AutoEG: Automated Experience Grafting for Off-Policy Deep Reinforcement Learning

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Abstract

Deep reinforcement learning (RL) algorithms frequently require prohibitive interaction experience to ensure the quality of learned policies. The limitation is partly because the agent cannot learn much from the many low-quality trials in early learning phase, which results in low learning rate. Focusing on addressing this limitation, this paper makes a twofold contribution. First, we develop an algorithm, called Experience Grafting (EG), to enable RL agents to reorganize segments of the few high-quality trajectories from the experience pool to generate many synthetic trajectories while retaining the quality. Second, building on EG, we further develop an AutoEG agent that automatically learns to adjust the grafting-based learning strategy. Results collected from a set of six robotic control environments show that, in comparison to a standard deep RL algorithm (DDPG), AutoEG increases the speed of learning process by at least 30%.

1 Introduction

Deep reinforcement learning (RL) algorithms recently have achieved great successes in a variety of applications, such as game playing and robot control [Mnih et al., 2013; Silver et al., 2016; Levine et al., 2016]. However, due to the high domain complexity, learning an effective action policy in such domains frequently requires a prohibitively large number of interaction samples, which significantly limits current RL algorithms’ applicability.

Data augmentation is one attractive way of enabling agents to learn from insufficient data [Tanner and Wong, 1987], and has been widely used by the machine learning community. Augmenting data is more difficult in RL tasks, because RL agents learn from trial-and-error experience, and the “data” is in the form of samples of interaction experiences. There are at least two very different ways of augmenting interaction data for RL. One points to the imagination-based methods that require learning and interacting with world models to generate artificial experience, e.g. [Racanière et al., 2017]. However, the imagination-based methods themselves are data-hungry so as to ensure the quality of the learned world models. Hind-sight experience replay (HER) [Andrychowicz et al., 2017] is another way of augmenting data for RL agents, where the agents synthesize samples without computing world models. However, the HER method is only applicable to domains where the goal condition is explicitly defined in the state space. For instance, HER was originally applied to a domain of a robot arm moving from one point to another, where the goal corresponds to a position in the 2D state space. In line with the HER method, we aim at post-processing experiences to generate “successful” samples. Beyond that, we focus on more challenging domains, where goal states do not exist. For instance, the Walker2D task in MuJoCo [Todorov et al., 2012] requires the agent running as fast as possible, rendering the original HER method inapplicable.

In this paper, we develop an algorithm, called Experience Grafting (EG), for generating high-quality, synthetic trajectories to speed up the agent’s learning process. In comparison to HER that manipulates individual trajectories, EG searches for pairs of trajectory segments, where one’s “head” state and the other’s “tail” state are of sufficient similarity. Moreover, we develop an Automated EG (AutoEG) algorithm that enables the RL agent to learn to dynamically adjust its grafting strategy. For instance, AutoEG enables an experienced agent to be very “picky” in grafting, because it is able to produce good-quality samples from its own interaction experience.

EG and AutoEG are generally applicable to off-policy RL algorithms, such as the value-based [Mnih et al., 2013] and policy gradient methods [Sutton et al., 2000; Schulman et al., 2017] among others. We use deep deterministic policy gradient (DDPG) [Lillicrap et al., 2015], which well accounts for continuous action spaces, for both learning the policy of interacting with the environments and learning the grafting policy, as shown in Figure 1. We have evaluated EG and AutoEG using six Roboschool environments, an extension to MuJoCo [Todorov et al., 2012]. We used a metric called area under the learning curve (AUC) to evaluate the speed of the learning process [Taylor and Stone, 2009; Stadie et al., 2015]. Results suggest that: 1) Although EG performs better than standard DDPG in most environments, its performance is sensitive to its handcrafted grafting strategy; and 2) AutoEG further enables the capability of grafting policy learning, and produces better performance (c.f., standard DDPG) in learning speed by at least 30% in all six Roboschool environments.

