REPAINT: KNOWLEDGE TRANSFER IN DEEP ACTOR-CRITIC REINFORCEMENT LEARNING

Anonymous authors
Paper under double-blind review

ABSTRACT

Accelerating the learning processes for complex tasks by leveraging previously learned tasks has been one of the most challenging problems in reinforcement learning, especially when the similarity between source and target tasks is low or unknown. In this work, we propose a **REP**resentation-**A**nd-**IN**stance **T**ransfer algorithm (REPAINT) for deep actor-critic reinforcement learning paradigm. In representation transfer, we adopt a kickstarted training method using a pre-trained teacher policy by introducing an auxiliary cross-entropy loss. In instance transfer, we develop a sampling approach, i.e., advantage-based experience replay, on transitions collected following the teacher policy, where only the samples with high advantage estimates are retained for policy update. We consider both learning an unseen target task by transferring from previously learned teacher tasks and learning a partially unseen task composed of multiple sub-tasks by transferring from a pre-learned teacher sub-task. In several benchmark experiments, REPAINT significantly reduces the total training time and improves the asymptotic performance compared to training with no prior knowledge and other baselines.

1 INTRODUCTION

Most reinforcement learning methods train an agent from scratch, typically requiring a huge amount of time and computing resources. Accelerating the learning processes for complex tasks has been one of the most challenging problems in reinforcement learning (Kaelbling et al., 1996; Sutton & Barto, 2018). In the past few years, deep reinforcement learning has become more ubiquitous to solve sequential decision-making problems in many real-world applications, such as game playing (OpenAI et al., 2019; Silver et al., 2016), robotics (Kober et al., 2013; OpenAI et al., 2018), and autonomous driving (Sallab et al., 2017). The computational cost of learning grows as the task complexity increases in the real-world applications. Therefore, it is desirable for a learning algorithm to leverage knowledge acquired in one task to improve performance on other tasks.

Transfer learning has achieved significant success in computer vision, natural language processing, and other knowledge engineering areas (Pan & Yang, 2009). In transfer learning, the teacher (source) and student (target) tasks are not necessarily drawn from the same distribution (Taylor et al., 2008a). The unseen student task may be a simple task which is similar to the previously trained tasks, or a complex task with traits borrowed from significantly different teacher tasks. Despite the prevalence of direct weight transfer, knowledge transfer from previously trained agents for reinforcement learning tasks has not been gaining much attention until recently (Barreto et al., 2019; Ma et al., 2018; Schmitt et al., 2018; Lazaric, 2012; Taylor & Stone, 2009).

In this work, we propose a knowledge transfer algorithm for deep actor-critic reinforcement learning, i.e., **REP**resentation **A**nd **IN**stance **T**ransfer (REPAINT). The algorithm can be categorized as a representation-instance transfer approach. Specifically, in representation transfer, we adopt a kickstarted training method (Schmitt et al., 2018) using a previously trained teacher policy, where the teacher policy is used for computing the auxiliary loss during training. In instance transfer, we develop a new sampling algorithm for the replay buffer collected from the teacher policy, where we only keep the transitions that have advantage estimates greater than a threshold. The experimental results across several transfer learning tasks show that, regardless of the similarity between source and target tasks, by introducing knowledge transfer with REPAINT, the number of training iterations needed by the agent to achieve some reward target can be significantly reduced when compared to

training from scratch and training with only representation transfer or instance transfer. Additionally, the agent's asymptotic performance is also improved by REPAINT in comparison with the baselines.

2 Related Work: Transfer Reinforcement Learning

Transfer learning algorithms in reinforcement learning can be characterized by the definition of transferred knowledge, which contains the *parameters* of the reinforcement learning algorithm, the *representation* of the trained policy, and the *instances* collected from the environment (Lazaric, 2012). When the teacher and student tasks share the same state-action space and they are similar enough (Ferns et al., 2004; Phillips, 2006), *parameter transfer* is the most straightforward approach, namely, one can initialize the policy or value network in the student tasks by that from teacher tasks (Mehta et al., 2008; Rajendran et al., 2015). Parameter transfer with different state-action variables is more complex, where the crucial aspect is to find a suitable mapping from the teacher state-action space to the student state-action space (Gupta et al., 2017; Talvitie & Singh, 2007; Taylor et al., 2008b).

Most of the transfer learning algorithms fall into the category of *representation transfer*, where the reinforcement learning algorithm learns a specific representation of the task or the solution, and the transfer algorithm performs an abstraction process to fit it into the student task. Konidaris et al. (2012) uses the *reward shaping* approach to learn a portable shaping function for knowledge transfer, while some other works use neural networks for feature abstraction (Duan et al., 2016; Parisotto et al., 2015; Zhang et al., 2018). *Policy distillation* (Rusu et al., 2015) or its variants is another popular choice for learning the teacher task representation, where the student policy aims to mimic the behavior of pre-trained teacher policies during its own learning process (Schmitt et al., 2018; Yin & Pan, 2017). Recently, *successor representation* has been widely used in transfer reinforcement learning, in which the rewards are assumed to share some common features, so that the value function can be simply written as a linear combination of the *successor features* (SF) (Barreto et al., 2017; Madarasz & Behrens, 2019). Barreto et al. (2019) extends the method of using SF and generalised policy improvement in Q-learning (Sutton & Barto, 2018) to more general environments. Borsa et al. (2018), Ma et al. (2018), and Schaul et al. (2015a) learn a universal SF approximator for transfer.

The basic idea of *instance transfer* algorithms is that the transfer of teacher samples may improve the learning on student tasks. Lazaric et al. (2008) and Tirinzoni et al. (2018) selectively transfer samples on the basis of the compliance between tasks in a model-free algorithm, while Taylor et al. (2008a) studies how a model-based algorithm can benefit from samples coming from the teacher task.

However, most of the aforementioned algorithms either assume specific forms of reward functions or perform well only when the teacher and student tasks are similar. Additionally, very few algorithms are designated to actor-critic reinforcement learning. In this work, we propose a representation-instance transfer algorithm to handle the generic cases of task similarity, which is also naturally fitted for actor-critic algorithms and can be easily extended to other policy gradient based algorithms.

3 Background: Actor-Critic Reinforcement Learning

A general reinforcement learning (RL) agent interacting with environment can be modeled in a Markov decision process (MDP), which is defined by a tuple $M = (S, A, p, r, \gamma)$, where S and A are sets of states and actions, respectively. The state transfer function $p(\cdot|s, a)$ maps a state and action pair to a probability distribution over states. $r : S \times A \times S \to \mathbb{R}$ denotes the reward function that determines a reward received by the agent for a transition from (s, a) to s'. The discount factor, $\gamma \in [0, 1]$, provides means to obtain a long-term objective. Specifically, the goal of an RL agent is to learn a policy π that maps a state to a probability distribution over actions at each time step t, so that $a_t \sim \pi(\cdot|s_t)$ maximizes the accumulated discounted return $\sum_{t\geq 0} \gamma^t r(s_t, a_t, s_{t+1})$.

