Offline Learning of Counterfactual Perception as Prediction for Real-World Robotic Reinforcement Learning

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Abstract—We propose a method for offline learning of counterfactual predictions to address real-world robotic reinforcement learning challenges. The proposed method encodes action-oriented visual observations as several “what if” questions learned offline from prior experience using reinforcement learning methods. These “what if” questions counterfactually predict how action-conditioned observation would evolve on multiple temporal scales if the agent were to stick to its current action. We show that combining these offline counterfactual predictions along with online in-situ observations (e.g. force feedback) allows efficient policy learning with only a sparse terminal (success/failure) reward. We argue that the learned predictions form an effective representation of the visual task, and guide the online exploration towards high-potential success interactions (e.g. contact-rich regions). Experiments were conducted in both simulation and real-world scenarios for evaluation. Our results demonstrate that it is practical to train a reinforcement learning agent to perform real-world fine manipulation in about half a day, without hand-engineered perception systems or calibrated instrumentation. Recordings of the real robot training can be found via https://sites.google.com/view/realrl.

I. INTRODUCTION

“Perceiving as predicting” [1, 2], an idea from cognitive science, suggests that the human brain is not a simplified “passive perceiving brain”, but rather an “active predicting brain” [3, 4] and that the cortical processing of sensory data plays the role of action-oriented inference that is driven by prior knowledge learned from endogenous experience. Counterfactual predictions [5] encode hypothesis-based inferences about what might happen in the near or long-term future if the agent acts differently from prior experience [6]. For example, we may improve our car control skills more efficiently by asking questions like “what if I steer slightly more towards left at the second step”. Can such insights benefit real-world robotic reinforcement learning?

Real-world robotic reinforcement learning remains a challenging task [7–10]. From a practical perspective, there are three major challenges: (1) how to reduce online training time due to concerns over hardware wear-out and safety issues [7]; (2) how to train using only a terminal reward (success/failure) — the known issues of reward shaping and tedious hand-engineered perception system or calibrated instrumentation to provide dense reward signals [8]; (3) how action-conditioned observations would evolve on multiple temporal scales if the agent were to stick to its current action.

The process of defining these “what if” questions provides a flexible way to incorporate human prior knowledge about what information is task relevant. And the offline training involves discovering multi-temporal structures from offline collected transition samples. These “what if” predictions not only form an effective representation of the visual task, but also guide online policy learning to explore regions with a higher chance of contact-rich interactions given only a terminal (success/failure) reward. At last, it makes unattended online training possible because exploration can now be guided by the human prior knowledge encoded in the counterfactual predictions.

We use a robotic insertion task (Fig. 2) as an example. The training process is as follows: (1) Human teaches the robot once where the target roughly is without having to insert the peg [1] (2) Collect offline samples by running the robot randomly close and far from the target, then offline train the general value functions [11] to learn counterfactual predictions. (3) Collect success/failure images, and use them problem setting where a policy maps multi-modal (vision and force) sensory inputs to a 7 dimensional continuous action space. Here the force feedback comes directly from the robot’s 7 joint actuators. We address the above challenges by encoding high-dimensional visual feedback as a limited number of “what if” questions learned from prior experience and apply such predictions in the online policy learning setting with additional in-situ (force) observations. These “what if” questions are counterfactual predictions about how action-conditioned observations would evolve on multiple temporal scales if the agent were to stick to its current action.

Fig. 1: Humans are good at learning from prior experience by asking counterfactual questions like “If I acted differently, how would the result be in the near and long-term future respectively”. Can we apply the same mechanism to address the challenges of real-world robotic reinforcement learning?

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\(^{1}\)This makes our method more practical because insertion depends more on contact-rich interactions which is difficult for human to demonstrate.
to train a terminal reward classifier. (4) Plug in the learned counterfactual predictor and terminal reward classifier, then do online policy training.

