Hardness of Samples Is All You Need: 
Protecting Deep Learning Models Using Hardness of Samples

Amir Mahdi Sadeghzadeh  
Sharif University of Technology  
am sadeghzadeh@ce.sharif.edu

Faezeh Dehghan  
Sharif University of Technology  
de hghanniri@ce.sharif.edu

Amir Mohammad Sobhanian  
Sharif University of Technology  
amsobhanian@ce.sharif.edu

Rasool Jalili  
Sharif University of Technology  
jalili@sharif.edu

Abstract
Several recent studies have shown that Deep Neural Network (DNN)-based classifiers are vulnerable against model extraction attacks. In model extraction attacks, an adversary exploits the target classifier to create a surrogate classifier imitating the target classifier with respect to some criteria. In this paper, we investigate the hardness degree of samples and demonstrate that the hardness degree histogram of model extraction attacks samples is distinguishable from the hardness degree histogram of normal samples. Normal samples come from the target classifier’s training data distribution. 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. We investigate the relation between hardness degree of samples and the trust in the classifier outputs. We propose Hardness-Oriented Detection Approach (HODA) to detect the sample sequences of attacks. The results demonstrate that HODA can detect the sample sequences of model extraction attacks with a high success rate by only watching 100 attack samples. We also investigate the hardness degree of adversarial examples and indicate that the hardness degree histogram of adversarial examples is distinct from the hardness degree histogram of normal samples.

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 to the models’ parameters. Users are only allowed to query the model via a prediction API and receive the prediction. Recent studies [22, 25, 39, 44, 52] demonstrate that an adversary can use the prediction API to extract a target model and create a surrogate classifier that imitates the target classifier with respect to some criteria, such as accuracy and fidelity. Such attacks are called model extraction attacks, and they violate the intellectual property of model creators. Furthermore, the surrogate classifier can be used to conduct other attacks on the target classifier in the black-box setting, such as adversarial example attacks [25, 44] and membership inference attacks [49].

Most of the model extraction attacks exploit the target classifier to label an unlabeled dataset to create the surrogate classifier’s training set [22,25,39,44,52]. There are two main approaches to defense against model extraction attacks, perturbing the target classifier’s outputs [27, 28, 35, 40] and detecting the sample sequences of attacks [25, 29]. To the best of our knowledge, PRADA [25] is the only approach attempting to detect the sample sequences of model extraction attacks on DNN-based classifiers. Other defenses perturb the outputs of target classifier to decrease the surrogate classifier performance. The methods assume that the outputs of target classifier is probability vectors, and the adversary uses these probability vectors as the labels of the surrogate classifier’s training data. These methods are not applicable to tasks that are sensitive to the actual values of the target classifier outputs, such as medical applications. Besides, when the adversary uses the argmax of the target classifier’s output, they have to decrease the accuracy of target classifier to reduce the performance of surrogate classifier.

In this paper, we propose Hardness-Oriented Detection Approach (HODA), a new approach to detect sample sequences of model extraction attacks. It outperforms PRADA [25] by a large margin and has significantly less computational overhead. Generally, the training process of DNNs is done in several epochs, and the resulted classifier at the end of the last epoch is considered as the final classifier. In the training process of the target classifier, we save the resulted classifier at the end of each epoch and call them subclassifiers. We say a sample is learned in the $i^{th}$ epoch, when the
subclassifier of the \( j^{th} \) epoch is the first subclassifier that all subsequent epochs subclassifiers agree with the predicted label of that subclassifier. We consider the index of the epoch in which a new sample is learned as the hardness degree of that sample. Therefore, when a sample is learned in the early epochs, the hardness degree of that sample is low, and when a sample is learned in the late epochs, the hardness degree of that sample is high.

We call samples that come from the target classifier’s training data distribution as normal samples, and demonstrate that the hardness degree histogram of normal samples is very distinct from the hardness degree histogram of model extraction attacks’ samples. HODA uses this property to detect model extraction attacks. HODA only uses 11 subclassifiers to determine the hardness degree of samples. 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 an adversary.

HODA can detect JBDA [44], JBRAND [25], and Knock-off Net [39] attacks with a high success rate by only watching 100 samples of attack. We demonstrate that HODA is also very effective when the target classifier is trained using transfer learning. We also indicate that the hardness degree histogram of adversarial examples [6, 9, 14, 37, 50] is distinct from the hardness degree histogram of normal samples. Hence, although HODA can not detect a single adversarial example, it can detect sample sequences that the whole or a fraction of them is adversarial examples with a high success rate. We also show the application of hardness degree in determining the trust in the classifiers’ outputs. It is indicated as the hardness degree of a normal sample is increased, the probability of misclassification of that sample is raised.

The main contributions of this paper are as follows:
- We define the hardness degree of samples and show that the hardness degree of samples is relatively transferable among various DNNs’ architectures.
- We show that the hardness degree can be considered as a measure of trust in the outputs of DNN-based classifiers.
- We demonstrate that the performance of model extraction attacks on harder normal samples is lower than easier ones.
- We demonstrate that the hardness degree histogram of normal samples is distinct from the hardness degree histograms of model extraction attacks samples and adversarial examples.
- We propose HODA to detect the sequence of model extraction attacks’ samples. HODA outperforms PRADA [25] by a large margin. We also show that HODA can detect a sequence of samples that includes adversarial examples.