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Data augmentation is widely used for enlarging training sets, and has become an essential step of mitigating over-fitting in supervised learning [Krizhevsky et al., 2012; Zhang et al., 2015; Jaitly and Hinton, 2013]. For instance, in image classification, linear transformations are commonly applied [Eigen et al., 2014], whereas text classification researchers often rephrase words or phrases with their synonyms [Zhang et al., 2012]. There is the recent effort on automated architecture search for data augmentation, where an AutoML approach was used to automatically generate data augmentation policies [Cubuk et al., 2018]. In comparison to these methods for supervised learning, this work is on augmenting trial-and-error experiences for RL agents.

Researchers have developed RL and planning methods to learn world models, and simulate experiences of agent interacting with the real world. One notable example of these methods is Dyna-Q [Sutton, 1990]. The agent learns an approximation function (e.g., neural networks) from experiences, and uses the (imperfect) world model to generate artificial trajectories to augment experiences [Racanière et al., 2017; Buckman et al., 2018]. Other examples include [Pascana et al., 2017; Peng et al., 2018; Su et al., 2018; Kalweit and Boedecker, 2017], as well as the imagination-based methods, e.g., [Racanière et al., 2017]. These approaches avoid the need of extensive interaction experience with the real world. However, these methods tend to be sensitive to the learned model’s quality, because an inaccurate model has a detrimental effect on performance [Gu et al., 2016]. Our EG and AutoEG algorithms provide an alternative way of generating artificial experiences for better learning performances, while avoiding the challenging task of learning world models.

Hindsight experience replay (HER) enables an agent to augment trajectories by replaying each episode with a goal that is different from the goal that the agent was originally trying to achieve [Andrychowicz et al., 2017]. HER provides a new way of augmenting interaction experiences for RL agents. More recent work has applied HER to dialogue domains, enabling the manipulation of trajectory segments to form new dialogues [Lu et al., 2018]. However, the HER-style methods has the limited applicability, requiring the goal condition being defined in the state space (e.g., the box’s target location in “pushing” task, and slots being filled in goal-oriented dialog agents). In comparison, our developed EG and AutoEG methods support tasks where goal states do not exist, e.g., the Walk2D task where the agent tries to walk fast, rendering the HER methods inapplicable.

Automated machine learning (AutoML) recently has emerged as a new area in the machine learning community [Quanming et al., 2018]. AutoML has been successfully applied to problems including neural architecture search (NAS) [Zoph and Le, 2017] and hyper-parameter optimization [Feurer and Hutter, 2018]. Inspired by the AutoML idea, we formulate the hyper-parameter search of EG as a separate RL problem, enabling one RL agent to learn a policy to tune the (experience grafting) parameter of another RL agent.

3 Algorithm

In this section, we describe our automated experience grafting (AutoEG) algorithms. Figure 1 summarizes the two learning agents within AutoEG: the EG agent learns from the trial-and-error experience with the environment, as well as the artificial trajectories from experience grafting; and the Tutor agent learns to adjust the EG agent’s grafting strategy on the fly. For instance, Tutor tends to make an “experienced” EG agent more cautious in utilizing synthetic trajectories, because the EG agent itself is able to produce high-quality trajectories.

3.1 Functions for Experience Grafting

We use the term of trajectory segment (or simply segment) to refer to a sequence of transitions, where each segment includes at least one transition. Each transition, $tr$, is in the form of a state-action-reward-state tuple, i.e., $tr = (s, a, r, s')$. For example, in the “pushing” task, a trajectory segment may include the agent pushing the box to its goal location in “pushing” task, and slots being filled in goal-oriented dialog agents. In comparison, our developed EG and AutoEG methods support tasks where goal states do not exist, e.g., the Walk2D task where the agent tries to walk fast, rendering the HER methods inapplicable.
Given two segments, $s, a, r, s_2$, where $s$ (or $s_2$) is the current (or next) state, $r$ is the reward, and $a$ is the action. A trajectory is a segment whose first transition starts with the initial state, and whose last transition leads to an terminal state.

