Beyond Tabula Rasa: Reincarnating
Reinforcement Learning

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Abstract
Learning tabula rasa, that is without any prior knowledge, is the prevalent workflow in reinforcement learning (RL) research. However, RL systems, when applied to large-scale settings, rarely operate tabula rasa. Such large-scale systems undergo multiple design or algorithmic changes during their development cycle and use ad hoc approaches for incorporating these changes without re-training from scratch, which would have been prohibitively expensive. Additionally, the inefficiency of deep RL typically excludes researchers without access to industrial-scale resources from tackling computationally-demanding problems. To address these issues, we present reincarnating RL as an alternative workflow, where prior computational work (e.g., learned policies) is reused or transferred between design iterations of an RL agent, or from one RL agent to another. As a step towards enabling reincarnating RL from any agent to any other agent, we focus on the specific setting of efficiently transferring an existing sub-optimal policy to a standalone value-based RL agent. We find that existing approaches fail in this setting and propose a simple algorithm to address their limitations. Equipped with this algorithm, we demonstrate reincarnating RL’s gains over tabula rasa RL on Atari 2600 games, a challenging locomotion task, and the real-world problem of navigating stratospheric balloons. Overall, this work argues for an alternate approach to RL research, which we believe could significantly improve real-world RL adoption and help democratize it further.

1 Introduction
Reinforcement learning (RL) is a general-purpose paradigm for making data-driven decisions. Due to this generality, the prevailing trend in RL research is to learn systems that can operate efficiently tabula rasa, that is without much previously learned knowledge about the problem. However, tabula rasa RL systems are typically the exception rather than the norm for solving large-scale RL problems [3, 11, 69, 79]. Such large-scale RL systems often need to function for long periods of time and continually experience new data; restarting them from scratch may require weeks if not months of computation, and there may be billions of data points to re-process – this makes the tabula rasa approach impractical. For example, the system that plays Dota 2 at a superhuman level [11] or the system that manipulates a robot hand for solving Rubik’s cube [3], underwent several months of RL training with continual changes (e.g., in model architecture, environment, etc) during their development; this necessitated building upon the previously trained system after such changes to circumvent re-training from scratch, which was done using ad hoc approaches. Furthermore, tackling challenging problems with deep RL often incurs substantial computational and financial cost: AlphaStar [79], which achieves grandmaster level in StarCraft, was trained using TPUs for more than a month and replicating it would cost several million dollars2. As a result, the majority of the RL community outside certain resource-rich labs is currently excluded from tackling such problems.

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2See Appendix A.1 for an estimate based on publicly available information.
Figure 1: A reincarnating RL workflow on ALE. The plots show Interquartile mean (IQM) [2] normalized scores over training, computed using 50 seeds, aggregated across 10 Atari games. The two vertical separators correspond to loading network weights and replay buffer for fine-tuning while offline pre-training on replay buffer using QDagger (Section 4.1) for reincarnation. Shaded regions show 95% confidence intervals. We assign a score of 1 to DQN (Adam) trained for 400M frames and 0 to a random agent. (Panel 1) Tabula rasa Nature DQN nearly converges in performance after training for 200M environment frames. (Panel 2) Reincarnation via fine-tuning Nature DQN with a reduced learning rate leads to 50% higher IQM with only 1M additional frames (leftmost point). Furthermore, fine-tuning Nature DQN while switching from RMSProp [34] to Adam [43] matches the performance of DQN (Adam) trained from scratch for 400M frames, using only 20M frames. (Panel 3) A modern ResNet (Impala-CNN [24]) with a better algorithm (Rainbow [32]) matches the performance of DQN (Adam) trained from scratch for 400M frames, using only 20M frames. Impala-CNN Rainbow outperforms tabula rasa Impala-CNN Rainbow throughout training and requires only 50M frames to nearly match its performance at 100M frames.

To address both the computational and sample inefficiencies of tabula rasa RL, we present reincarnation RL as an alternative research workflow. Reincarnating RL focuses on maximally leveraging existing computational work, such as learned network weights and collected data, to accelerate training across design iterations of an RL agent or when moving from one agent to another. In this workflow, agents need not be trained tabula rasa, except for initial forays into new problems. Reincarnating RL can be seen as an attempt to provide a more formal foundation for the prior ad hoc strategies to confront the challenges of large-scale RL model development [e.g., 3, 11].

Reincarnating RL also suggests a different benchmarking paradigm that can democratize RL by allowing the broader community to continually improve and update existing trained agents, and even collaboratively tackle problems that are currently infeasible with tabula rasa RL. For example, imagine a researcher who has trained a deep RL agent \(A_1\) for a long time (e.g., weeks), but now this or another researcher wants to experiment with better algorithms or architectures. While the tabula rasa workflow requires re-training another agent from scratch, reincarnating RL provides the more viable option of transferring \(A_1\) to another agent and training this agent further, or simply fine-tuning \(A_1\) (Figure 1). However, beyond some large-scale reincarnation efforts (Section 3), the research community has not focused much on reincarnating RL, in part due to the prevalence of tabula rasa RL. To this end, this work investigates this setting and its potential for accelerating RL research.

As a step towards developing broadly applicable reincarnation approaches, we focus on the specific setting of policy-to-value reincarnating RL (PVRL) for efficiently transferring a suboptimal teacher policy to a value-based RL student agent (Section 4). Since it is undesirable to maintain dependency on past teachers for successive reincarnations, we require a PVRL algorithm to “wean” off the teacher dependence as training progresses. We find that prior approaches, when evaluated for PVRL on the Arcade Learning Environment (ALE) [8], either result in small improvements over the tabula rasa student or exhibit degradation when weaning off the teacher. To address these limitations, we introduce QDagger, which combines Dagger [65] with \(n\)-step Q-learning, and outperforms prior approaches. Equipped with QDagger, we demonstrate the sample and compute-efficiency gains of reincarnating RL over tabula rasa RL, on ALE and a humanoid locomotion task. Reincarnating RL also makes it easier to make progress on a simulated real-world problem of navigating stratospheric balloons [9] in a computationally feasible manner (Section 5). We also discuss some considerations in reincarnating RL that require further investigation (Section 6). Finally, to improve the benchmarking ecosystem in reincarnating RL, we will open-source our code and trained agents.
2 Preliminaries

