Robust Deep Reinforcement Learning with Adversarial Attacks

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Abstract

This paper proposes adversarial attacks for Reinforcement Learning (RL) and then improves the robustness of Deep Reinforcement Learning algorithms (DRL) to parameter uncertainties with the help of these attacks. We show that even a naively engineered attack successfully degrades the performance of DRL algorithm. We further improve the attack using gradient information of an engineered loss function which leads to further degradation in performance. These attacks are then leveraged during training to improve the robustness of RL within robust control framework. We show that this adversarial training of DRL algorithms like Deep Double Q learning and Deep Deterministic Policy Gradients leads to significant increase in robustness to parameter variations for RL benchmarks such as Cart-pole, Mountain Car, Hopper and Half Cheetah environment.

1 Introduction

Advances in Deep Neural Networks (DNN) has a tremendous impact in addressing the curse of dimensionality in RL and offers state of the art results in several RL tasks (Levine et al. [2016], Schulman et al. [2015], Lillicrap et al. [2015], Mnih et al. [2015], Silver et al. [2016]). However, it has been shown in Goodfellow et al. [2014] that DNN can be fooled easily into predicting wrong label by perturbing the input with adversarial attacks. It opens up interesting frontier regarding robustness of machine learning algorithms in general. Robustness assumes greater importance in the context of robotics and safety critical systems where such adversarial noise may lead to undesirable and hazardous situations. Learning robust and high performance policies for continuous state-action reinforcement learning domains is critical to enable successful adoption of Deep Reinforcement Learning (DRL) in robotics, autonomy, and control problems. More specifically, robustness to real world parameter variations, such as changes in the weight, friction, or other environmental parameters of the dynamical system are critical.

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We address these challenges in an adversarial training framework. We first engineer “optimal” attack on the DRL agent and then leverage these attacks during training that leads to significant improvement in robustness and improves policy performance in challenging continuous domains. Our approach is loosely inspired from the idea of robust control, in which the best case policy is sought over the set containing the worst possible parameters of the system. We translate this into a problem of best performing policy trained in presence of adversary. The key difference, however, is that while robust control approaches tend to be conservative, our approach leverages the inherent optimization mechanisms in DRL to enable learning of policies that have even higher performance over a range of parameter and dynamical uncertainties like friction, mass etc.

In particular, the contributions of this paper are two-fold: First, we propose an objective function specifically in a reinforcement learning setting whose optimization degrades the performance of RL algorithms. Furthermore, we show that an attack designed to utilize the minima of our objective function ensures that the RL agent subject to the attack is fooled into thinking that it is in a state that leads to the worst possible action for its current state. This in itself is interesting and exposes critical robustness issues with prevalent DRL algorithms. These attacks severely degrade the performance during evaluation of RL policies. Interestingly, we observe that linearly parameterized RL algorithms are more robust to such adversarial attacks as compared to DRL. Our second contribution is improving the robustness of DRL algorithm to parameter uncertainties. We train the DRL with proposed engineered adversarial attack and show that it becomes robust to parameter or model uncertainties, that is, it shows significant improvement in performance across a wide range of parameters. Specifically, we train the DRL adversarially on “default” parameters, then this adversarially trained agent is tested on a wide range of parameters (and performs much better than baseline).

The paper is organized as follows. We provide introduction and related work that has been done in Section [1]. The background has been discussed in Section [2]. Adversarial attacks and their use for improving robustness have been described in Section [3] and results have been presented in Section [4]. Finally, concluding remarks and future directions have been discussed in Section [5].

1.1 Related Work

In Huang et al. [2017], interesting results have been presented regarding adversarial attack on reinforcement learning algorithms. The adversarial attacks in Huang et al. [2017] are similar in spirit to fast signed gradient Method (FSGM) (Goodfellow et al. [2014]). In Huang et al. [2017], the probability of an image being classified with a label is replaced by the probability of taking an action as in Goodfellow et al. [2014] and results were generated using RL algorithms for Atari game environment (using image observation). As we shall show in Section [3.1.2], the loss function presented in this paper is guaranteed to maximize the probability of taking the worst possible action which is not necessarily the case in Huang et al. [2017]. In Huang et al. [2017], the adversarial noise is generated without being certain (when the noise is generated) that it indeed causes adversarial attack. In contrast, we exploit the value function to ascertain the efficacy of our attack. In Kos and Song [2017], the authors have also used FSGM style of attack to cause performance failure in Atari game using Asynchronous Advantage Actor Critic (A3C) (Mnih et al. [2016]) algorithm. They reduced the frequency of attack by injecting noise only when trained value function is above a certain threshold. The intuition being that the agent should be disrupted only when it is more likely to win the game. They retrained using adversarial attacks and found that it becomes more resilient to adversarial attacks. Lin et al. [2017] proposed attack that is similar in spirit to Carlini and Wagner [2016] attack on images. In enchanting based attack, they tried to lure agent in bad states by first using a predictive model of video to try to find a sequence of actions that leads to good state. Then a random sequence of actions were generated which might to bad state, perturbation are generated so that the actions that agent takes is similar to this random sequence of action. However, it is interesting to note that the value function (of trained agents) itself contains information about this possible worst sequence of action. Hence, we have used value function instead to find adversarial action rather than trying to follow another random sequence of action. All these attacks have been performed on trained agents.