To address this problem, a popular choice to adopt is the model-free actor-critic architecture, e.g., Konda & Tsitsiklis (2000); Degris et al. (2012); Mnih et al. (2016); Schulman et al. (2015a; 2017), where the critic estimates the value function and the actor updates the policy distribution in the direction suggested by the critic. The *state value function* at time t is defined as

$$V^\pi(s) = \mathbb{E}_{a_i \sim \pi(\cdot|s_i)} \left[\sum_{i \geq t} \gamma^{i-t} r(s_i, a_i, s_{i+1}) \middle| s_t = s \right] . \tag{3.1}$$

Similarly, the *action value function* (also called Q function) is defined by

$$Q^{\pi}(s,a) = \mathbb{E}_{a_i \sim \pi(\cdot|s_i)} \left[\sum_{i \geq t} \gamma^{i-t} r(s_i, a_i, s_{i+1}) \middle| s_t = s, a_t = a \right] . \tag{3.2}$$

The actor-critic methods usually rely on the *advantage function*, which is computed as

$$A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s) . \tag{3.3}$$

Intuitively, the advantage can be taken as the extra reward that could be obtained by taking a particular action a. The advantage is usually approximated by generalized advantage estimator (GAE) (Schulman et al., 2015b), which is defined as the exponentially-weighted average of the k-step discounted advantage, namely,

$$\hat{A}_t = \hat{A}_t^{\text{GAE}(\gamma,\lambda)} := \sum_{l=0}^{\infty} (\gamma\lambda)^l \left(r_{t+l} + \gamma V^{\pi}(s_{t+l+1}) - V^{\pi}(s_{t+l}) \right) , \tag{3.4}$$

where the parameter $0 \leq \lambda \leq 1$ allows a trade-off of the bias and variance.

In deep RL, the critic and actor functions are usually parameterized by neural networks. Then the policy gradient methods can be used to update the actor network. For example, in the clipped proximal policy optimization (Clipped PPO) (Schulman et al., 2017), the policy's objective function is defined to be the minimum between the standard surrogate objective and an ϵ clipped objective:

$$L_{\text{clip}}(\theta) = \hat{\mathbb{E}}_t \left[\min \left(r_t(\theta) \cdot \hat{A}_t, \text{clip}\left(r_t(\theta), 1-\epsilon, 1+\epsilon\right) \cdot \hat{A}_t \right) \right] , \tag{3.5}$$

where the policy π is parameterized by θ, and $r_t(\theta)$ is the likelihood ratio that

$$r_t(\theta) = \frac{\pi_{\theta}(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)} . \tag{3.6}$$

Moreover, the clip function truncates $r_t(\theta)$ to the range of $(1-\epsilon, 1+\epsilon)$.

4 Representation and Instance Transfer in Actor-Critic RL

In this section, we describe our knowledge transfer algorithm, REPAINT, for actor-critic RL framework. There are two core concepts underlying our approach, i.e., representation transfer and instance transfer. In the representation transfer, we employ a kickstarted training approach (Schmitt et al., 2018) based on the policy distillation. Then, in the next iteration following the kickstarting, we update the student policy using an *advantage-based experience replay*. We do not assume that the teacher and student tasks are similar or drawn from the same distribution.

The REPAINT algorithm is provided in Algorithm 1, where the value function and policy function are parameterized by ν and θ, respectively. Without loss of generality, we demonstrate the policy update using the Clipped PPO loss stated in equation 3.5, and use a single teacher policy in both representation and instance transfers. In practice, it can be directly applied to any advantage-based policy gradient RL algorithms, and it is straightforward to have different and multiple teacher policies in each transfer step. The more general algorithm and several variants are presented in Section A.

4.1 Representation Transfer: Kickstarted Training

In representation transfer, we use a kickstarting training pipeline (Schmitt et al., 2018), which can be viewed as a combination of policy distillation (Rusu et al., 2015) and population based training (Jaderberg et al., 2017). The main idea is to employ an auxiliary loss function which encourages the student policy to be close to the teacher policy on the trajectories sampled by the student. Given a teacher policy π_{teacher}, we introduce the auxiliary loss as

$$L_{\text{distill}}(\theta) = H\left(\pi_{\text{teacher}}(a|s) \| \pi_{\theta}(a|s)\right) , \tag{4.1}$$

where $H(\cdot\|\cdot)$ is the cross-entropy. In order for the agent to maximize its own future rewards, kickstarting adds the above loss to the Clipped PPO objective function, i.e., equation 3.5, weighted at optimization iteration k by the scaling $\beta_k \geq 0$:

$$L_{\text{RL}}^{k}(\theta) = L_{\text{clip}}(\theta) - \beta_k L_{\text{distill}}(\theta) . \tag{4.2}$$

Algorithm 1 REPAINT algorithm with Clipped PPO

for iteration $k = 1, 2, \ldots$ **do**
  if k is odd **then**
    Collect trajectories $\mathcal{S} = \{(s, a, s', r)\}$ following $\pi_{\theta_{\text{old}}}(s)$
    Fit state value network V_ν using $\mathcal{S}$ to update ν
    Compute advantage estimates $\hat{A}_1, \ldots, \hat{A}_T$ using equation 3.4
    Perform gradient optimization on $L^k_{\text{RL}}(\theta)$ defined in equation 4.2 // representation transfer
  else
    Collect trajectories $\mathcal{S}' = \{(s, a, s')\}$ following $\pi_{\text{teacher}}(s)$ // instance transfer
    Compute r for each transition using current reward function and add to $\mathcal{S}'$
    Compute advantage estimates $\hat{A}'_1, \ldots, \hat{A}'_{T'}$ using equation 3.4
    for t=1,...,T' **do**
      if $\hat{A}'_t < \zeta$ **then**
        Remove $\hat{A}'_t$ and the corresponding transition (s_t, a_t, s_{t+1}, r_t) from $\mathcal{S}'$
    Perform gradient optimization on $L_{\text{clip}}(\theta)$ defined in equation 3.5

In our experiments, the weighting parameter β_k is relatively large at early iterations, and vanishes as k increases, which is expected to improve the initial performance of the agent while keeping it focused on the current task in later iterations.

4.2 Instance Transfer: Advantage-Based Experience Replay

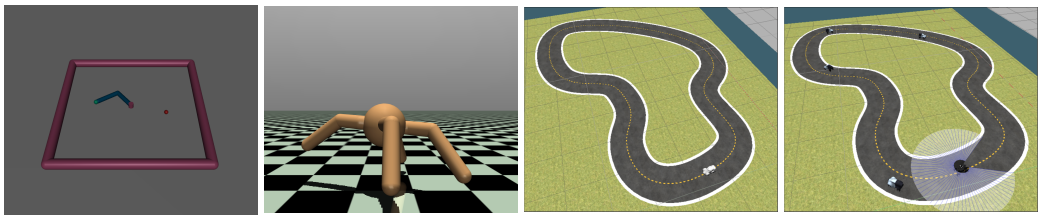
In the instance transfer iteration, we collect training samples following the teacher policy π_{teacher}, but compute the rewards using current reward function from the target task. Since the transitions are obtained from a different distribution, we do not update the value network in this iteration. When updating policy network, we prioritize the transitions based on the advantage values and only use the samples that have advantages greater than a given threshold ζ. Moreover, since the teacher policy has been used in collecting roll-outs, we compute the loss without the auxiliary cross-entropy.

The idea of prioritizing and filtering transitions is simple but intuitively effective. As mentioned in Section 3, the advantage can be viewed as the extra reward that could be obtained by taking a particular action. Therefore, by retaining only the "good" samples from the teacher policy, the agent can focus on learning useful behavior under current reward function. We note that our filtering approach is related to, but different from, the prioritized experience replay (Schaul et al., 2015b), which prioritizes the transitions in replay buffer by the temporal-difference error (TD error), and utilizes importance sampling for the off-policy evaluation. In comparison, our method uses experience replay in actor-critic framework, where the replay buffer is erased after each training iteration. Unlike the stochastic prioritization which imposes the probability of sampling on each transition, our method directly filters out most of the transitions from replay buffer and equally prioritizes the remaining data, which reduces the training iteration time. In addition, our method performs policy update without importance sampling. All transitions in a batch have the same weight, since the importance can be reflected by their advantage values. The experimental comparison can be found in Section 5.1.

