HODA: PROTECTING DNNS AGAINST MODEL EXTRACTION ATTACKS VIA HARDNESS OF SAMPLES

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Paper under double-blind review

ABSTRACT

Model Extraction attacks exploit the target model's prediction API to create a surrogate model in order to steal or reconnoiter the functionality of the target model in the black-box setting. Several recent studies have shown that a data-limited adversary who has no or limited access to the samples from the target model's training data distribution can use synthesis or semantically similar samples to conduct model extraction attacks. As the training process of DNN-based classifiers is done in several epochs, we can consider this process as a sequence of subclassifiers so that each subclassifier is created at the end of an epoch. We use the sequence of subclassifiers to calculate the hardness degree of samples. In this paper, we investigate the hardness degree of samples and demonstrate that the hardness degree histogram of a data-limited adversary's sample sequences is distinguishable from the hardness degree histogram of benign users' samples sequences, consisting of normal samples. Normal samples come from the target classifier's training data distribution. We propose Hardness-Oriented Detection Approach (HODA) to detect the sample sequences of model extraction attacks. The results demonstrate that HODA can detect the sample sequences of model extraction attacks with a high success rate by only watching 100 samples of them.

1 INTRODUCTION

Deep Neural Networks (DNNs) have shown impressive performance in various tasks in recent years that have encouraged the industry to deploy DNN-based models in a variety of real-world applications. Since the training process of DNNs and collecting training data is an expensive and tedious process, models are considered the intellectual property of organizations, and they must be kept secure. Therefore, models are often securely deployed on cloud servers, and only the creators can access the model parameters. Users are only allowed to query the model via a prediction API and receive predictions. Recent studies Tramèr et al. (2016); Papernot et al. (2017); Juuti et al. (2019); Orekondy et al. (2019); Jagielski et al. (2020) demonstrate that an adversary can exploit the prediction API to extract a target model and create a surrogate model in order to steal or reconnoiter the functionality of the target model. Such attacks are called *model extraction attacks*, and they violate the intellectual property of model owners. Furthermore, the surrogate model can be leveraged to conduct other attacks on the target model in the black-box setting, such as adversarial example attacks Papernot et al. (2017); Juuti et al. (2019) and membership inference attacks Shokri et al. (2017).

Most of the model extraction attacks use the target model's prediction API to label an unlabeled dataset to create the surrogate model's training set. In most real-world settings, the adversary has no or limited access to the samples from the target model's training set distribution, which is called *normal* or in-distribution samples. Hence, most proposed attacks in the previous studies use some form of out-of-distribution samples, such as synthesis Papernot et al. (2017); Juuti et al. (2019) or semantically similar samples to the target model's training set Orekondy et al. (2019); Pal et al. (2020) to conduct model extraction attacks. We focus on such attacks in this paper. There are two main approaches to defend against model extraction attacks, perturbing the target model outputs to prevent adversary from producing high quality surrogate model Lee et al. (2019); Orekondy et al. (2020); Kariyappa & Qureshi (2020); Kariyappa et al. (2021b) and detecting the sample sequences of model extraction attacks Kesarwani et al. (2018); Juuti et al. (2019). To the best of our knowledge, PRADA Juuti et al. (2019) is the only approach attempting to detect the sample sequences of model

extraction attacks on DNN-based classifiers. We propose Hardness-Oriented Detection Approach (HODA), a new approach to detect sample sequences of model extraction attacks, which outperforms PRADA by a large margin and has significantly less computational overhead.

Generally, the training process of DNN-based classifiers is done in several epochs, and the resulted classifier at the end of the last epoch is considered the final classifier. Therefore, we can consider the training process of DNN-based classifiers as a sequence of subclassifiers in which the ith subclassifier is created at the end of the ith epoch. We say a sample is learned in the ith epoch when the ith subclassifier is the first subclassifier that agrees with all subsequent subclassifiers predicted labels. We consider the index of the epoch in which a new sample is learned as the hardness degree of that sample. Consequently, easy samples being learned in the early epochs have low hardness degree, and harder ones being learned in the last epochs have high hardness degree. It is important to note that we must save subclassifiers in the training phase of classifiers and use their predictions to calculate the hardness degree of new samples. It is indicated the accuracy of classifiers is reduced by increasing the hardness degree of samples.

We demonstrate that the hardness degree histogram of normal sample sequences is distinguishable from the hardness degree histogram of model extraction attack sample sequences, and HODA uses this property to detect sample sequences of model extraction attacks. For each user, HODA calculates the distance between the hardness degree histograms of the user's samples and normal samples, and if the distance is greater than a threshold, the user is detected as an adversary. HODA can detect JBDA Papernot et al. (2017), JBRAND Juuti et al. (2019), and Knockoff Net Orekondy et al. (2019) attacks with a high success rate by only watching 100 samples of attack. We demonstrate that HODA is also highly effective when the target classifier is trained using transfer learning.

Contributions. (i) We demonstrate that the hardness degree histogram of normal samples is distinct from the hardness degree histograms of model extraction attack samples. (ii) We investigate the relationship between the hardness degree of samples and the training set distribution of the model being used to calculate the hardness degree of samples. (iii) We propose HODA to detect the sample sequences of model extraction attacks.

2 Related Work

Model Extraction Attacks: Primary model extraction attacks try to extract the exact value of parameters Lowd & Meek (2005); Tramèr et al. (2016) and hyperparameters Wang & Gong (2018) of shallow models. In recent years, the proposed attacks mainly aimed to steal or reconnoiter the functionality of deep neural networks by querying them in the black-box setting. It is often sensibly assumed in the literature that the adversary has no or limited access to samples from the training set distribution of target classifier. In order to overcome this issue, attacks generally use some form of out-of-distribution samples, such as synthesis or semantically similar samples, to create the surrogate classifier's training set. Knockoff Net Orekondy et al. (2019), ActiveThief Pal et al. (2020), and Copycat CNN da Silva et al. (2018) use semantically similar datasets to the target model's training set to train a surrogate classifier. In another line of studies, Papernot et al. (2017), Juuti et al. (2019), Yu et al. (2020), Truong et al. (2021), Kariyappa et al. (2021a), and Barbalau et al. (2020) use synthetic data to create the surrogate classifier's training set.

Model Extraction Defenses: Existing defense methods against model extraction attacks generally distribute into two branches: perturbation-based and detection-based. Perturbation-based defenses Lee et al. (2019), Orekondy et al. (2020), Kariyappa & Qureshi (2020), and Kariyappa et al. (2021b) attempt to prevent adversaries from producing high-quality surrogate classifiers by adding perturbation to the output of target classifier. Detection-based defenses attempt to detect the occurrence of model extraction attacks by observing successive input queries to the target classifier. Kesarwani et al. (2018) present a method to detect extraction attacks against Decision Tree models. PRADA Juuti et al. (2019) is the first proposed detection-based defense for DNN models. We propose a new defense detecting the sample sequences of model extraction attacks using hardness of samples.

3 Model Extraction Attacks

The model extraction attack is one of the most serious threats against machine learning-based classifiers on remote servers, such as Machine Learning as a Service (MLaaS). The adversary's goal is

to create a surrogate classifier f_s that imitates a target classifier f_t on task T. Most model extraction attacks exploit target model f_t to label unlabeled samples to create the surrogate model's training set. The adversary sends sample x_i to the target model and receives its output $f_t(x_i)$, and then she uses pair $(x_i, f_t(x_i))$ to train surrogate classifier f_s. The output type of target model can be label, label confidence, top-k values in probability vector, or the entire probability vector. We only consider label $\bar{f}_t(x_i)$ and the entire probability vector $f_t(x_i)$ as the output type of target classifiers in our experiments. There are two primary intents for adversaries to conduct model extraction attacks, *stealing* and *reconnaissance*.