Our contributions are:

- We address real-world robotic reinforcement learning challenges by using offline learned counterfactual predictions as the visual task representation that are further combined with in-situ observations (e.g. force feedback) in the online training.
- We show that offline counterfactual predictions improves online learning regarding sample efficiency and online exploration guidance towards high-potential success interactions (e.g. contact-rich regions) given only a terminal reward.
- Our proposed method provides a flexible and practical way to incorporate human prior knowledge and the guidance of online exploration makes unattended online training possible.

To support our claims, various baselines and evaluations were performed in both simulation and real-world scenarios.

II. RELATED WORKS

This work is inspired by the following topics from both the reinforcement learning (RL) and robotics community.

Real-world RL on robots: Addressing the various challenges of real-world robotic reinforcement learning has gained increasing interests recently [7–10]. There are a number of prior works tackling each of the challenges, for example, training efficiency [12, 13], generalization [14, 15], safer online explorations [9, 16], sim-to-real transfer [17, 18] and learning from sparse reward [19–21]. However very few works have been proposed to address the practicality of real-world robotic reinforcement learning. Recently, R3L [8] was proposed as a practical framework using a demo on a three-fingered robotic hand. It utilizes a VAE [22] to learn a compact state representation and VICE [21] to provide rewards and trains without running resets. Compared to R3L: (1) We consider a more general problem setting in a 7-Dof robotic manipulation that requires both vision and force feedback; (2) We consider learning human prior knowledge from offline experience to accelerate online training since offline samples are easier to collect and use, and the offline learned human prior knowledge provides online exploration guidance given only a terminal reward.

Offline Reinforcement Learning: Online training on a real-world robot is commonly considered expensive. Offline RL [5, 23] is quite appealing in robotics with the promise of learning only from offline samples without online exploration. However, there are situations when offline samples may not cover well the entire state-action space required when deploying the policy. For example, many manipulation tasks require both vision and force feedback. Collecting contact-rich interaction samples for offline learning (via either kinesthetic teaching [24] or teleoperation) is usually difficult in practice. In contrast, our approach combines offline and online learning in the use of counterfactual predictions learned offline to accelerate online policy learning.

**RL with Auxiliary tasks:** Our method shares similarities with auxiliary-task based approaches. Designing auxiliary tasks to facilitate main task-learning has proven effective in many computer vision [25, 26] and RL tasks [27–29]. Among various approaches, general value functions, or GVFs, provide a flexible way to define the auxiliary tasks [27, 28]. While GVFs can be a rich form of knowledge representation, defining the knowledge itself typically needs hand-designed perception or calibrated instrumentation systems to provide cumulant signals. Veeriah et al. (2019) [28] applied a metagradient method to address the knowledge discovery of GVFs from data. In this paper, we consider an assembly-from-disassembly [30, 31] approach used in robotic task learning to define the cumulant by human teaching. This approach makes defining human prior knowledge more practical.

**Robotic Insertion Task Learning:** Applying RL [32–37] or contact-model based control [38–40] in a robotic insertion (a.k.a. peg-in-hole) task, has been well studied in the literature [41]. However, typical simplifying assumptions are made in most works for the purpose of easier training, that impede their practicality. Our work stands out by addressing the practical considerations as follows: (1) The learned policy should be robust to variable grasping poses. A common assumption in prior works is that the peg is in a fixed pose w.r.t. the end effector [32, 33, 38, 39]. However, in the real world, the peg is generally grasped in slightly different ways over different repetitions. As pointed out by [33], such assumption does not consider a continuous process of peg feeding and inserting. (2) The learned policy should be a holistic motion controller that starts from an arbitrary grasping pose, instead of simply assuming a near-perfect pre-insertion pose [35–37, 39, 40] at each initialization. Such assumption is not practical since how perfect the starting pose should be is typically vague. As a consequence, adding visual feedback is important to guide robot motion starting from variable grasping poses. (3) Vision and force feedback should be combined in training [41]. Due to the stochastic nature of contact-rich interactions, precise insertion requires a force sensitive probing behavior. (4) The learned controller should output actions that directly apply to robot joints instead of a hand-engineered controller [32–35] (e.g., admittance-Cartesian controller) which requires additional fine tuning. (5) It is more practical to train only with a terminal success/failure reward instead of dense guidance signals [32] that need a time-consuming perception system or calibrated instrumentation to provide ground truth peg/slot poses. (6) The training should be efficient and finished within a reasonable time.

