Stealing Deep Reinforcement Learning Models for Fun and Profit

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Abstract—In this paper, we present the first attack methodology to extract black-box Deep Reinforcement Learning (DRL) models only from their actions with the environment. Model extraction attacks against supervised Deep Learning models have been widely studied. However, those techniques cannot be applied to the reinforcement learning scenario due to DRL models' high complexity, stochasticity and limited observable information. Our methodology overcomes those challenges by proposing two techniques. The first technique is an RNN classifier which can reveal the training algorithms of the target black-box DRL model only based on its predicted actions. The second technique is the adoption of imitation learning to replicate the model from the extracted training algorithm. Experimental results indicate that the integration of these two techniques can effectively recover the DRL models with high fidelity. We also demonstrate a use case to show that our model extraction attack can significantly improve the success rate of adversarial attacks, making the DRL models more vulnerable.

I. INTRODUCTION

Deep Reinforcement Learning has gained popularity due to its strong capability of handling complex tasks and environments. It integrates Deep Learning (DL) architectures and reinforcement learning algorithms to build sophisticated policies, which can accurately understand the environmental context (states), and make the optimal decisions (actions). Various DRL algorithms and methodologies have been designed to facilitate the application of DRL in different artificial intelligent tasks, e.g., autonomous driving [11], robot motion planning [2], video game playing [3], etc.

As DRL has been widely commercialized (e.g., autonomous driving framework Wayve [4], path planning system MobilEye [5]), it is of paramount importance for model owners to protect the intellectual property of their DRL-based products. DRL models are generally deployed as black boxes inside the applications, so the model designs and parameters are not disclosed to the public.

Problem statement. From the adversarial perspective, we want to address the following question in this paper: is it possible for an adversary to extract the properties (i.e., training algorithm) of a black-box DRL model, and produce a replicated model with the same behaviors? This is known as model extraction attacks, which have been widely studied in supervised DL models [6–8, 9–10, 11–12, 13–14, 15–16]. However, the possibility and feasibility of extracting DRL models have not been explored yet. We make a first step towards this goal.

It is worth noting that our goal is to extract the DRL model algorithm and replicate its behaviors. It is impossible to extract the values of model parameters: different parameter values can give the same model behaviors, which are indistinguishable from the adversary. Also the adversary cannot identify the values of dead neurons which never contribute to the model output.

Threat model. We assume the adversary has the domain knowledge of the target DRL model, i.e., the task the model is performing, the environmental context, and also the formats of the model input and output. However, he has little knowledge about the DRL model itself, including the model structures and parameter values, training methods and hyper-parameters, etc. We further assume the adversary is able to operate the DRL model or product in a controllable environment: he can set certain environmental states, and observe the model’s corresponding actions.

Challenges. Although various extraction techniques were designed against supervised DL models, it is hard to apply them to DRL models due to significant differences of model features and scenarios.

First, some attack approaches can only extract very simple models and datasets. For instance, the method in [9] can only work for two-layer neural networks (one hidden layer and a ReLU layer). The method in [6] is only applicable to simple models with simple datasets (e.g., MNIST) constrained by the computing power. In contrast, DRL models usually have more complicated and deeper network structures to handle complex tasks. As such, the above techniques fail to extract DRL models.

Second, the adversary in our threat model has less observable information for model extraction. Past works assume the adversary has access to the prediction confidence scores [9, 6–7, 12], gradients [10] or the side-channel execution characteristics [11, 13–14, 15]. In our scenario, the adversary can only observe the predicted actions from the DRL model. This can also invalidate the above methods.

Third, supervised DL models perform predictions over discrete input samples, which are independent of each other. However, DRL is a Markov Decision Process (MDP). Individual input samples cannot fully reflect the inherent features of DRL models and training algorithms. The adversary will lose the information of temporal relationships if he only observes these discrete data. Besides, compared to supervised DL models, DRL models are more stochastic and their behaviors
highly depend on the environments with different transition probabilities.

**Contribution.** We propose a novel model extraction approach for DRL model which can overcome the above challenges. It is composed of two techniques.

The first technique is to build a classifier which can identify the algorithm of the target DRL model based on its runtime actions. This technique has three innovations: (1) We use a timing sequence of actions as the feature of a DRL model to characterize its decision process and interaction with environment. (2) We utilize Recurrent Neural Networks as the structure of the classifier for training and prediction, which can better understand the temporal relationships inside the feature sequence. (3) For one DRL model with the same algorithm, we will generate different feature sequences in environments initialized with different random seeds. This guarantees that the training set of the classifier is comprehensive and including different behaviors of the same model.