Stealing: Producing a classifier with high performance is an expensive and time-consuming process and requires computational resources and experts. Besides, given that DNNs need a large number of training samples, collecting data and labeling them is a complex and costly procedure for most real-world applications. Therefore, adversaries are motivated to take advantage of a target classifier to reduce the cost of creating a new classifier. The adversary's goal in stealing is that the surrogate model achieves high *accuracy* on data distribution $\mathcal{D}_T$ Orekondy et al. (2019); Jagielski et al. (2020). Hence, the adversary's goal is:

$$\text{Maximize} \quad P_{(x,y)\sim\mathcal{D}_T} \bar{f}_s(x) = y \tag{1}$$

Reconnaissance: The model extraction attacks can be used to conduct other attacks in the black-box setting, such as adversarial example attacks Papernot et al. (2017); Goodfellow et al. (2015) and membership inference attacks Shokri et al. (2017). The adversary's goal in reconnaissance is to maximize the *fidelity* among surrogate and target classifiers in order to increase the success rate of black-box attacks. Similar to Jagielski et al. (2020), we consider label agreement among surrogate and target classifiers as the fidelity metric on data distribution $\mathcal{D}_T$. Hence, the adversary's goal is:

$$\text{Maximize} \quad P_{(x,y)\sim\mathcal{D}_T} \bar{f}_s(x) = \bar{f}_t(x) \tag{2}$$

Proposed model Extraction attacks create the surrogate classifier training set $\mathbb{X}_s = \{(x_i, f_t(x_i))\}_{i=1}^{B}$ by various methods, where B is the attack budget. The attack budget determines the number of samples that an adversary is allowed to send to the target classifier and receives their associated predictions. After creating $\mathbb{X}_s$, the adversary trains surrogate classifier f_s to minimize empirical loss on $\mathbb{X}_s$. We suppose that the adversary knows the architecture and hyperparameters of the target classifier and uses them to train the surrogate classifier. It is noteworthy that our proposed defense is independent of the training process of surrogate classifiers.

4 Our Proposal: Hardness-Oriented Detection Approach

We first introduce the hardness degree of samples and then show the hardness degree histogram of model extraction attack samples is distinct from the hardness degree histogram of normal samples. Using this observation, we propose Hardness-Oriented Detection Approach (HODA) to detect the sample sequences of model extraction attacks.

4.1 Hardness of Samples

The training process of a DNN-based classifiers can be considered a sequence of subclassifiers so that each subclassifier is created at the end of an epoch. Suppose that the classifier f_t is trained for m epochs. The training process of classifier f_t can be represented as the following sequence of subclassifiers:

$$< f_t^0, f_t^1, f_t^2, ..., f_t^{m-1} > \tag{3}$$

where subclassifier f_t^i is created at the end of the ith epoch. We say sample x_i is learned in epoch e when f_t^e is the first subclassifier that the assigned label by f_t^e is equal to all subsequent subclassifiers' predicted labels. Generally, as the number of epochs is increased, the performance of classifier f_t is improved so that easier samples are learned in the early epochs, and harder ones are learned in the last epochs. Therefore, the *hardness degree* of sample x_i for classifier f_t, which is displayed by $\phi_{f_t}(x_i)$, directly relates to the epoch number that x_i is learned by f_t. Hardness degree of sample x_i for classifier f_t is defined as follows:

$$\phi_{f_t}(x_i) = e \quad \text{s.t.} \quad \forall\, j \in [e, m-1],\ \bar{f}_t^{\,e}(x_i) = \bar{f}_t^{\,j}(x_i),\ \bar{f}_t^{\,e}(x_i) \neq \bar{f}_t^{\,e-1}(x_i). \tag{4}$$

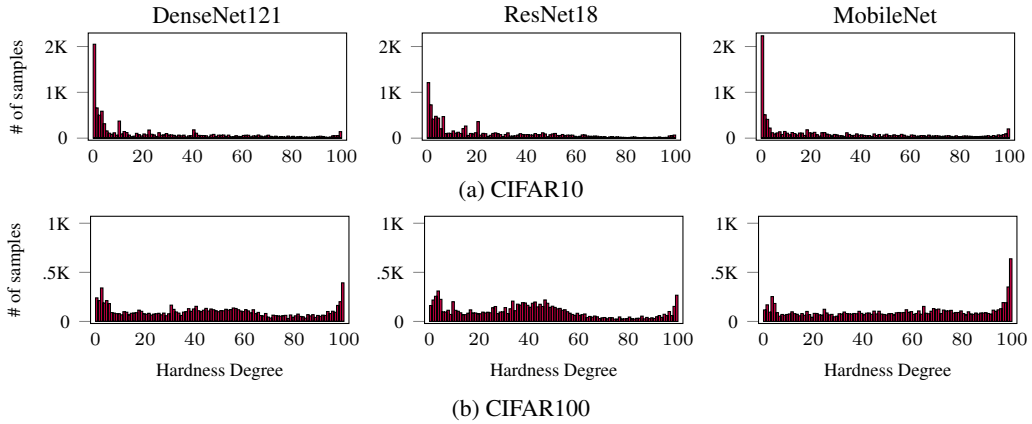


Figure 1: The hardness degree histograms of CIFAR10 and CIFAR100 test samples for DenseNet121, ResNet18, and MobileNet classifiers.

The hardness degree domain is dependent on the number of subclassifiers, and since we have m subclassifiers, the hardness degree of a sample is in the range $[0, m-1]$. To determine the hardness degree of unseen samples, we need to save the subclassifiers at the end of each or several epochs in the training phase of target classifiers. When a new sample arrives, it is fed to all subclassifiers, and using their predictions, the hardness degree of that sample is calculated. We train three various types of classifiers, including DenseNet121 Huang et al. (2017), ResNet18 He et al. (2016), and MobileNet Sandler et al. (2018), on CIFAR10 and CIFAR100 training sets for 100 epochs (details of datasets in Appendix A). All classifiers are trained using stochastic gradient descent with momentum 0.9 and batch size 128. The learning rate is 0.1 and it is scheduled to be decreased in each epoch by a constant factor 0.955. The accuracy of classifiers is presented in Table 1. We save all 100 subclassifiers in the training phase of each classifier and use them to calculate the hardness degree of samples. Figure 1 shows the hardness degree histogram of CIFAR10 and CIFAR100 test samples for various classifiers. The figure demonstrates that a large fraction of Cifar10 samples are easy, and many samples are learned in the first few epochs. However, the learning of Cifar100 samples is distributed over various epochs, and the number of hard samples is more than Cifar10.

Table 1: The accuracy of classifiers on CIFAR10 and CIFAR100 test sets.

	Acc(%)		
	ResNet18	DenseNet121	MobileNet
CIFAR10	94.36	94.92	93.59
CIFAR100	76.38	77.57	73.47

We divide the hardness degree domain into ten hardness degree ranges and partition the CIFAR10 and CIFAR100 test samples based on their hardness degrees into ten groups so that each group consists of samples whose hardness degrees belong to the associated hardness degree range. Figure 2 shows the accuracy of classifiers on samples in each range of hardness degrees. More than 99% and 95% of samples being learned in the first 30 epochs (hardness degree < 30) are correctly classified in CIFAR10 and CIFAR100 test sets, respectively. On the other side, less than 55% and 36% of samples being learned in the last 10 epochs (hardness degree ≥ 90) are correctly classified in Cifar10 and Cifar100 test sets, respectively. The results demonstrate that as the hardness degree of samples is increased, the accuracy of classifiers is reduced. We find ResNet18 architecture achieves strong performance on both datasets at a reasonable computational cost. Therefore, we use this architecture for target classifiers in the rest of the paper. We generate model extraction attack samples in the next subsection to depict the hardness degree histogram of them.

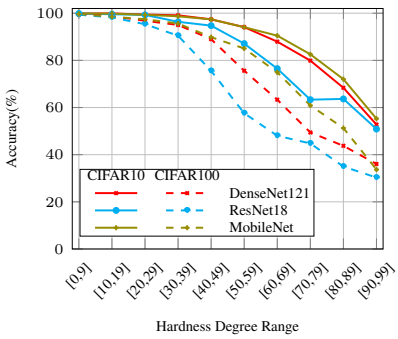


Figure 2: The accuracy of classifiers on samples in each range of hardness degrees.