The goal in RL is to maximize the long-term discounted reward in an environment. We model the environment as an MDP, defined as \((S, A, R, P, \gamma)\) [63], with a state space \(S\), an action space \(A\), a stochastic reward function \(R(s, a)\), transition dynamics \(P(s' | s, a)\) and a discount factor \(\gamma \in [0, 1)\). A policy \(\pi(\cdot | s)\) maps states to a distribution over actions. The Q-value function \(Q^\pi(s, a)\) for a policy \(\pi(\cdot | s)\) is the expected sum of discounted rewards obtained by executing action \(a\) at state \(s\) and following \(\pi(\cdot | s)\) thereafter. \(Q^\pi(s, a)\) is the fixed point of \(Q(s, a) = R(s, a) + \gamma E_{s' \sim P(\cdot | s, a), \pi(\cdot | s')}[Q(s', \pi(\cdot | s'))]\). DQN [56] builds on Q-learning [81] and parameterizes the Q-value function, \(Q_\theta\), with a neural net with parameters \(\theta\) while following an \(\epsilon\)-greedy policy with respect to \(Q_\theta\) for data collection. DQN minimizes the temporal difference (TD) loss, \(L_{TD}(D_S)\), on transition tuples, \((s, a, r, s')\), sampled from an experience replay buffer \(D_S\) collected during training:

\[
L_{TD}(D) = \mathbb{E}_{s,a,r,s' \sim D} \left[ (Q_\theta(s, a) - r - \gamma \max_{a'} Q_\theta(s', a'))^2 \right] \tag{1}
\]

where \(Q_\theta\) is a delayed copy of the same Q-network, referred to as the target network. Modern value-based RL agents, such as Rainbow [32], use \(n\)-step returns to further stabilize learning. Specifically, rather than training the Q-value estimate \(Q(s_t, a_t)\) on the basis of the single-step temporal difference error \(r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\), an \(n\)-step target \(\sum_{k=0}^{n-1} \gamma^k r_{t+k} + \gamma^n \max_{a'} Q(s_{t+n}, a') - Q(s_t, a_t)\) is used in the TD loss, with intermediate future rewards stored in the replay \(D\).

3 Related work

Large-scale reincarnation efforts. Several high-profile RL achievements employ a limited form of reincarnating RL. OpenAI Five [11], which can play Dota2 at a superhuman level, required 10 months of large-scale RL training and went through continual changes in code and environment (e.g., expanding observation spaces) during development. To avoid restarting from scratch after such changes, OpenAI Five used “surgery” akin to Net2Net [16] style transformations to convert a trained model to certain bigger architectures with custom weight initializations. AlphaStar [79] employs population-based training (PBT) [39], which periodically copies weights of the best performing value-based agents and mutates hyperparameters during training. Although PBT and surgery methods are efficient, they have they can not be used for reincarnating RL when switching to arbitrary architectures (e.g., feed-forward to recurrent networks) or from one model class to another (e.g., policy to a value function). In this work, we focus on reincarnating RL methods that allow such architecture and algorithm changes. Akkaya et al. [3] trained RL policies for several months to manipulate a robot hand for solving Rubik’s cube. To do so, they “rarely trained experiments from scratch” but instead initialized new policies, with architectural changes, from previous trained policies using behavior cloning via on-policy distillation [19, 62]. AlphaGo [69] also used behavior cloning on human replays for initializing the policy and fine-tuning it further with RL. However, behavior cloning is only applicable for policy for policy transfer and is inadequate for the PVRL setting of transferring a policy to a value function [e.g., 58, 77]. Several prior works also fine-tune existing agents with deep RL for reducing training time, especially on real-world tasks such as chip floor-planning [55], robotic manipulation [40], aligning language models [5], and compiler optimization [76]. In line with these works, we find that fine-tuning a value-based agent can be an effective reincarnation strategy (Figure 7). However, fine-tuning is constrained to use the same architecture as the agent being fine-tuned. Instead, we focus on reincarnating RL methods that do not have this limitation.

Leveraging existing agents. Existing policies have been previously used for improving data collection in RL [12, 15, 26, 71, 83]; we evaluate one such recent approach, JSRL [77], which improves exploration in goal-reaching RL tasks. However, our PVRL experiments indicate that JSRL performs poorly on ALE. Closely related to PVRL, Schmitt et al. [68] propose kickstarting to speed-up actor-critic agents using an interactive teacher policy by combining on-policy distillation [19, 62] with RL. Empirically, we find that kickstarting is a strong baseline for PVRL, however it exhibits unstable behavior without \(n\)-step returns and underperforms QDagger. PVRL also falls under the framework of agents teaching agents (ATA) [20] with RL-based students and teachers. While ATA approaches, such as action advice [75], emphasize how and when to query the teacher or evaluating the utility of teacher advice, PVRL focuses on sample-efficient transfer and does not impose constraints on querying the teacher. PVRL is also different from prior work on accelerating RL using a heuristic or oracle value function [7, 18, 72], as PVRL only assumes access to a suboptimal policy. Lee et al. [49] tackle robotic manipulation tasks given a teacher policy and find that training on both the teacher and student collected data, akin to QDagger, enables best performance. However, unlike PVRL methods

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that wean off the teacher, Lee et al. [49] propose methods that are constrained to stay close to the suboptimal teacher, which can limit the student’s performance with continued training (Figure 9).

**Leveraging prior data.** Learning from demonstrations (LfD) [4, 28, 33, 38, 66] approaches focus on accelerating RL training using demonstrations. Such approaches typically assume access to optimal or near-optimal trajectories, often obtained from human demonstrators, and aim to match the demonstrator’s performance. Instead, PVRL focuses on leveraging a suboptimal teacher policy, which can be obtained from any trained RL agent, that we wean off during training. Empirically, we find that DQfD [33], a well-known LfD approach to accelerate deep Q-learning, when applied to PVRL, exhibits severe performance degradation when weaning off the teacher. Rehearsal approaches [57, 61, 70] focus on improving exploration by replaying demonstrations during learning; we find that such approaches are ineffective for leveraging the teacher in PVRL. Offline RL [1, 48, 50] focuses on learning solely from fixed datasets while reincarnating RL focuses on leveraging prior information, which can also be presented as offline datasets, for speeding up further learning from environment interactions. Recent work [45, 49, 52, 58] use offline RL to pretrain on prior data and then fine-tune online. We also evaluate this pretraining approach for PVRL. However, PVRL is more flexible than only using a fixed dataset for pretraining, as it assumes access to an interactive teacher policy.

