Securing On-device Transformer with Hardware Binding and Reversible Obfuscation

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Background

Deep learning models are considered valuable assets of the owner:

- Proprietary Training Dataset
- Compute Power
- Training Expertise

Deep learning at the edge:

- Real-time processing with low latency
- Reduced cloud dependence
- Powerful functionality without internet connectivity
- Enhanced user privacy

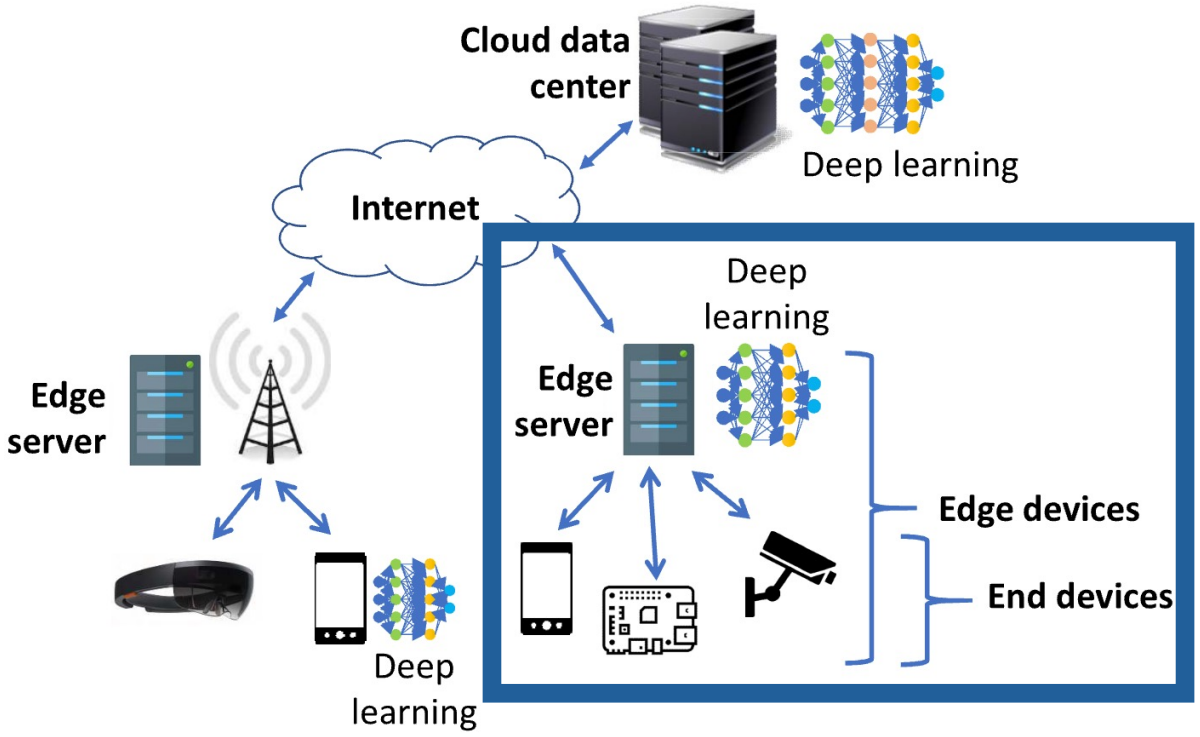


Figure: Chen, Jiasi, and Xukan Ran. "Deep learning with edge computing: A review." Proceedings of the IEEE 107.8 (2019): 1655-1674.

Motivation

Research Question: How to protect the **IP** (Intellectual Property) of a **transformer** model when it is **deployed at the edge**, potentially controlled by malicious parties?

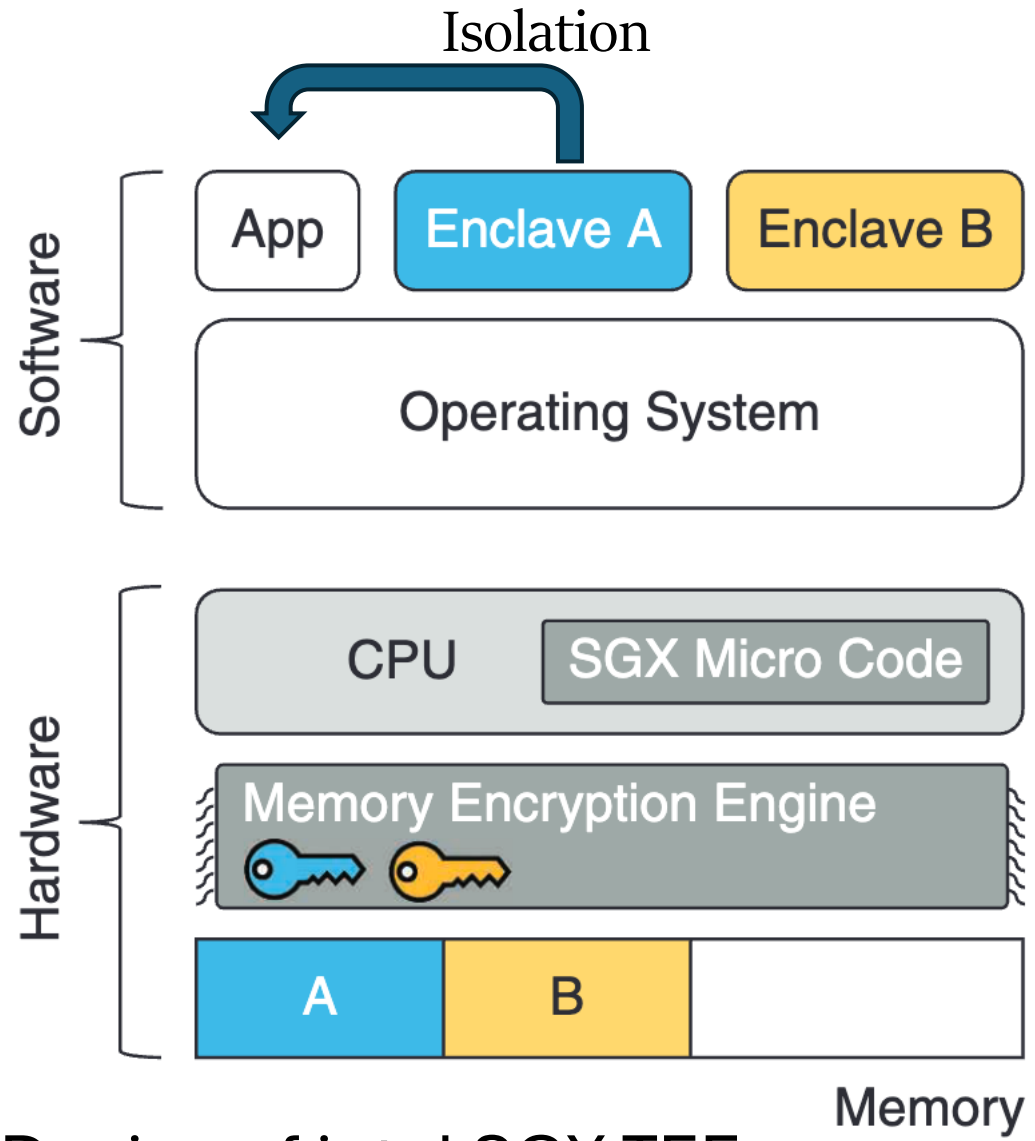
- On-device Model Extraction Attacks [Sun et al., 2021; Deng et al., 2022, Oygenblik et al., 2024]
  - Model De-compilation; Memory Search; API hooking
- Sun et al., 2021: 41% APPs leave plaintext weights from popular ML frameworks (e.g. PyTorch)
- Oygenblik et al., 2024: Recover weights from memory snapshots
- **Threats: Model Inversion Attacks on the Stolen Model, etc.**

Sun, Zhichuang, et al. “Mind your weight (s): A large-scale study on insufficient machine learning model protection in mobile apps.” *30th USENIX security symposium.* 2021.
Deng, Zizhuang, et al. “Understanding real-world threats to deep learning models in android apps.” Proceedings of the *2022 ACM SIGSAC CCS.* 2022.
Oygenblik, David, et al. “AI Psychiatry: Forensic Investigation of Deep Learning Networks in Memory Images.” 33rd USENIX Security Symposium. 2024.

Related Works

Solution 1:

- With TEE (Trusted Execution Environment)
  - Execute something on your machine
  - But you don't know what it is
- Problem:
  - ARM TrustZone: small memory size – not for ML workloads
  - Commercially Built on CPU – significant overhead compared to GPU baseline (5-10 x)



Design of intel SGX TEE.

Figure: Jauernig, Patrick, et al. "Trusted execution environments: properties, applications, and challenges." IEEE Security & Privacy 18.2 (2020): 56-60.

