

# A Middle Path for On-Premises LLM Deployment: Preserving Privacy Without Sacrificing Model Confidentiality

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## Abstract

Privacy-sensitive users require deploying large language models (LLMs) within their own infrastructure (*on-premises*) to safeguard private data and enable customization. However, vulnerabilities in local environments can lead to unauthorized access and potential model theft. To address this, prior research on small models has explored securing only the output layer within hardware-secured devices to balance model confidentiality and customization. Yet this approach fails to protect LLMs effectively. In this paper, we discover that (1) query-based distillation attacks targeting the secured top layer can produce a functionally equivalent replica of the victim model; (2) securing the same number of layers, bottom layers before a transition layer provide stronger protection against distillation attacks than top layers, with comparable effects on customization performance; and (3) the number of secured layers creates a trade-off between protection and customization flexibility. Based on these insights, we propose SOLID, a novel deployment framework that secures a few bottom layers in a secure environment and introduces an efficient metric to optimize the trade-off by determining the ideal number of hidden layers. Extensive experiments on five models (1.3B to 70B parameters) demonstrate that SOLID outperforms baselines, achieving a better balance between protection and downstream customization. Our code can be found at: <https://github.com/OTTO-OTO/SOLID-OnPremiseDeployment>.

## 1 Introduction

Vendors of Large Language Models (LLMs) have introduced advanced models with remarkable capabilities to address diverse user needs (Minaee et al., 2024; Zhao et al., 2023). To meet specific customization demands, vendors typically adopt two approaches. Closed-source vendors, such as OpenAI, provide fine-tuning APIs that allow users to upload data to customize proprietary models like

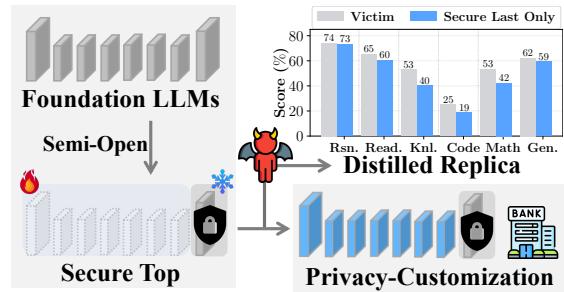


Figure 1: Semi-open Deployment.

**GPT-4.** In contrast, vendors like Meta offer open-weight models such as Llama3 (Dubey et al., 2024), which users can adapt within their own infrastructure, ensuring greater flexibility and control.

However, both approaches present notable limitations for privacy-sensitive users, such as health-care organizations, who prioritize data security. Strict regulations prohibit these users from uploading sensitive data to third-party API services, necessitating *on-premises deployment* of LLMs, where data processing and model customization are confined to local infrastructure (Nevo et al., 2024). Although fine-tuning open-weight models in such environments offers a viable path for customization, full disclosure of model architectures and weights increases the risk of exploitation by malicious actors, who may circumvent safety mechanisms (Hendrycks et al., 2023). Consequently, vendors may be hesitant to release SOTA models as open-weight, since uncontrolled access could lead to significant harm. Moreover, maintaining high-quality open-weight models imposes considerable computational and financial burdens (Wolfe et al., 2024). These growing concerns highlight the importance of *secure on-premises deployment of closed-source models*, which preserves control and ensures regulatory compliance.

Despite the advantages, deploying closed-source LLMs locally introduces the risk of model theft. Unauthorized users can extract model parameters and architectures directly from CPUs and memory

within local environments (Hu et al., 2020). To mitigate this, existing approaches use Trusted Execution Environments (TEEs) to protect proprietary models (Nayan et al., 2024; Narra et al., 2019). Yet, fully enclosing large models within TEEs results in prohibitive computational overhead, limiting their practicality (Li et al., 2024a).

Prior research has explored to mitigate this trade-off by securing only critical layers, such as the output layer, while leaving the remaining layers exposed for fine-tuning (Zhang et al., 2024b; Mo et al., 2020). However, studies have shown that even with only black-box access, adversaries may still be able to replicate the weights of DNNs (Tramèr et al., 2016; Truong et al., 2021). More recent works (Carlini et al., 2024; Finlayson et al., 2024) further suggests that the final-layer weights of large language models (LLMs) can be recovered from output logits alone, raising concerns about the robustness of such partial protection strategies. Consistent with previous findings, our results show that this partial protection remains vulnerable to distillation attacks (Zanella-Beguelin et al., 2021). When extended to Llama2-70B, we confirm that attackers can still extract nearly complete model functionality across six domains, as illustrated in Figure 1. These vulnerabilities raise skepticism about *whether model confidentiality and customization can truly coexist in on-premises deployment*, highlighting the need for security paradigms beyond output-layer protection.

In this paper, we show that this dilemma can be resolved. We begin by investigating the security-customization trade-off introduced by the placement of secured layers in LLMs. Specifically, we theoretically identify a transition layer in deep transformers, showing that securing bottom layers before this transition significantly reduces distillation success, while securing top layers has a more limited impact. Besides, we demonstrate that the number of secured layers creates a trade-off: securing more layers improves security but reduces customization flexibility. To optimize this trade-off, we introduce SOLID, a semi-open deployment framework that selectively secures a subset of bottom layers, using a distillation difficulty score to identify the optimal set for protection. Our experiments show that SOLID balances security and customization, achieving security comparable to fully secured models while maintaining strong customization flexibility, approaching full parameter fine-tuning. Our main contributions are as follows:

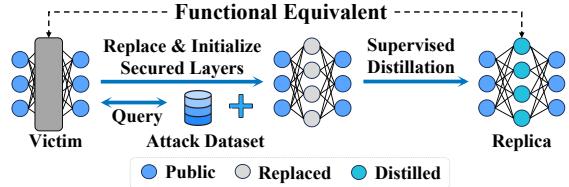


Figure 2: Workflow of model distillation attack

- We extend query-based distillation attacks to LLMs, demonstrating that existing on-premises frameworks risk full functionality replication.
- We identify the security-customization trade-off introduced by the placement of secured layers, and theoretically prove that securing bottom layers before the transition layer offers stronger protection with similar customization effects.
- We discover that the number of secured layers affects both security and customization. We propose SOLID, which optimizes the security-customization trade-off by using a fine-tuning-free metric to secure minimal bottom decoder layers, protecting the model from distillation attacks while preserving customization flexibility.
- We evaluate SOLID against three baselines across five models (1.3B to 70B parameters), assessing security across three distillation strategies on sixteen benchmarks and customization flexibility across six tasks. Extensive experiments show SOLID effectively balances security and customization, despite some limitations

## 2 Preliminaries

### 2.1 Security Threat: Model Distillation

**Adversary’s Objective.** The adversary aims to replicate the functionality of a semi-open victim LLM, partially secured in a protected environment, by training a substitute model. This replica facilitates white-box analysis to identify vulnerabilities, enhancing black-box attacks on related model families (Sitawarin et al., 2024). The agreement between the victim and replica is assessed via accuracy and fidelity on a designated test set.

**Adversary’s Knowledge.** It is assumed that the adversary knows the architectures of both secured and unsecured modules, as prior work (Gou et al., 2021; Boix-Adsera, 2024) has shown that using the same architecture as the secured module significantly improves the effectiveness of distillation attacks. However, the adversary knows only the parameters of the unsecured module, while those of the secured module remain unknown.

**Adversary’s Capability.** The adversary is capable of querying the semi-open model, obtaining both the semantic output produced by the complete model and the representation vector generated by the secured module. Utilizing this information, the adversary constructs a distillation attack dataset denoted as  $\mathcal{D}$ . Since the adversary knows the architecture of the secured module, the adversary next replaces the secured module with a randomly initialized module of the same architecture. Using the constructed set  $\mathcal{D}$ , the adversary employs three distinct supervised distillation strategies to replicate the functionality of the secured module: (1) **FT-all**: Fine-tunes both the replacement and unsecured modules using output of the entire model as training labels. (2) **FT-closed**: Fine-tunes only the replacement model using output of the entire model, keeping the unsecured module fixed. (3) **SEM** (Tamber et al., 2024): Fine-tunes the replacement model using outputs from the secured module without involving the unsecured component.

## 2.2 Problem Formulation

In this paper, we analyze the performance of a large language model under a defined distribution  $\mathbb{P}_{\mathbf{X} \times Y}$ , describing the relationship between input matrix  $\mathbf{X}$  and label  $Y$ . We assume the victim LLM  $f(\mathbf{X}; \boldsymbol{\theta})$  performs well on this distribution, and the attack set  $\mathcal{D}$  comprises samples drawn from  $\mathbb{P}_{\mathbf{X} \times Y}$ . To evaluate agreement between the distilled LLM and ground-truth labels, we use a scoring function  $s : \mathcal{Y} \times \mathcal{Y} \rightarrow \mathbb{R}^+$ . Secured layers are indexed by  $I \subseteq [L] = \{1, \dots, L\}$ . Let  $\boldsymbol{\theta}_{\text{dist}}(I, \mathcal{D})$  represent the parameter vector of the distilled replica of a victim model, where layers indexed by  $I$  are secured, and adversaries utilize the attack set  $\mathcal{D}$  to replicate its functionality. For each secured set  $I$ , we define the “**Distillation Ratio**”  $R(I)$ , which quantifies how well the distilled model  $\boldsymbol{\theta}_{\text{dist}}(I, \mathcal{D})$  replicates the behavior of  $f(\mathbf{X}; \boldsymbol{\theta})$ , expressed as

$$R(I) = \frac{\mathbb{E}[s(f(\mathbf{X}; \boldsymbol{\theta}_{\text{dist}}(I, \mathcal{D})), Y)]}{\mathbb{E}[s(f(\mathbf{X}; \boldsymbol{\theta}), Y)]}. \quad (1)$$

Here,  $\mathbb{E}$  in the numerator reflects the expectation computed over random samples  $(\mathbf{X}, Y)$  drawn from  $\mathbb{P}_{\mathbf{X} \times Y}$ , the random attack set  $\mathcal{D}$ , and the random initialization of parameters within the secured layers during fine-tuning. Conversely, the term  $\mathbb{E}$  in the denominator solely considers the expectation over random samples. With this definition,  $R([L])$  represents the distillation ratio when the

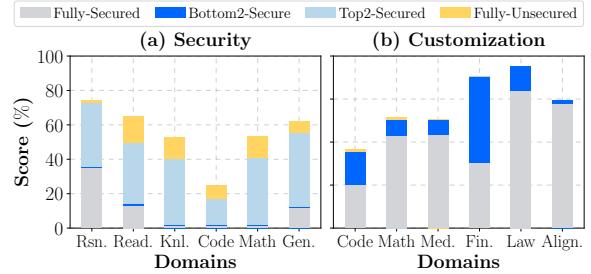


Figure 3: Security and adaptability comparison in Llama2-70B. Lower scores indicate better security in Fig. (a) and weaker adaptability in Fig. (b). Details can be found in Appendix C.1

entire model is secured, reflecting the highest level of security. This leads to the question:

What is the smallest secured set  $I$  such that

$$R(I) \text{ closely approximates } R([L])?$$

This question aims to identify the minimal secured set  $I$  such that securing the layers indexed by  $I$  achieves a level of security comparable to securing the entire model.

## 3 Methodology

In this section, we investigate the impact of securing specific layers on security and customization against distillation attacks. We begin with an experiment with two semi-open deployments of Llama2-70B: one securing the bottom two decoder layers (Bottom2-Secured) and the other securing the top two decoder layers (Top2-Secured). As shown in Figure 3, both deployments achieve similar customization performance in six downstream tasks. However, securing the bottom layers provides significantly stronger security. Additionally, comparing Bottom2-Secured to fully-secured deployment reveals comparable security with improved customizability. This suggests that securing a certain number of bottom layers can effectively balance strong security against distillation attacks and high customization performance.

### 3.1 Security Transition in Deep Transformers

**Model Overview.** In this subsection, we consider a deep transformer  $f$  with  $L$  layers, expressed as  $f(\mathbf{X}; \boldsymbol{\theta}) = \varphi_L \circ \dots \circ \varphi_1(\mathbf{X})$ . The input feature matrix  $\mathbf{X} \in \mathbb{R}^{n \times d}$  consists of  $n$  rows, each representing a  $d$ -dimensional token vector. Each layer  $\varphi_i$  is a transformer that incorporates a normalized residual self-attention mechanism, defined as:

$$\varphi_i(\mathbf{X}; K_i, Q_i) = \mathbf{X} + \text{softmax}\left(\frac{\mathbf{X}Q_i(\mathbf{X}K_i)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2}\right) \mathbf{X}$$

Here,  $Q_i \in \mathbb{R}^{d \times d_Q}$  and  $K_i \in \mathbb{R}^{d \times d_Q}$  are projection matrices for the query and key components, respectively. The terms  $\sqrt{d_Q}$  and  $\|\mathbf{X}\|$  serve as normalization factors, ensuring stable computations within the attention mechanism. We consider the semi-open deployment of securing the  $\alpha L$ -th layer with  $\alpha \in [0, 1]$  and  $\alpha L \in \mathbb{N}$  while keeping other layers unsecured. After the distillation attack, we assume the parameters of the distilled model in the unsecured layers are identical to the victim model, while those in the secured layer deviate. Let  $\hat{K}_{\alpha L}$  and  $\hat{Q}_{\alpha L}$  denote the distilled weight matrix of the proprietary layer, i.e.,  $\theta_{\text{dist}}(\{\alpha L\}) = \{(K_1, Q_1), \dots, (\hat{K}_{\alpha L}, \hat{Q}_{\alpha L}), \dots, (K_L, Q_L)\}$ . Let  $\hat{\varphi}_{\alpha L}$  denote the function of the distilled proprietary layer, i.e., the  $\alpha L$ -th layer, in the distilled model. In this subsection, we consider the normalized output of an infinitely deep model whose  $\alpha L$ -th layer is hidden and subjected to the attack. The output of the distilled model is

$$\hat{f}_\infty(\mathbf{X}) = \lim_{L \rightarrow \infty} \frac{f(\mathbf{X}; \theta_{\text{dist}}(\{\alpha L\}))}{\|f(\mathbf{X}; \theta_{\text{dist}}(\{\alpha L\}))\|_F},$$

where  $\|\cdot\|_F$  denotes the Frobenius norm. We consider an infinitely deep network as the ideal model, reflecting the sufficient depth of most large-scale models in practice. The following theorem establishes the existence of a critical value  $\alpha^*$  such that if  $\alpha < \alpha^*$ , the output matrix of the distilled LLM has rank one. Conversely, if  $\alpha > \alpha^*$ , the output matrix has rank strictly greater than one.

**Theorem 1.** *Assume that  $\mathbb{P}_{\mathbf{X} \times \mathbf{Y}}$  is defined on a countable domain  $\mathcal{X} \times \mathcal{Y}$  with  $\mathbf{0}_{n \times d} \notin \mathcal{X}$ . Assume that parameter matrices  $\{K_i, Q_i\}_{i \geq 1}$  in the victim model  $f$  have uniform bounded norms, i.e.,  $\|K_i\| \leq D$  and  $\|Q_i\| \leq D$  for some  $D > 0$ . There exists an  $\alpha^* \in (0, 1)$  depending on  $D$  such that the following two statements are true.*

(1) *If  $\alpha < \alpha^*$  and  $\{K_i, Q_i\}_{i \geq 1}$  are parameter matrices of the victim model, with  $\hat{K}_{\alpha L}$  and  $\hat{Q}_{\alpha L}$  as distilled parameters drawn from a continuous distribution on  $\mathbb{R}^{n \times d}$ , the matrix  $\hat{f}_\infty(\mathbf{X})$  almost surely has rank one for all inputs  $\mathbf{X}$ .*

(2) *If  $\alpha > \alpha^*$ , there exists a victim model with parameter sequence  $\{K_i, Q_i\}_{i \geq 1}$  such that for any distilled parameters  $\hat{K}_{\alpha L}$  and  $\hat{Q}_{\alpha L}$ , the matrix  $\hat{f}_\infty(\mathbf{X})$  has rank greater than one for some  $\mathbf{X}$ .*

**Remark 1:** The proof is provided in Appendix A. This theorem demonstrates that if the distilled parameters of the bottom layers (i.e.,  $\alpha < \alpha^*$ ) are obtained through a randomized algorithm, such

as stochastic gradient descent, with a continuous distribution supported on  $\mathbb{R}^{n \times d}$ , the distillation will certainly fail, as the feature matrix degenerate. In contrast, keeping the later layers secured (i.e.,  $\alpha > \alpha^*$ ) does not maintain this property, indicating that it is more effective to secure the bottom layers before the transition layer, rather than the later ones. Further remarks are in Appendix A.5.

### 3.2 SOLID: Semi-Open Local Infrastructure Deployment Framework

Theorem 1 shows that securing bottom layers improves security. Inspired by this insight, we propose a method to approximately find the smallest bottom layer index set  $I$  that satisfies  $R(I) \leq (1 + \varepsilon)R([L])$  for any small  $\varepsilon > 0$ . To achieve this, a straightforward implementation is to begin with  $A$ . A simple approach is to start with  $I_l = \{1, \dots, l\}$  for each  $l$  beginning from 1, then evaluate the distillation ratio  $R(I_l)$  after the attack, and identify the smallest  $l$  that meets the inequality. This extensive fine-tuning process is time-consuming, prompting the critical question: *Can we create a fine-tuning-free metric that predicts LLM performance under model distillation attacks?* Hence, our goal is to establish a metric directly correlated with the distillation ratio.

In the distillation ratio  $R(I)$ , each  $I$  has the same denominator, so our focus is on a metric related to the numerator, specifically  $\mathbb{E}[s(f(\mathbf{X}; \theta_{\text{FT}}(I, \mathcal{D})), Y)]$ , which measures the average performance score of the distilled model. This average performance score generally inversely correlates with the average testing loss with the expression  $L(\theta) \triangleq \mathbb{E}_{\mathbf{X} \times \mathbf{Y}}[\ell(f(\mathbf{X}; \theta), Y)]$ , where  $\ell$  denotes the cross-entropy loss employed by LLM. Hence, we aim at finding the smallest  $I$  such that

$$L(\theta_{\text{dist}}(I, \mathcal{D})) \geq (1 - \varepsilon)L(\theta_{\text{dist}}([L], \mathcal{D})).$$

However, calculating both sides of this inequality requires knowing the distilled parameters from the fine-tuning process. To bypass this, we aim for an approximate solution. The distilled parameters are generated through gradient descent, starting from the initial parameters  $\theta_0(I)$ , with the hidden layers being randomly initialized. Using the Taylor Expansion, we find

$$\begin{aligned} L(\theta_{\text{dist}}(I, \mathcal{D})) &= L(\theta_0(I, \mathcal{D})) \\ &+ \mathcal{O}(\mathbb{E}\|\theta_{\text{dist}}(I, \mathcal{D}) - \theta_0(I)\|_2). \end{aligned}$$

Previous research (Choi et al., 2024; Bailly et al., 2022) indicates that the difference  $\|\theta_{\text{dist}}(I, \mathcal{D}) -$

$\theta_0(I)\|_2$  is minimal in large networks compared to the dataset size  $|\mathcal{D}|$ . In models such as single-layer ReLU networks (Anthony et al., 1999; Zou et al., 2020), this difference scales as  $\mathcal{O}\left(\frac{|\mathcal{D}|}{\sqrt{N}}\right)$  (Jacot et al., 2018; Wei et al., 2019), where  $N$ , the number of model parameters, far exceeds the dataset size in large language models (LLMs) (Dubey et al., 2024; Liu et al., 2024). The first term, independent of fine-tuning, dominates and effectively predicts the distillation ratio. We refer to this term as the **Distillation Difficulty** ( $\text{DD}(I)$ ), defined as

$$\text{DD}(I) = \mathbb{E}[L(\theta_0(I))].$$

This score, which can be estimated using a sample average, represents the distilled model performance of the model when specific layers  $I$  are secured. A higher  $\text{DD}(I)$  suggests better security performance, indicating a lower distillation ratio  $R(I)$ . Therefore, our SOLID operates in the following way. SOLID begins by sampling evaluation data targeting general capabilities from the underlying distribution, and then computes  $\text{DD}(I_l)$  for each set of secured layers  $I_l = \{1, \dots, l\}$  for  $l = 1, \dots, L$ . SOLID stops at the smallest  $l^*$  that satisfies  $\text{DD}(I_{l^*}) \geq (1 - \varepsilon)\text{DD}([L])$ .

## 4 Experiments

In this section, we conduct experiments to answer the following research questions:

- **RQ1.** Can query-based distillation attack distill the functionality of the entire model under the baseline deployment that secures the top layer?
- **RQ2.** How do secured layer location and amount affect the security-customization trade-off?
- **RQ3.** Does SOLID offer a better balance between model theft risk and customization performance compared to baseline deployments?
- **RQ4.** How does SOLID optimize this trade-off? Is it effective for both large and small models?

### 4.1 Experimental Settings

We begin by introducing our experimental setups. Details can be found in Appendix B.

**Models.** We consider **five** open-source, decoder-only structured LLMs with various architectures. Specifically, we select Llama2-70B-chat, Llama2-7B-chat (Touvron et al., 2023), Mistral-7B-v0.1 (Jiang et al., 2023), Phi-2 (Abdin et al., 2024), and Phi-1.5 (Li et al., 2023). We designate these pre-trained models as the base models for adaptation and victims in model distillation attacks.

**Attack Methods.** We distill models produced by different protection approaches using three attack methods: FT-all, FT-closed and SEM. Following (He et al., 2021), a diverse attack set is required for full distillation. Therefore, we merge data evenly from two general datasets, MMLU benchmark (Hendrycks et al., 2021) and Alpaca 52k (Wang et al., 2022), resulting in a 51k combined set. Additionally, we build four larger general datasets (100k–500k) to strengthen the attack.

**Baselines.** We compare SOLID with three baselines: SAP-DP, the fully-secured approach (Eiras et al., 2024), and DarkneTZ (Mo et al., 2020). The SAP (Shen et al., 2023) framework exposes the first six decoder layers and secures the rest. SAP-DP extends SAP by adding Laplace noise to model outputs to enhance protection (Lee et al., 2018). The fully-secured approach represents the extreme, securing all layers for maximal security, while DarkneTZ protects only the final decoder layer.

**Implementation Details of SOLID.** We apply the SOLID algorithm to identify the smallest secure set  $I$  such that  $R(I) \leq (1 + \varepsilon)R([L])$ . To calculate distillation difficulty (DD), we use cross-entropy loss and approximate the expectation over samples distributed on the general domain and randomly initialized secured parameters. This is done using a 1,500-sample evaluation set randomly sampled from the MMLU benchmark and Alpaca 52k, with secured parameters initialized via Xavier initialization and averaged over three random seeds (20, 42, 1234). In our experiments, we find that  $\varepsilon = 0.05$  yields optimal performance.

