 |

Appendix A: Hyperparameters

We present the parameters we used for the benchmark tasks in Table 1.

Appendix B: Parameter Sweeps

We performed two sets of parameter sweeps for QXplore: varying the learning rates of $Q$ and $Q_x$, and varying the ratios of data sampled by each Q-function’s policy used in training batches for each method. For learning rate, we tested combinations $(QLR, QxLR)$ (0.01, 0.01), (0.01, 0.001), (0.001, 0.01), (0.001, 0.001), (0.001, 0.0001), (0.0001, 0.001), (0.0001, 0.0001).

For batch data ratios, we tested combinations (specified as self-fraction for $Q$, then self-fraction for $Q_x$) of (0, 1), (0.25, 0.75), (0.5, 0.5), (0.75, 0.25).

Results for these sweeps can be seen in Figures 6 and 7. QXplore is sensitive to learning rate, but relatively robust to the training data mix, to the point of $Q$ training strictly off-policy with only modest performance loss.

Appendix C: Unsuccessful Tasks

As part of our experiments, we attempted to train QXplore (and competing methods) on two extra tasks: FetchSlide-v1 and SwimmerGather-v1. We were unable to get any of the methods to train on them, but we believe this is because we trained for many fewer iterations and episodes than reported in previous work, and our lack of performance is consistent with other results at that time scale. See Figure 8.
Figure 6: Learning rate sweeps for $Q$ and $Q_x$.

Figure 7: Sample ratio sweeps for $Q$ and $Q_x$.

Figure 8: Tasks which we attempted on which no method trained successfully.