Related Works

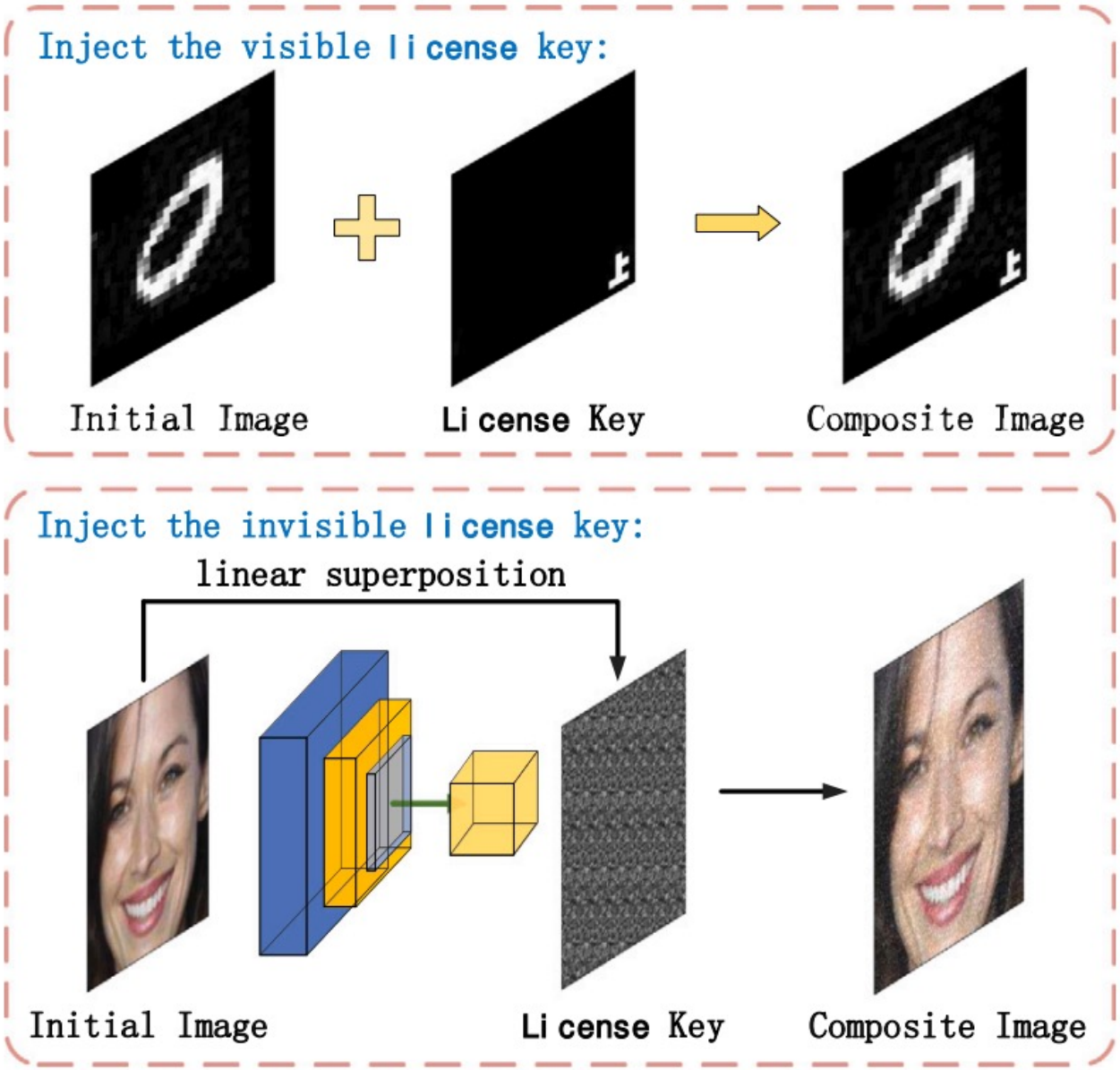
Solution 2: Ownership Verification

- **Watermark:** Embed hidden information into the model
- **Fingerprint:** Extract model-specific features
- Both:
  - **Passive** protection: not prevent misuse
  - **Impractical:**
    - Verification requires access to the suspected model
    - No trusted third party for verifying ownership
  - **Prone to Attacks**
    - Ambiguity Attacks
    - Removal Attacks

Related Works

Solution 3: Active Access Control

- **Retraining needed**
- e.g. only an image with a certain tag can be predicted correctly
- Problem:
  - **Reverse-engineering**
  - Application to other tasks (e.g. segmentation)



Li, Peihao, et al. "SecureNet: Proactive intellectual property protection and model security defense for DNNs based on backdoor learning." *Neural Networks* 174 (2024): 106199.

Related Work

Solution 4: GPU TEE

1. Mostly need host CPU TEE
2. Expensive Hardware (e.g. H100)
3. Significant HW/SW Changes

Existing systems	Host TCB	Required changes	
		HW	SW
Graviton [16]	Intel SGX + ○	SC	Runtime, drivers, CUDA
HIX [17]	Intel SGX + ●	SGX instruction, MMU, PCIe	GPU enclave, inter-enclave communication, CUDA
GraphcoreIPU [18]	○	CCU	XLA, poplar compiler, runtime
NvidiaCC (H100) [15]	C-VM + ●	Security processor	CUDA, C-VM
Apple PCC [39]	Enclave + PCC-OS + TXM [40] + ●	Custom Apple Silicon	SepOS, SW stack
sNPU [24]	Penglai Enclave + ◑ + SM	SoC-NoC, SC	SMMU, SM
StrongBox [25]	TrustZone + ◑ + SM	-	Runtime, driver, MMIO, TASK protector
Honeycomb [41]	AMD-SEV + ○ + Validator + SM	-	Validator, SVSM, SM, runtime
CAGE [23]	ARM CCA + ◑ + SM	-	API, monitors, ShadowTask
ACAI [22]	ARM CCA + ● + PCIe port	-	TF-A, SMMU, RMM
GR-T [26]	Trustzone + ● + cloudVM	-	Driver Shim, GPU_shim
HETEE [42]	● + SM	HETEE box, PCIe interconnect, (SC)	SC, API
ShEF [20]	○	-	ShEF runtime, Shield
GuardAIn	○	-	Driver, runtime, kernels (operators)

Table from: Dhar, Aritra, et al. "GuardAIn: Protecting Emerging Generative AI Workloads on Heterogeneous NPU." 2025 IEEE Symposium on Security and Privacy (SP). IEEE, 2025.

Related Work

Weakness of previous works:

- **Watermark/Fingerprint**: No Active Protection
- **Watermark**: Apply only on small networks (e.g. need retraining)
- **Active Access Control**: Require retraining the model, not scalable
- **CPU-TEE Protection**: Optimize compared to CPU baseline
- **CPU-/GPU-TEE Architecture**: Need significant changes of the whole stack

Design Goal:

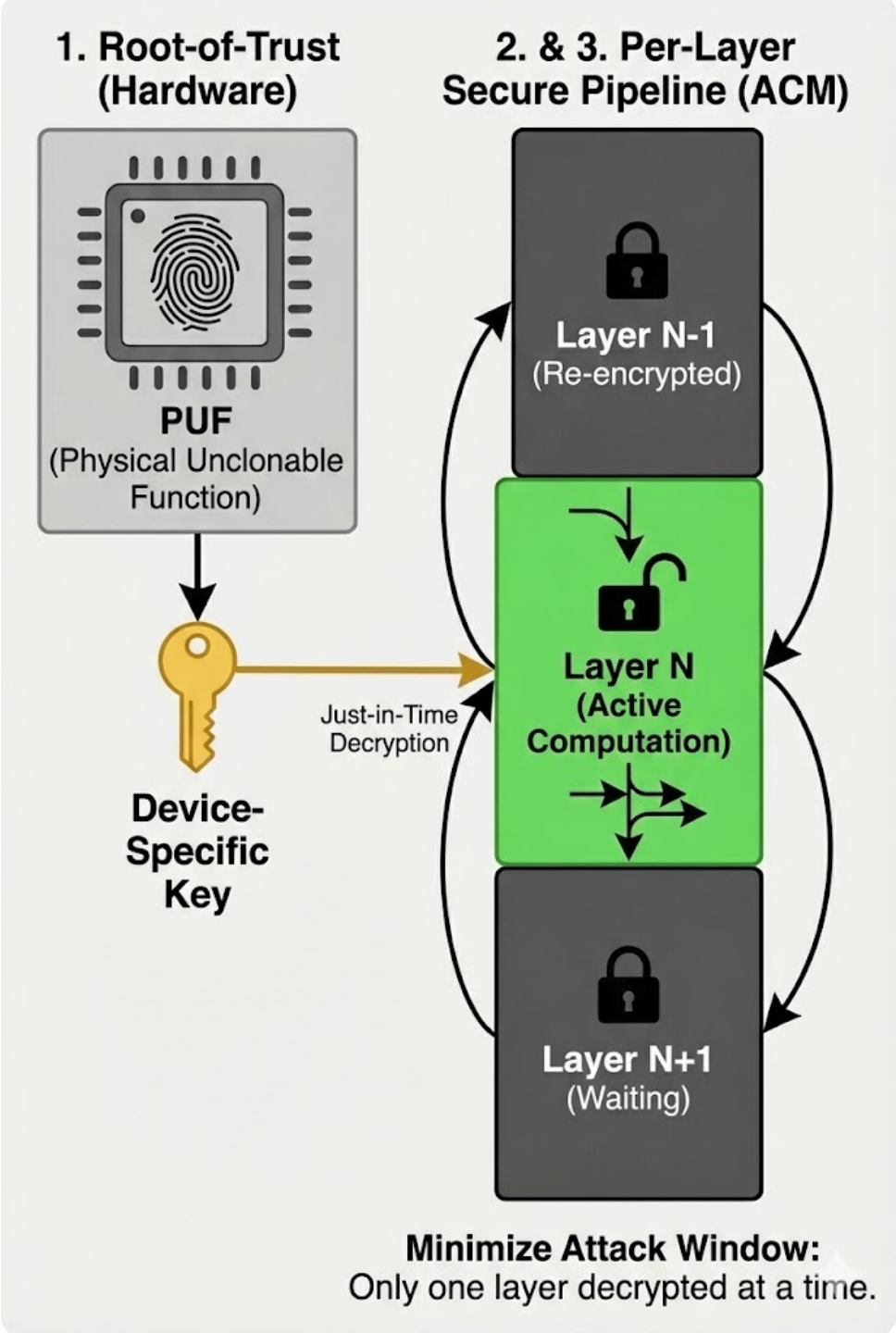
- Actively protect the model to **prevent stealing**
- Make good use of accelerators
- Not change the HW/SW significantly
- Lightweight and efficient