**Distance Function:** We introduce a distance function to measure the similarity between two states:

$$Dis(s, s_2) = W(P|s), P(s_2),$$

where function $P$ normalizes a state vector to a distributional representation, and $W(P_1, P_2)$ is the $1$st Wasserstein distance or earth mover’s distance [Rubner et al., 1998].

$$W(P_1, P_2) = \inf_{\gamma \in \Pi(P_1, P_2)} \mathbb{E}_{(x, y) \sim \gamma} [\| x - y \|],$$

where $\Pi(P_1, P_2)$ is the set of all joint distributions $\gamma(x, y)$ whose marginals are respectively $P_1$ and $P_2$. Intuitively, $\gamma(x, y)$ indicates how much “mass” must be transported from $x$ to $y$ in order to transform the distributions $P_1$ into distribution $P_2$. The earth mover’s distance then is the “cost” of the optimal transport plan.

**Error Function:** We say a segment is a head (tail) segment, if the last (first) transition of this segment is used for grafting. Accordingly, we graft head segments to tail segments. Given head segment $Seg_1$ and tail segment $Seg_2$, the grafting error is defined as below

$$Err(Seg_1, Seg_2) = Dis(\text{Term}(Seg_1), \text{Init}(Seg_2)),$$

where $\text{Term}(Seg)$ returns the terminal state of $Seg$, and $\text{Init}(Seg)$ returns the initial state of $Seg$. A smaller grafting error indicates that the generated synthetic trajectory is more realistic. Synthetic trajectories of high grafting errors are of low grafting quality.

**Union Function:** Given two segments $Seg_1$ (head) and $Seg_2$ (tail), the grafting union function generates a synthetic trajectory that grafts $Seg_1$ to $Seg_2$, if their grafting error is lower than $\epsilon$, the grafting threshold. It should be noted that $\epsilon$ plays an important role in later sections.

$$\text{Uni}(Seg_1, Seg_2) =
\begin{cases}
\text{append}(Seg_1, Seg_2) & \text{Err}(Seg_1, Seg_2) < \epsilon \\
\emptyset & \text{otherwise}
\end{cases}$$

The grafting union function ($\text{Uni}$) can be used for generating potentially many synthetic trajectories, and we selectively use only the “high-quality” trajectories for learning purposes.

**Performance Quality Function:** We use the accumulative reward of a trajectory to measure the trajectory’s performance quality.

$$\text{Qua}(Trj) = R_0(Trj)$$

It should be noted that a trajectory’s quality can be evaluated in two ways, i.e., being realistic and being effective to learning. For instance, a trajectory of a walker instantly changing its position from lying on the floor to jumping in the air is unrealistic, and hence is of poor grafting quality. A trajectory of a walker lying on the floor without any movement has good grafting quality, but its performance quality is poor, because an RL agent can hardly learn much from it.

**Algorithm 1 Experience Grafting**

**Input:** $\epsilon$ (grafting threshold), $T$ (authentic trajectory), $Lib$ (segment library), $N_{syn}$ (number of synthetic trajectories), and $N_{gft}$ (number of grafting positions)

**Output:** a set of synthetic trajectories

```plaintext
for i ← 1 to $N_{syn}$ do  // Start: Segment extraction
  1: Randomly select position $p = \text{random}(0, \text{size}(T))$
  2: Extract transition $T[p] = (s_p, a_p, r_p, s_{p+1})$ from $T$
  3: Add $s_p : T[p] : size(T)$ into $Lib$ as a new indexed segment, where $s_p$ is the key and $T[p : size(T)]$ is the value
end for // End: Segment extraction
for j ← 1 to $N_{gft}$ do  // Start: Trajectory synthesis
  4: Randomly select position $q = \text{random}(0, \text{size}(T))$
  5: Extract transition $T[q] = (s_q, a_q, r_q, s_{q+1})$
  6: Search $Lib$ for segments using $s_{q+1} : \text{Seg} = Lib.get(s_{q+1}, \epsilon)$
  7: Initialize a empty set of synthetic trajectory $syTrj = \emptyset$
  8: for $seg \in \text{Seg}$ do
  9:   $\text{syTrj} ← syTrj \cup syTrj$
end for
10: $syTrj \leftarrow syTrj$  // End: Trajectory synthesis
11: return $G(T, syTrj)$, where $G$ is the grafting function
```