An important point regarding prior work on adversarial attacks for DRL (Huang et al. [2017], Kos and Song [2017], Lin et al. [2017]) is that all of them have been performed in environments that use images, that is, high dimensional pixel input. It has been argued (Goodfellow et al. [2014]) that images are susceptible to attack given the high dimensional space of pixel inputs. Thus, most attacks on RL algorithms are similar in spirit to attacks used in case of images. Our work for RL algorithm
is not restricted to high dimensional image. We also point out concurrent work by Mandlekar et al. [2017]. However, they use a heuristic in objective function (minimize $||u||_2^2$ where $u$ is the action or control input) for adversarial attack which does not ensure that the attack is optimal as compared to our proposed objective for adversary that is optimal attack.

In Rajeswaran et al. [2016], an ensemble of models was for robust reinforcement learning. They sample model parameters and perform trajectory rollout with those parameter variations. Further, parameters are selected to be trained with based on worst performing percentile criteria. However, sampling trajectories with uncertain parameters can be risky. Moreover, sampling may be very difficult for a large number of parameters. Another approach to robust reinforcement learning has been provided in Morimoto and Doya [2005] and it has been extended with deep network in in Pinto et al. [2017]. Their objective was also to sample worst performing percentile trajectories. To achieve this, adversary and RL agent are trained alternatively with an expectation that the agent becomes robust to adversary. This is similar to max-min formulation of robust control. However, finding equilibrium of max-min formulation can be difficult. Our work provides a direct approach for sampling worst performing trajectories wherein the adversary fools the agent into believing that it is in states which lead the agent into taking bad actions leading to sampling of worst performing trajectories. In concurrent work, Mandlekar et al. [2017] have proposed adversarial perturbation of states and robust training using this perturbation. However, the objective function that adversary needs to optimize is heuristic and is given by $(||u||_2^2)$ where $u$ is the control input. They have reported high variance and the results that also have been reported in Mandlekar et al. [2017] is comparison of highest return over several random agents as opposed to averaging out the returns for all the agents.

Another relevant body of work in reinforcement learning is the risk sensitive reinforcement learning where the reward is augmented with risk. Risk can be seen as variance of long-term return. Here, higher variance implies more instability and hence, greater risk. The various risk criterion used in literature are variance penalized (Gosavi [2014]), weighted risk and return criterion (Geibel and Wysotzki [2005]) etc. A survey of risk sensitive RL can be found in García and Fernández [2015]. However, these methods do not scale well with respect to space and action complexity as explained in García and Fernández [2015].

2 Background

We briefly review the adversarial attacks on images (Goodfellow et al. [2014]) because they have been extended to image based DRL (Huang et al. [2017], Kos and Song [2017], Lin et al. [2017]). We also review some of the algorithms of DRL that have been used in this paper such as Deep Q Learning (DQN), Double Deep Q Learning (DDQN), and Deep Deterministic Policy Gradient (DDPG).

2.1 Adversarial attack on Deep Learning Network classifiers (Fast Signed Gradient Method)

One of the most popular ways to engineer adversarial attacks on deep learning classifiers (that have been extended to DRL) is fast signed gradient method (FSGM) (Goodfellow et al. [2014]) where a cost function is crafted whose optimization leads to increase in the probability of the network classifying a given image with a wrong label. It takes into account a linear approximation of deep learning model and engineers an attack. Assuming a linear model, $f(x) = w^T x$ ($x$ represents the input and $f(x)$ represents the output), the change in output due to perturbation of input by an amount $\eta$ is given by $\tilde{f}(x) = w^T x + w^T \eta$. We can get maximal perturbation in prediction with

$$\eta_{\text{min}} = \epsilon \text{sign}(w)$$

Here $\eta_{\text{min}}$ represents the best possible adversarial perturbation which is $l_\infty$ norm constrained ($\epsilon$). However, this attack has also been extended to nonlinear in parameter functions (multi-layer deep neural networks) and has successfully fooled the classifier networks into confident misclassification of images. The adversarial attack is

$$\eta_{\text{min}} = \epsilon \text{sign}(\nabla_x J(\theta, x, y))$$

Here, $J(\theta, x, y)$ is the respective loss function that is used during training or testing. Again with the underlying assumption that adversarial noise is $l_\infty$ norm bounded. In case of images, $J(\theta, x, y)$ is the cross entropy loss between the true image label and predicted distribution over labels of image.
2.2 Deep Q learning (DQN) and Deep Double Q Learning (DDQN)