We also consider how the sampling experiences from the teacher policy impact the policy gradient update. Our incremental update fits into the framework of the off-policy actor-critic (Degris et al., 2012; Zhang et al., 2019). We ignore the clip function in equation 3.5 for simplicity and get

$$\nabla_\theta L_{\text{clip}}(\theta) = \hat{\mathbb{E}}_{s \sim d_{\text{teacher}}, a \sim \pi_{\text{teacher}}} \left[\rho(s, a) \nabla_\theta \log \pi_\theta(a|s) \hat{A}^{\pi_{\theta_{\text{old}}}} \right] , \tag{4.3}$$

where $\rho(s, a) = \pi_\theta(a|s)/\pi_{\text{teacher}}(a|s)$, and the advantage estimator is from last kickstarted training iteration. With the new term $\rho(s, a)$, equation 4.3 can be viewed as a weighted sample expectation. Since the samples are drawn from the teacher policy, $\pi_{\text{teacher}}(a|s)$ usually has large values. At the early learning stage, our advantage-based filtering results in a large step size (due to large $\hat{A}^\pi$). Therefore, a small ρ serves as the compensation to the training, which can prevent the system from over-fitting. In later iterations when the student policy is closer to the teacher, the update is close to traditional actor update except the filtering approach, which introduces bias because it changes the distribution in an uncontrolled fashion. In practice, we can adopt REPAINT in the early training



(a) MuJoCo-Reacher (b) MuJoCo-Ant (c) Single-car time trial (d) Racing with bot cars

Figure 1: The simulation environments used in the experiments. Note that the racing car in (c) only has a monocular camera, while in (d) it is equipped by a stereo camera and a Lidar.

stage, and then reduce to traditional actor-critic algorithms. As a consequence, the agent first learns useful teacher behavior to achieve good initial performance, and focuses on the target task afterwards.

4.3 Discussion

A critical question in knowledge transfer for RL is how to characterize the *similarity* between source and target tasks, since most of the transfer learning algorithms perform well when the two are similar. If samples from the two MDPs are given, some metrics can be defined to compute or learn the task similarity, e.g., the Kantorovich distance based metric (Song et al., 2016), the restricted Boltzmann machine distance measure (Ammar et al., 2014), the policy overlap (Carroll & Seppi, 2005), and the task compliance defined in Lazaric et al. (2008). However, in general, the similarity is usually unknown before getting any samples, unless other specific information is given. For example, the methods using successor representation (Barreto et al., 2019; Borsa et al., 2018; Schaul et al., 2015a) assume that the reward functions among tasks are a linear combination of some common features, and they only differ in the feature weights, namely, $r(s, a, s') = \sum_i w_i \phi_i(s, a, s')$ with fixed ϕ_i's. Then the similarity can be characterized as the distance of the weight vectors.

In this paper, we aim to show that the proposed REPAINT algorithm handles generic cases in task similarity. To demonstrate that, for simplicity, we assume in the experiments that the state and action spaces stay the same between teacher and student tasks, and the reward functions have the form of linear combination of common features. However, we use the cosine distance function to define the task similarity in this paper, namely, the similarity between two tasks with reward functions $r_1(s, a, s') = \boldsymbol{\phi}(s, a, s')^\top \boldsymbol{w}_1$ and $r_2(s, a, s') = \boldsymbol{\phi}(s, a, s')^\top \boldsymbol{w}_2$ can be computed as

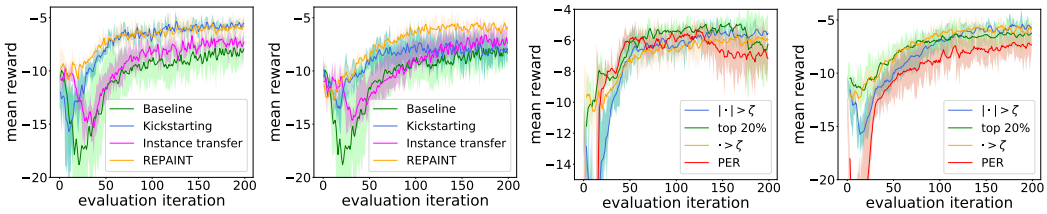
$$\mathrm{sim}(r_1, r_2) = \frac{\boldsymbol{w}_1 \cdot \boldsymbol{w}_2}{\|\boldsymbol{w}_1\| \|\boldsymbol{w}_2\|} \,. \tag{4.4}$$

We say the two tasks are *similar* if $\mathrm{sim}(r_1, r_2) > 0$. Otherwise, they are considered to be *different*.

5 Experiments

In this section, we use two platforms across multiple bench-marking tasks for assessing the REPAINT algorithm (see Figure 1). We first perform experiments on two continuous control tasks, i.e., Ant and Reacher, in MuJoCo simulator (Todorov, 2016). We compare the performance of REPAINT with training from scratch and training with only kickstarting or instance transfer. Note that since the value network cannot be updated in the instance transfer iteration, we implement training with only instance transfer by alternately applying Clipped PPO and instance transfer (namely, setting $\beta_k = 0$ in Algorithm 1). For discrete control tasks, we use the AWS DeepRacer simulator (Balaji et al., 2019) to evaluate different algorithms on complex tasks, such as single-car time-trial race and multi-car racing against bot cars. The detail of our experimental setup is presented in Section B.

We consider three different types of task similarities in the experiments based on the cosine similarity (equation 4.4), i.e., the teacher (source) task is a similar task, different task, or a sub-task of the target task (some feature weights are zero in the reward function). We also evaluate the effectiveness of using different teacher policies, cross-entropy weights, and advantage thresholds. Moreover, several prioritization (filtering) approaches in the instance transfer are investigated. More extensive results and discussion on the properties of REPAINT are presented in Section C for completeness.



(a) Comparison against baselines (b) Comparison of different instance prioritization rules

Figure 2: Evaluation performance for MuJoCo-Reacher, averaged across five runs. In each of (a) and (b), we consider both teacher task is similar to (left) and different from (right) the target task.

Table 1: Evaluation performance for MuJoCo-Ant, averaged across three runs. In this experiment, teacher task is similar to the target task.

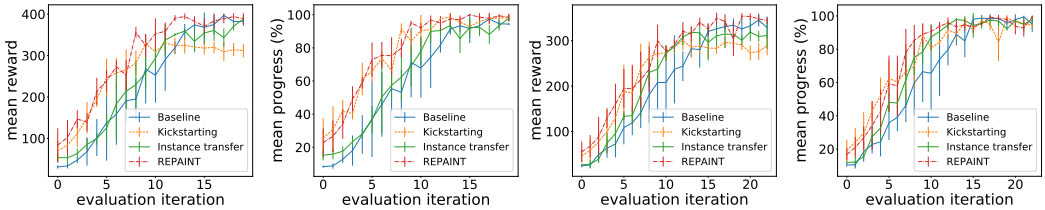
Model	Average return score of num_iterations$\pm$50						
	100	200	300	400	600	800	1000
Baseline	37	202	653	1072	1958	2541	3418
Kickstarting	1686	2657	2446	3688	4233	4744	4924
Instance transfer ($\zeta = 1.2$)	338	1058	1618	1973	3117	4163	4432
REPAINT ($\zeta = 1.2$)	1782	2663	3150	3789	4698	4996	5173
REPAINT ($\zeta = 0$)	1747	1932	2665	3245	4250	4561	4809
REPAINT ($\zeta = 0.8$)	2004	2593	2987	3638	4299	4847	5074
REPAINT ($\zeta = 1.5$)	2009	2605	2764	3309	4061	4838	5116