**Connection to other areas.** Reincarnating RL is complementary to RL sub-fields that focus on acquiring knowledge from a set of tasks to solve related new tasks, such as lifelong RL [42], meta RL [82], RL generalization [44], and transfer [74], as reincarnating RL focuses on changing our research workflow itself to incorporate prior knowledge on a given task. That said, we can also incorporate this workflow within these fields, e.g., investigating lifelong RL given an existing policy. Similar to the spirit of this work, Raffel [64] calls for collaboratively building and continually improving large pre-trained models in NLP and vision.

### 4 Case Study: Policy to Value Reincarnating RL

Reincarnating RL can leverage different ways of representing prior knowledge: logged datasets, learned policies, pretrained models (e.g., value functions, dynamics models), representations, and others. While prior large-scale efforts have used a limited form of reincarnating RL (Section 3), such as transferring one policy to another, it is unclear how to design reincarnation approaches that can be incorporated in any RL research project. To exemplify the challenges of designing such approaches, we focus on policy-to-value reincarnating RL (PVRL) for transferring a suboptimal teacher policy to a value-based student agent to accelerate learning. While we can obtain a policy from any RL agent, we chose this setting because value-based RL methods (Q-learning, actor-critic) can leverage off-policy data for better sample efficiency. The difficulty in PVRL arises from the fact that policies do not estimate discounted returns but only distribution over actions, while value functions do. To be broadly useful for reincarnating agents, a PVRL algorithm should satisfy the following desiderata:

- **Teacher-agnostic.** Reincarnating RL has limited utility if the student is constrained by the teacher’s architecture or learning algorithm. Thus, we require the student to be teacher-agnostic.
- **Weaning.** It is undesirable to maintain dependency on past teachers when reincarnation may occur several times over the course of a project, or one project to another. Thus, it is necessary that the student’s dependence on the teacher policy can be weaned off, as training progresses.
- **Sample-efficient.** Naturally, reincarnating RL is only useful if it is computationally cheaper than training from scratch. Thus, it is desirable that the student can recover and possibly improve upon the teacher’s performance using fewer environment samples than training tabula rasa.

**PVRL on Atari 2600 games.** Given the above desiderata for PVRL, we now empirically investigate whether existing methods that leverage existing data or agents (see Section 3) suffice for PVRL. The specific methods that we consider were chosen because they are simple to implement, and also because they have been designed with closely related goals in mind.

**Experimental setup.** We conduct experiments on ALE with sticky actions [54]. To reduce the computational cost of our experiments, we use a subset of 10 commonly-used Atari 2600 games: Asterix, Breakout, Space Invaders, Seaquest, Q* Bert, Beam Rider, Enduro, Ms Pacman, Bowling and River Raid. We obtain the teacher policy πT by running DQN [56] with Adam optimizer for 400 million environment frames, requiring 7 days of training per run with Dopamine [14] on P100 GPUs. Without loss of generality, we assume access to a dataset D_T that can be generated by the teacher. For this work, D_T corresponds to the final replay buffer (1 million transitions) of the teacher DQN. For a challenging PVRL setting, we use DQN as the student since tabula rasa DQN requires a substantial
amount of training to reach the teacher’s performance. To emphasize sample-efficient reincarnation, we train this student for only 10 million frames, a 40 times smaller sample budget than the teacher. Furthermore, we wean off the teacher at 6 million frames. See Appendix A.4 for more details.

**Evaluation.** For reliable evaluation, we follow the recommendations of Agarwal et al. [2] and report the Interquartile Mean (IQM) normalized scores with 95% bootstrap confidence intervals (CIs), aggregated across 10 Atari games with 3 seeds each. The normalisation is done such that the random policy corresponds to a score of 0 and the teacher policy π is aggregated across 10 million frames. Figure 2 shows the distribution of normalized scores across all 30 runs at the end of training (higher is better). The area under an algorithm’s profile corresponds to its mean performance while y value where the profile intersects y = 0.5 shows its median performance. QDagger stochastically dominates other algorithms and outperforms the teacher in 75% of runs.

![Sample efficiency curves based on IQM normalized scores](image)

**Figure 2:** Comparing PVRL algorithms for reincarnating a student DQN agent given a teacher policy (with normalized score of 1), obtained from a DQN agent trained for 400M frames (Section 4). Tabula rasa 3-step DQN student (--- line) obtains an IQM teacher normalized score around 0.39. Shaded regions show 95% bootstrap CIs. Left. Sample efficiency curves based on IQM normalized scores, aggregated across 10 games and 3 runs, over the course of training. Among all algorithms, only QDagger (Section 4.1) surpasses teacher performance within 10 million frames. Right. Performance profiles [2] showing the distribution of normalized scores across all 30 runs at the end of training (higher is better). The area under an algorithm’s profile corresponds to its mean performance while y value where the profile intersects y = 0.5 shows its median performance. QDagger stochastically dominates other algorithms and outperforms the teacher in 75% of runs.

- **Rehearsal:** Since the student, in principle, can learn using any off-policy data, we can replay teacher data \( D_T \) along with the student’s own interactions during training. Following Paine et al. [61], the student minimizes the TD loss on mini-batches that contain \( \rho \)% of the samples from \( D_T \) and the rest from the student’s replay \( D_S \) (different \( \rho \) and n-step values in Figure A.11).
- **JSRL** (Figure 3, left): JSRL [77] uses an interactive teacher policy as a “guide” to improve exploration and rolls in with the guide for a random number of environment steps. To evaluate JSRL, we vary the maximum number of roll-in steps, \( \alpha \), that can be taken by the teacher and sample a random number of roll-in steps between \([0, \alpha]\) every episode. As the student improves, we decay the steps taken by the teacher every iteration (1M frames) by a factor of \( \beta \).
- **RL Pretraining:** Given access to teacher data \( D_T \), we can pre-train the student using offline RL. To do so, we use CQL [46], a widely used offline RL algorithm, which jointly minimizes the TD and behavior cloning on logged transitions in \( D_T \) (Equation A.3). Following pretraining, we fine-tune the learned Q-network using TD loss on the student’s replay \( D_S \).
- **Kickstarting** (Figure 3, right): Akin to kickstarting [68], we jointly optimize the TD loss with an on-policy distillation loss on the student’s self-collected data in \( D_S \). The distillation loss uses the cross-entropy between teacher’s policy \( \pi_T \) and the student policy \( \pi(\cdot|s) = \text{softmax}(Q(s, \cdot)/\tau) \), where \( \tau \) corresponds to temperature. To wean off the teacher, we decay the distillation coefficient as training progresses. Note that kickstarting does not pretrain on teacher data.
- **DQfD** (Figure 4, left): Following DQfD [32], we initially pretrain the student on teacher data \( D_T \) using a combination of TD loss with a large margin classification loss to imitate the teacher actions (Equation A.4). After pretraining, we train the student on its replay data \( D_S \), again using a combination of TD and margin loss. While DQfD minimizes the margin loss throughout training, we decay the margin loss coefficient during the online phase, akin to kickstarting.

