EXTRACTING ROBUST MODELS WITH UNCERTAIN EXAMPLES

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ABSTRACT

Model extraction attacks are proven to be a severe privacy threat to Machine Learning as a Service (MLaaS). A variety of techniques have been designed to steal a remote machine learning model with high accuracy and fidelity. However, how to extract a robust model with similar resilience against adversarial attacks is never investigated. This paper presents the *first* study toward this goal. We first analyze that those existing extraction solutions either fail to maintain the model accuracy or model robustness, or lead to the robust overfitting issue. Then we propose Boundary Entropy Searching Thief (`BEST`), a novel model extraction attack to achieve both accuracy and robustness extraction under restricted attack budgets. `BEST` generates a new kind of *uncertain examples* for querying and reconstructing the victim model. These samples have uniform confidence scores across different classes, which can perfectly balance the trade-off between model accuracy and robustness. Extensive experiments demonstrate that `BEST` outperforms existing attack methods over different datasets and model architectures under limited data. It can also effectively invalidate state-of-the-art extraction defenses.

1 INTRODUCTION

Recent advances in deep learning (DL) and cloud computing technologies boost the popularity of Machine Learning as a Service (MLaaS), e.g., AWS SageMaker (sag, 2022), Azure Machine Learning (azu, 2022). This service can significantly simplify the DL application development and deployment at a lower cost. Unfortunately, it also brings new privacy threats: an adversarial user can query a target model and then reconstruct it based on the responses (Tramèr et al., 2016; Orekondy et al., 2019; Jagielski et al., 2020b; Yuan et al., 2020; Yu et al., 2020). Such model extraction attacks can severely compromise the intellectual property of the model owner (Jia et al., 2021), and facilitate other black-box attacks, e.g., data poisoning (Demontis et al., 2019), adversarial examples (Ilyas et al., 2018), membership inference (Shokri et al., 2017).

Existing model extraction attacks can be classified into two categories (Jagielski et al., 2020b). (1) *Accuracy extraction* aims to reconstruct a model with similar or superior accuracy compared with the target model. (2) *Fidelity extraction* aims to recover a model with similar prediction behaviors as the target one. In this paper, we propose and consider a new category of attacks: *robustness extraction*. As DNNs are well known to be vulnerable to adversarial attacks (Szegedy et al., 2014), it is common to train highly robust models for practical deployment, especially in critical scenarios such as autonomous driving (Shen et al., 2021), medical diagnosis (Rendle et al., 2016) and anomaly detection (Goodge et al., 2020). Then an interesting question is: *given a remote robust model, how can the adversary extract this model with similar robustness as well as accuracy under limited attack budgets?* We believe this question is important for two reasons. (1) With the increased understanding of adversarial attacks, it becomes a trend to deploy robust machine learning applications in the cloud (Goodman & Xin, 2020; Rendle et al., 2016; Shafique et al., 2020), giving the adversary opportunities to steal the model. (2) Training a robust model usually requires much more computation resources and data (Schmidt et al., 2018; Zhao et al., 2020), giving the adversary incentives to steal the model.

We review existing attack techniques and find that they are incapable of achieving this goal, unfortunately. Particularly, there can be two kinds of attack solutions. (1) The adversary adopts clean samples to query and extract the victim model (Tramèr et al., 2016; Orekondy et al., 2019; Pal et al., 2020). However, past works have proved that *it is impossible to obtain a robust model only from clean*

data (Zhao et al., 2020; Rebuffi et al., 2021). Thus, these methods cannot preserve the robustness of a robust victim model, although they can effectively steal the model's clean accuracy. (2) The adversary crafts adversarial examples (AEs) to query and rebuild the victim model (Papernot et al., 2017; Yu et al., 2020). Unfortunately, building models with AEs leads to two unsolved problems: (1) *improving the robustness with AEs inevitably sacrifices the model's clean accuracy* (Tsipras et al., 2019); (2) *with more training epochs, the model's robustness will decrease as it overfits the generated AEs* (Rice et al., 2020). We will conduct experiments to validate the limitations of prior works in Section 3.

To overcome these challenges in achieving robustness extraction, we design a new attack methodology: **B**oundary **E**ntropy **S**earching **T**hief (`BEST`). The key insight of `BEST` is the introduction of uncertain examples (UEs). These samples are located close to the junctions of classification boundaries, making the model give uncertain predictions. We synthesize such samples based on their prediction entropy. Using UEs to query the victim model, the adversary can asymptotically shape the classification boundary of the extracted model following that of the victim model. With more extraction epochs, the boundaries of the two models will be more similar, and the overfitting phenomenon will be mitigated. We perform comprehensive experiments to show that `BEST` outperforms different types of baseline methods over various datasets and models. For instance, `BEST` can achieve 13% robust accuracy and 8% clean accuracy improvement compared with the JBDA attack (Papernot et al., 2017) on CIFAR10.

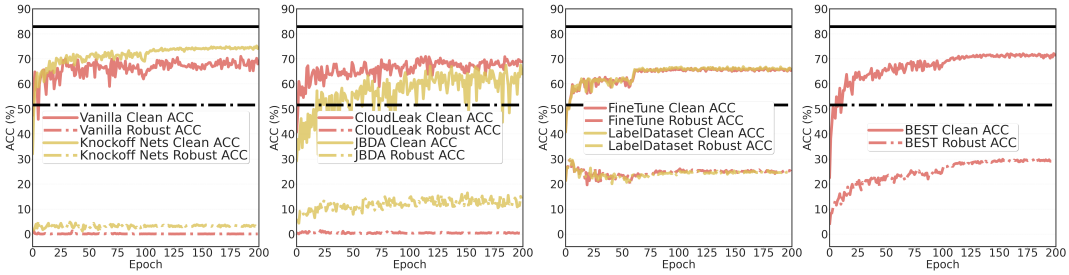
2 Threat Model

We consider the standard MLaaS scenario, where the victim model $M_{\mathcal{V}}$ is deployed as a remote service for users to query. We further assume this model is established with adversarial training (Madry et al., 2018; Zhang et al., 2019), and exhibits certain robustness against AEs. We consider adversarial training as it is still regarded as the most promising strategy for robustness enhancement, while some other solutions (Xu et al., 2017; Zhang et al., 2021a; Gu & Rigazio, 2014; Papernot et al., 2017) were subsequently proved to be ineffective against advanced adaptive attacks (Athalye et al., 2018; Tramer et al., 2020). We will consider more robustness approaches in future work (Section 7). An adversarial user $\mathcal{A}$ aims to reconstruct this model just based on the returned responses. The extracted model $M_{\mathcal{A}}$ should have a similar prediction performance as the target one, for both clean samples (clean accuracy) and AEs (robust accuracy). $\mathcal{A}$ has no prior knowledge of the victim model, including the model architecture, training algorithms, and hyperparameters. He is not aware of the adversarial training strategy for robustness enhancement, either. $\mathcal{A}$ can adopt a different model architecture for building $M_{\mathcal{A}}$, which can still achieve the same behaviors as the target model $M_{\mathcal{V}}$.

Prior works have made different assumptions about the adversary's knowledge of query samples. Some attacks assume the adversary has access to the original training set (Tramèr et al., 2016; Jagielski et al., 2020b; Pal et al., 2020), while some others assume the adversary can obtain the distribution of training samples (Papernot et al., 2017; Orekondy et al., 2019; Chandrasekaran et al., 2020; Yu et al., 2020; Pal et al., 2020). Different from those works, we consider a more practical adversary's capability: the adversary only needs to collect data samples from the same task domain of the victim model, which do not necessarily follow the same distribution of the victim's training set. This is feasible as the adversary knows the task of the victim model, and he can crawl relevant images from the Internet. More advanced attacks (e.g., data-free attacks (Truong et al., 2021; Kariyappa et al., 2021)) will be considered as future work.

The adversary can collect a small-scale dataset $D_{\mathcal{A}}$ with such samples to query the victim model $M_{\mathcal{V}}$. We consider two practical scenarios for the MLaaS: the service can return the predicted logits vector $\mathcal{Y}$ (Tramèr et al., 2016; Orekondy et al., 2019; Jagielski et al., 2020b; Pal et al., 2020) or a hard label Y (Tramèr et al., 2016; Papernot et al., 2017; Jagielski et al., 2020b; Pal et al., 2020) for every query sample. For each case, our attack is able to extract the model precisely.

Attack cost. Two types of attack budgets are commonly considered in model extraction attacks. (1) Query budget B_Q: this is defined as the number of queries the adversary sends to the victim model. As commercial MLaaS systems adopt the pay-as-you-use business scheme, the adversary wishes to perform fewer queries while achieving satisfactory attack performance. (2) Synthesis budget B_S: this is defined as the computation cost (e.g., number of optimization iterations) to generate each query sample. A smaller B_S will be more cost-efficient to the adversary and reduce the attack time. The design of a model extraction attack needs to consider the reduction of both budgets.



(a) Extraction-clean sample (b) Extraction-AE (c) Extraction-AT (d) BEST

Figure 1: Model extraction results on CIFAR10. The victim model is ResNet trained by PGD-AT on CIFAR10. The adversary model is ResNet. Black solid and dashed lines in each figure denote the clean and robust accuracy of the victim model.

To reduce the attack cost, we assume the adversary can download a public pre-trained model and then build the extracted model from it. This assumption is reasonable, as there are lots of public model zoos offering pre-trained models of various AI tasks (e.g., Hugging Face (hug, 2022) and ModelZoo (mod, 2022)). It is also adopted in (Yu et al., 2020), and justified in (Jagielski et al., 2020a). The training set of the pre-trained model can be totally different from that of the victim model.

3 Existing Attack Strategies and Their Limitations

A variety of attack techniques have been proposed to extract models with high accuracy and fidelity, which can be classified into the following two categories.

Extraction with Clean Samples. The adversary samples query data from a public dataset offline and trains the extracted model based on the data and victim model's predictions. The earlier work (Tramèr et al., 2016) adopts this simple strategy, and we denote this attack as "Vanilla" in the rest of this paper. Later on, advanced attacks are proposed, which leverage active learning (Chandrasekaran et al., 2020) to generate samples for querying the victim model and refine the local copy iteratively. Typical examples include Knockoff Nets (Orekondy et al., 2019) and ActiveThief (Pal et al., 2020) attacks. The adversary gets a huge database of different natural images. For each iteration, he actively searches the best samples from this database based on his current model for extraction.

Extraction with Adversarial Examples. The adversary crafts AEs to identify the classification boundaries. A representative example is CloudLeak (Yu et al., 2020). The adversary generates AEs based on a local surrogate model as the query samples. These AEs with the victim model's predictions form the training set for the adversary to train the extracted model. Some attacks also combine active learning to iteratively generate AEs. For instance, in the JBDA attack (Papernot et al., 2017), the adversary follows the FGSM (Goodfellow et al., 2015) idea to generate perturbed samples, queries the data, and then refines his local model repeatedly.

Limitations. These solutions may work well for accuracy or fidelity extraction. However, they are not effective in robustness extraction. We analyze their limitations from the following perspectives. First, according to previous studies (Zhao et al., 2020; Rebuffi et al., 2021), *it is impossible to train a robust model only with clean samples.* Therefore, the techniques using clean samples cannot steal the victim model's robustness. To confirm this conclusion, we train a robust model using the PGD-AT approach (Madry et al., 2018). This model adopts the ResNet-18 architecture (He et al., 2016) and is trained over CIFAR10. The black solid and dashed lines in Figure 1a denote the clean accuracy and robust accuracy of this model. We consider the scenario where this model only returns the predicted hard label for each query. Then we adopt the Vanilla and Knockoff Nets attack techniques to extract this model using the samples from part of the CIFAR10 test set[1]. Figure 1a shows the model accuracy over different extraction epochs, which is evaluated by another part of the CIFAR10 test set, disjoint with the extraction set. We observe that for these two approaches, the clean accuracy of the stolen model is very high. However, the robust accuracy of the replicated model against the PGD20 attack is close to 0, which indicates the extracted model does not inherit the robustness from the victim model at all.

Second, we consider the techniques based on AEs. Training (extracting) models with AEs can incur two unsolved issues. (1) *The participation of AEs in model training can sacrifice the model's clean*

[1]ActiveThief adopts the similar active technique as Knockoff Nets, so we omit its results here.

accuracy (Tsipras et al., 2019). Figure 1b shows the attack results of CloudLeak and JBDA. We observe that the clean accuracy of the extracted model from JBDA drops significantly compared to the extracted accuracy from Vanilla and Knockoff Nets (Figure 1a). (2) *Training a model with AEs can easily make the model overfit over the training data (Rice et al., 2020), which significantly decreases the robustness of the adversary's model with more query samples.* From Figure 1b, we observe the robust accuracy in JBDA decreases before the extraction is completed. It is worth noting that the clean and robust accuracy of CloudLeak is very close to the clean sample based approaches (Vanilla and Knockoff Nets). The reason is that pre-generated AEs have lower transferability towards the victim model compared to queries in active learning, and can still be regarded as clean samples.

Third, we further consider a straightforward strategy specifically for the robustness extraction scenario: the adversary conducts the accuracy extraction of the victim model, followed by adversarial training to obtain the robustness. We implement two attacks following this strategy: (1) *LabelDataset*: the adversary first obtains a labeled dataset from the victim model with Vanilla or CloudLeak, and then adopts adversarial training to train his model. (2) *FineTune*: the adversary first extracts the model with CloudLeak, and then fine-tunes it with AEs. We adopt the same training hyperparameters and protocol in (Rice et al., 2020). Furthermore, to avoid potential overfitting in the adversarial training process, we adopt Self-Adaptive Training (SAT) (Huang et al., 2020) combining with PGD-AT (Madry et al., 2018) in both attacks. The hyperparameters of SAT follow its paper. Figure 1c shows the extraction results of these two attacks. We observe that their clean accuracy is still compromised, and robust accuracy decays at the beginning (i.e., robust overfitting). The main reason is that the adversary does not have enough data to apply adversarial training due to the attack budget constraint (5,000 samples in our experiments), which could easily cause training overfitting and low clean accuracy.