2 Preliminaries

2.1 Deep Neural Networks (DNNs)

A Deep Neural Network (DNN)-based classifier is a hierarchical function \( f : X \rightarrow Y \) that maps the input space \( X \) to the output space \( Y \). DNNs have multiple layers that each layer includes an affine transformation followed up by a non-linear function called activation function. Each DNN has a parameter set \( \theta \) being tuned during the training process to minimize the loss function \( L \) on the training set \( \mathcal{X} \). The training set \( \mathcal{X} = \{(x_i, y_i)\}_{i=1}^N \) consists of \( N \) pairs that each pair includes a sample \( x_i \in \mathbb{R}^d \) and the corresponding label \( y_i \in [K] \), where \( d \) is the input’s dimension, and \( K \) is the number of classes. The output of classifier \( \hat{y}_i = f(x_i) \) is a probability vector over \( K \) classes. The \( j^{th} \) element of \( \hat{y}_i \) indicates the classifier’s confidence that \( x_i \) belongs to the \( j^{th} \) class. Hence, the label of data \( x_i \) is \( \arg\max \{f(x_i)\} \). The loss function \( L \) is used to calculate the distance between label \( y_i \) and the output of classifier \( \hat{y}_i = f(x_i) \) for sample \( x_i \). The minimization of loss function \( L \) is usually done using some common versions of the Stochastic Gradient Descent (SGD). SGD is an iterative algorithm that initializes the classifier’s parameters randomly and then takes a step in the inverse direction of the gradient of loss function with respect to the classifier’s parameters in each iteration.

\[
\theta_{t+1} = \theta_t - \eta_t \frac{\partial L}{\partial \theta}
\]

where \( \eta_t \) is learning rate that regulates the size of steps and is often scheduled to be decreased during the training process. Most often, SGD is run for multiple epochs. All samples in the training set are shuffled and then are partitioned into several mini-batches in each epoch. SGD uses each mini-batch to calculate loss function and updates classifier’s parameters for one step. There are some heuristic methods that determine the number of epochs. However, the number of training epochs is often considered as a hyperparameter and it is determined before the training phase. After the training process is done, the classifier is evaluated on unseen samples in the training phase, which is called test set, to determine the true performance of classifier in practice. For simplicity, we use classifier instead of DNN-based classifier in the rest of the paper.

2.2 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) [7, 10, 25, 36, 39, 44, 52]. The adversary’s goal is to create a surrogate classifier \( f_s \) that imitates a target classifier \( f_t \) on task \( T \). There are two primary intents for adversaries to conduct model extraction attacks, stealing and reconnaissance.

**Stealing** [10, 22, 39, 52]: 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 tasks. 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 the task $T$ data distribution $D_T$ [22, 39]. Hence, the adversary’s goal is:

Maximize $P_{(x,y) \sim D_T}\argmax(f_s(x)) = y$ \hfill (2)

**Reconnaissance** [22, 25, 44]: The model extraction attacks can be used to conduct other attacks in the black-box setting, such as adversarial example attacks [6, 14, 37, 50] and membership inference attacks [49]. Adversarial examples are maliciously crafted inputs that make the target classifier predict incorrectly. The transferability of adversarial examples empowers adversaries to create adversarial examples on the surrogate classifier and transfer them to the target classifier [14, 44]. The membership inference attack determines whether a sample exists in the training set of the target classifier or not [49]. The adversary’s goal in reconnaissance is to train a surrogate classifier that imitates the target classifier’s decision boundaries. As the fidelity of surrogate classifier to the target classifier is increased, the black-box attacks are more successful. Similar to [22], we consider label agreement among surrogate and target classifiers as the fidelity metric on the task $T$ data distribution $D_T$. Hence, the adversary’s goal is:

Maximize $P_{(x,y) \sim D_T}\argmax(f_s(x)) = \argmax(f_t(x))$ \hfill (3)

Existing model extraction attacks can be categorized into two main groups, direct extraction and learning-based extraction. In direct model extraction, adversaries attempt to extract the exact value of target classifier parameters (perfect fidelity) by theoretical approaches [4, 22, 46]. Albeit of the high quality of surrogate classifiers produced by these methods, they are futile against real-world deep classifiers and only work against shallow NNs. Also, they often need to send a sheer number of queries to the target classifier. In this study, we focus on learning-based extraction attacks [10, 22, 25, 39, 44]. In this category, adversaries exploit the target classifier responses as labels of the surrogate classifier’s unlabeled training set. The dataset being used by an adversary to create the surrogate classifier’s training set is a decisive factor of adversary’s strength.

**2.3 Threat Model**

The adversary must select a DNN architecture and create a training set to train a surrogate classifier. We suppose that the adversary knows the architecture, hyperparameters, and input and output types of the target classifier. The capability of an adversary to collect the surrogate model’s training samples can be divided into four categories based on the previous studies.

- **Same Distribution (SD)** [22]: The adversary has access to samples coming from the target model’s training samples distribution $D_T$. Such adversaries are very strong, and is hard to be resisted.

- **Limited Access Same Distribution (LASD)** [25, 44]: The adversary has access to the limited number of samples coming from the target model’s training samples distribution $D_T$. Such adversaries try to augment collected samples to increase the performance of the surrogate classifier.

- **Similar Distribution (SD)** [10, 39, 41]: The adversary has access to the natural samples whose distribution is similar to $D_T$. For example, Knockoff Net [39] uses ILSVRC12 dataset [11] to extract target image classifiers.

- **Synthetic Data (SyD)** [2, 26, 53]: The adversary neither has access to the samples of target model’s training set distribution $D_T$ nor natural samples from similar distributions. Hence, she uses synthetic samples to create surrogate classifier’s training set. Since proposed methods in this category must send a lot of samples (in order of millions) to the target classifier, they are impractical.

We focus on LASD and SiD adversaries in this study.