III. METHOD

**A. Background: Predictive Learning**

Inspired by the predictive representation hypothesis [42], modeling dynamic system states as predictions of future observations has been of research interest for decades [43–45]. Among the various approaches, general value functions (GVFs) [46] provide a flexible and rich form for knowledge
representation [28], which can be learned with off-the-shelf value function estimation methods based on temporal-difference (TD) [47]. The core task of GVFs is to learn “answers” to predictive questions (GVF-questions). These GVF-answers express the expected return of discounted cumulants \( c_t \) if the agent follows a policy \( \tau \) and then continues according to \( \gamma_t \) when at state \( s_t \):

\[
\psi = \phi^\tau(s) = \mathbb{E}_t[\sum_{k=0}^{\infty} (\prod_{j=0}^{k-1} \gamma_{t+j+1})c_{t+k+1}|s_t = s, a_t = a]
\]  

(1)

As noted above, a GVF-question is defined by a tuple \((\tau, c_t, \gamma_t)\). The cumulant \( c_t \) is similar to reward, and can flexibly capture human prior knowledge like “how close it is to the target”, “how smooth the controller is” [6], etc. Defining GVF-questions is hard since obtaining the cumulant signals often requires a hand-engineered or calibrated system to estimate measurements of “closeness” or “comfort”. Moreover defining \( \tau \) and \( \gamma_t \) can also be challenging. One promising approach is directly learning to discover GVF-questions from data [28], however, the problem still remains challenging.

B. Counterfactual Prediction Learning

Our proposed counterfactual prediction learning method tackles two major problems: (1) how to practically define the GVF-questions as mentioned above; (2) how to address the counterfactual nature of predictions, that are made based on a hypothetical behavior. The first question relates to the practicality of our approach, while the second one relates to the distributional shift problem as studied in the off-policy learning [48, 49] and offline (batch) RL literature [23]. We will elaborate on these two issues:

1) Human Prior Knowledge Teaching of GVF-questions: In the problem of robotic task learning with vision and force feedback, an important question is how robot action will affect future changes of task spatial information given visual observations. We encode such action-conditioned visual observation as GVF predictions \( \psi \). We use an \textit{assembly-from-disassembly} approach similar to [30, 31], which forms a practical solution of defining GVF-questions. This approach requires human teaching of a reference frame \( T_* \) defined in a robot base-coordinate system given randomized target locations. \( T_* \) defines roughly where the target is, however, it leaves the final success of task execution to incorporating more-in-situ observations (force feedback) in online training. For sample collection, let the current robot pose at time \( t \) be denoted as \( T_c \). The relative pose from current to reference frame is \( ^*T_c = (T_*)^{-1}T_c \), where \( ^*T_c \) can be written in its rotation and translation form as \( [^*R_c, ^*t_c] \), and \( ^*R_c \) has its axis-angle representation as \((\theta, u)\). Then the cumulant \( c_t \) is a 6 dimensional vector:

\[
c_t = -\lambda \begin{bmatrix} ^*t_c \\ \theta u \end{bmatrix}
\]  

(2)

, where \( \lambda \) is a parameter that decides the relevance factor of the spatial transformation. We set \( \lambda = 1 \) in our experiments.

