Human-guided Robot Behavior Learning: A GAN-assisted Preference-based Reinforcement Learning Approach

Huixin Zhan, Feng Tao, and Yongcan Cao

Abstract—Human demonstrations can provide trustful samples to train reinforcement learning algorithms for robots to learn complex behaviors in real-world environments. However, obtaining sufficient demonstrations may be impractical because many behaviors are difficult for humans to demonstrate. A more practical approach is to replace human demonstrations by human queries, i.e., preference-based reinforcement learning. One key limitation of the existing algorithms is the need for a significant amount of human queries because a large number of labeled data is needed to train neural networks for the approximation of a continuous, high-dimensional reward function. To reduce and minimize the need for human queries, we propose a new GAN-assisted human preference-based reinforcement learning approach that uses a generative adversarial network (GAN) to actively learn human preferences and then replace the role of human in assigning preferences. The adversarial neural network is simple and only has a binary output, hence requiring much less human queries to train. Moreover, a maximum entropy based reinforcement learning algorithm is designed to shape the loss towards the desired regions or away from the undesired regions. To show the effectiveness of the proposed approach, we present some studies on complex robotic tasks without access to the environment reward in a typical MuJoCo robot locomotion environment. The obtained results show our method can achieve a reduction of about 99.8% human time without performance sacrifice.

Index Terms—Reinforcement Learning, Generative Adversarial Network (GAN), Human Preferences

I. INTRODUCTION

The application of reinforcement learning (RL) in solving complex problems has demonstrated success in domains with well-specified reward functions, (see, e.g., [1]). The existence of correct reward functions is crucial for the subsequent development of robotic control systems via reinforcement learning algorithms. However, designing such a reward function often requires the consideration of different objectives that can potentially impact not only the learned behaviors but also the learning process. This difficulty underlies some recent concerns about the misalignment between the reward functions and the objectives in the development of reinforcement learning algorithms [2]. Hence, it is crucial to communicate the actual objectives via properly defined rewards or reward functions, which often need to reflect humans’ preferences since the mission objectives are often generated by humans.

To communicate humans’ preferences effectively, it is important to develop methods and algorithms that can parse humans’ intents and strategies. Two main approaches, namely, inverse reinforcement learning and human preference-based learning, have been proposed recently. Inverse reinforcement learning (see, e.g., [3], [4]) focuses on learning reward functions directly from human demonstrations. Human preference-based learning (see, e.g., [5], [6], [7]) focuses on maximizing the volume removed from the distribution of the weight vector by asking a human to pick between trajectory pairs until reaching convergence. While both approaches provide important advances, they still lack much-needed data efficiency. In particular, inverse reinforcement learning usually requires a large number of high-quality human demonstrations to obtain accurate reward functions given that the relationship between features of action-state pairs and the corresponding value in the form of reward is typically complex and difficult to be quantified. Nevertheless, obtaining a large volume of human demonstrations can be costly and even infeasible. Meanwhile, human preference-based learning also requires significant human feedback such that reward functions and/or control policies can be generated to produce robotic behaviors that meet humans’ preferences [8]. For example, in [9], human queries are used to learn rewards, which are then used to train a reinforcement learning algorithm to generate trajectories. Although the proposed approach therein can potentially reduce human time in some existing human preference-based learning approaches, e.g., [10], [11], a good amount of human queries are still needed to learn a high-dimensional (and often continuous) reward function. To practically design and train reinforcement learning algorithms with limited human feedback, it is essential to significantly decrease and minimize human feedback/efforts for efficiency and practicality.

In this paper, we propose a new GAN-assisted human preference-based reinforcement learning approach that can learn complex robotic behaviors with dramatically reduced human feedback. Fig. 1 shows the overall structure of the proposed approach. In the proposed approach, pairs of queries are
first sampled from the robot trajectories produced by the current policy and then sent to a human for selection of preferred ones. These (limited) human preference samples are used to train an adversarial neural network to learn human preference. The trained adversarial neural network is then used to replace human in the subsequent selection of preferred trajectories. The preference samples from humans and adversarial neural networks are used to learn reward functions. Then a maximum entropy based reinforcement learning algorithm is designed to effectively learn control policies that can generate robotic behaviors that meet human preferences. Instead of directly learning a high-dimensional reward function as in [9], one key novelty of our approach is the design of a low-dimensional adversarial neural network to learn human preferences. Due to the low-dimensional nature of the adversarial neural network, much less human queries are needed in the training process. Another key advantage of the proposed GAN-assisted human preference reinforcement learning approach is that one set of human queries can serve two different purposes, namely, (i) training a GAN that directly learns the principles of human preference, and (ii) learning reward functions for the control policy generation. Moreover, the construction of adversarial neural network does not depend on the reward function learning process. By sending queries to the trained adversarial neural network, rather than humans, in the reward learning and control policy generation process, more significant human time reduction can be achieved without performance sacrifice.