Threat Model

- **Attacker Can:**
  - Access **encrypted model weights** stored on disk.
  - Know the full model architecture.
  - Possess **partial training data** (e.g. up to 20% for ImageNet).
  - Perform **offline computation** to try recovering the model.
- **Attacker Cannot:**
  - Access **runtime plaintext weights** in **memory**.
  - Physically tamper with the hardware and extract keys from the root-of-trust.

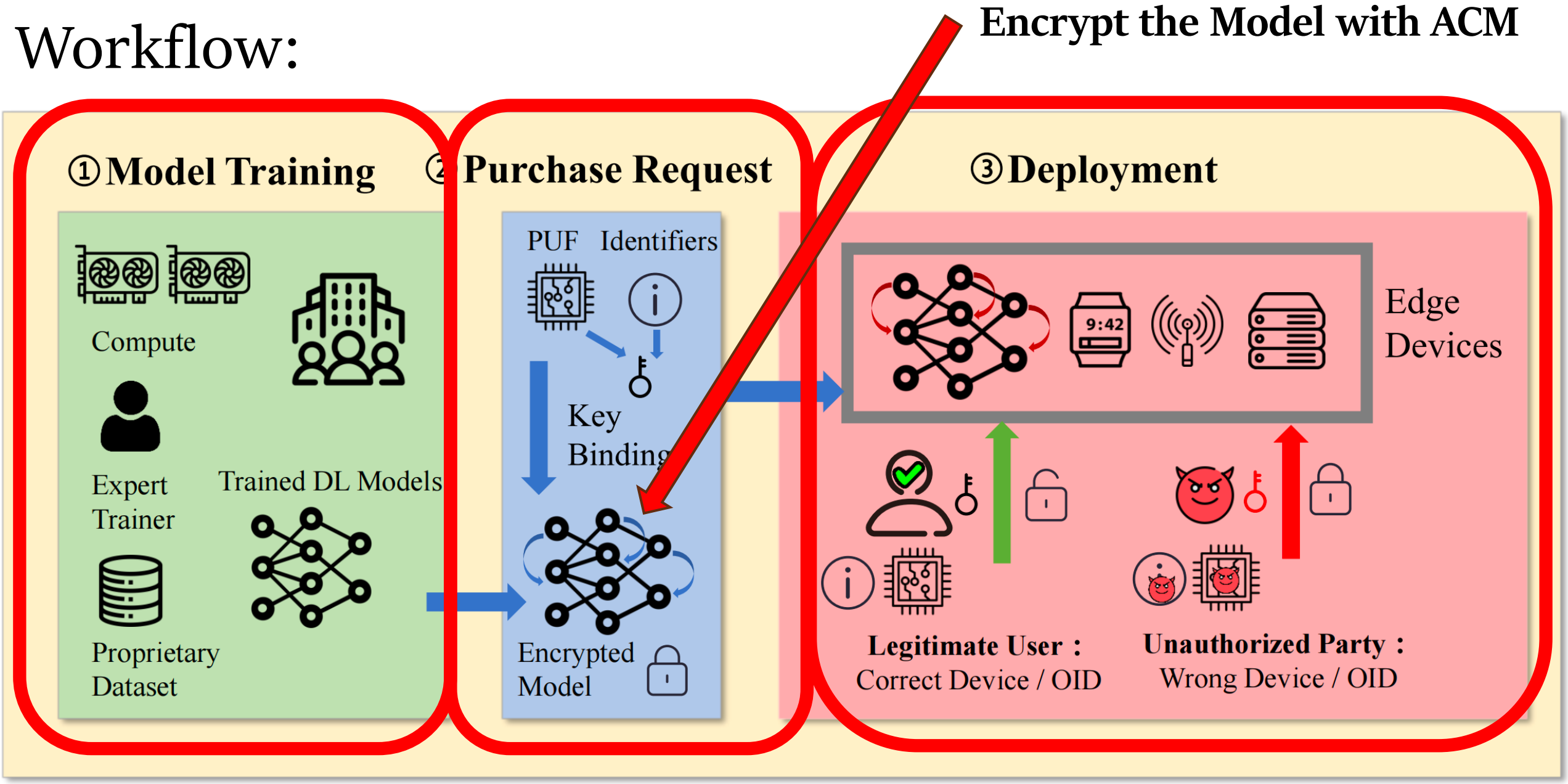
Overview

1. **Physical Unclonable Functions (PUF)** as a Root-of-Trust (RoT)
   - Lightweight, Stable
2. **Arnold Cat's Map (ACM)** for better efficiency
   - Weights have high redundancy, like images
   - Faster than AES on CPU/GPU
3. **Per-layer Decryption/Encryption** Pipeline:
   - Minimize Attack Window



Overview

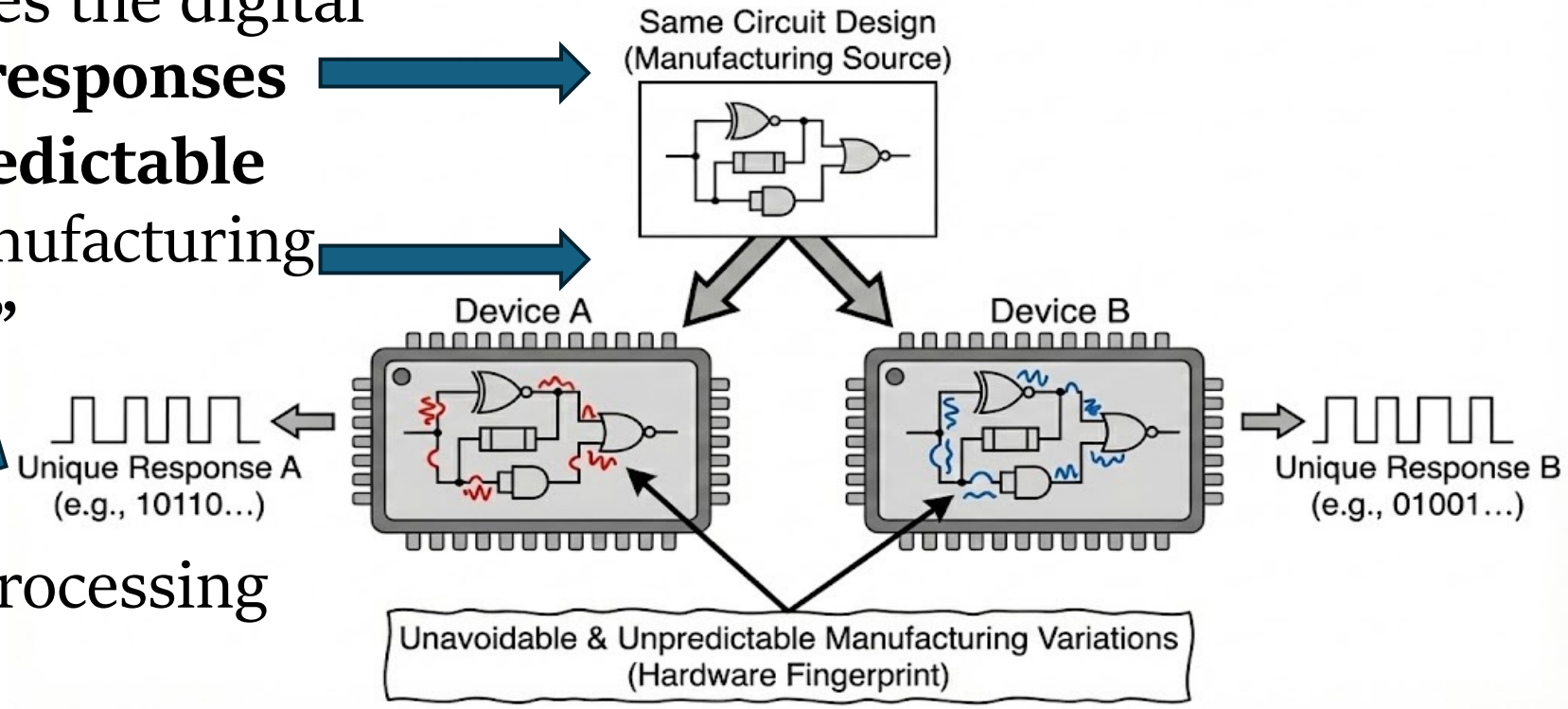
Workflow:



Methodology

Design Choice 1: PUF

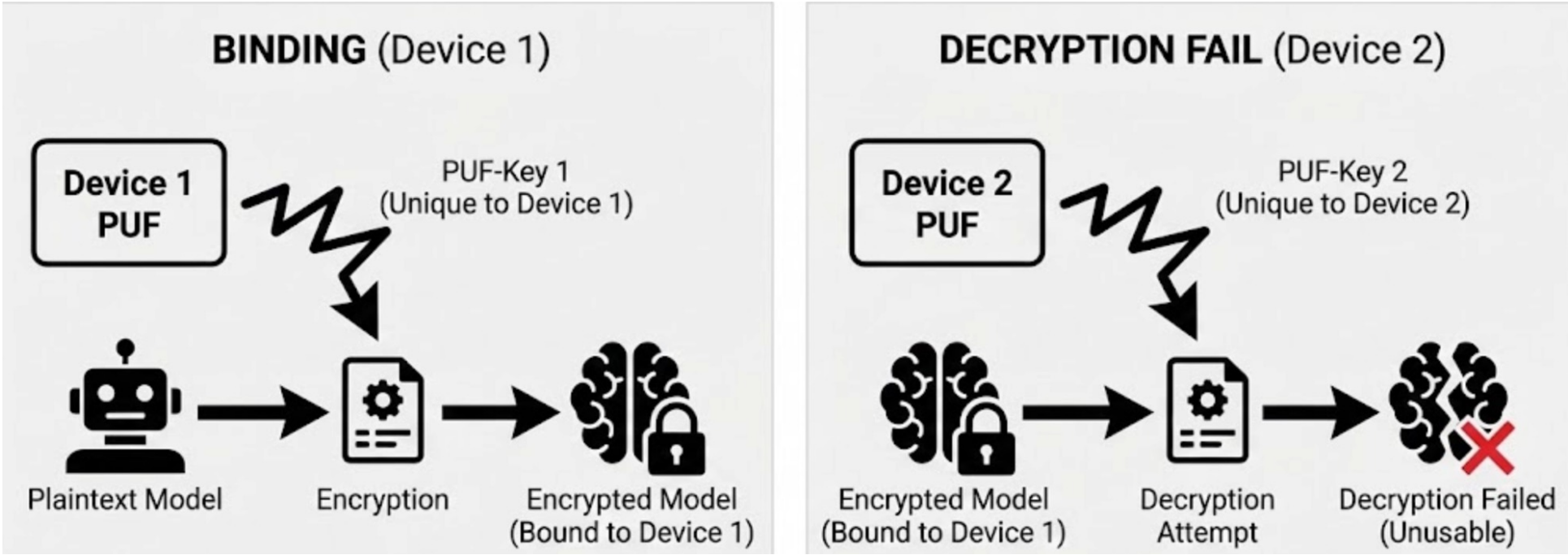
1. A circuit design that takes the digital **challenges** and output **responses**
2. **Unavoidable** and **Unpredictable** variations during the manufacturing
3. **"Hardware Fingerprint"**
4. **Advantages:**
   - Lightweight
   - Reliable (with Post-processing such as ECC)
   - Some designs don't require extra hardware
     - E.g. Memory PUFs with existing DRAM and SRAM



Methodology

Design Choice 1: PUF

- Use it as a key to encrypt the model **(Binding)**
  - only one specific device can unlock it during inference
- No training -> Scalable
- Stealing the encrypted weights do **not** give a usable model (shown later)

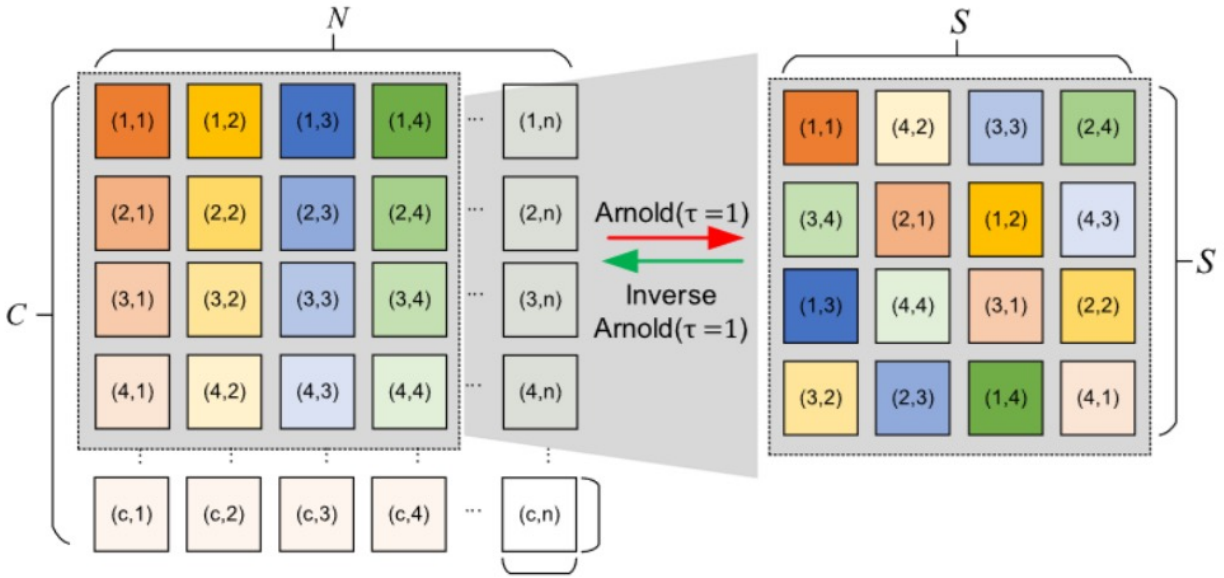


Methodology

Figure: Lin, Ning et al. (2020). Chaotic weights: A novel approach to protect intellectual property of deep neural networks. *IEEE TCAD.*

Design Choice 2: ACM Weight Permutation

- **What it is:** A chaotic map -> avalanche effect
- **Highly parallelizable** -> Fast on both CPUs and GPUs
- **Effective** -> Degrading performance



Encryption Key: 2×2 Matrix A

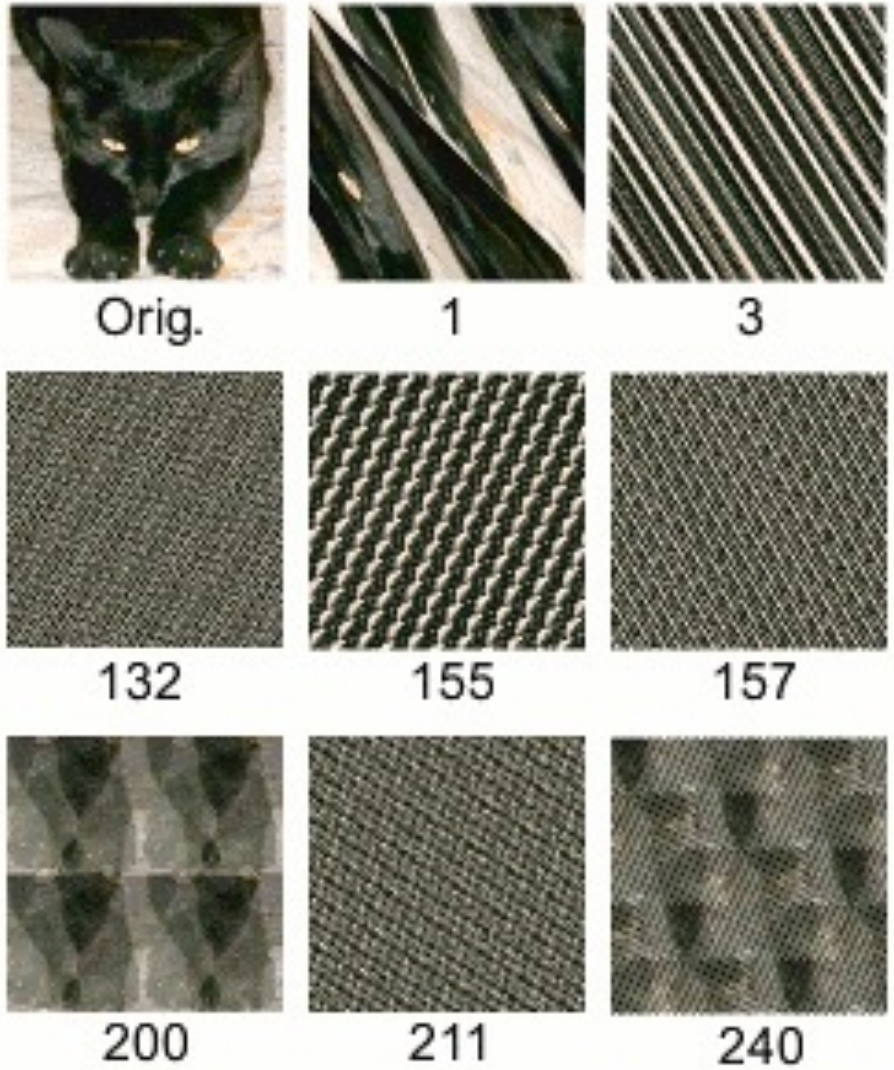
$$\begin{bmatrix} x_n \\ y_n \end{bmatrix} = A^n \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} \pmod{S} \qquad (1)$$