**Evaluation Benchmarks** We assess adaptability on six downstream tasks: Code (Zheng et al., 2024a), Math (Yue et al., 2023), Medical (Zhang et al., 2023), Finance (Wang et al., 2023a), Law (Guha et al., 2024), and Alignment (Meng et al., 2024). To fully evaluate recovered functionalities, we focus on six capabilities domains following Llama2 report (Touvron et al., 2023). Specifically, we assess the recovered model across **sixteen** benchmarks grouped into (1) *Commonsense Reasoning* (Rsn.); (2) *Reading Comprehension* (Read.); (3) *World Knowledge* (Knl.); (4) *Code*; (5) *Math*; and (6) *General Ability* (Gen.).

**Metrics.** We measure customization through model’s improvements on benchmarks. For security, we calculate the “Average Distillation Ratio” (ADR) by averaging the distillation ratios across benchmarks. A lower ADR indicates higher security offered by the secure set.

|                                      | <b>Benchmark</b> | <b>Llama2-70B</b>                   | <b>Llama2-7B</b>                    | <b>Mistral-7B</b>                   | <b>Phi-2</b>                        |
|--------------------------------------|------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|
| <b>Rsn.</b>                          | PIQA             | 62.6 59.8 63.0 99.3                 | 64.7 64.7 64.6 99.1                 | 63.0 61.2 60.2 92.2                 | 68.3 65.6 65.7 99.1                 |
|                                      | Winogrande       | 68.5 67.7 68.3 98.3                 | 76.8 74.8 76.6 100.                 | 67.2 69.0 68.3 89.5                 | 68.3 64.9 64.8 99.1                 |
|                                      | ARC-easy         | 31.9 32.8 31.3 98.5                 | 36.3 35.5 34.9 97.6                 | 32.3 34.7 32.0 86.6                 | 43.2 35.3 33.9 99.5                 |
|                                      | ARC-challenge    | 38.5 38.1 44.2 99.2                 | 47.8 46.6 50.9 100.                 | 39.7 42.6 44.5 81.4                 | 36.8 36.6 35.3 99.5                 |
| <b>Read.</b>                         | Hellaswag        | 31.4 31.4 32.4 98.1                 | 33.9 34.0 35.0 96.6                 | 32.2 32.0 31.3 84.6                 | 37.4 37.3 34.3 96.5                 |
|                                      | LAMBADA          | 0.01 0.00 0.00 88.6                 | 0.02 0.00 0.01 92.2                 | 0.16 0.00 0.01 67.9                 | 1.34 0.04 0.00 94.6                 |
|                                      | BoolQ            | 47.2 47.1 53.9 100.                 | 59.5 56.0 65.0 99.6                 | 48.3 46.8 56.7 97.3                 | 56.7 50.3 55.8 100.                 |
|                                      | SQuADv2          | 1.50 1.68 0.34 55.3                 | 0.68 0.88 0.82 59.5                 | 1.69 0.36 0.93 50.7                 | 3.65 0.39 0.90 62.9                 |
| <b>Knl.</b>                          | OBQA             | 54.5 54.5 57.1 99.6                 | 57.4 52.5 59.2 94.8                 | 57.7 56.8 56.3 84.0                 | 0.00 0.00 0.02 94.3                 |
|                                      | NaturalQuestions | 0.00 0.02 0.00 40.1                 | 0.01 0.01 0.08 53.6                 | 0.00 0.00 0.02 31.8                 | 0.01 0.00 0.06 87.4                 |
|                                      | TriviaQA         | 0.00 0.02 0.00 72.3                 | 0.00 0.00 0.03 73.8                 | 0.00 0.00 0.01 38.7                 | 0.01 0.00 0.01 68.9                 |
| <b>Code</b>                          | MBPP&H.E.        | 0.00 0.00 0.00 58.6                 | 0.00 0.00 0.00 90.9                 | 0.00 0.00 0.00 40.2                 | 0.00 0.00 0.00 91.1                 |
| <b>Math</b>                          | GSM8K            | 0.02 0.00 0.06 79.6                 | 0.00 0.00 0.00 78.6                 | 0.00 0.00 0.00 31.1                 | 0.00 0.00 0.00 86.2                 |
| <b>Gen.</b>                          | MMLU             | 36.8 38.3 36.5 96.7                 | 52.9 50.0 53.3 110.                 | 40.4 36.9 37.2 81.7                 | 42.6 40.3 40.5 99.5                 |
|                                      | BBH              | 0.00 0.00 0.00 93.3                 | 0.00 0.00 0.00 101.                 | 0.00 0.00 0.00 63.3                 | 0.01 0.00 0.00 94.8                 |
| <b>Average Distillation Ratio(↓)</b> |                  | <b>21.9</b>  21.8 22.8  <b>77.9</b> | <b>25.3</b>  24.4 25.9  <b>86.5</b> | <b>22.5</b>  22.4 22.8  <b>73.7</b> | <b>23.9</b>  22.3 22.4  <b>88.9</b> |
| <b>Secured Ratio(↓)</b>              |                  | <b>2.50</b>  92.5 100.  <b>1.25</b> | <b>3.16</b>  81.3 100.  <b>3.16</b> | <b>3.16</b>  81.3 100.  <b>3.16</b> | <b>6.25</b>  81.3 100.  <b>3.16</b> |

Table 1: Distillation ratios across six functionalities under FT-all (SOLID|SAP-DP|Fully-secured|DarkneTZ). “H.E.” in the Code domain denotes the benchmark HumanEval. Green and red indicate the overall best- and worst-performing methods, respectively. Additional results are provided in Appendix C.2.

## 4.2 Failure in Defense (RQ1)

We evaluate security of DarkneTZ using three distillation strategies. Based on the results shown in Tables 1 and 2, we have following observations.

**Obs1: DarkneTZ, which secures only the last decoder layer, fails to protect the model against all three attacks.** As shown in Table 1, DarkneTZ achieves ADRs generally exceeding 73%. Notably, on Llama2-7B, it surpasses 100% distillation ratio on the MMLU and BBH datasets, indicating that the distilled model outperforms the original on these tasks. Similarly, Table 2 highlights consistent failure patterns against FT-closed and SEM attacks, with DarkneTZ maintaining ADRs above 75%, demonstrating the ability of these strategies to recover significant model functionality.

## 4.3 Security-Customization Trade-off (RQ2)

We conduct two experiments to analyze the impact of secured layer placement and quantity on the trade-off between security and customization. First, we secure one layer in Llama2-7B and two in Phi-2, varying their placement. Second, we incrementally secure both models by adding protected layers, starting from the smallest module (k\_project) of the first decoder layer. These models are evaluated under the FT-all distillation attack and customized for the math domain. The results, as shown in

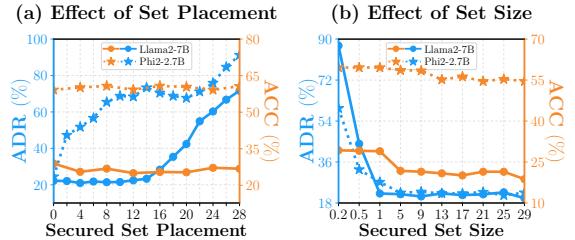


Figure 4: (a) shows the trade-off between security and customization for Llama2-7B and Phi-2 with different placements of same-sized secured sets. (b) shows the trade-off as the secured set size increases from the first decoder layer. Smaller ADR indicates higher security and higher ACC reflects better customizability.

Figure 4, lead to the following observations.

**Obs2: Secured layer placement significantly impacts security, consistent with Theorem 1, but has small effect on customization performance.**

As shown in Figure 4(a), for Llama2-7B, security transitions at the fourteenth layer, with ADR consistently near 20% for earlier sets, indicating stronger security than protecting later layers. Meanwhile, customization accuracy remains stable across placements, highlighting the advantage of securing pre-transition layers. In contrast, Phi-2 transitions earlier at the first layer set, where only the first set balances security and customization, with later sets reducing security. These results suggest that securing layers before the transition layer optimizes the security-customization trade-off. Results for

| Strat. | Method    | Rsn. | Read. | Knl. | C.&M. | Gen. | ADR  |
|--------|-----------|------|-------|------|-------|------|------|
| FT-c.  | SOLID     | 47.1 | 21.6  | 0.00 | 0.03  | 18.7 | 22.6 |
|        | SAP-DP    | 46.2 | 19.5  | 0.00 | 0.00  | 19.0 | 21.8 |
|        | F-Secured | 47.8 | 21.2  | 0.00 | 0.08  | 18.5 | 22.8 |
|        | DarkneTZ  | 98.7 | 69.3  | 58.3 | 65.9  | 95.0 | 78.1 |
| SEM    | SOLID     | 48.2 | 21.9  | 0.00 | 0.00  | 18.5 | 22.4 |
|        | SAP-DP    | 47.1 | 21.1  | 0.00 | 0.00  | 18.3 | 22.3 |
|        | F-Secured | 47.8 | 21.2  | 0.00 | 0.08  | 18.5 | 22.8 |
|        | DarkneTZ  | 98.8 | 71.2  | 54.2 | 66.3  | 94.1 | 77.4 |

Table 2: Distillation ratios of Llama2-70B under FT-closed and SEM attacks.

Mistral-7B and Phi-1.5 are in Appendix B.7.

**Obs3: Increasing the number of secured layers enhances security but reduces customization.**

As shown in Figure 4(b), the ADR of Llama2-7B decreases from 85% to 22% after securing an entire decoder layer, indicating improved security. However, customization accuracy drops from 29% to 21% as the number of secured layers increases from one to five, reflecting reduced customization flexibility. A similar trend is observed in Phi-2, suggesting that while increasing the number of secured layers enhances security (lower ADR), it negatively impacts customization flexibility (lower ACC) in both models. Further details are in Appendix B.8.

#### 4.4 Effectiveness of SOLID (RQ3)

We compare the security of SOLID with baseline deployments across three distillation strategies. The results lead to the following observations.

**Obs4: SOLID offers comparable security against model distillation to the highest level of protection (fully-secured), while securing significantly fewer parameters.** As shown in Table 1, SOLID achieves a similar security level (ADR) to SAP-DP and the fully-secured approach across four architectures and various domains, while securing at most 6.25% of parameters, compared to at least 80% for the others. For example, on Llama2-70B, SOLID secures only 1.25% of parameters yet achieves an ADR of 21.9%, comparable to SAP-DP (21.8%) and the fully-secured approach (22.8%), which protect 92.5% and 100% of parameters, respectively. Furthermore, under FT-closed and SEM attacks, SOLID also matches the security level provided by SAP-DP and the fully-secured approach. Table 2 shows that under FT-closed attack, the ADR differences between SOLID, SAP-DP, and the fully-secured approach remain below 2.1% across six domains. Similarly, under SEM attack, the distillation ratios closely aligned with the

| Scale | Rsn. | Read. | Knl. | C.&M. | Gen. | ADR  | ADR-Da. |
|-------|------|-------|------|-------|------|------|---------|
| 51k   | 51.7 | 21.6  | 0.01 | 0.00  | 28.3 | 25.3 | 86.5    |
| 100k  | 51.3 | 21.5  | 0.13 | 0.00  | 29.6 | 25.3 | 89.1    |
| 200k  | 51.4 | 21.7  | 0.11 | 0.00  | 29.7 | 25.2 | 91.3    |
| 300k  | 51.6 | 21.7  | 0.11 | 0.00  | 30.5 | 25.5 | 94.5    |
| 500k  | 51.8 | 22.0  | 0.09 | 0.00  | 30.8 | 25.8 | 96.9    |

Table 3: SOLID vs. Dataset scales. ADR-Da. represents the ADR by DarkneTZ. Details are in Appendix C.6.

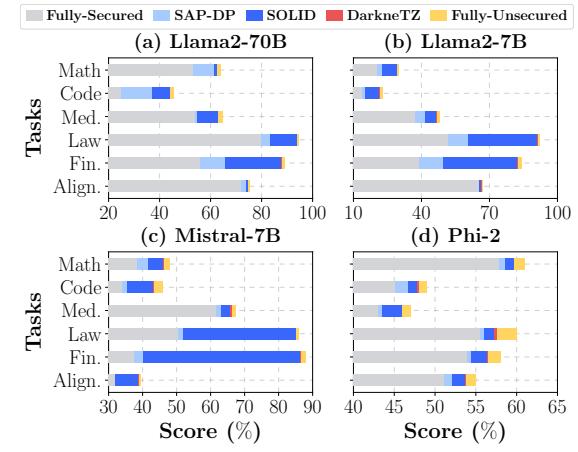


Figure 5: Customization performance comparison of secured models on six downstream tasks.

other two approaches. These results confirm that SOLID effectively protects against distillation attacks while securing significantly fewer parameters. More details are in Appendix C.4 and C.5.

**Obs5: The security of SOLID cannot be easily compromised by simply increasing the dataset scale.** As shown in Table 3, the distillation ratios for SOLID increase marginally with larger datasets, showing only a 0.5% ADR rise when scaling from 51k to 500k samples. In contrast, DarkneTZ exhibits a significant increase in the ADR, from 86.5% to 96.9%, over the same dataset size range. This highlights the robustness of SOLID’s security against increasing attack dataset sizes. Details of the attack datasets are provided in Appendix B.2.

**Obs6: SOLID consistently outperforms baseline deployments in customization while achieving security levels comparable to fully-secured approaches. Its customization performance closely matches full parameter fine-tuning.** As shown in Figure 5, SOLID improves scores in the Law domain by 10% over SAP-DP and fully-secured methods on Llama2-70B, and by 35% on 7B models. Similar trends are observed on Phi-2, though the gain in Law narrows to 1%. Additionally, the performance of SOLID consistently matches the performance of full parameter fine-

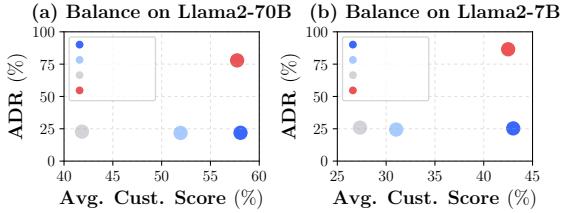


Figure 6: ADRs vs. average customization score. Points closer to the bottom-right indicate better balance.

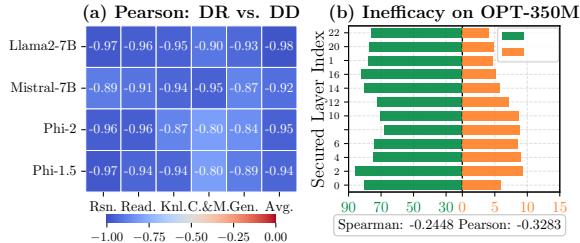


Figure 7: (a) presents the Pearson coefficient between distillation ratio (DR) and distillation difficulty (DD) across four models and six domains. (b) depicts the link between ADR and DD for Llama2-7B and OPT-350M.

tuning across four architectures, with differences within 4%. This indicates that securing a small subset of parameters preserves customization while ensuring strong protection against distillation attacks. Further results are in Appendix B.6 and C.3.

We summarize the security and customization performance of each deployment in Figure 6. SOLID achieves an optimal balance between distillation prevention and customization, outperforming other baselines. In the next subsection, we discuss how the distillation difficulty metric optimizes the security-customization trade-off.

#### 4.5 Discussion on DD (RQ4)

We assess the efficacy of distillation difficulty (DD) in estimating distilled model performance by calculating the Pearson and Spearman correlation coefficients between DD and ADR across different domains. To address uncertainties regarding the effectiveness of DD in shallow transformers, we secure and attack 2-layer secured sets in OPT-350M (Zhang et al., 2022), which has 350M parameters. Based on the results shown in Figure 7, we have following observations.

**Obs7: DD is effective in larger models, with a clear negative correlation between DD and average distillation ratios.** As shown in Figure 7 (a), the Pearson coefficient for Llama2-7B consistently remains below -0.80, reaching as low as -0.98. We also observe similar phenomena in other models with varying architectures and sizes, confirming

DD as a reliable predictor of distilles model performance and the effectiveness of SOLID. Results of Spearman coefficients are in Appendix B.9.

**Obs8: DD is ineffective in smaller OPT model, with notable inconsistencies with ADRs.** As shown in Figure 7 (b), DD exhibits weak negative correlation with ADR in OPT-350M (coefficients  $> -0.33$ ), showing its unsuitability for predicting distillation performance. Additionally, optimal security is achieved by protecting the middle layers rather than the initial or output layers, making SOLID unable to identify the smallest secured set. Further details are provided in Appendix C.9.

## 5 Related Works

**On-premises deployment.** Using LLM services for customization poses significant privacy risks, as user data may be exposed during transmission, storage, and processing (Li et al., 2024c). To mitigate this, privacy-sensitive sectors require *on-premises deployment* of LLMs, which retains both data and models within their local infrastructure (Schillaci, 2024; Nevo et al., 2024). However, this shifts security risks to vendors, who lose control over model use and face increased threats of theft, especially from hardware- and communication-based attacks on GPUs (Nayan et al., 2024; Rakin et al., 2022). To secure models locally, hardware-based protections such as TrustZone have been proposed (Pinto and Santos, 2019; Zhang et al., 2024a; Li et al., 2024a), but they are resource-intensive with limited flexibility (Mo et al., 2020). A more adaptable approach is *layer-wise security*, which protects only selected layers (Lin et al., 2024; Chen et al., 2024; Zhang et al., 2024b). While prior work suggests securing shallow (Elgamal and Nahrstedt, 2020), intermediate (Shen et al., 2022), or output layers (Huang et al., 2024), most studies focus on smaller models. Our results show that securing a few, well-chosen bottom layers of LLMs can enhance security while preserving fine-tuning flexibility for on-premises deployment.

**Model Distillation Attacks.** Model distillation attacks allow adversaries to replicate model functionality using only black-box access, a process also known as functional extraction (Nevo et al., 2024; Xu et al., 2024a; Ezzeddine et al., 2024). While distillation attacks have been extensively studied in smaller models, such as CNNs (Orekondy et al., 2018), BERT (Sanh et al., 2020; Zanella-Beguelin et al., 2021), and ReLU-

based models (Canales-Martínez et al., 2024; Jagielski et al., 2020), their effectiveness against LLMs remains an open question. Our work extends these attacks to Llama2-70B and demonstrates that securing only the output layer remains insufficient to prevent near-complete functionality replication.

## 6 Conclusion

In this paper, we explore minimal secured sets to protect LLMs from query-based distillation attacks while preserving customization flexibility in on-premises deployments. We find that (1) distillation attacks targeting the secured top layer can successfully replicate the victim model, and (2) both the placement and number of secured layers introduce a security-customization trade-off. Based on these insights, we propose SOLID, a theoretically inspired deployment that optimizes this trade-off. Through extensive experiments, we show that SOLID balances security and customization effectively, outperforming baseline deployments, though it also has certain limitations.

## Limitations

While our method effectively defends against distillation attacks and preserves model customization, it does not address other adversarial attacks in the black-box setting, such as membership inference attacks (MIA), as demonstrated in the Appendix B.10. To the best of our knowledge, this is the first work to explore a semi-open deployment framework for LLMs. However, the current algorithm still performs identification at the layer level and does not delve into the impact of different sub-modules within decoder layers on model security. Furthermore, our proposed metric exhibits reduced effectiveness when applied to smaller models, as discussed in Section 4.5. In future work, we aim to address these limitations by enhancing both the algorithm and the evaluation metric to improve the overall effectiveness of SOLID.

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## A Proof of Theorem 1

In this section, we prove Theorem 1. We first revisit the our model, present several important lemmas and finally present the proof. Additional explanatory remarks are included in Appendix A.5.

### A.1 Model Overview

The distilled model  $f(\mathbf{X}; \boldsymbol{\theta})$  is structured as a sequence of  $L$  transformer layers,

$$f(\mathbf{X}) = \varphi_L \circ \varphi_{L-1} \circ \dots \circ \varphi_{\alpha L+1} \circ \hat{\varphi}_{\alpha L} \circ \varphi_{\alpha L-1} \circ \dots \circ \varphi_1(\mathbf{X}), \quad (2)$$

where  $\mathbf{X} \in \mathbb{R}^{n \times d}$  represents the input, interpreted as an assembly of  $n$  tokens, each possessing  $d$  hidden dimensions. Each transformer layer, indexed by  $1 \leq i \leq L$ , is represented by  $\varphi_i$ , which maps  $\mathbb{R}^{n \times d}$  to  $\mathbb{R}^{n \times d}$  and can be defined as follows,

$$\varphi_i(\mathbf{X}; K_i, Q_i) = \left[ \mathbf{I}_n + \text{softmax} \left( \frac{\mathbf{X} Q_i (\mathbf{X} K_i)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right) \right] \mathbf{X}, \quad (3)$$

where  $Q_i \in \mathbb{R}^{d \times d_Q}$ ,  $K_i \in \mathbb{R}^{d \times d_Q}$  represent projection parameter matrices. Here, the  $\alpha L$ -th layer is the distilled layer and the others are the public layers. For simplicity, we use the function  $\hat{\varphi}_{\alpha L}$  to denote mapping of the distilled layer, i.e.,  $\hat{\varphi}_{\alpha L}(\mathbf{X}) = \varphi_{\alpha L}(\mathbf{X}; \hat{K}_{\alpha L}, \hat{Q}_{\alpha L})$ .

### A.2 Bounds on Different Orthogonal Components

**Lemma 1.** For any  $1 \leq l \leq L$ ,  $1 \leq p \leq d$ , any  $\mathbf{X} \in \mathbb{R}^{n \times d}$ , we have

$$\begin{aligned} & \max_{\mathbf{v}: \|\mathbf{v}\|_2=1, \mathbf{v} \perp \mathbb{I}_n} \left| \mathbf{v}^\top \varphi_l(\mathbf{X}; K_l, Q_l) [p] \right| \\ & \leq (1 + \beta_D) \max_{\mathbf{v}: \|\mathbf{v}\|_2=1, \mathbf{v} \perp \mathbb{I}_n} \left| \mathbf{v}^\top \mathbf{X} [p] \right| \end{aligned} \quad (4)$$

where  $\mathbb{I}_n$  is a column vector with dimensions  $n \times 1$  and each element is 1,  $\mathbf{X}[p]$  is the  $p$ -th column of the input  $\mathbf{X}$ ,  $\varphi_l(\mathbf{X}; K_l, Q_l) [p]$  is the  $p$ -th column of the  $l$ -th self-attention output, the coefficient  $\beta_D$  satisfies  $0 < \beta_D < 1$  and it is related to the upper bound of the L2-norm of matrices  $K_l, Q_l$ .