This paper has three main contributions. First, we create a new GAN-assisted human preference-based reinforcement learning approach that trains a low-dimensional adversarial neural network to learn and predict human preferences based on very limited human queries. The trained adversarial neural network can then replace the role of humans in labeling the trajectory pairs, which can dramatically reduce human labeling time. Second, we propose a maximum entropy reinforcement learning algorithm using a new nonlinear objective function based on human preferences when human preferences among trajectory pairs are used to shape the loss towards the desired regions or away from the undesired regions. Third, we conduct experiments on complex robotic tasks to show that the proposed approach can outperform the state-of-the-art methods. In particular, the proposed approach can further reduce 84% human time needed in [9] while achieving better performance. Overall, the proposed method can reduce approximately 99.8% human time without performance sacrifice.

II. RELATED WORK

Some interesting studies have been conducted on the development of reinforcement learning algorithms based on human ratings or rankings (see, e.g., [11], [12], [13], [14], and [15]). Additional interesting research can be found in, e.g., [10], which focuses on the general problem of reinforcement learning from preferences instead of absolute reward values. In [17], the research focus is on tuning the task specific policy using observable dynamics of the environment instead of an explicit reward function. In [18], [9], the research focus is on optimization using human preferences in settings other than reinforcement learning.

Integrating human demonstrations and preferences fits a recent trend of communicating complex personalized objectives to deep learning systems in, e.g., inverse reinforcement learning [6], [19], [20], imitation learning [21], guided cost learning [22], and semi-supervised skill generalization [23]. For example, [6] assumed that the reward function is parameterized by a linear function of hand-coded features. First, a probabilistic model was implemented to capture the preference. Then the Bayesian inference approach was developed to fit the reward function. Finally, a constrained optimization problem was formulated to solve the trajectory selection problem without using reinforcement learning based methods. One key challenge in the approaches proposed in the aforementioned references is the consideration of complex robotic tasks while addressing human preferences specified via limited actual human queries.

In [24], [25], experiments were performed that involve reinforcement learning from actual human feedback. In [24], similar to the standard reward-based reinforcement learning, a classifier was first trained on an initial set of trajectories. Then a binary variable is used to cast success as the reward. In the training process, only the state with the largest value for success will be selected for query. This labeled state is added to the trajectories for the fine-tuning of the classifier. Note that the proposed method in [24], similar to that in [9], does not include the active learning of human preferences. In other words, no model is trained to predict and replace human queries. Hence, the required human time is still high (1-4 hours).

Our work focuses on improving the sample efficiency of reinforcement learning algorithms with human preferences when learning complex robotic behaviors. Although the proposed approach has a similar structure as [9], there are two fundamental differences. First, we design an adversarial neural network that directly learns human preference while [9] does not include the direct human preference learning process. The trained adversarial neural network can replace humans in the labeling of trajectory pairs, hence dramatically reducing human time. Because the adversarial neural network only outputs preferences rather than rewards, very limited human queries are required. Second, a standard reinforcement learning algorithm is used in [9], which requires longer training time with a higher chance of finding locally optimal control policies (a common issue in reinforcement learning [26]). We adopt a maximum entropy based reinforcement learning algorithm with a newly designed nonlinear objective function, which can shape the loss towards the desired regions or away from the undesired regions. Hence, the proposed approach can reduce human/GAN-assisted queries while improving performances.

III. TECHNICAL APPROACH

In this section, we will provide details about the proposed GAN-assisted preference-based reinforcement learning approach. For the purpose of generality, we consider a general environment modeled as a Markov decision process (MDP), defined by the tuple \((S,A,T,r,y,q_0)\), where \(S\) is the (continuous) state space, \(A\) is the (continuous) action space, \(T\)
is the dynamics or transition distribution, $\gamma \in (0, 1]$ is the discount factor, $r$ is the reward function, and $q_0$ is the initial state distribution. We further use $\rho_\pi(s, a)$ to denote the state-action marginal of the trajectory distribution induced by a policy $\pi(s) = a$.