The second technique is to adopt imitation learning to replicate the behaviors of the target model based on the extracted algorithm. We use the Generative Adversarial Imitation Learning (GAIL) framework [17] to achieve this process. The contest between the discriminative model and generative model can guarantee that our replication has similar behaviors as the target one within the environment.

The integration of RNN classification and imitation learning can produce replicated models with high similarity of training algorithm, behavior and performance with the target model. This can bring severe threats of copyright infringement and economic loss to the DRL-based applications and products. More seriously, we provide a use case to show that this attack approach can significantly enhance the adversarial attacks by increasing the attack transferability and success rate. This demonstrates the practical value of our study, and is expect to raise people’s awareness about the privacy threats of DRL models, as well as the necessity of defense solutions.

**II. BACKGROUND**

**Deep Reinforcement Learning.** DRL adopts deep learning technology to instruct an agent to act in a given task, in order to maximize the expected cumulative rewards. The deep neural networks adopted by DRL are powerful to understand and interpret complex environmental states, and make the optimal decisions. There are three common approaches to solve reinforcement learning tasks. The first one is value function based methods. The DRL algorithm trains deep neural networks to approximate the optimal value functions. For instance, a common value-based algorithm is deep Q-network (DQN) [3], which learns Q value estimates for each state-action pair independently. The second category is policy search based methods. The DRL algorithm attempts to identify the optimal policy. Typical examples include REINFORCE [18] which optimize policies directly. The third category is the hybrid of value function and policy search (actor-critic approach). These algorithms learn both a policy and a state value function to reduce variance and accelerate learning. State-of-the-art algorithms include Proximal policy optimisation (PPO) [19], Actor-Critic with Experience Replay (ACER) [20] and Actor-Critic using Kronecker-Factored Trust Region (ACKTR) [21].

**Imitation Learning.** Imitation learning [22] is a process of acquiring skills or behaviors by observing demonstrations of an expert performing the corresponding tasks. It was originally for learning from human demonstrations. Then the concept of imitation learning was applied to the domain of artificial experts, such as reinforcement learning agents. Various imi-
Adversarial Examples. It has been found that small and undetectable perturbations in input samples could affect the results of a target classifier [24]. Following this initial study, many researchers designed various attack methods to attack supervised DL models [25, 26, 27]. Adversarial attacks on RL policies have also received some attention for the past years. Huang et al. [28] made an initial attempt to attack neural network policies by applying FGSM to the state at each time step. Following this work, black-box adversarial attacks against DRL were demonstrated in [29]. Russo and Proutiere [30] found the adversarial examples can be also transferred across different DRL models.

Privacy in Machine Learning. There have been a quantity of works on the privacy threats of deep learning models and data. Model extraction attacks aim to steal model parameters or architectures [7, 6]. Membership inference attacks [31] are designed to determine if a given data sample has been included in the training data. Model inversion attacks [32] aim to leverage model predictions to inverse the training data properties. In this paper, we are focusing on model extraction attacks.

III. ATTACK METHODOLOGY

Our attack approach consists of two stages. At the first stage, we construct a classifier, which can predict the training algorithm of a given black-box DRL model based on its runtime behavior. At the second stage, based on the extracted algorithm, we adopt state-of-the-art imitation learning technique to generate and fine-tune a model with the similar behaviors as the victim one. Figure 1 illustrates the methodology overview, and Algorithm 1 describes the detailed steps.

Algorithm 1: Extracting DRL models

```
/* Stage 1 */
1. Dataset D = \emptyset
2. for each p ∈ P do
   3. m = train_DRL(env, p);
   4. A = GenSequence(m, env, T);
   5. D.add([A, p]);
4. end
5. end

/* Stage 2 */
6. C = train_RNN(D);
7. A' = GenSequence(M', env, T);
8. P* = C.predict(A')
9. while evaluate(M', env) < evaluate(M', env) do
10.   M' = ImitationLearning(M', P*, env);
11. end
12. return M'
```

A. Extracting DRL Model Algorithms via RNN Classification

As the first stage, we train a RNN classifier, whose input is a DRL model’s action sequence, and output is the model’s training algorithm. With this classifier, we are able to identify the algorithm of an arbitrary black-box DRL model.