Deep Q learning (DQN) has achieved superhuman results on Atari games\cite{Mnih2015}. Q learning is a value function based algorithm (we refer to both state-action value function and state-value function as value function). Q values of a state-action pair represent how good the action being contemplated by the agent is for its current observation. The learning agent updates the Q value using temporal difference error and simultaneously acts to maximize its return in the long run. In DQN algorithm, the agent uses a Deep neural network to approximate this Q function. The DQN algorithm achieved stability in training primarily by using experience replay and the use of target network. For experience replay, it stores past state, action, reward, next state sequence and these are used to update the Q network just as in supervised learning with these sequences being picked randomly from memory. This breaks the strong correlation between samples. For this “supervised” learning type of update, DQN has another neural network, called target network which provides the Q values for the next state(s). The target network is updated by hard transfer of online weights after a fixed number of iterations. This two network structure led to “stability” in training. However, Van Hasselt et al.\cite{Van2016} showed that DQN overestimates the Q values and proposed Double Deep Q Learning (DDQN) where the action selection was still performed by online network but it’s value estimate for update was done using the target network. This mitigated the overestimation of value function.

2.3 Radial Basis Function based Q learning

In radial basis function based Q learning (Geramifard et al.\cite{Geramifard2013}), the DNN is replaced by RBF with gaussian kernel. Here experience replay and target networks are typically not used. The networks learns through stochastic gradient descent using temporal difference error.

2.4 Deep Deterministic Policy Gradient (DDPG)

Deep deterministic policy gradient (DDPG) (Lillicrap et al.\cite{Lillicrap2015}) uses both an actor and a critic for learning. The critic evaluates a given policy generated by the actor. The weights of critic and actor are updated by gradient descent. The critic network uses the prior concepts of experience replay and target network for its update. The only difference between these update and that of Deep Q learning is that instead of “hard” transfer of weights to target after a fixed number of iterations, there is “soft” transfer of weights where the weights of target network are incremented by a very small amount towards the online network.

3 Method

In this section, we explain our methods for adversarial attack and further use these attacks for significantly improving the robustness and performance of reinforcement learning algorithm.

3.1 Adversarial Attack

In this subsection, we concentrate on generating adversarial attacks which will cause a trained RL agent to fail. We assume that the mechanism of the attack is by corrupting the observations of the agent of its current state, fooling it into believing it is in a state that causes it to follow a sub-optimal policy for its actual state. We begin by defining what we mean by an adversarial attack in the context of value function based reinforcement learning algorithms:

**Definition 1.** An adversarial attack is any possible perturbation that leads the agent into increased probability of taking “worst” possible action in that state. Here, the “worst” possible action for a trained RL agent is the action which corresponds to least Q value in that state.

It is important to note that Def. 1 is valid only for value function based algorithms, that is, the algorithms that use value function to predict the optimality of actions in a given state. Most of the popular state-of-art algorithms such as A3C and DDPG are value function based. We shall see the objective function that needs to be optimized for achieving adversarial attacks in the context of reinforcement learning in section 3.1.2. There is a subtle but important difference as compared to image classification wherein attack is considered successful if a given image is classified as any other image. There is no concept of “worst” possible image whereas RL agents can have “worst” possible
action. Another assumption is that the agent has been trained sufficiently well so that Q values are close to optimal. This is true in case of tabular Q learning as training time tends to infinity (but this has not been proved in general for nonlinear function approximators like DNN) and serves as motivation for this assumption.

An important point to note is that throughout the paper we have bounded the adversarial attack noise by $l_2$ norm constraint. It is possible to use other norm constraints as well and Papernot et al. [2016] showed that distillation is secure under $l_\infty$. Another point is that the RL environments are scaled so that the state space is normalized between $[0, 1]$. The magnitude of attack is also normalized.

### 3.1.1 Naive adversarial attack

First, we propose a naive method of generating adversarial attack. The idea behind this attack is to generate random noise (several times in current state that the agent is in) and add it to current state with hope that one of these noise samples will cause the agent to take “bad” action, that is, sub-optimal action. The quality of attack can be ascertained by the value function. Algo. 1 outlines the naive adversarial attack for DDQN.

