Efficient Robotic Manipulation Through Offline-to-Online Reinforcement Learning and Goal-Aware State Information

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\textbf{Abstract}—End-to-end learning robotic manipulation with high data efficiency is one of the key challenges in robotics. The latest methods that utilize human demonstration data and unsupervised representation learning has proven to be a promising direction to improve RL learning efficiency. The use of demonstration data also allows “warming-up” the RL policies using offline data with imitation learning or the recently emerged offline reinforcement learning algorithms. However, existing works often treat offline policy learning and online exploration as two separate processes, which are often accompanied by severe performance drop during the offline-to-online transition. Furthermore, many robotic manipulation tasks involve complex sub-task structures, which are very challenging to be solved in RL with sparse reward. In this work, we propose a unified offline-to-online RL framework that resolves the transition performance drop issue. Additionally, we introduce goal-aware state information to the RL agent, which can greatly reduce task complexity and accelerate policy learning. Combined with an advanced unsupervised representation learning module, our framework achieves great training efficiency and performance compared with the state-of-the-art methods in multiple robotic manipulation tasks.

\section{I. INTRODUCTION}

In recent few years, deep reinforcement learning (RL) has seen great success in solving complex tasks such as games [1]–[3] and robotic control [4]–[7]. The nice feature that RL can perform end-to-end learning with high-dimensional imagery input has made it a popular direction for dexterous robotic manipulation policy learning [8]–[13]. Due to relatively high data collection cost on a real robot, developing high data-efficiency RL algorithms has become a key research focus in this area [8], [12], [13].

Past studies on high data-efficiency RL-based robotic manipulation methods mainly follow three direction. The first stream of works focus on replacing the sparse reward in robotic manipulation tasks with dense reward [14] or introduce special reward structures [15], [16]. Using more informative task reward can effectively reduce task complexity and lead to faster learning. However, this also has the drawback of involving heavy human engineering in the reward design, which loses generalizability across tasks as compared with the simple sparse reward. Another line of research is through Sim2Real, which learns an RL agents in simulation and then transfer to real world [12], [17], [18]. The downsides of this approach are high-variance in the learned polices and extensive computation involved due to training with domain randomization [19].

A more recent and effective direction to address the data-efficiency issue is through collecting small-scale real-world expert demonstration data for representation learning as well as policy pre-training via imitation learning [20], [21], and then training the RL agent either in simulation or real world. This approach has achieved state-of-the-art performance and data-efficiency in various robotic manipulation tasks [13]. The state representation is learned from real-world data, which commits lower error during Sim2Real adaptation. The pre-trained policy also facilitate faster online RL training. Inspired by existing studies and our empirical findings, we draw several new insights toward designing highly data-efficient robotic control RL algorithms. First, informative state representations, including representations learned from expert demonstrations, as well as state observations that encode goal-stage information plays a very important role in accelerating policy learning (see Figure 1a and 1b). State representations learned from expert demonstrations and non-expert data, although both produces meaningful visual representations, has distinct impact on RL learning performance (Figure 1a). This suggests that discriminating expert experi-

\begin{figure}[h]
\centering
\includegraphics[width=\linewidth]{fig1.png}
\caption{Impacting issues in vision-based robotic manipulation. All tasks are the OpenAI Gym Fetch suite [22]. Results in (a) and (b) are produced using FERM [13].}
\end{figure}

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enced states over the less helping states is very beneficial. Moreover, many complex tasks involve multiple stages (e.g. move, open/raise/close the gripper etc.), let the agent know the current task-stage and goal-related information can lead to faster learning even with sparse reward (Figure 1b). Second, use expert demonstrations to “warm-up” policies and Q-functions to accelerate algorithm convergence is already adopted in a number of approaches [13], [23]–[25]. However, as we observe in empirical studies (Figure 1c), the transition stage between offline pre-training and online RL learning is often accompanied by severe performance drop, primarily caused by distributional shift of the policy and Q-function at the beginning of online RL training. The policy and Q-function are offline trained with respect to expert data, online exploitation and exploration may result in data not in the distribution of expert data, causing exploitation error in Q-function and distorting policy learning. This phenomenon is similar to the distributional shift issue in offline RL problems [26], [27]. Thus a better and more unified approach should be introduced to abridge the online-to-offline transition without performance loss. Moreover, as a stronger alternative to imitation learning, offline RL allows performing data-driven optimization upon a static offline dataset, which can achieve higher performance as compared with imitation learning methods, e.g. behavior cloning (BC) that naively imitates the data.