4.2 Model Extraction Attacks Setup

In line with prior works (Orekondy et al. (2020); Kariyappa & Qureshi (2020); Kariyappa et al. (2021b)), we select JBDA Papernot et al. (2017), JBRAND Juuti et al. (2019), and Knockoff Net Orekondy et al. (2019) model extraction attacks to evaluate our defense method. These attacks broadly represent two main strategies (synthesis or semantically similar samples) to conduct model extraction attacks. Jacobian-Based Dataset Augmentation (JBDA) Papernot et al. (2017) and its improvement (JBRAND) Juuti et al. (2019) assume that the adversary has access to the limited number of samples from the target classifier's training data distribution called seed samples, and they aim to augment seed samples using adversarial examples to increase the *fidelity* of the surrogate classifier to the target classifier. Orekondy et al. (2019) propose Knockoff Net (K.Net) attack that uses large public datasets that is semantically similar to the target classifier dataset to increase the *accuracy* of the surrogate classifier. We consider two versions of K.Net attack, K.Net CIFARX, and K.Net TIN. K.Net CIFARX attack uses CIFAR100 training set to extract CIFAR10 target classifier and vice versa. K.Net TIN employs TinyImageNet training set to extract target classifiers. More details about attacks and their implementations are presented in Appendix C.

To evaluate the performance of model extraction attacks, we use two ResNet18 classifiers being trained on CIFAR10 and CIFAR100 training sets as the target classifiers and conduct all four attacks on them. The default value of the attack budget in our experiments is 50000 (B=50K). Table 2 shows the accuracy and the fidelity of surrogate classifiers created by various model extraction attacks on CIFAR10 and CIFAR100 test samples. The results demonstrate that K.Net attacks have significantly better performance than jacobian-based attacks (JBDA and JBRAND), and when the output of target classifiers is probability vector, the performance of attacks is considerably increased.

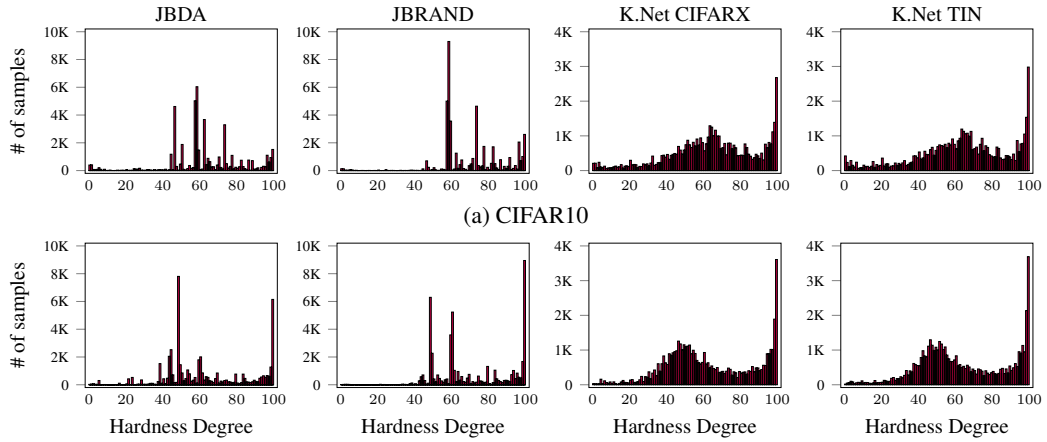
Table 2: The Accuracy (Acc) and the Fidelity (Fid) of surrogate classifiers being created by four various model extraction attacks on two target classifiers CIFAR10 and CIFAR100. The output type of target classifiers can be Label or Probability Vector (Prob. Vec.).

f_t	Metric	Output type	JBDA	JBRAND	K.Net CIFARX	K.Net TIN
CIFAR10 ResNet18 (Acc: 94.36%)	Acc(%)	Prob. Vec.	41.00	43.33	79.86	78.86
		Label	34.57	34.35	66.88	71.29
	Fid(%)	Prob. Vec.	41.16	43.63	81.36	80.18
		Label	34.86	34.45	67.98	72.43
CIFAR100 ResNet18 (Acc: 76.38%)	Acc(%)	Prob. Vec.	16.44	18.78	51.09	60.36
		Label	8.62	8.07	23.20	32.88
	Fid(%)	Prob. Vec.	16.90	19.13	54.59	64.90
		Label	8.91	8.29	24.72	34.58

4.3 Hardness Degree of Model Extraction Attack Samples

Figure 3 depicts the hardness degree histogram of 50000 samples being generated by various attacks for CIFAR10 and CIFAR100 target classifiers. In this experiment, the architecture of target and surrogate classifiers is ResNet18. We also present the hardness degree histogram of attack samples when the architecture of target classifiers is Densenet121 in Appendix D. Figure 3 demonstrates that the samples generated by various attacks have a very small number of easy samples, and a majority of samples have medium and high hardness degrees. However, Figure 1 indicates that a high number of normal samples that are from the same distribution as the target classifier's training set are easy.

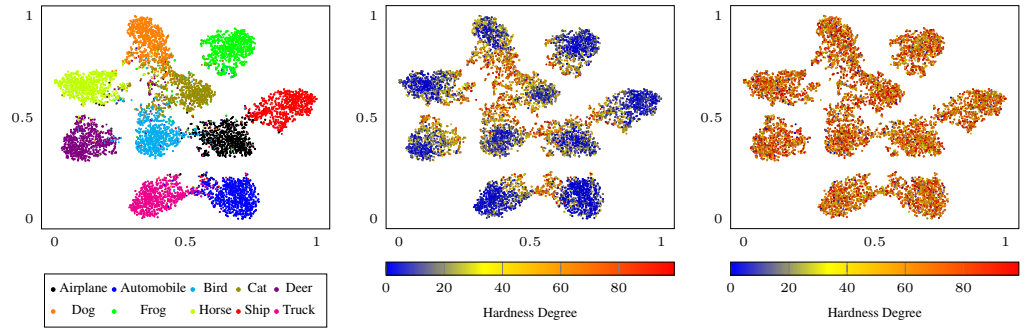
To investigate more on the hardness degree of attack and normal samples, Figure 4 displays two-dimensional visualization of CIFAR10 test samples using t-SNE. Figure 4a uses the logits of the CIFAR10 classifier to visualize CIFAR10 test samples, and the color of each sample is determined by its label. This figure has ten sample clusters where most samples of each cluster are from one class. Figure 4b illustrates the hardness degree of CIFAR10 test samples in which the hardness degree of samples is calculated by CIFAR10 target classifier. This figure demonstrates that most of the easy samples are in the high-density regions inside clusters, and most of the hard samples are in the low-density regions in the borders of clusters. Figure 4c is similar to Figure 4b, but the hardness degree of each sample is calculated via CIFAR100 target classifier. This figure demonstrates when the training data distribution of the classifier being used to calculate the hardness degree of samples becomes different from the distribution of CIFAR10 test samples, the hardness degree of a high number of samples is changed. Figure 4c shows hard and medium samples are distributed among clusters, and the number of easy samples is very small. Similar to Figure 4, we visualize CIFAR100 test samples and their hardness for CIFAR10 and CIFAR100 target classifiers in Appendix E. Figures



(a) CIFAR10

(b) CIFAR100

Figure 3: The hardness degree histograms of samples of four various model extraction attacks for CIFAR10 and CIFAR100 target classifiers. The budget of model extraction attacks is 50000.



(a) (b) (c)

Figure 4: (a) Visualization of CIFAR10 test samples. (b) Hardness of CIFAR10 test samples being calculated by CIFAR10 classifier. (c) Hardness of CIFAR10 test samples being calculated by CIFAR100 classifier.

3 and 4 demonstrate that when an adversary uses samples from a different distribution than the target model's training set distribution, the hardness degree histogram of the adversary's samples is distinct from the hardness degree histogram of normal samples being used by benign users. We use this observation to detect model extraction attacks that use samples from a different distribution than the target model's training data distribution. We use histogram rather than hardness degree histogram in the rest of the paper for simplicity.