An important point to note is that the attacks are generated during evaluation phase. The adversarial attack is essentially a search across nearby observation which will cause the agent to take wrong action. For generating adversarial attack on the DRL policies, we sample a noise with finite (small) support. Noise is not generated once during every iteration, rather it is sampled for a number of times every iteration with a search for best adversarial noise ($beta$ distributed noise with shifted 0 mean was used for generic setting but in our experiments the parameters of beta distribution were (1, 1) which corresponds to uniform noise with 0 mean). The particular noise that causes least estimate of the value function is selected as adversarial noise. Then this noise is added to the current observation. Algo. 1 is outlined for naive attack on DDQN.

For naive attack on DDPG, the critic network can be used to ascertain value functions when required and actor network determines the behavior policy to pick action. Thus, the objective function used by adversary in this case is the $Q^*_critic(s, a)$, that is, the value function determined by the trained critic network. Algorithm for naive attack on DDPG has been provided in Algo. 2 and is similar to Algo. 1.

**Algorithm 1 Naive attack (DDQN)**

```plaintext
1: procedure NAIVE(Q_{\text{target}}, Q, s, \epsilon, n, \alpha, \beta)   \triangleright Naive attack function takes Q network (Q), current state(s), adversarial attack magnitude constraint(\epsilon), parameters of beta distribution(\alpha, \beta) and number of times to sample noise(n) as input
2:   a^* = \arg \max_a Q(s, a), Q^* = \max_a Q_{\text{target}}(s, a) \triangleright Determine optimal action value function
3:   for i = 1 : n do \triangleright Sample a few times
4:     \:
5:     \:
6:     \:
7:     \:
8:   end for \triangleright Determine the value of potential adversarial action corresponding to potential adversarial state for current state
9: if $Q^*_{\text{target}} < Q^*_adv$ then \triangleright if the potential adversarial state leads to bad action
10:   $Q^* = Q^*_{\text{target}}$ \triangleright Store the value function of that potential bad action
11:   $s_{adv} = s_i$ \triangleright Store possible adversarial state
12: else
13:   do nothing
14: end if
15: return $s_{adv}$ \triangleright Adversarial state
16: end procedure
```
Algorithm 2 Naive attack (DDPG)

1: procedure NAIVE($Q_{target}$, $U$, $s$, $\epsilon$, $n$, $\alpha$, $\beta$) \hfill $\triangleright$ Naive attack function takes trained target critic network $Q_{target}$, trained actor network $U$, current state($s$), adversarial attack magnitude constraint($\epsilon$), parameters of beta distribution($\alpha$, $\beta$) and number of times to sample noise($n$) as input
2: \hspace{0.5cm} $a^* = U(s)$, $Q^* = Q_{target}(s, a^*)$ \hfill $\triangleright$ Determine optimal action and action value function
3: \hspace{0.5cm} for $i = 1 : n$ do \hfill $\triangleright$ Sample a few times
4: \hspace{1cm} $n_i \sim \text{beta}$(\alpha, \beta) - 0.5 \hfill $\triangleright$ Sample noise
5: \hspace{1cm} $s_i = s + \epsilon \times n_i$ \hfill $\triangleright$ Possible adversarial state determined by sampled noise
6: \hspace{1cm} $a_{adv} = U(s_i)$ \hfill $\triangleright$ Determine optimal action in potential adversarial state
7: \hspace{1cm} $Q_{adv} = Q_{target}(s, a_{adv})$ \hfill $\triangleright$ Determine the value of potential adversarial action corresponding to potential adversarial state for current state
8: \hspace{1cm} if $Q_{adv} < Q^*$ then \hfill $\triangleright$ if the potential adversarial state leads to bad action
9: \hspace{1.5cm} $Q^* = Q_{adv}$ \hfill $\triangleright$ Store the value function of that potential bad action
10: \hspace{1cm} $s_{adv} = s_i$ \hfill $\triangleright$ Store possible adversarial state
11: \hspace{0.5cm} else \hfill $\triangleright$ do nothing
12: \hspace{1cm} end if
13: \hspace{0.5cm} end for
14: \hspace{0.5cm} end procedure
15: \hspace{0.5cm} return $s_{adv}$ \hfill $\triangleright$ Adversarial state
16: end procedure

3.1.2 Gradient based adversarial attack

In this subsection, we show that a proposed cost function different from the one used in traditional FSGM (Huang et al. [2017])) is more effective in finding worst possible action in the context of reinforcement learning with discrete actions.