Dataset Preparation. A dataset is necessary to train this classifier. It should consist of enough samples to cover models with different algorithms, as well as various behaviors. We train a large quantity of shadow DRL models in the same environment but with various algorithms, and collect their behaviors to form this dataset. Specifically, we set up a algorithm pool P that includes all the training algorithm in our consideration. We prepare a set \( S \) of random seeds for environment initialization. Then for each algorithm in the pool \( P \), we train some DRL models with this algorithm in various environments initialized by different random seeds in \( S \). We evaluate the performance of each trained DRL model by measuring its reward and comparing it with a reward threshold \( R \); we only select the DRL models whose reward is higher than \( R \). For each qualified model, we collect \( N \) different state-action sequences with a length of \( T \): \( \{(s_1, a_1), (s_2, a_2), ..., (s_T, a_T)\} \). Then samples are generated with the action sequences \( A = \{a_1, a_2, ..., a_T\} \) as the feature and the training algorithm as the label, to construct the dataset.

Training. We train a Recurrent Neural Network over the prepared dataset for the classifier. A RNN is competent of processing sequence data of arbitrary lengths by recursively applying a transition function to its internal hidden state vector of the input. It is generally used to map the input sequence to a fixed-sized vector, which will be further fed to a softmax layer for classification. However, vanilla RNNs are well-known to suffer from the gradient vanishing and exploding problem: during training, components of the gradient vector can grow or decay exponentially over long sequences. To address this issue, we adopt the Long Short-Term Memory (LSTM) network [33] in our approach. LSTMs can selectively remember or forget things regulated by a set of gates. Each gate in LSTM units is composed of a sigmoid neural net layer and a pointwise multiplication operation, which can filter the information through the network. As a result, LSTM units can maintain information in memory for a long period under the control of gates. To train the classifier, for each input sequence \( A = \{a_1, a_2, ..., a_T\} \), we first apply a set of LSTM layers to obtain its vector representation. Then we attach a fully-connected layer and a non-linear softmax layer after the LSTMs to output the probability distribution over all classes of possible model algorithms. We use cross-entropy of the predicted and ground-truth labels as the loss function to identify the optimal parameters for this classifier by minimizing the loss function.

Extracting model algorithms. With this RNN classifier, we
are now able to predict the training algorithm of a given back-box DRL model. We operate this target model in the same environment with certain random seed and collect the action sequence for $T$ rounds. We query the classifier with this sequence and get the probability of each candidate algorithm. We select the one with the highest probability as the attack result. To further increase the confidence and eliminate the stochastic effects, we can run the target model in different initialized environments and collect the sequences for predictions. We choose the most-predicted label as the target model’s algorithm.

### B. Replicating DRL Models via Imitation Learning

With the extracted model algorithm, the adversary can train a new model (or just pick a shadow DRL model during the classifier training step) with the same algorithm as the replica of the target model. However, due to the complexity of DRL algorithms and variance of initial environment, this replicated model can still exhibit distinct behaviors from the real one, even they are from the same algorithm. This stage aims to refine the replicated model via imitation learning.

Imitation learning aims to mimic expert behavior in a given task. An imitation model learns skills to perform a task from expert demonstrations by learning a mapping between observations and actions [22]. Recently, several works conduct model imitating on DRL models, e.g., GAIL [17] and DQfD [23]. In our case, we adopt the GAIL algorithm to replicate DRL models. GAIL is a model-free learning algorithm that can obtain significant performance gains in imitating complex behaviors in large-scale and high-dimensional environments. Specifically, two models are constructed to contest with each other during the imitation process: a generative DRL model $G$ with the extracted algorithm, and a discriminative model $D$ whose job is to distinguish the distribution of data generated by $G$ from the ground-truth data distribution (i.e., expert trajectory) from the target DRL model. The trajectory data for generative model and target model is a sequence of $\{(s_1, a_1), (s_2, a_2), ..., (s_T, a_T)\}$. The generative model $G$ iteratively refines its parameters based on the feedback from $D$ until $D$ cannot distinguish the data generated from $G$ or the target model.

After the imitated model is produced, considering the stochasticity of learning progress, it is possible that it cannot reach the same reward although it has the same behaviors as the target model. Therefore, we repeat the GAIL process until a qualified model is obtained which has high very similar performance (i.e., reward) as the target model.

### IV. Evaluation

#### A. Implementation and Experimental Setup

Our attack approach is general-purpose and applicable to various reinforcement learning environments. Without loss of generality, we consider two popular environments: Cart-Pole and Atari Pong [34]. For each environment, we train DRL models with five mainstream DRL algorithms (DQN [3], PPO [19], ACER [20], (ACKTR) [21] and A2C [35]). We use the default training settings and hyperparameters in the OpenAIBaselines framework. For each environment, we select 50 trained models whose rewards are higher than the baseline $R$ as introduced in OpenAI Baselines framework [34].