**3 Hardness of Samples**

As mentioned in section 2.1, the training process of classifiers is done in several epochs. Hence, we can consider a classifier’s training process as a sequence of classifiers in which the last classifier is considered the final classifier being deployed in practice. Suppose that the classifier $f_i$ is trained for $m$ epochs. The training process of classifier $f_i$ can be represented as the following sequence:

$< f_i^0, f_i^1, f_i^2, ..., f_i^{m-1} >$ \hfill (4)

where $f_i^j$ is the classifier $f_i$ at the end of the $j^{th}$ epoch. The classifiers being created at the end of each epoch is called sub-classifiers, and the $i^{th}$ sub-classifier $f_i^j$ is the classifier being created at the end of epoch $i$. We say sample $x_i$ is learned in epoch $e$ when $f_i^e$ is the first sub-classifier that the assigned label by $f_i^e$ is equal to all subsequent sub-classifiers. Generally, as the number of epochs is increased, the performance of classifier $f_i$ is improved. Hence, when a sample is learned in the early epochs, we consider it as a easy sample, and when it is learned in higher epochs, we consider it as a harder
The hardness degree of a sample is in the range \( m \) subclassifiers. When we have \( m \) subclassifiers, the hardness degree range is dependent on the number of subclassifiers. Therefore, the hardness degree of sample \( x_i \) for classifier \( f_i \), which is displayed by \( \phi_{f_i}(x_i) \), directly relates to the epoch number that \( x_i \) is learned by \( f_i \). Hence, \( \phi_{f_i}(x_i) \) is defined as follows:

\[
\phi_{f_i}(x_i) = e \quad \text{s.t.} \quad e \in [0, m - 1], \forall j \in [e, m - 1], \\
argmax(f_j^e(x_i)) = \argmax(f_i^j(x_i)), \\
argmax(f_j^e(x_i)) \neq \argmax(f_i^{e-1}(x_i)). 
\]

The hardness degree range is dependent on the number of subclassifiers. When we have \( m \) subclassifiers, the hardness degree of a sample is in the range \([0, m - 1]\). We train three various types of classifiers, including DenseNet121 [21], ResNet18 [18], and MobileNet [48], on CIFAR10 and CIFAR100 training sets [31] for 100 epochs. The details of datasets are presented in Appendix A. All classifiers are trained using stochastic gradient descent with momentum 0.9 and batch size 128. The learning rate is scheduled to be decreased in each epoch by a constant factor 0.955, so that starts by 0.1 and finishes by 0.001. The accuracy of classifiers is presented in Table 1. We save all 100 subclassifiers in the training process of each classifier and use them to calculate the hardness degree of a sample. Figure 1 shows the hardness degree histogram of CIFAR10 and CIFAR100 test sets 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.

### 3.1 Hardness Transferability

We introduce hardness rank to evaluate the dependency between classifiers’ architectures and the hardness of samples. The hardness rank of sample \( x_i \) for classifier \( f_i \), which is displayed by \( \Omega_f(x_i) \), determines the rank of sample \( x_i \) among all samples based on the hardness degree \( \phi_{f}(x_i) \). Let \( S \) is the set of all samples, and the function \( \text{sort} \) ascending sorts all samples based on the hardness degree. The hardness rank of sample \( x_i \) is \( r \), if sample \( x_i \) is the \( r^{th} \) element of the sorted sample set \( \text{sort}(S) \). We have:

\[
\Omega_f(x_i) = r \quad \text{s.t.} \quad \text{sort}(S)[r] = x_i 
\]

where \( \text{sort}(S)[r] \) is the \( r^{th} \) element of \( \text{sort}(S) \). 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 classifiers, we compare the hardness rank of samples among multiple pairs of classifiers. For two 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 sets for the classi-
The new classifier is trained the same as the other classifiers. Each plot of Figure 2 shows the hardness rank of samples for a pair of classifiers. The first row of Figure 2 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 2 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. We also investigate the correlation between samples’ hardness degrees among pairs of classifiers in Appendix B.

We find ResNet18 architecture achieves strong performance on both datasets at a reasonable computational cost. Therefore, we use this architecture for the classifiers in the rest of the paper.

3.2 Hardness-Based Trust Measure

One of the most important challenges in trustworthy machine learning is to measure the trust in the classifier’s outputs. It is vital to determine the magnitude of trust in the classifier’s outputs in critical and security-sensitive tasks [24]. We use the hardness degree of samples as a new measure for estimating the trust in the classifier’s outputs. Figure 3 shows the percentage of samples being classified correctly and wrongly in 10 ranges of hardness degrees for CIFAR10 and CIFAR100 test sets. The results demonstrate that as the hardness degree of samples is increased, the fraction of samples being correctly classified is reduced. 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 datasets, respectively. Therefore, as the hardness degree of a sample is increased, the magnitude of trust in the classifier’s output for that sample is reduced. Let the hardness degree of sample $x_j$ is $h$. The magnitude of trust in the classifier’s output is equal to the percentage of test samples being correctly classified, and their hardness degree is in range $R$, where $h \in R$. For example, suppose that the classifier is ResNet18 and the dataset is Cifar10, based on Figure 3 the magnitude of trust in the classifier’s output for sample $x_j$ with hardness degree $\phi_f(x_j) = 67$ is 76.48% ($R = [60, 69]$).
4 Model Extraction Attacks

As mentioned in section 2.3, the existing model extraction attacks can be partitioned into four categories, SD, LASD, SiD, and SyD. We consider two attacks, Jacobian-Based Dataset Augmentation (JBDA) [44] and its improvement (JBRAND) [25], in LASD category. These attacks assume that the adversary has access to the limited number of samples from the target classifier’s training data distribution called seed samples. Both attacks aim to augment seed samples using adversarial examples to increase the fidelity of the surrogate classifier to the target classifier. The JBDA attack uses Fast Gradient Sign Method (FGSM) [14] attack in multiple rounds to augment seed samples. The JBRAND attack is proposed to improve the performance of JBDA attack. It uses iterative FGSM in multiple rounds to augment seed samples and makes targeted adversarial examples with random targets.