5.1 Continuous Action Control in MuJoCo Physics Simulator

MuJoCo-Reacher. In the target task, the agent is rewarded by getting close to the goal point (distance reward) with less movement (control reward). We first compare our REPAINT algorithm against training with only kickstarting or instance transfer and with no prior knowledge (baseline), based on two different teacher tasks. The first teacher policy is trained with similar reward function but a higher weight on the control reward, where we set it to be 3 as an example, so that the cosine similarity is positive and the learning is transferred from a *similar* task. Another teacher policy is trained in a *different* task, where the agent is penalized when it is close to the goal. In this case, the cosine similarity is zero. After each training iteration, we evaluate the policy for another 20 episodes. The evaluation performance is presented in Figure 2(a). We remark that same trends can be observed from figures of training performance against steps. REPAINT outperforms baseline algorithm and instance transfer in both cases of task similarities, regarding the training convergence time, the asymptotic performance, and the initial performance boosting. Although kickstarted training can improve the initial performance, it has no performance gain in convergence when the teacher behavior is opposed to the expected target behavior. On the other hand, while instance transfer does not boost the initial performance, it surpasses the baseline performance asymptotically in both cases.

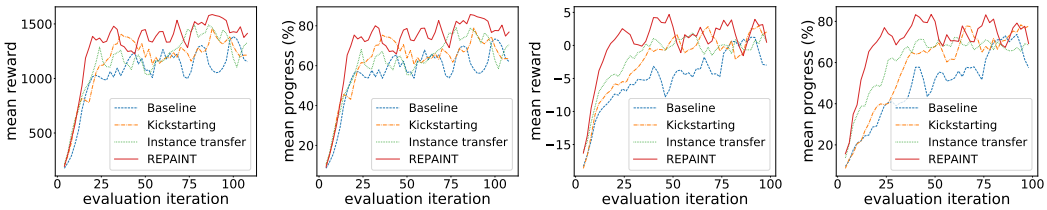
We also compare the performance of several advantage prioritization (filtering) rules in the instance transfer of REPAINT, which includes keeping transitions with high absolute values of advantages ($|\cdot| > \zeta$), keeping top 20% of transitions in the advantage value ranking (top 20%), our proposed filtering rule ($\cdot > \zeta$), and prioritized experience replay described in Schaul et al. (2015b) (PER). For PER, we used the advantage estimates to compute the prioritization instead of TD errors for a fair comparison, and slightly tuned the α and β parameters in the probability computation and importance-sampling weights, respectively. From Figure 2(b), we can observe that the proposed filtering rule and top 20% rule perform better than others on the initial performance, where most of the samples are removed for policy update. Moreover, PER does not work as well as other approaches when task similarity is low, since it includes all low-advantage teacher samples which have no merits for the student policy to learn. Therefore, we suggest to use the proposed filtering rule with a threshold ζ or the ranking-based filtering rule with a percentage threshold in the instance transfer.

MuJoCo-Ant. Other than the comparison against baselines, we also assess our REPAINT algorithm with different filtering thresholds here, i.e., the parameter ζ in Algorithm 1. In this target task,



(a) Outer-lane reward task with inner-lane teacher (b) Inner-lane reward task with outer-lane teacher

Figure 3: Evaluation performance for DeepRacer single-car time-trial race, including mean accumulated rewards and mean progress (lap completion percentage), averaged across five runs.



(a) Task with advanced reward (b) Task with progress-based reward

Figure 4: Evaluation performance for DeepRacer multi-car racing against bot cars, averaged across three runs. The value at each iteration is smoothed by the mean value of nearest 3 iterations.

the agent is rewarded by survival and moving forward, and penalized by control and contact cost. The teacher task is a *similar* task, which has the reward function with a higher weight on moving forward. In the experiments, we train each model for 1100 iterations, and evaluate each training iteration for another 5 episodes. The evaluation results are shown in Table 1. We can again observe that, when task similarity is high, training with REPAINT or kickstarting significantly improves the initial performance, reduces the learning cost of achieving a certain performance level, and improves the asymptotic performance. The table also indicates that our algorithm is robust to the threshold parameter. Similar learning progresses are observed from training with different ζ values.

5.2 Autonomous Racing in AWS DeepRacer Simulator

Single-car time trial. In this experiment, we use two different reward functions, one of which encourages the agent to stick to the inner lane (left of the yellow center-line) and the other rewards the agent when it is in the outer lane. When we use one reward function in the student task, we provide the teacher policy that is trained with the other reward. Therefore, the cosine similarity of teacher and target task is zero. We evaluate the policy for 5 episodes after each iteration. The evaluation performance is presented in Figure 3, where both average return and progress (percentage of a lap the agent accomplished when it went out of track) are given. Although upon convergence, all models can finish a lap without going off-track, REPAINT and kickstarting again significantly boost the initial performance. However, when the teacher task is very different from the target task, training with kickstarting cannot improve the final performance via transfer. In contrast, instance transfer can still reduce the training convergence time with a final performance better than kickstarting.

In Section C, we also compare the REPAINT algorithm with a commonly used *parameter transfer* approach, i.e., *warm start*, when the task similarity is low. Furthermore, the effect of different cross-entropy weights β_k or instance filtering thresholds ζ is studied, which is presented in Section C.3.

Racing against bot cars. The REPAINT algorithm is still helpful when the RL agent needs to learn multiple skills in a task. In the environment of racing against bot cars, the agent has to keep on the track while avoiding slow-moving cars in order to obtain a high return score. Therefore, we first train a teacher policy which is good at object avoidance, namely, the agent is rewarded when it keeps away from all bot cars and gets a penalty when the agent is too close to a bot car and heads towards to it. Then in the target tasks, we use two different reward functions to assess the models. First, we use an *advanced reward* where other than keeping on track and object avoidance, it also penalizes the agent when it detects some bot car from the stereo camera and is in the same

Table 2: Summary of the experimental results.

Env.	Teacher type	Target score	K_{Baseline}	K_{KS} (pct. reduced)	K_{IT} (pct. reduced)	K_{REP} (pct. reduced)	Best scores (KS, IT, REP)
Reacher	similar	-7.4	173	51 (71%)	97 (44%)	42 (76%)	-5.3,-5.9,-5.4
	different			73 (58%)	127 (27%)	51 (71%)	-6.9,-6.4,-5.2
Ant	similar	3685	997	363 (64%)	623 (38%)	334 (66%)	5464,5172,5540
Single-car	different	394	18	–	–	13 (28%)	331,388,396
	different	345	22	–	–	15 (32%)	300,319,354
Multi-car	sub-task	1481	100	34 (66%)	75 (25%)	29 (71%)	1542,1610,1623
	sub-task	2.7	77	66 (14%)	53 (31%)	25 (68%)	4.9,4.2,6.1

lane with the bot. The evaluation performance is shown in Figure 4(a). Since the environment has high randomness, such as agent and bot car initial locations and bot car lane changing, we only report average results across three runs but omit the error bars. One can observe that REPAINT outperforms other baselines regarding the training time needed for some certain performance level and the asymptotic performance. Moreover, another target task with a *progress-based reward* is also investigated, where the agent is only rewarded based on its completion progress, but gets large penalty when it goes off-track or crashes with bot cars. The evaluation performance is provided in Figure 4(b). When the target task is complex and the reward is simple as in this case, it is sometimes difficult for the agent to learn a good policy as it lacks guidance from the reward on its actions. However, a teacher policy can provide guidance for the agent to achieve high accumulated rewards at the early stage of training. From the figure, we can again see that training with REPAINT not only reduces the convergence time, but also largely improves the asymptotic performance compared to other models.