For RNN classification, we consider different sequence lengths $T$ (50, 100 and 200), and compare their impacts on the RNN classification accuracy. For each trained DRL model, we collect 50 sequences of actions as the training input of our RNN classifier. Therefore, for Cart-Pole and Atari Pong, the sizes of the data set we collected from 250 trained DRL models are both 12,500. To evaluate the trained RNN classifier, we splits the data set to training and test sets randomly. Moreover, we consider various RNN structures. During the training process, the initial learning rate is set to 0.005 with a decay factor of 0.7 whenever loss plateaus, and the batch size is set to 32. We stop the training after $N = 100$ iterations.
B. Results of RNN Classification

Impact of hyper-parameters. The prediction accuracy of the RNN classifier can be affected by a few hyper-parameters, e.g., the length of the input sequence, the number of hidden layers. Figure 3 shows the accuracy under different combinations of these hyper-parameters. First, we observe that the length of the input sequence can affect the classification performance: a longer input sequence can give a higher accuracy. Therefore, for Cart-Pole environment, we take all the actions within one episode as the input sequence ($T=200$). For Atari Pong environment, one episode can have up to 10,000 actions. It is not recommended to take the entire episode as input, which can incur very high cost and training over-fitting. Since $T = 200$ can already give us very satisfactory accuracy, we will set the length of input sequence to 200 as well.

Second, we consider different numbers of hidden LSTM layers (1 and 2) for the classifier. We observe that this factor has slight influence on the accuracy of the classifier. One hidden layer can already validate the effectiveness of the RNN classification. So in the following experiments, we will adopt a 1-layer RNN for simplicity.

Third, the action space can also affect the classification accuracy. Higher-dimensional actions can contain more information about the DRL model. Thus, it will be easier and more accurate to classify them. In our case, the action space of Cart-Pole environment is 2 while that of Atari Pong environment is 6. Then the classifier of Atari Pong has a higher accuracy than Cart-Pole, as reflected in Figure 3.

Accuracy of each class. Figure 2 shows the confusion matrix for both two environments. We observe the RNN classifier can distinguish DRL models of each algorithm with very high confidence. For most cases, the prediction accuracy is above 70%; the best case is up to 100% (i.e. DQN models in Atari Pong); the worst case is 54% (ACER models in Cart-Pole), which is still much higher than random choice (20%). The prediction accuracy of the DQN model is particularly high (0.95 in Cart-Pole, and 1 in Atari Pong). The reason behind this is that DQN is a value-based algorithm while all the other four algorithms are actor-critic methods. So DQN models are easier to be distinguished.

C. Explanation of RNN Classification

We quantitatively explain and validate why our RNN classifier is able to distinguish different DRL algorithms. We adopt the Local Interpretable Model-agnostic Explanations (LIME) framework [36], which attempts to understand a model by perturbing its input and observing how the output changes. Specifically, it modifies a single data sample by tweaking the feature values and observes the resulting impact on the output to determine which features play an important role in the model predictions.

In our case, we build a explainer with LIME on our RNN classifier. Then, we randomly select 200 explanation instances from the training data of the classifier from the shadow DRL models trained in Atari Pong environment in Section III-A. We feed these instances to the explainer and obtain the explanation results. For each explanation instance, we identify the feature (i.e., one action of input sequence) which contributes most to the prediction. Through the analysis of these features, we can discover the different behaviors of DRL models trained from different algorithms. Fig. 4 shows the contribution of the actions (UP, DOWN, IDLE) with prominent impacts on the prediction in each input sequence. We can observe that different DRL algorithms give very different behavior preferences. A2C tends to issue important actions
of UP at the beginning of the sequence; ACKTR prefers to give the action of DOWN also at the task beginning; DQN has a higher chance to predict IDLE clustering at the beginning; PPO issues the DOWN action all over the sequence with a large variance of contribution factor; ACER has important actions of UP and IDLE with similar contributions spanning all over the sequence. This shows those DRL algorithms have quite different characteristics in making action decisions, giving the classifier an opportunity to distinguish them just based on the action sequence.

D. Results of Imitation Learning

We demonstrate the effectiveness of imitation learning for model replication. To train the replicated models, GAIL algorithm is applied to imitate behaviors from the target model. As implemented in OpenAI baseline [34], the generator of GAIL can be PPO or TRPO policies. Without loss of generality, we select PPO as the generator.