4 METHODOLOGY

We introduce a new attack methodology, which can extract both the clean accuracy and robustness of the victim model. Figure 1d shows the extraction results of our method under the same setting as other approaches. We observe it can effectively overcome the above challenges and outperform other attack strategies. Below we give the detailed mechanism and algorithm of our solution.

4.1 UNCERTAIN EXAMPLE

Our methodology is inspired by the limitations of AE-based attacks. It is well-known that AEs are very close to the model's classification boundaries, and can better depict the boundary shape (He et al., 2018). However, they also exhibit the γ*-useful robust feature* (Ilyas et al., 2019), i.e., having very high confidence scores (larger than γ) for the correct label. Such robust features can lead to clean accuracy degradation (Tsipras et al., 2019; Ilyas et al., 2019) as well as robust overfitting (Rice et al., 2020). Therefore, to precisely extract both the clean and robust accuracy of the victim model, the query samples should satisfy two properties: (**P1**) they cannot have the robust feature obtained from the AE generation process to avoid overfitting; (**P2**) they should reflect the shape of the model classification boundaries. These properties motivate us to design a new way to depict the victim model's boundary. We propose a novel **uncertain example** (UE), which can meet the above requirements and is qualified for model extraction. It is formally defined as follows.

Definition 1 (δ-uncertain example) *Given a model $M : \mathcal{R}^N \mapsto \mathcal{R}^n$, an input $x \in \mathcal{R}^N$ is said to be a δ-uncertain example (δ-UE), if it satisfies the following relationship:*

$$\mathrm{softmax}(M(x))_{\max} - \mathrm{softmax}(M(x))_{\min} \leq \delta \tag{1}$$

Figure 2 illustrates the positions of clean samples, AEs and UEs. Compared to other types of samples, a UE aims to make the model confused about its label. Clearly, every sample in $\mathcal{R}^n$ is a 1-UE. To query and extract the victim model, we expect to make δ as small as possible. On one hand, a UE with a small δ does not have the robust feature, satisfying the property **P1**. On the other hand, a sample far away from the model's classification boundary normally has higher prediction confidence (Cortes & Vapnik, 1995; Mayoraz & Alpaydin, 1999). The uncertainty in the UEs makes them closer to

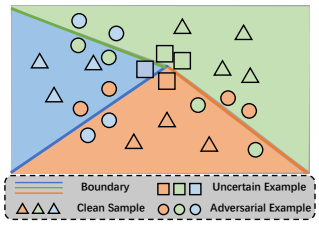


Figure 2: An illustration of clean samples, AEs and UEs. Each color represents a class.

the boundary, satisfying the property **P2**. Therefore, model extraction with UEs can better preserve the clean accuracy without causing robust overfitting, compared to AE-based approaches.

4.2 Boundary Entropy Searching Thief Attack

We propose **B**oundary **E**ntropy **S**earching **T**hief (`BEST`), a novel extraction attack based on UEs. Particularly, similar as (Pal et al., 2020; Papernot et al., 2017; Orekondy et al., 2019), we also adopt the active learning fashion, as it can give more accurate extraction results than the non-active attacks. In each iteration, the adversary queries the victim model with δ-UEs. Based on the responses, he refines the local model to make it closer to the victim one in terms of both clean and robust accuracy.

For some active learning based attacks (e.g., Knockoff Nets, ActiveThief), the adversary searches for the best sample from a huge database for each query. This strategy is not feasible under our threat model, where the adversary has a limited number of data samples. Besides, it is hard to directly sample qualified δ-UEs from the adversary's training set $D_{\mathcal{A}}$: according to previous studies (Li & Liang, 2018; Allen-Zhu et al., 2019), the trained model will gradually converge on the training set, making the training samples far from the boundary and reducing the chances of finding UEs under a small δ. Instead, the adversary can synthesize UEs from natural data in each iteration. This can be formulated as a double-minimization problem, with the following objective:

$$\min_{M_{\mathcal{A}}} L(x, y, M_{\mathcal{A}}) \min_{x} (\text{softmax}(M_{\mathcal{A}}(x))_{\max} - \text{softmax}(M_{\mathcal{A}}(x))_{\min}). \tag{2}$$

In the inner minimization, we first identify the UE x that makes its confidence variance as small as possible. Then in the outer minimization, we optimize the adversary's model $M_{\mathcal{A}}$ with such UE x and its label y obtained from the victim model's prediction to minimize the loss function L.

Algorithm 1 describes the `BEST` attack in detail. We first define a new uncertain label $\mathcal{Y}_p$ with the same confidence score of each class (**Line 2**). In each iteration within the query budget B_Q, we collect some natural samples from the adversary's dataset $D_{\mathcal{A}}$ and synthesize the corresponding UEs. We adopt the Kullback-Leibler divergence $\text{KLD}(\cdot, \cdot)$ to compute the distance between $\text{softmax}(M_{\mathcal{A}}(X_i))$ and $\mathcal{Y}_p$ (**Line 7**), and apply the PGD technique (Madry et al., 2018) under the synthesis budget B_S to make $\text{softmax}(M_{\mathcal{A}}(X_i))$ closer to $\mathcal{Y}_p$, i.e., minimizing δ (**Line 8**). Then we query the victim model $M_{\mathcal{V}}$ with the generated UEs and obtain the corresponding responses (**Line 10**). Different from previous works, we only need to obtain the hard label from $M_{\mathcal{V}}$, which is enough for minimizing the Cross-Entropy loss L for model training (**Line 12**), which makes it harder to defeat our attack, as it can invalidate the mainstream extraction defenses which perturb the logits vectors (Lee et al., 2019).

Algorithm 1 Boundary Entropy Searching Thief

1: **Input:** Adversary model $M_{\mathcal{A}}$, victim model $M_{\mathcal{V}}$, adversary dataset $D_{\mathcal{A}}$, # of classes K, query budget B_Q, synthesis budget B_S, hyperparameters ϵ, η
2: $\mathcal{Y}_p = [\frac{1}{K}, \ldots, \frac{1}{K}]$, $b_q = 0$
3: **while** $b_q \leq B_Q$ **do**
4: **for** $X \in D_{\mathcal{A}}$ **do**
5: $X_0 = X + \text{Random Noise}$
6: **for** i in range (B_S) **do**
7: $\mathcal{L} = -\text{KLD}(\text{softmax}(M_{\mathcal{A}}(X_i)), \mathcal{Y}_p)$
8: $X_{i+1} = \Pi_{X,\epsilon}(X_i + \eta * \text{sgn}(\nabla_{X_i}\mathcal{L}))$
9: **end for**
10: $\mathcal{Y} = M_{\mathcal{V}}(X_{B_S})$
11: $Y = \arg\max \mathcal{Y}$
12: Train $M_{\mathcal{A}}$ with (X_{B_S}, Y)
13: Update b_q
14: **end for**
15: **end while**
16: **Return** $M_{\mathcal{A}}$

5 Experiments

5.1 Configurations

Datasets and Models. Our attack method is general for different datasets, models, and adversarial training strategies. Without loss of generality, we choose two datasets: CIFAR10 (Krizhevsky et al., 2009) and CIFAR100 (Krizhevsky et al., 2009), which are the standard datasets for adversarial training studies (Madry et al., 2018; Zhang et al., 2019; Rice et al., 2020; Jang et al., 2019; Raghunathan et al., 2018; Xiao et al., 2020; Balaji et al., 2019). Prior model extraction attacks adopt data samples from or following the same distribution of the victim's training set (Tramèr et al., 2016; Jagielski et al., 2020b; Pal et al., 2020; Papernot et al., 2017; Orekondy et al., 2019; Chandrasekaran et al.,

Method		Best model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	`Vanilla`	58.74	64.02	5.26	4.84	5.60	3.70	74.12	81.58	3.22	2.74	3.20	1.92
	`JBDA`	64.20	71.80	16.48	16.22	16.80	15.42	63.96	71.36	13.24	12.96	13.44	12.08
	`ARD`	57.82	65.86	29.98	29.88	29.22	27.94	51.86	58.18	19.36	19.10	19.64	18.38
	`IAD`	55.10	62.92	30.04	29.98	29.20	28.08	52.86	60.00	20.44	20.18	20.76	19.34
	`RSLAD`	54.72	63.46	30.10	29.9	29.20	28.18	53.44	60.48	21.96	21.86	22.34	21.08
Logits	`Vanilla`	76.14	82.78	1.82	1.50	1.08	0.46	75.84	82.22	1.80	1.30	1.06	0.36
	`JBDA`	69.74	76.94	10.38	9.54	10.68	7.94	67.78	74.18	7.84	7.22	8.18	5.76
	`ARD`	67.36	76.32	30.52	30.08	28.86	26.98	64.10	73.06	26.44	26.06	24.80	22.98
	`IAD`	63.90	71.84	28.48	28.22	26.54	24.68	58.18	65.76	21.90	21.58	20.14	18.42
	`RSLAD`	66.16	74.92	28.92	28.56	27.04	24.88	60.40	67.94	22.00	21.64	19.64	17.98
`BEST`		71.24	82.12	29.88	29.68	30.56	29.20	71.50	82.34	29.76	29.54	30.52	29.12

Table 1: Model extraction attack results on CIFAR10.

2020; Yu et al., 2020; Pal et al., 2020), which may not be possible in some practical scenarios. Our attack only requires the data from the same task domain. In our implementation, we split the test sets of CIFAR10 and CIFAR100 into two disjointed parts: (1) an extraction set $D_{\mathcal{A}}$ is used by the adversary to steal the victim model; (2) a validation set $D_{\mathcal{T}}$ is used to evaluate the attack results and the victim model's performance during its training process. Both $D_{\mathcal{A}}$ and $D_{\mathcal{T}}$ contain 5,000 samples. We also evaluate other types of extraction set in Section 5.3. The adversary adopts pre-trained models of various architectures trained over Tiny-ImageNet. The benefit from the pre-trained models is evaluated in Appendix C.3. We consider two types of extraction outcomes. (1) *Best model with the highest robustness*: the adversary picks the model with the highest robustness (against PGD20) during extraction. (2) *Final model after extraction*: the adversary picks the model from the last epoch.

The victim model $M_{\mathcal{V}}$ is selected from ResNet-18 (ResNet) (He et al., 2016) or WideResNet-28-10 (WRN) (Zagoruyko & Komodakis, 2016). The adversary model $M_{\mathcal{A}}$ may be different from the victim model, and we use two more model structures in our experiments, i.e., MobileNetV2 (MobileNet) (Sandler et al., 2018), and VGG19BN (VGG) (Simonyan & Zisserman, 2015). We adopt two mainstream adversarial training approaches, i.e., PGD-AT (Madry et al., 2018) and TRADES (Zhang et al., 2019), to enhance the robustness of victim models. This results in ResNet-AT (WRN-AT) and ResNet-TRADES (WRN-TRADES), respectively. The clean and robust accuracy of the victim models can be found in Appendix B.2.

Baselines. We adopt five different baseline methods for comparison. The first two are representatives of model extraction attacks discussed in Section 3. (1) `Vanilla` (Tramèr et al., 2016) is the most basic extraction technique using clean samples to query the victim model. (2) `JBDA` (Papernot et al., 2017) leverages active learning to generate AEs, which gives the best extraction performance over other methods in Section 3. We also choose three robust knowledge distillation methods as our baselines: (3) `ARD` (Goldblum et al., 2020), (4) `IAD` (Zhu et al., 2022) and (5) `RSLAD` (Zi et al., 2021). Robust knowledge distillation aims to train a student model from a large teacher model, where the student model can obtain better robustness than the teacher model. This is very similar to our robustness extraction goal. However, it requires the user to have the entire training set, as well as white-box access to the teacher model, which disobeys our threat model. So, we modify these methods with the same knowledge of the victim model and dataset for fair comparisons. Due to the page limit, we leave the baseline details and settings of these attacks in Appendix B.1.

Metrics. We consider three metrics to comprehensively assess the attack performance. For clean accuracy evaluation, we measure **clean accuracy** (*CA*), which is the accuracy of the extracted models over clean samples in $D_{\mathcal{T}}$. We also consider **relative clean accuracy** (*rCA*), which checks whether the $M_{\mathcal{A}}$ gives the same label as $M_{\mathcal{V}}$ for each x_i in $D_{\mathcal{T}}$. For robustness evaluation, we measure **robust accuracy** (*RA*) against various adversarial attacks. We choose four L_∞-norm non-targeted attacks: PGD20, PGD100 (Madry et al., 2018), CW100 (Carlini & Wagner, 2017) and AutoAttack (AA) (Croce & Hein, 2020). The attack settings are $\epsilon = 8/255$ and $\eta = 2/255$. The number of attack steps is 20 for PGD20, and 100 for PGD100 and CW100. The results under L_2-norm attacks can be found in Appendix C.1. The formal definitions of our metrics can be found in Appendix B.3.