In this study, we propose a new unified offline-to-online RL framework, combined with goal-aware state information and unsupervised representation learning, which achieves highly efficient robotic manipulation learning with simple sparse reward. Our proposed offline-to-online transition scheme can effectively alleviate the aforementioned performance drop. With additionally introduced goal-aware state information, our approach greatly accelerate RL training process and lead to higher data-efficiency. We evaluate the proposed framework on multiple tasks from the OpenAI Gym Fetch suite. Our method outperforms the latest state-of-the-art method FERM [13] with much higher data-efficiency and ability to better solve harder tasks with sparse reward.

II. RELATED WORK

A. Online Reinforcement Learning for Robotic Control

Applying deep reinforcement learning for robotic control with visual inputs have received great attention and achieved some good progress in tasks such as manipulation [5], grasping [10] and locomotion [4], [6]. However, the adoption of RL on real-world robots are still bottle-necked due to the data-inefficiency and safety issues. Online RL algorithms rely heavily on interactive exploration with the environment, which poses great challenge in relative expensive real-world data collection. To remedy this difficulty, new methods have been proposed by utilizing dense or structured reward signals [14]–[16], Sim2Real techniques [12], [17], [18] or imitation learning approaches [20], [28]. More recent studies began to combine online RL with imitation learning and unsupervised representation learning when given a small-set of human demonstration data [13], [23]–[25]. These methods enable fully utilizing information contained in the demonstration data, which greatly accelerates the policy learning and improves data-efficiency.

B. Offline Reinforcement Learning

Offline RL (also called batch RL [29]) tackles the problem of learning policies solely from offline, static datasets, which has already achieved more performant results compared with imitation learning. A major challenge of offline RL is distributional shift [27], which occurs when the distribution induced by the learned policy deviates largely from the data distribution. Policies can make counterfactual queries on unknown out-of-distribution (OOD) actions, causing serious overestimation of Q-values during RL training updates. Although off-policy RL methods [30]–[32] are designed to learn from a replay buffer, they typically fail to learn solely from fixed offline dataset and still require collecting online samples for good performance.

Existing offline RL methods address the distributional shift issue by following three main directions. Most model-free offline RL methods constrain the learned policy to be “close” to behavior policy either by deviation clipping [33] or incorporate additional divergence penalties (such as KL divergence or MMD) [26], [34]. Other model-free offline RL algorithms modifies Q-function training objective to learn a conservative, underestimated Q-function [35], [36]. Model-based offline RL algorithms adopt a pessimistic MDP framework [37], where the rewards of model predicted samples are penalized if they have high uncertainty [37]–[39].

To strive for simplicity in offline RL, Fujimoto and Gu [40] proposes a minimalist approach, TD3+BC, which simply adds a behavior cloning term to the policy update of TD3 [31], which balances between RL and imitation learning.

C. Data Augmentation and Unsupervised Representation Learning

Data augmentation is a widely used approach for improving data efficiency. As showed in recent studies [7], [41], [42], simple data manipulation on images, like rotation, cropping and flipping, can greatly improve data-efficiency and performance of vision-based RL tasks. Data augmentation also plays a key role in contrastive learning and unsupervised representation learning in computer vision [43]–[45]. Contrastive learning is a kind of self-supervised learning approach. By maximizing the agreement between similar samples and the difference between dissimilar samples, contrastive learning can obtain the informative representation of samples in an unsupervised manner. Recent studies [43]–[45] have shown that pre-training on unlabeled ImageNet datasets using contrastive learning sometimes achieves better results than supervised learning on downstream classification tasks. The unsupervised representation learning methods have been applied in RL tasks in several studies [13], [41], [42], which demonstrate great improvement over data-efficiency.
III. PRELIMINARIES