Decryption:

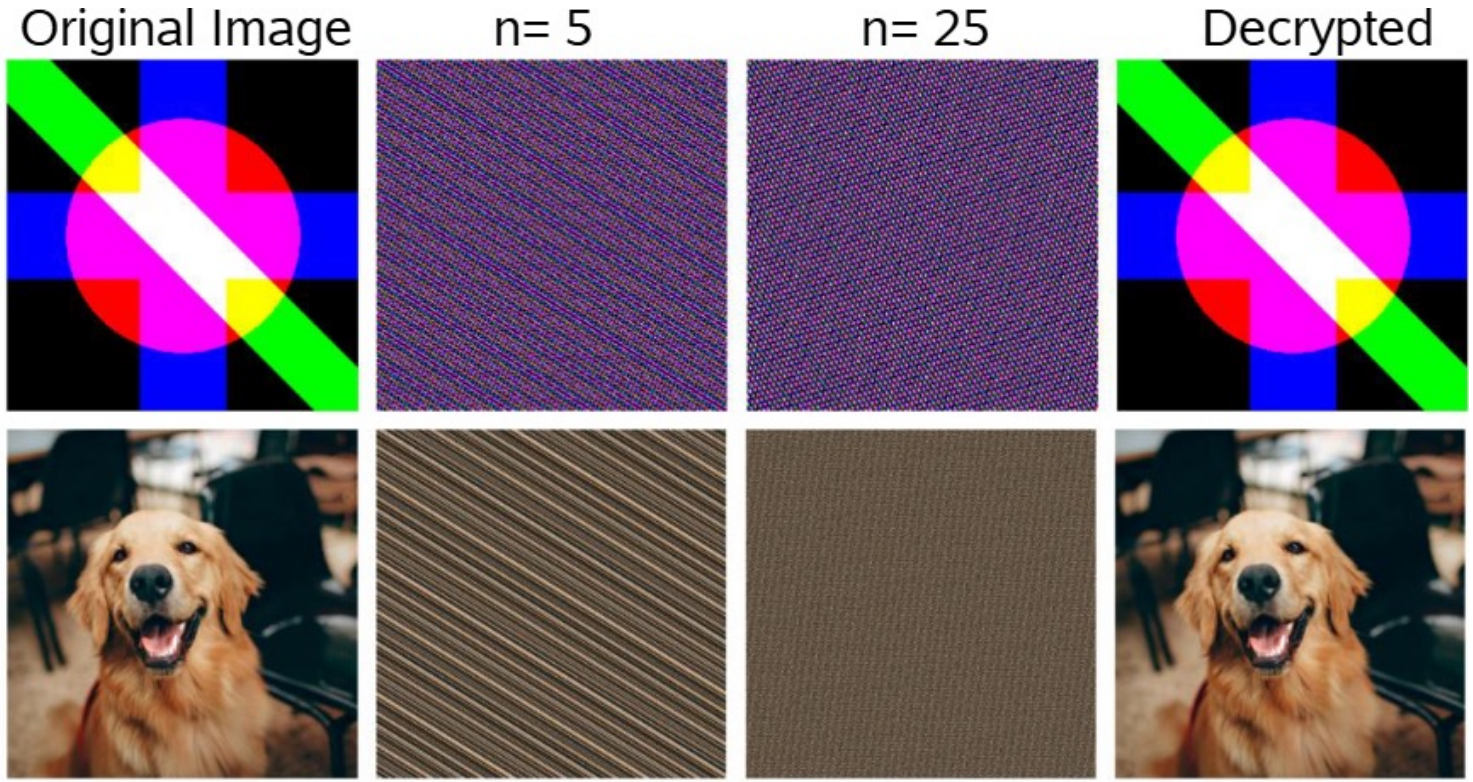
$$\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = A^{-n} \begin{bmatrix} x_n \\ y_n \end{bmatrix} \pmod{S} \qquad (2)$$

Methodology

Design Choice 2: ACM Weight Permutation



Example: Image Encryption



Methodology

Design Choice 2: ACM Weight Permutation

TABLE 7. ENCRYPTION/DECRYPTION RUNTIMES.

Method	Time (seconds) on ViT-B	Time on ViT-L	Device
AES-CBC	2.30	9.02	CPU
AES-CTR	1.34	5.17	CPU
AES-GCM	1.45	5.18	CPU
TEA	19.63	69.51	CPU
XOR Cipher	3.72	13.47	CPU
Our Method w. CPU	**1.19**	**2.58**	CPU
XOR Cipher w. GPU	**0.043**	0.22	GPU
Our Method	**0.044**	**0.051**	GPU

Evaluations are carried out on 330MB ViT-B model and 1161MB ViT-L. Each experiment is carried out 5 times and the average is taken. For ACM, n is set to 3, and the encrypted layers are 6 for ViT-B and 7 for ViT-L, aligning our previous experiment.

Faster on both GPU and CPU

Including AES with AES-NI (hardware-accelerated) support

Methodology

Design Choice 3: Per-layer decryption/encryption

- **To reduce the attack window**
- Only one decrypted layer will exist in the memory at a time

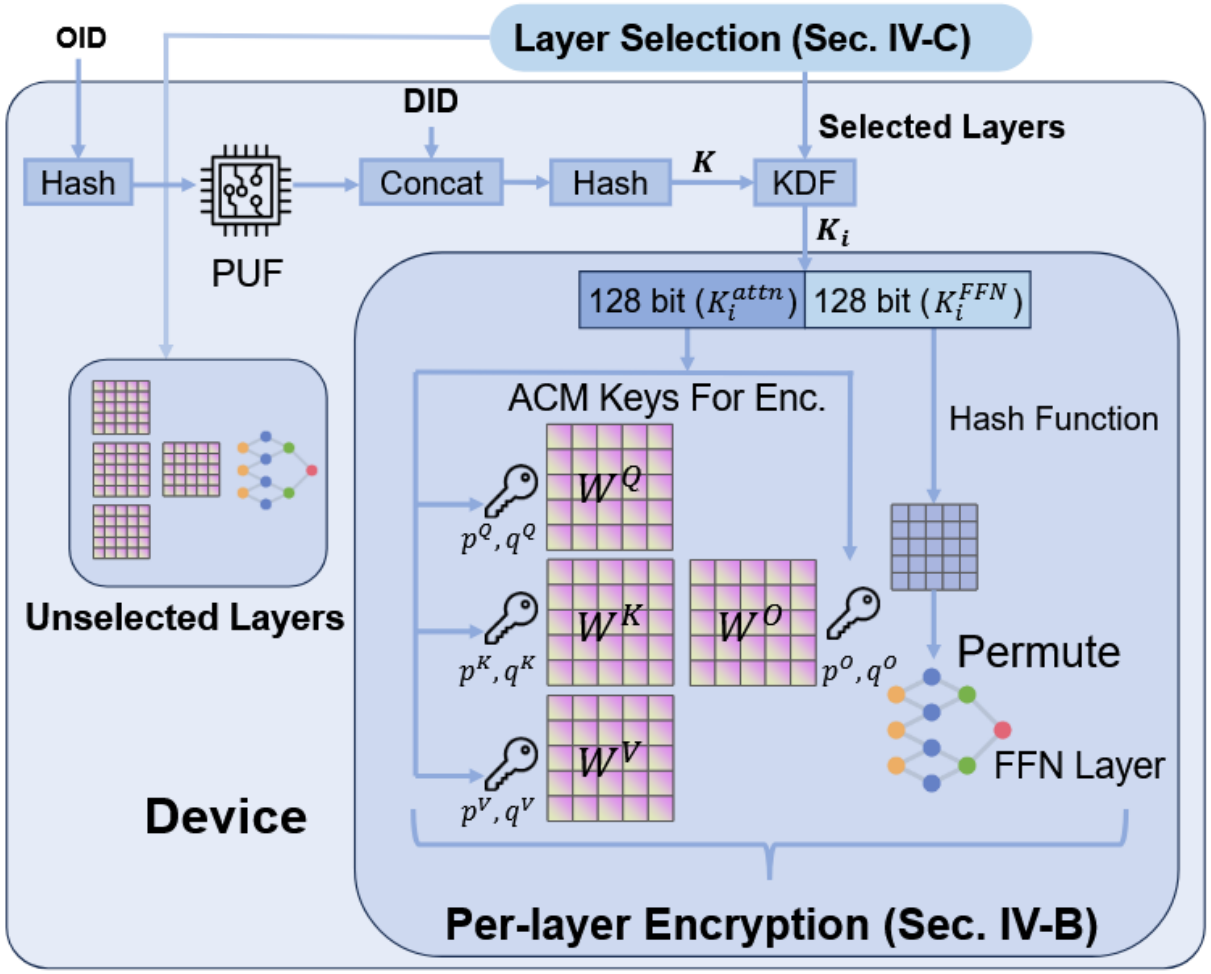
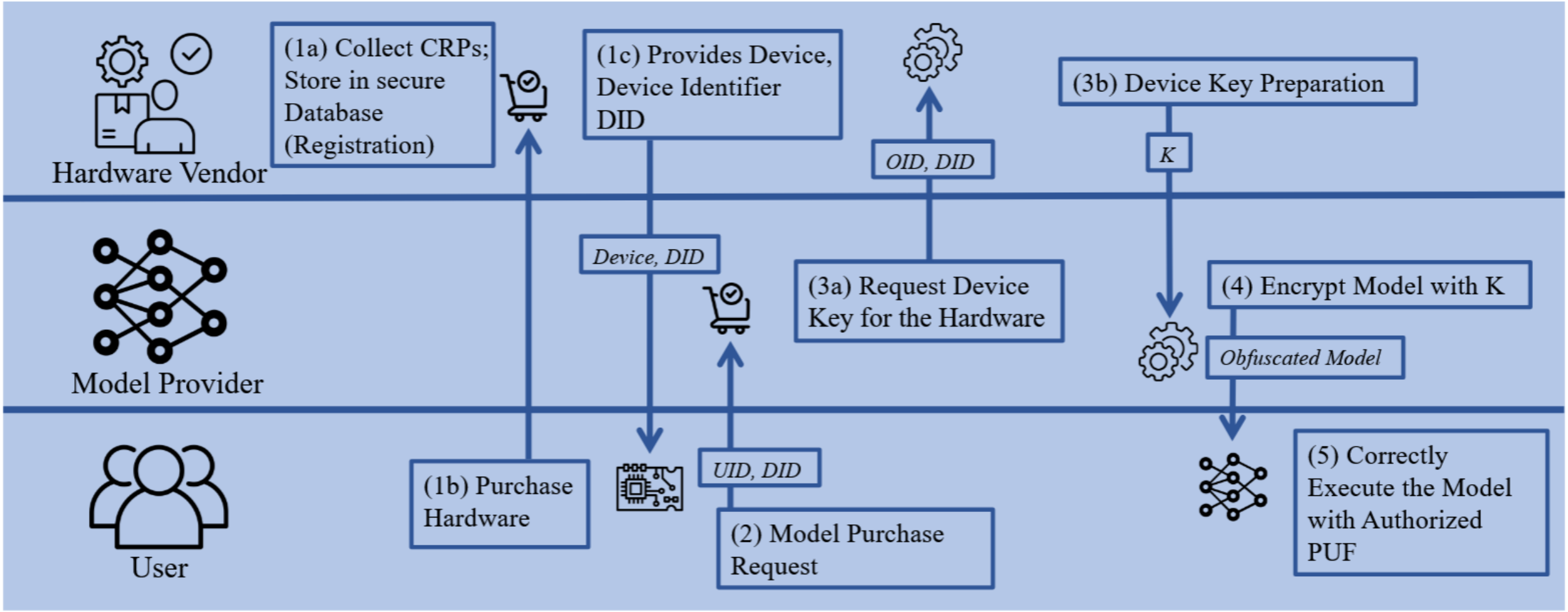