**Results.** Rehearsal, with best-performing teacher data ratio (\( \rho = 1/16 \)), is marginally better than tabula rasa DQN but significantly underperforms the teacher (Figure 2, teal), which seems related to the difficulty of standard value-based methods to learn from off-policy teacher data [60]. JSRL does
After pretraining, we minimize \( \lambda \) which combines distillation loss with the TD loss, weighted by a constant. To address the limitations of prior approaches, we propose QDagger, a simple method for PVRL that combines Dagger [65], an interactive imitation learning algorithm, with \( n \)-step Q-learning (Figure 4, right). Specifically, we first pre-train the student on teacher data \( D_T \) by minimizing \( L_{QDagger}(D_T) \), which combines distillation loss with the TD loss, weighted by a constant \( \lambda \). This pretraining phase helps the student to mimic the teacher’s state distribution, akin to the behavior cloning phase in Dagger. After pretraining, we minimize \( L_{QDagger}(D_S) \) on the student’s replay \( D_S \), akin to kickstarting, where the teacher “corrects” the mistakes on the states visited by the student. As opposed to minimizing the Dagger loss indefinitely, QDagger decays the distillation loss coefficient \( \lambda_t \) (\( \lambda_0 = \lambda \)) as training.

### 4.1 QDagger: A simple PVRL baseline

To address the limitations of prior approaches, we propose QDagger, a simple method for PVRL that combines Dagger [65], an interactive imitation learning algorithm, with \( n \)-step Q-learning (Figure 4, right). Specifically, we first pre-train the student on teacher data \( D_T \) by minimizing \( L_{QDagger}(D_T) \), which combines distillation loss with the TD loss, weighted by a constant \( \lambda \). This pretraining phase helps the student to mimic the teacher’s state distribution, akin to the behavior cloning phase in Dagger. After pretraining, we minimize \( L_{QDagger}(D_S) \) on the student’s replay \( D_S \), akin to kickstarting, where the teacher “corrects” the mistakes on the states visited by the student. As opposed to minimizing the Dagger loss indefinitely, QDagger decays the distillation loss coefficient \( \lambda_t \) (\( \lambda_0 = \lambda \)) as training.
progresses, to satisfy the weaning desiderata for PVRL. Weaning allows QDagger to deviate from the suboptimal teacher policy $\pi_T$, as opposed to being perpetually constrained to stay close to $\pi_T$ (Figure 9). We find that both decaying $\lambda_t$ linearly over training steps or using an affine function of the ratio of student and teacher performance worked well (Appendix A.4). Assuming the student policy $\pi(\cdot | s) = \text{softmax}(Q(s, \cdot) / \tau)$, the QDagger loss is given by:

$$L_{QDagger}(D) = L_{TD}(D) + \lambda_t \mathbb{E}_{s \sim D} \left[ \sum_a \pi_T(a|s) \log \pi(a|s) \right]$$ (2)

Figure 2 shows that QDagger outperforms prior methods and surpasses the teacher. We remark that DQfD can be viewed as a QDagger ablation that uses a margin loss instead of a distillation loss, while kickstarting as another ablation that does not pretrain on teacher data. Equipped with QDagger, we show how to incorporate PVRL into our workflow and demonstrate its benefits over tabula rasa RL.

5 Reincarnating RL as a research workflow

Revisiting ALE. As Mnih et al. [56]’s development of Nature DQN established the tabula rasa workflow on ALE, we demonstrate how iterating on ALE agents’ design can be significantly accelerated using a reincarnation RL workflow, starting from Nature DQN, in Figure 1. Although Nature DQN used RMSProp, Adam yields better performance than RMSProp [1, 59]. While we can train another DQN agent from scratch with Adam, fine-tuning Nature DQN with Adam and 3-step returns, with a reduced learning rate (Figure 7), matches the performance of this tabula rasa DQN trained for 400M frames, using a 20 times smaller sample budget (Panel 2 in Figure 1). As such, on a P100 GPU, fine-tuning only requires training for a few hours rather than a week needed for tabula rasa RL. Given this fine-tuned DQN, fine-tuning it further results in diminishing returns with additional frames due to being constrained to use the 3-layer convolutional neural network (CNN) with the DQN algorithm.

Let us now consider how one might use a more general reincarnation approach to improve on fine-tuning, by leveraging architectural and algorithmic advances since DQN, without the sample complexity of training from scratch (Panel 3 in Figure 1). Specifically, using QDagger to transfer the fine-tuned DQN, we reincarnate Impala-CNN Rainbow that combines Dopamine Rainbow [32], which incorporates distributional RL [10], prioritized replay [67] and $n$-step returns, with an Impala-CNN architecture [24], a deep ResNet with 15 convolutional layers. Tabula rasa Impala-CNN Rainbow outperforms fine-tuning DQN further within 25M frames. Reincarnated Impala-CNN Rainbow quickly outperforms its teacher policy within 5M frames and maintains superior performance over its tabula rasa counterpart throughout training for 50M frames. To catch up with the performance of this reincarnated agent’s performance, the tabula rasa Impala-CNN Rainbow requires additional training for 50M frames (48 hours on a P100 GPU). See Appendix A.5 for more training details. Overall, these results indicate how past research on ALE could have been accelerated by incorporating a reincarnation RL approach to designing agents, instead of always re-training agents from scratch.