5.2 Main Results

Comparisons with Baselines. We compare the attack effectiveness of `BEST` with other baselines. Due to page limit, we only show the results under one configuration: $M_{\mathcal{V}}$ is ResNet-AT, $M_{\mathcal{A}}$ is ResNet, and the dataset is CIFAR10. The other configurations give the same conclusion,

Dataset	Adversary Model	Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
CIFAR10	ResNet	71.24	82.12	29.88	29.68	30.56	29.20	71.50	82.34	29.76	29.54	30.52	29.12
	WRN	74.30	84.64	31.90	31.70	32.52	31.22	73.40	83.86	31.24	31.08	31.84	30.72
	VGG	66.84	77.18	27.54	27.46	27.88	26.76	66.34	76.02	25.42	25.34	25.68	24.68
	MobileNet	68.50	78.54	26.52	26.22	26.96	25.72	68.70	78.48	24.74	24.46	25.44	23.88
CIFAR100	ResNet	44.38	64.50	14.26	14.22	15.24	13.74	44.78	65.96	13.72	13.52	14.56	13.14
	WRN	47.20	68.56	15.78	15.66	17.00	15.02	46.90	67.82	15.40	15.24	16.62	14.68
	VGG	30.64	44.60	10.86	10.64	11.70	10.24	31.58	45.62	10.10	9.98	10.90	9.54
	MobileNet	41.48	60.74	12.84	12.68	13.44	12.20	41.40	60.84	12.64	12.50	13.34	12.04

Table 2: Results of BEST under different adversary model architectures. Victim model is ResNet-AT.

Dataset	Victim Model	Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
CIFAR10	ResNet-AT	71.24	82.12	29.88	29.68	30.56	29.20	71.50	82.34	29.76	29.54	30.52	29.12
	ResNet-TRADES	68.60	78.78	28.82	28.62	29.30	28.36	70.06	79.58	28.10	27.90	28.66	27.52
	WRN-AT	72.06	78.84	26.58	26.24	27.22	25.72	72.56	79.40	25.86	25.64	26.44	25.20
	WRN-TRADES	70.20	78.34	28.44	28.28	29.04	27.82	69.70	78.26	27.90	27.74	28.56	27.26
CIFAR100	ResNet-AT	44.38	64.50	14.26	14.22	15.24	13.74	44.78	65.96	13.72	13.52	14.56	13.14
	ResNet-TRADES	41.86	60.44	12.64	12.48	13.28	12.14	42.30	60.74	12.26	12.18	12.98	11.78
	WRN-AT	45.52	60.96	12.36	12.20	13.34	11.72	45.86	61.12	11.78	11.52	12.66	11.10
	WRN-TRADES	42.80	58.26	12.32	12.06	12.96	11.56	43.04	58.18	12.00	11.88	12.70	11.42

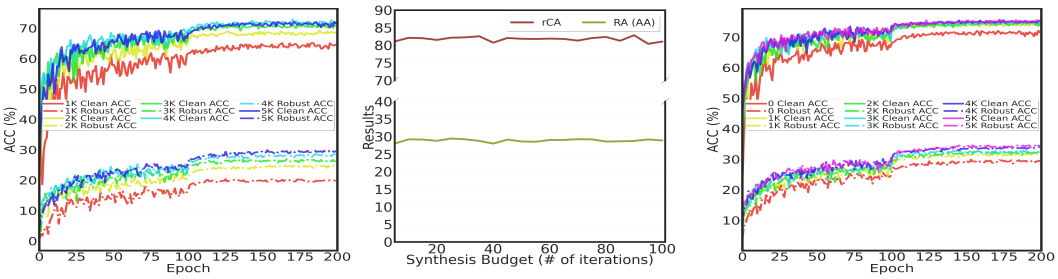
Table 3: Results of BEST under different victim model architectures and adversarial training approaches. The adversary model is ResNet.

and the results can be found in Appendix C.7. Table 1 shows the comparison results. First, our BEST generally performs much better than the baseline methods. It has similar clean accuracy *CA* as Vanilla, which is significantly higher than other methods. For robustness, it also outperforms these baselines, especially Vanilla. Vanilla can only obtain clean accuracy, but not robustness. Other baseline methods can increase the robustness of the extracted model, but their (relative) clean accuracy *(r)CA* is much lower. Particularly for the robust knowledge distillation methods, when we restrict the adversary to have black-box access towards the victim model and limited test samples, they cannot obtain the expected performance for both clean and robust accuracy. Second, for most baseline methods, the final model has lower robust accuracy *RA*, compared to the best model during extraction. It is caused by the robust overfitting issue in the training process (Rice et al., 2020). In contrast, our BEST can reduce the accuracy gap between the best model and the final model. Because the UEs generated in BEST give the extracted model a lower risk to overfit data. Third, when the victim model returns logits vectors, the (relative) clean accuracy *(r)CA* of the baseline methods increases, while the model robustness decreases. Because the robust features make the victim model give more uncertain predictions, and learning such logits vectors directly is more difficult. Our BEST does not depend on the returned prediction type.

Impact of Model Architecture and Adversarial Training Strategy. We first consider the case where the adversary adopts different model architectures from the victim. Table 2 shows the results when we vary the architecture of the adversary model. We observe that our methodology enables the adversary to obtain the maximal performance within the selected architecture. The clean and robust accuracy of VGG and MobileNet is a bit lower than ResNet and WRN, which is caused by the capability of the architectures themselves. Table 3 shows the attack performance against different victim model architectures with different adversarial training approaches. We observe that the attack performance is very stable across different configurations, and the deviations of *rCA* and robustness *RA* do not exceed 7% and 4%, respectively.

Impact of Attack Budgets. We first explore how the query budget B_Q can affect the performance of our BEST. We perform model extraction with different sizes of $D_{\mathcal{A}}$ from 1,000 to 5,000. Figure 3a shows the clean and robust accuracy trends during the extraction under different query budgets. We clearly observe that a larger B_Q can increase both the clean and robust accuracy. Importantly, even using a very small $D_{\mathcal{A}}$, the overfitting issue does not occur at the end of the attack, which indicates our method is stable and powerful. We give a detailed analysis in Appendix C.2.

We further consider the impact of the synthesis budget. We vary the value of B_S and measure the relative clean accuracy *rCA* and robust accuracy *RA* against AA for the extracted model with the highest robustness during extraction. The results are shown in Figure 3b. First, we observe that our BEST can achieve excellent attack performance even under a very low synthesis budget. Second, a larger B_S will not increase the *rCA* and *RA* significantly. We think this is because it is easy to generate query samples, and increasing B_S does not improve the quality or quantity of the query



(a) Impact of the query budget. (b) Impact of the synthesis budget. (c) Adding victim's training data.

Figure 3: Exploration of the attack budget and training data. The dataset is CIFAR10. The victim model is ResNet-AT. The adversary model is ResNet.

samples with a smaller δ. This indicates our attack is much more efficient than previous works, which rely on larger synthesis budgets. We give a more detailed analysis in Appendix C.2, where we use a single V100 GPU card to generate all required data in one epoch, and present the GPU time (in seconds) to prove our method's efficiency.

5.3 Model Extraction with Different Types of Data

In the above experiments, the adversary adopts the samples from the same distribution of the victim model's test data to synthesize uncertain examples. In this section, we consider and evaluate some alternatives for query sample generation.

Incorporating Training Samples. In some cases, the adversary may have the victim's original training data, e.g., the victim's model is trained over a public dataset. Then the adversary can add the training samples into $D_{\mathcal{A}}$ for model extraction. This threat model has been considered in prior works (Tramèr et al., 2016; Jagielski et al., 2020b; Pal et al., 2020). In our experiments, we first set $D_{\mathcal{A}}$ with 5,000 samples of the test data's distribution, and then add different numbers of victim's training samples into $D_{\mathcal{A}}$. Figure 3c shows the extracted clean and robust accuracy with different configurations. We observe that the incorporation of training samples is very helpful for improving the attack performance since they are directly related to the victim model. Even with 1,000 training samples, the clean and robust accuracy is improved by 2.64% and 1.88%, respectively.

Adopting Different Distributions of Samples. We consider another scenario where the adversary does not know the distribution of the victim model's test data. He may use samples from a different distribution to synthesize the uncertain examples for extraction. Table 4 shows the evaluation result of such a case, where the victim model is trained over CIFAR10, while the adversary uses data from CIFAR10 (in-distribution) as well as SVHN, CIFAR100, STL10 (out-of-distribution) to perform attacks. To be specific, the data distribution of STL10 is the closest one to the CIFAR10, while the data distribution of SVHN is the furthest one to the CIFAR10. We observe that model extraction with a different distribution of samples has much lower clean and robust accuracy. Combining the results in the above paragraph, we conclude that a reduced gap between the distributions of the victim's training data and the adversary's extraction data can increase the clean accuracy and robust accuracy. We provide more discussions about how to enhance the attack with out-of-the-distribution data in Appendix C.4.

Applying Data Augmentations. Data augmentation has been a popular strategy to enhance the model's robustness. We can also leverage this technique to generate uncertain examples, which could possibly improve the attack performance. Table 5 compares the results with and without augmentation. Details about the adopted augmentation operations can be found in Appendix B.1. Clearly, when the adversary uses data augmentation to first augment the clean sample and then generate the query sample, the clean accuracy and robustness are significantly higher than the case without data augmentation. Besides, using data augmentation can also help the adversary bypass the victim's defense, which will be discussed in Appendix C.5.

5.4 More Evaluations

We perform more perspectives of evaluations, and the results are in the Appendix. In particular,

$D_{\mathcal{A}}$	Extracted model with the highest robustness						Final model after extraction					
	CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
			PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
CIFAR10	71.24	82.12	29.88	29.68	30.56	29.20	71.50	82.34	29.76	29.54	30.52	29.12
SVHN	40.36	47.58	15.50	15.38	15.78	15.10	42.02	48.78	15.00	14.80	15.26	14.66
CIFAR100	59.82	69.44	20.42	20.30	20.94	19.96	59.16	69.98	20.24	20.10	21.10	19.76
STL10	63.48	73.00	22.62	22.50	23.60	22.26	63.90	73.20	21.86	21.64	22.64	21.30

Table 4: Results of different query distributions. The victim model is ResNet-AT trained on CIFAR10. The adversary model is ResNet.

Data Augmentation	Extracted model with the highest robustness						Final model after extraction					
	CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
			PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
✓	71.24	82.12	29.88	29.68	30.56	29.2	71.5	82.34	29.76	29.54	30.52	29.12
✗	65.54	73.6	22.1	21.76	22.64	21.02	70.3	77.9	19.4	19.06	20.34	18.46

Table 5: Attack results with and without data augmentation. The victim model is ResNet-AT trained on CIFAR10. The adversary model is ResNet. The adversary's dataset is from CIFAR10.

Bypassing SOTA Defenses. Our attack can bypass existing defense solutions for model extraction. We consider two types of state-of-the-art defense strategies: perturbing outputs (Lee et al., 2019) and anomaly detection (Juuti et al., 2019; Zhang et al., 2021b). Results and analysis are in Appendix C.5.

Extracting Non-robust Models. Our method is general and can extract non-robust models as well. Given a model trained normally, `BEST` is able to precisely extract its clean accuracy. Extraction results can be found in Appendix C.6.

Transferability Stabilization. Our attack enjoys high transferability stabilization (Papernot et al., 2017), i.e., AEs generated from the victim model can achieve similar accuracy as the extracted models, and vice versa. We demonstrate this feature with different model architectures in Appendix C.8.

6 Discussions

The traditional model extraction problem was introduced many years ago and has been well-studied. In contrast, this is the first time to propose *robustness extraction*. As an initial attempt, our attack method also has some limitations. We expect this paper can attract more researchers to explore this problem and come up with better solutions. Below we discuss some open questions for future work.

- Although our method outperforms existing SOTA solutions, there still exists a robustness gap between the extracted model and the victim model. One possible solution to reduce such a gap is to increase the number of query samples (Appendix C.4). In the future, it is important to improve the extracted robustness in a more efficient way.
- In this paper, we mainly consider adversarial training for building a robust model, which is the most popular strategy. There can be other robust solutions, e.g., certified defense (Cohen et al., 2019; Li et al., 2019), which will be considered in the future. Besides, we mainly focus on the image classification task. It is also interesting to extend this problem to other AI tasks and domains.
- Recent works proposed data-free attacks (Truong et al., 2021; Kariyappa et al., 2021), where the adversary trains a GAN to generate query samples from noise. We find these techniques cannot achieve promising results for extracting the model's robustness. How to design data-free techniques for robustness extraction is a challenging problem, and we leave it for future work.
- In Appendix C.5 we show that our attack can invalidate existing defense solutions. It is important to design more effective approaches to protect a remote model from robustness extraction. Possible directions include detection of UEs and extraction-aware adversarial training algorithms.

7 Conclusion

In this paper, we present the first study on the robustness extraction of deep learning models. We design `BEST`, a new model extraction technique, which synthesizes uncertain examples to obtain the clean accuracy and robustness of the victim model simultaneously. Experimental results indicate that `BEST` outperforms prior attack methods, which are designed only for accuracy or fidelity extraction.

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A RELATED WORKS

A.1 ACTIVE LEARNING IN MODEL EXTRACTION ATTACKS

Model extraction attacks can adopt active learning algorithms (Chandrasekaran et al., 2020). There are three basic types of sampling-based active learning algorithms. The first type is randomly sampling, which means for each query, the adversary randomly sends some samples to the victim, and uses the returned label to train his model. The second one is uncertainty strategy (Lewis & Gale, 1994). The adversary will choose the most uncertain samples to query the victim and use them to train his model. The third one is k-center strategy (Sener & Savarese, 2018; Pal et al., 2020). The adversary will generate cluster centers based on each sample's prediction, and then choose the most distant sample for each cluster to make the query sample. The model is trained based on these samples, and the adversary will update the cluster centers after every training step. The sampling-based active learning methods require millions or billions of data, and their threat model assumes that the adversary can have lots of data and use them to query the victim model. However, this threat model gives the adversary too much power, and the sampling process needs lots of local computation, which decreases the willingness to steal the victim model.