4.4 Hardness-Oriented Detection Approach

We propose Hardness-Oriented Detection Approach (HODA) to detect sample sequences of model extraction attacks. HODA requires normal histogram H_n representing the histogram of normal samples. When a new sample x_i from user u arrives, HODA calculates the hardness degree of that sample, and the histogram belongs to that user H_u is updated. After the number of samples being sent by user u reaches a specific number num_s, HODA calculates Pearson distance between the histograms of normal samples H_n and user samples H_u, and if the distance is greater than a threshold δ, the user u is detected as an adversary. Pearson Distance (PD) between two random variable X and Y is defined as follows:

$$PD(X, Y) = 1 - \frac{\text{Cov}(X, Y)}{\rho_X \rho_Y} \tag{5}$$

where $\text{Cov}(X, Y)$ is the covariance between random variables X and Y, and ρ_X is the standard deviation of random variable X. The output of Pearson distance is in the range [0,2]. To calculate the Pearson distance between two histograms, HODA first transforms histograms into probability vectors by dividing the value of histogram bins by the total number of samples in the histogram ($H_n/sum(H_n)$ and $H_u/sum(H_u)$) and then calculates the Pearson distance between them.

HODA uses normal sample set S_{HODA} to create H_n and calculate δ. It randomly selects num_{seq} sample sequences with size num_s from the sample set S_{HODA} and for each sample sequence, produces a histogram and adds it to the histogram set $HistSet$. The normal histogram H_n is the average of all histograms in $HistSet$, and δ is the maximum Pearson distance between H_n and all histograms in $HistSet$. Since δ is independent of attacks and only relies on normal samples, HODA is not dependent on any attacks. Notably, HODA does not need to save samples of each user or their hardness degrees. It only keeps a vector (H_u) that indicates the values of histogram bins for each user. Algorithm 1 in Appendix F describes HODA in details.

5 Setup and Evaluation

Two normal sample sets S_{HODA} and S_u are required to evaluate the performance of HODA. S_u is used to simulate benign users. We randomly select 40% and 60% of test samples of each dataset for S_{HODA} and S_u, respectively. We randomly select $num_{seq} = 40000$ sequences with size num_s from S_{HODA} to create H_n and calculate δ. To evaluate the performance of HODA against model extraction attacks, we simulate 10000 benign users and 10000 adversaries for each attack. Each benign user sends a sequence of num_s samples randomly selected from S_u, and each adversary sends a sequence of num_s samples randomly selected in the order they were generated from 50000 samples of attack.

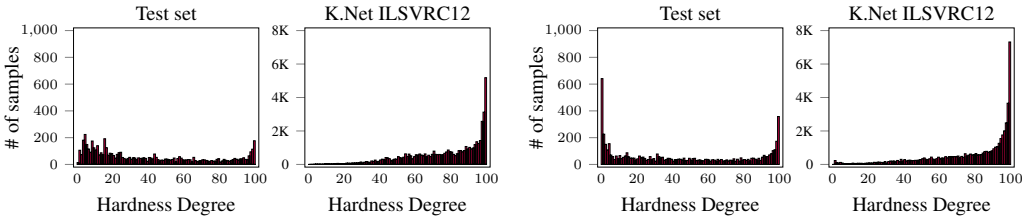
So far, we have used 100 subclassifiers to calculate the hardness degree of samples. However, it may not be possible to classify each sample by a high number of subclassifiers in practice. So in order to reduce the computational cost of HODA, we only use 11 subclassifiers to calculate the hardness degree of each sample, and these subclassifiers are saved in the training phase of target classifier f_t at the end of each 10 epochs $< f_t^0, f_t^9, f_t^{19}, f_t^{29}, f_t^{39}, f_t^{49}, f_t^{59}, f_t^{69}, f_t^{79}, f_t^{89}, f_t^{99} >$. Since the hardness degree domain depends on the number of subclassifiers, the hardness degree of a sample in HODA is in the range [0,10].

To the best of our knowledge, PRADA Juuti et al. (2019) is the only defense that is comparable to HODA. PRADA declares that the histogram of minimum L_2 distance between a new sample and all previous samples of a benign user follows a Gaussian distribution. Hence, it uses the Shapiro-Wilk normality test to determine that a sample sequence belongs to a benign user or an adversary. Similar to HODA, PRADA also uses threshold δ to detect sample sequences of model extraction attacks, and δ is the only parameter of PRADA. Since PRADA needs to save each user's samples and calculate L_2 distance between them, it has a high computational overhead.

Table 3: The detection rate and False Positive Rate (PFR) of PRADA and HODA against four various model extraction attacks on CIFAR10 and CIFAR100 target classifiers.

					Detection Rate of Attacks(%)			
		num_s	δ	FPR(%)	JBDA	JBRAND	K.Net CIFARX	K.Net TIN
CIFAR10	PRADA	100	0.818	0.01	0	0	0	0
		500	0.973	0.05	96.7	94.2	4.4	1.6
	HODA	50	0.290	0.02	100	100	99.92	99.73
		100	0.154	0.02	100	100	100	100
CIFAR100	PRADA	500	0.550	0.01	0	0	0	0
		1000	0.953	0.03	67.3	73.5	0	0
	HODA	50	0.716	0.02	94.65	100	90.68	89.06
		100	0.349	0.02	100	100	100	100

Table 3 indicates the detection rate and False Positive Rate (PFR) of PRADA and HODA against four various model extraction attacks on CIFAR10 and CIFAR100 target classifiers. We evaluate HODA when it only watches 50 and 100 samples of each user ($num_s = 50$ and $num_s = 100$), and since PRADA needs to watch more samples to detect attacks, we use larger num_s to evaluate PRADA. PRADA and HODA have very low false-positive rates. False-Positive Rate (FPR) indicates the percentage of benign users' sample sequences wrongly detected as an attack. The results demonstrate that HODA is very effective against model extraction attacks, and it outperforms



(a) CUB200 (b) Caltech256

Figure 5: The left histogram in subfigures a and b shows the hardness degree histogram of CUB200 and Caltech256 test samples, respectively. The right histogram in each subfigure indicates the hardness degree histograms of K.Net ILSVRC12 attack samples on CUB200 (a) and Caltech256 (b) target classifiers.

PRADA by a large margin. Since HODA does not rely on the distance between the attack samples, it can detect knockoff Net attacks that use natural samples. HODA also has better performance on jacobian-based attacks. The runtime and the number of samples that need to be stored by PRADA depend on the attack. Nevertheless, for $num_s = 500$ and CIFAR10 target classifier, the average runtime of PRADA for each user is 0.47 seconds on Tesla K80 GPU, and 471 samples are stored for each user on average. For each user, the average runtime of HODA is 0.0012 seconds, and it only stores a vector with size 11 representing the hardness degree histogram. Although HODA requires the predictions of 11 models to calculate the hardness degree of each sample, there is no sequential relationship between models, and they can predict parallelly so HODA does not increase the prediction time of target models.

5.1 Transfer Learning

Transfer learning is a machine learning technique that initializes the parameters of the target task classifier using the parameters of a pre-trained source task classifier. We train two new target classifiers on CUB200 and Caltech256 datasets using transfer learning (details of datasets in Appendix A). The training process of new target classifiers is the same as CIFAR10 and CIFAR100 target classifiers (Section 4.1). We initialize the parameters of target classifiers from a pre-trained ImageNet Deng et al. (2009) classifier and train all layers of target classifiers. Orekondy et al. (2020) indicate that jacobian-based model extraction attacks have very poor performance on high dimensional datasets. Thereby, we only evaluate the performance of target classifiers against K.Net ILSVRC12 attack. K.Net ILSVRC12 is the Knockoff Net attack that uses ILSVRC12 dataset as the surrogate classifier's training set. The budget of K.Net ILSVRC12 is 50000, and the output of target classifiers is the entire probability vector. The accuracy of CUB200 target classifier and its surrogate classifier is 73.7% and 59.3%, respectively, and the accuracy of Caltech256 target classifier and its surrogate classifier is 77.2% and 72.2%, respectively.