Learning or defining the counterfactual policy \( \tau \) could be intricate. One heuristic choice [6] is a delayed-action-conditioned policy \( \tau(a_t|s_t, a_{t-1}) = \mathcal{N}(a_{t-1}, \Sigma) \) which means “continuing with my previous action while allowing some randomness”. Thus the predictions encode how task spatial information will evolve if the agent continues on previous actions. These predictions form corrective signals for decision making. Lastly, \( \gamma \) controls a temporal time horizon that a prediction is made for. As shown in [6, 45], multi-temporal-scale predictions help learning more efficiently. In our experiments, we consider predictions on four different time scales for the near and long-term future with \( \gamma = [0, 0.5, 0.9, 0.95] \).

Next we perform data collection by automatically running the robot towards target points randomly sampled both near and far from \( T_* \), without necessarily having the peg inserted. A PBVS [50] controller with random noise is used for sample collection.
2) The Distributional Shift Problem: Given samples $D$ collected using a potentially unknown behavior policy $\mu$, for example, the policy used to collect samples in the robotic insertion task, learning counterfactual predictions needs to address the distributional shift issue since the counterfactual policy $\tau$ that defines GVF-questions is different from $\mu$ represented in the samples. We apply the method proposed in [11] by estimating density ratio and using importance resampling to address this issue. A density ratio trick is applied to transform the problem of estimating ratio of two policy distributions $\mu(a|s)$ and $\tau(a|s)$ to the problem of training a discriminator $g(a, s)$ that distinguish samples from each. Readers are referred to [11] for algorithmic details.

C. Online Training

Input state is $[\psi, \text{joint pos}, \text{joint torques}]$, where $\psi$ are multi-temporal-scale counterfactual predictions. In our experiments, $\psi$ is a 24 dimensional vector considering four different time horizons. Counterfactual predictions help online training in two ways: (1) effective representation of the visual task; (2) task spatial information guidance for the online exploration by augmenting the terminal reward function using a corrective minimization term, which we name as corr-reward since, as stated in Sec. III-B.1, $\psi$ actually provides corrective signals to the decision making agent. corr-reward is defined as:

$$corr_R_t = \begin{cases} R_{success} & \text{if succeed,} \\ e^{-\|\phi(s_t, a_t, \gamma_{t+1}, s_{t+1})\|} & \text{otherwise} \end{cases}$$

where $\|\phi(s_t, a_t, \gamma_{t+1}, s_{t+1})\|$ defines the counterfactual prediction of $s_{t+1}$ when the agent is at $s_t$ and takes action $a_t$, considering a multi-temporal-scale horizon $\gamma_{t+1}$. Similar to [8, 33], an offline trained classifier is used to determine the terminal success/failure status. We used SAC [51] as a standard actor-critic learning during online training.

IV. Evaluation

We evaluate on four objectives: (1) The viability of our method in a real-world learning task; (2) From a representation learning perspective, how counterfactual predictions perform when compared to other methods commonly used in the literature [32, 33]; (3) For online exploration guidance, whether the proposed corr-reward helps online training given only a terminal reward; (4) Why combining offline learned counterfactual predictions and online in-situ observations (force feedback) is necessary. Besides the four objectives, though not directly related to our claimed contributions, we also evaluated the generalization capability when zero-transferring the learned policy on different peg/slot scales.

Experiments were conducted both in a real-world and simulation scenario which share the same experimental setup, including an eye-in-hand camera and a 7 DoF robotic arm (Fig. 3B). Each initialization will randomize the poses of robot joints, grasping peg and the slot, resulting in a distance of 20~40cm between peg and slot (Fig. 3B). In real-world experiments, peg grasping pose was randomized by human disturbance (Fig. 3 A). Due to technical limitations of online slot relocation, the slot pose was fixed during training. Nevertheless, because the robot acquired force sensitive probing skills (Fig. 4), we found the learned policy is relatively robust to slot displacement $<1$cm (Fig. 3 C3).