*Proof.* Let  $\mathbf{u} = \{\mathbf{u}_{l,1} = \frac{\mathbb{I}_n}{\sqrt{n}}, \mathbf{u}_{l,2}, \dots, \mathbf{u}_{l,n}\}$  denote the eigenvectors of  $\text{softmax} \left( \frac{\mathbf{X} Q_l (\mathbf{X} K_l)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right)$ . Assume  $\sigma_{l,1}, \sigma_{l,2}, \dots, \sigma_{l,n}$  denote the eigenvalues of  $\text{softmax} \left( \frac{\mathbf{X} Q_l (\mathbf{X} K_l)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right)$  and  $-1 < \sigma_{l,n} < \beta_D$

for any  $l, n$ . Thus we have

$$\mathbf{v}^\top \varphi_l(\mathbf{X}; K_l, Q_l) [p] \quad (5a)$$

$$= \mathbf{v}^\top \left[ \mathbf{I}_n + \text{softmax} \left( \frac{\mathbf{X} Q_l (\mathbf{X} K_l)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right) \right] \mathbf{X} [p] \quad (5b)$$

$$= \mathbf{v}^\top \left[ \mathbf{I}_n + \text{softmax} \left( \frac{\mathbf{X} Q_l (\mathbf{X} K_l)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right) \right] \sum_{k=1}^n \alpha_{pk} \mathbf{u}_{l,k} \quad (5c)$$

$$= \mathbf{v}^\top \sum_{k=1}^n \alpha_{pk} (1 + \sigma_{l,k}) \mathbf{u}_{l,k} \quad (5d)$$

$$\leq \max_{\mathbf{v}: \|\mathbf{v}\|_2=1, \mathbf{v} \perp \mathbb{I}_n} \left| \sum_{k=2}^n \alpha_{pk} (1 + \sigma_{l,k}) \mathbf{v}^\top \mathbf{u}_{l,k} \right| \quad (5e)$$

$$= \left\| \sum_{k=2}^n \alpha_{pk} (1 + \sigma_{l,k}) \mathbf{u}_{l,k} \right\|_2 \quad (5f)$$

$$= \left[ \sum_{k=2}^n \alpha_{pk}^2 (1 + \sigma_{l,k})^2 \right]^{1/2} \quad (5g)$$

$$\leq (1 + \beta_D) \max_{\mathbf{v}: \|\mathbf{v}\|_2=1, \mathbf{v} \perp \mathbb{I}_n} \left| \mathbf{v}^\top \mathbf{X} [p] \right|, \quad (5h)$$

where

$$\beta_D = \max_{\substack{\|\mathbf{K}_l\|_2 \leq D, \|\mathbf{Q}_l\|_2 \leq D \\ \|\mathbf{Q}_l\|_2 \leq D}} \max_{\substack{\mathbf{v}: \|\mathbf{v}\|_2=1 \\ \mathbf{v} \perp \mathbb{I}_n}} \left\| \text{softmax} \left( \frac{\mathbf{X} Q_l (\mathbf{X} K_l)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right) \mathbf{v} \right\|_2 \\ < 1$$

The equation (5d) is due to  $\mathbf{u}_{l,k}$  are the eigenvectors of  $\text{softmax} \left( \frac{\mathbf{X} Q_l (\mathbf{X} K_l)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right)$ . The inequality (5f) is because when  $\mathbf{v} = \frac{\sum_{k=2}^n \alpha_{pk} (1 + \sigma_{l,k}) \mathbf{u}_{l,k}}{\|\sum_{k=2}^n \alpha_{pk} (1 + \sigma_{l,k}) \mathbf{u}_{l,k}\|_2}$ , we have the maximum value.  $\square$

**Lemma 2.** For any  $K_l, Q_l \in \mathbb{R}^{d \times s}$  and any  $\mathbf{X} \in \mathbb{R}^{n \times d}$ , the following equation always holds:

$$\left| \mathbb{I}_n^\top \varphi_l(\mathbf{X}; K_l, Q_l) [p] \right| = 2 \left| \mathbb{I}_n^\top \mathbf{X} [p] \right|, \quad (6)$$

where  $\mathbf{X}[p]$  is the  $p$ -th column of the input  $\mathbf{X}$ ,  $\varphi_l(\mathbf{X}; K_l, Q_l) [p]$  is the  $p$ -th column of the  $l$ -th self-attention output.

*Proof.* Assume that a set of orthogonal basis for  $\mathbb{R}^n$  is  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n\}$ , where  $\mathbf{u}_1 = \frac{\mathbb{I}_n}{\sqrt{n}}$ . Then we can rewrite  $\mathbf{X}[p]$  as  $\mathbf{X}[p] = \sum_{j=1}^n \alpha_{pj} \mathbf{u}_j$ , where  $\alpha_{pj}$  ( $1 \leq p \leq d$ ) are the corresponding coefficients for the  $p$ -th column of  $\mathbf{X}$  under the orthogonal basis. Next, we calculate  $|\mathbb{I}_n^\top f(\mathbf{X})[p]|$  and  $|\mathbb{I}_n^\top \mathbf{X}[p]|$ , respectively. Note that  $\mathbb{I}_n^\top \mathbf{u}_j = 0$  for all  $j \neq 1$ . Therefore, we can obtain that,

$$\mathbb{I}_n^\top \mathbf{X}[p] = \sqrt{n} \alpha_{p1}. \quad (7)$$

Then we can get

$$\left| \mathbb{I}_n^\top \mathbf{X}[p] \right| = |\sqrt{n} \alpha_{p1}|. \quad (8)$$

Let  $\sigma_{i1}, \sigma_{i2}, \dots, \sigma_{in}$  denote the eigenvalues of softmax  $\left( \frac{\mathbf{X} Q_i (\mathbf{X} K_i)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right)$ . Applying the Perron–Frobenius theorem for Markov matrices (Lemmens and Nussbaum, 2012), we deduce that for the matrix softmax  $\left( \frac{\mathbf{X} Q_i (\mathbf{X} K_i)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right)$ , there exists only one eigenvalue equal to 1, while all other eigenvalues in absolute value are strictly less than 1. Without loss of generality, we assume  $\sigma_{i1} = 1$ , implying  $|\sigma_{ij}| < 1$  for  $j \neq 1$ . Recalling the definition of  $\varphi_i(\mathbf{X}; K_i, Q_i)$  and considering the linear operation, we can rewrite it as follows:

$$\varphi_i(\mathbf{X}; K_i, Q_i)[p] = \sum_{j=1}^n \alpha_{pj} (1 + \sigma_{ij}) \mathbf{u}_j. \quad (9)$$

Then we calculate the term  $|\mathbb{I}_n^\top \varphi_i(\mathbf{X}; K_i, Q_i)[p]|$  as follows,

$$\left| \mathbb{I}_n^\top \varphi_i(\mathbf{X}; K_i, Q_i)[p] \right| = \left| \mathbb{I}_n^\top \left( \sum_{j=1}^n \alpha_{pj} (1 + \sigma_{ij}) \mathbf{u}_j \right) \right| \quad (10a)$$

$$= |\sqrt{n} (\alpha_{p1} (1 + \sigma_{i1}))| \quad (10b)$$

$$= 2|\sqrt{n} \alpha_{p1}|, \quad (10c)$$

where (10a) is induced by substituting the equation (9) into  $|\mathbb{I}_n^\top \varphi_i(\mathbf{X}; K_i, Q_i)[p]|$ , (10b) is due to  $\mathbb{I}_n^\top \mathbf{u}_j = 0$  for all  $j \neq 1$ , (10c) follows the fact that  $\sigma_{i1} = 1$ .  $\square$

### A.3 Proof of Theorem 1

We first prove the following result. For simplicity of notations, we use  $f(\mathbf{X})[p]$  to denote the  $p$ -th ( $1 \leq p \leq d$ ) column of the the distilled model  $f(\mathbf{X})$ , where the parameters in the  $\alpha L$ -th layer is replaced with the matrices  $\hat{K}_{\alpha L}$  and  $\hat{Q}_{\alpha L}$ . We use the function  $\hat{\varphi}_{\alpha L}(\mathbf{X}) = \varphi_{\alpha L}(\mathbf{X}; \hat{K}_{\alpha L}, \hat{Q}_{\alpha L})$  to denote the mapping of the  $(\alpha L)$ -th layer. Then we are going to show that there exists  $\alpha^* = \log_2 \frac{2}{1+\beta_D}$  and  $0 < \beta_D < 1$  makes the following equations hold.

(1) Assume  $\alpha < \alpha^*$ . For any  $\mathbf{X}$ ,  $\|K_i\|_2 \leq D$ ,  $\|Q_i\|_2 \leq D$ , there exists a zero measure set  $\mathcal{K}(\mathbf{X})$  and  $\mathcal{Q}(\mathbf{X})$  such that

$$\lim_{L \rightarrow \infty} \left\| \frac{f(\mathbf{X})[p]}{\|f(\mathbf{X})[p]\|_2} - \frac{\mathbb{I}_n}{\sqrt{n}} \right\|_2 = 0. \quad (11)$$

(2) For any  $\alpha > \alpha^*$ , there exists a sequence of matrix  $\{K_i, Q_i\}_{i \geq 1}$  such that for any distilled matrix  $K_{\alpha L}$  and  $Q_{\alpha L}$ , we have  $\|K_i\|_2 \leq D$ ,  $\|Q_i\|_2 \leq D$ , we have,

$$\lim_{L \rightarrow \infty} \left\| \frac{f(\mathbf{X})[p]}{\|f(\mathbf{X})[p]\|_2} - \frac{\mathbb{I}_n}{\sqrt{n}} \right\|_2 = \sqrt{2}. \quad (12)$$

*Proof.* Based on Lemma (1), we obtain that

$$\begin{aligned} & \max_{\mathbf{v}: \|\mathbf{v}\|_2=1, \mathbf{v} \perp \mathbb{I}_n} \left| \mathbf{v}^\top f(\mathbf{X})[p] \right| \\ & \leq (1 + \beta)^L \max_{\mathbf{v}: \|\mathbf{v}\|_2=1, \mathbf{v} \perp \mathbb{I}_n} \left| \mathbf{v}^\top \mathbf{X}[p] \right|. \end{aligned} \quad (13)$$

Based on Lemma (2), we know that

$$\begin{aligned} & \left| \mathbb{I}_n^\top f(\mathbf{X})[p] \right| \\ & = 2^{(1-\alpha)L-1} \left| \mathbb{I}_n^\top \hat{\varphi}_{\alpha L} \circ \varphi_{\alpha L-1} \circ \dots \circ \varphi_1(\mathbf{X})[p] \right|. \end{aligned} \quad (14)$$

We firstly prove the equation (11). When

$$\left| \mathbb{I}_n^\top f(\mathbf{X})[p] \right| \neq 0, \quad (15)$$

then we have

$$\left\| \frac{f(\mathbf{X})[p]}{\|f(\mathbf{X})[p]\|_2} - \frac{\mathbb{I}_n}{\sqrt{n}} \right\|_2 \quad (16a)$$

$$= \left[ 2 - \frac{2 \mathbb{I}_n^\top f(\mathbf{X})[p]}{\sqrt{n} \sqrt{\frac{(\mathbb{I}_n^\top f(\mathbf{X})[p])^2}{n} + (\mathbf{v}^\top f(\mathbf{X})[p])^2}} \right]^{1/2} \quad (16b)$$

$$= \sqrt{2} \left[ 1 - \frac{1}{\sqrt{1 + \frac{n(\mathbf{v}^\top f(\mathbf{X})[p])^2}{(\mathbb{I}_n^\top f(\mathbf{X})[p])^2}}} \right]^{1/2} \quad (16c)$$

$$\leq \sqrt{2} \left[ 1 - \frac{1}{\sqrt{1 + \frac{n(1+\beta)^{2L} |\mathbf{v}^\top \mathbf{X}[p]|^2}{2^{2[(1-\alpha)L-1]} |\mathbb{I}_n^\top \hat{\varphi}_{\alpha L} \circ \dots \circ \varphi_1(\mathbf{X})[p]|^2}}} \right]^{1/2} \quad (16d)$$

$$\leq 2\sqrt{2n} \left( \frac{1+\beta}{2^{1-\alpha}} \right)^L \frac{|\mathbf{v}^\top \mathbf{X}[p]|}{|\mathbb{I}_n^\top \hat{\varphi}_{\alpha L} \circ \varphi_{\alpha L-1} \circ \dots \circ \varphi_1(\mathbf{X})[p]|}, \quad (16e)$$

where the inequality (16d) is based on the inequality (13) and (14). The inequality (16e) is based on Lemma (3). Therefore, if  $\alpha < \log_2 \frac{2}{1+\beta_D}$  and  $|\mathbb{I}_n^\top f(\mathbf{X})[p]| \neq 0$ , then we have  $\lim_{L \rightarrow \infty} \left( \frac{1+\beta_D}{2^{1-\alpha}} \right)^L = 0$ . Now we can consider when  $|\mathbb{I}_n^\top f(\mathbf{X})[p]| = 0$ . In fact, it is easy to show that this can only happens when  $\hat{K}_{\alpha L}$  and  $\hat{Q}_{\alpha L}$  belong to certain sets making  $|\mathbb{I}_n^\top f(\mathbf{X})[p]| = 0$ , which corresponds to zero measure set  $\mathcal{K}(\mathbf{X})$  and  $\mathcal{Q}(\mathbf{X})$  depending on the input  $\mathbf{X}$ . Since the input space is countable, therefore,

the union  $\cup_{\mathbf{X} \in \mathcal{X}} \mathcal{K}(\mathbf{X})$  and  $\cup_{\mathbf{X} \in \mathcal{X}} \mathcal{Q}(\mathbf{X})$  are also zero-measure sets.

To prove equation (12), let  $K^*$ ,  $Q^*$  with  $\|K^*\|_2 \leq D$ ,  $\|Q^*\|_2 \leq D$  satisfy the following condition,

$$\max_{\mathbf{v}: \|\mathbf{v}\|_2=1, \mathbf{v} \perp \mathbb{I}_n} \left\| \text{softmax} \left( \frac{\mathbf{X} Q_l (\mathbf{X} K_l)^\top}{\sqrt{d_Q} \|\mathbf{X}\|^2} \right) \mathbf{v} \right\|_2 = \beta_D. \quad (17)$$

Let  $\mathbf{v}^*$  be the solver of the above optimization problem (17) and consider the  $K_l = K^*$ ,  $Q_l = Q^*$  and  $\mathbf{X}^* = [\mathbf{v}^*, \mathbf{v}^*, \dots, \mathbf{v}^*]$ . Clearly,  $\mathbf{v}^* \perp \mathbb{I}_n$ . Assume there exists  $\mathbf{u} : \|\mathbf{u}^*\|_2 = 1$  satisfying  $\mathbf{u}^* \perp \mathbb{I}_n$ ,  $\mathbf{u}^* \perp \mathbf{v}^*$ , therefore we can rewrite  $f(\mathbf{X}^*)[p]$  as follows,

$$\begin{aligned} f(\mathbf{X}^*)[p] &= \frac{\mathbb{I}_n^\top}{\sqrt{n}} f(\mathbf{X}^*) \frac{\mathbb{I}_n}{\sqrt{n}} \\ &\quad + \mathbf{v}^{*\top} f(\mathbf{X}^*) \mathbf{v}^* + \mathbf{u}^{*\top} f(\mathbf{X}^*) \mathbf{u}^*. \end{aligned} \quad (18)$$

For any  $1 \leq l \leq L$ , based on Lemma (1), we know that

$$\left| \mathbf{v}^{*\top} f(\mathbf{X}^*)[p] \right| = (1 + \beta_D)^L \left| \mathbf{v}^{*\top} \mathbf{X}^*[p] \right|. \quad (19)$$

Since

$$\left| \mathbb{I}_n^\top f(\mathbf{X}^*)[p] \right| = 2^L \left| \mathbb{I}_n^\top \mathbf{X}^*[p] \right| = \left| \mathbb{I}_n^\top \mathbf{v}^* \right| = 0 \quad (20)$$

and

$$\left| \mathbf{v}^{*\top} f(\mathbf{X}^*)[p] \right| = (1 + \beta_D)^L \left| \mathbf{v}^{*\top} \mathbf{X}^*[p] \right| \neq 0. \quad (21)$$

Then we have

$$\left\| \frac{f(\mathbf{X}^*)[p]}{\|f(\mathbf{X}^*)[p]\|_2} - \frac{\mathbb{I}_n}{\sqrt{n}} \right\|_2 \quad (22a)$$

$$= \left[ 2 - \frac{2\mathbb{I}_n^\top f(\mathbf{X}^*)[p]}{\sqrt{n} \|f(\mathbf{X}^*)[p]\|_2} \right]^{1/2} \quad (22b)$$

$$= \left[ 2 - \frac{2\mathbb{I}_n^\top}{\sqrt{n}} \cdot \frac{f(\mathbf{X}^*)[p]}{\sqrt{\frac{1}{n} (\mathbb{I}_n^\top f(\mathbf{X}^*)[p])^2 + (\mathbf{v}^{*\top} f(\mathbf{X}^*)[p])^2}} \right]^{1/2} \quad (22c)$$

$$\geq \left[ 2 - \frac{2\mathbb{I}_n^\top}{\sqrt{n}} \frac{f(\mathbf{X}^*)[p]}{\sqrt{\frac{1}{n} (\mathbb{I}_n^\top f(\mathbf{X}^*)[p])^2 + (\mathbf{v}^{*\top} f(\mathbf{X}^*)[p])^2}} \right]^{1/2} \quad (22d)$$

$$= \left[ 2 - 2 \frac{\mathbb{I}_n^\top \mathbf{v}^{*\top} f(\mathbf{X}^*)[p]}{\sqrt{1 + \frac{\|\mathbb{I}_n^\top f(\mathbf{X}^*)[p]\|^2}{n \|\mathbf{v}^{*\top} f(\mathbf{X}^*)[p]\|^2}}} \right]^{1/2} \quad (22e)$$

$$= \left[ 2 - 2 \frac{\frac{2^{(1-\alpha)L-1} \|\mathbb{I}_n^\top \varphi_{\alpha L} \circ \varphi_{\alpha L-1} \circ \dots \circ \varphi_1(\mathbf{X}^*)[p]\|}{\sqrt{n}(1+\beta_D)^L \|\mathbf{v}^{*\top} \mathbf{X}^*[p]\|}}{\sqrt{1 + \frac{2^{2((1-\alpha)L-1)} \|\mathbb{I}_n^\top \varphi_{\alpha L} \circ \varphi_{\alpha L-1} \circ \dots \circ \varphi_1(\mathbf{X}^*)[p]\|^2}{n(1+\beta_D)^{2L} \|\mathbf{v}^{*\top} \mathbf{X}^*[p]\|^2}}} \right]^{1/2} \quad (22f)$$

where equation (22c) is based on (18), equation (22f) is based on (21) and (14). When  $\alpha > \log_2 \frac{2}{1+\beta_D}$ , we have  $\lim_{L \rightarrow \infty} \left( \frac{2^{1-\alpha}}{1+\beta_D} \right)^L = 0$ . Thus we have  $\lim_{L \rightarrow \infty} \left\| \frac{f(\mathbf{X}^*)[p]}{\|f(\mathbf{X}^*)[p]\|_2} - \frac{\mathbb{I}_n}{\sqrt{n}} \right\|_2 = \sqrt{2}$ . This indicates that the  $p$ -th column of the output matrix  $f(\mathbf{X}^*)$  is not parallel to  $\mathbf{I}_n$  for any  $p$ . This further indicates that the output matrix does not have the identical vector in each row.  $\square$

#### A.4 Technical Lemma

**Lemma 3.** For any  $x \in (0, 1)$ , it always holds  $\left[ 1 - \frac{1}{\sqrt{1+x^2}} \right]^{1/2} \leq x$ .

*Proof.* To establish the inequality  $\left[ 1 - \frac{1}{\sqrt{1+x^2}} \right]^{1/2} \leq x$ , we begin by proving,

$$1 - \frac{1}{\sqrt{1+x^2}} \leq x^2. \quad (23)$$

To demonstrate (23), we equivalently show

$$1 - x^2 \leq \frac{1}{\sqrt{1+x^2}}. \quad (24)$$

Subsequently, it suffices to verify

$$(1 - x^2)(\sqrt{1+x^2}) \leq 1. \quad (25)$$

This is equivalent to proving

$$(1 - x^2)^2(1 + x^2) \leq 1. \quad (26)$$

Thus, our focus shifts to demonstrating

$$(1 - x^2)(1 - x^4) \leq 1. \quad (27)$$

Clearly, (27) holds true for any  $x \in (0, 1)$ .  $\square$

#### A.5 Remarks

**Remark 2:** The existence of  $\hat{f}_\infty(\mathbf{X})$  is a non-trivial result. While the mapping  $\varphi_i$  admits a fixed point at  $\mathbf{X} = \mathbf{0}_{n \times d}$ , the convergence of the iterative process governed by  $\varphi_i$  cannot be guaranteed using the contraction mapping theorem, as  $\varphi_i$  does not satisfy the contraction property for any pair  $(Q_i, K_i)$ . This complexity becomes particularly evident in the special case where  $n = 1$  and  $\mathbf{X}$  is a column vector. Here, the output of  $\varphi_i$  satisfies the relation  $\langle \mathbf{1}_d, \varphi_i(\mathbf{X}; K_i, Q_i) \rangle = 2\langle \mathbf{1}_d, \mathbf{X} \rangle$ , implying that the iteration diverges unless  $\mathbf{X}$  is orthogonal to  $\mathbf{1}_d$ . However, the divergence is not arbitrary; rather, the theorem reveals that it occurs

in a fixed, well-defined direction. This insight ensures the existence of a normalized output, which remains stable and meaningful despite the lack of strict convergence.

**Remark 3:** The existence of  $\alpha^* \in (0, 1)$  is also a non-trivial statement, as  $\alpha^*$  could potentially be zero, which would imply the absence of a critical layer such that securing layers prior to it guarantees the failure of the recovered model’s functionality. The primary challenge lies in demonstrating that perturbations to the earlier layers result in rank-one outputs, a property that does not universally hold for arbitrary perturbations. To address this, we establish an alternative result: given an input matrix  $\mathbf{X}$ , rank-one outputs can be guaranteed if the perturbation matrices  $K_i$  and  $Q_i$  are chosen to avoid specific zero-measure sets, denoted as  $\mathcal{K}(\mathbf{X})$  and  $\mathcal{Q}(\mathbf{X})$ , respectively. Assuming a countable domain  $\mathcal{X} \times \mathcal{Y}$ , which is typical for structured inputs such as sentences or images, it follows that the perturbation matrices to be avoided belong to the countable union of these sets, defined as  $\mathcal{K} = \bigcup_{\mathbf{X} \in \mathcal{X}} \mathcal{K}(\mathbf{X})$  and  $\mathcal{Q} = \bigcup_{\mathbf{X} \in \mathcal{X}} \mathcal{Q}(\mathbf{X})$ . Since this union remains a zero-measure set, avoiding these specific sets ensures that the conditions of the theorem are satisfied for any input matrix  $\mathbf{X}$ .

## B Experiment Details

To more intuitively compare the security differences between the SOLID method and a fully-secured approach, we define  $\Delta\text{ADR}(I) = \text{ADR}(I) - \text{ADR}([L])$  to assess the resilience of the secured set  $I$  relative to the fully-secured approach. A smaller value of  $\Delta\text{ADR}$  indicates resilience similar to that of the fully-secured model.