The adversary in SiD category has access to natural samples from the distribution close to the target classifier’s training data distribution. Orekondy et al. [39] propose Knockoff Net (K.Net) attack that uses large public datasets to increase the accuracy of the surrogate classifier. K.Net attack sends natural samples in public datasets to the target classifier and uses the target classifier’s output as the label of the surrogate classifier’s training set. We consider two versions of K.Net attack, K.Net CIFARX, and K.Net TIN. The K.Net CIFARX attack uses CIFAR100 training set to extract the target classifier being trained on CIFAR10 training set and vice versa. K.Net TIN employs TinyImageNet [34] training set to extract target classifiers. More details about attacks and their implementations are presented in Appendix C.

4.1 Model Extraction Attacks Evaluation

All mentioned attacks create the surrogate classifier training set \( \mathcal{X}_s = \{(x_i, f_t(x_i))\}_{i=1}^B \) by various methods, where \( B \) is the attack budget. The attack budget determines the number of samples that an adversary sends to the target classifier and receives their associated outputs. After creating \( \mathcal{X}_s \), all attacks train a surrogate classifier \( f_s \) on \( \mathcal{X}_s \). Previous studies [39, 44] demonstrate that surrogate classifier’s architecture has a low impact on the performance of model extraction attacks. Hence, we consider the architecture and the training process of surrogate classifiers as the same as the architecture and the training process of target classifiers.

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 output type of target classifiers can be different, such as label, label confidence, top-k value in probability vector, and entire probability vector. We only consider label and entire probability vector as the output type of target classifiers in our experiments. The default value of the attack budget in our experiments is 50000 (B=50K). We evaluate the accuracy and the fidelity of a surrogate classifier on the test set of the target classifier dataset.

Table 2 shows the accuracy and the fidelity of various
attacks on two target classifiers. 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. The performance of K.Net CIFARX and K.Net TIN are close to each other on CIFAR10 target classifier; however, K.Net TIN has better performance on CIFAR100 target classifier. An interesting observation is that the fidelity and the accuracy of various attacks are close together. We suppose the output type of target classifiers is probability vector in the rest of the paper.

4.2 Hardness Analysis of Attacks

To give new insight into model extraction attacks, we investigate the performance of model extraction attacks on 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 samples’ hardness degree. 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 4 shows the accuracy and the fidelity of attacks over 10 hardness groups when the output of target classifier is a probability vector. We also replicate this experiment when the output of target classifier is only label, and the results are presented in Appendix D. 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 3 that the accuracy of target classifiers is decreased by increasing the hardness of samples, and Figure 4 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 4 shows the percentage of samples being classified correctly by both surrogate classifier and target 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. [22] 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 dis-
agreement 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.

5 Hardness-Oriented Detection Approach

We propose a new method to detect sample sequences of model extraction attacks, based on the distinction among the hardness of normal and attack samples called Hardness-Oriented Detection Approach (HODA). HODA uses the hardness degree histogram of samples to detect model extraction attacks. Figure 5 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 attacks’ samples when the architecture of target classifiers is Densenet121 in Appendix E. Figure 5 demonstrates that the samples generated by various attacks have a very small number of easy samples, and a majority of samples have average and high hardness degrees. However, Figure 1 indicates that a high number of samples from the same distribution as the target classifier’s training set (normal samples) are easy. We use histogram rather than hardness degree histogram in the rest of the paper for simplicity.

HODA uses Pearson metric to evaluate the histogram of samples sent by a user to detect model extraction attacks. Hence, HODA only keeps a histogram for each user. Notably, HODA does not need to save samples of each user or their hardness degree. 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. Hence, HODA only keeps a vector of integers that indicates the number of samples in each bin of the histogram. So far, 100 subclassifiers have classified each sample to create the hardness degree histograms. However, it may not be possible to classify each sample by a high number of subclassifiers in practice. Hence, HODA only uses 11 subclassifiers to calculate the hardness degree of each sample, and these subclassifiers are selected in the training phase of target classifier $f_t$ at the end of each 10 epochs $<f_t^0, f_t^1, f_t^2, f_t^3, f_t^4, f_t^5, f_t^6, f_t^7, f_t^8, f_t^9, f_t^{10} >$. Since the range of hardness degrees is dependent on the number of subclassifiers being used to calculate hardness degree, the hardness degree of a sample in HODA is in the range $[0, 10]$.

Pearson distance between two random variable $X$ and $Y$ is defined as follows:

$$Dist_P(X, Y) = 1 - \rho_{XY}$$

where $\rho_{XY}$ is Pearson correlation which is defined as follows:

$$\rho_{XY} = \frac{COV(X, Y)}{\rho_X \rho_Y}$$

(8)

where $COV(X, Y)$ is the covariance between random variables $X$ and $Y$, and $\rho_X$ 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, we first divide the number of samples in each bin of a histogram by the total number of samples in that histogram to transform a histogram into a probability distribution and then calculate the Pearson distance between two probability distributions.

HODA requires normal histogram $H_n$ that represents the histogram of a normal user’s samples. When the number of samples being sent by a user reaches a specific number $num_u$, HODA calculates Pearson distance between the histograms of normal samples $H_n$ and user samples $H_u$. If the distance is greater than a threshold $\delta$, the user $u$ is detected as an adversary, or in MLaaS, the price of each query can be increased.