A. Real-world Robotic RL Training

The total training time of our real-world experiment was about 13 hrs which contains 4.5 hrs offline and 8.5 hrs online training. Benefiting from our automatic sample collection, 40K offline samples were collected by 400 episodes which took 0.5 hr including human teaching time. Soft-actor-critic [51] was used in online training with a 30Hz control frequency matches the frame rate of our vision sensor.
Joint velocity actions were directly sent to the franka ROS controller at 30Hz and the internal controller of the Franka arm runs at 1000Hz controlling robot motions with default and unknown parameters without fine tuning. This hierarchical controller approach makes our learned policy generate smooth motions.

Similar to [33], we used two success/failure classifiers independently trained to avoid false positive results of the terminal reward. The learned policy was then evaluated under situations of human random feeding, moving the peg and slot (Fig. 3 C). Evaluation results shown in Fig. 3 demonstrate the practicality of our proposed method for training a real-world robotic RL agent to acquire fine manipulation skills in one day, without hand-engineered perception systems or calibrated instrumentation.

### B. Quantitative Evaluations

We perform quantitative evaluations in a simulation environment for the purpose of providing ground truth metrics. Three baselines (Table 1) were designed, chosen from both the real-world robotic RL and robotic insertion task learning literature: (1) Pose Regression assumes knowing the ground truth of peg/slot poses and predicts the relative pose based on images observations. Output of the pose regressor is a 5-dimensional pose prediction where we ignored the yaw angles in this cylinder problem because of symmetry; (2) Reward Classifier was trained by collecting success/failure images [33], where 8-dimensional vector from its second last layer was then used in online training; (3) End2end was trained using raw images. Note that the commonly used behavior cloning baseline does not apply since the offline samples do not include any successful insertions but only target approaching samples.

Given offline samples \( D = \{ (s_t, a_t, c_{t+1}, \gamma_{t+1}) \} \), comparison between the above methods can be made from perspectives of what source information and prior knowledge were used in training (Table 1). All methods were trained using 40K offline collected samples, except for the End2end baseline and the Pose Regression one which consumed 1 million offline samples. The learned representation was then used as visual features in online training where the soft-actor-critic [51] method was used. Evaluation metric Success Rate was based on the last 100 trials.

1) **Under practical concerns**: Due to practical concerns as discussed in Sec. I and Sec. II, a realistic training environment should be without hand-engineered perception system or calibrated instrumentation, namely given only a terminal reward. On this regard, five baselines were designed by combining different representation methods and techniques dealing with sparse reward, including a variant of VICE reward [8, 21] and our corr-reward. Evaluation results (Fig. 5A) show our proposed counterfactual prediction as both state representation and corr-reward works the best. Further analysis show all the baselines failed mainly because the agent found difficulties to even touch the target, thus couldn’t learn from contact interactions that would lead to successful insertion. By contrast, our proposed method benefited from the counterfactual predictions that gradually guided online exploration to contact rich interactions.

2) **Given an oracle reward**: To further study each component of our proposed method, we firstly gave the same oracle reward to all methods in order to evaluate from a representation learning perspective. So this evaluation was merely testing how effective the counterfactual predictions are. Like in [32], assuming we had instrumentation to measure precisely the peg/slot pose, the oracle reward was a fine tuned stage-dense reward function based on peg/slot pose. Results (Fig. 5B) show counterfactual predictions perform best in terms of sample efficiency.