Instead of assuming that the environment directly produces a reward, we consider the case when there exists a human who observes and expresses his/her preferences between pairs of trajectory segments $(\tau_1, \tau_2)$ produced based on the current policy $\pi$. The trajectory segment is typically of the form $(s_1, a_1, s_{i+1}, a_{i+1}, \ldots, s_{i+k})$. At each time step, the proposed method includes the construction of three components: (1) a control policy $\pi : S \rightarrow A$; (2) an adversarial network that prefers one trajectory (say, $\tau_1$) to another (say, $\tau_2$), whose quantitative representation is given by $p(\tau_1 > \tau_2)$, where $p(\tau_1 > \tau_2)$ denotes the probability of selecting $\tau_1$ not $\tau_2$ by the human; and (3) an estimated reward function $\hat{r}(s, a) : S \times A \rightarrow R$.

Note that all three components involve the construction and update of deep neural networks based on the interaction with the environment. In particular, we propose to update the three networks iteratively via the following steps:

1. Send pairs of segments $(\tau_1, \tau_2)$ produced via the current control policy $\pi$ as human queries;
2. Update an adversarial neural network, projecting trajectories $\tau_1$ to their preferences $\xi$, to learn human preference, where $\xi$ is a distribution over $\{1, 2\}$ indicating which segment is preferred;
3. Train a reward model to predict the human preference-based Q value;
4. Update parameters to obtain a new control policy by a maximum entropy based reinforcement learning algorithm to maximize the human preference-based Q value.

The four steps run iteratively until the three neural networks produce stable outcomes, namely, the difference between two consecutive steps being smaller than a threshold. More technical details are provided in the following subsections.

A. Preference Queries

At each time step $t$, a robot receives an observation $s_t \in S$ from the environment and then generates an action $a_t \in A$ for the robot to interact with the environment. In the policy evaluation step, the Q value can be computed iteratively, starting from any function $Q : S \times A \rightarrow R$ and repeatedly applying a modified Bellman backup operator $\psi^\pi$ given by [26]

$$[\psi^\pi Q](s_t, a_t) \triangleq \hat{r}(s_t, a_t) + \gamma E_{s_{t+1} \sim p_\pi}[V(s_{t+1})],$$

where $V(s) = E_{a \sim \pi}[Q(s, a) - \log \pi(a|s)]$ and $E$ is the expectation operator. The agent’s goal is to maximize the discounted sum of the reward values. Because the environment may not produce a reward signal, we assume that the human can provide preferences between trajectory segments.

In particular, for a pair of trajectory segments $\tau_1$ and $\tau_2$, we follow the definition of preference over trajectories in [8]. More specifically, the notation $\tau_1 > \tau_2$ means that the first choice is strictly preferred. The notation $\tau_2 > \tau_1$ means that the second choice is strictly preferred. The notation $\tau_1 \sim \tau_2$ means that the two choices are indifferent, i.e., neither $\tau_1 > \tau_2$ nor $\tau_2 > \tau_1$ holds. The goal of the robot is to produce trajectories that are preferred by the human, while requiring as few human queries as possible.

We here define the criteria for preferences over trajectories in three ways:

C1. Start from a goal expressed in natural language, ask the human to evaluate the behavior, and then give a binary feedback to indicate whether $\tau_1 > \tau_2$.

C2. Start from a goal expressed in natural language, ask the adversarial neural network to evaluate the behavior, and then give a binary feedback to indicate if $\tau_1 > \tau_2$.

C3. For a given estimated reward function $\hat{r} : S \times A \rightarrow R$, the preference yields $\tau_1 > \tau_2$ if $\sum_{i=1}^k \gamma^{i-1} \hat{r}(s_{i+1}^\tau, a_{i+1}^\tau) > \sum_{i=1}^k \gamma^{i-1} \hat{r}(s_{i+1}^\sigma, a_{i+1}^\sigma)$, where $\tau_1 = \{(s_{i+1}^\tau, a_{i+1}^\tau), i = 1, \ldots, k\}$ and $\tau_2 = \{(s_{i+1}^\sigma, a_{i+1}^\sigma), i = 1, \ldots, k\}$, and $\tau_2 > \tau_1$ otherwise.

C1 and C3 were proposed in [21] to generate references quantitatively. In particular, C1 uses direct human queries to obtain references, while C3 seeks to use the learned reward to generate references based on their accumulated rewards. Because C3 involves two steps of approximation, namely, approximation of both the reward and the policy, it requires a good reward model in order to yield high-quality trajectory selection subject to human preferences. In addition, the reward function to be learned is typically high-dimensional. In contrast, the proposed C2 seeks to learn the binary human preferences directly, namely, $\tau_1 > \tau_2$ or $\tau_2 > \tau_1$, hence requiring less data to train a good model that can predict binary human references. In particular, the proposed C2 method is motivated by the construction of generative models to directly generate samples in GAN [27]. Instead of generating close-to-true (yet fake) samples in GAN, the proposed C2 seeks to generate a close-to-true prediction of binary human preferences.