Figure 5 depicts the hardness degree histogram of CUB200 and Caltech256 test sets on the associated target classifier and also the hardness degree histogram of K.Net ILSVRC12 samples for both target classifiers. The figure demonstrates that the majority number of K.Net ILSVRC12 attack samples are hard (hardness degree $>$ 70), and the number of easy samples (hardness degree $<$ 30) is very small. We replicate the experiment of the previous section to evaluate the performance of HODA against K.Net ILSVRC12 attack with the same parameters. Table 4 shows the performance of HODA against K.Net ILSVRC12 attack on both target classifiers. The results demonstrate that even the starting point of target classifiers' parameters is not random, HODA is very effective in detecting K.Net ILSVRC12 attack.

Table 4: The detection rate and False Positive Rate (PFR) of HODA against K.Net ILSVRC12 attack.

Target Model	num_s	δ	FPR(%)	Detection Rate(%) K.Net ILSVRC12
CUB200	50	0.973	0.01	97.50
	100	0.393	0.02	100
Caltech256	50	0.694	0.01	99.98
	100	0.152	0.01	100

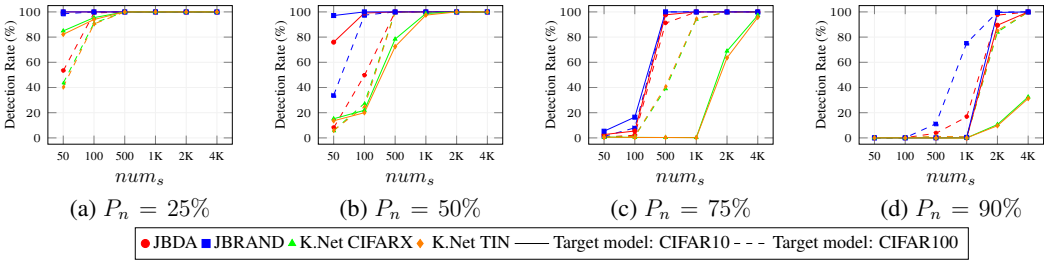


Figure 6: The detection rate of HODA for various percentages of normal samples P_n over different values of num_s.

6 Discussion on Adaptive Adversary

An adaptive adversary who is aware of HODA must send her queries based on the hardness degree histogram of normal samples to evade HODA. We consider two scenarios for an adaptive adversary to conduct model extraction attacks. In the first scenario, the adversary has no access to normal samples, and she only can use synthetic or semantically similar samples to extract the target model. There are two reasons why such attacks are hard to conduct. First, the adversary needs samples with various degrees of hardness; however, since the adversary has no access to the target classifier, she can not determine the hardness degree of her samples for the target classifier. Second, the adversary has no access to the histogram of normal samples to generate her samples based on it.

In the second scenario, we assume the adversary has access to a limited number of normal samples, and she can use normal samples to make her hardness degree histogram more similar to the hardness degree histogram of normal samples. To evaluate HODA in this scenario, we suppose that the adversary has access to 1000 normal samples from S_{user} and she sends a sample sequence of which $P_n\%$ is filled by normal samples, and the rest is filled by model extraction attack samples. Notably, when the number of normal samples in the sequence exceeds 1000, the adversary sends duplicate normal samples. It is important to note that the cost of attack is increased by a factor of $\frac{1}{1-(P_n/100)}$ in this scenario. Figure 6 shows the detection rate of HODA for various P_n over different values of num_s. The false-positive rate of all experiments is less than 0.2%. The figure demonstrates that increasing num_s improves the detection rate of HODA. Except for K.Net attacks on CIFAR10 target classifier in $P_n = 90\%$, HODA can detect all attacks with a high success rate by increasing num_s. Due to the dataset limitation, we can not evaluate HODA for $num_s > 4000$. However, we think the detection rate of HODA against K.Net attacks on CIFAR10 target classifier in $P_n = 90\%$ will be improved for $num_s > 4000$. Altogether, we think the main challenge of an adaptive adversary to evade HODA is to collect easy samples, which are very rare in out-of-distribution samples based on our experiments.

7 Conclusions

This paper demonstrates that the hardness degree of samples is important in trustworthy machine learning. We investigated the hardness degree of samples and demonstrated that the hardness degree histogram of model extraction attack samples is different from the hardness degree histogram of normal samples. Using this observation, we proposed Hardness-Oriented Detection Approach (HODA) to detect sample sequences of model extraction attacks. HODA can detect the sample sequences of model extraction attacks with a high success rate by only watching 100 samples of attacks.

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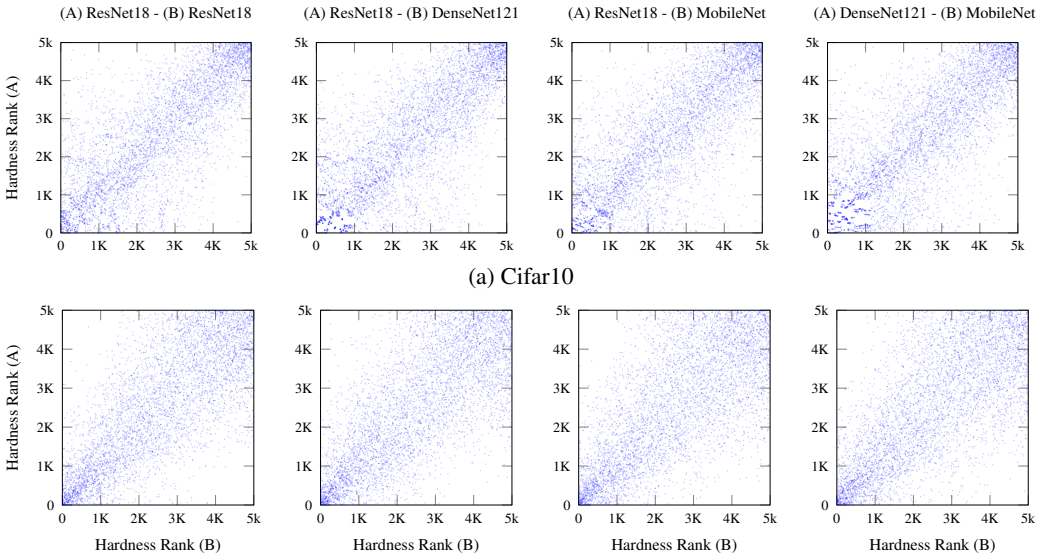


(a) Cifar10

(b) Cifar100

Figure 7: Hardness rank of 5000 test samples of CIFAR10 and CIFAR100 datasets for various pairs of classifiers.

A DATASETS

CIFAR10 Krizhevsky (2009): CIFAR-10 dataset consists of 60K 32×32 color images in 10 classes, including airplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks. It has 6K images per class, where 5K images is in the training set and 1K images is in the test set.

CIFAR100 Krizhevsky (2009): CIFAR100 dataset consists of 60K 32×32 color images in 100 classes. It has 600 images per class, where 500 images is in the training set and 100 images is in the test set.

TinyImageNet Le & Yang (2015): TinyImageNet is a subset of ILSVRC12 Deng et al. (2009) dataset, and contains 200 image classes. It has 500 training samples and 50 test samples for each class. The size of images is 64×64. We resize all images to 32×32.

CUB200 Wah et al. (2011): CUB200 dataset contain 200 classes of bird categories. It consists of about 6K training and about 6K test samples. The size of images is 224×224.

Caltech256 Griffin et al. (2007): Caltech256 dataset contain 256 classes of common objects categories. It consists of about 24K training and about 6K test samples. The size of images is 224×224.

ILSVRC12 Deng et al. (2009): ILSVRC12 uses a subset of ImageNet and consists of 1.2 million training images, 50,000 validation images, and 100,000 test images. The dataset has 1000 classes and the size of images is 224×224.