A. Reinforcement Learning Settings

We model our robotic manipulation task as a Markov decision process (MDP) process, which is represented as a tuple \( (S, A, r, T, \gamma) \), where \( S \) and \( A \) denote the state and action set, \( r(s,a) \) is the sparse reward function, which takes the value 1 if the agent reaches the goal, -1 otherwise; \( T(s' | s, a) \) denotes the transition dynamics from current state-action pair \((s, a)\) to next state \(s'\) and \( \gamma \in (0, 1) \) is the discount factor. To enhance the data efficiency, the states \( s \) considered in our problem are the state representations encoded from the raw imagery inputs using an unsupervised representation learning model [46], which is trained with a small set of human expert demonstration data \( D \). We use reinforcement learning to solve above MDP problem, with the objective to find the optimal policy \( a = \pi(s) \) to maximize the cumulative expected return \( J(\pi) = \mathbb{E}_{\pi} \left[ \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right] \).

In the commonly used actor-critic RL paradigm, one optimizes the policy \( \pi(s) \) by alternatively learning a Q-function \( Q^\pi_B \) to minimize the Bellman error over transitions \((s, a, r, s')\) from a replay buffer \( B \) as

\[
J(Q) = \mathbb{E}_{s,a,r,s' \sim B} \left[ (y - Q^\pi_B(s, a))^2 \right]
\]

where \( y = r + \gamma \max_{a'} Q^\pi_B(s', a') \) is the target Q-value and \( Q^\pi_B \) denotes a target Q-function, which is periodically synchronized with the current Q-function. Then, the policy is updated to maximize the Q-value, \( E_{a \sim \pi_\theta} \left[ Q^\pi_B(s, a) \right] \).

B. TD3

The backbone RL algorithm used in our proposed offline-to-online framework is based on the twin delayed deep deterministic policy gradient algorithm (TD3) [31]. TD3 is an off-policy RL algorithm that learns a deterministic policy. In TD3, two critic Q-functions \( Q^\pi_\theta \) and \( Q^\pi_\delta \) are learned, and the target value is evaluated by taking the minimum of the two Q-functions’ estimates as follows:

\[
y = r + \gamma \min_{i=1,2} Q^\pi_{\theta_i}(s', \pi(s') + \varepsilon) + \varepsilon
\]

\[
\varepsilon \sim \text{clip}(N(0, \sigma), -c, c)
\]

The scheme used in Equation 2 is termed as clipped double Q-learning, which is shown to be highly effective in reducing overestimation error in off-policy learning. This treatment is also adopted in other off-policy RL method like SAC [32]. TD3 additionally adds a small amount of random noise \( \varepsilon \) to the target policy, so as to smooth the value estimates and improve robustness of the learned Q-functions.

Though much simpler compared with state-of-the-art off-policy RL method SAC [32], TD3 offers comparative performance against SAC. TD3 also has a huge advantage of learning a deterministic policy as well as Q-functions less prone to value overestimation, which can be easily extended into a offline RL algorithm [40] as will be discussed in the following content. This offers an opportunity to develop an unified framework that combines offline and online learning. By contrast, SAC learns an stochastic policy and solves a maximum entropy RL problem by adding an entropy term in the Q-value estimates. Although such a treatment can improve exploration in online RL, incorporating an entropy term and maximize over it can be very harmful in offline RL, as it could introduce more potential OOD errors as well as severe distributional shift.

C. Offline RL via TD3+BC

As an extension of TD3, Fujimoto and Gu [40] proposes a minimalist algorithm for offline RL, called TD3+BC, which simply adds a behavior cloning regularization term to the policy update of TD3:

\[
\pi = \arg\max_{\pi} \mathbb{E}_{(s,a) \sim D} \left[ \lambda Q(s, \pi(s)) - (\pi(s) - a)^2 \right]
\]

with \( \lambda = \alpha / |s,a| \), action ranges are set as \([-1,1]\). TD3+BC uses the BC term to force the policy do not deviate too much from the behavior policy of the offline dataset, while allowing the policy to be optimized with respect to the Q-function. The parameter \( \alpha \) is used to control the degree of the regularize. A larger \( \alpha \) will make the algorithm approach more RL (\( \alpha = 4 \)), while a small \( \alpha \) will favor more imitation (\( \alpha = 1 \)).