Besides these basic active learning methods, Papernot et al. (Papernot et al., 2017) proposed Jacobian-Based Dataset Augmentation (JBDA) can be seen as an active learning algorithm performing automated data augmentation, which aims to make the boundary of the adversary's model close to the boundary of the victim model. Orekondy et al. (Orekondy et al., 2019) introduced reinforcement learning into model extraction attacks to restructure the adversary's dataset, improving the attack efficiency. Yuan et al. (Yuan et al., 2020) proposed a GAN-based model extraction attack, and then data-free attacks (Truong et al., 2021; Kariyappa et al., 2021) and data-free adversarial training (Zhou et al., 2020) followed this work and improved it. The adversary trains a GAN during the model extraction process through the gradient estimation from the victim model's outputs. Then the adversary train his model with GAN-generated samples. The GAN-based active learning methods do not need the adversary to have any data. However, the adversary must query the victim model to train a GAN. For a low-resolution dataset, for example, CIFAR-10, training such a GAN is not difficult. But, when we do a model extraction attack on a high-resolution dataset, for example, ImageNet, the computational overhead of training a GAN appears.

Compared with our `BEST`, conventional model extraction attacks cannot generate classification boundary-sensitive queries. In our experiment, we show previous works cannot steal the victim model's robustness and analyze the gap between robust model extraction and naive model extraction.

A.2 ROBUST KNOWLEDGE DISTILLATION

Knowledge distillation (Hinton et al., 2015) aims to use a small student model to learn a larger teacher model's knowledge. Robustness can be seen as specific knowledge from the teacher model. To distill robust knowledge, Goldblum et al. (Goldblum et al., 2020) propose a robust knowledge distillation method, named ARD. They aim to train a small student model from a large teacher model, and the student model can obtain better robustness than the teacher model. Zhu et al. (Zhu et al., 2022) propose the IAD to distill robust knowledge from a teacher model to a student model with the same model architecture. The IAD can automatically detect whether the teacher is good at predicting adversarial examples and adopt proper training loss to learn the teacher's knowledge. Zi et al. (Zi et al., 2021) propose RSLAD to further improve the student model's robustness. The core insight behind these methods is using the student model to generate adversarial examples and using the prediction of clean images from the teacher model as the label of these adversarial examples.

Different from model extraction attacks, model distillation supposes that the user has a full training set and can obtain the teacher model as his property. So, blindly using robust knowledge distillation as a model extraction attack to steal the victim model's robustness can cause reliability problems. In our experiments, we do comprehensive experiments to verify that under the model extraction threat model, robust knowledge distillation cannot guarantee advanced results.

B EXPERIMENT SETTINGS.

B.1 DETAILS OF CONFIGURATIONS

In all experiments, the learning rate of model extraction is set as 0.1 at the beginning and decays at the 100th and 150th epoch with a factor of 0.1. The total number of extraction epochs is 200. In each epoch, the adversary queries all data in his/her training set $D_{\mathcal{A}}$. The batch size is 128. The hyperparameter in `JBDA` for Jacobian matrix multiplication is $\beta = 0.1$. For `ARD`, `IAD`, `RSLAD` and our `BEST`, the hyperparameters for query sample generation under L_∞-norm are $\epsilon = 8/255$, $\eta = 2/255$ and $B_S = 10$.

We consider two settings for the victim's MLaaS: returning the logits vector or the hard label for each query. For the former setting, all baseline methods adopt Kullback-Leibler divergence as the loss function. For the later setting, we replace the Kullback-Leibler divergence with the Cross-Entropy loss, which is the same as previous works.

For both our method and baselines, we apply data augmentation when generating query samples. It includes central cropping, adding Gaussian noise, random image flipping, and random rotation. We show this augmentation can help increase the attack performance and bypass the defense in the experiments.

B.2 DETAILS OF VICTIM MODELS

In Table 1, we show the detailed information of all victim models used in our experiments, including their clean accuracy and robustness under various attacks.

Dataset	Model	Clean	PGD20	PGD100	CW100	AA
CIFAR10	ResNet-AT	82.92	51.62	51.42	50.14	47.90
	ResNet-TRADES	83.24	53.30	53.02	51.08	49.62
	WRN-AT	86.86	53.68	53.48	53.22	50.92
	WRN-TRADES	84.78	55.68	55.34	53.46	52.16
CIFAR100	ResNet-AT	56.58	29.24	28.94	27.30	24.82
	ResNet-TRADES	57.44	29.70	29.58	26.10	25.10
	WRN-AT	62.54	31.88	31.70	30.42	27.96
	WRN-TRADES	62.02	31.76	31.56	28.58	27.12

Table 1: The detailed information of victim models.

B.3 DETAILS OF METRICS

The formula of ***rCA*** is:

$$rCA(M_{\mathcal{A}}, M_{\mathcal{V}}, D_{\mathcal{T}}) = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}(\max(M_{\mathcal{A}}(x_i)) = \max(M_{\mathcal{V}}(x_i))), x_i \in D_{\mathcal{T}} \tag{3}$$

where $M_{\mathcal{A}}$ is the adversary's model, $M_{\mathcal{V}}$ is the victim's model, and $D_{\mathcal{T}}$ is the validation set.

The formula of ***RA*** is:

$$RA(M_{\mathcal{A}}, D_{\mathcal{T}}) = \frac{1}{N}\sum_{i=1}^{N} \Pr[M_{\mathcal{A}}(x_i + \epsilon_i) = M_{\mathcal{A}}(x_i) | \epsilon_i \in \mathcal{B}^p_{(\mathbf{0},\epsilon)}], x_i \in D_{\mathcal{T}} \tag{4}$$

where p is the norm and ϵ is the maximum perturbation margin, which together constrain the perturbation ϵ_i in a hypersphere $\mathcal{B}^p_{(\mathbf{0},\epsilon)}$, whose center is the origin.

C MORE RESULTS

C.1 EXTRACTION RESULTS UNDER L_2-NORM ATTACKS

In Table 2, we evaluate the results under various L_2-norm attacks. The $\epsilon = 0.5$ and $\eta = 0.1$. The victim model is ResNet-18, which is trained by PGD-AT. The adversary's model is ResNet18. The

Method		Extracted model with the highest robustness					Final model after extraction				
		CA	rCA	RA			CA	rCA	RA		
				PGD20	PGD100	CW			PGD20	PGD100	CW
Label	Vanilla	58.74	64.02	23.74	23.36	47.54	74.12	81.58	28.74	28.00	62.06
	JBDA	64.20	71.80	39.20	39.08	57.52	63.96	71.36	36.06	35.84	56.72
	ARD	57.82	65.86	42.56	42.50	53.92	51.86	58.18	32.12	32.08	47.22
	IAD	55.10	62.92	41.98	41.92	51.56	52.86	60.00	33.92	33.80	47.70
	RSLAD	54.72	63.46	40.80	40.72	51.02	53.44	60.48	35.06	35.00	48.76
Logits	Vanilla	76.14	82.78	25.10	23.60	61.22	75.84	82.22	24.38	22.98	61.48
	JBDA	69.74	76.94	38.54	38.22	60.36	67.78	74.18	35.44	35.02	57.34
	ARD	67.36	76.32	49.38	49.44	62.72	64.10	73.06	45.94	45.88	58.98
	IAD	63.90	71.84	47.72	47.66	58.72	58.18	65.76	40.48	40.42	52.84
	RSLAD	66.16	74.92	49.42	49.36	60.98	60.40	67.94	41.46	41.44	54.46
BEST		71.24	82.12	49.68	49.52	65.98	71.50	82.34	49.48	49.38	66.06

Table 2: Model extraction attack results on CIFAR10.

Query Budget	Extracted model with the highest robustness					
	CA	rCA	RA			
			PGD20	PGD100	CW100	AA
5k * 100	71.24	82.12	29.88	29.68	30.56	29.20
5k * 80	68.50	78.78	27.02	26.90	27.90	26.40

Table 3: Model extraction attack results under different Query Budgets.

dataset is CIFAR10. The results indicate that our method can achieve better robustness and avoid robust overfitting during the model extraction, which are the same conclusions in our main paper.

C.2 Analysis of Attack Budgets

Query Budget Analysis. Our method requires additional queries to obtain the boundary information of the victim model, which is an indispensable procedure in robustness improvement. It is inevitable because training a robust model requires much more computational cost (Zhao et al., 2020). We can adopt early learning decay to decrease the query budget. In our experiments, all the highest robustness models are with query budgets of about 1K – 5K * 100. With the early learning decay method, we restore the victim model with 5K * 80 query budgets. The results in Table 3 indicate that reducing the query budgets will not significantly decrease the restored model's clean accuracy and robustness.

On the other hand, we find that using more accounts can reduce query costs. For example, AWS[2] provides a Free Tier for new accounts to analyze 5,000 images per month for free. Google[3] provides all accounts with a discount to predict 1,000 images per month free. Microsoft[4] provides all accounts with a discount to predict 5,000 images per month for free. Considering that using more accounts to steal the victim model can significantly reduce the money cost, and creating new accounts is easy and trivial, the query budget should not be the principal limitation in model extraction attacks.

Synthesis Budget Analysis. Our method is computational efficiency because the scale of UEs that need to be generated in one training epoch for the adversary is small. To better quantify the B_S in the model extraction attack, we measure the time cost for the UE generation process. In our experiments, the adversary only needs to generate 5,000 UEs in one epoch. Specifically, when $B_S = 10$, for ResNet-18, it costs about 16s on V100 to generate 5,000 UEs. For WRN-28-10, it costs about 80s on V100 to generate 5,000 UEs.

C.3 Impact of Pre-trained Models

We evaluate the improvement from a pre-trained model in Table 4. The results indicate that under limited data, the pre-trained model can significantly improve clean accuracy and robustness. Furthermore, the pre-trained model is not robust, and our method can recover the robustness without

[2]https://aws.amazon.com/rekognition/pricing/?nc1=h_ls

[3]https://cloud.google.com/vision/product-search/pricing

[4]https://azure.microsoft.com/en-us/pricing/details/cognitive-services/computer-vision/

Pre-trained Model	Extracted model with the highest robustness					
	CA	rCA	RA			
			PGD20	PGD100	CW100	AA
w/	71.24	82.12	29.88	29.68	30.56	29.20
w/o	60.84	70.30	21.56	21.28	22.20	20.72

Table 4: Model extraction attack results when the pre-trained model is adopted or not.

$D_{\mathcal{A}}$	Extracted model with the highest robustness						Final model after extraction					
	CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
			PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
CIFAR10	71.24	82.12	29.88	29.68	30.56	29.20	71.50	82.34	29.76	29.54	30.52	29.12
CIFAR10+CIFAR100	73.30	85.48	33.38	33.20	33.88	32.72	73.70	85.60	32.34	32.28	33.00	31.76
CIFAR10+STL10	74.46	86.14	34.26	34.04	34.74	33.50	74.66	86.66	33.42	33.24	34.20	32.66

Table 5: Model extraction attack results under different extraction datasets.

using pre-trained models. Using pre-trained models in model extraction attacks is based on a very practical fact that they are widely existed in various tasks, beyond image domain and computer vision tasks, and can be easily downloaded. For example, the well-known website ModelZoo mod (2022) provides various pre-trained models for different tasks, including natural language processing, text-to-speech, audio generation, and image-to-text. It covers different intelligent tasks, like NLP, Audio, and Multimodality.

C.4 Adopting More Samples

We explore how to further improve the results under our threat model. In experiments in our main paper, there are only 5,000 data that the adversary can use to query the victim model, so the gap between the victim model and the restored model can be decreased by adding more data. So, we compare the results under 5,000 CIFAR10 data and 5,000 CIFAR100 or 5,000 STL10 data. The results in Table 5 indicate that increasing the number of query data is an efficient way to improve our results, even though the data distribution is different. It is to say that our method can suit a mixture of distributions, which is meaningful if there is not enough data from a single distribution for the adversary to collect.

C.5 Bypassing Model Extraction Defenses

Past works have proposed defense solutions to alleviate model extraction threats, which can be classified into two categories. The first kind of defense is to add perturbations into the logits vectors without changing the prediction labels (Lee et al., 2019). Since our `BEST` only needs the hard labels of the query samples to extract models, such defenses do not work.

The second type of defense is to detect malicious query samples. Upon the identification of a suspicious sample, the victim model will return an incorrect prediction. One typical solution following this strategy is PRADA (Juuti et al., 2019). It detects malicious samples based on a priori hypothesis that the differences between normal samples in the same class obey a Gaussian distribution, while the differences between synthesized samples often follow long-tailed distributions. We reproduce this defense method and evaluate its effectiveness in detecting `BEST`. We observe that initially, PRADA needs to establish knowledge about the anomalous distributions of malicious samples. After 6,180 queries, it is able to identify each uncertain example. To bypass such detection, the adversary can apply data augmentation for generating uncertain examples (Section 5.1). The randomness in these augmentation operations can disrupt the defender's knowledge about anomalous queries. Our experiments show that PRADA fails to detect any adversary's query sample when it is generated with data augmentation. New detection methods are needed to defeat `BEST`, which will be our future work.