HODA uses normal sample set $S_{normal}$ to create $H_n$ and calculate $\delta$. It creates sequence set $Seq_{normal}$ from $S_{normal}$ so that each sequence has $num_s$ samples and samples are randomly selected from $S_{normal}$. Then, HODA creates a set of hardness degree histograms called $H_{Seq_{normal}}$ through producing a hardness degree histogram for each sequence in $Seq_{normal}$. The normal histogram $H_n$ is the average of all histograms in $H_{Seq_{normal}}$, and $\delta$ is the maximum Pearson distance between $H_n$ and all histograms in $H_{Seq_{normal}}$. Since $\delta$ is independent of attacks and only relies on normal samples, HODA is not dependent on any attacks.

5.1 Setup and Evaluation

We need two sets of normal samples to evaluate HODA, $S_{HODA}$ and $S_a$. We randomly select 40% and 60% of test samples of each dataset for $S_{HODA}$ and $S_a$, respectively. $S_a$ is used to simulate benign users. We consider 10000 benign users, and each benign user sends a sequence of $num_s$ samples being randomly selected from $S_a$. We consider 40000 sequences of $num_s$ samples drawn randomly from $S_{HODA}$ to create $H_n$ and calculate $\delta$. We simulate 10000 adversaries for each attack to evaluate the performance of HODA against various model extraction attacks. We have generated 50000 samples for each attack in previous experiments. For each attack, the adversary sends a sequence of $num_s$ samples drawn randomly with preserve order from 50000 samples of that attack.

To the best of our knowledge, PRADA [25] is the only defense that is comparable to HODA. PRADA declares that the distribution of the minimum distance between samples of benign users is normal. Hence, it uses the Shapiro-Wilk normality test to determine that a sequence of samples belongs to a benign user or an adversary. Similar to HODA, PRADA
Figure 5: 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.

Table 3: The detection rate and False Positive Rate (FPR) of PRADA and HODA against four various model extraction attacks. The FPR indicates the percentage of benign users’ sample sequences that are detected as the sample sequence of model extraction attacks.

| num_s | Detection Rate of Attacks(%) | PRADA | HODA |
|-------|------------------------------|-------|------|
|       | num_s | δ     | FPR(%) | JBDA | JBRAND | K.Net CIFARX | K.Net TIN |
| CIFAR10 | 100  | 0.929 | 0.15   | 68.0 | 51.3 | 0.2 | 0.1 |
|        | 500  | 0.984 | 0.00   | 96.5 | 100  | 1.9 | 0.3 |
| CIFAR100 | 100 | 0.141 | 0.04   | 100  | 100  | 100 | 100 |
|        | 500  | 0.025 | 0.06   | 100  | 100  | 100 | 100 |

Table 3 indicates the performance of PRADA and HODA for both target classifiers, CIFAR10 and CIFAR100. We evaluate PRADA and HODA when the number of a user’s samples reaches 100 and 500 (num_s = 100 and num_s = 500). False-Positive Rate (FPR) indicates the percentage of benign users’ sample sequences being detected as an attack. PRADA and HODA have very low false-positive rates. The results demonstrate that HODA is very effective against model extraction attacks, and it outperforms PRADA. Since knockoff Net attacks [39] use natural samples, PRADA can also uses threshold δ to detect the 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.

5.2 Transfer Learning

Transfer learning is a machine learning technique that initializes the parameters of the target task classifier using the parameters of a trained source task classifier. The target task classifier uses the knowledge in the pre-trained classifier and attempts to tune the parameters of the pre-trained classifier to adapt to the target task domain. Many studies have shown that the DNN’s layers trained on a source task with a large-scale labeled dataset can be used as starting point of a target task classifier having substantially less available data [42]. We train two new target classifiers on CUB200 [54] and Caltech256 [15] datasets using transfer learning. The details of datasets are presented in Appendix A, and the training process of new target classifiers is the same as the CIFAR10 and CIFAR100 target classifiers (Section 3). We initialize the parameters of target classifiers from a pre-trained ImageNet [11] classifier and train all layers of target classifiers. Notably, the last layer of target classifiers is trained from scratch. Orekondy et al. [40] indicate that jacobian-based model extraction attacks have very poor performance on high dimensional datasets. Hence, we only evaluate the performance of target classifiers against K.Net ILSVRC12. K.Net ILSVRC12 is the Knockoff Net attack that uses ILSVRC12 [11] dataset as the surrogate classifier’s training set. The accuracy of target classifiers and K.Net ILSVRC12 surro-
Table 4: The accuracy of CUB200 and Caltech256 target classifiers, and the accuracy of K.Net ILSVRC12 surrogate classifiers on both target classifiers.

| Test set       | CUB200 | Caltech256 | K.Net ILSVRC12 |
|----------------|--------|------------|----------------|
| Accuracy (%)   | 73.7   | 77.2       | 59.3           |

Table 5: The detection rate and False Positive Rate (PFR) of HODA against K.Net ILSVRC12 attack.

| num_s | Detection Rate (%) | FPR(%) | K.Net ILSVRC12 |
|-------|--------------------|--------|----------------|
| CUB200| 100                | 0.152  | 0.01           |
| 500   | 0.017              | 0.02   | 100            |
| Caltech256| 100 | 0.393  | 0.02           |
| 500   | 0.076              | 0.02   | 100            |

6 Adversarial Examples (AEs)

Adversarial examples (AEs) are maliciously crafted inputs that cause the target classifier to misclassify input. 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 as follows:

$$x' = x + \eta \quad s.t. \quad f_t(x') = y', \quad y \neq y', \quad \| \eta \|_p \leq \varepsilon. \quad (9)$$

There are numerous methods to generate adversarial examples such as L-BFGS [50], FGSM [14], C&W [6], PGD [37], and AutoAttack (AA) [9]. Also, there are several defenses against adversarial examples, such as adversarial training [32,37], adversarial example detection [16,38], and certified robustness [45, 55]. The defense methods commonly focus on creating a robust classifier or detecting a single adversarial example. Some previous studies investigate the performance of proposed defenses and demonstrate their limitations [5,33,58]. To investigate the hardness of adversarial examples, we use FGSM [14], C&W [6], PGD [37], and AA [9] 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. The details of these four attacks and their implementations are presented in Appendix F. Figure 7 indicates 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.