### B.1 Model Details.

The foundation models we use in our experiments are selected from open-source repositories, and Table 4 shows the basic information of the models and their sources. Specifically, we employ Llama2-70B-chat<sup>1</sup> (Touvron et al., 2023), Llama2-7B-chat<sup>2</sup> (Touvron et al., 2023), and Mistral-7B-v0.1<sup>3</sup> (Jiang et al., 2023). For smaller models, we select Phi-2<sup>4</sup> (Abdin et al., 2024) and Phi-1.5<sup>5</sup> (Li et al., 2023). We also consider OPT model<sup>6</sup> (Zhang et al., 2022), which has only 350 million parameters and 24 decoder layers.

| Model           | Size | Decoder Layers |
|-----------------|------|----------------|
| Llama2-70B-chat | 70B  | 80             |
| Llama2-7B-chat  | 7B   | 32             |
| Mistral-7B-v0.1 | 7B   | 32             |
| Phi-2           | 2.7B | 32             |
| Phi-1.5         | 1.3B | 24             |
| OPT             | 350M | 24             |

Table 4: Model Info

### B.2 Distillation Attacks.

**Attack implementation details.** In performing FT-all and FT-secure model distillation attacks, we adhere to the training hyper-parameters outlined in the Llama2 report (Touvron et al., 2023), employing the AdamW optimizer with a cosine learning rate scheduler. The initial learning rate is set to  $2 \times 10^{-5}$ , with a weight decay of 0.1, a batch size of 128, and bfloat16 precision for input sequences of 512 tokens. The LLaMA2-70B model is trained for 3 epochs with a random seed of 42, while other models are trained for 5 epochs across three seeds: 42, 1234, and 20. Despite limiting training to 3

<sup>1</sup><https://huggingface.co/meta-llama/Llama-2-70b-chat-hf>

<sup>2</sup><https://huggingface.co/meta-llama/Llama-2-7b-chat-hf>

<sup>3</sup><https://huggingface.co/mistralai/Mistral-7B-v0.1>

<sup>4</sup><https://huggingface.co/microsoft/phi-2>

<sup>5</sup>[https://huggingface.co/microsoft/phi-1\\_5](https://huggingface.co/microsoft/phi-1_5)

<sup>6</sup><https://huggingface.co/facebook/opt-350m>

epochs for the 70B model, the training loss stabilized effectively. Our implementation builds upon the [llama-recipes](#) repository provided by META.

For SEM attacks, distinct configurations were employed for SOLID and SAP-DP. In the case of SOLID, hidden representations from the secure-source components were collected and paired with the input data to train a substitute model. In contrast, for SAP-DP, representations from the sixth decoder layer and the model’s final logits were utilized to construct the training dataset. In accordance with (Tamber et al., 2024), we applied a learning rate of 1.5e-4, a weight decay of 0.01, and a linear learning rate scheduler with 500 warmup steps. Both training and validation batch sizes were set to 32, with MSE as the loss function. SOLID was trained for 30 epochs due to its smaller model size, whereas SAP-DP was trained for 5 epochs.

All distillation experiments were conducted on Nvidia 4090 24G, 6000 Ada 48G, and A100 80G GPUs, utilizing PyTorch 2.2.0 and CUDA 11.8 on Ubuntu 20.04.6 LTS.

**Base 51k Distillation Dataset.** We ensure dataset coverage and reliability by using a 1:1 ratio of the MMLU <sup>7</sup> (Hendrycks et al., 2021) auxiliary training set and Alpaca dataset <sup>8</sup> (Taori et al., 2023), extracting 25.5k samples from each. From the MMLU auxiliary training data, we sample 50%, and from Alpaca, we use a step size of 2 to enhance diversity. The datasets are then formatted for model training, applying Alpaca and MMLU prompts from Table 5.

**Extra Distillation Datasets.** To enhance dataset diversity, the 100K, 200K, 300K, and 500K datasets integrate additional specialized sources. As detailed in Table 6, these sources include Baize (Xu et al., 2023) (158K English multi-turn conversations via ChatGPT’s self-chat), MathInstruct (Yue et al., 2023) (260K curated math instruction instances focusing on hybrid reasoning), and OpenOrca (Mukherjee et al., 2023) (augmented FLAN collection with 1M GPT-4 completions and 3.2M GPT-3.5 completions). These enrichments are intended to support complex computational and theoretical tasks, offering broader topic coverage.

**Validation Datasets.** Table 7 outlines the composition of the validation datasets. For *Validation Dataset 1*, we extracted 50% from each of the 57 MMLU validation sub-datasets, totaling 1.5K in-

stances, paired with Alpaca data selected using a step size of 751. This dataset is used with the 51K and 100K training sets. For larger training sets (200K, 300K, and 500K), *Validation Dataset 2* was created by adding 400 instances from three Baize subsets, expanding the validation set to 4.0K.

### B.3 Baselines.

In this section, we provide further details on the baselines used in our comparisons: SAP-DP and fully-secured. These schemes represent different strategies, each with distinct trade-offs in terms of customizability and security against model distillation attacks.

**SAP.** The Split-and-Privatize (SAP) framework (Shen et al., 2023) offers an approach to balance between protecting model privacy and data privacy while maintaining competitive performance. Specifically, the SAP framework keeps the bottom six encoder layers open, allowing user access and fine-tuning while securing the deeper layers on the vendor.

**SAP-DP.** To further strengthen protection while maintaining competitive performance, we extend SAP by incorporating differential privacy techniques by adding Laplace noise to perturb the logits during the fine-tuning process (Lee et al., 2018). The Laplace Distribution with mean  $\mu$  and scale  $b$  is the distribution with probability density function:

$$\text{Laplace}(x|\mu, b) = \frac{1}{2b} \exp\left(-\frac{|x - \mu|}{b}\right)$$

Specifically, in SAP-DP, the noise  $n$  is sampled:  $n \sim \text{Laplace}(0, 0.5)$  and added to the output logits of the model to balance privacy protection and model performance.

**Fully-secured.** Following (Eiras et al., 2024), we use the fully-secured approach as a baseline. This assumes the adversary has no access to internal model parameters, treating the model as a black-box, where only output data can be collected. We slightly broaden this setup by assuming the adversary knows the model’s architecture but no other details. Thus, distilling the fully-secured model involves using the collected data to retrain a model with the same architecture to restore its general functionality.

**DarkneTZ.** Based on the work of (Mo et al., 2020), we use DarkneTZ as a baseline to test whether protecting only the output layers is sufficient to defend against distillation attacks. In this setup, we assume the adversary has no access to the

<sup>7</sup><https://github.com/hendrycks/test>

<sup>8</sup>[https://github.com/tatsu-lab/stanford\\_alpaca/blob/main/alpaca\\_data.json](https://github.com/tatsu-lab/stanford_alpaca/blob/main/alpaca_data.json)

| Dataset | Prompt Type        | Description   |
|---------|--------------------|---|
| Alpaca  | with input         | Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request. |
|         | w/o input          | Below is an instruction that describes a task. Write a response that appropriately completes the request.   |
| MMLU    | Question Answering | Below is a question with no choices. Write the correct answer that appropriately solves the question.   |
|         | Multiple Choice    | The following is a multiple choice question, paired with choices. Answer the question in the format: “Choice:content”.  |

Table 5: Prompts for Alpaca and MMLU auxiliary training data

| Raw Data Set                | 51k  | 100k | 200k | 300k | 500k |
|-----------------------------|------|------|------|------|------|
| Alpaca                      | 25.5 | 50   | 40   | 50   | 50   |
| MMLU auxiliary training set | 25.5 | 50   | 40   | 100  | 100  |
| Baize-MedQuAD               | 0    | 0    | 40   | 50   | 50   |
| Baize-Quora                 | 0    | 0    | 40   | 50   | 50   |
| Baize-Stackoverflow         | 0    | 0    | 40   | 50   | 50   |
| MathInstruct                | 0    | 0    | 4    | 6    | 20   |
| OpenOrca                    | 0    | 0    | 0    | 0    | 180  |

Table 6: Composition of variously sized datasets

model parameters of the output layers, specifically the last decoder layer. Similar to the SAP framework, this approach allows the adversary to access and fine-tune all layers except the final decoder layer.

#### B.4 Implementation Details of SOLID.

**Evaluation Datasets.** We created a 1.5K Evaluation Set to assess model security under various secure-sourcing strategies. This set includes 50% of entries from each of the 57 MMLU validation sub-datasets (Hendrycks et al., 2021), distinct from Validation Set outlined in Table 7. Additionally, we selected an equal number of Alpaca dataset (Taori et al., 2023), using a step size of 751, ensuring no overlap with the Validation Set.

**Hyper-parameter Sensitivity.** As shown in Figure 8, we evaluate SOLID’s sensitivity to tolerance magnitude  $\varepsilon$ , adjusting it from 0.05 to 1 in 0.05 increments while calculating the  $\Delta\text{ADR}$  for six distilled models. The results indicate that SOLID is minimally sensitive to changes in  $\varepsilon$ , with  $\Delta\text{ADR}$  values stabilizing as  $\varepsilon$  increases. This stability arises from the need for a smaller secured layer at higher  $\varepsilon$ , allowing the condition  $R(I) \leq (1 + \varepsilon)R([L])$  to be met with fewer layers. Additionally, the increase in  $\Delta\text{ADR}$  is smaller for larger models, suggesting that privatizing more parameters beyond a certain point offers diminishing

returns in security.

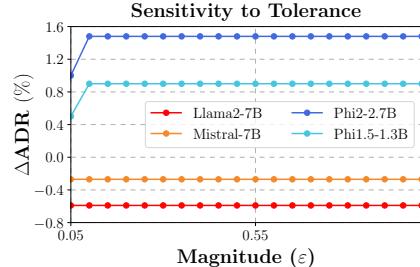


Figure 8: Sensitivity on  $\varepsilon$ .

#### B.5 Evaluation Benchmarks

Most of our evaluations are conducted using the lm-evaluation suite (Gao et al., 2023), the bigcode-evaluation-harness platform (Ben Allal et al., 2022), and MT-Bench (Zheng et al., 2023). For specific domains, such as finance and law, we utilize the official benchmark testing codes provided by their respective communities, as detailed below.

**Evaluation on Customizabilities.** We assess the customizability of models across six domains, as detailed in Table 8. Each domain includes specific benchmarks and metrics designed to evaluate different aspects of the model’s performance in relation to customizability. In particular, for evaluating medical capabilities, we select two sub-categories from the MMLU benchmark that are

| Raw Data Set                | Validation Set | Evaluation Set |
|-----------------------------|----------------|----------------|
| Alpaca                      | 765            | 765            |
| MMLU auxiliary training set | 751            | 751            |
| Baize-MedQuAD               | 0              | 850            |
| Baize-Quora                 | 0              | 850            |
| Baize-Stackoverflow         | 0              | 850            |
| <b>Total Length</b>         | 1516           | 4066           |

Table 7: Composition of validation datasets of different sizes

related to the medical domain: *mmlu\_anatomy* and *mmlu\_professional\_medicine*. For assessing legal reasoning, we select 10 multiple-choice and judgment-based subcategories from Legalbench. The performance of the model in these legal tasks is measured using perplexity, following the prompt structure provided by Legalbench. Specifically, the selected subcategories include:

- *cuad\_audit\_rights*
- *canada\_tax\_court\_outcomes*
- *definition\_classification*
- *cuad\_affiliate\_licensee*
- *learned\_hands\_business*
- *contract\_nli\_survival\_of\_obligations*
- *contract\_nli\_explicit\_identification*
- *contract\_nli\_confidentiality\_of\_agreement*
- *hearsay*
- *contract\_qa*

**Evaluation on Security.** We follow the Llama-2 report (Touvron et al., 2023) to evaluate the distilled model, including 16 benchmarks, which are categorized into 6 groups. Table 9 summarizes the functionality benchmarks used in our experiments, along with their test methods and performance metrics. Our model ranks choices in multiple-choice tasks and generates answers for open-ended generation tasks.

## B.6 Model Customization

**Datasets.** To fine-tune the models for domain-specific tasks, we utilized several datasets tailored to different sectors, including Code (Zheng et al., 2024a), Math (Yue et al., 2023), Medical (Zhang et al., 2023), Finance (Wang et al., 2023a), Law (Guha et al., 2024), and Alignment (Meng et al., 2024). Table 10 lists the customization training datasets used in the experiments. For the code domain, we combine the datasets from **CodeFeedback** and **CodeAlpaca**. For law and finance, we merge all training datasets

from **Legalbench** and **FinGPT** respectively. These datasets are then prepared for model training using the Alpaca prompts outlined in Table 5. Additionally, we randomly select 3,000 samples to serve as the validation dataset.

**Customization Training Hyperparameters.** In model customization, we use different hyperparameters depending on the model size. For LLaMA2-70B, we apply QLoRA with the settings outlined in Table 11, while for 7B models, we use LoRA. For smaller models like Phi2 and Phi-1.5, we fine-tune all model parameters. For LLaMA2-70B, we fine-tune it as a quantized 4-bit model over 1 epoch, starting with a learning rate of  $1.5 \times 10^{-6}$ . For the 7B models, we train for 3 epochs, with a seed value of 42. The training setup includes a weight decay of 0.1, a batch size of 128, a warmup ratio of 0.03, and input sequences of 512 tokens, following standard experimental practices (Hu et al., 2021). For Phi2 and Phi-1.5, we use the training hyperparameters from the LLaMA2 report. We employ the AdamW optimizer with a cosine learning rate scheduler, starting with a learning rate of  $2 \times 10^{-5}$ , a weight decay of 0.1, a batch size of 128, and use bfloat16 precision for 512-token input sequences. Specifically, for alignment, we follow SimPO (Meng et al., 2024) and set the preference parameters  $\beta = 2$  and  $\gamma = 1$ . The learning rate is  $1 \times 10^{-6}$  for LLaMA2-70B and  $5 \times 10^{-7}$  for the 7B and smaller models. All experiments are conducted using the **LLaMA-Factory** on Nvidia 4090 24G, 6000 Ada 48G, and A100 80G GPUs, with PyTorch 2.2.0 and CUDA 11.8 on Ubuntu 20.04.6 LTS.

## B.7 Security and Customization Transitions

For the LLaMA2-7B model, the smallest secure-source layer set identified by SOLID consists of a single decoder layer, whereas for Phi-2, it includes two decoder layers. Consequently, for LLaMA2-

| Domain           | Benchmark    | Metric      | n-shot  | Reference                |
|------------------|--------------|-------------|---------|--------------------------|
| <b>Code</b>      | HumanEval    | Pass@1      | 0       | (Chen et al., 2021)      |
|                  | MBPP         | Pass@1      | 1       | (Austin et al., 2021)    |
| <b>Math</b>      | GSM8K        | Exact Match | 8       | (Cobbe et al., 2021)     |
| <b>Medical</b>   | MMLU_Medical | Accuracy    | 5       | (Hendrycks et al., 2021) |
| <b>Finance</b>   | FPB          | F1          | 0       | (Wang et al., 2023b)     |
| <b>Law</b>       | LegalBench   | Accuracy    | 0       | (Guha et al., 2023)      |
| <b>Alignment</b> | MT-Bench     | Score       | (GPT-4) | (Zheng et al., 2023)     |

Table 8: Details of the Six Customizability Benchmarks

| Domain                       | Benchmark        | Metric      | n-shot | Reference                  |
|------------------------------|------------------|-------------|--------|----------------------------|
| <b>Commonsense Reasoning</b> | PIQA             | Accuracy    | 0      | (Bisk et al., 2020)        |
|                              | Hellaswag        | Accuracy    | 0      | (Zellers et al., 2019)     |
|                              | Winogrande       | Accuracy    | 0      | (Sakaguchi et al., 2019)   |
|                              | ARC_easy         | Accuracy    | 0      | (Clark et al., 2018)       |
|                              | ARC_challenge    | Accuracy    | 0      | (Clark et al., 2018)       |
| <b>Reading Comprehension</b> | OpenBookQ        | Accuracy    | 0      | (Mihaylov et al., 2018)    |
|                              | LAMBADA          | Accuracy    | 0      | (Paperno et al., 2016)     |
|                              | BoolQ            | Accuracy    | 0      | (Clark et al., 2019)       |
|                              | SQuADv2          | HasAns_EM   | 2      | (Rajpurkar et al., 2018)   |
|                              | SQuADv2          | HasAns_F1   | 2      | (Rajpurkar et al., 2018)   |
| <b>World Knowledge</b>       | NaturalQuestions | Exact Match | 5      | (Kwiatkowski et al., 2019) |
|                              | TriviaQA         | Exact Match | 5      | (Joshi et al., 2017)       |
| <b>Code</b>                  | HumanEval        | Pass@1      | 0      | (Chen et al., 2021)        |
|                              | MBPP             | Pass@1      | 1      | (Austin et al., 2021)      |
| <b>Math</b>                  | GSM8K            | Exact Match | 8      | (Cobbe et al., 2021)       |
| <b>General Ability</b>       | MMLU             | Accuracy    | 5      | (Hendrycks et al., 2021)   |
|                              | BBH              | Accuracy    | 3      | (Suzgun et al., 2022)      |

Table 9: Details of the Sixteen Functionality Benchmarks

7B, we opted to secure-source each even-indexed layer, while for Phi-2, we chose to secure-source non-overlapping pairs of layers (e.g., layers 0-1, 2-3). For each selected layer set, we first secure-source them, then subjected the semi-open model to FT-all attacks, and subsequently calculated the  $\Delta$ ADR of the layer set to assess its security.

When verifying the customization transition, due to computational constraints, we validated only every other layer set for both models (e.g., secure-source layers 0, 0-4, 0-8 ...). Specifically, we applied LoRA-based customization on LLaMA2-7B in the math domain, while for Phi-2, we utilized the full finetuning approach. The experimental hyperparameters remain consistent with those outlined in the Appendix B.6.

We further computed the  $\Delta$ ADR for each secure-source set within Mistral-7B-v0.1 and Phi-1.5. In these models, the smallest secure-source set identi-

fied by SOLID consists of one decoder layer and two decoder layers, respectively. Following the same experimental configuration as LLaMA2-7B and Phi-2, we secured each even-indexed layer for Mistral-7B, and non-overlapping pairs of layers for Phi-1.5. The complete results demonstrating the transition layers within the Mistral-7B and Phi-1.5 model that secure two non-overlapping consecutive layers are depicted in Figure 9. Once again, we observed a distinct presence of transition layers. Specifically, in Mistral-7B, the transition layer appears at the 24th layer, while in Phi-1.5, it is located within the first layer set. Further results for can be found in Appendix C.7.

## B.8 Security Across Secure Sizes

To examine the influence of Secure layer size on model security, we conduct experiments on Secure-sourcing different amounts and proportions of pa-

| Domain           | Dataset Name    | Size | Reference             |
|------------------|-----------------|------|-----------------------|
| <b>Code</b>      | CodeFeedback    | 156k | (Zheng et al., 2024b) |
|                  | CodeAlpaca      | 20k  | (Chaudhary, 2023)     |
| <b>Math</b>      | MathInstruction | 262K | (Yue et al., 2023)    |
| <b>Medical</b>   | MedMCQA         | 183k | (Zhang et al., 2023)  |
| <b>Law</b>       | Legalbench      | 90k  | (Guha et al., 2023)   |
| <b>Finance</b>   | FinGPT          | 204k | (Wang et al., 2023b)  |
| <b>Alignment</b> | Ultrafeedback   | 62k  | (Cui et al., 2024)    |

Table 10: Customization Training Datasets Composition

| Model             | Method | Rank $r$ | Lora $\alpha$ | Dropout | Learning Rate | Epochs | Warmup R. |
|-------------------|--------|----------|---------------|---------|---------------|--------|-----------|
| <b>Llama2-70B</b> | QLoRA  | 96       | 16            | 0.05    | 1.50E-04      | 1      | 0.03      |
| <b>Llama2-7B</b>  | LoRA   | 32       | 64            | 0.05    | 2.00E-05      | 3      | 0.03      |
| <b>Mistral-7B</b> | LoRA   | 32       | 64            | 0.05    | 1.00E-06      | 3      | 0.03      |

Table 11: The Hyperparameters for Customization Training.

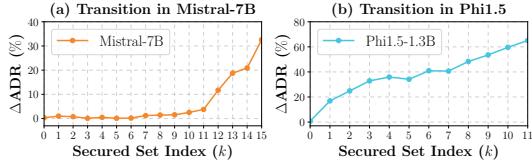


Figure 9: Security changes in Mistrat-7B and Phi-1.5.

rameters in the model’s decoder layer. We give instructions on the detailed setting of secured models in Table 12. The module names are all derived from the overall implementation functions of each model in the Transformers open-source repositories in Table 4. We utilize abbreviated module names to denote specific settings.

We further computed  $\Delta\text{ADR}$  by close-sourcing varying quantities and proportions of parameters under FT-all attacks on three additional models. As shown in Figure 10 and Figure 11(a), we observed the same pattern as with Llama2-7B, where security emerges once a sufficient number of parameters are secured. For example, on Mistrat-7B, security occurs after secure-sourcing 100 million parameters, which is less than a single decoder layer. Secure-sourcing fewer parameters leads to a notable drop in security, with  $\Delta\text{ADR}$  rising to around 40%. Beyond this threshold, security stabilizes near 0%  $\Delta\text{ADR}$ . This pattern holds across all models, highlighting a critical threshold for effective secure-source. Furthermore, different architectures require varying secure-sourcing quan-

ties to achieve security, even with similar model sizes. For instance, Mistrat-7B reaches security by secure-sourcing 100 million parameters, Llama2-7B requires 200 million, and Phi-1.5 needs a higher rate of 7%, compared to 3% for Llama2-7B.

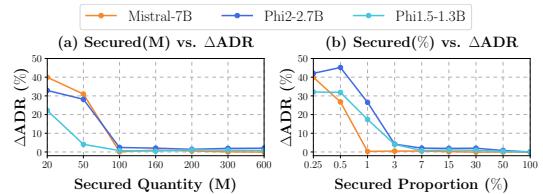


Figure 10:  $\Delta\text{ADR}$  for different secure parameter quantities and proportions.

We explore how secured parameter ratio impacts the model security in Llama2-7B, as shown in Figure 11(b). For instance, technical skills such as Math show earlier transitions, with security emerging at 1% parameters secured, whereas domains such as Commonsense Reasoning require hiding 3%. In summary, secure-sourcing a small portion of parameters can provide sufficient security against model distillation, meanwhile, technical capabilities tend to be more challenging to distill than other domains.