We further consider the SEAT (Zhang et al., 2021b). Different from the PRADA, a global detection method, it is an account-based detection method. To bypass the SEAT, the adversary only needs to register more accounts and use them to query the victim model. In Appendix C.2, we have analyzed the benefits of creating more accounts in model extraction attacks, so we only consider the PRADA in our experiments.

C.6 EXTRACTING NON-ROBUST VICTIM MODEL

In addition to robust models, our approach can also extract non-robust models, just for clean accuracy. Figure 4 shows the attack results, where the victim model is trained with the normal method (ResNet architecture and CIFAR10 dataset). The adversary uses ResNet for model extraction. Black solid and dashed lines denote the clean and robust accuracy of the victim model. We observe that the extracted model can inherit clean accuracy as well as non-robustness (against PGD20) from the victim model. Therefore, we can draw two conclusions: (1) our BEST is general for both robust and non-robust models. (2) For robustness extraction, the high robustness of the extracted model is indeed learned from the victim, rather than from the synthesized uncertain examples.

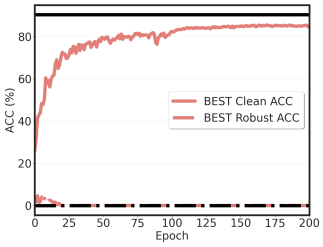

Figure 4: Clean and robust accuracy of extracting a non-robust model.

C.7 RESULTS OF VARIOUS VICTIM MODELS

In Tables 6 to 20, we display the results of different attack scenarios on CIFAR10. In Tables 21 to 36, we display the results of different attack scenarios on CIFAR100. The victim models include ResNet-AT, ResNet-TRADES, WRN-AT, and WRN-TRADES. The adversary models include ResNet, WRN, VGG, and MobileNet. Clearly, our BEST outperforms other baselines under various settings. And we have the same conclusions as in the main paper. Especially, when the adversary adopts VGG as his model to steal a victim model with logits, other baselines cannot make the model converge on CIFAR100. This is because using logits as labels can introduce more noise during the training process, and training VGG is more difficult when compared with training other models. Our BEST can keep stable when the adversary uses VGG as his model, as our method only requires the hard labels.

Method		**Extracted model with the highest robustness**						**Final model after extraction**					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	61.44	64.96	3.74	3.10	3.86	2.34	76.14	80.82	1.58	1.36	1.58	0.84
	JBDA	65.38	70.34	16.00	15.80	16.78	15.18	64.06	68.74	10.56	10.24	11.18	9.28
	ARD	55.60	61.28	29.06	28.78	26.96	25.44	50.20	53.96	16.58	16.34	16.70	15.50
	IAD	56.40	61.32	30.08	30.02	28.02	26.50	57.22	62.24	19.54	19.20	19.52	18.44
	RSLAD	58.36	63.50	29.52	29.32	27.82	26.14	57.44	62.48	18.86	18.48	18.90	17.70
Logits	Vanilla	78.44	82.14	0.86	0.52	0.48	0.12	78.30	82.18	0.76	0.36	0.40	0.06
	JBDA	67.10	71.64	9.96	9.14	10.14	7.60	68.88	73.00	7.00	6.32	7.40	5.16
	ARD	65.88	71.32	27.70	27.10	25.64	23.80	61.18	66.36	22.58	22.42	20.58	19.32
	IAD	62.60	67.84	27.42	27.14	25.30	23.26	57.76	62.96	18.82	18.50	16.78	15.38
	RSLAD	65.76	71.26	25.52	25.14	23.62	21.88	58.86	63.64	18.48	18.18	16.10	14.74
BEST		72.06	78.84	26.58	26.24	27.22	25.72	72.56	79.40	25.86	25.64	26.44	25.20

Table 6: Results of model extraction attacks on CIFAR10. The victim model is WRN-AT. The adversary model is ResNet.

Method		**Extracted model with the highest robustness**						**Final model after extraction**					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	66.68	73.18	5.36	4.82	5.44	4.20	73.20	79.90	3.04	2.62	3.10	1.90
	JBDA	61.66	68.58	17.88	17.70	18.52	17.20	59.72	66.94	14.92	14.60	15.64	13.98
	ARD	53.56	61.74	32.20	32.16	31.38	30.20	57.14	65.86	27.68	27.52	27.42	26.56
	IAD	54.42	62.28	31.18	31.12	30.14	28.88	54.72	62.44	22.06	21.86	21.86	20.92
	RSLAD	56.38	64.74	31.66	31.62	30.82	29.76	58.90	67.28	25.54	25.30	25.84	24.72
Logits	Vanilla	72.26	79.64	2.72	1.96	0.82	0.38	72.66	79.72	2.42	1.74	0.74	0.34
	JBDA	61.76	69.02	10.26	9.44	8.62	6.70	63.50	70.40	7.82	7.14	7.26	5.46
	ARD	59.52	68.50	31.50	31.56	28.56	27.44	59.54	68.64	28.96	28.92	26.26	25.12
	IAD	61.18	70.14	30.04	29.88	27.46	25.86	57.46	66.14	25.14	24.84	22.24	20.56
	RSLAD	61.50	70.84	30.58	30.44	27.04	25.66	59.44	68.44	26.04	25.90	22.64	21.52
BEST		68.60	78.78	28.82	28.62	29.30	28.36	70.06	79.58	28.10	27.90	28.66	27.52

Table 7: Results of model extraction attacks on CIFAR10. The victim model is ResNet-TRADES. The adversary model is ResNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	61.64	66.96	5.00	4.58	5.02	3.74	72.30	78.60	2.76	2.28	2.74	1.62
	JBDA	62.20	68.40	17.72	17.48	18.26	16.86	58.84	63.74	11.10	10.82	11.60	10.28
	ARD	47.30	54.74	28.04	28.00	26.56	25.80	47.60	54.76	23.86	23.80	22.94	22.26
	IAD	47.48	54.80	28.10	28.10	26.90	26.18	47.90	54.94	23.48	23.50	22.80	22.18
	RSLAD	55.70	63.46	30.84	30.72	30.42	29.12	56.26	63.64	24.66	24.68	24.98	24.28
Logits	Vanilla	73.14	79.98	2.04	1.48	0.76	0.34	73.22	79.76	1.76	1.34	0.54	0.26
	JBDA	62.42	68.36	10.22	9.32	9.46	7.58	63.82	69.92	6.78	6.00	5.92	4.46
	ARD	60.10	68.80	30.86	30.76	27.68	26.60	58.34	66.56	28.02	27.98	24.64	23.50
	IAD	59.96	67.86	29.36	29.14	26.80	25.36	54.98	62.40	23.08	22.82	20.10	18.88
	RSLAD	60.44	69.16	29.56	29.50	26.24	25.28	58.20	66.18	25.26	25.12	21.54	20.54
BEST		70.20	78.34	28.44	28.28	29.04	27.82	69.70	78.26	27.90	27.74	28.56	27.26

Table 8: Results of model extraction attacks on CIFAR10. The victim model is WRN-TRADES. The adversary model is ResNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	71.78	78.16	5.02	4.64	5.24	3.44	76.72	83.72	2.54	2.22	2.32	1.36
	JBDA	66.46	74.16	18.94	18.68	19.72	17.98	65.42	72.16	14.62	14.38	15.40	13.76
	ARD	56.24	63.80	33.90	33.82	32.96	31.78	59.76	67.90	26.16	25.94	26.60	25.18
	IAD	56.22	63.78	32.54	32.40	32.40	31.14	51.26	57.28	17.84	17.56	17.80	16.74
	RSLAD	55.40	62.60	31.32	31.18	30.20	29.46	57.72	64.32	17.46	17.00	17.88	16.22
Logits	Vanilla	79.34	84.36	2.56	1.78	1.24	0.48	78.78	84.72	2.34	1.74	1.42	0.48
	JBDA	54.58	58.88	6.38	5.76	5.96	4.48	62.10	67.96	6.12	5.28	5.98	3.84
	ARD	70.78	79.36	29.40	28.82	28.20	26.10	65.76	74.10	25.50	25.12	23.86	21.84
	IAD	66.92	74.80	26.92	26.88	24.72	23.04	62.46	70.20	20.02	19.58	18.48	16.02
	RSLAD	70.12	79.04	27.32	26.92	25.94	23.72	64.14	72.78	21.12	20.92	19.28	17.24
BEST		74.30	84.64	31.90	31.70	32.52	31.22	73.40	83.86	31.24	31.08	31.84	30.72

Table 9: Results of model extraction attacks on CIFAR10. The victim model is ResNet-AT. The adversary model is WRN.

C.8 Transferability Stabilization

Transferability stabilization is defined as the AEs generated from the victim model that can achieve similar accuracy over the extracted models. Simultaneously, it requires the extracted models with different structures can generate AEs having similar transferability among each extracted model.

Our BEST can help $M_{\mathcal{A}}$ have various architectures obtain similar classification boundaries as the victim model's ones to achieve transferability stabilization. To verify this point, we plot the adversarial examples' transferability in Figure 5. The results show that the accuracy of the adversary model under the victim model's adversarial examples is close to the accuracy of the victim model's accuracy. Furthermore, the adversary models having different structures can obtain similar accuracy under attacks from other structure adversarial model's adversarial examples. These two points indicate that our BEST can make $M_{\mathcal{A}}$ achieve transferability stabilization.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	65.44	68.68	4.06	3.72	4.10	3.00	78.76	82.30	1.36	1.12	0.92	0.50
	JBDA	64.38	68.20	15.50	15.22	16.52	14.62	67.24	72.14	11.40	11.20	12.16	10.66
	ARD	62.12	67.72	32.54	32.40	31.80	30.36	60.00	64.26	14.42	14.14	15.18	13.46
	IAD	59.74	65.86	32.96	32.84	31.38	29.74	58.26	62.98	19.30	18.84	19.94	18.28
	RSLAD	61.50	65.96	29.96	29.78	28.66	27.30	56.00	60.02	13.24	13.04	13.60	12.56
Logits	Vanilla	81.02	83.74	1.40	0.94	0.78	0.16	80.60	83.46	1.20	0.76	0.64	0.16
	JBDA	69.18	72.52	7.14	6.22	6.62	4.30	66.26	69.14	5.80	5.26	5.50	3.84
	ARD	70.00	75.26	27.86	27.34	26.92	24.92	66.50	71.62	22.26	21.76	21.52	19.14
	IAD	67.10	72.46	25.60	25.18	24.30	21.98	62.64	67.32	17.52	16.76	16.30	14.30
	RSLAD	69.36	73.88	25.52	25.12	24.04	21.82	63.38	68.28	16.94	16.46	15.74	13.54
BEST		75.76	82.38	28.68	28.50	29.66	28.08	73.82	80.40	27.56	27.28	28.46	27.02

Table 10: Results of model extraction attacks on CIFAR10. The victim model is WRN-AT. The adversary model is WRN.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	66.08	71.42	6.26	5.86	5.94	4.32	75.46	81.80	2.60	2.26	1.98	1.14
	JBDA	64.80	72.40	19.76	19.62	20.80	19.22	63.64	69.60	16.12	15.84	17.00	15.10
	ARD	63.12	72.36	33.04	32.78	32.22	31.24	61.66	70.10	26.76	26.48	27.16	25.82
	IAD	58.42	66.52	34.10	34.06	33.24	32.24	57.78	64.76	19.72	19.56	20.10	18.66
	RSLAD	61.30	69.46	32.84	32.88	32.64	31.54	58.40	65.74	20.52	20.22	21.12	19.76
Logits	Vanilla	76.02	82.50	2.92	2.08	0.94	0.40	76.10	82.28	2.84	2.00	0.96	0.38
	JBDA	66.68	72.74	5.50	4.54	3.40	2.48	61.42	66.04	4.44	3.68	3.74	2.32
	ARD	61.78	70.40	30.00	29.88	27.34	25.88	60.22	69.44	27.38	27.30	24.90	23.26
	IAD	64.64	73.36	31.38	31.20	28.94	27.26	61.36	70.56	27.06	26.78	24.34	22.58
	RSLAD	65.66	74.38	29.00	28.74	26.38	24.70	62.40	71.38	25.38	25.14	22.10	20.40
BEST		72.18	82.32	31.02	30.82	31.80	30.30	71.26	81.26	30.42	30.22	31.18	30.12

Table 11: Results of model extraction attacks on CIFAR10. The victim model is ResNet-TRADES. The adversary model is WRN.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	71.52	77.08	4.30	3.88	4.14	2.28	76.04	81.22	1.28	1.02	1.30	0.56
	JBDA	64.36	70.02	17.54	17.30	18.46	16.88	64.24	69.34	14.00	13.64	14.82	13.18
	ARD	57.82	65.02	32.64	32.58	31.22	30.24	58.78	65.62	19.10	18.88	19.76	18.10
	IAD	58.78	66.44	33.64	33.52	32.88	31.66	56.54	63.36	19.72	19.56	20.08	18.94
	RSLAD	59.58	66.70	31.02	30.96	30.14	28.86	54.00	60.74	15.26	15.10	15.66	14.48
Logits	Vanilla	76.64	81.88	2.58	1.84	1.16	0.50	76.32	81.66	2.42	1.76	0.96	0.32
	JBDA	50.02	52.24	5.80	5.12	4.68	3.52	55.96	60.06	4.38	3.56	3.10	2.02
	ARD	62.68	70.54	29.78	29.54	27.46	25.80	59.40	67.14	25.08	24.90	22.46	21.02
	IAD	61.98	69.70	30.26	29.98	27.34	25.96	58.48	66.02	23.44	23.12	21.38	19.66
	RSLAD	63.56	71.06	28.08	27.94	25.32	24.08	61.32	68.56	21.80	21.34	18.80	17.18
BEST		70.76	80.02	31.24	31.08	31.70	30.72	70.30	79.58	29.80	29.54	30.36	29.22