**Grafting Function:** Given an authentic trajectory, $auTrj$, and a set of synthetic trajectories, $syTrj$, we use $syTrj$ to represent the set of synthetic trajectories whose quality is higher than that of the authentic trajectory. To avoid the grafting function generating too many trajectories, we introduce $\Theta$, the maximum number of synthetic trajectories allowed given one authentic trajectory. In case more than $\Theta$ trajectories are qualified, the grafting function $G$ sorts the trajectories using their qualities, and outputs the top $\Theta$ trajectories:

$$syTrj = \{ syTrj | Qua(syTrj) \geq Qua(auTrj), syTrj \in syTrj \},$$

$$G(auTrj, syTrj) = \{ syTrj[1 : \Theta] \text{ if } syTrj > \Theta \} \text{ otherwise}$$

While using this grafting function, we force the set of synthetic trajectories to be those that are generated with grafting with the authentic trajectory. The union and grafting functions together ensure that the synthetic trajectories used for RL are both realistic and potentially effective for learning.

**3.2 Experience Grafting**

Algorithm 1 presents our experience grafting (EG) algorithm that includes two phases for segment extraction and trajectory synthesis respectively. The input of EG includes $\epsilon$ (grafting threshold), $T$ (an authentic trajectory), $Lib$ (a segment library), and two parameters of $N_{syn}$ and $N_{gft}$.

Lines 1-5 in Algorithm 1 presents the steps for segment extraction. There are $N_{syn}$ iterations in this phase, where one segment is generated in each iteration. Position $p$ is randomly selected in trajectory $T$. From the $p$ position, $T$ is cut into two segments, where $EG$ saves the tail (i.e., from position $p$ to the end) to segment library $Lib$. EG uses the initial state $s_p$ as the key for indexing, because segments in $Lib$ will be used for grafting as the tail segment in later steps. It should be noted that EG only presents the steps of processing one authentic trajectory. In practice, EG is repeatedly called whenever a new authentic trajectory comes in. As a result, in most cases, $Lib$ already includes many segments each time EG is activated.
The segment library, $Lib$, stores segments and indexes the segments using their initial state, where EG discretizes the state space for the indexing purpose. This operation ensures efficient search in $Lib$, and is important from the practical perspective.

Lines 6-15 in Algorithm 1 presents the trajectory synthesis steps. EG randomly selects a transition in trajectory $T$ in Line 7, and uses $s_{t+1}$, the resulting state of $T$, to search for segment candidates for grafting in $Lib$ (Line 9). Entering the inner for-loop (Lines 11-14), in each iteration, EG uses the union function ($\cup$) to generate one or zero synthetic trajectory ($syTrj$) with the guarantee that the generated synthetic trajectory is realistic. $syTrj$ saves a set of realistic synthetic trajectories. Finally, EG uses the grafting function to output a set of synthetic trajectories that are of both good performance quality and good grafting quality (defined in Section 3.1).

Remark: EG enables an RL agent to more efficiently utilize its trial-and-error experiences by synthesizing good-quality trajectories. $\epsilon$ is an important parameter in this grafting process that directly determines how many trajectories can be synthesized, as well as how realistic these trajectories are. Intuitively, when $\epsilon$ is small (e.g., close to zero), the generated trajectories are very realistic (i.e., can hardly be distinguished from the authentic ones), but the issue of small $\epsilon$ values is that very few trajectories can be synthesized. When $\epsilon$ is large, more synthetic trajectories can be generated, but they might look very artificial, e.g., a robot lying on the floor instantly changes its position to be jumping in the air, which is certainly detrimental to agent learning. The trade-off between synthetic trajectories’ quality and quantity motivates the development of AutoEG for learning to adjust $\epsilon$ for adaptive learning behaviors.