Tackling a challenging control task. To show how reincarnating RL can enable faster experimentation, we apply PVRL on the humanoid:run locomotion task, one of the hardest control problems in DMC [73] due to its large action space (21 degrees of freedom). For this experiment, shown in Figure 5, we use actor-critic agents in Acme [35]. For the teacher policy, we use TD3 [27] trained for 10M environment steps and pick the best run. We find that fine-tuning this TD3 agent degrades performance after 15M environment steps (other learning rates in Appendix A.5), which may be related to capacity loss in value-based RL with prolonged training [47, 53]. For reincarnation, we use single-actor D4PG [6], a distributional RL variant of DDPG [51], with a larger policy and critic architecture than TD3. Reincarnated D4PG performs better than its tabula rasa counterpart for the first 10M environment interactions. Both these agents converge to similar performance, which is likely a limitation of QDagger. This result also raises the question of whether better PVRL methods can lead to reincarnated agents that outperform their tabula rasa counterpart throughout learning. Nevertheless, tabula rasa D4PG requires additional training for 10-12 hours on a V100 GPU to match reincarnated D4PG’s performance, which might quickly add up to a substantial savings in compute when running a large set of experiments (e.g., architectural or hyperparameter sweeps).

Balloon Learning Environment (BLE) [30]. One of the motivations for our work is to be able to use deep RL in real-world tasks in a data and computationally efficient manner. To this end, the BLE provides a high-fidelity simulator for navigating stratospheric balloons using RL [9]. An agent in the BLE can choose from three actions to control the balloon: move up, down, or stay in place. The balloon can only move laterally by “surfing” the winds at its altitude; the winds change over time and vary as the balloon changes position and altitude. Thus, the agent is interacting with a partially
When fine-tuning, we are reloading the weights from Perciatelli, which was notably trained on a what is used by the other agents; this is likely the reason that fine-tuning does remarkably well relative to other agents in BLE. Efficiently transferring information in Perciatelli’s weights to another agent without the replay data from the Loon simulator presents an interesting challenge for future work. Overall, the improved efficiency of reincarnating RL (fine-tuning and PVRL) over tabula rasa RL, as evident on the BLE, could make deep RL more accessible to researchers without access to industrial-scale resources as they can build upon prior computational work, such as model checkpoints, enabling the possible reuse of months of prior computation (e.g., Perciatelli).

6 Considerations in Reincarnating RL

Reincarnation via fine-tuning. Given access to model weights and replay of a value-based agent, a simple reincarnation strategy is to fine-tune this agent. While naive fine-tuning with the same learning rate (lr) as the original agent does not exhibit improvement, fine-tuning with a reduced lr, for only 1 million additional frames, results in 25% IQM improvement for DQN (Adam) and 50% IQM improvement for Nature DQN trained with RMSProp (Figure 7). As reincarnating RL leverages existing computational work (e.g., model checkpoints), it allows us to easily experiment with such hyperparameter schedules, which can be expensive in the tabula rasa setting. Note that when fine-tuning,

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3R2D6 builds on recurrent replay distributed DQN (R2D2) [41], which uses a LSTM-based policy, and incorporates dueling networks [80], distributional RL [10], DenseNet [37], and double Q-learning [78].
one is forced to keep the same network architecture; in contrast, reincarnating RL grants flexibility in architecture and algorithmic choices, which can surpass fine-tuning performance (Figures 1 and 5).

**Difference with tabula rasa benchmarking.** Are student agents that are more data-efficient when trained from scratch also better for reincarnating RL? In Figure 8, we answer this question in the negative, indicating the possibility of developing better students for utilizing existing knowledge. Specifically, we compare Dopamine Rainbow [32] and DrQ [84], under tabula rasa and PVRL settings. DrQ outperforms Rainbow in low-data regime when trained from scratch but underperforms Rainbow in the PVRL setting as well as when training longer from scratch. Based on this, we speculate that reincarnating RL comparisons might be more consistent with asymptotic tabula rasa comparisons.

**Reincarnation vs. Distillation.** PVRL is different from imitation learning or imitation-regularized RL as it focuses on using an existing policy only as a launchpad for further learning, as opposed to imitating or staying close to it. To contrast these settings, we run two ablations of QDagger for reincarnating Impala-CNN Rainbow given a DQN teacher policy: (1) Dagger [65], which only minimizes the on-policy distillation loss in QDagger, and (2) Dagger + QL, which uses a fixed distillation loss coefficient throughout training (as opposed to QDagger, which decays it; see Equation 2). As shown in Figure 9, Dagger performs similarly to the teacher while Dagger + QL improves over the teacher but quickly saturates in performance. On the contrary, QDagger substantially outperforms these ablations and shows continual improvement with additional environment interactions.

**Dependency on prior work.** Findings in reincarnating RL are dependent on existing computational work (e.g., teacher policies). This is similar to machine learning areas, such as NLP and computer vision, where building upon pretrained models is the dominant paradigm [e.g., 17, 23, 31, 36]. To investigate teacher dependence in PVRL, we reincarnate a fixed student from three different DQN teachers (Figure 10). As expected, we observe that a higher performing teacher results in a better performing student. However, reincarnation from two distinct policies that perform similarly results in different performance trends. This suggests that a reincarnated student’s performance depends not only on the teacher’s performance but also on its behavior, which opens up the possibility for creating teacher policies that may be more suited for reincarnation (e.g., pre-trained exploratory policies [13]).
7 Conclusion

This work shows that reincarnating RL is a more compute and data efficient workflow than tabula rasa RL. Nevertheless, our results also open several avenues for future work. Particularly, more research is needed for enabling workflows that can incorporate knowledge provided in a form other than a policy, such as pretrained models or representations, developing better methods for PVRL, and extending PVRL to transfer a policy to model-based agents. We hope that this work motivates RL researchers to release computational work (e.g., model checkpoints) for their publications, which would allow others to directly build on their work. In this regards, we will open-source our code and trained agents. Concurrent to this work, Gogianu et al. [29] released 25,000 trained Atari agents, which we believe would further facilitate reincarnating RL. As Newton put it “If I have seen further it is by standing on the shoulders of giants”, we argue that reincarnating RL can substantially accelerate progress by building on prior computational work, as opposed to always redoing this work from scratch.