Table 12: Results of model extraction attacks on CIFAR10. The victim model is WRN-TRADES. The adversary model is WRN.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	65.24	72.24	7.86	7.30	7.60	6.36	73.10	80.64	6.24	5.64	6.20	4.86
	JBDA	57.80	64.40	32.06	31.74	19.22	17.36	55.26	59.76	24.38	23.82	15.88	14.24
	ARD	49.84	57.18	30.64	30.60	29.24	27.90	46.50	52.76	27.02	27.08	25.82	24.64
	IAD	48.68	55.28	30.48	30.30	29.54	27.98	44.88	50.94	27.32	27.30	25.90	24.88
	RSLAD	50.82	58.54	29.96	29.82	29.14	27.60	45.46	52.38	26.84	26.92	25.44	24.46
Logits	Vanilla	13.92	13.36	10.00	10.00	0.30	0.02	73.50	79.78	2.30	1.66	2.00	0.58
	JBDA	54.00	58.80	13.70	13.02	14.00	10.28	48.10	51.58	10.12	9.60	10.20	8.06
	ARD	58.98	66.64	27.80	27.58	25.90	23.66	57.84	64.88	24.94	24.58	23.48	21.18
	IAD	54.02	61.08	26.40	26.16	24.22	22.06	48.40	54.58	22.04	21.96	20.44	18.58
	RSLAD	57.80	66.16	25.64	25.24	23.72	22.10	54.84	61.92	22.32	22.14	21.02	19.18
BEST		66.84	77.18	27.54	27.46	27.88	26.76	66.34	76.02	25.42	25.34	25.68	24.68

Table 13: Results of model extraction attacks on CIFAR10. The victim model is ResNet-AT. The adversary model is VGG.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	45.70	48.00	5.94	5.74	8.18	4.60	74.78	79.22	4.56	3.86	4.50	3.38
	JBDA	59.98	64.22	33.38	32.76	18.42	16.74	62.38	67.04	29.00	27.90	17.00	15.18
	ARD	49.46	54.24	30.34	30.40	28.30	27.06	47.72	52.06	27.76	27.72	26.62	25.60
	IAD	50.12	54.36	28.22	28.00	27.58	26.08	40.44	43.28	23.84	23.78	22.68	21.94
	RSLAD	57.14	62.72	30.64	30.60	29.84	28.50	56.44	61.68	27.42	27.34	27.08	25.72
Logits	Vanilla	10.00	8.62	10.00	10.00	10.00	10.00	76.40	80.56	1.08	0.66	0.96	0.30
	JBDA	56.24	59.18	13.12	12.22	12.82	9.70	58.78	62.14	11.74	11.04	11.84	9.32
	ARD	58.76	64.74	27.08	26.86	26.38	23.50	56.38	61.34	24.20	23.94	23.50	20.62
	IAD	53.00	56.58	25.38	25.22	23.94	21.52	50.00	53.00	21.64	21.48	20.66	17.86
	RSLAD	57.92	63.54	24.12	23.94	23.38	21.54	50.78	55.62	19.60	19.22	18.56	17.18
BEST		67.84	74.50	27.92	27.66	28.16	26.90	68.72	75.50	27.08	26.88	27.46	26.32

Table 14: Results of model extraction attacks on CIFAR10. The victim model is WRN-AT. The adversary model is VGG.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	40.22	43.40	8.30	8.16	9.24	7.44	71.30	77.94	6.78	6.14	6.58	5.42
	JBDA	51.74	58.14	33.46	33.18	19.06	18.16	49.22	52.70	21.98	21.50	15.44	13.76
	ARD	49.96	57.86	31.68	31.74	29.92	29.00	46.84	52.98	28.50	28.46	26.50	25.72
	IAD	46.02	52.88	29.88	29.84	27.38	26.22	41.92	47.40	26.40	26.32	25.36	24.16
	RSLAD	50.98	59.10	31.38	31.48	29.22	28.36	51.38	59.38	28.58	28.64	27.26	26.18
Logits	Vanilla	10.00	8.54	10.00	10.00	9.98	10.00	69.48	76.08	2.66	1.90	1.78	0.82
	JBDA	49.10	53.44	12.76	12.00	13.72	9.16	46.18	49.44	8.62	8.18	9.08	7.00
	ARD	52.44	60.28	27.98	27.94	25.30	23.24	51.86	59.12	25.84	25.66	23.52	21.44
	IAD	51.40	59.10	26.74	26.62	24.46	22.24	46.96	53.88	24.12	24.04	21.64	19.56
	RSLAD	52.02	60.70	27.22	27.16	24.82	23.56	52.02	60.14	24.82	24.58	23.24	21.52
BEST		65.26	75.40	28.54	28.42	29.24	27.72	66.12	75.22	27.66	27.52	28.24	26.78

Table 15: Results of model extraction attacks on CIFAR10. The victim model is ResNet-TRADES. The adversary model is VGG.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	43.68	47.16	7.78	7.42	8.20	6.76	71.48	77.60	5.94	5.22	5.88	4.30
	JBDA	53.78	58.90	31.40	31.14	21.14	19.68	56.26	60.98	27.82	27.16	19.04	17.48
	ARD	45.92	52.78	29.64	29.66	27.48	26.56	42.86	49.32	26.88	26.82	25.08	24.48
	IAD	43.80	49.90	29.12	29.12	27.22	26.38	37.74	43.10	25.30	25.30	23.96	23.40
	RSLAD	50.90	58.20	31.84	31.80	29.54	28.66	50.08	57.46	28.50	28.48	27.38	26.50
Logits	Vanilla	10.00	10.38	10.00	10.00	10.00	10.00	71.28	77.28	2.08	1.34	1.30	0.46
	JBDA	48.56	52.00	12.02	11.24	12.64	8.74	54.86	59.70	9.96	9.40	10.58	7.70
	ARD	51.48	58.52	27.18	27.12	25.36	23.40	49.38	56.00	25.68	25.52	23.20	21.36
	IAD	49.16	55.72	26.98	26.86	24.50	22.98	46.26	52.68	23.88	23.74	21.84	20.26
	RSLAD	53.92	61.76	27.20	26.98	24.92	23.72	50.02	57.20	24.84	24.74	22.80	21.46
BEST		65.76	75.14	28.88	28.54	29.20	27.88	66.22	75.24	27.72	27.70	28.36	27.22

Table 16: Results of model extraction attacks on CIFAR10. The victim model is WRN-TRADES. The adversary model is VGG.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	62.12	67.66	3.54	3.06	3.26	2.42	72.28	79.80	2.00	1.60	2.02	0.92
	JBDA	51.26	57.24	12.22	11.96	12.92	11.40	53.34	59.02	6.40	6.08	7.00	5.42
	ARD	57.30	66.32	32.58	32.50	31.26	30.00	56.46	64.96	26.82	26.58	26.32	25.12
	IAD	58.42	67.64	32.18	32.04	31.32	30.06	55.56	63.98	26.36	26.18	26.04	25.20
	RSLAD	58.32	67.10	31.56	31.26	30.78	29.94	57.14	65.66	26.38	26.14	26.16	25.18
Logits	Vanilla	74.58	80.32	2.08	1.46	1.38	0.48	75.88	81.62	1.68	1.20	0.98	0.44
	JBDA	62.24	68.68	11.62	10.84	11.02	8.58	62.10	68.58	7.82	7.34	7.86	6.08
	ARD	66.06	74.96	30.28	30.16	28.48	26.60	64.22	72.40	27.38	26.92	25.18	23.32
	IAD	62.80	71.80	31.08	30.70	27.82	26.18	59.54	67.72	25.32	25.18	22.36	20.72
	RSLAD	64.22	74.24	31.46	31.30	29.22	27.58	62.82	71.84	27.28	27.08	24.34	22.64
BEST		68.50	78.54	26.52	26.22	26.96	25.72	68.70	78.48	24.74	24.46	25.44	23.88

Table 17: Results of model extraction attacks on CIFAR10. The victim model is ResNet-AT. The adversary model is MobileNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	51.26	53.04	3.78	3.54	3.30	2.64	72.92	77.06	0.70	0.48	0.72	0.24
	JBDA	44.28	48.04	10.60	10.42	11.12	10.10	47.34	51.68	8.20	7.94	8.52	7.48
	ARD	55.50	61.06	30.60	30.62	29.04	27.78	46.58	51.16	23.56	23.42	21.98	21.28
	IAD	53.80	59.52	31.52	31.38	29.38	28.10	44.28	48.40	24.06	24.04	22.54	21.76
	RSLAD	59.62	65.54	30.42	30.32	30.24	29.02	49.88	54.74	21.62	21.36	21.04	20.08
Logits	Vanilla	76.04	80.30	1.20	0.76	0.58	0.28	76.62	80.62	1.02	0.62	0.60	0.14
	JBDA	64.78	69.32	9.80	8.94	9.78	7.28	59.90	64.34	7.98	7.40	8.04	6.38
	ARD	65.48	71.02	27.72	27.24	26.80	24.42	60.54	65.90	23.66	23.36	21.58	19.94
	IAD	60.84	66.02	28.40	28.34	25.56	24.02	54.30	58.70	21.74	21.56	18.52	17.02
	RSLAD	63.34	68.38	28.54	28.54	25.90	24.04	61.18	66.08	23.84	23.70	20.52	18.90
BEST		70.18	76.38	24.48	24.16	25.04	23.58	69.20	75.06	23.44	23.12	24.16	22.52

Table 18: Results of model extraction attacks on CIFAR10. The victim model is WRN-AT. The adversary model is MobileNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	65.02	70.86	3.14	2.76	2.70	1.86	70.88	78.26	1.92	1.60	1.86	0.78
	JBDA	59.14	65.92	14.24	13.86	14.88	13.38	49.78	55.42	9.40	9.24	9.88	8.64
	ARD	56.10	65.48	33.10	33.08	31.80	30.84	55.14	63.98	26.84	26.62	26.22	25.24
	IAD	56.56	65.02	33.12	33.04	32.06	30.78	55.42	63.90	27.10	26.88	26.14	25.10
	RSLAD	57.16	66.78	32.26	32.22	31.40	30.14	59.34	68.94	26.90	26.70	26.86	25.84
Logits	Vanilla	70.86	77.18	3.14	2.28	1.34	0.70	72.20	78.56	2.42	1.84	1.06	0.50
	JBDA	61.10	67.46	10.96	10.12	8.92	7.38	58.40	64.16	6.58	6.16	5.98	4.94
	ARD	59.70	68.86	32.28	32.18	29.20	28.08	59.28	68.40	30.86	30.66	27.80	26.30
	IAD	59.00	68.20	32.34	32.14	29.02	27.72	56.12	64.82	28.36	28.32	25.22	24.08
	RSLAD	63.72	73.86	31.98	31.72	29.12	27.28	57.96	67.12	28.14	27.96	24.48	23.56
BEST		67.14	76.60	25.88	25.60	26.28	25.12	67.14	76.30	24.86	24.66	25.22	24.04

Table 19: Results of model extraction attacks on CIFAR10. The victim model is ResNet-TRADES. The adversary model is MobileNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	52.08	57.34	5.92	5.28	3.78	3.14	70.00	76.36	1.64	1.22	1.28	0.76
	JBDA	55.16	60.84	13.76	13.56	14.18	12.98	49.44	53.98	9.94	9.80	10.26	9.22
	ARD	52.68	61.08	32.58	32.62	30.90	30.34	47.90	55.40	26.20	26.14	25.18	24.46
	IAD	54.24	62.60	32.48	32.40	31.12	30.18	48.88	56.24	26.70	26.70	25.70	24.86
	RSLAD	57.48	65.78	31.50	31.50	30.62	29.80	50.92	58.58	25.02	25.08	24.22	23.46
Logits	Vanilla	69.32	74.80	2.56	1.88	1.10	0.56	71.72	77.30	2.20	1.68	0.64	0.34
	JBDA	59.52	64.86	10.60	9.80	9.38	7.94	54.96	59.62	8.94	8.62	8.30	7.02
	ARD	59.42	67.80	31.42	31.32	28.28	26.86	56.64	64.42	27.60	27.36	24.00	23.08
	IAD	58.20	65.40	30.90	30.86	28.12	26.84	52.48	59.52	25.54	25.42	21.60	20.72
	RSLAD	61.84	70.20	30.84	30.58	27.50	26.22	58.08	65.98	27.80	27.60	23.56	22.56
BEST		66.40	74.84	25.82	25.46	26.26	25.04	66.02	74.34	24.80	24.58	25.22	24.14

Table 20: Results of model extraction attacks on CIFAR10. The victim model is WRN-TRADES. The adversary model is MobileNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	38.30	50.72	3.22	2.86	3.38	2.24	45.78	61.54	2.54	2.24	2.82	1.86
	JBDA	31.42	41.94	7.74	7.56	8.32	7.14	28.62	38.02	4.96	4.92	5.42	4.50
	ARD	33.64	48.86	14.80	14.66	14.24	13.66	31.72	46.40	11.42	11.26	11.36	10.44
	IAD	34.52	50.50	14.96	14.78	14.62	13.62	31.58	45.54	10.60	10.50	10.58	9.92
	RSLAD	31.26	43.36	13.92	13.76	12.96	12.22	31.48	45.34	10.16	10.16	10.08	9.48
Logits	Vanilla	38.86	47.88	2.10	1.70	1.42	0.58	38.56	47.22	2.02	1.72	1.46	0.62
	JBDA	17.16	21.28	1.52	1.28	1.20	0.64	16.62	19.94	0.94	0.68	0.80	0.42
	ARD	13.32	18.62	5.04	5.02	2.54	2.04	13.42	18.90	4.36	4.26	2.52	1.90
	IAD	16.26	22.54	10.32	10.28	8.52	8.00	15.72	21.74	9.08	8.98	7.44	6.92
	RSLAD	23.74	32.96	10.88	10.92	7.62	6.96	23.28	32.56	10.24	10.24	7.50	6.52
BEST		44.38	64.50	14.26	14.22	15.24	13.74	44.78	65.96	13.72	13.52	14.56	13.14