It is obvious that HODA can not detect a single adver-
Figure 7: 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.

Figure 7: 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.

sarial example. However, there are situations that an adversary sends several samples to the target classifier that a fraction of which is adversarial examples. For example, when an adversary wants to send spam emails to several victims or send several malicious network flows to various receivers, she must generate several adversarial examples to evade DNN-based spam detectors [13] or network traffic classifiers [47]. In these situations, HODA can be used to separate adversaries from benign users. To evaluate HODA in this setting, we replicate the experiments performed to detect model extraction attacks; however, rather than an adversary sends samples of model extraction attacks, she sends a set of samples that a fraction of them is adversarial examples and the rest of them is normal samples. We consider four scenarios in which 10%, 25%, 50%, and 100% of an adversary’s samples are adversarial examples. We suppose a defender can monitor samples that each user sends to the target classifier. Table 6 indicates the performance of HODA in four mentioned scenarios for CIFAR10 and CIFAR100 target classifiers, when HODA only watches 100 or 500 samples of each user (\(num_s = 100\) and \(num_s = 500\)). Notably, Since HODA only dependent on the histogram of normal samples, we use the same \(\delta\) that we used to detect model extraction attacks. AE percentage indicates what percentage of adversaries’ sample sequences are adversarial examples. For CIFAR10 target classifier, the performance of HODA against FGSM and C&W attacks is similar to CIFAR10 target classifier; however, HODA performs relatively poor against PGD and AA attacks. We indicate that the performance of HODA against PGD and AA attacks considerably improves when HODA uses 100 subclassifiers to determine the hardness degree of samples in Appendix G.

7 Discussion

An adaptive adversary who is aware of HODA can potentially modify her attack to evade it. Fundamentally, model extraction attacks can evade HODA if they have access to the samples that come from the target classifier’s training data distribution. However, this is a strong threat model, and in most studies, it is supposed that there is no such access [25, 39, 44]. An adaptive adversary must send her queries based on the hardness degree histogram of normal samples to evade HODA. There are two reasons why such attack is hard to conduct.

1. 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.

2. The adversary has no access to the histogram of normal samples to generate samples based on it.

We propose HODA to detect sample sequences of model extraction attacks. However, some other policies can be de-
Table 6: The detection rate and False Positive Rate (FPR) of HODA against four various adversarial example attacks. The FPR indicates the percentage of benign users’ sample sequences that are detected as sample sequences of attacks. AE percentage indicates what percentage of adversaries’ sample sequences are adversarial examples.

|               | CIFAR10                  | CIFAR100                  |
|---------------|--------------------------|---------------------------|
|               | Detection Rate of Attacks(%) | Detection Rate of Attacks(%) |
|               | AE Percentage(%) | FGSM | C&W | PGD | AA | AE Percentage(%) | FGSM | C&W | PGD | AA |
| **num:** 100  | 10                       | 0.07 | 0.17 | 0.11 | 0.18 | 10                       | 0.46 | 0.4  | 0.06 | 0.06 |
| **δ:** 0.141  | 25                       | 1.41 | 2.02 | 3.61 | 8.49 | 25                       | 6.45 | 9.27 | 0.09 | 0.2  |
| **FPR:** 0.04%| 50                       | 85.98| 95.79| 82.3 | 97.47| 50                       | 88.52| 98.49| 0.37 | 1.51 |
|               | 100                      | 100 | 100 | 100 | 100 | 100                      | 100 | 100 | 100 | 100 |
| **num:** 500  | 10                       | 0.56 | 0.42 | 1.01 | 2.2 | 10                       | 2.64 | 2.5  | 0.29 | 0.29 |
| **δ:** 0.025  | 25                       | 57.24| 63.99| 90.18| 99.28| 25                       | 82.38| 96.81| 0.37 | 12.42|
| **FPR:** 0.06%| 50                       | 100 | 100 | 100 | 100 | 50                       | 100 | 100 | 5.86 | 20.42|
|               | 100                      | 100 | 100 | 100 | 100 | 100                      | 100 | 100 | 5.86 | 20.42|
| **num:** 500  | 10                       | 2.64 | 2.5  | 0.29 | 0.29 | 10                       | 82.38| 98.49| 0.37 | 59.02|
| **δ:** 0.263  | 25                       | 82.38| 96.81| 13.24| 12.44| 25                       | 100 | 100 | 5.86 | 20.42|
| **FPR:** 0.05%| 50                       | 100 | 100 | 100 | 100 | 50                       | 100 | 100 | 5.86 | 20.42|
|               | 100                      | 100 | 100 | 100 | 100 | 100                      | 100 | 100 | 5.86 | 20.42|

8 Related Works

Some recent studies investigate the dynamic of the DNNs training process [12, 17]. Hacohen et al. [17] demonstrate that DNNs learn samples in both the training and test sets in a similar order. Frankle et al. [12] indicate that the DNN-based classifiers undergo substantial changes in the first few SGD iterations. The magnitude of gradients in the first iterations is larger than the next iterations, and the sign of most parameters is determined in the first few iterations. In the following, we briefly review the most prominent model extraction attacks and defenses presented so far.