### 3.3 AutoEG: Learning Grafting Strategies

Recent research on AutoML [Qunanning et al., 2018] and neural architecture search [Zoph and Le, 2017] has shown promising results on “learning to learn” methods. In line with these methods, we develop another learning agent, called Tutor, that guides the EG agent by learning to adjust its grafting strategy throughout the EG agent’s trial-and-error process. We use Automated EG (AutoEG) to refer to the combination of Tutor and EG. The Tutor agent is modeled as a DDPG-based RL problem, which is defined below.

**State:** The Tutor agent only exchanges information with the EG agent, and has no direct interaction with the working environment. Tutor’s state space is specified using two state features:

- The ratio of transitions from synthetic trajectories to all transitions in the replay buffer; and
- The ratio of synthetic trajectories from the grafting function to $\Theta$, the maximum number of synthetic trajectories allowed given one authentic trajectory (Sec. 3.1).

**Action:** The Tutor agent’s action is in the form of a real number, ranging from 0.0 to 1.0, where an action directly corresponds to a grafting threshold ($\epsilon$).

**Reward:** We define a finite time horizon for the interactions between the Tutor agent and the EG agent. Tutor’s reward function is defined as the average of the rewards the EG agent receives within this horizon. Accordingly, the goal of this Tutor agent is to maximize the accumulative reward of the EG agent in its next $H$ steps, where $H$ is the time horizon. To be more specific, each step of the Tutor agent corresponds a complete episode of the EG agent interacting with the environment.

It makes sense to model the Tutor agent as an RL problem, because the tutor agent’s reward is noisy and is not immediate. As a result, it is necessary for the Tutor agent to learn an action policy to tune the EG agent’s grafting threshold in a way that the EG agent’s long-term reward is maximized.

Algorithm 2 presents our Automated EG (AutoEG) framework. There are two agents being learned, namely the EG agent and the Tutor agent. The EG agent is responsible for interacting with the environment for a certain task (Lines 4-16), while Tutor learns a grafting policy for the EG agent (Lines 17-26). Synthetic trajectories are generated once each authentic trajectory is sampled, and are used for updating EG’s policy by augmenting its replay buffer (Lines 11-16). Tutor’s each episode corresponds to the EG agent interacting with the environment.

### Algorithm 2: Automated EG (AutoEG)

**Input:** $M$ (number of episodes), $N_{EG}$ (size of minibatch of the EG agent), $N_{Tutor}$ (size of minibatch of the Tutor agent), Maximal number of Synthetic Trajectory in one time $\Theta$, Horizon $H$