Table 21: Results of model extraction attacks on CIFAR100. The victim model is ResNet-AT. The adversary model is ResNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	41.60	51.30	2.22	1.94	2.46	1.62	47.40	58.92	1.44	1.16	1.56	0.92
	JBDA	31.54	38.58	6.86	6.70	7.20	6.24	28.36	34.84	4.54	4.42	4.82	4.16
	ARD	31.22	41.60	13.30	13.14	12.42	11.62	29.46	39.90	9.56	9.38	9.40	8.64
	IAD	34.40	46.06	13.80	13.60	13.66	12.76	31.38	41.86	9.76	9.58	9.64	8.92
	RSLAD	33.22	44.24	13.20	13.04	12.68	11.72	31.58	41.80	9.36	9.26	9.18	8.52
Logits	Vanilla	40.58	47.96	1.62	1.32	1.08	0.34	40.04	47.70	1.44	1.18	1.10	0.34
	JBDA	18.00	21.04	1.70	1.48	1.50	0.94	18.54	21.84	1.24	1.08	1.10	0.78
	ARD	13.28	16.60	4.72	4.64	2.28	1.98	13.02	16.38	4.24	4.18	2.38	2.06
	IAD	17.22	22.36	10.44	10.34	8.60	8.08	16.68	22.04	9.14	9.18	7.70	7.18
	RSLAD	25.56	32.08	10.76	10.78	7.70	6.82	23.62	30.40	9.20	9.24	6.78	5.92
BEST		45.52	60.96	12.36	12.20	13.34	11.72	45.86	61.12	11.78	11.52	12.66	11.10

Table 22: Results of model extraction attacks on CIFAR100. The victim model is WRN-AT. The adversary model is ResNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	32.42	42.80	2.94	2.68	3.30	2.28	43.42	56.40	1.80	1.74	2.20	1.34
	JBDA	32.16	42.30	7.72	7.68	8.16	7.30	29.28	38.38	5.76	5.76	6.20	5.62
	ARD	29.66	42.10	13.66	13.52	12.42	11.78	28.86	41.84	9.58	9.48	9.50	8.90
	IAD	27.58	39.96	13.60	13.48	12.66	11.80	28.50	40.44	9.08	8.94	8.86	8.30
	RSLAD	32.10	45.52	13.24	13.24	12.96	12.18	30.08	42.64	10.36	10.28	10.34	9.62
Logits	Vanilla	31.98	39.84	2.50	2.14	1.22	0.56	32.50	40.66	2.18	1.98	1.10	0.56
	JBDA	14.44	18.58	1.02	0.88	0.72	0.36	14.20	18.28	0.62	0.48	0.46	0.20
	ARD	10.40	16.02	4.08	4.02	2.00	1.76	10.60	16.36	3.76	3.78	1.90	1.64
	IAD	14.10	20.44	9.46	9.42	7.62	7.22	13.68	19.88	8.46	8.52	6.96	6.52
	RSLAD	19.32	27.98	9.30	9.28	6.90	6.32	19.32	28.26	8.72	8.58	6.50	5.90
BEST		41.86	60.44	12.64	12.48	13.28	12.14	42.30	60.74	12.26	12.18	12.98	11.78

Table 23: Results of model extraction attacks on CIFAR100. The victim model is ResNet-TRADES. The adversary model is ResNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	39.16	48.00	2.76	2.46	2.82	1.90	44.88	56.32	1.54	1.34	1.72	1.10
	JBDA	28.96	37.06	7.60	7.44	8.04	7.24	29.22	37.28	6.50	6.36	6.74	5.92
	ARD	29.80	40.82	13.66	13.68	12.60	11.70	29.40	40.56	9.26	9.14	9.32	8.62
	IAD	31.98	44.12	13.62	13.58	12.84	12.32	29.34	40.74	9.32	9.16	9.34	8.56
	RSLAD	32.30	43.92	13.56	13.54	12.78	11.78	30.32	40.88	9.40	9.36	9.18	8.66
Logits	Vanilla	33.66	40.44	2.52	2.12	1.18	0.60	33.48	40.60	2.42	2.00	1.04	0.54
	JBDA	15.02	18.28	1.08	0.80	0.66	0.34	14.52	17.80	0.94	0.70	0.84	0.36
	ARD	9.60	13.44	2.98	3.00	1.26	1.12	9.58	13.42	2.88	2.80	1.30	1.12
	IAD	15.52	20.18	9.58	9.66	7.90	7.48	15.00	19.44	8.82	8.72	7.16	6.54
	RSLAD	21.54	28.76	9.52	9.44	6.90	6.04	20.60	27.26	8.64	8.54	6.28	5.58
BEST		42.80	58.26	12.32	12.06	12.96	11.56	43.04	58.18	12.00	11.88	12.70	11.42

Table 24: Results of model extraction attacks on CIFAR100. The victim model is WRN-TRADES. The adversary model is ResNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	40.12	52.04	3.50	3.06	3.96	2.38	47.94	64.54	2.72	2.32	2.82	1.64
	JBDA	32.56	42.70	7.68	7.56	8.22	7.14	26.60	35.62	3.82	3.76	4.46	3.52
	ARD	33.92	49.10	14.18	14.12	14.00	13.16	31.44	45.22	9.82	9.62	9.90	9.14
	IAD	34.78	48.78	14.68	14.64	14.30	13.54	30.34	43.14	9.64	9.54	9.60	9.00
	RSLAD	34.58	49.10	14.58	14.52	13.68	12.76	32.00	44.98	9.46	9.30	9.54	8.64
Logits	Vanilla	35.36	40.90	2.38	2.10	0.92	0.30	35.32	41.22	2.08	1.86	0.82	0.26
	JBDA	12.98	15.20	1.24	1.12	0.42	0.24	11.08	13.28	0.82	0.78	0.30	0.16
	ARD	6.96	9.06	2.64	2.64	1.04	0.90	7.54	9.80	2.18	2.16	0.92	0.74
	IAD	13.08	17.00	8.02	8.00	6.36	5.82	12.16	16.88	6.94	6.88	5.48	5.10
	RSLAD	16.96	21.92	7.96	7.96	5.74	5.30	15.86	21.52	6.76	6.68	5.18	4.62
BEST		47.20	68.56	15.78	15.66	17.00	15.02	46.90	67.82	15.40	15.24	16.62	14.68

Table 25: Results of model extraction attacks on CIFAR100. The victim model is ResNet-AT. The adversary model is WRN.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	42.80	50.68	2.44	2.24	2.40	1.58	50.62	62.02	1.38	1.18	1.38	0.78
	JBDA	37.68	45.60	7.66	7.42	8.26	6.70	33.88	40.86	5.62	5.50	6.10	5.12
	ARD	34.58	45.26	14.28	14.12	13.54	12.54	30.32	40.14	8.12	7.94	8.34	7.56
	IAD	34.58	45.26	14.18	14.08	13.62	12.54	30.18	39.92	8.18	8.00	8.22	7.38
	RSLAD	37.68	48.60	14.10	13.86	13.96	13.08	32.96	43.00	9.10	8.94	9.20	8.36
Logits	Vanilla	35.28	39.52	1.74	1.44	0.92	0.32	35.70	39.98	1.56	1.30	0.94	0.28
	JBDA	12.18	13.84	1.12	0.92	0.40	0.14	11.52	12.72	0.78	0.64	0.36	0.12
	ARD	6.28	8.06	2.10	2.12	1.12	0.92	6.38	8.10	1.88	1.86	0.90	0.80
	IAD	14.24	17.54	8.32	8.32	6.52	6.14	13.32	17.08	7.06	7.04	5.38	4.92
	RSLAD	18.22	22.02	8.22	8.12	6.20	5.62	16.96	21.04	6.70	6.54	4.86	4.38
BEST		49.22	65.68	14.84	14.64	15.78	14.16	49.20	64.80	13.66	13.44	14.68	12.94

Table 26: Results of model extraction attacks on CIFAR100. The victim model is WRN-AT. The adversary model is WRN.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	37.48	46.98	2.92	2.68	3.06	1.80	46.64	58.62	1.18	1.02	1.34	0.74
	JBDA	32.56	42.90	8.40	8.24	8.94	8.08	32.60	43.34	8.00	7.84	8.44	7.56
	ARD	34.94	48.56	14.16	13.90	13.40	12.70	30.12	42.08	9.98	9.86	9.96	9.26
	IAD	34.46	48.18	14.84	14.80	14.26	13.54	30.68	42.54	11.28	11.16	11.18	10.44
	RSLAD	32.74	44.62	13.54	13.48	13.10	12.16	30.36	41.82	8.66	8.58	8.68	8.02
Logits	Vanilla	26.66	31.72	3.22	2.70	1.04	0.34	26.24	31.56	2.72	2.34	0.82	0.30
	JBDA	9.28	11.22	1.10	0.96	0.12	0.06	8.38	10.18	0.60	0.56	0.08	0.06
	ARD	6.52	8.62	1.78	1.74	0.58	0.44	6.84	9.44	1.48	1.40	0.42	0.34
	IAD	10.96	16.04	7.44	7.42	5.70	5.54	10.80	15.92	6.72	6.76	5.28	5.12
	RSLAD	14.72	20.18	6.56	6.50	4.34	4.00	14.10	19.06	5.96	5.86	4.08	3.70
BEST		45.92	64.18	14.54	14.34	15.16	13.98	44.94	62.54	13.84	13.70	14.72	13.46

Table 27: Results of model extraction attacks on CIFAR100. The victim model is ResNet-TRADES. The adversary model is WRN.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	40.12	49.52	2.82	2.48	2.88	1.76	49.42	61.02	1.62	1.46	1.70	1.12
	JBDA	34.80	44.12	8.56	8.42	9.08	8.10	29.48	37.16	6.62	6.44	7.06	6.28
	ARD	35.34	48.74	15.46	15.34	14.76	13.98	32.34	43.90	10.96	10.86	10.88	9.94
	IAD	34.70	46.94	14.48	14.34	14.12	13.12	28.80	38.80	8.54	8.54	8.52	7.80
	RSLAD	36.68	49.72	15.40	15.24	14.76	13.98	34.24	46.66	11.92	11.84	11.82	11.10
Logits	Vanilla	27.66	30.64	2.34	2.00	0.78	0.30	27.74	30.72	2.34	1.94	0.80	0.32
	JBDA	9.36	11.30	1.18	1.02	0.34	0.16	8.30	9.92	0.80	0.78	0.34	0.20
	ARD	5.30	6.78	1.52	1.54	0.48	0.42	5.38	6.82	1.38	1.38	0.42	0.36
	IAD	10.12	13.20	6.70	6.70	5.00	4.82	10.16	13.18	5.80	5.76	4.38	4.10
	RSLAD	14.04	17.50	6.12	6.08	4.04	3.58	14.04	17.34	5.30	5.22	3.60	3.22
BEST		48.30	63.58	14.68	14.52	15.26	14.08	46.78	61.70	13.60	13.38	14.66	13.12

Table 28: Results of model extraction attacks on CIFAR100. The victim model is WRN-TRADES. The adversary model is WRN.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	36.32	50.00	3.10	2.84	3.50	2.52	38.40	52.12	2.72	2.50	2.92	2.08
	JBDA	14.80	19.12	9.00	8.90	4.32	3.68	13.74	18.00	7.26	7.30	3.64	3.22
	ARD	20.02	30.02	11.80	11.82	11.16	10.58	19.40	29.24	10.92	10.90	10.02	9.66
	IAD	20.14	29.44	12.08	12.04	11.14	10.64	19.48	28.52	11.30	11.26	10.70	10.14
	RSLAD	28.46	41.04	13.08	12.90	12.82	11.82	27.54	40.04	12.22	12.14	12.06	11.14
Logits	Vanilla	4.92	5.56	1.78	1.56	0.30	0.12	5.08	5.90	1.72	1.46	0.32	0.12
	JBDA	1.00	1.12	0.92	0.94	0.02	0.02	1.72	1.78	0.16	0.10	0.04	0.00
	ARD	1.00	1.06	0.98	0.94	0.04	0.00	1.00	1.06	1.00	1.00	1.00	1.00
	IAD	1.00	1.06	1.00	0.98	0.46	0.22	1.00	1.06	1.00	1.00	1.00	1.00
	RSLAD	1.00	1.06	1.00	1.00	0.72	0.60	1.00	1.06	1.00	1.00	1.00	1.00
BEST		30.64	44.60	10.86	10.64	11.70	10.24	31.58	45.62	10.10	9.98	10.90	9.54