Societal Impacts

In this work, we present reincarnating RL an alternative workflow for doing RL research. This workflow could positively impact society by reducing the computational burden on researchers and is more environment friendly than tabula rasa RL. For example, reincarnating RL allow researchers to train super-human Atari agents on a single GPU within a span of few hours as opposed to training for a few days. Additionally, reincarnating RL is more accessible to the wider research community, as researchers without sufficient compute resources can build on prior computational work from resource-rich groups, and even improve upon them using limited resources. Furthermore, this democratization could directly improve RL applicability for practical applications, as most businesses that could benefit from RL often cannot afford the expertise to design in-house solutions. However, this democratization could also make it easier to apply RL for potentially harmful applications. Additionally, reincarnating RL could carry forward the bias or undesirable traits from the previously learned systems. As such, we urge practitioners to be mindful of how RL fits into the wider socio-technical context of its deployment.

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Author Contributions

Rishabh Agarwal led the project, defined the scope of the work to focus on policy to value reincarnation, came up with a successful algorithm for PVRL, and performed the literature survey. He designed, implemented and ran most of the experiments on ALE, Humanoid-run and BLE, and wrote the paper.

Max Schwarzer was the main collaborator and helped run DQfD experiments on ALE and as well as setting up some agents for the BLE codebase with Acme, was involved in project discussions and edited the paper. Work done while a student researcher at Google.

Pablo Samuel Castro advised the project and was involved in project discussions, helped in setting up the BLE environment and implemented the initial Acme agents, and helped with paper editing.

Aaron Courville advised the project, helped with project direction and provided feedback on writing.

Marc Bellemare advised the project and suggested the idea of reusing existing agent checkpoints into our workflow, and provided feedback on writing.

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A Appendix

A.1 AlphaStar cost estimation

We estimate the cost of AlphaStar [79] based on the following description in the paper: “In StarCraft, each player chooses one of three races — Terran, Protoss or Zerg — each with distinct mechanics. We trained the league using three main agents (one for each StarCraft race), three main exploiter agents (one for each race), and six league exploiter agents (two for each race). Each agent was trained using 32 third-generation tensor processing units (TPUv3) over 44 days.”

This corresponds to a total of 12 agents (= 3 main + 3 exploiter + 6 league) trained for a total of 1056 TPU hours = 44 days * 24 hours/day on 32 TPU v3 chips. As per current pricing\footnote{https://cloud.google.com/tpu/pricing}, TPUv3 (v3-8) cost $8 per hour. Based on this, we estimate the cost of replicating AlphaStar results for an independent researcher would be at \(1056 \times 12 \times 32 \times $8 = $3,244,032\). Please note that we are only considering the cost of replication and not accounting for other costs such as hyperparameter tuning and evaluation.

A.2 Open-source code and checkpoints

We will open-source our code for ALE experiments at agarwl.github.io/reincarnating_rl. Since the model checkpoints for ALE require a large amount of memory, we have released them in the public GCP bucket gs://rl_checkpoints\footnote{https://console.cloud.google.com/storage/browser/rl_checkpoints}, which can be easily downloaded using gsutil.

A.3 Compute resources for PVRL experiments

For experiments in section 4, we used a P100 GPU. For obtaining the teacher policy, the cost of running the tabula rasa DQN for 400M frames for 10 games on 3 seeds each roughly amounts to 7 days x 30 = 210 days of compute on a P100 GPU. For each of the PVRL methods, we trained on 10 games with 3 runs each for 10M frames, which roughly translates to 4-5 hours. For offline pretraining, we train methods for 1 million gradient steps with a batch size of 32, which roughly amounts to 6-7 hours (this could be further sped up by using large-batch sizes). We list the number of configurations we evaluated for each method below.

- Rehearsal: We tried 5 values of teacher data ratio \(\rho \times 4\) \(n\)-step values, amounting to a total of 20 configurations.
- JSRL: We tried 4 values of teacher roll-in steps \(\alpha \times 2\) values of decay parameter \(\beta \times 2\) values of \(n\)-step, amounting to 16 configurations.
- RL Pretraining: We tried 2 values of \(\lambda \times 4\) values of \(n\)-step, amounting to 8 configurations.
- Kickstarting: We report results for 4 values of \(n\)-step for a specific temperature and distillation loss coefficient. For hyperparameter tuning, we evaluated 2 temperature values and 2 loss coefficients with a specific \(n\)-step. Overall, this corresponds to a total of 8 configurations.
- DQfD: We report results for 4 \(n\)-step values for a specific temperature and distillation loss coefficient. For hyperparameter tuning, we evaluated 2 different temperature and loss coefficients with a specific \(n\)-step, akin to kickstarting. Overall, this amounts to 8 configurations.
- QDagger: We report results for 4 \(n\)-step values for a specific temperature and distillation loss coefficient. For hyperparameter tuning, we evaluated 2 different temperature and loss coefficients with a specific \(n\)-step, akin to kickstarting. Overall, this amounts to 8 configurations.

Based on the above, we evaluated a total of 60 (=20 + 16 + 16 + 8) configurations without pretraining while 32 configurations with pretraining. Each of these configurations was evaluated for 30 seeds. This amounts to a total compute time of 300-375 days for runs without pretraining on offline data while 400-480 days of GPU compute for runs involving pretraining, resulting in a total compute time of around 700 - 855 days on a P100 GPU.

A.4 PVRL: Experimental details

Atari 2600 Games: The subset of games in the paper includes games from the original Atari training set used by Bellemare et al. [8] (Asterix, Beam Rider, Seaquest and Space Invaders) as well as

\footnote{https://cloud.google.com/tpu/pricing}
Figure A.11: **Rehearsal** for PVRL. The plots show IQM teacher normalized scores after training for 10M frames, aggregated across 10 Atari games with 3 seeds each. Each point in the above plots correspond to a distinct experiment setting evaluated using 30 seeds. Shaded regions show 95% CIs [2].

Figure A.12: **RL pretraining** using CQL [46], followed by fine-tuning with **Left.** CQL coefficient 0.3, and **Right.** CQL coefficient 1.0. The plots show IQM teacher normalized scores over the course of training, computed across 30 seeds, aggregated across 10 Atari games. Online fine-tuning degrades performance with 1-step returns, which is more pronounced with higher CQL loss coefficient.

Validation games used by Mnih et al. [56] (Breakout, Enduro, River Raid), except the games which are nearly solved by DQN, such as Freeway and Pong. We do not use any hard exploration games as a DQN teacher does not provide a meaningful teacher policy for such games. The remaining three games were chosen to test the student agent in environments with challenging characteristics such as requiring planning as opposed to being reactive (e.g., Ms Pacman, Q∗Bert), and sparse-reward games that require long-term predictions (Bowling). Furthermore, most of these games can be significantly improved over the teacher DQN performance, which is sub-human on half of the games (Ms Pacman, Q∗Bert, Bowling, Seaquest and Beam Rider). Refer to Table A.2 for per-game teacher scores.