1. Initialize two DDPGs for the EG and Tutor agents, including their replay buffers of $\mathcal{R}^{EG}$, and $\mathcal{R}^{Tutor}$
2. Initialize horizon $H = 0$, Tutor’s current state, $s^{Tutor} = (0, 0)$; and EG’s sum of rewards in horizon $H$, $\text{Sum}_{of} \text{Reward} = 0$
3. for episode $\leftarrow 1$ to $M$ do
4. Initialize trajectory $T = \emptyset$, and receive initial observation state $s_1$ // Start: the EG agent
5. while current state $s_t$ is not terminal do
6. Select action $a_t = \pi^{EG}(s_t)$ for the EG agent, and execute $a_t$, and observe reward $r_t$ and new state $s_{t+1}$
7. Store transition $(s_t, a_t, r_t, s_{t+1})$ in $\mathcal{R}^{EG}$
8. $\text{Sum}_{of} \text{Reward} \leftarrow \text{Sum}_{of} \text{Reward} + r_t$, and records current transition $T = T \cup (s_t, a_t, r_t, s_{t+1})$
9. Sample a random minibatch of $N^{EG}$ transitions $(s_t, a_t, r_t, s_{t+1})$ from $\mathcal{R}^{EG}$ and update $\pi^{EG}$, the policy of the EG agent
10. end while
11. Get current grafting threshold using the Tutor agent’s action policy, $\epsilon = \pi^{Tutor}(s^{Tutor})$
12. Call Algorithm 1 to generate a set of synthetic trajectories, $syTrj$, using $\epsilon$
13. for $syTrj \in syTrj$ do
14. Store transition $(s_t, a_t, r_t, s_{t+1})$ in $syTrj$ into $\mathcal{R}^{EG}$
15. Update the EG agent’s policy $\pi^{EG}$ with a minibatch of $N^{EG}$ transitions from $\mathcal{R}^{EG}$
16. end for // End: the EG agent
17. Update $r^{Tutor}$, the ratio of transitions from synthetic trajectories to all transitions in $\mathcal{R}^{EG}$ // Start: the Tutor agent
18. Update $r^{Tutor}$, the ratio of generated synthetic trajectories to $\Theta$, i.e., $r^{Tutor} = \text{len}(syTrj)/\Theta$
19. Get the Tutor agent a new state, $s^{Tutor} = (s^{Tutor}, r^{Tutor})$
20. if horizon $< H$ then
21. Store transition $(s^{Tutor}, r, s^{Tutor})$ in $\mathcal{R}^{Tutor}$, and update $s^{Tutor} \leftarrow s^{Tutor}$ and horizon $\leftarrow$ horizon + 1
22. else
23. Store the following transition in $\mathcal{R}^{Tutor}$
24. Remove all synthetic transitions from $\mathcal{R}^{EG}$, and initialize $s^{Tutor} = (0, 0)$; horizon $\leftarrow 0$; and $\text{Sum}_{of} \text{Reward} = 0$
25. end if
26. Update $\pi^{Tutor}$, the policy of Tutor, with a minibatch of $N^{Tutor}$ transitions from $\mathcal{R}^{Tutor}$ // End: the Tutor agent
27. end for
environment for $H$ times, i.e., EG’s $H$ episodes. After the EG agent completing each of its $H'$th episodes, all the synthetic trajectories augmented in its replay buffer are cleared to get prepared for the Tutor agent’s next episode.

4 Experiment

EG and AutoEG have been evaluated using six robotic environments in Roboschool from OpenAI. In this section, we introduce the experimental setup, and implementation details of EG and AutoEG, where both EG and Tutor agents are implemented using DDPG as the RL algorithm. Although AutoEG is generally applicable to off-policy RL algorithms, we selected DDPG in the evaluation due to its relatively longer history and (arguably) better popularity. Our main evaluation metric is called area under the learning curve (AUC), which has been used for evaluating the speed of the learning process [Taylor and Stone, 2009; Stadie et al., 2015]. Another metric used in this work is called policy quality, which is measured by taking the average of total rewards over the last 1000 episodes.

Our main hypotheses include: I) Well-tuned EG agents perform better than a standard DDPG agent (referred to as no-EG) in AUC; but their performances can be sensitive to the handcrafted grafting strategies; and II) AutoEG produces the best performance in both learning speed and policy quality in comparison to EG and no-EG methods.

4.1 Implementation Details

Six robotic environments from Roboschool have been used for evaluations. Relatively low-dimensional environments include Walker2d-v1, HalfCheetah-v1, Hopper-v1, while the others are high-dimensional, more challenging environments, including AtlasForwardWalk-v1, Humanoid-v1, and HumanoidFlagrun-v1.

In all tasks, we follow the original DDPG architecture (for both EG and Tutor agents), including the hyper-parameters and network initialization [Lillicrap et al., 2015]. In the EG implementations, the replay buffer size is $1e6$, and experience replay starts when the buffer size reaches $1e4$. In the Tutor implementation, the replay buffer size is the same, while experience replay starts when the size of buffer reaches 100.