**Theorem 1.** Let the optimal policy be given by conditional probability mass function (pmf) $\pi^*(a|s)$, the action which has maximum pmf be given as $a^*$ and the worst possible action be given by $a_w$. Then the objective function whose minimization leads to optimal adversarial attack on RL agent is given by

$$J(s, \pi^*) = -\sum_{i=1}^{n} p_i \log \pi^*_i$$

where $\pi^*_i = \pi^*(a_i|s)$, $p_i = P(a_i)$, the adversarial probability distribution $P$ is given by

$$P(a_i) = \begin{cases} 1, & \text{if } a_w = 1 \\ 0, & \text{otherwise} \end{cases}$$ (1)

In other words, this is the cross entropy loss between the adversarial probability distribution and optimal policy generated by the RL agent.

Q values can be converted into pmf by passing them through softmax function.

**Proof.** We shall show that $\min_s J(s, \pi^*)$ achieves the objective of def. 1

$$J(s, \pi^*) = -\sum_{i=1}^{n} p_i \log (\pi^*_i)$$

$$= -p_w \log (\pi^*_w) = -\log (\pi^*_w) \quad \text{from (1)}$$

$$\Rightarrow \min_s J(s, \pi^*) = \min_s -\log (\pi^*_w)$$

$$\min_s J(s, \pi^*) = \max_s \log (\pi^*_w)$$

Since log is monotonically increasing,

$$\min_s J(s, \pi^*) = \max_s \pi^*_w$$
Thus, we have shown that the objective function that should be used for engineering attack on RL algorithm should be given by Theorem 1 as it is consistent with Def. 1. FSGM algorithm can be used to minimize this objective function. We must point out that this objective function is different from ones in literature Huang et al. [2017]. The objective functions mentioned in Huang et al. [2017] will result in min \( \pi^*(a^*|s) \) \( (a^* \text{ is the best possible action for given state } s) \). This leads to decrease in the probability of taking best possible action. This won’t necessarily lead to increase in probability of taking worst possible action. The gradient based attack for DDQN has been explained in Algo. 3. The gradient based attack for DDPG is similar to DDQN with the objective function that adversary need to minimize being given by the optimal value function of critic \( (Q^*(s,a)) \). Here the gradient is given by

\[
\nabla_s Q^*(s,a) = \frac{\partial Q^*}{\partial s} + \frac{\partial Q^*}{\partial U^*} \frac{\partial U^*}{\partial s}
\]

where \( U^* \) represents the optimal policy given by actor. The algorithm has been provided in Algo. 4 and is similar to Algo. 5.

**Algorithm 3** Gradient based attack (DDQN)

1: \textbf{procedure} \textsc{Grad}(\textsc{Q}^\text{target}, \textsc{Q}, s, \epsilon, n, \alpha, \beta) \hfill \triangleright \text{Gradient based attack function takes Q network (Q), current state(s), adversarial attack magnitude constraint(\epsilon), parameters of beta distribution(\alpha, \beta) and number of times to sample noise(n) as input}
2: \hspace{1em} a^* = \arg \max_a Q(s,a), Q^* = \max_a Q^\text{target}(s,a) \hfill \triangleright \text{Determine optimal action and value function}
3: \hspace{1em} \pi^\text{target} = \text{softmax}(\textsc{Q}^\text{target}) \hfill \triangleright \text{Pass Q through softmax layer to convert it into pmf}
4: \hspace{1em} \text{grad} = \nabla_s J(s,\pi^\text{target}) \hfill \triangleright \text{Determine the gradient}
5: \hspace{1em} \text{grad\_dir} = \frac{\nabla_s J(s,\pi^\text{target})}{\| \nabla_s J(s,\pi^\text{target}) \|^2} \hfill \triangleright l_2 \text{ constrained norm of gradient}
6: \hspace{1em} \text{for } i = 1 : n \text{ do} \hfill \triangleright \text{Sample a few times}
7: \hspace{2em} n_i \sim \text{beta}(\alpha, \beta) \hfill \triangleright \text{Sample noise}
8: \hspace{2em} s_i = s - n_i \times \text{grad\_dir} \hfill \triangleright \text{Possible adversarial state determined by sampled noise in the direction of gradient}
9: \hspace{1em} a_{\text{adv}} = \arg \max_a Q(s_i,a) \hfill \triangleright \text{Determine optimal action in potential adversarial state}
10: \hspace{1em} \textsc{Q}^\text{target}_{\text{adv}} = Q^\text{target}(s,a_{\text{adv}}) \hfill \triangleright \text{Determine the value of potential adversarial action corresponding to potential adversarial state for current state}
11: \hspace{1em} \text{if } \textsc{Q}^\text{target}_{\text{adv}} < Q^* \text{ then} \hfill \triangleright \text{if the potential adversarial state leads to bad action}
12: \hspace{2em} Q^* = \textsc{Q}^\text{target}_{\text{adv}} \hfill \triangleright \text{Store the value function of that potential bad action}
13: \hspace{2em} s_{\text{adv}} = s_i \hfill \triangleright \text{Store that state as possible adversarial state}
14: \hspace{1em} \text{else} \hfill \triangleright \text{do nothing}
15: \hspace{1em} \text{end if}
16: \hspace{1em} \text{end for}
17: \hspace{1em} \textbf{return} s_{\text{adv}} \hfill \triangleright \text{Return adversarial state}
18: \textbf{end procedure}