IV. METHOD

A. Goal-aware State Information

1) Importance of representation learning with expert data:

Based on our empirical observations, the state representations obtained using unsupervised representation learning from expert demonstrations and non-expert data, although both provide meaningful visual representations, have huge performance differences on robotic manipulation tasks (see Figure 1a and Section V.C.1). State representations learned from expert data greatly accelerates the convergence speeds compared with using non-expert data. A possible explanation could be that unsupervised representation learning via contrastive learning tend to overfit expert data, producing somewhat different state representations for expert experienced states and uncovered states, which allows the RL agents to easily discriminate different types of states during training. Since expert experienced states correspond to high-reward, successful trajectories, this in fact enforces an expert-imitative behavior during RL training, which results in accelerated learning in robotic manipulation tasks.

2) Goal-aware observations: Many robotic manipulation tasks contain complex internal structures that can be seen as ensembles of a series ordered sub-tasks, with each corresponds to a stage and sub-goal. Solving such tasks using sparse reward is quite challenging, as the reward signal it self does not contain any task structure information. Given that vision-based robotic manipulation tasks often correspond to partially observable Markov decision processes, if involving a goal-stage aware observation that contains the information reflecting the current stage of the task, it could provide important supplementary information. This insight is also observed in several studies that exploit specially designed
reward structures to enable accelerated learning [15], [16]. An example for this is the use of hand-eyed view camera [10] for robotic grasping tasks, which has been shown to greatly improve the reinforcement learning performance.

In order to fully exploit the potential of task-stage information, we introduce additional goal-aware state information (GSI) to each task. For many robotic manipulation tasks, GSI can simply be a camera view aiming right at the goal (GSI) to each task. For many robotic manipulation tasks, GSI can greatly improve the reinforcement learning performance. [10] for robotic grasping tasks, which has been shown to reward structures to enable accelerated learning [15], [16].

An example for this is the use of hand-eyed view camera [10] of the same observation. Different from the original CURL method CURL [46], which is the same method used in CURL [46]. To address the aforementioned performance drop issue and maintain the performance of the offline learned policy using expert demonstrations \( \mathcal{D} \), and the latter produces both offline learned policy \( \pi(s) \) and Q-function \( Q^\pi(s,a) \). The replay buffer \( \mathcal{B} \) of the off-policy RL algorithm is initialized with \( \mathcal{D} \) for online learning.

During online learning, the first case learns a Q-function \( Q^\pi \) from the scratch using the off-policy RL. Since \( Q^\pi \) is not well-learned initially, updating the policy by maximizing the Q-value \( \pi = \arg \max_{a \sim \mathcal{B}} Q^\pi(s,a) \) can suffer from huge performance degeneration in policy learning, even if exploring with the reasonable actions produced by the BC policy.

For the second case, after switching to online RL, both solely exploiting with the learned policy \( \hat{a} \sim \pi \) or performing regular exploration \( \hat{a} = \pi(s) + \eta \) with exploration noise \( \eta \) are likely to produce state-action pairs \((s, \hat{a})\) that are not in the current replay buffer \( \mathcal{B} \) in which the offline policy and Q-function are trained. Evaluation on such OOD samples will cause the similar distributional shift issue as in offline RL setting [26], [27]. As online RL lacks policy constraints or regularization that present in offline RL for combating the distributional shift, such error is not well-handled at the initial stage of online training, which potentially causes severe exploitation error and performance degeneration.