Common hyperparameters. We list the hyperparameters shared by all PVRL methods in Table A.1. For all methods, we swept over $n$-step returns in $\{1, 3, 5, 10\}$ except for DQfD [33], which originally used 10-step returns, where we only tried 3-step and 10-step returns and JSRL for which we tried only 1-step and 3-step returns. For PVRL methods without any pretraining phase, we use a learning rate of $6.25e^{-5}$ (JSRL, Rehearsal), following the hyperparameter configuration for Dopamine [14]. For methods that pretrain on offline data, we sweep over $\{6.25e^{-5}, 1e^{-5}\}$ and found the learning rate of $1e-5$ to perform better in our early experimentation and use it for our main results. We discuss the method specific hyperparameters below. For obtaining the teacher policy using value-based agent, we use the $\text{softmax}(Q_T(s, \cdot)/\tau)$ over the teacher’s Q-function $Q_T$ and use the same temperature coefficient $\tau$ for both the student and teacher policy.

- **Rehearsal**: We tried 5 different values of the teacher data ratio ($\rho$) in $\{0, 1/256, 1/64, 1/16, 1/4\}$. The loss, $L_{\text{Rehearsal}}$, can be written as: $L_{\text{Rehearsal}} = \rho L_{TD}(D_T) + (1 - \rho)L_{TD}(D_S)$. As can be seen from the results in Figure A.11, we
Table A.1: **Common hyperparameters** used by PVRL experiments using a DQN student agent on ALE in Section 4. These hyperparameters are based on the ones used by the Jax implementation of DQN in Dopamine [14].

| Hyperparameter                  | Setting               |
|---------------------------------|-----------------------|
| Sticky actions                  | Yes                   |
| Sticky action probability       | 0.25                  |
| Grey-scaling                    | True                  |
| Observation down-sampling       | (84, 84)              |
| Frames stacked                  | 4                     |
| Frame skip (Action repetitions) | 4                     |
| Reward clipping                 | [-1, 1]               |
| Terminal condition              | Game Over             |
| Max frames per episode          | 108K                  |
| Discount factor                 | 0.99                  |
| Mini-batch size                 | 32                    |
| Target network update period    | every 2000 updates    |
| Min replay history              | 20000 steps           |
| Environment steps per training iteration | 250K                           |
| Update period every             | 4 environment steps   |
| Training ε                       | 0.01                  |
| Training ε-decay steps          | 50K                   |
| Evaluation ε                     | 0.001                 |
| Evaluation steps per iteration  | 125K                  |
| Q-network: channels             | 32, 64, 64            |
| Q-network: filter size          | 8 x 8, 4 x 4, 3 x 3   |
| Q-network: stride               | 4, 2, 1               |
| Q-network: hidden units         | 512                   |
| Hardware                        | P100 GPU              |
| Offline gradient steps per iteration | 100K                           |
| Offline training iterations     | 10                    |
| Offline learning rate           | 0.0001                |

Table A.2: Average scores for the random agent, human agent and the DQN (Adam) trained for 400 million frames (based on 5 runs). For teacher normalized scores reported in the paper, the random agent is assigned a score of 0 while the DQN (Adam) agent is assigned a score of 1. Normalization using teacher allow us to compare the performance of student agents relative to the teacher and avoid high performing outliers (such as Breakout and Space Invaders) in terms of human normalized scores.

| Game         | Human   | DQN @400M | Random |
|--------------|---------|-----------|--------|
| Asterix      | 8503.3  | 13682.6   | 210.0  |
| Beam Rider   | 16926.5 | 6608.4    | 363.9  |
| Bowling      | 160.7   | 33.9      | 23.1   |
| Breakout     | 30.5    | 234.2     | 1.7    |
| Enduro       | 860.5   | 1142.0    | 0.0    |
| Ms Pacman    | 6951.6  | 4366.2    | 307.3  |
| Q*bert       | 13455.0 | 11437.3   | 163.9  |
| River Raid   | 17118.0 | 17061.9   | 1338.5 |
| Seaquest     | 42054.7 | 14228.2   | 68.4   |
| Space Invaders | 1668.7 | 7613.6    | 148.0  |

find a small value of teacher data ratio ($\rho = 1/16$) with 3-step returns to be the best performing configuration.

• **JSRL.** As shown in Figure 4 (left), we swept over the maximum number of teacher roll in steps of $\alpha$ in $\{0, 100, 1000, 5000\}$, and the decay parameter $\beta$, which governs how fast we decay the roll-in steps, in $\{0.8, 1.0\}$. Note that $\beta = 1.0$ corresponds to JSRL-Random, which was found to be competitive in performance to JSRL [77].
• **RL Pretraining:** We use CQL, which optimizes the following loss:

$$L_{\text{Pretrain}} = L_{TD}(\mathcal{D}_T) + \lambda \mathbb{E}_{s,a \sim \mathcal{D}_T} \left[ \log \left( \sum_{a'} Q(s, a') \right) - Q(s, a) \right]$$

(A.3)

The choice of CQL is motivated by its simplicity as well as recent findings that offline RL methods that do not estimate the behavior policy are more suited for online fine-tuning [58]. We tried two different values of CQL coefficient $\lambda$ (0.3 and 1.0), as shown in Figure A.12, and report the results for the better performing coefficient ($\lambda = 0.3$) in the main paper.

• **Kickstarting.** Kickstarting [68] uses the same loss as QDagger (Equation 2), but as discussed in the main paper, kickstarting does not have any pretraining phase on offline data. For the temperature hyperparameter $\tau$ for obtaining the policy $\pi(\cdot|s) = \text{softmax}(Q(s, \cdot)/\tau)$, we tried 0.1 and 1.0. Similarly, we swept over two initial values for distillation loss coefficient ($\lambda_0$), namely 1.0 and 3.0. For experiments with the DQN student, we found the coefficient 3.0 and temperature 0.1 to perform the best.