In the process of preference queries, two trajectory segments in the form of short video clips are provided to the human or the adversarial neural network for labeling. In particular, these video clips will be sent to the human at the beginning and the adversarial neural network later once the trained adversarial neural network model, via using the human selection samples, can provide a very high accuracy of human selections. Afterwards, the human or the adversarial neural network indicates which segment is preferred, or the two segments are indifferent. The outcomes are stored in a database $D$ in the form of a tuple $(\tau_1, \tau_2, \xi)$, where $\tau_1$ and $\tau_2$ are the two clips and $\xi$ is a discrete distribution over $\{1, 2\}$ indicating which clip the human or the adversarial neural network prefers. In particular, if one clip is preferred, $\xi$ puts all of its mass on that choice. If the clips are equally preferable, then $\xi$ is uniform. Moreover, the human has one more option, i.e., marking the trajectory segments as incomparable. In this case, the comparison will not be included in the database $D$.

B. Training Adversarial Neural Network

We now move to the discussion of training the adversarial neural network in criterion C2. The objective of an adversarial

\footnote{In our experiments, these clips have a duration of 5 seconds.}
neural network is to create a model that can actively learn human preference so that human queries can be replaced by adversarial neural network queries. Moreover, the trained adversarial neural network can be used to correct human labels if the human provides incorrect labels due to, e.g., fatigue. We here propose to train a discriminative neural network model $Y_{di}$, parameterized by $\theta_{di}$, that can learn the probability of selecting a sample trajectory by the human. Let $D_o$ denote the preferred trajectory set selected from the sampled trajectories set $D$, and $D_{np}$ denote $D \backslash D_o$, i.e., the non-preferred trajectory set. The model parameter $\theta_{di}$ can be updated by the stochastic gradient ascent algorithm as

$$\theta_{di} \leftarrow \theta_{di} + \nabla_{\theta_{di}} E_{\tau_i \in D_{np}} \log (1 - Y_{di}(\tau_i)) + \nabla_{\theta_{di}} E_{\tau_i \in D_o} \log Y_{di}(\tau_i).$$

(C. Training Reward Function)

Since the environment reward is unavailable, we here propose to leverage the GAN-assisted human preference to approximate the reward function. Human preference is needed at the very beginning to produce reasonable data points to train the adversarial neural network and the adversarial neural network can be used to replace human queries once it provides a good approximation of human preferences.

In the case of human preference, we can interpret a preference-based Q value function estimation $Q(s, a_t)$ as a preference predictor if we view $\hat{r}$ as a latent factor explaining the human’s judgments. In other words, we have $Q(s, a_t) = \sum_i \hat{r}(s_{t+i}, a_{t+i})$. By following [6], we here assume that the human’s probability of preferring a clip $\tau_i$ depends exponentially on the value of the latent reward summed over the length of the clip. Then we can calculate the probability $\xi$ as capturing the preference with respect to $Q(s, a_t)$, such that,

$$\hat{p}(\tau_1 > \tau_2) = \frac{1}{1 + \exp(Q(s_1', a'_1) - Q(s_2', a'_2))},$$

$$\hat{p}(\tau_2 > \tau_1) = \frac{1}{1 + \exp(Q(s_1', a'_2) - Q(s_2', a'_1))},$$

where $\hat{p}(\tau_1 > \tau_2)$ means the estimated probability of selecting $\tau_1$ not $\tau_2$, namely, $p(\tau_1 > \tau_2)$, and $\hat{p}(\tau_2 > \tau_1)$ means the estimated probability of selecting $\tau_2$ not $\tau_1$, namely, $p(\tau_2 > \tau_1)$. Following the idea in [9], we can update the Q value function to minimize the cross-entropy loss $L_{a}$ between the calculated human preference-based labels from [2] and the actual human labels as

$$L_{a} = - \sum_{(\tau_1, \tau_2, \xi) \in D} [\xi(1) \log \hat{p}(\tau_1 > \tau_2) + \xi(2) \log \hat{p}(\tau_2 > \tau_1)].$$

(D. Training a Maximum Entropy Reinforcement Learning Algorithm)