To address the aforementioned performance drop issue and maintain the performance of the offline learned policy using expert demonstrations, we design a new unified offline-to-online RL framework based on TD3 [31] and TD3+BC [40]. The key idea is to maintain part of the offline RL property (i.e. constrain policy update with respect to behavioral distribution) during the offline-to-online transition phase to overcome the distributional shift issue. Formally, our offline-to-online RL framework uses the following policy update objective:

\[
\pi = \arg \max_{\pi} \mathbb{E}_{(s,a) \sim \mathcal{B}} \left[ Q(s, \pi(s)) - \frac{1}{\lambda} f(t)(\pi(s) - a)^2 \right] \tag{5}
\]

Specifically, \( f(t) \) is a weighting function of training step \( t \) that weights the BC penalty as follows:

\[
f(t) = \begin{cases} 1, & \text{if } t \leq N_{\text{off}} \\ 1 - \frac{t - N_{\text{off}}}{\Delta_{\text{trans}}}, & \text{if } N_{\text{off}} < t \leq N_{\text{off}} + \Delta_{\text{trans}} \\ 0, & \text{if } t > N_{\text{off}} + \Delta_{\text{trans}} \end{cases} \tag{6}
\]

where \( N_{\text{off}} \) and \( \Delta_{\text{trans}} \) denote the training steps of offline learning and offline-to-online transition length. During offline learning \( (t < N_{\text{off}}) \), \( f(t) = 1 \) and the policy updates
using the same objective as in TD3+BC; during offline-to-online transition phase, \( f(t) \) decreases linearly from 1 to 0; finally, after the transition phase \((t > N_{\text{off}} + \Delta_{\text{trans}})\), the policy is updated normally as in online TD3.

To further reduce the potential serious OOD error caused by online exploration at the beginning of online learning, we introduce another weighting factor \( g(t) \) to scale the exploration noise \( \eta \) in TD3 (i.e. explore with action \( a = \pi(s) + g(t)\eta \)), which increase from 0 to 1 linearly during offline-to-online transition phase, and remains 1 afterwards.

Our framework perfectly merges the offline RL and online RL learning into a unified framework. And as showed in our ablation study, our framework can effectively alleviate the performance drop during the offline-to-online transition stage. This offers several benefits: first, the expert policy recovered from offline RL stage can be maximally preserved to better facilitate online RL training; second, as we observe in empirical results, this treatment also leads to smaller variance during performance evaluation (see Section V-C.2).

\[\begin{align*}
\text{Offline Learning} & \quad \text{Online Learning} \\
\text{Offline-to-Online Transition} & \\
\end{align*}\]

Fig. 3: Illustration of the weighting function design

V. EXPERIMENTS

In this section, we present detailed experiment results and ablations of our method. We examine its training efficiency as well as the performance against state-of-the-art high data-efficiency robotic manipulation baseline FERM [13].

A. Experiment Settings

Tasks: we evaluate our framework on three representative robotic manipulation tasks from the OpenAI Gym Fetch suite [22], including: 1) Reach: reaching an object; 2) PickAndPlace: picking up a block and moving it to a target location; 3) Push: push the block to a target location. We consider two harder tasks (PickAndPlace and Push) as compared with the tasks benchmarked in the FERM paper. PickAndPlace is a composition of Pickup and Move task in the FERM paper; and for Push, FERM fails to obtain a high performance policy. The three tasks as well as their observational camera views for RL training are illustrated in Figure 4.

We train our RL framework and the FERM baseline in OpenAI Gym Fetch simulation environment. We keep the experiment and hyperparameter configurations the same as FERM, except for our TD3-based offline-to-online RL framework, as FERM uses SAC for online learning. Both the RL algorithms of our method and FERM are trained with random crop image augmentation.

B. Comparative Results

We compare in Table 1 the results of FERM, our method, as well as a variant that without the goal-aware state information (GSI). We compare the performance of the three methods in all three tasks and investigate the training steps needed for 90% success rate and the final performance.

Our proposed offline-to-online RL framework with or without GSI achieves much better training efficiency compared with FERM and converge to better results. For all three tasks, our method uses much fewer steps to reach 90% success rate as well as the optimal policy. By applying GSI on top of our offline-to-online RL algorithm, our method achieves the best performance in most cases. The only exception is the Push task, where its convergence speed dropped slightly compared with our no-GSI variant, but still achieves better final success rate, much higher compared with the success rate of 63% in FERM.