3.1.3 SGD based attack

We also used Stochastic Gradient Descent approach for adversarial attack wherein instead of sampling a few times and selecting best possible attack amongst these samples, we followed the gradient descent for same number of sampling time and selected the state that we end up in as adversarial state.

3.2 Adversarial Training through Robust Control framework

In this subsection, we propose robust adversarial training and show equivalence to robust control.
Algorithm 4 Gradient based attack (DDPG)

1: procedure GRAD($Q_{\text{target}}$, $U$, $s$, $\epsilon$, $n$, $\alpha$, $\beta$) ▷ Gradient based attack function takes target Q network (critic) $Q_{\text{target}}$, actor network $U$, current state(s), adversarial attack magnitude constraint($\epsilon$), parameters of beta distribution($\alpha$, $\beta$) and number of times to sample noise($n$) as input

2: $\mathbf{a}^* = U(s)$, $Q^* = Q_{\text{target}}(s, \mathbf{a}^*)$ ▷ Determine optimal action and value function

3: $\mathbf{grad} = \nabla_s Q_{\text{target}}(s, \mathbf{a})$ ▷ Determine the gradient

4: $\mathbf{grad}_{\text{dir}} = \frac{\nabla_s Q_{\text{target}}(s, \mathbf{a})}{||\nabla_s Q_{\text{target}}(s, \mathbf{a})||}$ ▷ $l_2$ constrained norm of gradient

5: for $i = 1$ : $n$ do ▷ Sample a few times

6: $n_i \sim \text{beta}(\alpha, \beta)$ ▷ Sample noise

7: $s_i = s - n_i * \mathbf{grad}_{\text{dir}}$ ▷ Possible adversarial state determined by sampled noise in the direction of gradient

8: $\mathbf{a}_{\text{adv}} = U(s_i)$ ▷ Determine optimal action in potential adversarial state

9: $Q_{\text{target}}^\text{adv} = Q_{\text{target}}(s, \mathbf{a}_{\text{adv}})$ ▷ Determine the value of potential adversarial action corresponding to potential adversarial state for current state

10: if $Q_{\text{target}}^\text{adv} < Q^*$ then ▷ if the potential adversarial state leads to bad action

11: $Q^* = Q_{\text{target}}^\text{adv}$ ▷ Store the value function of that potential bad action

12: $s_{\text{adv}} = s_i$ ▷ Store that state as possible adversarial state

13: else

14: do nothing

15: end if

16: end for

17: return $s_{\text{adv}}$ ▷ Return adversarial state

18: end procedure

3.2.1 Robust Control Framework

In RL, the typical objective that an agent seeks to maximize is its expected long term return ($\eta$) (over possible trajectories $\tau$) assuming a fixed transition model $T(s_t, a_t; \phi)$ characterized by parameters $\phi$

$$\eta(\pi, T) = E_{\tau}\left[ \sum_{t=0}^{T} \gamma^t r(s_t, a_t) | s_0, \pi, T \right]$$

However, if there is variation in transition model, then criteria might be to perform well in expectation over all the possible transition models. Thus, leading to optimization of the mean performance of agent. The objective function in this scenario can be modified to

$$\eta(\pi) = E_{T}[\eta(\pi, T)]$$

This is popularly known as risk neutral formulation. However, it has an underlying assumption that the distribution over transition model parameters are known apriori. It may not perform well over the transition model distributions because of high variance in transition model distribution. Thus, conditional value of risk (CVaR) can be used as optimization criteria for robust control (Tamar et al. [2015])

$$\eta_{\text{RC}}(\pi) = E_{T}[\eta(\pi, T)| \mathbb{P}(\eta(\pi, T) \leq \beta) = \alpha]$$

So, the problem boils down to maximizing the expected return over worst $\alpha$ percentile of returns. Thereafter, for sampling these bad trajectories [Rajeswaran et al. [2016] changed transition model parameters and sample trajectories by performing rollouts with different parameters. Morimoto and Doya [2005] and Pinto et al. [2017] took an indirect approach where instead of sampling worst trajectory from rollout, they employ an adversary which applies control action and tries to push the RL agent into possible bad states. They train the adversary whose reward was negative of the reward of RL agent resulting in max-min game theoretic formulation. But it is usually difficult to find this equilibrium.
3.2.2 Adversarial Training