6 Summary and Future Work

In this work, we have proposed a knowledge transfer algorithm for deep actor-critic reinforcement learning. The REPAINT algorithm performs representation transfer and instance transfer alternately, and uses a simple yet effective method to supplement the kickstarted training, i.e., the advantage-based experience replay. The experiments across several tasks with continuous and discrete state-action spaces have demonstrated that REPAINT significantly reduces the training time needed by an agent to reach a specified performance level, and also improves the asymptotic performance of the agent, when compared to training with no prior knowledge and only kickstarting or instance transfer.

We provide a summary of the transfer performance on the experiments we have conducted, which is given in Table 2. The teacher type indicates whether the teacher task is a sub-task of or similar to the target task, based on the cosine similarity in equation 4.4. The target score is the best return that can be obtained by training from scratch. Then we provide the number of training iterations needed by each model to achieve the target score. The models include training with baseline, kickstarting (KS), instance transfer (IT), and REPAINT (REP). In Section C.5, we also provide the data of wall-clock time. Finally, in the last column, we present the best scores that each knowledge transfer model can achieve in the evaluation. Unlike other baseline algorithms, the superior performance of REPAINT is observed regardless of the task similarity. In contrast, for example, the kickstarted training provides 71% and 58% reduction on MuJoCo-Reacher, when the teacher task is similar versus different. The difference of performance is even larger on DeepRacer multi-car racing when different reward functions are used in the target task. For the DeepRacer single-car time trial, where the teacher task is significantly different from the target task, although the improvement of REPAINT is not as notable as in other tasks, it still outperforms the baseline algorithms. In this case, the kickstarting and instance transfer models are not able to reach the performance level of baseline upon convergence.

In future work, we aim to study how our proposed algorithm can automatically learn the task similarity if unknown, and spontaneously determine the best β_k and ζ values in the training based on the similarity. Our preliminary results in Section C.3 indicate that when the task similarity is low, larger β_k values may reduce the asymptotic performance of the agent. Moreover, we are also interested in the dependency of transfer performance on the neural network architectures. We provide some preliminary experimental results in Section C.4.

REFERENCES

Haitham Bou Ammar, Eric Eaton, Matthew E Taylor, Decebal Constantin Mocanu, Kurt Driessens, Gerhard Weiss, and Karl Tuyls. An automated measure of mdp similarity for transfer in reinforcement learning. In *Workshops at the Twenty-Eighth AAAI Conference on Artificial Intelligence*, 2014.

Bharathan Balaji, Sunil Mallya, Sahika Genc, Saurabh Gupta, Leo Dirac, Vineet Khare, Gourav Roy, Tao Sun, Yunzhe Tao, Brian Townsend, et al. Deepracer: Educational autonomous racing platform for experimentation with sim2real reinforcement learning. *arXiv preprint arXiv:1911.01562*, 2019.

André Barreto, Will Dabney, Rémi Munos, Jonathan J Hunt, Tom Schaul, Hado P van Hasselt, and David Silver. Successor features for transfer in reinforcement learning. In *Advances in neural information processing systems*, pp. 4055–4065, 2017.

André Barreto, Diana Borsa, John Quan, Tom Schaul, David Silver, Matteo Hessel, Daniel Mankowitz, Augustin Žídek, and Remi Munos. Transfer in deep reinforcement learning using successor features and generalised policy improvement. *arXiv preprint arXiv:1901.10964*, 2019.

Diana Borsa, André Barreto, John Quan, Daniel Mankowitz, Rémi Munos, Hado van Hasselt, David Silver, and Tom Schaul. Universal successor features approximators. *arXiv preprint arXiv:1812.07626*, 2018.

James L Carroll and Kevin Seppi. Task similarity measures for transfer in reinforcement learning task libraries. In *Proceedings. 2005 IEEE International Joint Conference on Neural Networks, 2005.*, volume 2, pp. 803–808. IEEE, 2005.

Thomas Degris, Martha White, and Richard S. Sutton. Off-policy actor-critic. *CoRR*, abs/1205.4839, 2012. URL `http://arxiv.org/abs/1205.4839`.

Yan Duan, John Schulman, Xi Chen, Peter L Bartlett, Ilya Sutskever, and Pieter Abbeel. Rl˜2: Fast reinforcement learning via slow reinforcement learning. *arXiv preprint arXiv:1611.02779*, 2016.

Norm Ferns, Prakash Panangaden, and Doina Precup. Metrics for finite markov decision processes. In *UAI*, volume 4, pp. 162–169, 2004.

Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.

Abhishek Gupta, Coline Devin, YuXuan Liu, Pieter Abbeel, and Sergey Levine. Learning invariant feature spaces to transfer skills with reinforcement learning. *arXiv preprint arXiv:1703.02949*, 2017.

Max Jaderberg, Valentin Dalibard, Simon Osindero, Wojciech M Czarnecki, Jeff Donahue, Ali Razavi, Oriol Vinyals, Tim Green, Iain Dunning, Karen Simonyan, et al. Population based training of neural networks. *arXiv preprint arXiv:1711.09846*, 2017.

Leslie Pack Kaelbling, Michael L Littman, and Andrew W Moore. Reinforcement learning: A survey. *Journal of artificial intelligence research*, 4:237–285, 1996.

Jens Kober, J Andrew Bagnell, and Jan Peters. Reinforcement learning in robotics: A survey. *The International Journal of Robotics Research*, 32(11):1238–1274, 2013.

Vijay R Konda and John N Tsitsiklis. Actor-critic algorithms. In *Advances in neural information processing systems*, pp. 1008–1014, 2000.

George Konidaris, Ilya Scheidwasser, and Andrew Barto. Transfer in reinforcement learning via shared features. *Journal of Machine Learning Research*, 13(May):1333–1371, 2012.

Alessandro Lazaric. Transfer in reinforcement learning: a framework and a survey. In *Reinforcement Learning*, pp. 143–173. Springer, 2012.

Alessandro Lazaric, Marcello Restelli, and Andrea Bonarini. Transfer of samples in batch reinforcement learning. In *Proceedings of the 25th international conference on Machine learning*, pp. 544–551, 2008.

Chen Ma, Junfeng Wen, and Yoshua Bengio. Universal successor representations for transfer reinforcement learning. *arXiv preprint arXiv:1804.03758*, 2018.

Tamas Madarasz and Tim Behrens. Better transfer learning with inferred successor maps. In *Advances in Neural Information Processing Systems*, pp. 9026–9037, 2019.

Neville Mehta, Sriraam Natarajan, Prasad Tadepalli, and Alan Fern. Transfer in variable-reward hierarchical reinforcement learning. *Machine Learning*, 73(3):289, 2008.

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 *International conference on machine learning*, pp. 1928–1937, 2016.

OpenAI, Marcin Andrychowicz, Bowen Baker, Maciek Chociej, Rafał 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`.

OpenAI, Christopher Berner, Greg Brockman, Brooke Chan, Vicki Cheung, Przemysław Debiak, Christy Dennison, David Farhi, Quirin Fischer, Shariq Hashme, Chris Hesse, Rafal Józefowicz, Scott Gray, Catherine Olsson, Jakub Pachocki, Michael Petrov, Henrique Pondé de Oliveira Pinto, Jonathan Raiman, Tim Salimans, Jeremy Schlatter, Jonas Schneider, Szymon Sidor, Ilya Sutskever, Jie Tang, Filip Wolski, and Susan Zhang. Dota 2 with large scale deep reinforcement learning. 2019. URL `https://arxiv.org/abs/1912.06680`.

Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2009.

Emilio Parisotto, Jimmy Lei Ba, and Ruslan Salakhutdinov. Actor-mimic: Deep multitask and transfer reinforcement learning. *arXiv preprint arXiv:1511.06342*, 2015.

Caitlin Phillips. Knowledge transfer in markov decision processes. Technical report, Technical report, McGill University, School of Computer Science, 2006. URL . . . , 2006.

Janarthanan Rajendran, Aravind S Lakshminarayanan, Mitesh M Khapra, P Prasanna, and Balaraman Ravindran. Attend, adapt and transfer: Attentive deep architecture for adaptive transfer from multiple sources in the same domain. *arXiv preprint arXiv:1510.02879*, 2015.

Andrei A. Rusu, Sergio Gomez Colmenarejo, Caglar Gulcehre, Guillaume Desjardins, James Kirkpatrick, Razvan Pascanu, Volodymyr Mnih, Koray Kavukcuoglu, and Raia Hadsell. Policy distillation, 2015.

Ahmad EL Sallab, Mohammed Abdou, Etienne Perot, and Senthil Yogamani. Deep reinforcement learning framework for autonomous driving. *Electronic Imaging*, 2017(19):70–76, 2017.

Tom Schaul, Daniel Horgan, Karol Gregor, and David Silver. Universal value function approximators. In *International Conference on Machine Learning*, pp. 1312–1320, 2015a.

Tom Schaul, John Quan, Ioannis Antonoglou, and David Silver. Prioritized experience replay. *arXiv preprint arXiv:1511.05952*, 2015b.

Simon Schmitt, Jonathan J Hudson, Augustin Zidek, Simon Osindero, Carl Doersch, Wojciech M Czarnecki, Joel Z Leibo, Heinrich Kuttler, Andrew Zisserman, Karen Simonyan, et al. Kickstarting deep reinforcement learning. *arXiv preprint arXiv:1803.03835*, 2018.

John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. Trust region policy optimization. In *International conference on machine learning*, pp. 1889–1897, 2015a.

John Schulman, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. High-dimensional continuous control using generalized advantage estimation. *arXiv preprint arXiv:1506.02438*, 2015b.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *nature*, 529(7587):484, 2016.

Jinhua Song, Yang Gao, Hao Wang, and Bo An. Measuring the distance between finite markov decision processes. In *Proceedings of the 2016 international conference on autonomous agents & multiagent systems*, pp. 468–476, 2016.

Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

Erik Talvitie and Satinder P Singh. An experts algorithm for transfer learning. In *IJCAI*, pp. 1065–1070, 2007.

Matthew E Taylor and Peter Stone. Transfer learning for reinforcement learning domains: A survey. *Journal of Machine Learning Research*, 10(Jul):1633–1685, 2009.

Matthew E Taylor, Nicholas K Jong, and Peter Stone. Transferring instances for model-based reinforcement learning. In *Joint European conference on machine learning and knowledge discovery in databases*, pp. 488–505. Springer, 2008a.

Matthew E Taylor, Gregory Kuhlmann, and Peter Stone. Autonomous transfer for reinforcement learning. In *AAMAS (1)*, pp. 283–290. Citeseer, 2008b.

Andrea Tirinzoni, Andrea Sessa, Matteo Pirotta, and Marcello Restelli. Importance weighted transfer of samples in reinforcement learning. *arXiv preprint arXiv:1805.10886*, 2018.

Emo Todorov. Mujoco: Modeling, simulation and visualization of multi-joint dynamics with contact. *Seattle WA: Roboti Publishing*, 2016.

Haiyan Yin and Sinno Jialin Pan. Knowledge transfer for deep reinforcement learning with hierarchical experience replay. In *Thirty-First AAAI Conference on Artificial Intelligence*, 2017.

Amy Zhang, Harsh Satija, and Joelle Pineau. Decoupling dynamics and reward for transfer learning. *arXiv preprint arXiv:1804.10689*, 2018.

Shangtong Zhang, Wendelin Boehmer, and Shimon Whiteson. Generalized off-policy actor-critic. In H. Wallach, H. Larochelle, A. Beygelzimer, F. dAlché-Buc, E. Fox, and R. Garnett (eds.), *Advances in Neural Information Processing Systems 32*, pp. 2001–2011. Curran Associates, Inc., 2019. URL http://papers.nips.cc/paper/8474-generalized-off-policy-actor-critic.pdf.

A ALGORITHM

In order to directly compare with the baseline algorithms regarding the reduction of number of training iterations, we adopt representation transfer and instance transfer alternately in Algorithm 1, so that the REPAINT performs policy update one time per iteration. Indeed, Algorithm 1 can be easily extended with different alternating ratios other than 1:1 alternating. The corresponding results and discussion can be found in Section C.1. More generically, we can integrate the two transfer steps in one iteration, which is shown in the following integrated REPAINT algorithm with Clipped PPO.

Algorithm 2 Integrated REPAINT algorithm with Clipped PPO

for iteration $k = 1, 2, \ldots$ **do**
  Collect samples $\mathcal{S} = \{(s, a, s')\}$ by $\pi_{\theta_{\text{old}}}(s)$, and $\mathcal{S}' = \{(s, a, s')\}$ by $\pi_{\text{teacher}}(s)$
  Compute r for each transition using current reward function and add to $\mathcal{S}$ and $\mathcal{S}'$, respectively
  Fit state value network V_ν using only $\mathcal{S}$ to update ν
  Compute advantage estimates $\hat{A}_1, \ldots, \hat{A}_T$ for $\mathcal{S}$ and $\hat{A}'_1, \ldots, \hat{A}'_{T'}$ for $\mathcal{S}'$ by equation 3.4
  for t=1,...,T' **do**
    if $\hat{A}'_t < \zeta$ **then**
      Remove $\hat{A}'_t$ and the corresponding transition (s_t, a_t, s_{t+1}, r_t) from $\mathcal{S}'$
  Compute sample gradient of $L^k_{\text{RL}}(\theta)$ defined in equation 4.2 using $\mathcal{S}$
  Compute sample gradient of $L_{\text{clip}}(\theta)$ defined in equation 3.5 using $\mathcal{S}'$
  Update policy network by $\theta \leftarrow \theta + \alpha_1 \nabla_\theta L^k_{\text{RL}}(\theta) + \alpha_2 \nabla_\theta L_{\text{clip}}(\theta)$

Note that in Algorithm 2, we can use different learning rates α_1 and α_2 to control the update from representation transfer and instance transfer, respectively.

So far, we have only used a single teacher policy in the knowledge transfer, and adopt the objective function from only Clipped PPO algorithm. However, it is straightforward to using multiple teacher policies in each transfer step, and our algorithm can be directly applied to any advantage-based policy gradient RL algorithms. Assume there are m previously trained teacher policies $\pi_1, \ldots, \pi_m$. In the instance transfer, we can form the replay buffer $\mathcal{S}'$ by collecting samples from all teacher policies. Then in the representation transfer, the objective function can be written in a more general way:

$$L^k_{\text{RL}}(\theta) = L_{\text{clip}}(\theta) - \sum_{i=1}^{m} \beta^k_i H\left(\pi_i(a|s) \| \pi_\theta(a|s)\right) , \tag{A.1}$$

where we can impose different weighting parameters for different teacher policies.