After obtaining the estimated reward $\hat{r}$, we are left with the design of a reinforcement learning algorithm for control policy generation. Because the reward function $r$ may be nonstationary and a sample-efficient deep reinforcement learning algorithm is preferred, we here focus on a maximum entropy reinforcement learning problem that combines off-policy updates with a stable stochastic actor-critic formulation. Since the objective is to learn the optimal policy $\pi^*$, the maximum entropy reinforcement learning problem can be written as

$$\pi^* = \arg \max_{\pi} \sum_i \gamma^i E_{(s_i, a_i)} \log \pi^{ME}(s_i, a_i, \pi),$$

where $r^{ME}(s_i, a_i, \pi) \equiv \hat{r}(s_i, a_i) + \alpha H(\pi(\cdot|s_i))$ is a more general maximum entropy reward in the maximum entropy reinforcement learning setting [25] that favors stochastic policies, and $\alpha$ is a parameter that determines the relative importance of entropy $H(\pi(\cdot|s_i))$ with respect to the reward $r(s_i, a_i)$. Based on the structure in [5], we now define a new preference-based policy learning problem as

$$\pi^* = \arg \max_{\pi} \sum_i \left\{ E_{D_p} \left[ \gamma^i r^{ME}(s_{t+i}, a_{t+i}, \pi) \right] - E_{D_{np}} \log \left( \frac{\exp[\gamma^i r^{ME}(s_{t+i}, a_{t+i}, \pi)]}{\pi(a_{t+i}|s_{t+i})} \right) \right\}.$$
in (7) can be written as

\[
L(\theta) = \sum_{t} \left\{ E_{D_p} \left[ y^l_{ME} (s_{t+1}, a_{t+1}, \pi_\theta) \right] - E_{D_{np}} \log \left( \frac{\exp[y^l_{ME} (s_{t+1}, a_{t+1}, \pi_\theta)]}{\pi_\theta (a_{t+1}|s_{t+1})} \right) \right\}, \quad (8)
\]

where \( \pi_\theta \) denotes the parameterized \( \pi \). Let \( q = \sum_i w_i \) and

\[
w_i = \exp[y^l_{ME} (s_{t+1}, a_{t+1}, \pi_\theta)] / \pi_\theta (a_{t+1}|s_{t+1}).
\]

The gradient of \( L(\theta) \) is given by

\[
\frac{dL}{d\theta} = E_{D_p} \sum_t d(y^l_{ME} (s_{t+1}, a_{t+1}, \pi_\theta)) / d\theta - E_{D_{np}} \frac{1}{q} \sum_t w_i d(y^l_{ME} (s_{t+1}, a_{t+1}, \pi_\theta)) / d\theta. \quad (9)
\]

From the gradient computation in (9), we can get some insights of the policy derived from (7). First, the magnitude of the maximum entropy reward directly contributes to the gradient ascent while the human preferred trajectories can shape the loss towards the desired regions and the human unpreferred trajectories can shape the loss away from undesired regions. Second, the denominator \( \pi (a_{t+1}|s_{t+1}) \) in (7) denotes the background distribution from which the trajectories \( \tau_i \) are sampled using the current policy \( \pi_\theta \).

E. Pseudocode of the Overall Approach

The pseudocode for the proposed GAN-assisted human preference-based reinforcement learning approach is shown in Algorithm 1.

Algorithm 1: Pseudocode for the proposed GAN-assisted human preference-based reinforcement learning approach

**Data:** initial state distribution \( q_0 (s) \); initial policy \( \pi_0 \); iteration limit \( m \); state sample limit \( n \); rollout limit \( k \); time step size for fine-tuning adversarial neural network \( T \).

**Result:** improved policy: \( \pi_i \)

\( A(s) \): the set of actions available in states

\[
\text{for } i = 1 \text{ to } m \text{ do } \quad \text{for } 0 \text{ to } n \text{ do }
\]

\[
s \sim q_0 (s)
\]

\[
\tau = \emptyset, \xi = \emptyset
\]

\[
\text{for } \forall a \in A(s) \text{ do }
\]

\[
\text{for } 0 \text{ to } k \text{ do }
\]

\[\tau \leftarrow \tau \cup \text{ROLLOUT}(s, a, \pi_i)\]

end

end

if \text{OBTAIN PREFERENCE VIA C2 and PATHBACK}(T) then

\[
D_p, D_{np} \leftarrow \text{C1 or C3}
\]

\[
\text{FINE-TUNE}(\tau, D_p, D_{np}) \text{ by maximizing (1) via stochastic gradient ascent}
\]