B HARDNESS TRANSFERABILITY

We introduce *hardness rank* to evaluate the dependency between classifier and the hardness of samples. The hardness rank of sample x_i for classifier f, which is displayed by $\Omega_f(x_i)$, determines the rank of sample x_i among all samples based on its hardness degree $\phi_f(x_i)$. Let S is the set of all samples, and the function $sort$ ascending sorts all samples based on their hardness degrees. The hardness rank of sample x_i is r, if sample x_i is the rth element of the sorted sample set ($sort(S)$). We have:

$$\Omega_f(x_i) = r \;\; \text{s.t.} \;\; sort(S)[r] = x_i \tag{6}$$

where $sort(S)[r]$ is the rth element of $sort(S)$. The hardness rank has a direct relation with the hardness of a sample. In order to demonstrate that the hardness of a sample is relatively independent

of the classifier architecture, we compare the hardness rank of samples among multiple pairs of classifiers. When the hardness rank of a high number of samples for one classifier is close to another one, it demonstrates that the hardness of samples is transferable among those classifiers.

We calculate the hardness rank of 5000 samples (randomly selected) of CIFAR10 and CIFAR100 test samples for the classifiers mentioned in Section 4.1 and a new ResNet18 classifier. The new classifier is trained the same as the other classifiers. Each plot of Figure 7 shows the hardness rank of samples for a pair of classifiers. The first row of Figure 7 demonstrates that the hardness rank of a high number of CIFAR10 samples is highly correlated between each pair of classifiers. Hence, the hardness of CIFAR10 samples is very transferable among various classifiers. The second row of Figure 7 indicates that the hardness rank of a high number of CIFAR100 samples is correlated between each pair of classifiers; however, they are not as correlated as CIFAR10 samples. Notably, when two ResNet18 classifiers are trained in the same way, the hardness rank of samples is not the same due to the different initial parameters and the stochasticity of the optimization algorithm. For both datasets, the number of samples that is hard (hardness rank < 3000) for one classifier and is easy (hardness rank < 2000) for another classifier is very small and vice versa.

The Pearson correlation coefficient calculates the linear correlation between two random variables X and Y. It is defined as follows:

$$\rho_{XY} = \frac{\text{Cov}(X, Y)}{\rho_X \rho_Y} \tag{7}$$

where $\text{Cov}(X, Y)$ is the covariance between random variables X and Y, and ρ_X is the standard deviation of random variable X. Table 5 shows the Pearson correlation coefficient of CIFAR10 and CIFAR100 test samples' hardness degree for various pairs of classifiers. The results demonstrate that the hardness degree of CIFAR10 and CIFAR100 samples are highly correlated among various pairs of classifiers. It means that when a sample has a high hardness degree for one classifier, it has a high hardness degree for other classifiers with high probability and vice versa.

Table 5: Pearson correlation coefficient of CIFAR10 and CIFAR100 test samples' hardness degree for various pairs of classifiers.

ρ_{XY}	CIFAR10	CIFAR100
ResNet18-ResNet18	0.784	0.687
ResNet18-DenseNet121	0.775	0.685
ResNet18-MobileNet	0.765	0.688
DenseNet121-MobileNet	0.769	0.706

C Details of Model Extraction Attacks

Jacobian-Based Dataset Augmentation (JBDA) Papernot et al. (2017): The goal of JBDA attack is to increase the fidelity of the surrogate classifier to the target classifier in order to produce adversarial examples for the target classifier in the black-box setting. The authors assume that the adversary has access to a limited number of normal samples called seed samples. JBDA augment seed samples using adversarial examples to improve the performance of model extraction attacks. The augmentation process is conducted in multiple rounds, and each round has the following steps:

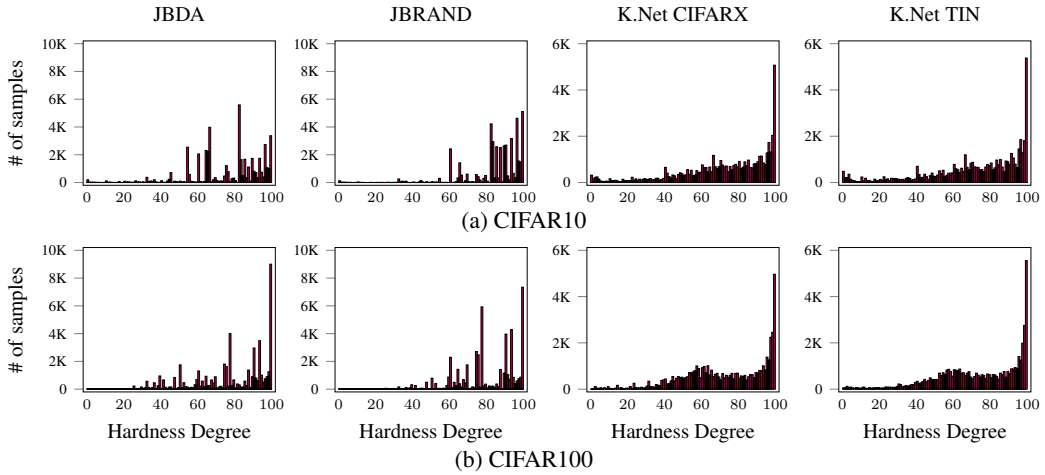
1. In the first round ($\rho = 0$), the target classifier labels the seed samples, and then, the labeled samples are added to the surrogate training set $\mathbb{X}_s$. In the next rounds ($\rho > 0$), new unlabeled perturbed samples ($\mathbb{S}_s^{\rho+1}$ / $\mathbb{S}_s^{\rho}$) are labeled by the target classifier and then, they are added to the surrogate training set $\mathbb{X}_s$.
2. The surrogate classifier f_s is trained on $\mathbb{X}_s$.
3. For each sample in $\mathbb{S}_s \subset \mathbb{X}_s$ (size $\mathbb{S}_s$ is κ), a new perturbed sample is created according to the following equation and is added to $\mathbb{S}_s$.

$$\mathbb{S}_s^{\rho+1} = \mathbb{S}_s^{\rho} \cup \{x + \lambda_{\rho+1}.\text{sign}(J_{f_s}[f_t(x)]) : x \in \mathbb{S}_s^{\rho}\} \tag{8}$$

where $\mathbb{S}_s^{\rho}$ is the surrogate training set in round ρ, λ is step size, and J is jacobian function.

The attack is implemented with $\lambda = 0.1$ and $\kappa = 2000$. The seed samples are selected from the test set of datasets. We use 50 and 10 samples of each class for the seed samples of JBDA attack on CIFAR10 and CIFAR100 target classifiers, respectively.

Jacobian-Based Random Target (JBRAND) Juuti et al. (2019): The goal of JBRAND is to improve the performance of JBDA. It perturbs each sample in multiple iterations to generate more



(a) CIFAR10

(b) CIFAR100

Figure 8: The hardness degree histograms of samples of four various model extraction attacks on CIFAR10 and CIFAR100 target classifiers. The budget of model extraction attacks is 50000. The architecture of target classifiers is DenseNet121.

powerful adversarial examples and generates targeted adversarial examples with random targets. We generate three adversarial examples with random targets for each sample in $\mathbb{X}_s$ and use the same seed samples as JBDA. Each sample is perturbed in five iterations with $\epsilon = \frac{64}{225 \times 5}$. The attack is implemented with $\lambda = \frac{64}{255}$ and $\kappa = 2000$.