Figure 4. Our obfuscation scheme detailed in Sec. 4.

Methodology

Overall Flow (Proposed protocol)



Evaluation

Experiments

1. **Effectiveness:** one layer of encryption is enough to degrade the model into random guessing
2. **Fully Reversible:** important as an encryption

TABLE 2. MODELS, PARAMETER COUNTS, AND BASELINE VS. LOCKED ACCURACIES.

Model	ViT-B	ViT-B-384	ViT-L	ViT-L-384	Swin-B	Swin-B-384	BeiT-B	DeiT-B	ViT-B-8b	ViT-B-4b
Params(M)	86	86	307	307	88	88	86	86	86	86
$Acc_0(\%)$	80.33	83.91	81.98	84.96	85.14	86.44	84.54	80.20	80.24	80.20
$Acc_{dec}(\%)$	80.33	83.91	81.98	84.96	85.14	86.44	84.54	80.20	80.24	80.20
$Acc_1(i)(\%)$	0.08 (0, 10)	0.09 (0, 11)	0.1 (1)	0.1 (1)	0.10 (2-9, 2-8)*	0.10 (2-9, 3-1)	0.11 (2, 9)	0.11 (8, 0)	0.07 (6)	0.08 (7)
$Acc'(\%)$	0.10 | 6	0.09 | 6	0.10 | 7	0.07 | 7	0.10 | 6	0.08 | 6	0.14 | 6	0.10 | 6	0.11 | 5	0.10 | 5

Acc_0 is the original accuracy. Acc_{dec} is the accuracy after decryption with the correct key, demonstrating full performance restoration. $Acc_1(i)$ denotes accuracy after Algorithm 1 has encrypted the layers listed in parentheses. The notation x|y in Acc' indicates final accuracy $x\%$ when y layers are encrypted.
*We treat two blocks in Swin Transformer as one layer and use (x-y) to denote the "y-th" layer in the "x-th" stage.

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Evaluation

1. Re-training attacks: we assume the attackers could possess up to 20% of the original dataset

- **More data** could lead to higher attack accuracy
- **>15% performance gap (71% vs. 86%)** compared with the original model

TABLE 3. SAME-APPLICATION RETRAINING ATTACK RESULTS.

Epoch	ViT-B [10%]	ViT-B	ViT-B-384	Swin-B-224	Swin-B-384
1	13.5	32.4	31.0	67.5	66.9
3	41.7	53.9	56.5	71.4	70.5
5	47.1	56.4	59.3	71.4	70.8
10	47.2	56.4	59.3	71.4	70.8
20	47.9	\	\	\	\

ViT-B[10%] is retrained with 10% of the original dataset. Others are retrained with up to 20% of the original dataset.

Evaluation

2. Transfer Learning Attacks

- **Up to 20%** ImageNet + **full** downstream datasets
- **Still non-trivial performance gap (81% vs. 91% for CIFAR-100)**

TABLE 4. DOMAIN-TRANSFER RETRAINING ATTACK RESULTS ON VIT-B.

Downstream	Original	ViT-B[0%]	ViT-B[10%]	ViT-B[20%]
CIFAR-10	97.25	76.62	94.01	94.20
CIFAR-100	91.71	46.93	77.93	81.10
Caltech 101	98.16	58.35	91.42	94.47

ViT-B is fine-tuned on CIFAR-10, CIFAR-100, and Caltech 101 with varying amounts of the original dataset. ViT-B[0%] uses no original data.

Evaluation

3. No hint for correct decryption

- When more than one layer is encrypted, **decrypting one layer does not bring noticeable accuracy boost**

TABLE 6. MODEL ACCURACY CHANGE AFTER ANY LAYER IS TOTALLY DECRYPTED.

Layer	ViT-B	DeiT-B	BeiT-B
1	+0.01% (0)	+0.04% (8)	-0.04% (9)
2	+0.01% (2)	+0.01% (2)	-0.04% (0)
3	0% (10)	+0.01% (0)	+0.03% (5)
4	0% (4)	+0.01% (3)	+0.01% (4)
5	0% (11)	+0.01% (7)	0% (2)
6	0% (5)	0% (1)	0% (6)

For example, +0.01%(0) means the model accuracy increased 0.01% after decrypting the 0^{th} layer of the ViT-B model.