end

\[
\xi \leftarrow \text{OBTAIN PREFERENCE VIA C2}
\]

end

\[
\pi_i \leftarrow \text{UPDATE POLICY by maximizing (8)}
\]

\[
Q_0(s, a) \leftarrow Q_0(s, \arg \max_a Q_0(s, a)) \text{ by minimizing (5) via stochastic gradient descent}
\]

end

IV. Experiments

In this section, we will present some experimental results to evaluate the performance and effectiveness of the proposed method. All experiments are conducted on the MuJoCo physics engine [28]. For the actor network, we adopt a simple convolutional neural network with two hidden layers of size 64 using ReLU [29] as the activation function. The discount factor is selected as \( \gamma = 0.99 \). The critic network has one hidden layer of size 64. Both the adversarial neural network and the neural network that estimates the human-preference based Q values have two hidden layers of size 64. We use the asynchronous advantage actor-critic (A3C) setting [30] and execute parallel episodes in one batch. For all experiments, the number of environment copies is selected as 6. The parameters are optimized using the stochastic gradient descent (SGD) algorithm [31] and a learning rate of \( 3 \times 10^{-4} \). All experiments are performed using TensorFlow, which supports automatic differentiation through the gradient updates [32].

In the following part of the section, we will demonstrate how robotic behavior learning tasks are solved using the proposed GAN-assisted preference-based reinforcement learning approach without accessing the true reward. In the setting of human queries, the human is first given a natural language description of each task and then provided some examples of labeling the trajectory clips based on the description. Then the human is asked to compare non-labeled clip pairs as the feedback. In particular, we consider two types of human queries, namely, human-175 and human-345. In particular, human-175 (respectively, human-345) asks the human to first label 175 clips (respectively, 345 clips) and then only label 6 online clips per episode during the training process for each task. Each trajectory segment has a duration of 5 seconds. Typically, the human can respond to the query in 5 seconds. Since the clips are automatically generated without the need for human supervision, the human time is only calculated based on the approximated human labeling time under the assumption that each query takes 5 seconds. Under this setting, typical experiments involving direct human queries requires less than 1 hour of human time.

For comparison, we also run experiments using a synthetic (quantitative) oracle whose preferences over trajectory pairs exactly reflect accumulated reward in each specific task. In our quantitative oracle, instead of sending the queries to the human, the feedback is labeled by selecting clips receiving a higher reward in that task via the trained maximum entropy reinforcement learning algorithm in Section III-E. In the setting of synthetic queries, we consider the case synthetic-175 when 175 clips were first labeled by the trained maximum entropy reinforcement learning algorithm and 175 more online clips were labeled for every 100 episodes during the training of the reinforcement learning algorithm.
Finally, we also run experiments using human preferences learned by the adversarial neural network in Section III-C. In particular, the GAN-assisted human preferences are obtained via a pre-trained adversarial neural network based on learning the human’s preferences over clip pairs. Instead of labeling the queries using the trained maximum entropy reinforcement learning algorithm, the adversarial neural network can directly label the clip pairs since it aims to produce a close-to-true prediction of human preferences. In the setting of GAN-assisted queries, we consider two types of GAN-assisted queries, namely, GAN-assisted-50 and GAN-assisted-175. Specifically, GAN-assisted-50 (respectively, GAN-assisted-175) asks the adversarial neural network to first label 50 (respectively, 175) video clips and then labels 50 (respectively, 175) online clips for every 100 episodes during the training of the reinforcement learning algorithm.

A. Results and Comparison

This subsection presents the results of the methods described earlier in this section. In particular, we conduct experiments on four types of robotic behaviors (namely, swimmer, hopper, cheetah, and ant) based on the MuJoCo physics engine. Figure 2 shows the comparison of the rewards obtained via, respectively, real reward, synthetic-175, human-175, human-345, GAN-assisted-50, and GAN-assisted-175. For human-175 and human-345, we conduct three runs. For all other methods, we conduct six runs. Fig. 2 shows the plots of the collective real rewards using these methods for the four types of robotic behaviors. The solid line represents the average reward while the shadow area represents the variance. Table I shows the final reward comparison using these methods for the four types of robotic behaviors. It can be observed from Fig. 2 and Table I that GAN-assisted-50 and GAN-assisted-175 yield much better performance than real reward, human-175, and human-345. GAN-assisted-175 also shows improved performance over (or very close performance as) synthetic-175. It can also be observed from Table I that GAN-assisted-50 and GAN-assisted-175 yield similar rewards except for cheetah. Further comparison with the results in |c.f. the last row in Table I| shows that the proposed GAN-assisted-175 outperforms the approach proposed in |9| for all four cases. The proposed GAN-assisted-50 outperforms the approach proposed in |9| for three cases except for Cheetah.