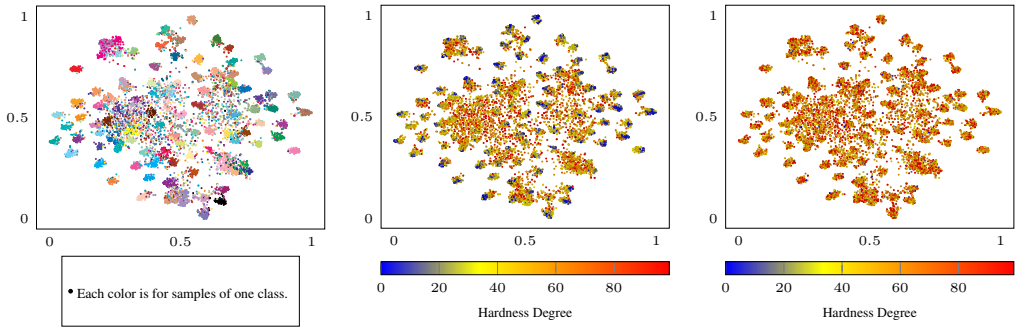
Knockoff Net (K.Net) Orekondy et al. (2019): Knockoff Net attack fills the surrogate classifier's training set by natural samples from large public datasets that are semantically similar to the target model's training samples. It has two strategies to select the surrogate classifier's training set, adaptive and random. Since the adaptive strategy has very marginal benefits, we only consider the random strategy to implement this attack. Knockoff Net randomly selects a subset of a public dataset and feeds the target classifier by these samples. It uses the outputs of the target classifier as the labels of samples in the surrogate classifier's training set ($\mathbb{X}_s = \{(x_i, f_t(x_i))\}_{i=1}^{B}$). Finally, it uses the surrogate classifier's training set to train a surrogate classifier.

D Hardness Degree Histograms for DenseNet121 Target Classifiers

Figure 8 shows the hardness degree histograms of samples of four model extraction attacks on CIFAR10 and CIFAR100 target classifiers. The architecture of target classifiers is DenseNet121.

E Visualization of CIFAR100 samples and Their Hardness

Figure 9 displays two-dimensional visualization of CIFAR100 test samples using t-SNE. Figure 9a uses the logits of CIFAR100 classifier to visualize CIFAR100 test samples, and the color of each sample is determined by its label. Figure 9b uses the sample representation of figure 9a, and the color of each sample shows the hardness degree of that sample being calculated by CIFAR100 target classifier. Figure 9c is similar to figure 9b, but the hardness degree of each sample is calculated using CIFAR10 target classifier.



(a) (b) (c)

Figure 9: (a) Visualization of CIFAR100 test samples. (b) Hardness of CIFAR100 test samples being calculated by CIFAR100 classifier. (c) Hardness of CIFAR100 test samples being calculated by CIFAR10 classifier.

F HODA ALGORITHM

Algorithm 1 Hardness-Oriented Detection Approach (HODA)

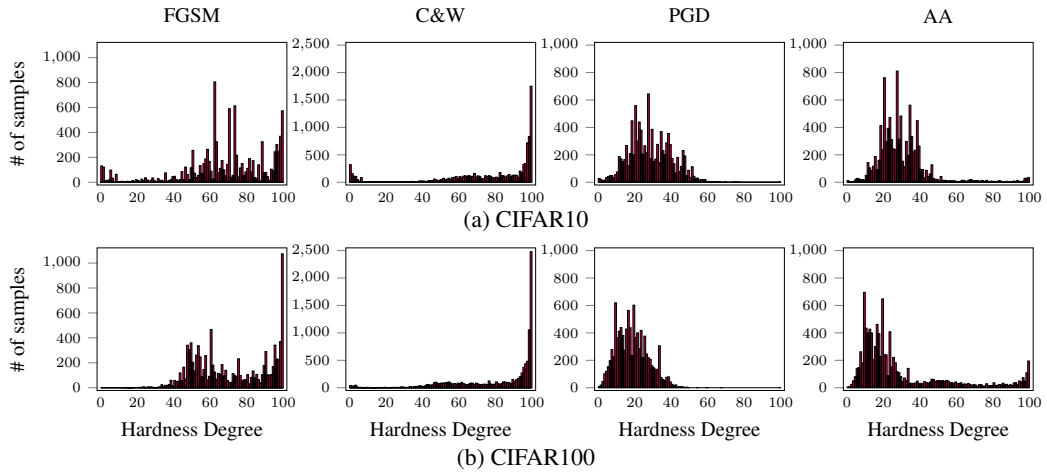
Inputs: S_{HODA} is a set of normal samples, num_s is the size of sample sequences, num_{seq} is the number of sample sequences, $SubClfSeq$ is the subclassifier sequence of target model, $NewQuery$ is the newest query being received by the target model, and $UserID$ is the ID of the owner of $NewQuery$.

Outputs: H_n is the histogram of normal samples, δ is the attack detection threshold of HODA, $AttackAlarm$ declares the occurrence of attack.

function PEARSONDIST(H_n, H_u)
  return $PD(H_n/Sum(H_n), H_u/Sum(H_u))$
end function
function HODAINITIALIZATION($S_{HODA}, num_s, num_{seq}, SubClfSeq$)
  $HistSet \leftarrow \emptyset$
  for $i \leftarrow 0, num_{seq}$ **do**
    $seq \leftarrow$ Randomly select num_s samples from S_{HODA}
    $Hist \leftarrow \emptyset$
    for s **in** seq **do**
      $HD =$ GetHardnessDegree($s, SubClfSeq$)
      $Hist[HD] += 1$
    $HistSet \leftarrow HistSet \cup Hist$
  $H_n \leftarrow Avg(HistSet)$
  $DistList \leftarrow \emptyset$
  for $Hist$ **in** $HistSet$ **do**
    $DistList$.append(PEARSONDIST($H_n, Hist$))
  $\delta \leftarrow Max(DistList)$
  return H_n, δ
end function
function HODA($NewQuery, UserID, H_n, \delta, num_s, SubClfSeq$)
  $AttackAlarm \leftarrow False$
  $H_u \leftarrow$ GetUserHisogram($UserID$)
  $HD \leftarrow$ GetHardnessDegree($NewQuery, SubClfSeq$)
  $H_u[HD] += 1$
  if $Sum(H_u) == Num_s$ **then**
    if PEARSONDIST(H_n, H_u) $> \delta$ **then**
      $AttackAlarm \leftarrow True$
  SaveUserHistogram($H_u, UserID$)
  return $AttackAlarm$
end function

G ADVERSARIAL EXAMPLES (AEs)

Adversarial examples (AEs) are maliciously crafted inputs that cause the target classifier to misclassify inputs. Generally, adversarial examples are created by adding small, often imperceptible, perturbations to normal samples to force a classifier to predict incorrectly. Given that large perturbations can change the true class of samples, the magnitude of perturbation is often restricted by L_p-norms $\| \cdot \|_p$. Suppose that the label of sample x is y, adversarial example x' can be formulated



(a) CIFAR10

(b) CIFAR100

Figure 10: The hardness degree histograms of samples of four various adversarial example attacks on CIFAR10 and CIFAR100 target classifiers. Each attack uses 10000 natural samples in the test set associated with the target classifier dataset to create 10000 adversarial examples.

as follows:

$$x' = x + \eta \quad s.t. \quad f_t(x') = y',\ y \neq y',\ \| \eta \|_p \leq \epsilon, x' \in domain(x) \tag{9}$$

There are numerous methods to generate adversarial examples such as L-BFGS Szegedy et al. (2014), FGSM Goodfellow et al. (2015), C&W Carlini & Wagner (2017), PGD Madry et al. (2018), and AutoAttack (AA) Croce & Hein (2020). To investigate the hardness of adversarial examples, we use FGSM ($\epsilon = 0.1$), C&W (L_2), PGD ($\epsilon = 8/255, \alpha = 3/255$), and AA ($L_\infty, \epsilon = 8/255$) attacks to generate adversarial examples on CIFAR10 and CIFAR100 test sets. The adversarial examples are created in the white-box setting, and they are untargeted. Figure 10 indicates the hardness degree of adversarial examples on two target classifiers CIFAR10 and CIFAR100. Although the distance between normal samples and adversarial examples is very small, Figure 10 demonstrates that the hardness degree histograms of adversarial examples are very different from normal samples (Figure 1). Most adversarial examples being generated by FGSM and C&W are harder than adversarial examples being generated by PGD and AA. We think this is because the size of perturbations being added to normal samples by FGSM and C&W is larger than PGD and AA. An intriguing observation is that almost all adversarial examples being generated by PGD are not hard (hardness degree > 70). AA has relatively the same behavior, and the number of its hard adversarial examples is very small.