In contrast to approaches given in Rajeswaran et al. [2016] and Morimoto and Doya [2005] where it might be difficult to find equilibrium, we take a direct approach where the adversary fools the agent into believing that it’s in a “fooled” state different from actual state such that the optimal action in “fooled” state leads to worst action in actual current state. In other words, the adversary fools the agent into sampling worst trajectories directly. We first train the algorithm using “vanilla” DRL (DDQN or DDPG), the trained agent is then made robust to model uncertainties through adversarial training. We have used gradient based attack for adversarial training as it performed best amongst all attacks (results presented in Section 4). Adversarial training algorithm has been discussed in Algo. 5 (DDQN) and Algo. 6 (DDPG). In our approach, worst $\alpha$ percentile of returns is related to the magnitude of adversarial attack, higher adversary magnitude corresponds to optimization for higher $\alpha$ worst percentile.

Algorithm 5 Training with adversarial perturbation (DDQN)

1: procedure ADV TRAIN ($Q_{target}$, $Q$) \(\triangleright\) Gradient based adversarial training method takes pre-trained network
2: for $i = 1 : \text{iterations}$ do \(\triangleright\) Train adversarially for number of timesteps
3: Reset the environment and receive observation
4: while not terminal or not max time steps per episode reached do
5: \(s_{adv} = \text{Grad}(Q_{target}, Q, s, \epsilon, n, \alpha, \beta)\) \(\triangleright\) Fool the agent
6: \(a = \text{argmax}_a Q(s_{adv}, a)\) \(\triangleright\) Fooled agent takes action according to behavior policy
7: \(s, r = \text{Env}(a, s)\) \(\triangleright\) Environment returns next state and reward corresponding to state $s$ and action $a$
8: Update the weights of network according to DDQN algorithm
9: end while
10: end for
11: end procedure

Algorithm 6 Training with adversarial perturbation (DDPG)

1: procedure ADV TRAIN ($Q_{target}$, $Q$, $U_{target}$) \(\triangleright\) Gradient based adversarial training method takes pre-trained network
2: for $i = 1 : \text{iterations}$ do \(\triangleright\) Train adversarially for number of timesteps
3: Reset the environment and receive observation
4: while not terminal or not max time steps per episode reached do
5: \(s_{adv} = \text{Grad}(Q_{target}, U, s, \epsilon, n, \alpha, \beta)\) \(\triangleright\) Fool the agent
6: \(a = U(s_{adv})\) \(\triangleright\) Fooled agent takes action according to behavior policy
7: \(s, r = \text{Env}(a, s)\) \(\triangleright\) Environment returns next state and reward corresponding to state $s$ and action $a$
8: Update the weights of network according to DDPG algorithm
9: end while
10: end for
11: end procedure

4 Results

In this section, we discuss results related to proposed adversarial attack and adversarially trained robust policy. We report improvement to robustness over two algorithms (DDQN and DDPG). All the experiments have been performed within OpenAi gym environment [Brockman et al. [2016]] with MuJoCo [Todorov et al. [2012]] (Fig. 1).

4.1 Adversarial Attack

We show that the proposed attack(s) outperform attacks in Huang et al. [2017] as shown in Fig. 2. Here NS refers to naive sampling attack, GB refers to gradient based attack, HFSGM refers to the attack in Huang et al. [2017] and SGD refers to the stochastic gradient descent attack. In Fig. 2
the rewards as well as magnitude of adversarial attacks have been normalized to 1 where reward of 1 corresponds to the average reward received without adversarial attack and adversary magnitude of 1 corresponds to maximum possible value of the state. As we can observe from Fig. 2 the adversarial attacks have degraded the performance of deep learning based algorithms. Furthermore, naive sampling based attacks and gradient based attacks perform better FSGM and SGD. Amongst naive sampling and gradient based attack, gradient based attack performs better. Another observation is the relative resilience of RBF based Q learning algorithm as compared to DDQN. This can be explained by the fact that Deep Networks might be providing “jerky” or piecewise linear function approximators as opposed to smoother interpolation of RBF. Thus, a small perturbation in state causes agent to take bad action. The piecewise linear function approximation of DNN can be attributed to the use of “popular” ReLu (or leaky ReLu) activation function as the output is ultimately a composition of piecewise linear functions.