| Table I: Performance Comparison (Final Reward) |
|-----------------------------------------------|
| Methods | Swimmer | Hopper | Cheetah | Ant |
| Real Reward | 88 | 3322 | 1882 | 8 |
| Synthetic-175 | 140 | 4063 | 5514 | 617 |
| Human-175 | 107 | 1462 | 1158 | -128 |
| Human-345 | 140 | 2758 | 2712 | 292 |
| GAN-assisted-50 | 167 | 3961 | 3485 | 808 |
| GAN-assisted-175 | 131 | 4124 | 8238 | 878 |
| Method in | 100 | 3900 | 5600 | -100 |

It is also interesting to notice that human-175 is less effective than the typical reinforcement learning method using real reward. However, human-345 outperforms (or yields a similar performance as) the typical reinforcement learning method using real reward. It is our hypothesis that human provides enough correct data for reward shaping in human-345 while not in human-175 because human can make mistakes in providing preferences. Hence, the typical reinforcement learning method using real reward may outperform human-175 because the shaped reward may not be accurate. One unique advantage of the proposed GAN-assisted human-preference reinforcement learning approach is to separate the labeling of trajectory pairs and the creation of reinforcement learning algorithm to learn appropriate control policies. In other words, one set of human queries are used to create two sets of valuable outcomes, namely, an adversarial neural network model to directly learn human preferences and the learning of reward functions for control policy generation. Moreover, the adversarial neural network to be learned with a binary output is low-dimensional, and hence can be trained via a very small amount of human queries. In addition, GAN-based human preference queries via the learned adversarial neural network can be used to replace active human queries (required in, e.g., [24]) in the reward shaping and control policy generation. Hence, the proposed new GAN-assisted preference-based reinforcement learning approach can provide much more effective human preference-based reinforcement learning algorithms for the generation of trajectories that meet human preferences.

To demonstrate the effectiveness of the proposed GAN-assisted preference-based reinforcement learning approach, we also conducted some comparison of the human time when using the proposed approach and a baseline approach presented in |9|. Under the assumption that the human can respond to each query in 5 seconds, the total human time needed in |9| ranges from 0.5 ~ 5 hours. Correspondingly, the proposed GAN-assisted preference-based reinforcement learning approach requires only 0.08 ~ 0.83 hours, further reducing about 84% human time needed in |9|.

B. Discussion on GAN-assisted Human Performance Learning

To quantitatively evaluate the effectiveness of the proposed GAN-assisted preference-based reinforcement learning algorithm, we now provide some discussion about its performance. In particular, we use the metric GAN-test that was developed in |33|. GAN-test refers to the accuracy of a neural network, trained on physical data, evaluated on the generated data. In the context of this paper, we train the adversarial neural network on sampled trajectory pairs and then evaluate it on the newly generated trajectories to see if the output probability for human preference fits the synthetic oracle. A high GAN-test value means that the generated samples are good approximation of the (unknown) distribution of human preference-based models. An example of the GAN-test result for the hopper robot case is shown in Fig. 3. In the experiment, each episode has 4e5 time steps. In particular, for GAN-assisted-175, we fine tune the adversarial neural network using the human preferences at episode 77. This means that less than 1% human queries are used. If we assume that the human can respond to each query in 5 seconds, a total of 17.5 hours of human labeling
time can be saved. For GAN-assisted-50, we only fine tune the adversarial neural network using the human preferences at episodes 90 and 182. This means that only 1.1% human queries are used. In both cases, a high GAN-test value can be maintained, as shown in Fig. 3. One can also observe that GAN-assisted-175 yields a higher and more stable GAN-test value than GAN-assisted-50 because GAN-assisted-175 outputs a better model than GAN-assisted-50. Since GAN-assisted-175 already provides a very high GAN-test value, it is expected that more human queries may help gain very limited, if not no, performance improvements.

V. CONCLUSION

Effective human-robot interaction is essential for the development of sophisticated robotic systems that can act properly when interacting with real-world environments, subject to human’s personalized preferences. We showed in the paper that robots can learn complex robotic behaviors with a reduction of about 99.8% human time (or a reduction of 84% human time from the baseline approach in [9]) when an adversarial neural network and a maximum entropy reinforcement learning algorithm are designed appropriately. This shows the feasibility of training sophisticated robotic systems to learn human preferences efficiently. The proposed techniques and algorithms present an important step towards practical application of deep reinforcement learning in complex real-world robotic tasks when robots only need sparse human queries to learn human preferences and complex novel behaviors without access to reward functions.