H Performance Analysis of Model Extraction Attacks

To give new insight into model extraction attacks, we investigate the performance of model extraction attacks on normal samples that have various levels of hardness. For this purpose, the test sets of CIFAR10 and CIFAR100 datasets are partitioned into 10 hardness groups based on hardness degree of samples. The hardness group i consists of samples that their hardness degree is in range $[i \times 10, (i + 1) \times 10]$. Hence, the first hardness group consists of the easiest samples, and the last hardness group consists of the hardest ones. Figure 11 shows the accuracy and the fidelity of attacks over 10 hardness groups when the output of target classifier is a probability vector. The results demonstrate that the accuracy and the fidelity of all attacks are decreased as the hardness of samples is increased. We knew from Figure 2 that the accuracy of target classifiers is decreased by increasing the hardness of samples, and Figure 11 indicates the surrogate classifiers also have the same behavior. Nevertheless, the results demonstrate that the accuracy of K.Net attacks (specially K.Net TIN) is close to the target classifier accuracy on the first two hardness groups, and then, the distance between the accuracy of target classifiers and surrogate classifiers is increased.

An intriguing observation is that the accuracy of the K.Net surrogate classifiers approaches the accuracy of target classifiers on the last two hardness groups. To investigate this observation, Figure 11 shows the percentage of samples being classified correctly by both surrogate classifier and target

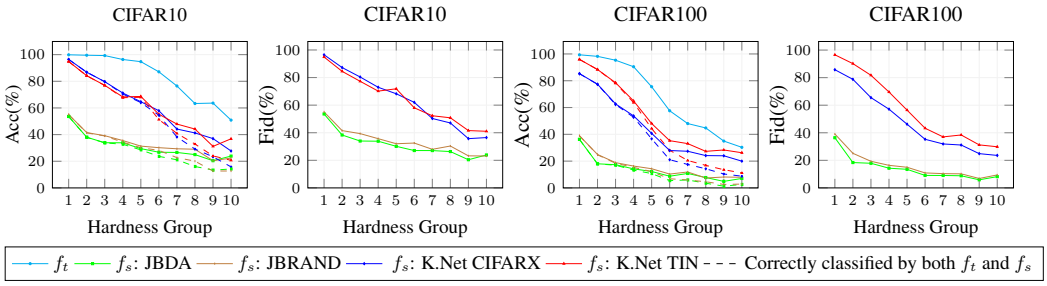


Figure 11: The accuracy and the fidelity of four surrogate classifiers over various hardness groups. The test set of each dataset is partitioned into 10 hardness groups so that hardness group 1 consists of the easiest samples and hardness group 10 consists of the hardest samples. The dashed lines indicate the percentage of samples being correctly classified by both target classifier f_t and surrogate classifier f_s.

classifier for all attacks over various hardness groups with dashed lines. The results demonstrate that all samples correctly classified by surrogate classifiers are also correctly classified by target classifiers in the first two hardness groups. However, by increasing the hardness of samples, the surrogate classifiers correctly classify some samples that are not correctly classified by the target classifier, and the number of such samples is increased by increasing the hardness of samples. Jagielski *et al.* Jagielski et al. (2020) demonstrate that labels from the target classifier are more informative than dataset labels. We think the information in the labels that come from the target model causes the surrogate classifiers to correctly classify hard samples that are not correctly classified by the target classifier.

The fidelity of all surrogate classifiers is decreased by increasing the hardness of samples, which means that the disagreement among surrogate classifiers and target classifiers is raised on harder samples. Therefore, the outputs of target classifier for harder samples have more information about the target classifier for attackers than easier ones. Another intriguing observation is that the fidelity of surrogate classifiers to the target classifiers on correctly classified samples by target classifiers is much more than wrongly classified samples.

I Comprehensive Related Work

Some recent studies investigate the dynamic of DNNs training process Hacohen et al. (2020); Frankle et al. (2020); Mangalam & Prabhu (2019) show that DNNs learn samples that are learnable by shallow models in early epochs of training before learning harder ones. Hacohen et al. (2020) demonstrate that DNNs learn samples in both training and test sets in a similar order. Pliushch et al. (2021) discuss correlation between learning order of samples with image statistics like segment count, edge strengths, image intensity entropy, and DCT coefficient matrix. Frankle et al. (2020) indicate that the DNN-based classifiers undergo substantial changes in the first few SGD iterations. In the following, we briefly review the most prominent model extraction attacks and defenses presented so far.

I.1 Model Extraction Attacks

For the first time, Lowd & Meek (2005) demonstrate the possibility of stealing simple linear machine learning models through only interaction with them. Tramèr et al. (2016) show the feasibility of model extraction attacks on commercial MLaaS. Papernot et al. (2017) and Juuti et al. (2019) investigate stealing DNN-based classifiers and propose jacobian-based model extraction attacks for creating a surrogate classifier in order to generate adversarial examples in the black-box setting. Chandrasekaran et al. (2020) explore the connection between active learning and model extraction attacks. They implement two query synthesis active learning algorithms to extract machine learning models, such as decision trees. Jagielski et al. (2020) use semi-supervised learning methods to improve the performance of model extraction attacks. Knockoff Net Orekondy et al. (2019), ActiveThief Pal et al. (2020), and Copycat CNN da Silva et al. (2018) use a semantically similar

dataset to the target classifier's training set to create the surrogate classifier's training set. They employ different strategies for selecting samples from attack datasets to extract more information from the target classifier. Yu et al. (2020) employ active learning, transfer learning, and a new method for generating adversarial examples to improve model extraction attacks efficiency. A line of studies Truong et al. (2021); Kariyappa et al. (2021a); Barbalau et al. (2020) use synthetic data to create the training set of surrogate classifiers. Although their methods do not need to have access to natural samples, they send a high number of queries to the target classifier, which makes their methods impractical. For example, Truong et al. (2021) and Kariyappa et al. (2021a) send millions of queries to extract a CIFAR10 target classifier. While most model extraction attacks have focused on the vulnerabilities of image classifiers, recent studies demonstrate the vulnerability of NLP Krishna et al. (2020), Graph DNN He et al. (2021), and Reinforcement learning Chen et al. (2021) models against model extraction attacks. Another type of model extraction attack uses hardware side-channel vulnerabilities to extract a target classifier Zhu et al. (2021); Batina et al. (2019); Hong et al. (2018); Yan et al. (2020). However, these attacks have a very strong threat model and suppose the adversary has access to the hardware that hosts the target classifier.

I.2 Defenses against Model Extraction Attacks

Existing defense methods against model extraction attacks generally distribute into two branches: perturbation-based and detection-based defenses. Perturbation-based defenses Lee et al. (2019); Orekondy et al. (2020); Kariyappa & Qureshi (2020); Kariyappa et al. (2021b) attempt to prevent adversaries from producing high-quality surrogate classifiers by adding perturbation to the output of target classifier. These methods generate the perturbation with various strategies to minimize the accuracy of surrogate classifiers. Proposed detection-based defenses Kesarwani et al. (2018); Juuti et al. (2019) attempt to detect the occurrence of model extraction attacks by observing successive input queries to the target classifier. Kesarwani et al. (2018) propose a method to measure adversary perceived knowledge from target classifier, but this method only works for Decision Tree models. PRADA Juuti et al. (2019) is the first proposed detection-based defense for DNN models. PRADA uses the histogram of the minimum L_2 distance among a new sample and all previous samples to detect model extraction attacks. Aside from its high computational overhead, it has been shown that Prada is unable to detect model extraction attacks when an adversary uses natural samples Pal et al. (2020). Watermarking neural networks Jia et al. (2021); Zhang et al. (2018); Szyller et al. (2019); Adi et al. (2018) is another type of defense against model extraction attacks. These methods prove ownership of a surrogate classifier instead of preventing the occurrence of model extraction attacks.