Imitating Performance. The replicated model with the same algorithm can reach similar performance (i.e., reward) as the target model after imitation learning. Without loss of generality, we show this effect in Cart-Pole environment. We consider the adversary has identified the training algorithm via RNN classification, and then use this algorithm for imitation learning. Figure 5a shows the fine-tuning process (the target model is trained with PPO). We can observe that in the first imitation cycle, the replicated model cannot reach the same performance as the target one, as it has been supervised to learn the random behaviors of the target model with low rewards. Then we start a new imitation cycle, and now the learned model can get the same reward as the victim model. We can stop with this replica, or continue to identify more qualified ones (at the 6th cycle). In contrast, we also consider a case where the adversary does not know the training algorithm, and randomly pick one for imitation learning. Figure 5b shows the corresponding imitation process (the target model uses DQN while the adversary selects PPO generator). Now the replicated model can never get the same performance as the target model. This indicates the importance of extracted algorithm from the RNN classification, in order to perform high-quality imitation learning.

Imitating behaviors. In addition to performance, the repli-
cated model can also learn the similar behaviors as the target model. Since the output of a DRL model is a probability distribution over legal actions, we adopt the Jensen-Shannon (JS) divergence [37] to measure the similarity of the action probability distributions between the replicated model and the target model. We still use the PPO policy in the Cart-Pole environment for illustration. We consider three cases: (1) the similarity between the target model and itself (i.e., collecting the behaviors twice). This serves as the baseline for comparison. (2) the similarity between the target model and the replicated model from imitation learning; (3) the similarity between the target model and a shadow model with the same training algorithm. For each case, we feed the same states to the two models in comparison, sample 100 actions from each model, compute the action probability distributions and the divergence between these two action distributions. Fig. 6 shows the cumulative probability of the JS divergence for each case. We can observe that cumulative probability of JS divergence in both case (1) and (2) increases sharply to 1. This indicates that the replicated model indeed has very similar behaviors as the target model. In contrast, the divergence of action probability distributions between the shadow model and target model can be very high. Even they are trained from the same algorithm, their behaviors are still quite distinct in the same environment. We can conclude that through imitation learning with the extracted algorithm, the replicated model can behave very closely with the target one.

V. CASE STUDY: ENHANCING ADVERSARIAL ATTACKS

In this section, we present a case study to show how an adversary can leverage the model extraction technique to cause severe damages to the victim.

Generally, there are three types of adversarial attacks, white-box, grey-box and black-box attacks, determined by the adversary’s knowledge of the victim model [38]. The black-box scenario is the most realistic setting as the information and details of the DL models are usually confidential for intellectual property protection. However, black-box attacks have lower success rates than grey-box attacks due to the low transferability across models with different algorithms. Such distinction is more prominent for DRL models for their complexity and large diversity. So to enhance the adversarial attacks against black-box DRL models, we can use the proposed model extraction attack to turn the black-box models into grey-box ones. Specifically, we extract the training algorithm from the black-box DRL model and replicate a new one. Then we generate adversarial examples via conventional methods from the parameters of the replicated model, and use them to attack the target black-box one.

Implementation. We evaluate the effectiveness of adversarial examples in Atari Pong environment. The target black-box model can use one training algorithm and configurations. The adversary may choose an arbitrary different algorithm to train a shadow model, or use model extraction method to identify the target model algorithm and replicate a new model. For each case, we adopt the FGSM technique [25] to generate 1,000 adversarial examples and measure their success rates on the target model.

Results. Fig. 7 reports the transferability of adversarial examples across different DRL algorithms under the same perturbation scale. We can observe that the success rate increases when the replicated model has the same training algorithm as the target model. The reason behind this is that the gradients of the DRL models with the same algorithm are closer than the ones with different algorithms. Therefore, adversarial examples are easier to be transferred to the models with the same algorithm, even when their parameters are different. This indicates that our model extraction technique can significantly enhance the adversarial attack effects on the black-box DRL models.

VI. CONCLUSION

In this paper, we design a novel attack methodology to steal DRL models. We utilize RNN classification and Generative Adversarial Imitation Learning, to extract the model algorithms, imitate their behaviors and performance. With such powerful attack techniques, an adversary can recover the DRL models with high fidelity only by observing the actions other than prediction confidence score. Such minimal attack requirements can invalidate the common defenses against model extraction attacks, e.g., perturbing the output probability [7, 39, 40], removing the probabilities for some classes [7], returning only the class output [7, 39], query pattern analysis [41, 42], watermarking [43, 44]. We expect this study can inspire people’s awareness about the severity of DRL model privacy issue, and come up with better solutions to mitigate such model extraction attacks.

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