In addition, the first term in equation A.1, i.e., $L_{\text{clip}}(\theta)$, can be replaced by the objective of other RL algorithms, e.g., A2C (classical gradient policy):

$$L_{\text{A2C}}(\theta) = \hat{\mathbb{E}}_t \left[\log \pi_\theta(a|s) \hat{A}_t\right] , \tag{A.2}$$

and TRPO (Schulman et al., 2015a):

$$L_{\text{TRPO}}(\theta) = \hat{\mathbb{E}}_t \left[\frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)} \hat{A}_t - \beta \text{KL}[\pi_{\theta_{\text{old}}}(\cdot|s), \pi_\theta(\cdot|s)]\right] \tag{A.3}$$

for some coefficient β of the maximum KL divergence computed over states.

B EXPERIMENTAL SETUP

B.1 ENVIRONMENTS

We now provide the details of our experimental setup. MuJoCo is a well-known physics simulator for evaluating agents on continuous motor control tasks with contact dynamics. In AWS DeepRacer simulator[1], the RL agent, i.e., an autonomous car, learns to drive by interacting with its environment,

[1] https://github.com/awslabs/amazon-sagemaker-examples/tree/master/reinforcement_learning/rl_deepracer_robomaker_coach_gazebo

e.g., the track with moving bot cars, by taking an action in a given state to maximize the expected reward. Figures 1(c) and 1(d) present two environmental settings investigated in this work, i.e., single-car time-trial race, where the goal is to finish a lap in the shortest time, and racing against moving bot cars, where four bot cars are generated randomly on the track and the RL agent learns to finish the lap with overtaking bot cars.

In single-car racing, we only install a front-facing camera on the RL agent, which obtains an RGB image with size $120 \times 160 \times 3$. The image is then transformed to gray scale and fed into an input embedder. For simplicity, the input embedder is set to be a three-layer convolutional neural network (CNN) (Goodfellow et al., 2016). For the RL agent in racing against bot cars, we use a stereo camera and a Lidar as sensors. The stereo camera obtains two images simultaneously, transformed to gray scale, and concatenates the two images as the input, which leads to a $120 \times 160 \times 2$ input tensor. The input embedder for stereo camera is also a three-layer CNN by default. The stereo camera is used to detect bot cars in the front of learner car, while the Lidar is used to detect any car behind. The backward-facing Lidar has an angle range of 300 degree and a 64 dimensional signal. Each laser can detect a distance from 12cm to 1 meter. The input embedder for Lidar sensor is set to be a two-layer dense network. In both environments, the output has two heads, V head for state value function output and policy head for the policy function output, each of which is set to be a two-layer dense networks but with different output dimensions. The action space consists of a combination of five different steering angles and two different throttle degrees, which forms a 10-action discrete space. In the evaluation of DeepRacer experiments, the generalization around nearby states and actions is also considered (Balaji et al., 2019), where we add small noises to the observations and actions.

B.2 HYPERPARAMETERS

We have implemented our algorithms based on Intel Coach[2]. The MuJoCo environments are from OpenAI Gym[3]. If not specified explicitly in the paper, we always use Adam as the optimizer with a learning rate of 3×10^{-4}, minibatch size as 64, clipping parameter ϵ as 0.2, $\beta_0 = 0.2$ and $\beta_{k+1} = 0.95\beta_k$ throughout the experiments. The other hyperparameters are presented below.

Table 3: Hyperparameters used in the MuJoCo simulations.

Hyperparameter	Value
Num. of rollout steps	2048
Num. training epochs	10
Discount (γ)	0.99
GAE parameter (λ)	0.95
Beta entropy	0.0001
Reacher - Advantage Threshold (ζ)	0.8
Reacher - Num. REPAINT iterations	15
Ant - Num. REPAINT iterations	50

Table 4: Hyperparameters used in the DeepRacer simulations.

Hyperparameter	Value
Num. of rollout episodes	20
Num. of rollout episodes when using π_{teacher}	2
Num. training epochs	8
Discount (γ)	0.999
GAE parameter (λ)	0.95
Beta entropy	0.001
Advantage Threshold (ζ)	0.2
Single-car - Num. REPAINT iterations	4
Multi-car - Num. REPAINT iterations	20

[2] https://github.com/NervanaSystems/coach
[3] https://gym.openai.com/envs/#mujoco

C EXTENSIVE EXPERIMENTAL RESULTS

C.1 ALTERNATING RATIOS

In Algorithm 1, we alternate representation transfer and instance transfer after each iteration. Here, we aim to illustrate the effect of using different alternating ratios by the MuJoCo-Reacher environment. We compare the 1:1 alternating with a 2:1 ratio, namely, two representation transfer (kickstarting) iterations before and after an instance transfer iteration. The evaluation performance is shown in Figure 5. When the teacher task is similar to the target task, adopting more kickstarted training iterations leads to faster convergence, due to the policy distillation term in the loss function. On the other hand, when the task similarity is low, instance transfer contributes more to the knowledge transfer due to the advantage-based experience replay. Therefore, we suggest to set the alternating ratio in Algorithm 1, or the α_1 and α_2 parameters in Algorithm 2, according to the task similarity between source and target tasks. However, the task similarity is usually unknown in most of the real-world applications, or the similarities are mixed when using multiple teacher policies. It is interesting to automatically learn the task similarity and determine the best ratio/parameters before actually starting the transfer learning. We leave the investigation of this topic as a future work.

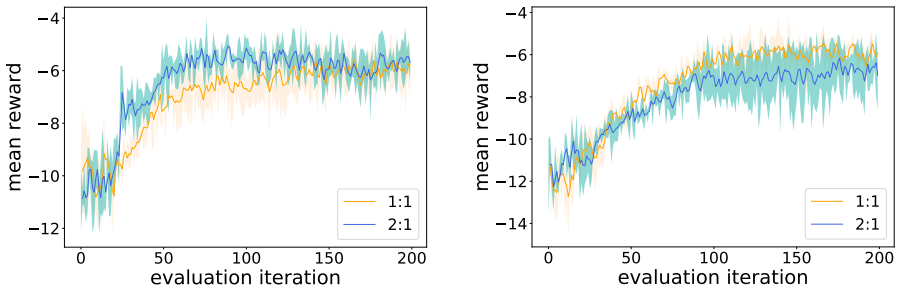
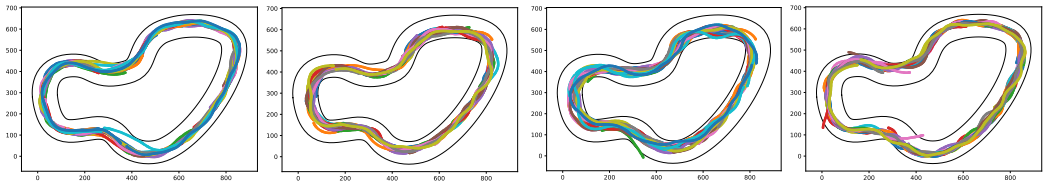


Figure 5: Evaluation performance for MuJoCo-Reacher, averaged across five runs. Left: Teacher task is similar to the target task. Right: Teacher task is different from the target task.

C.2 REPAINT *vs.* WARM-START

We also want to compare our hybrid *representation-instance* transfer algorithm with a widely-used *parameter* transfer approach, i.e., warm-start. In warm-start, the agent initializes with parameters from the teacher policy and conducts the RL algorithm after that. When the target task is similar to the teacher task, it usually works well. But here we compare the two algorithms in the DeepRacer single-car experiment, where the two tasks are significantly different. Figure 6 visualizes the trajectories of the agent on the track during evaluations. Each model is trained for two hours and evaluated for another 20 episodes. From both cases, we can see that although the two reward functions encode totally different behaviors, REPAINT can still focus on current task while learning from the teacher policy. This again indicates the effectiveness of the advantage-based experience replay in the instance transfer. In comparison, training with warm start cannot get rid of the unexpected behavior at convergence due to the reason that it may be stuck at some local optimum. Therefore, initialization with previously trained policies can sometimes jump-start the training with good initial performance, but the method contributes to the final performance only when two tasks are highly related.