## B.9 Effectiveness of distillation difficulty

The complete Pearson and Spearman results are presented in Table 13, revealing a negative correlation between RS and the average distillation

|            | Llama-7B | Mistral-7B                   | Phi2-2.7B                    | Phi1.5-1.3B          |
|------------|----------|------------------------------|------------------------------|----------------------|
| Proportion | 0.25%    | $W_k$                        | $W_q, W_k$                   | $W_k$                |
|            | 0.50%    | $W_q, W_k$                   | $W_o, MLP_{up}$              | $W_q, W_k$           |
|            | 1%       | $W_q, W_k, W_v, W_o$         | $W_q, W_k, W_v, W_o$         | $W_q, W_k, W_v, W_d$ |
|            | 3%       | 0                            | 0                            | 0                    |
|            | 7%       | 0-1                          | 0-1                          | 0-1                  |
|            | 15%      | 0-4                          | 0-4                          | 0-3                  |
|            | 30%      | 0-9                          | 0-9                          | 0-9                  |
|            | 50%      | 0-15                         | 0-15                         | 0-15, $W_{em}$       |
|            | 100%     | Fully-secured                | Fully-secured                | Fully-secured        |
|            |          |                              |                              | $0-11, W_{em}$       |
| Quantity   | 20M      | $W_k$                        | $W_q, W_k$                   | $W_q, W_k, W_v, W_d$ |
|            | 50M      | $W_q, W_k, W_v$              | $W_q, W_k, W_v, W_o$         | $W_q, W_k, W_v$      |
|            | 100M     | $W_q, W_k, W_v, MLP$         | $W_q, W_k, W_v, W_o, MLP$    | $0, W_q, W_k, W_v$   |
|            | 160M     | $W_q, W_k, W_v, W_o, MLP$    | $W_q, W_k, W_v, W_o, MLP$    | 0-1                  |
|            | 200M     | 0                            | 0                            | 0-2                  |
|            | 300M     | $0, W_q, W_v, W_o, MLP_{up}$ | $0, W_q, W_v, W_o, MLP_{up}$ | 0-3                  |
|            | 600M     | 0-2                          | 0-2                          | 0-7                  |
|            |          |                              |                              | 0-11                 |

Table 12: Secured Sizes Setting. “\*” indicates an entire decoder layer.

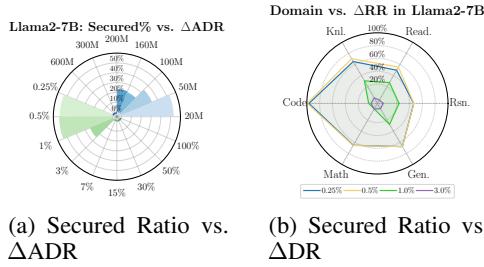


Figure 11:  $\Delta ADR$  and  $\Delta DR$  changes in Llama2-7B with varying secured parameter ratios.

ratio. For example, in Llama2-7B, both Pearson and Spearman coefficients fall below -0.77. Similar trends are seen in models with varying architectures and sizes, confirming that RD is a reliable predictor of distilled model performance and demonstrating the effectiveness of SOLID. Additionally, Figure 12 shows scatter plots depicting the relationship between  $\Delta ADR$  and Distillation Difficulty( $\uparrow$ s) across four models, along with the corresponding Pearson and Spearman correlation coefficients. The Distillation Difficulty( $\uparrow$ s) were obtained from Section 4.3. As illustrated in Figure 12, we observe a clear trend: an increase in  $\Delta ADR$  corresponds to a decrease in model scores across all models analyzed. This inverse relationship is consistently supported by strong negative values for both Pearson and Spearman correlation coefficients, with the most significant negative correlation seen in Phi2-2.7B, indicating a substantial drop in model scores as  $\Delta ADR$  increases.

## B.10 Adversarial Attack

In this section, we provide a detailed comparison of SOLID and SAP-DP in their effectiveness against three types of black-box adversarial attacks on the Llama2-7B model. The attacks considered include Membership Inference Attacks (MIA), Attribute

Inference Attacks (AIA), and Prompt Injection Attacks (PIA).

**Membership Inference Attack (MIA):** This attack aims to determine whether a specific data point was included in the training dataset of the model. Attackers utilize model outputs to infer membership status, potentially exposing sensitive information about the training data (Fu et al., 2023; Chen and Pattabiraman, 2024). We conducted our experiment following SPV\_MIA<sup>9</sup>, which provides a robust framework for assessing model vulnerabilities. We focus on the AUC scores for SPV-MIA against semi-open models across Ag News datasets (Zhang et al., 2016).

**Attribute Inference Attack (AIA):** In this scenario, the adversary attempts to infer specific attributes of training data based on the model’s outputs. This can lead to privacy breaches, particularly when sensitive attributes are involved (Staab et al., 2023; Li et al., 2024b). We conducted our experiments following the methodology outlined in (Staab et al., 2023)<sup>10</sup> and evaluated the top-3 accuracy on the PersonalReddit (PR) Dataset.

**Prompt Injection Attack (PIA):** This attack manipulates input prompts to coerce the model into producing desired outputs that may compromise the integrity or security of the system (Zhao et al., 2024; Xu et al., 2024b). In our experiment, we follow AutoDAN<sup>11</sup>, which can automatically generate stealthy jailbreak prompts by the carefully designed hierarchical genetic algorithm. We evaluate the effectiveness of these prompts using the *keyword-based attack success rate* (ASR), which measures the presence of predefined keywords in responses generated LLMs. For gold stan-

<sup>9</sup><https://github.com/wjfu99/MIA-LLMs>

<sup>10</sup><https://github.com/eth-sri/llmprivacy>

<sup>11</sup><https://github.com/SheltonLiu-N/AutoDAN>

| Model      | Rsn.          | Read.         | Knl.          | Code & Math   | Gen.          | Avg.          |
|------------|---------------|---------------|---------------|---------------|---------------|---------------|
| Llama2-7B  | -0.83   -0.97 | -0.77   -0.96 | -0.83   -0.95 | -0.85   -0.90 | -0.82   -0.93 | -0.80   -0.98 |
| Mistral-7B | -0.83   -0.89 | -0.82   -0.91 | -0.82   -0.94 | -0.78   -0.95 | -0.76   -0.87 | -0.87   -0.92 |
| Phi-2      | -0.93   -0.96 | -0.84   -0.96 | -0.84   -0.87 | -0.84   -0.80 | -0.84   -0.84 | -0.87   -0.95 |
| Phi-1.5    | -0.86   -0.97 | -0.78   -0.94 | -0.83   -0.94 | -0.90   -0.80 | -0.84   -0.89 | -0.80   -0.94 |

Table 13: Correlation coefficients (Spearman | Pearson) between distillation ratio and distillation difficult.

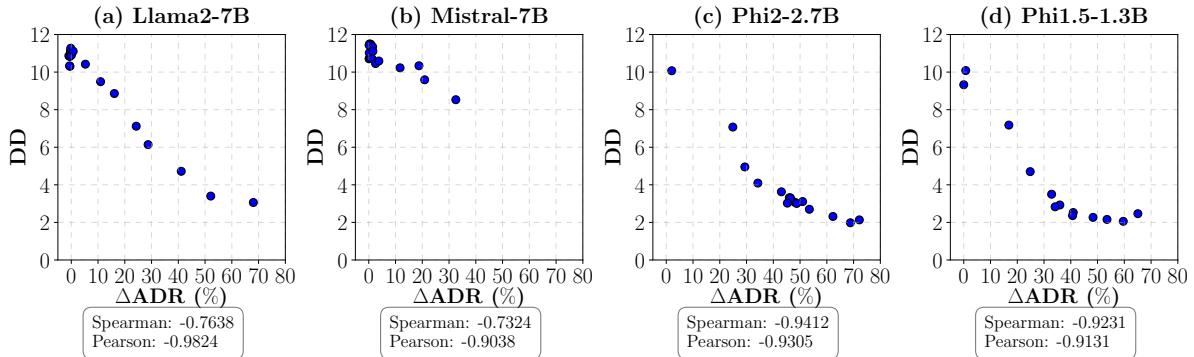


Figure 12: Correlation Analysis of  $\Delta\text{ADR}$  and Distillation Difficulty Across Different Models.

dard, LED<sup>12</sup>, significantly enhances the security of LLMs against prompt injection attacks (PIA), reducing the ASR to 0.

#### Limited Defense against Adversarial Attack.

We compare SOLID and SAP-DP in defending against three black-box adversarial attacks on Llama2-7B. Specifically, we apply the membership inference (Fu et al., 2023) (MIA), attribute inference (Staab et al., 2023) (AIA), and prompt injection (Liu et al., 2023) (PIA) attacks to the semi-open models produced by SAP-DP and SOLID. As shown in Table 14, we observe that SAP-DP outperforms SOLID across all three attacks, but still performs worse than the gold standard. This is because SOLID does not introduce additional output perturbation and thus provide limited defense against black-box adversarial attacks. Details can be found in Appendix B.10.

| Approach  | MIA $\downarrow$ | AIA $\downarrow$ | PIA $\downarrow$ |
|-----------|------------------|------------------|------------------|
| Gold Std. | 58.0             | 43.9             | 0.00             |
| SCARA     | 72.3             | 85.0             | 26.5             |
| SAP-DP    | 72.2             | 83.9             | 24.9             |

Table 14: Performance of SCARA defending adversarial attacks.  $\downarrow$  indicates the smaller the better.

<sup>12</sup><https://github.com/ledllm/ledllm>

## C Detailed Results

### C.1 Comparison in two semi-open Llama2-70B

In this experiment, we examine two semi-open Llama2-70B models, where either the first two decoder layers are secure-source (referred to as Bottom2-Secured) or the last two decoder layers are secure-source (referred to as Top2-Secured). The objective is to compare their performance in terms of customization and their security under the distillation attack. The results are summarized in Table 15 and Table 16.

### C.2 Evaluation Results under FT-all attack

In this section, we provide a comprehensive analysis of the evaluation results, comparing SOLID with two baseline methods: SAP-DP and a fully-secured approach. This comparison is conducted across 16 benchmarks under the FT-all attack scenario. The detailed results for Llama2-70B are presented in Table 17, while the results for Llama2-7B and Mistral-7B are shown in Table 18. Additionally, the outcomes for Phi-2 and Phi-1.5 are provided in Tables 19.

### C.3 Customization Performance of Models

In this section, we present detailed evaluation results of the model customization performance across six downstream tasks used in our experi-

|                        | <b>Math</b> | <b>Code</b> | <b>Medical</b> | <b>Law</b> | <b>Finance</b> | <b>Alignment</b> |
|------------------------|-------------|-------------|----------------|------------|----------------|------------------|
| <b>Fully Secured</b>   | 53.15       | 24.90       | 53.68          | 79.63      | 37.54          | 7.19             |
| <b>Bottom2-Secured</b> | 62.40       | 43.99       | 62.73          | 93.85      | 87.51          | 7.46             |
| <b>Top2-Secured</b>    | 62.53       | 42.36       | 62.72          | 93.91      | 87.90          | 7.46             |

Table 15: Customization Performance of Llama2-70B under Different Secured Layers

|  | <b>Benchmarks</b> | <b>Fully Secured</b> | <b>Semi-Open-1</b> | <b>Semi-Open-2</b> |
|--|-------------------|----------------------|--------------------|--------------------|
| <b>Rsn.</b>  | PIQQA             | 50.82                | 50.49              | 79.05              |
|  | winogrande        | 51.07                | 51.22              | 72.93              |
|  | arc_easy          | 25.17                | 25.63              | 76.30              |
|  | arc_challenge     | 23.55                | 20.48              | 50.17              |
|  | Hellaswag         | 26.65                | 25.77              | 79.49              |
| <b>Read.</b>   | lambada           | 0.00                 | 0.01               | 57.25              |
|  | BoolQ             | 43.30                | 37.92              | 84.95              |
|  | SQuADv2_EM        | 0.00                 | 0.00               | 1.54               |
|  | SQuADv2_f1        | 0.23                 | 1.01               | 35.59              |
|  | OBQA              | 25.60                | 24.40              | 44.00              |
| <b>Knl.</b>  | NQ                | 0.00                 | 0.00               | 15.18              |
|  | TriviaQA          | 0.00                 | 0.00               | 52.67              |
| <b>Code</b>  | mbpp              | 0.00                 | 0.00               | 16.00              |
|  | HumanEval         | 0.00                 | 0.00               | 13.41              |
| <b>Math</b>  | GSM8K             | 0.03                 | 0.01               | 27.75              |
| <b>Gen.</b>  | MMLU              | 23.01                | 23.22              | 63.61              |
|  | BBH               | 0.00                 | 0.00               | 49.45              |
| <b>Average Distillation Ratio(<math>\downarrow</math>)</b> |                   | 22.55                | 21.73              | 74.94              |

Table 16: Customization Performance of Llama2-70B under Different Secured Layers

ments. The detailed results for Llama2-70B are presented in Table 20, while the results for Llama2-7B and Mistral-7B are shown in Table 21 and Table 22. Additionally, the outcomes for Phi-2 and Phi-1.5 are provided in Tables 23 and Table 24.

#### C.4 Comparison in deployment baselines on Llama2-70B

We compare the distillation security of SOLID with SAP-DP and Fully-secured as baselines under FT-secure and SEM attack strategies. The evaluation results on sixteen benchmarks are shown in Table 25.

#### C.5 Comparison in Distillation Attack Strategies

In this section, we present detailed evaluation results of the model distillation performance of SOLID under FT-secure and SEM attack strategies

across six functionalities used in our experiments. The detailed results under the FT-secure distillation strategy are presented in Table 26. The results under SEM attack strategies are shown in Table 27.

#### C.6 Comparison in Distillation datasets scales

To investigate the impact of attack dataset scales on the efficiency of SOLID, we conduct model distillation attack on the Llama2-7B model using four different attack datasets of varying sizes: 100k, 200k, 300k, and 500k. The evaluation performance under different attack set scales are in Table 28

#### C.7 Transition Layer Results.

**Security Performance.** We close same-sized layer sets with different start points, and attack them using FT-all. Specifically, the sets consist of one layer for Llama2-7B (Table 29, Table 30), and two layers for Phi-2 (Table 33, Table 34). We further com-

|  |                  | Pre-train | SOLID | SAP-DP | Fully-secured |
|--|------------------|-----------|-------|--------|---------------|
| <b>Rsn.</b>  | PIQA             | 80.69     | 50.49 | 48.26  | 50.82         |
|  | Winogrande       | 74.74     | 51.22 | 50.59  | 51.07         |
|  | ARC-easy         | 80.35     | 25.63 | 26.35  | 25.17         |
|  | ARC-challenge    | 53.24     | 20.48 | 20.31  | 23.55         |
| <b>Read.</b>   | Hellaswag        | 82.15     | 25.77 | 25.76  | 26.65         |
|  | LAMBADA          | 75.07     | 0.01  | 0.00   | 0.00          |
|  | BoolQ            | 86.70     | 37.92 | 37.83  | 43.30         |
|  | SQuADv2_EM       | 51.23     | 0.00  | 0.00   | 0.00          |
|  | SQuADv2_f1       | 67.43     | 1.01  | 1.13   | 0.23          |
| <b>Knl.</b>  | OBQA             | 44.80     | 24.40 | 24.40  | 25.60         |
|  | NaturalQuestions | 32.38     | 0.00  | 0.00   | 0.00          |
|  | TriviaQA         | 73.47     | 0.00  | 0.02   | 0.00          |
| <b>Code</b>  | MBPP             | 24.80     | 0.00  | 0.00   | 0.00          |
|  | HumanEval        | 25.00     | 0.00  | 0.00   | 0.00          |
| <b>Math</b>  | GSM8K            | 53.15     | 0.01  | 0.00   | 0.03          |
| <b>Gen.</b>  | MMLU             | 63.09     | 23.22 | 24.19  | 23.01         |
|  | BBH              | 61.40     | 0.00  | 0.00   | 0.00          |
| <b>Average Distillation Ratio(<math>\downarrow</math>)</b> |                  | -         | 21.73 | 21.64  | 22.55         |

Table 17: Evaluation results of Llama2-70B under FT-all attack

puted the  $\Delta$ ADR for each secure-source set within Mistral-7B-v0.1 and Phi-1.5 in Appendix B.7. The results for the Mistral-7B-v0.1 model are presented in Table 31 and Table 32. Additionally, the performance outcomes for the Phi-1.5 model can be found in Table 35.

In all the above tables, “Pretrain” represents the model’s original performance without any layers secured. These columns indicate the index of layers in the model that have been secured. “\*” indicates fully-secured. All evaluation scores are averages from three different seed tests, corresponding to the values 20, 42, and 1234, following the details of the Sixteen Functionality Benchmarks in Appendix B.5.

**Customizability Performance.** We close varying numbers of layers from the start and fine-tune the open set, and then we observe the customizability transition in models. Table 36 shows the detailed evaluation results of Llama2-7B and Phi-2 on GSM8k benchmark.

## C.8 Evaluation Results under Different Secure size

In this section, we present a comprehensive evaluation of the model’s performance across sixteen

benchmarks utilized in our experiments. The evaluation results for LLaMA2-7B, categorized by varying quantities and proportions of secure-source parameters, are displayed in Table 37 and Table 38, respectively. For the Mistral-7B model, the results are summarized in Table 39 and Table 40. Furthermore, the evaluation outcomes for the Phi-2 model can be found in Tables 41 and Table 42. The performance results for Phi-1.5 are also included in Tables 43 and Table 44 for comparison. For further details regarding the secure-source settings employed in our experiments, please refer to Appendix C.8.

## C.9 Limitation on OPT-350M

To investigate the limitations of SOLID, we calculate the Distillation ratio of each secure-source set within the smaller model, OPT-350M (Zhang et al., 2022) with only 350M parameters. We set the secure-source set size to 2 and subsequently calculate  $\Delta$ ADRs for each secure-source set. The detailed results are shown in Figure 45.

|  |                  | Llama2-7B |        |               | Mistral-7B |        |               |
|--|------------------|-----------|--------|---------------|------------|--------|---------------|
|  |                  | SOLID     | SAP-DP | Fully-secured | SOLID      | SAP-DP | Fully-secured |
| Rsn.                                       | PIQA             | 49.56     | 49.56  | 49.47         | 51.63      | 50.22  | 49.35         |
|  | Winogrande       | 50.99     | 49.66  | 50.83         | 49.78      | 51.07  | 50.59         |
|  | ARC-easy         | 27.04     | 26.43  | 25.98         | 26.12      | 28.03  | 25.83         |
|  | ARC-challenge    | 21.07     | 20.56  | 22.47         | 19.94      | 21.42  | 22.35         |
|  | Hellaswag        | 25.56     | 25.69  | 26.39         | 26.10      | 25.97  | 25.39         |
| Read.                                      | LAMBADA          | 0.01      | 0.00   | 0.01          | 0.12       | 0.00   | 0.01          |
|  | BoolQ            | 44.30     | 41.70  | 48.34         | 39.05      | 37.83  | 45.80         |
|  | SQuADv2_EM       | 0.00      | 0.00   | 0.00          | 0.00       | 0.00   | 0.00          |
|  | SQuADv2_f1       | 0.49      | 0.63   | 0.59          | 1.21       | 0.26   | 0.66          |
|  | OBQA             | 25.13     | 23.00  | 25.93         | 25.60      | 25.20  | 25.00         |
| Knl.                                       | NaturalQuestions | 0.01      | 0.01   | 0.04          | 0.00       | 0.00   | 0.02          |
|  | TriviaQA         | 0.00      | 0.00   | 0.02          | 0.00       | 0.00   | 0.01          |
| Code                                       | MBPP             | 0.00      | 0.00   | 0.00          | 0.00       | 0.00   | 0.00          |
|  | HumanEval        | 0.00      | 0.00   | 0.00          | 0.00       | 0.00   | 0.00          |
| Math                                       | GSM8K            | 0.00      | 0.00   | 0.00          | 0.00       | 0.00   | 0.00          |
| Gen.                                       | MMLU             | 24.26     | 22.92  | 24.45         | 25.24      | 23.05  | 23.26         |
|  | BBH              | 0.00      | 0.00   | 0.00          | 0.00       | 0.00   | 0.00          |
| Average Distillation Ratio( $\downarrow$ ) |                  | 25.03     | 24.16  | 25.62         | 22.41      | 22.28  | 22.68         |

Table 18: Evaluation results of 7B models under FT-all attack

|       |                  | Phi-2 |        |               | Phi-1.5 |        |               |
|-------|------------------|-------|--------|---------------|---------|--------|---------------|
|       |                  | SOLID | SAP-DP | Fully-secured | SOLID   | SAP-DP | Fully-secured |
| Rsn.  | PIQA             | 54.17 | 52.01  | 52.07         | 53.43   | 52.61  | 50.44         |
|       | Winogrande       | 51.56 | 48.93  | 48.91         | 51.09   | 49.25  | 49.12         |
|       | ARC_easy         | 34.57 | 28.20  | 27.03         | 30.81   | 28.79  | 27.50         |
|       | ARC_challenge    | 19.45 | 19.37  | 18.66         | 20.56   | 19.80  | 21.22         |
|       | Hellaswag        | 27.61 | 25.32  | 25.26         | 26.27   | 25.66  | 25.05         |
| Read. | LAMBADA          | 0.75  | 0.02   | 0.00          | 0.59    | 0.00   | 0.00          |
|       | BoolQ            | 45.29 | 40.21  | 44.60         | 46.98   | 41.80  | 46.28         |
|       | SQuADv2_EM       | 0.02  | 0.00   | 0.00          | 0.00    | 0.00   | 0.00          |
|       | SQuADv2_f1       | 2.61  | 0.28   | 0.64          | 0.78    | 0.65   | 1.60          |
|       | OBQA             | 24.80 | 26.60  | 25.80         | 26.60   | 28.60  | 26.87         |
| Knl.  | NaturalQuestions | 0.00  | 0.00   | 0.02          | 0.04    | 0.00   | 0.00          |
|       | TriviaQA         | 0.01  | 0.00   | 0.01          | 0.01    | 0.00   | 0.00          |
| Code  | MBPP             | 0.00  | 0.00   | 0.00          | 0.00    | 0.00   | 0.00          |
|       | HumanEval        | 0.00  | 0.00   | 0.00          | 0.00    | 0.00   | 0.00          |
| Math  | GSM8K            | 0.00  | 0.00   | 0.00          | 0.00    | 0.00   | 0.00          |
| Gen.  | MMLU             | 24.16 | 22.87  | 22.95         | 24.07   | 22.95  | 22.95         |
|       | BBH              | 0.01  | 0.00   | 0.00          | 0.00    | 0.00   | 0.00          |

Table 19: Evaluation results of small models under FT-all attack

|                     | Math  | Code  | Medical | Law   | Finance | Alignment |
|---------------------|-------|-------|---------|-------|---------|-----------|
| <b>Fully-Secure</b> | 53.15 | 24.90 | 53.68   | 79.63 | 55.63   | 7.19      |
| <b>SAP-DP</b>       | 61.10 | 36.87 | 54.55   | 83.40 | 65.78   | 7.41      |
| <b>SOLID</b>        | 62.40 | 43.99 | 62.73   | 93.85 | 87.51   | 7.46      |
| <b>Fully-Open</b>   | 64.06 | 44.58 | 63.40   | 94.17 | 88.22   | 7.42      |