8.1 Model Extraction Attacks

For the first time Lowd and Meek [36] demonstrate the possibility of stealing simple linear machine learning models through only interaction with them. Tramer et al. [52] show the feasibility of model extraction attacks on commercial MLaaS. Papernot et al. [44] and Juuti et al. [25] investigate stealing DNN-based classifiers and propose jacobian-based model extraction attacks for creating a surrogate classifier to generate adversarial examples in the black-box setting. Chandrasekaran et al. [7] 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. [22] exploit unlabeled samples using semi-supervised learning to improve the performance of model extraction attacks. Knockoff Net [39], ActiveThief [41], and Copycat CNN [10] use a 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. [57] employ active learning, transfer learning, and a new method for generating adversarial examples to improve model extraction attack efficiency. A line of studies [2, 26, 53] uses synthetic data to create the training set of surrogate classifier. 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, [53] and [26] 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 [30], Graph DNN [19], and Reinforcement learning [8] models against model extraction attacks. Another type of model extraction attack uses hardware side-channel vulnerabilities to extract a target classifier [3,20,56,60]. However, these attacks have a very strong threat model and suppose the adversary has access to the hardware that hosts the target classifier.

8.2 Defenses against Model Extraction Attacks

Existing defense methods against model extraction attacks generally distribute into two branches: perturbation-based and detection-based. Perturbation-based defenses [27, 28, 35, 40] attempt to prevent adversaries from producing high-quality surrogate classifiers by adding perturbation to the output of target classifier. These methods assume that the output of target classifier is a probability vector, and the adversary uses these probability vectors as the labels of the surrogate classifier’s training data. These methods have two main drawbacks. First, perturbing the probability vector may have severe impacts on the decisions made based on the tar-
get classifier’s output in critical applications. Second, when the adversary uses the argmax of the target classifier’s output, they have to decrease the accuracy of target classifier to reduce the performance of surrogate classifier. Proposed detection-based defenses [25,29] attempt to detect the occurrence of model extraction attacks by observing successive input queries to the target classifier. Kesarwani et al. [29] propose a method to measure adversary perceived knowledge from target classifier, but this method only works for Decision Tree models. Prada [25] is the first proposed detection-based defense for DNN models. Prada uses the histogram of the minimum $L_2$-norm 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 [41]. Watermarking neural networks [1, 23, 51, 59] 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.

9 Conclusions

This paper demonstrates that the hardness degree of samples is important in trustworthy machine learning. We defined the hardness degree of samples and demonstrated that the hardness of a sample is relatively transferable among various architectures of classifiers. We investigated the hardness degree of samples of model extraction attacks and showed that the hardness degree histogram of these samples is different from the hardness degree histogram of normal samples. Using this property, Hardness-Oriented Detection Approach (HODA) can detect sample sequences of model extraction attacks. It is also indicated that HODA is effective even when the target classifier is trained using transfer learning. 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 attacks. We indicated that the hardness degree histogram of adversarial examples differs from the hardness degree histogram of normal samples, and HODA can detect sample sequences partially included by adversarial examples. We also showed that the hardness degree could be used as a measure of trust in the output of classifiers.

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A Datasets

CIFAR10 [31]: 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 [31]: 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 [34]: TinyImageNet is a subset of ILSVRC12 [11] 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 [54]: 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 [15]: 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 [11]: 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 Degree Correlation

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

\[ \rho_{XY} = \frac{\text{COV}(X, Y)}{\rho_X \rho_Y} \]  \hspace{1cm} (10)

where \( \text{COV}(X, Y) \) is the covariance between random variables X and Y, and \( \rho_X \) is the standard deviation of random variable X. The Pearson correlation coefficient \( \rho_{XY} \) is in the range \([-1, 1]\). When \( \rho_{XY} \) is close to one, two random variables are highly correlated which means that if one of them is increased, the other one is increased, too, and vice versa. Table 7 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.

C Details of Model Extraction Attacks

Jacobian-Based Dataset Augmentation (JBDA) [44]: The goal of JBDA attack is to increase the fidelity of the surrogate classifier to the target classifier 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. The target classifier labels the seed samples in the first step, and these samples are added to the surrogate training set \( \mathcal{X}_s \). In the next steps, new perturbed samples \( (\mathcal{S}_s^{p+1} / \mathcal{S}_s^p) \) are labeled by the target classifier and are added to the surrogate training set \( \mathcal{X}_s \).

2. The surrogate classifier \( f_s \) is trained on \( \mathcal{X}_s \).

3. The samples in the training set \( \mathcal{X}_s \) is called sample set \( \mathcal{S}_s \). For each sample in \( \mathcal{S}_s \), a new perturbed sample is created according to the following equation and is added to \( \mathcal{S}_s \):

\[ \mathcal{S}_s^{p+1} = \mathcal{S}_s^p \cup \{ x + \lambda_{p+1} \cdot \text{sign}(J_{f_s}(x)) : x \in \mathcal{S}_s^p \} \]  \hspace{1cm} (11)

where \( \mathcal{S}_s^p \) is the surrogate training set in round \( p \), \( \lambda \) is step size, and \( J \) is jacobian function.

The attack is implemented with default hyperparameters (\( \lambda = 0.1 \)). 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) [25]: The goal of JBRAND is to improve the performance of JBDA. It perturbs each sample in multiple iterations to generate more powerful adversarial examples and generates targeted adversarial examples with random targets. We generate three adversarial examples with random targets for each sample in

Table 7: Pearson correlation coefficient of CIFAR10 and CIFAR100 test samples’ hardness degree for various pairs of classifiers.

| \( \rho_{XY} \) | 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    |
\( x \) and use the same seed samples as JBDA. Each sample is perturbed in five iterations with \( \varepsilon = \frac{64}{225} \). The other hyperparameters are set by default values \( (\lambda = \frac{64}{225}) \).

**Knockoff Net (K.Net)** [39]: Knockoff Net attack fills the surrogate classifier’s training set by natural samples from a distribution that is close to the target classifier’s training set distribution. The attack uses large public datasets, such as ILSVRC12, to create the surrogate classifier’s training set. 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 random strategy. 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 \( \mathcal{X}_s = \{(x_i, f_s(x_i))\}_{i=1}^\gamma \). Finally, it uses the surrogate classifier’s training set to train a surrogate classifier.