Table 29: Results of model extraction attacks on CIFAR100. The victim model is ResNet-AT. The adversary model is VGG.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	28.06	34.76	2.40	2.24	2.70	1.88	38.74	48.46	1.98	1.74	2.02	1.50
	JBDA	16.06	20.42	8.06	7.86	5.26	4.64	12.54	15.40	5.64	5.64	3.60	3.10
	ARD	21.30	28.80	11.50	11.48	10.26	9.76	20.38	27.96	10.70	10.72	9.86	9.30
	IAD	18.78	25.24	11.28	11.20	10.24	9.52	18.58	25.06	11.08	11.08	10.06	9.54
	RSLAD	25.14	33.44	12.14	12.02	11.50	10.82	25.38	33.74	11.12	11.12	11.04	9.96
Logits	Vanilla	1.34	1.50	1.82	1.78	0.22	0.20	5.48	5.88	1.46	1.38	0.52	0.08
	JBDA	1.78	1.74	1.08	1.06	0.70	0.62	2.56	2.80	0.64	0.52	0.10	0.08
	ARD	1.14	0.92	0.98	0.96	0.00	0.00	1.00	0.38	1.00	1.00	0.48	0.22
	IAD	1.08	1.10	0.98	0.94	0.02	0.02	1.00	1.08	1.00	1.00	0.98	0.98
	RSLAD	1.10	1.12	0.94	0.92	0.00	0.00	1.00	1.08	1.00	1.00	0.94	0.94
BEST		32.60	43.54	10.02	9.78	10.62	9.30	32.62	43.76	9.90	9.80	10.76	9.32

Table 30: Results of model extraction attacks on CIFAR100. The victim model is WRN-AT. The adversary model is VGG.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	31.54	41.96	3.26	3.06	3.50	2.58	35.42	45.90	2.68	2.46	2.76	2.08
	JBDA	16.04	20.80	9.32	9.22	5.16	4.64	13.66	17.20	7.44	7.36	4.36	3.92
	ARD	20.36	29.86	11.58	11.52	10.58	9.94	20.00	29.54	11.22	11.14	10.46	9.68
	IAD	18.96	28.34	11.48	11.40	10.66	10.12	18.96	27.70	10.72	10.74	10.26	9.56
	RSLAD	23.92	34.90	12.54	12.50	12.02	11.24	24.94	35.36	11.70	11.64	11.58	10.74
Logits	Vanilla	2.06	2.70	1.48	1.44	0.14	0.12	3.54	4.46	1.46	1.46	0.14	0.10
	JBDA	1.12	1.18	1.08	1.10	0.02	0.02	1.06	1.12	0.92	0.80	0.54	0.46
	ARD	0.96	1.48	1.00	1.00	0.00	0.00	1.00	1.54	1.00	1.00	0.00	0.00
	IAD	1.00	1.54	1.00	1.00	0.00	0.00	1.00	1.54	1.00	1.00	1.00	1.00
	RSLAD	0.94	1.48	0.98	0.94	0.00	0.00	1.00	1.54	1.00	1.00	0.32	0.44
BEST		29.74	41.90	10.76	10.56	11.34	9.98	29.74	41.98	9.90	9.80	10.66	9.36

Table 31: Results of model extraction attacks on CIFAR100. The victim model is ResNet-TRADES. The adversary model is VGG.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	33.80	43.22	3.18	2.90	3.62	2.50	35.92	46.08	2.82	2.62	3.00	2.24
	JBDA	17.88	23.00	9.30	9.32	6.40	5.32	14.84	18.94	7.84	7.74	4.98	4.24
	ARD	19.90	27.50	11.52	11.46	10.68	10.28	19.76	27.22	10.86	10.86	9.90	9.44
	IAD	18.58	25.80	11.42	11.34	10.20	9.82	18.32	24.80	10.60	10.60	9.82	9.44
	RSLAD	25.26	34.82	12.34	12.38	11.78	11.06	24.18	32.94	11.62	11.60	11.32	10.68
Logits	Vanilla	1.90	2.26	1.66	1.52	0.00	0.00	3.26	3.68	1.44	1.34	0.00	0.00
	JBDA	1.14	1.54	1.02	1.00	0.12	0.04	1.50	1.82	0.42	0.40	0.12	0.10
	ARD	1.00	1.02	1.00	0.98	0.02	0.04	1.00	1.02	1.00	1.00	1.00	1.00
	IAD	1.04	1.10	0.96	0.94	0.06	0.00	1.00	1.06	1.00	1.00	1.00	1.00
	RSLAD	1.00	1.06	1.00	1.00	1.00	1.00	1.00	1.06	1.00	1.00	0.24	0.06
BEST		29.66	40.04	10.40	10.18	10.78	9.70	29.66	40.04	10.38	10.18	10.72	9.70

Table 32: Results of model extraction attacks on CIFAR100. The victim model is WRN-TRADES. The adversary model is VGG.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	43.26	60.20	2.74	2.32	3.00	1.56	43.78	60.64	2.36	2.20	2.70	1.52
	JBDA	23.70	30.32	5.88	5.78	6.12	5.42	20.62	26.08	4.20	4.02	4.48	3.86
	ARD	33.30	48.40	16.34	16.22	15.56	14.64	31.60	46.46	13.36	13.36	12.82	12.10
	IAD	32.74	48.12	16.06	15.98	15.22	14.22	31.88	46.14	13.58	13.48	13.06	12.18
	RSLAD	34.14	50.10	15.14	14.98	14.32	13.42	32.00	47.20	13.18	13.06	12.44	11.82
Logits	Vanilla	37.24	46.90	1.74	1.42	1.04	0.36	37.32	47.10	1.70	1.40	1.00	0.40
	JBDA	12.02	14.48	1.26	1.08	1.10	0.52	11.60	13.76	0.98	0.84	0.94	0.54
	ARD	14.24	19.44	5.30	5.16	2.74	2.14	14.54	19.70	4.94	4.88	2.76	2.12
	IAD	17.84	25.32	11.00	10.96	9.12	8.52	16.66	23.98	10.06	10.04	8.24	7.66
	RSLAD	24.36	34.30	11.96	11.96	9.04	7.92	23.98	34.12	11.36	11.32	8.66	7.50
BEST		41.48	60.74	12.84	12.68	13.44	12.20	41.40	60.84	12.64	12.50	13.34	12.04

Table 33: Results of model extraction attacks on CIFAR100. The victim model is ResNet-AT. The adversary model is MobileNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	29.36	36.28	1.68	1.48	1.56	1.00	45.06	57.26	1.20	1.00	1.32	0.74
	JBDA	16.22	19.50	4.02	3.92	4.30	3.72	11.78	14.08	1.90	1.90	2.00	1.76
	ARD	33.72	46.22	15.66	15.56	14.72	13.64	32.18	43.90	12.72	12.64	11.96	11.24
	IAD	32.66	43.86	15.42	15.32	14.36	13.58	30.86	41.26	11.54	11.38	11.32	10.40
	RSLAD	34.24	45.96	15.28	15.18	14.26	13.46	33.52	44.96	12.98	12.92	12.38	11.68
Logits	Vanilla	39.54	46.90	1.36	1.14	0.82	0.34	39.10	46.70	1.28	1.06	1.02	0.36
	JBDA	12.60	14.48	0.96	0.82	0.84	0.44	8.64	9.66	0.42	0.42	0.50	0.20
	ARD	13.84	17.62	5.12	5.16	3.14	2.66	12.96	17.38	4.30	4.28	2.92	2.42
	IAD	17.72	23.18	10.62	10.58	8.96	8.30	16.92	22.26	9.30	9.30	7.62	7.10
	RSLAD	25.32	33.14	11.56	11.48	8.60	7.46	24.34	31.70	10.04	9.94	7.76	7.04
BEST		42.72	57.38	12.00	11.72	12.78	11.26	42.20	56.84	11.38	11.26	12.32	10.76

Table 34: Results of model extraction attacks on CIFAR100. The victim model is WRN-AT. The adversary model is MobileNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	29.44	39.94	2.34	2.06	2.10	1.48	42.22	55.66	1.90	1.66	1.98	1.10
	JBDA	20.22	26.28	5.34	5.24	5.50	5.06	18.84	23.08	3.96	3.92	4.14	3.72
	ARD	33.06	47.64	15.22	15.08	14.26	13.50	30.54	43.80	13.30	13.22	12.60	11.94
	IAD	30.46	44.24	15.00	14.92	14.14	13.24	29.76	42.48	12.94	12.92	11.98	11.40
	RSLAD	32.44	46.64	14.84	14.72	14.06	13.24	31.14	44.78	12.88	12.76	12.40	11.56
Logits	Vanilla	31.94	41.48	2.30	1.92	1.02	0.36	31.82	41.16	2.16	1.76	1.04	0.36
	JBDA	12.52	15.94	0.86	0.64	0.50	0.24	11.76	15.18	0.82	0.68	0.40	0.18
	ARD	11.62	17.60	5.06	4.90	2.68	2.12	11.54	17.48	4.68	4.66	2.66	2.24
	IAD	15.18	22.40	9.36	9.34	7.54	7.14	14.30	21.12	9.04	9.02	7.26	6.82
	RSLAD	21.06	30.50	10.24	10.16	7.22	6.54	20.82	30.06	9.74	9.78	7.06	6.60
BEST		37.84	54.10	12.54	12.30	13.06	11.88	38.74	55.68	11.88	11.68	12.34	11.28

Table 35: Results of model extraction attacks on CIFAR100. The victim model is ResNet-TRADES. The adversary model is MobileNet.

Method		Extracted model with the highest robustness						Final model after extraction					
		CA	*rCA*	*RA*				*CA*	*rCA*	*RA*			
				PGD20	PGD100	CW100	AA			PGD20	PGD100	CW100	AA
Label	Vanilla	30.18	39.02	2.36	2.16	2.26	1.40	43.10	55.04	1.48	1.28	1.50	0.94
	JBDA	20.64	26.36	5.44	5.32	5.74	5.12	14.54	18.28	2.36	2.34	2.48	2.16
	ARD	32.00	44.30	15.80	15.80	14.48	14.00	31.28	42.92	12.80	12.72	12.34	11.58
	IAD	32.04	43.88	15.76	15.68	14.64	14.02	30.66	42.22	12.16	12.12	11.56	10.94
	RSLAD	31.34	43.56	15.16	15.04	14.20	13.24	31.02	43.04	12.36	12.26	11.90	11.30
Logits	Vanilla	33.16	40.56	2.24	1.82	1.12	0.54	33.04	40.26	2.02	1.84	1.24	0.46
	JBDA	10.86	13.36	0.94	0.88	0.54	0.30	7.44	8.74	0.66	0.56	0.42	0.26
	ARD	10.92	15.72	3.90	3.80	1.96	1.66	10.56	15.14	3.26	3.32	1.96	1.58
	IAD	15.82	20.68	10.16	10.24	8.12	7.70	15.28	20.24	8.90	8.94	7.28	6.86
	RSLAD	22.00	29.50	10.94	10.82	7.66	6.84	21.10	28.34	9.56	9.48	6.94	6.12
BEST		39.90	54.44	12.04	11.82	12.66	11.26	40.26	55.08	11.52	11.38	12.06	10.94

Table 36: Results of model extraction attacks on CIFAR100. The victim model is WRN-TRADES. The adversary model is MobileNet.

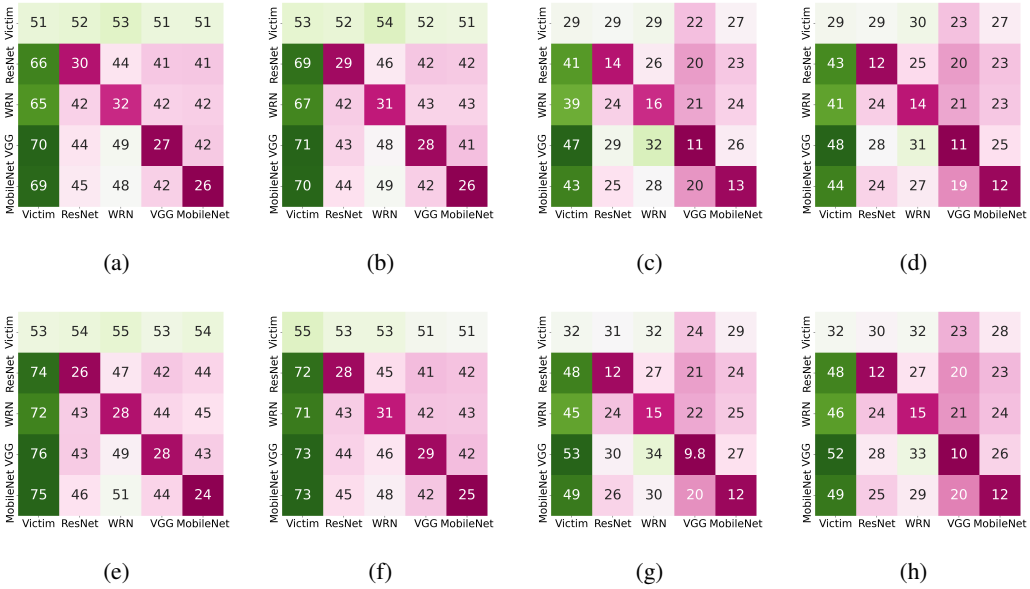

Figure 5: Transferability stabilization of our BEST. The dataset of (a), (b), (e) and (f) is CIFAR10. The dataset of (c), (d), (g) and (h) is CIFAR100. The victim model of (a) and (c) is ResNet-AT. The victim model of (e) and (g) is WRN-AT. The victim model of (b) and (d) is ResNet-TRADES. The victim model of (f) and (h) is WRN-TRADES. We generate adversarial examples by using PGD100. The vertical axis represents the model which generates adversarial examples. The horizontal axis represents the model which is attacked by other models' adversarial examples. The number inside each square is the prediction accuracy.