Evaluation

4. Even knowing which layers are encrypted does not lead to better attacks

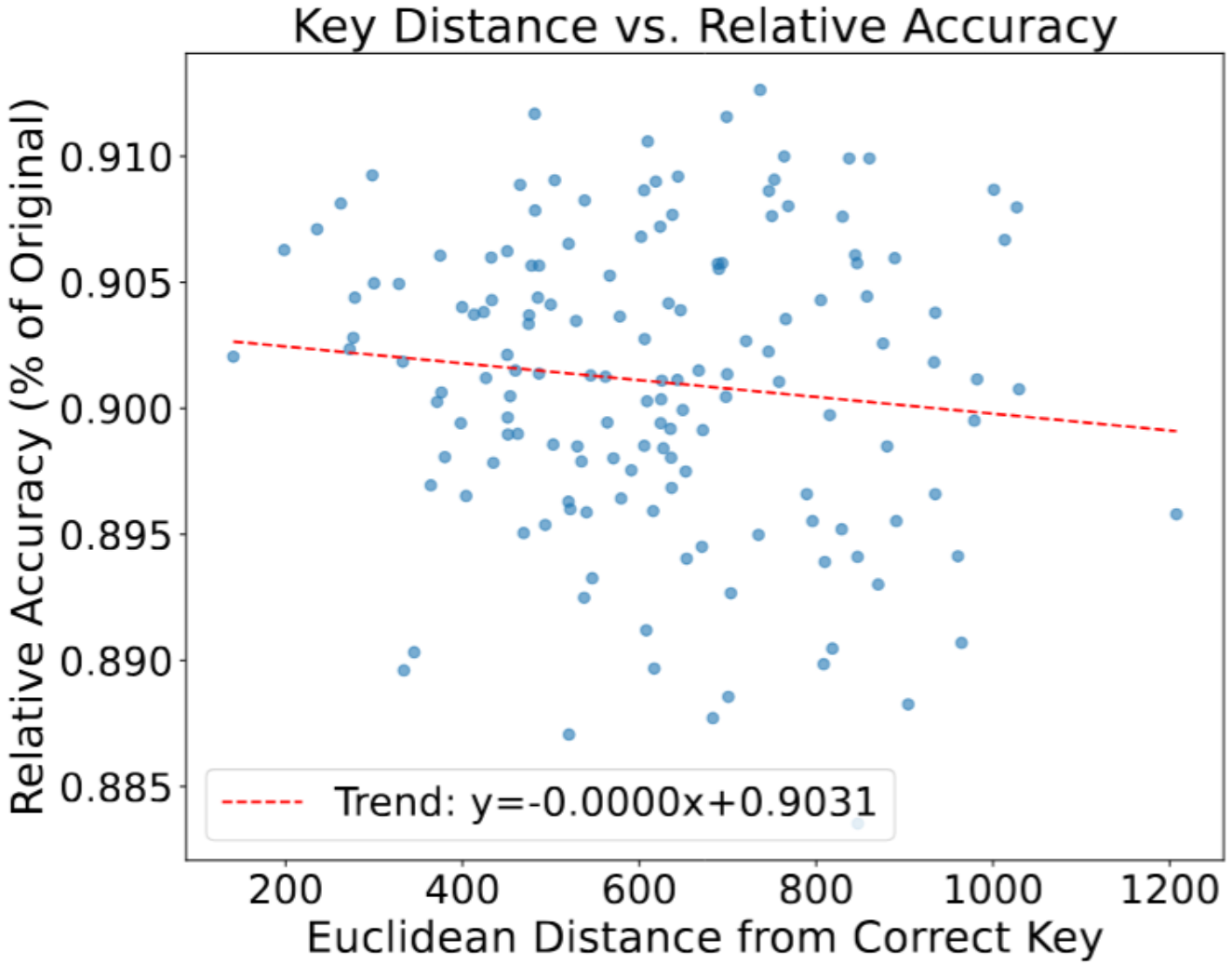
- Training **only on encrypted weights** do **not** give higher accuracy

TABLE 5. FINE-TUNING ONLY ENCRYPTED LAYERS WITH A SUBSET OF THE ORIGINAL DATASET.

Epoch	ViT-B [20%]	ViT-B [10%]
1	7.7	4.7
3	17.3	11.0
5	23.7	14.9
10	31.2	17.9
20	31.2	17.9

Evaluation

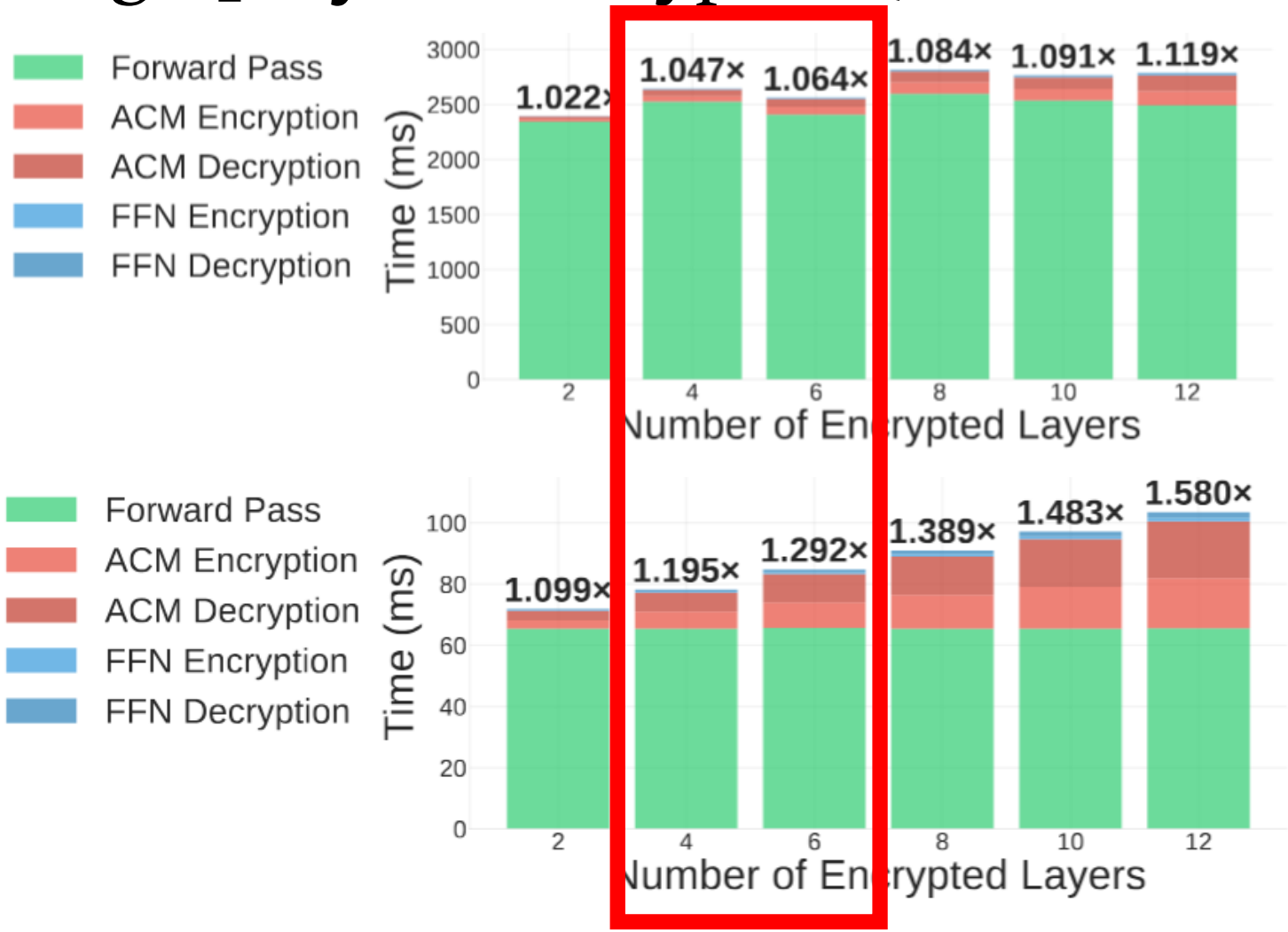
5. **Key guessing attack is hard**, as the accuracy drop is **not correlated** with the Euclidean distance from the correct key (avalanche effect)



Evaluation

6. Moderate or low overhead on both CPU and GPU

Default config: **4** layers encrypted (robustness evaluation)



Evaluation

7. Encrypting more layers enhance robustness

- After a certain number, the robust encrypting more layers saturates.

Num. of Extra Security Layers	Best Top-1 Acc. after Retraining (%)
0	69.7
1	68.1
2	58.4
3	54.5
4	56.4

Summary

- **Contribution compared with previous work:**
  - **Active Protection** vs. passive protection (Watermark, Fingerprint)
  - **Training-free** vs. retraining required (Watermark, Active Access Control)
  - **Less hardware dependency** vs. high-end hardware support (CPU&GPU TEE)
  - **Focus on Large Transformers** vs. small traditional neural networks
  - **Secure Weights Enc.** vs. linear cipher for efficient encryption (TransLinkGuard)

TABLE 8. COMPARISON OF PRIOR IP PROTECTION METHODS.

Work	Type	Mechanism	Retrain?	Target Models	Inference Overhead	Acc. Loss
Uchida et al. [59]	Passive	White-box Watermarks	Yes	ConvNet	None	✓
Adi et al. [60]	Passive	Backdoor Training	Yes	ConvNet	None	✓
Chen and Wu [61]	Active	Active Control Module	Yes	ConvNet	Low (Anti-piracy module)	✓
M-LOCK [62]	Active	Data Poisoning	Yes	ConvNet	None	✓
DeepIPR [63]	Active	Passport-based Verification	Yes	ConvNet	Low (Around 10%)	✓
NNLock [64]	Active	Weight Encryption	No	ConvNet	Moderate (1.5-2x)	×
Phantom [65]	Active	Architecture Obfuscation with TEE	Yes$^{\sharp}$	ConvNet	Moderate (3.5x$^{\natural}$)	×$^{\natural}$
ChaoW [25]	Active	Weight Encryption	No	ConvNet, RNN	Moderate	×
TransLinkGuard [13]	Active	Weight Permutation	No	Transformers	High (TEE†)	×
Ours	**Active**	Weight Encryption	**No**	**Transformers**	Low ($\approx 0.2x^{\ddagger}$)	×

Summary

- **Active IP Protection:** hardware-bound framework that **proactively** prevents unauthorized execution of **on-device Transformer** models.
- **Security Primitives:** Our solution combines Physical Unclonable Functions (PUF) for device binding with reversible Arnold's Cat Map (ACM) for weight obfuscation.
- **Robust Defense:** The method renders stolen models useless (random accuracy) and resists retraining, key-guessing, and leakage attacks.
- **Efficient Deployment:** This approach requires no model retraining and incurs minimal runtime overhead, making it practical for edge devices.