Table 20: Detailed results of Llama2-70B secure by SOLID on six downstream tasks.

|                     | <b>Math</b> | <b>Code</b> | <b>Medical</b> | <b>Law</b> | <b>Finance</b> | <b>Alignment</b> |
|---------------------|-------------|-------------|----------------|------------|----------------|------------------|
| <b>Fully-Secure</b> | 20.24       | 13.75       | 36.91          | 51.80      | 38.71          | 6.51             |
| <b>SAP-DP</b>       | 20.24       | 13.75       | 36.91          | 51.80      | 38.71          | 6.52             |
| <b>SOLID</b>        | 28.96       | 21.37       | 46.52          | 90.84      | 81.95          | 6.63             |
| <b>Fully-Open</b>   | 29.34       | 21.265      | 47.60          | 90.49      | 84.09          | 6.63             |

Table 21: Detailed results of Llama2-7B secure by SOLID on six downstream tasks.

|                     | <b>Math</b> | <b>Code</b> | <b>Medical</b> | <b>Law</b> | <b>Finance</b> | <b>Alignment</b> |
|---------------------|-------------|-------------|----------------|------------|----------------|------------------|
| <b>Fully-Secure</b> | 38.21       | 33.83       | 61.50          | 50.47      | 37.39          | 3.20             |
| <b>SAP-DP</b>       | 41.47       | 34.44       | 63.08          | 50.37      | 38.10          | 2.47             |
| <b>SOLID</b>        | 46.10       | 43.16       | 66.78          | 84.94      | 86.19          | 3.87             |
| <b>Fully-Open</b>   | 45.26       | 46.08       | 66.47          | 88.13      | 84.91          | 3.78             |

Table 22: Detailed results of Mistral-7B secure by SOLID on six downstream tasks.

|                     | <b>Math</b> | <b>Code</b> | <b>Medical</b> | <b>Law</b> | <b>Finance</b> | <b>Alignment</b> |
|---------------------|-------------|-------------|----------------|------------|----------------|------------------|
| <b>Fully-Secure</b> | 57.77       | 47.59       | 43.13          | 56.46      | 54.07          | 5.22             |
| <b>SAP-DP</b>       | 58.52       | 46.65       | 43.40          | 56.81      | 54.37          | 5.11             |
| <b>SOLID</b>        | 59.59       | 47.79       | 45.85          | 57.11      | 56.26          | 5.26             |
| <b>Fully-Open</b>   | 59.60       | 48.40       | 45.93          | 57.19      | 56.68          | 5.27             |

Table 23: Detailed results of Phi-2 secure by SOLID on six downstream tasks.

|                     | <b>Math</b> | <b>Code</b> | <b>Medical</b> | <b>Law</b> | <b>Finance</b> | <b>Alignment</b> |
|---------------------|-------------|-------------|----------------|------------|----------------|------------------|
| <b>Fully-Secure</b> | 30.33       | 35.09       | 30.78          | 52.18      | 34.60          | 3.24             |
| <b>SAP-DP</b>       | 30.25       | 35.45       | 32.66          | 51.99      | 34.27          | 3.68             |
| <b>SOLID</b>        | 33.66       | 37.10       | 33.14          | 52.26      | 39.60          | 3.87             |
| <b>Fully-Open</b>   | 34.49       | 37.45       | 33.23          | 52.34      | 39.90          | 3.68             |

Table 24: Detailed results of Phi-1.5 secure by SOLID on six downstream tasks.

|                                      |                  | FT-secure |        | SEM   |        |
|--------------------------------------|------------------|-----------|--------|-------|--------|
|                                      |                  | SOLID     | SAP-DP | SOLID | SAP-DP |
| <b>Rsn.</b>                          | PIQA             | 49.78     | 49.40  | 48.62 | 49.00  |
|                                      | Winogrande       | 51.30     | 49.01  | 50.99 | 51.13  |
|                                      | ARC-easy         | 26.43     | 25.59  | 25.33 | 24.55  |
|                                      | ARC-challenge    | 21.41     | 21.42  | 22.01 | 20.93  |
|                                      | Hellaswag        | 26.07     | 26.10  | 25.90 | 25.22  |
| <b>Read.</b>                         | LAMBADA          | 0.00      | 0.00   | 0.00  | 0.00   |
|                                      | BoolQ            | 45.09     | 37.83  | 44.95 | 39.80  |
|                                      | SQuADv2_EM       | 0.00      | 0.00   | 0.00  | 0.00   |
|                                      | SQuADv2_f1       | 0.98      | 1.01   | 0.59  | 1.00   |
|                                      | OBQA             | 24.40     | 23.80  | 25.03 | 22.96  |
| <b>Knl.</b>                          | NaturalQuestions | 0.00      | 0.00   | 0.00  | 0.00   |
|                                      | TriviaQA         | 0.00      | 0.00   | 0.00  | 0.00   |
| <b>Code</b>                          | MBPP             | 0.00      | 0.00   | 0.00  | 0.00   |
|                                      | HumanEval        | 0.00      | 0.00   | 0.00  | 0.00   |
| <b>Math</b>                          | GSM8K            | 0.00      | 0.00   | 0.00  | 0.00   |
| <b>Gen.</b>                          | MMLU             | 23.18     | 23.66  | 22.98 | 22.83  |
|                                      | BBH              | 0.00      | 0.00   | 0.00  | 0.00   |
| <b>Average Distillation Ratio(↓)</b> |                  | 22.60     | 21.80  | 22.40 | 22.30  |

Table 25: Evaluation results of Llama2-70B under FT-secure and SEM attack

|                                      |                  | Llama2-7B | Mistral-7B | Phi-2 | Phi-1.5 |
|--------------------------------------|------------------|-----------|------------|-------|---------|
| <b>Rsn.</b>                          | PIQA             | 49.95     | 49.55      | 54.57 | 52.45   |
|                                      | Winogrande       | 49.88     | 49.68      | 52.33 | 52.41   |
|                                      | ARC-easy         | 27.65     | 25.88      | 33.33 | 31.06   |
|                                      | ARC-challenge    | 20.81     | 22.69      | 19.03 | 18.77   |
|                                      | Hellaswag        | 26.04     | 25.01      | 27.62 | 26.88   |
| <b>Read.</b>                         | LAMBADA          | 0.00      | 0.00       | 0.77  | 0.71    |
|                                      | BoolQ            | 38.13     | 46.01      | 44.34 | 57.49   |
|                                      | SQuADv2_EM       | 0.00      | 0.00       | 0.00  | 0.00    |
|                                      | SQuADv2_f1       | 0.22      | 0.36       | 3.07  | 2.27    |
|                                      | OBQA             | 25.70     | 25.12      | 24.40 | 25.20   |
| <b>Knl.</b>                          | NaturalQuestions | 0.00      | 0.00       | 0.00  | 0.00    |
|                                      | TriviaQA         | 0.00      | 0.00       | 0.01  | 0.00    |
| <b>Code</b>                          | MBPP             | 0.00      | 0.00       | 0.00  | 0.00    |
|                                      | HumanEval        | 0.00      | 0.00       | 0.00  | 0.00    |
| <b>Math</b>                          | GSM8K            | 0.00      | 0.00       | 0.00  | 0.00    |
| <b>Gen.</b>                          | MMLU             | 24.23     | 23.56      | 23.03 | 24.10   |
|                                      | BBH              | 0.00      | 0.00       | 0.00  | 0.00    |
| <b>Average Distillation Ratio(↓)</b> |                  | 24.80     | 22.50      | 23.56 | 26.97   |

Table 26: Distillation Performance of SOLID under FT-Secure attacks.

|                                      |                  | <b>Llama2-7B</b> | <b>Mistral-7B</b> | <b>Phi-2</b> | <b>Phi-1.5</b> |
|--------------------------------------|------------------|------------------|-------------------|--------------|----------------|
| <b>Rsn.</b>                          | PIQA             | 51.52            | 48.53             | 49.46        | 50.82          |
|                                      | Winogrande       | 50.28            | 51.02             | 48.70        | 50.59          |
|                                      | ARC-easy         | 24.83            | 25.83             | 25.93        | 24.62          |
|                                      | ARC-challenge    | 24.99            | 22.35             | 20.65        | 21.08          |
| <b>Read.</b>                         | Hellaswag        | 25.58            | 25.39             | 25.84        | 25.39          |
|                                      | LAMBADA          | 0.00             | 0.01              | 0.00         | 0.01           |
|                                      | BoolQ            | 53.30            | 45.80             | 38.41        | 61.07          |
|                                      | SQuADv2_EM       | 0.00             | 0.00              | 0.00         | 0.00           |
|                                      | SQuADv2_f1       | 0.77             | 0.66              | 0.00         | 1.35           |
| <b>Knl.</b>                          | OBQA             | 25.00            | 25.00             | 27.80        | 30.40          |
|                                      | NaturalQuestions | 0.00             | 0.02              | 0.00         | 0.00           |
|                                      | TriviaQA         | 0.00             | 0.01              | 0.01         | 0.00           |
| <b>Code</b>                          | MBPP             | 0.00             | 0.00              | 0.00         | 0.00           |
|                                      | HumanEval        | 0.00             | 0.00              | 0.00         | 0.00           |
| <b>Math</b>                          | GSM8K            | 0.00             | 0.00              | 0.00         | 0.00           |
| <b>Gen.</b>                          | MMLU             | 25.39            | 23.26             | 22.95        | 23.11          |
|                                      | BBH              | 0.00             | 0.00              | 0.00         | 0.00           |
| <b>Average Distillation Ratio(↓)</b> |                  | 25.00            | 22.00             | 22.10        | 24.70          |

Table 27: Distillation Performance of SOLID under SEM attacks.

|                                      |                  | <b>51K</b> | <b>100K</b> | <b>200K</b> | <b>300K</b> | <b>500K</b> |
|--------------------------------------|------------------|------------|-------------|-------------|-------------|-------------|
| <b>Rsn.</b>                          | PIQA             | 49.56      | 49.89       | 49.18       | 49.18       | 49.59       |
|                                      | Winogrande       | 50.99      | 47.99       | 49.49       | 50.20       | 50.20       |
|                                      | ARC-easy         | 27.04      | 27.06       | 27.06       | 27.02       | 27.01       |
|                                      | ARC-challenge    | 21.07      | 21.33       | 20.90       | 21.16       | 21.48       |
| <b>Read.</b>                         | Hellaswag        | 25.56      | 26.49       | 26.46       | 26.50       | 26.19       |
|                                      | LAMBADA          | 0.01       | 0.01        | 0.00        | 0.00        | 0.01        |
|                                      | BoolQ            | 44.30      | 44.41       | 44.10       | 44.07       | 44.96       |
|                                      | SQuADv2_EM       | 0.00       | 0.00        | 0.00        | 0.02        | 0.00        |
|                                      | SQuADv2_f1       | 1.05       | 0.32        | 0.51        | 0.52        | 0.71        |
| <b>Knl.</b>                          | OBQA             | 25.13      | 25.00       | 23.80       | 25.20       | 25.60       |
|                                      | NaturalQuestions | 0.01       | 0.08        | 0.08        | 0.06        | 0.06        |
|                                      | TriviaQA         | 0.00       | 0.02        | 0.01        | 0.03        | 0.01        |
| <b>Code</b>                          | MBPP             | 0.00       | 0.00        | 0.00        | 0.00        | 0.00        |
|                                      | HumanEval        | 0.00       | 0.00        | 0.00        | 0.00        | 0.00        |
| <b>Math</b>                          | GSM8K            | 0.00       | 0.00        | 0.00        | 0.00        | 0.00        |
| <b>Gen.</b>                          | MMLU             | 24.26      | 25.34       | 25.43       | 26.14       | 26.41       |
|                                      | BBH              | 0.00       | 0.00        | 0.00        | 0.00        | 0.00        |
| <b>Average Distillation Ratio(↓)</b> |                  | 25.07      | 25.03       | 24.89       | 25.26       | 25.48       |

Table 28: Evaluation Results of SOLID on Llama2-7B under Various Attack Set Scales.

|                                      |                  | Pretrain | 0     | 1     | 2     | 3     | 4     | 5     | 6     | 7     |
|--------------------------------------|------------------|----------|-------|-------|-------|-------|-------|-------|-------|-------|
| Rsn.                                 | PIQA             | 76.66    | 49.56 | 51.43 | 49.53 | 50.45 | 49.84 | 50.27 | 50.96 | 51.09 |
|                                      | Hellaswag        | 75.45    | 25.56 | 25.75 | 25.88 | 26.16 | 25.91 | 27.20 | 29.39 | 28.89 |
|                                      | Winogrande       | 66.38    | 50.99 | 50.86 | 50.15 | 49.75 | 49.96 | 50.91 | 51.64 | 51.36 |
|                                      | ARC_easy         | 74.41    | 27.04 | 27.23 | 26.10 | 26.30 | 25.51 | 26.44 | 28.24 | 27.96 |
|                                      | ARC_challenge    | 44.11    | 21.07 | 20.31 | 20.19 | 21.30 | 22.04 | 21.56 | 20.62 | 22.92 |
| Read.                                | OpenBookQA       | 68.49    | 0.01  | 0.11  | 0.02  | 0.02  | 0.01  | 0.00  | 0.05  | 0.04  |
|                                      | LAMBADA          | 80.67    | 44.30 | 41.22 | 38.36 | 41.43 | 38.08 | 38.14 | 38.40 | 41.55 |
|                                      | BoolQ            | 59.48    | 0.00  | 0.04  | 0.00  | 0.00  | 0.00  | 0.00  | 0.01  | 0.03  |
|                                      | SQuADv2_em       | 71.88    | 1.05  | 1.31  | 0.63  | 1.07  | 0.45  | 0.44  | 1.13  | 1.10  |
|                                      | SQuADv2_f1       | 43.80    | 25.13 | 24.60 | 23.60 | 24.93 | 25.67 | 24.47 | 25.07 | 26.00 |
| Knl.                                 | NaturalQuestions | 22.47    | 0.01  | 0.00  | 0.01  | 0.03  | 0.02  | 0.01  | 0.13  | 0.08  |
|                                      | TriviaQA         | 57.23    | 0.00  | 0.01  | 0.00  | 0.02  | 0.01  | 0.01  | 0.07  | 0.10  |
| Code                                 | HumanEval        | 10.90    | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | MBPP             | 16.60    | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| Math                                 | GSM8K            | 20.24    | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| Gen.                                 | MMLU             | 45.83    | 24.26 | 25.37 | 23.98 | 24.26 | 24.75 | 24.01 | 25.23 | 27.45 |
|                                      | BBH              | 39.86    | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.50  | 0.38  |
| <b>Avg. Performance Score(↓)</b>     |                  | 51.44    | 15.82 | 15.78 | 15.20 | 15.63 | 15.43 | 15.50 | 15.97 | 16.41 |
| <b>Average Distillation Ratio(↓)</b> |                  | -        | 30.76 | 30.67 | 29.55 | 30.39 | 29.99 | 30.13 | 31.04 | 31.90 |
| <b>Distillation Difficulty(↑)</b>    |                  | -        | 11.11 | 11.27 | 10.87 | 10.31 | 10.83 | 10.33 | 10.90 | 11.11 |

Table 29: Evaluation Results of Llama2-7B under Different Secure Layers (Part1)

|                                      |                  | 16    | 18    | 20    | 22    | 24    | 26    | 28    | 30    | *     |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Rsn.                                 | PIQA             | 51.47 | 52.99 | 58.22 | 65.83 | 69.60 | 73.45 | 75.46 | 75.99 | 49.47 |
|                                      | Hellaswag        | 31.38 | 36.55 | 45.61 | 56.60 | 62.70 | 67.88 | 71.37 | 72.94 | 26.39 |
|                                      | Winogrande       | 53.09 | 55.98 | 58.96 | 64.12 | 64.80 | 65.25 | 65.46 | 66.53 | 50.83 |
|                                      | ARC_easy         | 30.58 | 35.35 | 43.85 | 55.92 | 62.56 | 68.36 | 70.85 | 72.60 | 25.98 |
|                                      | ARC_challenge    | 24.26 | 26.85 | 30.97 | 35.38 | 38.17 | 41.41 | 43.00 | 44.17 | 22.47 |
| Read.                                | OpenBookQA       | 0.28  | 1.58  | 6.79  | 30.88 | 44.58 | 56.23 | 62.33 | 63.11 | 0.01  |
|                                      | LAMBADA          | 57.55 | 70.53 | 71.36 | 78.85 | 79.69 | 80.29 | 79.39 | 80.40 | 48.34 |
|                                      | BoolQ            | 0.08  | 0.90  | 2.34  | 7.07  | 6.04  | 6.87  | 3.54  | 9.46  | 0.00  |
|                                      | SQuADv2_em       | 2.21  | 13.48 | 21.47 | 35.72 | 36.96 | 39.32 | 37.08 | 42.08 | 0.59  |
|                                      | SQuADv2_f1       | 27.33 | 28.20 | 30.47 | 32.13 | 34.93 | 39.27 | 39.93 | 41.53 | 25.93 |
| Knl.                                 | NaturalQuestions | 0.13  | 0.41  | 1.60  | 2.94  | 4.29  | 2.69  | 7.28  | 11.87 | 0.04  |
|                                      | TriviaQA         | 0.25  | 1.79  | 4.93  | 11.02 | 15.73 | 17.95 | 33.19 | 42.26 | 0.02  |
| Code                                 | HumanEval        | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 3.25  | 8.34  | 10.98 | 0.00  |
|                                      | MBPP             | 0.00  | 0.00  | 0.00  | 0.07  | 0.47  | 2.27  | 8.80  | 13.27 | 0.00  |
| Math                                 | GSM8K            | 0.00  | 0.00  | 0.00  | 0.13  | 0.81  | 8.42  | 6.90  | 15.77 | 0.00  |
| Gen.                                 | MMLU             | 43.17 | 48.20 | 49.38 | 49.58 | 49.72 | 50.03 | 50.75 | 50.61 | 24.45 |
|                                      | BBH              | 0.76  | 11.44 | 19.79 | 28.87 | 31.16 | 35.98 | 38.24 | 40.54 | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 18.97 | 22.60 | 26.22 | 32.65 | 35.42 | 38.76 | 41.29 | 44.36 | 16.15 |
| <b>Average Distillation Ratio(↓)</b> |                  | 36.89 | 43.94 | 50.98 | 63.48 | 68.87 | 75.35 | 80.27 | 86.24 | 31.39 |
| <b>Distillation Difficulty(↑)</b>    |                  | 10.42 | 9.49  | 8.86  | 7.12  | 6.14  | 4.72  | 3.40  | 3.06  | 11.19 |

Table 30: Evaluation Results of Llama2-7B under Different Secured Layers (Part2). “\*” indicates the fully secured model.

|                                      | Pretrain         | 0     | 1     | 2     | 3     | 4     | 5     | 6     | 7     |       |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 81.99 | 51.63 | 53.20 | 53.63 | 53.47 | 51.56 | 52.61 | 50.71 | 55.15 |
|                                      | Hellaswag        | 81.04 | 26.10 | 26.36 | 26.36 | 26.66 | 27.10 | 25.51 | 26.18 | 28.16 |
|                                      | Winogrande       | 74.03 | 49.78 | 49.78 | 51.01 | 50.38 | 49.91 | 50.14 | 49.70 | 51.17 |
|                                      | ARC_easy         | 80.77 | 33.03 | 31.96 | 30.71 | 29.66 | 30.25 | 30.35 | 26.44 | 32.38 |
|                                      | ARC_challenge    | 50.26 | 19.94 | 21.27 | 20.45 | 19.60 | 20.05 | 21.36 | 21.25 | 20.73 |
| <b>Read.</b>                         | OpenBookQA       | 44.40 | 25.60 | 25.20 | 25.20 | 25.47 | 25.87 | 26.33 | 25.07 | 27.20 |
|                                      | LAMBADA          | 73.29 | 0.12  | 0.44  | 1.91  | 2.08  | 0.80  | 0.30  | 0.17  | 1.95  |
|                                      | BoolQ            | 83.67 | 39.05 | 53.12 | 45.95 | 38.61 | 47.35 | 38.06 | 46.44 | 47.66 |
|                                      | SQuADv2_em       | 64.04 | 0.00  | 0.00  | 0.01  | 0.01  | 0.01  | 0.00  | 0.00  | 0.01  |
|                                      | SQuADv2_f1       | 71.37 | 1.21  | 0.84  | 1.05  | 1.03  | 1.27  | 0.43  | 0.07  | 0.86  |
| <b>Knl.</b>                          | NaturalQuestions | 28.98 | 0.00  | 0.01  | 0.00  | 0.04  | 0.01  | 0.00  | 0.02  | 0.07  |
|                                      | TriviaQA         | 70.79 | 0.00  | 0.00  | 0.02  | 0.01  | 0.01  | 0.01  | 0.00  | 0.16  |
| <b>Code</b>                          | HumanEval        | 29.88 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | MBPP             | 38.40 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Math</b>                          | GSM8K            | 38.21 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Gen.</b>                          | MMLU             | 62.50 | 25.24 | 24.68 | 25.11 | 23.43 | 23.65 | 24.26 | 24.26 | 24.99 |
|                                      | BBH              | 56.40 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.01  |
| <b>Avg. Performance Score(↓)</b>     |                  | 60.59 | 15.98 | 16.87 | 16.55 | 15.91 | 16.34 | 15.84 | 15.90 | 17.09 |
| <b>Average Distillation Ratio(↓)</b> |                  | -     | 26.38 | 27.85 | 27.32 | 26.25 | 26.97 | 26.15 | 26.24 | 28.20 |
| <b>Average Distillation Ratio(↓)</b> |                  | -     | 11.50 | 11.31 | 11.48 | 10.71 | 10.77 | 11.44 | 11.02 | 10.71 |