4.2 Robust Training

We present results that show significant improvement in robustness because of proposed adversarial training algorithm. For robust adversarial training, we first trained an agent with “vanilla” DRL (DDQN, DDPG) on “default” parameters. The trained agent is then made robust through adversarial training with gradient based adversarial attacks on same parameters. For evaluation, we tested this adversarially trained agent on a wide range of parameters and compared it to “vanilla” DRL. Figures 3 shows improvement in performance owing to robust training. In Fig. 3a, 3b, there is significant improvement in the overall reward for cartpole environment. The agent receives reward of 1 for each time step during which the cartpole is balanced. In 3a it seems that the agent receives uniform reward because of the scale used. A “zoomed” image of it is provided in Appendix. In mountain car environment (Fig. 3c and 3d), the agent receives a negative reward of -1 for each timestep that it takes to reach the goal. The episode ends either when the car reaches goal or takes up 500 timesteps to reach the target. It is interesting to observe significant gains because of robust training around diagonal where the power coefficient is just enough to push the mountain car. In the lower triangular region, there is no improvement because the power coefficient is not enough for the mountain car and is underpowered. In the upper right region, it is overpowered. Hence, it reaches goal easily. For hopper environment (Fig. 3e and 3f), higher return over DDPG can be attributed to adversarial
Figure 3: Subfigure (a) shows the average return per episode for DDQN algorithm in Cart-pole environment across variations of mass of cart and length of pole. Subfigure (b) shows the average return per episode of Robust DDQN algorithm. Similar results have been provided in Subfig. (c) and (d) for Mountain Car environment. We can observe high return over wide range of parameters and over “default” parameter owing to robust training. Subfigures (e) and (f) show efficacy of robust training of DDPG algorithm. Subfigures (g) and (h) again demonstrate superior performance of Robust DDPG for Half-Cheetah environment.

training (robust DDPG). Similar results can also be observed for Half-Cheetah environment (Fig. 3g and 3h). These results show average return of 100 episodes for each set of parameter variation over 4 different seeds. The number of training steps is same for both vanilla algorithms and adversarially trained algorithms. Thus, the improvement is not because of more training.

5 Conclusion

In this paper, we have proposed adversarial attack for reinforcement learning algorithms. We show that DRL can be fooled easily as compared to reinforcement learning algorithms based on Radial Basis Function (RBF) network. Interestingly, naive adversarial attacks on DRL can degrade it as opposed to robust policy learnt by RBF. We leveraged these attacks to train RL agent that led to robust performance across parameter variations for DDPG and DDQN. Future direction involves providing theoretical relationship between these attacks and robustness of the algorithms (to parameter variation).

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APPENDIX

A  Experimental setup

A.1  DDQN

The Deep Double Q learning for cart pole environment used 3 layers of 16 units each with Rectified Linear Unit (ReLu) activation function whereas the mountain car environment used 2 hidden layers of 100 units each of ReLu activation function. The discount factor for both of them was set at 0.99 and target network update rate were $10^{-2}$. The “supervised learning” of networks was done with Adam optimization and learning rate of $10^{-3}$. The cartpole environment was trained for 50000 timesteps while Mountain Car was trained for 40000 time steps. The repository that we used was Keras-rl (Plappert [2016]).

A.2  RBF

For Cart-pole, each dimension of state input was divided into 3 bins (b). The centroids were uniformly distributed along those bins. The variance of radial activation were $\frac{2}{b^2}$. Discount factor of 0.99 was used. The learning rate was given by 0.001. It was trained for 40000 time steps For Mountain car environment, the learning rate was 0.01 and number of bins were 4. The discount factor was 0.99. Total number of timesteps were 60000

A.3  DDPG

For hopper and half cheetah environment, there were 2 hidden layers of 400 and 300 ReLu units for both actor and critic networks. The number of time steps it was trained were 1 million. Discount factor was 0.99. The learning rate of critic network was $10^{-3}$ while the learning rate of actor was $10^{-4}$. Half cheetah also used the same network as hopper. It also had the same learning rate and discount factor. It was trained for 2 million time steps. The repository that we used was rllab (Duan et al. [2016]).

A.4  Adversarial Training

For adversarial training, the number of times sampling was done was 200 and the vanilla trained network was re-trained adversarially for same amount of time steps. The adversarial magnitude used was 0.05 for half cheetah and 0.03 for hopper. The sampling frequency 100. We must point out that for the results shown in paper, comparison has been shown between both vanilla and adversarially trained networks that have been trained for exactly same number of timesteps.

B  Robust Training Colormap for Cartpole
Figure 4: Subfigure (a) shows the average return per episode for cart-pole environment using DDQN algorithm across variation of mass of cart and length of pole. Subfigure (b) shows the same information for adversarially trained DDQN agent. We can observe significant improvement over the return for agent across different parameters. “Zoomed” colormap for DDQN cartpole comparison has been presented.