3) **Plug in and out using corr-reward**: As shown in Sec. IV-B.1 lacking a guidance to make contact-rich interactions are the major reason of task failure. For the purpose of testing if our proposed corr-reward will provide such guidance, we compare methods using the same representation with three different results: our corr-reward, the Oracle dense reward and a terminal reward. We tested the three different rewards on counterfactual predictions and reward classifier’s latent vector respectively. As shown in Fig. 5C, corr-reward archives competitive performance compared to the fine tuned Oracle reward. Results with a terminal reward were not included in Fig. 5C since their success rate kept 0% along the training. So corr-reward significantly improves online estimation accuracy and had no success in either training settings.
Fig. 5: Quantitative evaluation results. Success rate is measured based on the last 100 trials and the horizontal axis represents episodes. For a better visualization, curves were cut off after 3.3K episodes, but all baselines were continuously trained more episodes, e.g., the End2end (0/1) baseline was trained after 100k episodes. A: Results when evaluated under practical concerns given only a terminal success/failure reward (marked as “0/1” above). Baselines were designed by combining different representation methods and techniques dealing with sparse reward, including a variant of VICE reward [8, 21] and our corr-reward. “counter” means using counterfactual predictions. Baselines using only a terminal reward all achieved success rate lower than 4%, so their curves overlap with the horizontal axis. B: Evaluation results of counterfactual prediction compared to other representation methods give the same Oracle reward. C: Evaluation results of our corr-reward compared to the Oracle dense reward. D: Testing if the online training could be done using only offline learned counterfactual prediction. “w/ force” indicates in-situ observations (force feedback) were used while “w/o force” indicates not.

Fig. 6: Additionally, we test zero-transfer of the policy trained only with scale ratio=1.0, but having counterfactual predictions offline trained with scale ratios=[0.8, 1.0, 1.2]. Note that the offline training has no contact-rich interaction samples of each scale ratio but only learns to encode action-conditioned visual observations.

| # 100 Trials | 0.7 | 0.8 | 0.9 | 1.0 | 1.1 | 1.2 | 1.3 |
|--------------|-----|-----|-----|-----|-----|-----|-----|
| Success Rate | 22% | 66% | 80% | 100% | 91% | 85% | 70% |

learning given only a terminal reward.

4) Plug out in-situ observations during online training:
We now examine if the online training could be done using only offline learned counterfactual predictions, namely, without any more in-situ observations. So comparison baselines that removes the force feedback during online training were tested under two different rewards respectively. Results (Fig. 5D) show that either with corr_reward or the Oracle reward, online training without in-situ observations (force feedback) archives lower performance. We find that learning based only on counterfactual predictions will guide to contact-rich interactions, but the absence of force feedback makes it hard to make sense of the contact, leading a lower success rate in the final insertion stage.

5) Generalization to different scales: Though not directly related to our claimed contributions, we additionally test our proposed method’s generalization capability given different peg/slot scales. The counterfactual predictions were trained based on 120K samples collected using scale ratios [0.8,1.0,1.2] with 40K of each respectively. But the policy was trained only for scale ratio=1.0. Then we test the generalization performance when zero-transfering the learned policy to different scale ratios [0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3] (Fig. 7) given randomized initialization in the simulator. Initial results show the generalization capability of the learned policy. The generalization ability of predictive learning has been reported in several prior works [42, 45], however, its shape generalization capability of visual representations in a robotic reinforcement learning task is worth further investigation.

V. CONCLUSION
We propose an offline counterfactual prediction learning method to address real-world robotic reinforcement learning challenges. The proposed method encodes high-dimensional visual observations as “what if” questions learned from prior experience using offline trained the general value functions [11] to learn counterfactual predictions. We show that combining these offline counterfactual predictions along with online in-situ observations (e.g. force feedback) enables efficient RL policy training when given only a terminal (success/failure) reward. The learned predictions form an effective representation of the visual task, and are capable of guiding the online exploration towards high-potential success interactions (e.g. contact-rich regions).

Although we demonstrated the viability in a real-world robotic insertion task, only task-relevant spatial information was encoded in the counterfactual predictions via our proposed GV-question teaching method (Sec. III-B.1). However, plenty of other information could also be used for counterfactual predictions given the rich representation nature of visual feedback. One example is the semantic meaning [53] of visual features that indicates how a task should be planned [54]. However, teaching such GV-questions remains an unsolved problem. Methods that automatically discover useful GV-questions offline from collected samples will be an interesting direction to explore.
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