**D Label-Only Attacks Hardness Analysis**

Figure 8 shows the accuracy and the fidelity of attacks over 10 hardness groups when the output of target classifier is only label.

**E DenseNet121 Hardness Degree Histograms**

Figure 9 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.

**F Details of Adversarial Example Attacks**

We employ Adversarial Robustness Toolbox (ART)\(^1\) and AutoAttack\(^2\) repositories to generate adversarial examples. Except for attacks’ hyperparameters being mentioned in the following, we use the default values for the rest of the hyperparameters. All attacks generate untargeted adversarial examples in the white-box setting. The success rates of attacks are presented in Table 8.

**Fast Gradient Sign Method (FGSM)** [14]: FGSM is a one-step attack that uses \( L_\infty \)-norm to control the magnitude of perturbations being added to normal samples. This attack calculates the gradient of the loss function with respect to the input and takes one step with size \( \varepsilon \) in the gradient’s direction.

\[
    x' = x + \varepsilon \cdot sign(\nabla_x L(\theta, x, y))
\]  

(12)

We use \( \varepsilon = 0.1 \) to generate adversarial examples.

**Carlini and Wagner (C&W)** [6]: Carlini and Wagner propose an iterative attack to break defensive distillation

\[
    x_{t+1} = x_t + \eta \cdot sign(\nabla_x L(\theta, x_t, y))
\]  

(13)

\[
    s.t. \ x + \eta \in Domain(x)
\]

(14)

where \( D(x, x + \eta) + c \cdot g(x + \eta) \) is the objective function. The authors consider several objective functions and pick one of them based on the experiments. We use \( L_\infty \)-norm variant to generate adversarial examples in five iterations and use five binary search steps to select \( c \).

**Projected Gradient Decent (PGD)** [37]: PGD is an iterative method that improves FGSM to generate more powerful adversarial examples. In each iteration, PGD takes one step with size \( \alpha \) in the direction of loss function gradient with respect to the input. It uses projection \( \Pi_{\varepsilon} \) to restrict the \( L_\infty \)-norm of perturbation to \( \varepsilon \).

\[
    x_{t+1} = \Pi_{\varepsilon}(x_t' + \alpha \cdot sign(\nabla_x L(\theta, x_t, y)))
\]  

(13)

We use 50 iterations to generate each adversarial example with \( \alpha = \frac{3}{255} \) and \( \varepsilon = \frac{8}{255} \).

**AutoAttack (AA)** [9]: AA using some techniques, such as step size selection, improves the performance of PGD attack. AA is a parameter-free attack. We use \( L_\infty \)-norm to restrict the size of perturbation and \( \varepsilon = \frac{8}{255} \) to generate adversarial examples.

**G Detecting Adversarial Example Sequences**

Table 9 shows the performance of HODA against four adversarial examples attacks when HODA uses 100 subclassifiers to calculate the hardness degree of samples. We observed that when we use hardness degree histograms that have 10 bins rather than 100 bins, the performance of HODA is increased. Hence, although the hardness degree of samples is in the range \([0,99]\), we divide the hardness degree of samples by 10 to the number of bins in hardness degree histograms decreases to 10.

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\(^1\)https://github.com/Trusted-AI/adversarial-robustness-toolbox

\(^2\)https://github.com/fra31/auto-attack
Figure 8: The accuracy and the fidelity of four model extraction attack surrogate classifiers on both target classifiers CIFAR10 and CIFAR100 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 $f_s$. The output of target classifiers are only labels.

Figure 9: 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.
Table 9: The detection rate and False Positive Rate (PFR) of HODA against four various adversarial example attacks. HODA uses 100 subclassifiers to calculate the hardness degree of samples. The FPR indicates the percentage of benign users’ sample sequences that are detected as sample sequences of attacks. AE percentage indicates what percentage of adversaries’ sample sequences are adversarial examples.

|                  | Detection Rate of Attacks(%) | CGSM | C&W  | PGD  | AA   |
|------------------|-----------------------------|------|------|------|------|
| **CIFAR10**      |                             |      |      |      |      |
| num.; 100        | 10                          | 0.02 | 0.08 | 0.2  | 0.2  |
| δ: 0.164         | 25                          | 1.8  | 11.8 | 10.4 | 21.5 |
| FPR: 0.04%       | 50                          | 96.6 | 99.9 | 97.1 | 99.1 |
|                  | 100                         | 100  | 100  | 100  | 100  |
| num.; 500        | 10                          | 0.12 | 0.89 | 15.35| 31.1 |
| δ: 0.022         | 25                          | 83.3 | 99.9 | 99.9 | 99.5 |
| FPR: 0.07%       | 50                          | 100  | 100  | 100  | 100  |
|                  | 100                         | 100  | 100  | 100  | 100  |
| **CIFAR100**     |                             |      |      |      |      |
| num.; 100        | 10                          | 0.03 | 0.16 | 0.02 | 0.03 |
| δ: 0.660         | 25                          | 3.2  | 10.6 | 0.3  | 0.3  |
| FPR: 0.01%       | 50                          | 74.6 | 98.8 | 11.2 | 13.7 |
|                  | 100                         | 99.8 | 100  | 97.4 | 99.1 |
| num.; 500        | 10                          | 2.3  | 21.6 | 3.2  | 1.9  |
| δ: 0.144         | 25                          | 94.6 | 100  | 97.3 | 85.7 |
| FPR: 0.03%       | 50                          | 100  | 100  | 100  | 100  |
|                  | 100                         | 100  | 100  | 100  | 100  |