Table 31: Evaluation Results of Mistral-7B under Different Secured Layers (Part1)

|                                      | 16               | 18    | 20    | 22    | 24    | 26    | 28    | 30    | *     |       |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 54.50 | 52.32 | 52.72 | 57.13 | 62.82 | 64.67 | 67.23 | 75.61 | 49.35 |
|                                      | Hellaswag        | 29.31 | 29.02 | 29.99 | 33.46 | 46.21 | 52.12 | 52.46 | 67.73 | 25.39 |
|                                      | Winogrande       | 51.20 | 54.17 | 51.07 | 55.75 | 58.59 | 62.41 | 63.09 | 66.33 | 50.59 |
|                                      | ARC_easy         | 32.84 | 29.35 | 30.80 | 38.04 | 47.24 | 51.99 | 54.74 | 69.95 | 25.83 |
|                                      | ARC_challenge    | 21.19 | 23.04 | 23.78 | 26.34 | 30.86 | 33.22 | 35.04 | 40.53 | 22.35 |
| <b>Read.</b>                         | OpenBookQA       | 26.00 | 27.87 | 26.87 | 29.67 | 28.73 | 32.67 | 33.40 | 36.40 | 25.00 |
|                                      | LAMBADA          | 2.61  | 0.18  | 1.28  | 4.17  | 21.89 | 29.93 | 24.49 | 48.32 | 0.01  |
|                                      | BoolQ            | 53.98 | 53.60 | 58.79 | 55.76 | 64.10 | 74.72 | 68.48 | 81.30 | 45.80 |
|                                      | SQuADv2_em       | 0.01  | 0.00  | 0.47  | 0.13  | 2.39  | 3.59  | 1.87  | 1.82  | 0.00  |
|                                      | SQuADv2_f1       | 0.96  | 0.18  | 1.27  | 2.60  | 14.88 | 22.61 | 21.12 | 34.16 | 0.66  |
| <b>Knl.</b>                          | NaturalQuestions | 0.01  | 0.10  | 0.19  | 0.58  | 1.84  | 3.15  | 3.53  | 8.87  | 0.02  |
|                                      | TriviaQA         | 0.03  | 0.01  | 0.61  | 0.62  | 5.14  | 7.51  | 10.32 | 25.44 | 0.01  |
| <b>Code</b>                          | HumanEval        | 0.00  | 0.00  | 0.00  | 0.61  | 2.24  | 4.88  | 2.44  | 9.75  | 0.00  |
|                                      | MBPP             | 0.00  | 0.00  | 0.00  | 2.00  | 4.33  | 8.33  | 0.93  | 13.07 | 0.00  |
| <b>Math</b>                          | GSM8K            | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.25  | 0.00  |
| <b>Gen.</b>                          | MMLU             | 24.30 | 25.84 | 29.54 | 24.55 | 34.77 | 40.77 | 40.84 | 50.44 | 23.26 |
|                                      | BBH              | 0.00  | 0.00  | 0.02  | 0.30  | 7.55  | 18.76 | 21.05 | 30.07 | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 17.47 | 17.39 | 18.08 | 19.51 | 25.51 | 30.08 | 29.47 | 38.83 | 15.78 |
| <b>Average Distillation Ratio(↓)</b> |                  | 28.83 | 28.71 | 29.84 | 32.20 | 42.09 | 49.64 | 48.64 | 64.08 | 26.05 |
| <b>Average Distillation Ratio(↓)</b> |                  | 11.34 | 11.11 | 10.45 | 10.59 | 10.23 | 10.34 | 9.59  | 8.53  | 11.20 |

Table 32: Evaluation Results of Mistral-7B under Different Secured Layers (Part2)

|                                      | Pretrain         | 0     | 2     | 4     | 6     | 8     | 10    | 12    | 14    |       |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Rsn.                                 | PIQA             | 79.27 | 54.17 | 72.85 | 73.76 | 75.03 | 76.75 | 78.00 | 78.91 | 77.84 |
|                                      | Hellaswag        | 73.73 | 27.61 | 56.49 | 57.73 | 60.47 | 62.84 | 66.39 | 66.91 | 66.95 |
|                                      | Winogrande       | 75.45 | 51.56 | 59.17 | 59.98 | 59.88 | 64.32 | 68.11 | 68.95 | 70.38 |
|                                      | ARC_easy         | 79.92 | 34.57 | 72.94 | 73.40 | 73.97 | 76.51 | 78.33 | 78.66 | 78.63 |
|                                      | ARC_challenge    | 52.90 | 19.45 | 41.75 | 39.82 | 44.11 | 45.65 | 47.92 | 49.74 | 48.78 |
| Read.                                | OpenBookQA       | 51.20 | 25.80 | 35.73 | 37.47 | 40.13 | 42.00 | 44.00 | 45.67 | 44.80 |
|                                      | LAMBADA          | 56.28 | 3.25  | 28.55 | 30.42 | 34.64 | 40.05 | 45.41 | 45.52 | 46.66 |
|                                      | BoolQ            | 83.36 | 47.29 | 65.20 | 62.64 | 66.39 | 71.39 | 73.42 | 72.95 | 75.83 |
|                                      | SQuADv2_em       | 61.30 | 0.02  | 10.49 | 17.63 | 21.94 | 33.94 | 19.54 | 19.15 | 29.14 |
|                                      | SQuADv2_f1       | 71.38 | 2.61  | 37.22 | 40.35 | 45.53 | 59.16 | 48.21 | 50.09 | 54.87 |
| Knl.                                 | NaturalQuestions | 9.58  | 0.00  | 3.60  | 4.97  | 6.13  | 7.55  | 7.95  | 8.10  | 9.25  |
|                                      | TriviaQA         | 39.29 | 0.01  | 13.57 | 16.29 | 24.74 | 28.60 | 31.58 | 33.71 | 32.79 |
| Code                                 | HumanEval        | 48.78 | 0.00  | 1.42  | 6.50  | 10.98 | 16.66 | 22.76 | 19.51 | 23.17 |
|                                      | MBPP             | 46.80 | 0.00  | 5.07  | 6.87  | 9.47  | 19.60 | 25.67 | 23.47 | 25.73 |
| Math                                 | GSM8K            | 57.77 | 0.00  | 7.25  | 8.64  | 4.42  | 9.63  | 14.18 | 11.35 | 17.31 |
| Gen.                                 | MMLU             | 56.73 | 26.16 | 34.29 | 37.01 | 39.90 | 43.11 | 45.63 | 48.17 | 49.82 |
|                                      | BBH              | 59.53 | 0.01  | 15.27 | 18.37 | 16.38 | 14.58 | 4.93  | 4.35  | 11.37 |
| <b>Avg. Performance Score(↓)</b>     |                  | 59.02 | 17.21 | 32.99 | 34.81 | 37.30 | 41.90 | 42.47 | 42.66 | 44.90 |
| <b>Average Distillation Ratio(↓)</b> |                  | -     | 29.15 | 55.90 | 58.99 | 63.21 | 71.00 | 71.97 | 72.28 | 76.09 |
| <b>Distillation Difficulty(↑)</b>    |                  | -     | 10.07 | 7.07  | 4.95  | 4.09  | 3.63  | 3.31  | 3.31  | 3.11  |

Table 33: Evaluation Results of Phi-2 under Different Secured Layers (Part 1)

|                                      |                  | 16    | 18    | 20    | 22    | 24    | 26    | 28    | 30    | *     |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Rsn.                                 | PIQA             | 77.44 | 77.80 | 77.69 | 76.77 | 76.89 | 77.55 | 78.16 | 78.58 | 52.07 |
|                                      | Hellaswag        | 67.20 | 66.90 | 67.13 | 68.00 | 68.86 | 70.01 | 71.44 | 71.18 | 25.26 |
|                                      | Winogrande       | 70.82 | 71.40 | 73.11 | 74.46 | 75.79 | 75.72 | 75.93 | 74.77 | 48.91 |
|                                      | ARC_easy         | 78.30 | 77.27 | 77.33 | 76.82 | 78.09 | 77.76 | 79.53 | 79.56 | 27.03 |
|                                      | ARC_challenge    | 49.71 | 48.29 | 48.52 | 48.04 | 49.80 | 50.68 | 53.16 | 52.67 | 18.66 |
| Read.                                | OpenBookQA       | 46.53 | 46.47 | 45.87 | 45.27 | 46.33 | 45.53 | 46.53 | 48.27 | 20.80 |
|                                      | LAMBADA          | 45.67 | 46.88 | 47.95 | 50.17 | 50.54 | 52.77 | 53.01 | 53.23 | 0.00  |
|                                      | BoolQ            | 80.56 | 80.72 | 82.22 | 83.31 | 83.98 | 83.54 | 82.54 | 83.41 | 39.60 |
|                                      | SQuADv2_em       | 7.88  | 1.30  | 1.69  | 1.31  | 0.15  | 0.23  | 3.54  | 10.03 | 0.56  |
|                                      | SQuADv2_f1       | 40.84 | 34.51 | 34.25 | 35.94 | 35.64 | 36.68 | 39.57 | 44.87 | 0.90  |
| Knl.                                 | NaturalQuestions | 8.90  | 6.09  | 6.40  | 6.79  | 6.86  | 6.85  | 7.20  | 8.37  | 0.02  |
|                                      | TriviaQA         | 31.48 | 27.03 | 25.08 | 24.54 | 22.89 | 22.99 | 24.24 | 26.93 | 0.01  |
| Code                                 | HumanEval        | 22.56 | 21.34 | 25.41 | 32.52 | 38.01 | 46.14 | 46.54 | 43.90 | 0.00  |
|                                      | MBPP             | 26.73 | 25.33 | 24.80 | 31.73 | 36.67 | 41.80 | 43.13 | 43.20 | 0.00  |
| Math                                 | GSM8K            | 16.68 | 16.02 | 14.66 | 12.31 | 17.24 | 30.12 | 45.41 | 49.79 | 0.00  |
| Gen.                                 | MMLU             | 52.69 | 53.45 | 55.68 | 56.61 | 56.93 | 56.59 | 56.86 | 56.47 | 22.95 |
|                                      | BBH              | 3.42  | 17.36 | 8.33  | 18.24 | 30.09 | 48.12 | 52.28 | 56.36 | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 42.79 | 42.25 | 42.12 | 43.70 | 45.57 | 48.42 | 50.53 | 51.86 | 15.10 |
| <b>Average Distillation Ratio(↓)</b> |                  | 72.51 | 71.58 | 71.38 | 74.04 | 77.22 | 82.04 | 85.63 | 87.87 | 25.59 |
| <b>Distillation Difficulty(↑)</b>    |                  | 3.07  | 3.29  | 3.03  | 3.01  | 2.70  | 2.32  | 1.98  | 2.13  | 11.32 |

Table 34: Evaluation Results of Phi-2 under Different Secured Layers (Part2). “\*” indicates the fully secured model.

|                                      |                  | Pretrain | 0-1   | 2-3   | 4-5   | 6-7   | 8-9   | 10-11 | 12-13 | 14-15 | 16-17 | 18-19 | 20-21 | 22-23 | *     |
|--------------------------------------|------------------|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 75.68    | 53.43 | 69.52 | 71.53 | 73.50 | 74.76 | 75.08 | 74.94 | 74.64 | 73.90 | 74.63 | 74.54 | 74.81 | 50.44 |
|                                      | Hellaswag        | 62.56    | 26.27 | 46.66 | 50.71 | 52.98 | 54.51 | 55.11 | 56.01 | 56.78 | 57.90 | 58.76 | 59.35 | 58.58 | 25.05 |
|                                      | Winogrande       | 72.69    | 51.09 | 54.91 | 59.22 | 61.75 | 64.85 | 67.95 | 68.88 | 68.98 | 71.25 | 71.19 | 72.87 | 70.66 | 49.12 |
|                                      | ARC_easy         | 76.14    | 30.81 | 61.70 | 65.70 | 70.10 | 71.38 | 70.01 | 71.72 | 71.93 | 72.34 | 73.39 | 74.16 | 73.74 | 27.50 |
|                                      | ARC_challenge    | 44.62    | 20.56 | 32.85 | 34.10 | 38.08 | 40.05 | 40.30 | 39.48 | 40.87 | 41.52 | 42.84 | 42.58 | 45.42 | 21.22 |
| <b>Read.</b>                         | OpenBookQA       | 48.00    | 26.60 | 33.93 | 35.73 | 40.40 | 41.13 | 40.67 | 41.73 | 41.67 | 40.27 | 41.33 | 43.27 | 45.47 | 26.87 |
|                                      | LAMBADA          | 44.10    | 0.59  | 17.96 | 26.45 | 29.37 | 33.83 | 33.85 | 36.46 | 37.06 | 37.96 | 39.98 | 41.10 | 40.49 | 0.00  |
|                                      | BoolQ            | 75.05    | 46.98 | 59.12 | 52.42 | 57.41 | 65.68 | 68.52 | 63.47 | 65.12 | 66.52 | 73.91 | 75.17 | 77.0  | 46.28 |
|                                      | SQuADv2_em       | 48.01    | 0.00  | 5.82  | 10.94 | 18.34 | 13.96 | 14.70 | 23.22 | 16.98 | 26.05 | 22.04 | 20.16 | 26.86 | 0.00  |
|                                      | SQuADv2_f1       | 60.84    | 0.78  | 24.49 | 26.04 | 34.86 | 32.17 | 32.36 | 43.14 | 38.23 | 48.03 | 45.75 | 45.56 | 49.62 | 1.60  |
| <b>Knl.</b>                          | NaturalQuestions | 5.46     | 0.04  | 1.68  | 2.73  | 3.41  | 3.06  | 3.21  | 4.25  | 4.03  | 4.06  | 4.54  | 4.17  | 4.45  | 0.01  |
|                                      | TriviaQA         | 16.94    | 0.01  | 5.70  | 7.77  | 10.85 | 11.03 | 9.11  | 12.11 | 11.84 | 11.86 | 12.02 | 12.11 | 13.19 | 0.01  |
| <b>Code</b>                          | HumanEval        | 35.98    | 0.00  | 3.05  | 10.57 | 12.20 | 16.26 | 13.82 | 17.48 | 18.70 | 23.17 | 29.68 | 31.91 | 31.71 | 0.00  |
|                                      | MBPP             | 35.40    | 0.00  | 2.80  | 7.80  | 10.93 | 17.40 | 16.53 | 16.13 | 16.67 | 22.27 | 27.33 | 28.27 | 28.53 | 0.00  |
| <b>Math</b>                          | GSM8K            | 30.33    | 0.00  | 0.05  | 0.73  | 0.15  | 0.23  | 0.75  | 0.50  | 2.17  | 4.98  | 9.73  | 17.77 | 23.45 | 0.00  |
| <b>Gen.</b>                          | MMLU             | 42.44    | 24.07 | 26.56 | 28.77 | 32.51 | 32.87 | 36.09 | 39.42 | 39.72 | 43.23 | 42.51 | 42.82 | 43.66 | 23.95 |
|                                      | BBH              | 28.80    | 0.00  | 2.07  | 3.97  | 8.38  | 7.37  | 2.81  | 7.79  | 4.12  | 10.63 | 6.94  | 10.34 | 11.45 | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 47.24    | 16.54 | 26.40 | 29.13 | 32.66 | 34.15 | 34.17 | 36.28 | 35.85 | 38.59 | 39.80 | 40.95 | 42.30 | 15.94 |
| <b>Average Distillation Ratio(↓)</b> |                  | -        | 35.02 | 55.90 | 61.66 | 69.14 | 72.29 | 72.34 | 76.80 | 75.90 | 81.68 | 84.25 | 86.69 | 89.56 | 33.75 |
| <b>Average Distillation Ratio(↓)</b> |                  | -        | 10.08 | 7.18  | 4.70  | 3.50  | 2.93  | 2.83  | 2.53  | 2.36  | 2.27  | 2.16  | 2.06  | 2.46  | 9.33  |

Table 35: Evaluation Results of Phi-1.5 under Different Secured Layers

| Llama2-7B           |          | Phi-2               |          |
|---------------------|----------|---------------------|----------|
| Secure Layers       | GSM8K(↑) | Secure Layers       | GSM8K(↑) |
| <b>Fully-open</b>   | 29.34    | <b>Fully-open</b>   | 59.60    |
| <b>0</b>            | 28.96    | <b>0-1</b>          | 59.59    |
| <b>0-4</b>          | 21.76    | <b>0-5</b>          | 58.60    |
| <b>0-8</b>          | 21.46    | <b>0-9</b>          | 58.45    |
| <b>0-12</b>         | 20.85    | <b>0-13</b>         | 55.19    |
| <b>0-16</b>         | 20.11    | <b>0-17</b>         | 56.25    |
| <b>0-20</b>         | 21.46    | <b>0-21</b>         | 54.59    |
| <b>0-24</b>         | 21.44    | <b>0-25</b>         | 55.34    |
| <b>0-28</b>         | 18.73    | <b>0-29</b>         | 54.59    |
| <b>Fully-Secure</b> | 20.32    | <b>Fully-Secure</b> | 57.77    |

Table 36: Customization Performance under Different Secure Sets

|                                      |                  | 0.25% | 0.5%  | 1%    | 3%    | 7%    | 15%   | 30%   | 50%   | 100%  |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 77.78 | 77.69 | 67.73 | 49.42 | 49.55 | 50.05 | 49.98 | 49.31 | 49.47 |
|                                      | Hellaswag        | 71.40 | 71.54 | 52.39 | 25.74 | 26.03 | 26.25 | 25.67 | 25.48 | 26.39 |
|                                      | Winogrande       | 64.64 | 65.64 | 54.12 | 50.38 | 50.43 | 49.65 | 49.59 | 49.62 | 50.83 |
|                                      | ARC_easy         | 74.69 | 75.04 | 53.82 | 26.03 | 26.76 | 26.46 | 26.64 | 26.66 | 25.98 |
|                                      | ARC_challenge    | 43.66 | 43.29 | 26.99 | 20.16 | 21.39 | 19.74 | 21.44 | 21.73 | 22.47 |
| <b>Read.</b>                         | OpenBookQA       | 63.15 | 63.62 | 33.20 | 0.01  | 0.00  | 0.02  | 0.01  | 0.01  | 0.01  |
|                                      | LAMBADA          | 80.66 | 80.78 | 62.10 | 38.22 | 39.33 | 43.45 | 39.39 | 41.83 | 48.34 |
|                                      | BoolQ            | 11.39 | 12.14 | 5.47  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | SQuADv2_em       | 40.24 | 40.74 | 32.65 | 0.78  | 0.20  | 0.24  | 2.09  | 2.13  | 0.59  |
|                                      | SQuADv2_f1       | 40.73 | 40.67 | 30.47 | 22.93 | 23.40 | 25.53 | 24.07 | 23.07 | 25.93 |
| <b>Knl.</b>                          | NaturalQuestions | 7.83  | 7.89  | 5.61  | 0.00  | 0.01  | 0.02  | 0.01  | 0.00  | 0.04  |
|                                      | TriviaQA         | 44.29 | 45.95 | 18.78 | 0.00  | 0.01  | 0.00  | 0.00  | 0.00  | 0.02  |
| <b>Code</b>                          | HumanEval        | 11.39 | 12.00 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | MBPP             | 15.20 | 15.33 | 1.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Math</b>                          | GSM8K            | 13.22 | 13.29 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Gen.</b>                          | MMLU             | 45.04 | 45.03 | 30.90 | 24.06 | 24.04 | 25.01 | 23.19 | 23.11 | 24.45 |
|                                      | BBH              | 37.45 | 37.51 | 17.36 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 43.69 | 44.01 | 28.98 | 15.16 | 15.36 | 15.67 | 15.42 | 15.47 | 16.15 |
| <b>Average Distillation Ratio(↓)</b> |                  | 84.94 | 85.56 | 56.33 | 29.48 | 29.86 | 30.47 | 29.97 | 30.07 | 31.39 |
| <b>Distillation Difficulty(↑)</b>    |                  | 1.96  | 1.93  | 8.66  | 10.87 | 11.75 | 11.48 | 11.65 | 11.57 | 11.19 |

Table 37: Evaluation Results of Llama2-7B under Different Secure-source Proportion

|                                      |                  | 20M   | 50M   | 100M  | 160M  | 200M  | 300M  | 600M  |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 77.78 | 73.49 | 67.55 | 67.12 | 49.42 | 50.36 | 49.97 |
|                                      | Hellaswag        | 71.40 | 63.47 | 51.67 | 51.27 | 25.74 | 25.70 | 25.78 |
|                                      | Winogrande       | 64.64 | 57.54 | 53.07 | 52.04 | 50.38 | 49.28 | 50.49 |
|                                      | ARC_easy         | 74.69 | 66.50 | 51.97 | 52.11 | 26.03 | 26.43 | 26.29 |
|                                      | ARC_challenge    | 43.66 | 36.04 | 26.51 | 25.99 | 20.16 | 20.79 | 21.70 |
| <b>Read.</b>                         | OpenBookQA       | 63.15 | 45.34 | 30.22 | 28.75 | 0.01  | 0.05  | 0.01  |
|                                      | LAMBADA          | 80.66 | 69.47 | 62.28 | 62.59 | 38.22 | 39.03 | 40.80 |
|                                      | BoolQ            | 11.39 | 2.21  | 4.18  | 7.24  | 0.00  | 0.00  | 0.01  |
|                                      | SQuADv2_em       | 40.24 | 33.98 | 28.98 | 31.05 | 0.78  | 0.74  | 0.37  |
|                                      | SQuADv2_f1       | 40.73 | 33.93 | 29.13 | 30.00 | 22.93 | 23.80 | 23.53 |
| <b>Knl.</b>                          | NaturalQuestions | 7.83  | 2.98  | 5.33  | 5.73  | 0.00  | 0.00  | 0.02  |
|                                      | TriviaQA         | 44.29 | 15.28 | 13.71 | 17.25 | 0.00  | 0.00  | 0.01  |
| <b>Code</b>                          | HumanEval        | 11.39 | 0.41  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | MBPP             | 15.20 | 6.87  | 1.00  | 0.80  | 0.00  | 0.00  | 0.00  |
| <b>Math</b>                          | GSM8K            | 9.00  | 0.10  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Gen.</b>                          | MMLU             | 45.04 | 36.15 | 28.95 | 29.04 | 24.06 | 23.70 | 23.45 |
|                                      | BBH              | 37.45 | 28.53 | 14.99 | 16.99 | 0.00  | 0.00  | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 43.44 | 33.66 | 27.62 | 28.12 | 15.16 | 15.29 | 15.44 |
| <b>Average Distillation Ratio(↓)</b> |                  | 84.46 | 65.44 | 53.69 | 54.66 | 29.48 | 29.72 | 30.01 |
| <b>Distillation Difficulty(↑)</b>    |                  | 1.96  | 5.48  | 8.95  | 9.25  | 10.87 | 10.93 | 10.81 |