REFERENCES

[1] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, S. Petersen, C. Beattie, I. A. Amir Sadik, H. King, D. Kumaran, D. Wierstra, S. Legg, and D. Hassabis, “Human-level control through deep reinforcement learning,” Nature, vol. 518, no. 7540, p. 529, 2015.
[2] S. Russell, “Should we fear supersmart robots?,” Scientific American, vol. 314, no. 6, pp. 58–59, 2016.
[3] P. Abbeel and A. Y. Ng, “Apprenticeship learning via inverse reinforcement learning,” in Proceedings of the International Conference on Machine Learning, p. 1, 2004.
[4] B. D. Ziebart, A. Maas, J. A. Bagnell, and A. K. Dey, “Maximum entropy inverse reinforcement learning,” 2008.
[5] B. Eric, N. D. Freitas, and A. Ghosh, “Active preference learning with discrete choice data,” in Advances in Neural Information Processing Systems, pp. 409–416, 2008.
[6] A. D. D. Dorsa Sadigh, S. Sastry, and S. A. Seshia, “Active preference-based learning of reward functions,” in Robotics: Science and Systems, 2017.
[7] M. Palan, N. C. Landolfi, G. Shevchuk, and D. Sadigh, “Learning reward functions by integrating human demonstrations and preferences,” arXiv preprint arXiv:1906.08928, 2019.
[8] C. Wirth, A. Kaur, G. Neumann, and J. Fürnkranz, “A survey of preference-based reinforcement learning methods,” The Journal of Machine Learning Research, vol. 18, no. 1, pp. 4945–4990, 2017.
[9] P. F. Christiano, J. Leike, T. Brown, M. Martic, S. Legg, and D. Amodei, “Deep reinforcement learning from human preferences,” in Advances in Neural Information Processing Systems, pp. 4299–4307, 2017.
[10] J. Fürnkranz, E. Hüllermeier, W. Cheng, and S.-H. Park, “Preference-based reinforcement learning: a formal framework and a policy iteration algorithm,” Machine Learning, vol. 89, no. 1-2, pp. 123–156, 2012.
Fig. 3: GAN-test value for the hopper robot example (Top: GAN-assisted-175; Bottom: GAN-assisted-50). The red dots represent the number of episodes at which human queries are used.

[11] R. Akrour, M. Schoenauer, and M. Sebag, “April: Active preference learning-based reinforcement learning,” in Proceedings of the Joint European Conference on Machine Learning and Knowledge Discovery in Databases, pp. 116–131, 2012.

[12] R. Akrour, M. Schoenauer, M. Sebag, and J.-C. Souplet, “Programming by feedback,” in Proceedings of the International Conference on Machine Learning, vol. 32, pp. 1503–1511, 2014.

[13] C. Daniel, O. Kroemer, M. Viering, J. Metz, and J. Peters, “Active reward learning with a novel acquisition function,” Autonomous Robots, vol. 39, no. 3, pp. 389–405, 2015.

[14] L. El Asri, B. Piot, M. Geist, R. Laroch, and O. Pietquin, “Score-based inverse reinforcement learning,” in Proceedings of the International Conference on Autonomous Agents & Multiagent Systems, pp. 457–465, 2016.

[15] S. I. Wang, P. Liang, and C. D. Manning, “Learning language games through interaction,” arXiv preprint arXiv:1606.02447, 2016.

[16] C. Wirth, J. F¨urnkranz, and G. Neumann, “Model-free preference-based reinforcement learning,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2016.

[17] Y. Yang, K. Caluwaerts, A. Iscen, J. Tan, and C. Finn, “Norml: No-reward meta learning,” in Proceedings of the International Conference on Autonomous Agents & Multiagent Systems, 2019.

[18] P. D. Sørensen, J. M. Olsen, and S. Risi, “Breeding a diversity of super mario behaviors through interactive evolution,” in Proceedings of the IEEE Conference on Computational Intelligence and Games, pp. 1–7, 2016.

[19] E. Bıyık and D. Sadigh, “Batch active preference-based learning of reward functions,” arXiv preprint arXiv:1810.04303, 2018.

[20] J. Fu, A. Singh, D. Ghosh, L. Yang, and S. Levine, “Variational inverse control with events: A general framework for data-driven reward definition,” in Advances in Neural Information Processing Systems, pp. 8538–8547, 2018.