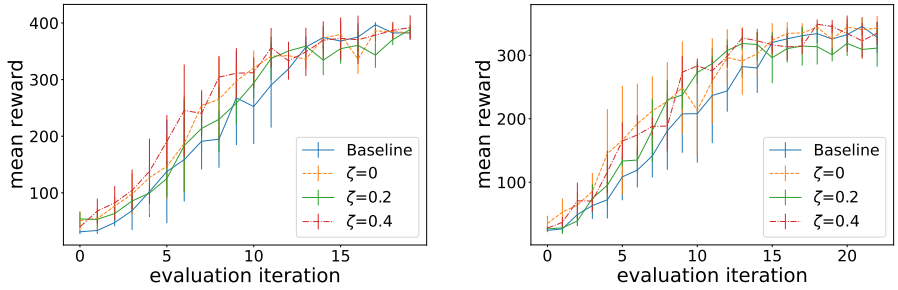


(a) Outer-lane task: REPAINT *vs.* warm-start (b) Inner-lane task: REPAINT *vs.* warm-start

Figure 6: Trajectories of policy evaluations. In each of (a) and (b), evaluation of the models trained from REPAINT is visualized on the left and that trained with warm-start is on the right.

C.3 More Results on DeepRacer Single-Car Time Trial

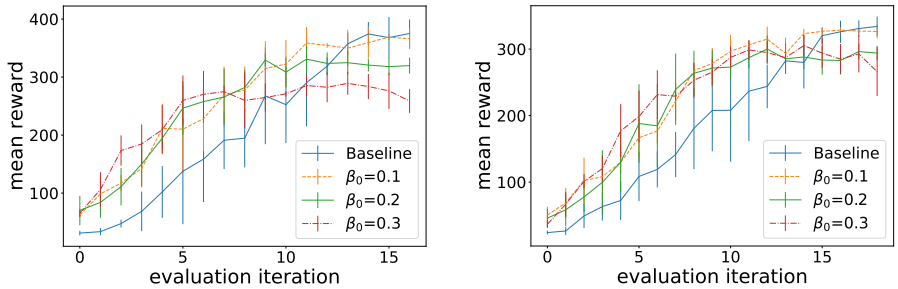
In the DeepRacer single-car time-trial task, we also study the effect of different cross-entropy weights β_k and instance filtering thresholds ζ, as mentioned in the paper. We first present the results of instance transfer learning with different ζ values in Figure 7, where we can see that our proposed advantage-based experience replay is robust to the threshold parameter.



(a) Outer-lane task with inner-lane teacher (b) Inner-lane task with outer-lane teacher

Figure 7: Evaluation performance with respect to different ζ's, averaged across five runs.

We then study the performance of training with different cross-entropy loss weights β_k. For simplicity, we fix the diminishing factor to be 0.95, namely, $\beta_{k+1} = 0.95\beta_k$, and only test different β_0's. From Figure 8, we can see that training with all β_0 values can improve the initial performance compared to the baseline. However, when the teacher task is different from the target task, larger β_0 values, like 0.3, may reduce the agent's asymptotic performance since the agent overshoots learning from teacher policy. It is of interest to automatically determine the best β_k values during training, which needs further investigation. We leave it as another future work.



(a) Outer-lane task with inner-lane teacher (b) Inner-lane task with outer-lane teacher

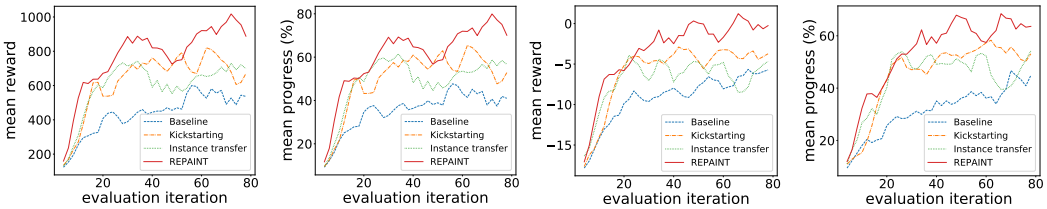
Figure 8: Evaluation performance with respect to different initial β_0's, averaged across five runs.

C.4 Neural Network Architectures

For completeness of the experiments, we also provide some results regarding different neural network architectures in this section. Take the DeepRacer task of multi-car racing against bot cars as an example, we have used three-layer CNN as the default architecture in experiments. Here, we present the comparison of REPAINT against other baselines with the evaluation performance using four-layer CNN (Figure 9) and five-layer CNN (Figure 10).

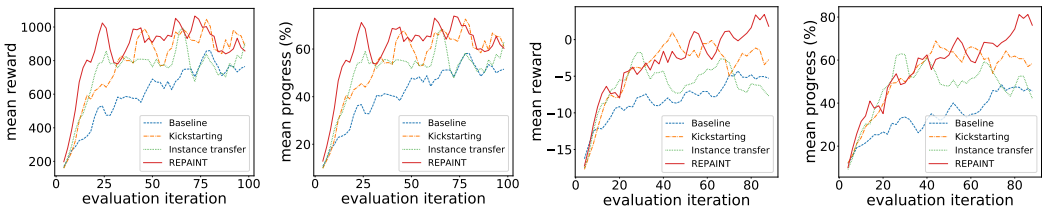
C.5 Summary of Wall-Clock Training Time

In addition to the summary of reduction performance with respect to number of training iterations presented in Table 2, we also provide the data of wall-clock time in Table 5 below. Again, we can see a significant reduction by training with REPAINT, which reaches at least 60% besides the DeepRacer single-car time trial. The kickstarted training performs well when a similar teacher policy is used. Although training with only instance transfer cannot boost the initial performance, it still reduces the training cost to achieve some specified performance level.



(a) Task with advanced reward (b) Task with progress-based reward

Figure 9: Evaluation performance for DeepRacer multi-car racing against bot cars, using 4-layer CNN. The value at each iteration is smoothed by the mean value of nearest 3 iterations.



(a) Task with advanced reward (b) Task with progress-based reward

Figure 10: Evaluation performance for DeepRacer multi-car racing against bot cars, using 5-layer CNN. The value at each iteration is smoothed by the mean value of nearest 3 iterations.

Table 5: Summary of wall-clock time of experiments.

Env.	Training hardware	Teacher type	Target score	$T_{Baseline}$ (hrs)	T_{KS} (pct. reduced)	T_{IT} (pct. reduced)	T_{REP} (pct. reduced)
Reacher	laptop	similar	-7.4	2.1	0.6 (71.4%)	1.1 (47.6%)	0.4 (81.0%)
		different			0.9 (57.1%)	1.4 (33.3%)	0.6 (71.4%)
Ant	laptop	similar	3685	19.1	8.0 (58.1%)	12.8 (33.0%)	7.5 (60.7%)
Single-car	AWS, p2	different	394	2.2	–	–	1.5 (31.8%)
	AWS, p2	different	345	2.3	–	–	1.5 (34.8%)
Multi-car	AWS, p2	sub-task	1481	16.4	4.8 (70.7%)	12.6 (23.2%)	4.5 (72.6%)
	AWS, p2	sub-task	2.7	9.6	9.3 (3.1%)	8.3 (13.5%)	3.7 (61.5%)