The experience reply starts late in EG, because it cannot adjust its grafting strategy and re-playing a small amount of experience is detrimental. The size of minibatch is 16 in the DDPG-EG setting, and it is 10 in the DDPG-AutoEG setting (time horizon $H$ is 10). The value of $\Theta$ is 5. There is the discretization in $\text{Lib}$ (segment library) to allow efficient search, where each bin is sized 1.0 in each dimension, and includes at most 1000 segments. Each data point in the figures of this paper is an average of five runs, where we also report the standard deviations.

4.2 Illustrative Example

Figure 2 shows an example of experience grafting process in the Walker2d environment. The segment library $\text{Lib}$ saves a set of trajectory segments (Line 4 in Algorithm 1), where each segment is indexed using its initial state. In this case, the very left state of the “pink” (second half) segment in Trajectory 2 was used a key state for indexing. Given the key state and its “Tail segment”, EG searched over all new trajectories, and found Trajectory 1 has a state of significant similarity, while the corresponding “Head segment” is of good quality. EG then initiated the grafting (Line 12 in Algorithm 1), and produced the synthetic trajectory of high quality.

4.3 Experimental Results

Figure 3 shows the experimental results from comparisons among no-EG, EG (with different $\epsilon$ values), and AutoEG agents. From all the curves, we see the EG agents perform better than naive DDPG (corresponding to the “no EG” curves) in most cases, and AutoEG performs the best in all environments. A side observation is that the same grafting threshold produces different performances in different environments. For example, in Walker2d, the grafting threshold of 0.5 produces the best performance whereas in HumanoidFlagrun, 0.2 works better. In addition, the same grafting threshold might be good in early learning phase, but is not as good when the agent has more online experiences. For instance, in the Walker2d environment, 1.0 is initially a good grafting threshold, but not anymore after 3k episodes. This observation further justifies the need of the Tutor agent that learns to tune the EG agent’s grafting threshold at runtime. For no-EG, EG, and AutoEG agents, the “Overall Rewards” (y-axis of Figure 3) reflects the accumulative reward
Figure 3: Overall rewards of AutoEG, EG with different grafting thresholds, and a no-EG baseline (vanilla DDPG). EG agents perform better than “no EG” in most cases, and AutoEG performs the best in all environments. Table 1 presents the quantitative analysis.

Table 1: AutoEG improves the performance in AUC by at least 30% in comparison to the no-EG baseline (DDPG). AutoEG performs the best in policy quality, while EG’s performance is sensitive to the $\epsilon$ value.

| Environments          | AUC Improvement (%) | Policy Quality |
|-----------------------|---------------------|----------------|
|                       | $\epsilon = 0.2$ (EG) | $\epsilon = 0.5$ (EG) | $\epsilon = 1.0$ (EG) | AutoEG | no EG | $\epsilon = 0.2$ (EG) | $\epsilon = 0.5$ (EG) | $\epsilon = 1.0$ (EG) | AutoEG |
| Walker2d              | 62.6                | 51.3            | 53.4            | 99.5       | 110.3  | 127.9          | 142.5          | 105.2          | 162.5  |
| Hopper                | 27.2                | 58.6            | 24.9            | 57.4       | 150.1  | 135.3          | 163.3          | 129.9          | 176.0  |
| HalfCheetah           | 22.9                | 65.4            | -39.7           | 84.2       | 139.0  | 145.7          | 181.8          | 65.0           | 207.4  |
| AtlasForwardWalk      | 66.8                | 78.7            | 78.3            | 92.5       | 27.2   | 30.7           | 34.5           | 32.3           | 39.6   |
| Humanoid              | -12.7               | -10.0           | -13.2           | 30.7       | -10.2  | -14.5          | -13.7          | -14.4          | -7.5   |

2Formally, the AUC improvement is computed using $(A - B)/|B|$, where $A$ and $B$ are areas under the two curves respectively, and $B$ is the baseline method’s area.
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