Table 38: Evaluation Results of Llama2-7B under Different Secure-source Quantity

|                                      |                  | 0.25% | 1%    | 0.5%  | 3%    | 7%    | 15%   | 30%   | 50%   | 100%  |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 77.79 | 74.36 | 52.16 | 53.34 | 52.07 | 52.19 | 50.04 | 50.60 | 49.35 |
|                                      | Hellaswag        | 71.31 | 65.50 | 26.50 | 26.16 | 25.92 | 25.91 | 25.87 | 25.61 | 25.39 |
|                                      | Winogrande       | 67.09 | 60.32 | 49.22 | 51.65 | 50.01 | 51.36 | 51.36 | 49.65 | 50.59 |
|                                      | ARC_easy         | 74.52 | 69.51 | 29.95 | 30.82 | 29.73 | 30.44 | 28.20 | 27.45 | 25.83 |
|                                      | ARC_challenge    | 42.32 | 38.40 | 20.76 | 20.71 | 21.10 | 20.25 | 22.61 | 22.47 | 22.35 |
| <b>Read.</b>                         | OpenBookQA       | 42.13 | 34.60 | 25.13 | 25.33 | 26.47 | 26.07 | 25.20 | 25.87 | 25.00 |
|                                      | LAMBADA          | 55.99 | 44.36 | 0.73  | 1.66  | 0.96  | 0.31  | 0.03  | 0.02  | 0.01  |
|                                      | BoolQ            | 78.35 | 74.06 | 43.18 | 42.01 | 42.09 | 40.02 | 38.53 | 39.91 | 45.80 |
|                                      | SQuADv2_em       | 13.91 | 6.97  | 0.00  | 0.01  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | SQuADv2_f1       | 41.13 | 33.88 | 1.60  | 0.93  | 1.27  | 0.71  | 0.99  | 0.86  | 0.66  |
| <b>Knl.</b>                          | NaturalQuestions | 8.46  | 5.82  | 0.03  | 0.00  | 0.02  | 0.03  | 0.00  | 0.00  | 0.02  |
|                                      | TriviaQA         | 34.04 | 17.03 | 0.01  | 0.01  | 0.02  | 0.01  | 0.00  | 0.00  | 0.01  |
| <b>Code</b>                          | HumanEval        | 11.99 | 6.51  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | MBPP             | 16.93 | 12.80 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Math</b>                          | GSM8K            | 6.32  | 0.45  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Gen.</b>                          | MMLU             | 44.17 | 37.98 | 23.98 | 24.34 | 25.10 | 23.91 | 23.68 | 24.12 | 23.26 |
|                                      | BBH              | 35.44 | 27.27 | 0.02  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 42.46 | 35.87 | 16.08 | 16.29 | 16.16 | 15.95 | 15.68 | 15.68 | 15.78 |
| <b>Average Distillation Ratio(↓)</b> |                  | 70.08 | 59.20 | 26.53 | 26.89 | 26.67 | 26.33 | 25.87 | 25.88 | 26.05 |
| <b>Distillation Difficulty(↑)</b>    |                  | 2.22  | 5.48  | 10.92 | 11.29 | 11.35 | 11.19 | 11.17 | 11.20 | 11.20 |

Table 39: Evaluation Results of Mistral-7B under Different Secured Proportion

|                                      |                  | 20M   | 50M   | 100M  | 160M  | 200M  | 300M  | 600M  |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 77.79 | 73.74 | 51.36 | 52.86 | 53.34 | 50.98 | 51.62 |
|                                      | Hellaswag        | 71.31 | 65.51 | 26.49 | 27.98 | 26.16 | 26.27 | 26.04 |
|                                      | Winogrande       | 67.09 | 64.51 | 50.06 | 49.51 | 51.65 | 50.17 | 50.85 |
|                                      | ARC_easy         | 74.52 | 68.29 | 27.84 | 30.95 | 30.82 | 27.36 | 28.30 |
|                                      | ARC_challenge    | 42.32 | 37.97 | 20.85 | 21.67 | 20.71 | 21.28 | 20.17 |
| <b>Read.</b>                         | OpenBookQA       | 42.13 | 37.27 | 25.60 | 25.87 | 25.33 | 26.60 | 27.00 |
|                                      | LAMBADA          | 55.99 | 47.63 | 1.16  | 4.74  | 1.66  | 0.43  | 0.53  |
|                                      | BoolQ            | 78.35 | 75.00 | 40.17 | 47.05 | 42.01 | 42.05 | 39.03 |
|                                      | SQuADv2_em       | 13.91 | 8.65  | 0.01  | 0.04  | 0.01  | 0.01  | 0.00  |
|                                      | SQuADv2_f1       | 41.13 | 35.50 | 1.01  | 0.49  | 0.93  | 0.28  | 0.39  |
| <b>Knl.</b>                          | NaturalQuestions | 8.46  | 7.82  | 0.02  | 0.05  | 0.00  | 0.01  | 0.02  |
|                                      | TriviaQA         | 34.04 | 22.89 | 0.02  | 0.19  | 0.01  | 0.01  | 0.01  |
| <b>Code</b>                          | HumanEval        | 11.99 | 7.93  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | MBPP             | 16.93 | 11.87 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Math</b>                          | GSM8K            | 6.32  | 2.48  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Gen.</b>                          | MMLU             | 44.17 | 41.28 | 24.22 | 24.44 | 24.34 | 23.78 | 23.33 |
|                                      | BBH              | 35.44 | 33.43 | 0.00  | 0.40  | 0.00  | 0.00  | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 42.46 | 37.75 | 15.81 | 16.84 | 16.29 | 15.84 | 15.72 |
| <b>Average Distillation Ratio(↓)</b> |                  | 70.08 | 62.31 | 26.10 | 27.79 | 26.89 | 26.14 | 25.95 |
| <b>Distillation Difficulty(↑)</b>    |                  | 2.22  | 3.44  | 11.14 | 10.85 | 11.10 | 11.23 | 11.22 |

Table 40: Evaluation Results of Mistral-7B under Different Secured Quantity

|                                      |                  | 0.25% | 0.5%  | 1%    | 3%    | 7%    | 15%   | 30%   | 50%   | 100%  |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 70.40 | 70.71 | 74.64 | 54.43 | 54.17 | 54.75 | 54.37 | 52.39 | 52.07 |
|                                      | Hellaswag        | 53.13 | 52.99 | 62.84 | 27.88 | 27.61 | 27.77 | 28.01 | 26.30 | 25.26 |
|                                      | Winogrande       | 66.17 | 66.43 | 69.93 | 51.49 | 51.56 | 51.46 | 51.44 | 49.12 | 48.91 |
|                                      | ARC_easy         | 64.62 | 65.33 | 72.55 | 33.39 | 34.57 | 32.00 | 32.18 | 29.97 | 27.03 |
|                                      | ARC_challenge    | 43.26 | 43.86 | 40.67 | 20.82 | 19.45 | 20.00 | 20.56 | 19.88 | 18.66 |
| <b>Read.</b>                         | OpenBookQA       | 41.80 | 42.67 | 38.87 | 26.87 | 25.80 | 26.33 | 26.53 | 26.07 | 20.80 |
|                                      | LAMBADA          | 32.51 | 32.25 | 40.24 | 10.58 | 3.25  | 3.87  | 6.06  | 0.66  | 0.00  |
|                                      | BoolQ            | 65.77 | 65.27 | 76.84 | 48.13 | 47.29 | 45.62 | 46.15 | 40.50 | 39.60 |
|                                      | SQuADv2_em       | 0.36  | 9.09  | 3.31  | 0.02  | 0.02  | 0.01  | 0.01  | 0.00  | 0.56  |
|                                      | SQuADv2_f1       | 24.81 | 30.83 | 30.47 | 0.45  | 2.61  | 0.57  | 2.52  | 1.67  | 0.90  |
| <b>Knl.</b>                          | NaturalQuestions | 5.70  | 5.06  | 1.14  | 0.03  | 0.00  | 0.01  | 0.07  | 0.03  | 0.02  |
|                                      | TriviaQA         | 20.27 | 21.50 | 8.78  | 2.02  | 0.01  | 0.02  | 0.01  | 0.01  | 0.01  |
| <b>Code</b>                          | HumanEval        | 22.16 | 26.83 | 17.68 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | MBPP             | 25.07 | 26.40 | 9.73  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Math</b>                          | GSM8K            | 29.26 | 31.36 | 2.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Gen.</b>                          | MMLU             | 41.76 | 42.17 | 43.86 | 30.31 | 26.16 | 25.79 | 24.85 | 24.03 | 22.95 |
|                                      | BBH              | 18.98 | 21.55 | 9.59  | 3.06  | 0.01  | 0.79  | 0.24  | 0.00  | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 36.83 | 38.49 | 35.48 | 18.20 | 17.21 | 17.00 | 17.24 | 15.92 | 15.10 |
| <b>Average Distillation Ratio(↓)</b> |                  | 62.40 | 65.22 | 60.12 | 30.95 | 29.15 | 28.81 | 29.21 | 26.97 | 25.59 |
| <b>Distillation Difficulty(↑)</b>    |                  | 6.70  | 6.65  | 2.00  | 9.14  | 10.07 | 10.13 | 10.14 | 9.82  | 11.32 |

Table 41: Evaluation Results of Phi-2 under Different Secured Proportion

|                                      |                  | 20M   | 50M   | 100M  | 160M  | 200M  | 300M  | 600M  |
|--------------------------------------|------------------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 73.70 | 70.00 | 53.90 | 54.17 | 53.01 | 54.75 | 54.28 |
|                                      | Hellaswag        | 59.75 | 55.64 | 28.26 | 27.61 | 26.90 | 27.77 | 28.61 |
|                                      | Winogrande       | 66.61 | 67.17 | 51.96 | 51.56 | 52.28 | 51.46 | 50.88 |
|                                      | ARC_easy         | 70.96 | 67.02 | 35.17 | 34.57 | 31.84 | 32.00 | 31.62 |
|                                      | ARC_challenge    | 48.30 | 42.52 | 21.84 | 19.45 | 20.39 | 20.00 | 20.56 |
| <b>Read.</b>                         | OpenBookQA       | 45.33 | 41.27 | 26.13 | 25.80 | 25.60 | 26.33 | 26.53 |
|                                      | LAMBADA          | 35.64 | 25.34 | 1.93  | 3.25  | 2.17  | 3.87  | 5.78  |
|                                      | BoolQ            | 75.37 | 66.25 | 51.66 | 47.29 | 40.81 | 45.62 | 47.69 |
|                                      | SQuADv2_em       | 10.62 | 0.10  | 0.14  | 0.02  | 0.02  | 0.01  | 0.00  |
|                                      | SQuADv2_f1       | 38.28 | 22.83 | 1.33  | 2.61  | 1.36  | 0.57  | 1.13  |
| <b>Knl.</b>                          | NaturalQuestions | 5.44  | 4.51  | 0.06  | 0.00  | 0.02  | 0.01  | 0.05  |
|                                      | TriviaQA         | 12.34 | 12.77 | 0.05  | 0.01  | 0.01  | 0.02  | 0.01  |
| <b>Code</b>                          | HumanEval        | 20.94 | 10.98 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | MBPP             | 12.60 | 13.40 | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Math</b>                          | GSM8K            | 7.52  | 7.78  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Gen.</b>                          | MMLU             | 43.07 | 39.45 | 26.26 | 26.16 | 25.85 | 25.79 | 25.38 |
|                                      | BBH              | 12.35 | 18.02 | 0.00  | 0.01  | 0.00  | 0.79  | 0.12  |
| <b>Avg. Performance Score(↓)</b>     |                  | 37.57 | 33.24 | 17.57 | 17.21 | 16.49 | 17.00 | 17.22 |
| <b>Average Distillation Ratio(↓)</b> |                  | 63.67 | 56.32 | 29.77 | 29.15 | 27.93 | 28.81 | 29.17 |
| <b>Distillation Difficulty(↑)</b>    |                  | 2.07  | 7.96  | 9.25  | 9.96  | 10.08 | 10.13 | 10.22 |

Table 42: Evaluation Results of Phi-2 under Different Secured Quantity

|                                      |                  | <b>0.25%</b> | <b>0.5%</b> | <b>1%</b> | <b>3%</b> | <b>7%</b> | <b>15%</b> | <b>30%</b> | <b>50%</b> | <b>100%</b> |
|--------------------------------------|------------------|--------------|-------------|-----------|-----------|-----------|------------|------------|------------|-------------|
| <b>Rsn.</b>                          | PIQA             | 68.21        | 68.37       | 69.68     | 65.85     | 53.43     | 52.94      | 52.36      | 51.25      | 50.44       |
|                                      | Hellaswag        | 49.05        | 49.18       | 49.30     | 30.72     | 26.27     | 26.74      | 27.02      | 26.10      | 25.05       |
|                                      | Winogrande       | 63.83        | 64.91       | 61.20     | 58.04     | 51.09     | 51.38      | 50.25      | 50.22      | 49.12       |
|                                      | ARC_easy         | 62.94        | 62.89       | 62.25     | 35.15     | 30.81     | 29.27      | 29.64      | 27.99      | 27.50       |
|                                      | ARC_challenge    | 36.98        | 37.49       | 32.91     | 25.97     | 20.56     | 20.36      | 20.08      | 20.88      | 21.22       |
| <b>Read.</b>                         | OpenBookQA       | 39.07        | 40.20       | 35.00     | 33.87     | 26.60     | 27.67      | 27.73      | 26.47      | 26.87       |
|                                      | LAMBADA          | 24.71        | 24.99       | 25.36     | 0.11      | 0.59      | 0.78       | 1.15       | 0.06       | 0.00        |
|                                      | BoolQ            | 59.43        | 59.35       | 63.49     | 41.01     | 46.98     | 51.59      | 46.46      | 44.02      | 46.28       |
|                                      | SQuADv2_em       | 15.65        | 16.00       | 3.13      | 0.50      | 0.00      | 0.01       | 0.03       | 0.00       | 0.00        |
|                                      | SQuADv2_f1       | 32.62        | 32.62       | 14.88     | 0.56      | 0.78      | 1.24       | 2.29       | 1.58       | 1.60        |
| <b>Knl.</b>                          | NaturalQuestions | 2.72         | 2.64        | 0.32      | 0.03      | 0.04      | 0.03       | 0.05       | 0.03       | 0.01        |
|                                      | TriviaQA         | 8.17         | 7.96        | 5.69      | 0.01      | 0.01      | 0.01       | 0.01       | 0.01       | 0.01        |
| <b>Code</b>                          | HumanEval        | 14.43        | 13.41       | 2.03      | 0.00      | 0.00      | 0.00       | 0.00       | 0.00       | 0.00        |
|                                      | MBPP             | 17.20        | 18.67       | 6.47      | 0.00      | 0.00      | 0.00       | 0.00       | 0.00       | 0.00        |
| <b>Math</b>                          | GSM8K            | 4.88         | 4.90        | 0.25      | 0.00      | 0.00      | 0.00       | 0.00       | 0.00       | 0.00        |
| <b>Gen.</b>                          | MMLU             | 30.12        | 29.88       | 28.98     | 27.78     | 24.07     | 24.22      | 24.66      | 24.28      | 22.95       |
|                                      | BBH              | 4.34         | 3.19        | 0.98      | 0.50      | 0.00      | 0.00       | 0.00       | 0.00       | 0.00        |
| <b>Avg. Performance Score(↓)</b>     |                  | 31.43        | 31.57       | 27.17     | 19.41     | 16.54     | 16.84      | 16.57      | 16.05      | 15.94       |
| <b>Average Distillation Ratio(↓)</b> |                  | 66.54        | 66.83       | 57.52     | 41.11     | 35.02     | 35.64      | 35.08      | 33.98      | 33.75       |
| <b>Distillation Difficulty(↑)</b>    |                  | 6.18         | 6.15        | 2.76      | 9.28      | 10.08     | 11.19      | 10.54      | 10.23      | 11.26       |

Table 43: Evaluation Results of Phi-1.5 under Different Secured Proportion

|                                      |                  | <b>20M</b> | <b>50M</b> | <b>100M</b> | <b>160M</b> | <b>200M</b> | <b>300M</b> | <b>600M</b> |
|--------------------------------------|------------------|------------|------------|-------------|-------------|-------------|-------------|-------------|
| <b>Rsn.</b>                          | PIQA             | 69.80      | 65.85      | 53.43       | 52.52       | 52.94       | 53.06       | 53.81       |
|                                      | Hellaswag        | 49.51      | 25.72      | 30.27       | 26.31       | 26.74       | 27.05       | 26.51       |
|                                      | Winogrande       | 62.56      | 58.04      | 51.09       | 50.83       | 51.38       | 50.57       | 49.99       |
|                                      | ARC_easy         | 62.41      | 30.15      | 30.81       | 29.14       | 29.27       | 29.62       | 29.67       |
|                                      | ARC_challenge    | 32.51      | 25.97      | 20.56       | 19.97       | 20.36       | 20.48       | 20.79       |
| <b>Read.</b>                         | OpenBookQA       | 35.53      | 33.87      | 26.60       | 26.93       | 27.67       | 28.20       | 26.87       |
|                                      | LAMBADA          | 28.14      | 0.11       | 0.59        | 0.45        | 0.78        | 1.30        | 0.61        |
|                                      | BoolQ            | 64.77      | 41.01      | 46.98       | 47.33       | 51.59       | 46.09       | 45.59       |
|                                      | SQuADv2_em       | 4.67       | 0.50       | 0.00        | 0.00        | 0.01        | 0.01        | 0.00        |
|                                      | SQuADv2_f1       | 22.47      | 0.56       | 0.78        | 1.02        | 1.24        | 2.31        | 2.01        |
| <b>Knl.</b>                          | NaturalQuestions | 1.64       | 0.03       | 0.04        | 0.05        | 0.03        | 0.06        | 0.03        |
|                                      | TriviaQA         | 5.93       | 0.01       | 0.01        | 0.01        | 0.01        | 0.02        | 0.01        |
| <b>Code</b>                          | HumanEval        | 7.73       | 0.00       | 0.00        | 0.00        | 0.00        | 0.00        | 0.00        |
|                                      | MBPP             | 7.87       | 0.00       | 0.00        | 0.00        | 0.00        | 0.00        | 0.00        |
| <b>Math</b>                          | GSM8K            | 0.28       | 0.00       | 0.00        | 0.00        | 0.00        | 0.00        | 0.00        |
| <b>Gen.</b>                          | MMLU             | 31.11      | 27.78      | 24.07       | 23.41       | 24.22       | 24.54       | 24.68       |
|                                      | BBH              | 3.38       | 0.50       | 0.00        | 0.00        | 0.00        | 0.00        | 0.00        |
| <b>Avg. Performance Score(↓)</b>     |                  | 28.84      | 19.89      | 16.54       | 16.35       | 16.84       | 16.67       | 16.50       |
| <b>Average Distillation Ratio(↓)</b> |                  | 61.06      | 41.11      | 35.02       | 34.61       | 35.64       | 35.28       | 34.94       |
| <b>Distillation Difficulty(↑)</b>    |                  | 2.81       | 9.28       | 10.26       | 11.65       | 11.19       | 10.87       | 10.49       |

Table 44: Evaluation Results of Phi-1.5 under Different Secured Quantity

|                                      |                  | Pretrain | 0-2   | 3-5   | 6-8   | 9-11  | 12-14 | 15-17 | 18-20 | 21-23 | 24-26 | 27-29 | 30-32 | 33-35 | *     |
|--------------------------------------|------------------|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <b>Rsn.</b>                          | PIQA             | 64.69    | 61.40 | 62.50 | 61.11 | 56.46 | 58.47 | 58.94 | 61.86 | 62.59 | 63.13 | 61.93 | 62.67 | 63.11 | 49.53 |
|                                      | Hellaswag        | 36.68    | 34.03 | 34.27 | 33.69 | 31.79 | 32.24 | 32.78 | 33.27 | 33.68 | 33.25 | 33.94 | 33.63 | 33.07 | 25.77 |
|                                      | Winogrande       | 52.09    | 51.62 | 52.96 | 51.57 | 50.83 | 52.83 | 51.06 | 51.52 | 51.85 | 52.06 | 52.04 | 51.99 | 50.94 | 49.85 |
|                                      | ARC_easy         | 44.02    | 40.46 | 40.66 | 40.07 | 35.41 | 37.50 | 37.81 | 39.91 | 40.70 | 41.12 | 41.19 | 40.84 | 39.92 | 26.53 |
|                                      | ARC_challenge    | 20.82    | 22.27 | 22.61 | 21.25 | 21.39 | 21.25 | 22.01 | 21.36 | 20.25 | 20.48 | 19.88 | 20.99 | 20.28 | 19.82 |
| <b>Read.</b>                         | OpenBookQA       | 28.00    | 27.60 | 27.47 | 27.40 | 27.40 | 27.27 | 26.20 | 26.47 | 27.67 | 26.80 | 28.67 | 27.67 | 27.13 | 27.47 |
|                                      | LAMBADA          | 40.47    | 30.62 | 32.97 | 28.62 | 21.65 | 23.87 | 28.23 | 29.07 | 29.83 | 29.81 | 31.72 | 31.43 | 18.08 | 0.00  |
|                                      | BoolQ            | 57.74    | 50.87 | 48.51 | 50.58 | 51.60 | 52.83 | 53.42 | 54.37 | 53.30 | 51.42 | 59.79 | 53.14 | 60.42 | 37.83 |
|                                      | SQuADv2_em       | 11.34    | 6.87  | 7.88  | 4.74  | 4.19  | 0.27  | 0.87  | 2.22  | 3.79  | 3.05  | 4.11  | 4.69  | 2.35  | 0.00  |
|                                      | SQuADv2_f1       | 19.35    | 16.27 | 17.00 | 12.00 | 11.72 | 9.04  | 6.92  | 10.11 | 10.90 | 10.08 | 8.88  | 11.47 | 7.30  | 0.01  |
| <b>Knl.</b>                          | NaturalQuestions | 1.08     | 1.05  | 0.83  | 0.83  | 0.78  | 0.55  | 0.69  | 0.41  | 1.00  | 0.85  | 0.71  | 0.52  | 0.75  | 0.04  |
|                                      | TriviaQA         | 4.48     | 2.24  | 2.66  | 2.01  | 2.16  | 1.41  | 1.06  | 2.39  | 2.38  | 2.29  | 1.57  | 1.90  | 1.76  | 0.02  |
| <b>Code</b>                          | HumanEval        | 0.00     | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                                      | MBPP             | 0.00     | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Math</b>                          | GSM8K            | 1.59     | 0.15  | 0.25  | 0.00  | 0.08  | 0.00  | 0.05  | 0.00  | 0.03  | 0.18  | 0.00  | 0.00  | 0.00  | 0.00  |
| <b>Gen.</b>                          | MMLU             | 26.05    | 25.52 | 26.02 | 25.20 | 25.60 | 25.05 | 25.73 | 23.97 | 25.57 | 26.04 | 25.13 | 25.17 | 25.73 | 22.95 |
|                                      | BBH              | 16.97    | 6.87  | 12.58 | 5.51  | 5.11  | 2.55  | 5.98  | 2.74  | 11.15 | 13.98 | 14.25 | 13.02 | 12.57 | 0.00  |
| <b>Avg. Performance Score(↓)</b>     |                  | 25.02    | 22.23 | 22.89 | 21.44 | 20.36 | 20.30 | 20.69 | 21.16 | 22.04 | 22.03 | 22.58 | 22.30 | 21.38 | 15.28 |
| <b>Average Distillation Ratio(↓)</b> |                  | -        | 88.83 | 91.49 | 85.71 | 81.38 | 81.13 | 82.69 | 84.55 | 88.08 | 88.05 | 90.23 | 89.13 | 85.43 | 61.08 |
| <b>Distillation Difficulty(↑)</b>    |                  | -        | 5.92  | 9.32  | 9.04  | 8.60  | 8.83  | 8.73  | 7.17  | 5.82  | 5.18  | 4.65  | 4.92  | 4.15  | 10.89 |

Table 45: Evaluation Results of OPT-350M under Different Secured Layers. “\*” indicates the fully secured model.