• **DQfD.** Following Hester et al. [33], DQfD uses the following loss for training:

$$L_{DQfD}(\mathcal{D}) = L_{TD}(\mathcal{D}) + \eta \mathbb{E}_{s \sim \mathcal{D}} \left[ \max_a (Q(s, a) + f(a_t(s), a)) - Q(s, a_T(s)) \right]$$

(A.4)

where $\eta$ corresponds to the margin loss coefficient, $a_T(s) = \text{argmax}_a \pi_T(a|s)$ and $f(a_t, a)$ is a margin function that is 0 when $a = a_T$ and a positive margin $m$ otherwise. We swept over the values {1.0, 3.0} for both the margin parameter $m$ and initial values $\eta_0$ of the margin loss coefficient $\eta$. For the DQN student, we report the results for the better performing margin coefficients in the main paper.

• **QDagger.** Akin to kickstarting, we swept over the values of temperature $\tau$ in {0.1, 1.0} and distillation coefficient $\lambda_0$ in {1.0, 3.0}. For ALE experiments, we decay the distillation loss coefficient every training iteration (1M environment frames) using the fraction of expected returns obtained by the student policy $\pi$ compared to the teacher policy $\pi_T$, that is, $\lambda_t = 1_{t < t_0} \max(1 - G^\pi/G^T_0, 0)$. For fair comparisons with other methods, we use the same strategy for decaying the distillation loss coefficient $\lambda_t$ for Kickstarting and the margin loss coefficient $\eta_t$ for DQfD.

A.5 Reincarnating RL as a workflow: Additional details

**Revisting ALE.** We used the final model checkpoints of Nature DQN [56] from Agarwal et al. [1], which was trained for 200M frames using the hyperparameters in Dopamine [14]. The fine-tuned DQN (Adam) in panel 2 in Figure 1 uses 3-step returns. For the tabula rasa Impala-CNN Rainbow, we use similar hyperparameters to Dopamine Rainbow except for learning rate ($lr$), for which we
Figure A.15: **Effect of QDagger temperature** $\tau$ on the performance of reincarnating Impala CNN-Rainbow from **Left**. DQN (Adam) @ 20M, and **Right**. DQN (Adam) @ 400M. Notably, the better performing temperature $\tau$ is dependent on the teacher policy. Lower $\tau$ results in cloning a more “spikier” teacher policy. With a reasonably good teacher policy (DQN @ 400M), $\tau$ value of 0.1 performs better than 1.0 while with a more suboptimal teacher policy (DQN @ 20M), the higher temperature coefficient of 1.0 performs better than 0.1.

Figure A.16: **Fine-tuning TD3**. Results for fine-tuning a trained Acme TD3 agent with different learning rates. All the different learning rates exhibit similar performance trends including severe degradation after prolonged training.

Figure A.17: **Effect of varying initial QDagger distillation coefficient** $\lambda_0$ on the performance of reincarnated D4PG. Higher coefficient (0.3) results in faster transfer but converges to similar performance to the runs with lower coefficient (0.1).

ran a sweep over $\{1e-4, 1e-5, 3e-5\}$, shown in Figure A.13, and use the best performing $lr$ of $3e-5$. For the reincarnated Impala-CNN Rainbow in Panel 3, we use a QDagger distillation coefficient of 1.0 and sweep over temperature parameter $\tau$ in $\{0.1, 1.0\}$, as shown in Figure A.14. Consistent with our other fine-tuning results on ALE, in Panel 3, using a reduced $lr$ of $3e-6$ for fine-tuning the already fine-tuned DQN agent results in better performance, compared to using an $lr$ of $1e-5$, as used by fine-tuned DQN.

**Humanoid:Run.** For tabula rasa TD3 [27], we used a learning rate ($lr$) of $3e-4$ for both the policy and critic, which are represented using a MLP with 2 hidden layers of size (256, 256). For other hyperparameters, we used the default values in Acme’s TD3 implementation. For fine-tuning TD3, we use the last 500K environment steps from the TD3’s replay buffer and use the same hyperparameters as tabula rasa TD3 except for $lr$. Specifically, we swept over the $lr$ in $\{1e-4, 3e-4, 3e-5\}$, shown in Figure A.16, and find that all $lrs$ exhibit performance degradation with prolonged training.

For the tabula rasa D4PG [6], we use MLP networks with 3 hidden layers of size (256, 256, 256) for the policy and (512, 512, 256) for the critic. We used $3e-4$ as the learning rate and a sigma value of 0.2 that sets the variance of the Gaussian noise to the behavior policy. Other hyperparameters use the default values for D4PG implementation in Acme. For reincarnating D4PG using QDagger, we minimize a distillation loss between the D4PG’s actor policy and the teacher policy from TD3 jointly with the actor-critic losses. For QDagger specific hyperparameters, we pretrain using 200K gradient updates as well as decay $\lambda_t$ to 0 over a period of 200K gradient updates during the online training phase. Additionally, we sweep over distillation coefficient $\lambda_0$ in $\{0.1, 0.3\}$, as shown in Figure A.17. Note that both TD3 and D4PG use 5-step returns by default in Acme.
**BLE.** For BLE, we set most hyperparameters for our distributed RL agents based on configuration of the BLE Quantile agent, which can be found at agents/configs/quantile.gin. The network architecture used by QR-DQN and Perciatelli is an MLP with 7 hidden layers of size 600 each with ReLU activations and approximate the distribution using 51 fixed quantiles. For the DenseNet architecture [37] employed by IQN and R2D6, we use 7 hidden layers of size 512 each (for TPU-efficiency), which contains significantly more parameters than the Perciatelli MLP. Additionally, R2D6 uses a LSTM layer of size 512 on top of the DenseNet encoder with QR-DQN loss, while IQN samples 128 quantiles for minimizing the implicit quantile regression loss.

For tabula rasa agents, we swept over the $lr$ in $\{2e - 6, 6e - 6, 1e - 5\}$ and found $1e - 5$ to be the best performing $lr$. However, for fine-tuning Perciatelli, we found that a lower $lr$ of $1e - 6$ performs better. For reincarnated R2D6 and IQN, we use a $lr$ of $1e - 5$ and $6e - 6$ respectively during the online phase while $2 \times lr$ in the offline pretraining phase. We set distillation temperature $\tau$ to be equal to 1.0 and linearly decay the QDagger distillation coefficient $\lambda_t$ over a fixed number of learner steps (1M for R2D6 and 160000 for IQN). Furthermore, we swept over the initial value of $\lambda_t (\lambda_0)$ in $\{0.3, 1.0\}$ and found 1.0 to be better for R2D6 while 0.3 for IQN.