C. Ablation Study

1) Impact of the goal-aware state information: To study the different impact between the state representations learned from a expert demonstration (success in every trial) and non-expert (~20% success rate) data. We evaluate our method with expert/non-expert demonstrations as well as with/without GSI. We plot the success rate evaluation results during the training process with our framework with 3 random seeds.

We find in Figure 5 that without expert demonstration and GSI, the algorithm failed to converge to any useful policy. However, with expert demonstrations, our RL agent is able to converge very quickly. Adding GSI can further accelerate convergence.

Moreover, based on the results reported in Table I and Figure 5, we find that GSI enhances both convergence and final performance in most tasks, especially in task with sequential execution property like PickAndPlace. However, when a complex task could not be well-divided into fixed-order sub-tasks such as Push, GSI method does not guarantee boost on convergence speed, but still helpful to improve the performance of the final policy.

2) Offline-to-Online Learning: To systematically evaluate the performance of our offline-to-online RL framework, we compare our method with three baselines, including: 1) TD3: using off-policy TD3 for both offline and online learning; 2) BC→TD3: offline learning using BC, online learning using TD3; 3) TD3+BC→TD3: offline learning using TD3+BC, online learning using TD3.

Based on the evaluation results plotted in Figure 6, we find our approach is the only method that successfully avoids the large performance drop during offline-to-online transition phase. Our offline-to-online RL framework also achieves faster learning speed, and more importantly, has very small policy evaluation variance during the training process compared with other methods. Comparing other methods, it is observed that off-policy RL algorithm (TD3) failed during offline learning, which is as expected and also confirmed in many recent studies [26], [27]. It is also
TABLE I: Performance comparison on Reach, PickAndPlace and Push Tasks. All compared methods are given 10 expert demonstrations, resulting a offline expert dataset that contains 1000 transition samples \((s,a,r,s')\).

| Tasks      | Metrics                          | Reach | PickAndPlace | Push |
|------------|----------------------------------|-------|--------------|------|
|            | # steps to 90% success rate      | 7k    | 93k          | -    |
| FERM       | # steps to convergence           | 16k   | 100k         | 200k |
|            | Final success rate (%)           | 100%  | 100%         | 63%  |
| Ours without GSI | # steps to 90% success rate       | 5k    | 81k          | 90k  |
|            | # steps to convergence           | 12k   | 88k          | 100k |
|            | Final success rate (%)           | 100%  | 96%          | 88%  |
| Ours      | # steps to 90% success rate      | 4k    | 42k          | 97k  |
|           | # steps to convergence           | 10k   | 52k          | 110k |
|           | Final success rate (%)           | 100%  | 100%         | 91%  |

Fig. 4: The tasks evaluated in this work and the three observational camera inputs used in the RL agent.

observed that naively combine offline RL and online RL lead to poor performance, due to severe distributional shift at the beginning stage of online learning. Lastly, using BC for policy pre-training only and then switch to TD3 works better compared with pure TD3 and TD3+BC→TD3, but still experiences large performance drop. As discussed in Section IV-C.1, this scheme is less impacted as Q-function is learned from the scratch only during online training. The performance degeneration is mainly due to optimizing with respect to the not-well learned Q-function, but suffers less severe distributional shift.

VI. CONCLUSIONS

In this work, we propose a new offline-to-online RL framework for data-efficient robotic manipulation tasks. Our proposed method successfully resolves the performance drop issue when combining offline and online RL policy learning. Through empirical studies and mechanism analysis, we also find that the performance of expert demonstrations as well as goal-stage aware state information play an important role in enhancing RL data-efficiency and convergence performance. We evaluate our method against the state-of-the-art baseline method as well as several variants of our approach on three robotic manipulation tasks. The experiment results show that our approach can greatly accelerate the learning process of fixed-order-decomposable manipulation tasks and achieves strong performance on all tested tasks.
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