Limitation and Future Work

1. **Speed**
   - Possible speedup: NVIDIA TensorRT
2. **Other Applications:** CNNs, LLMs, Diffusion Models…
3. **Protect Model Architecture:** Compatibility with model architectural obfuscation (Li et al., 2021)
4. **Granularity:** protect in a more fine-grained way (e.g. distinguishing Attention and FFN weights)
   - Less weights encrypted, less overhead

Li, Jingtao, et al. "Neurobfuscator: A full-stack obfuscation tool to mitigate neural architecture stealing." *2021 IEEE International Symposium on Hardware Oriented Security and Trust (HOST)*. IEEE, 2021.

Thank You Very Much for Listening!

For any additional questions:

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Securing On-device Transformer with Hardware Binding and Reversible Obfuscation

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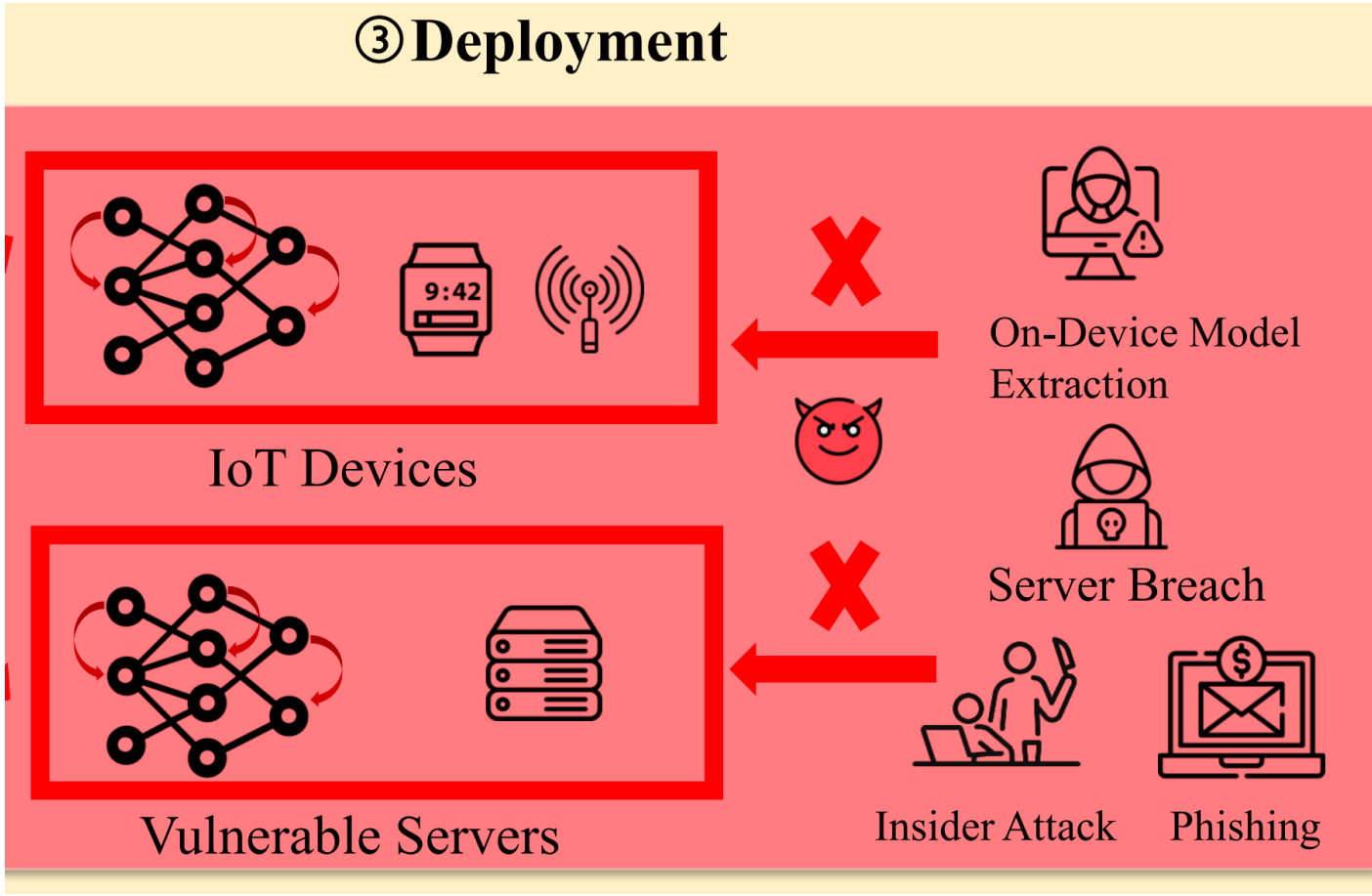
Practical Scenario

1. ⭐ **Reverse engineering of edge software:** from an app/firmware image
2. **Insider Attack**: Model weights cannot be copied and transferred
3. **Supply-chain and distribution compromise:** update server, CDN, or customer distribution channel is breached
4. **Phishing**: Model Exfiltration



Details on Encryption

- **ACM typically works on squares**
  - Most transformers have square attention weights
  - For FFN weights we use linear transformation for better efficiency

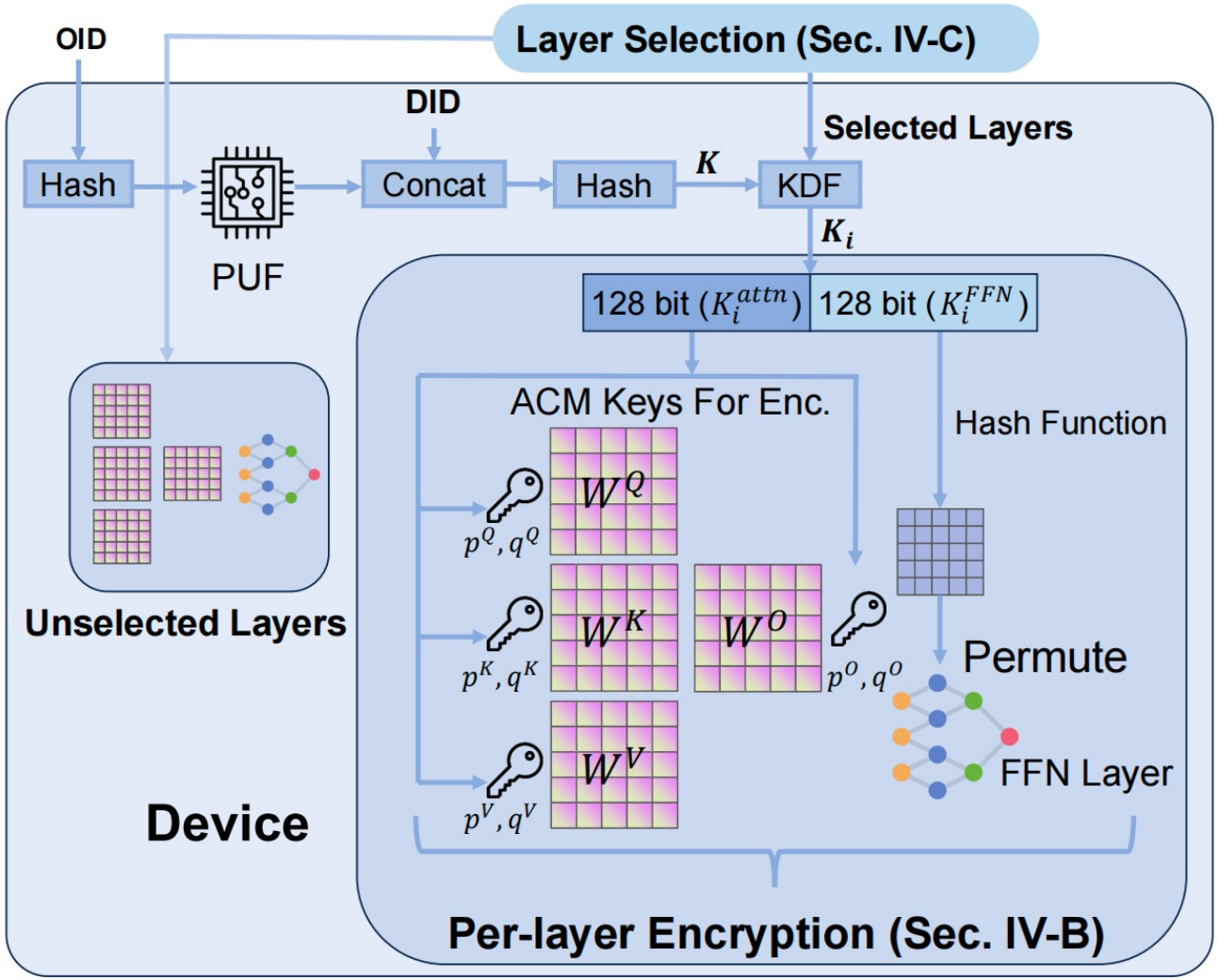


Figure 4. Our obfuscation scheme detailed in Sec. 4.

Details on Encryption

- **Known problem (after we finish this work):** linear transformation preserves the *relative* directions of the weight vectors
- Fine-tuning in transformers typically does not alter this fact much (Low-rank adaptation)
- Easy to guess and reverse-engineer the FFN weights -> impair security

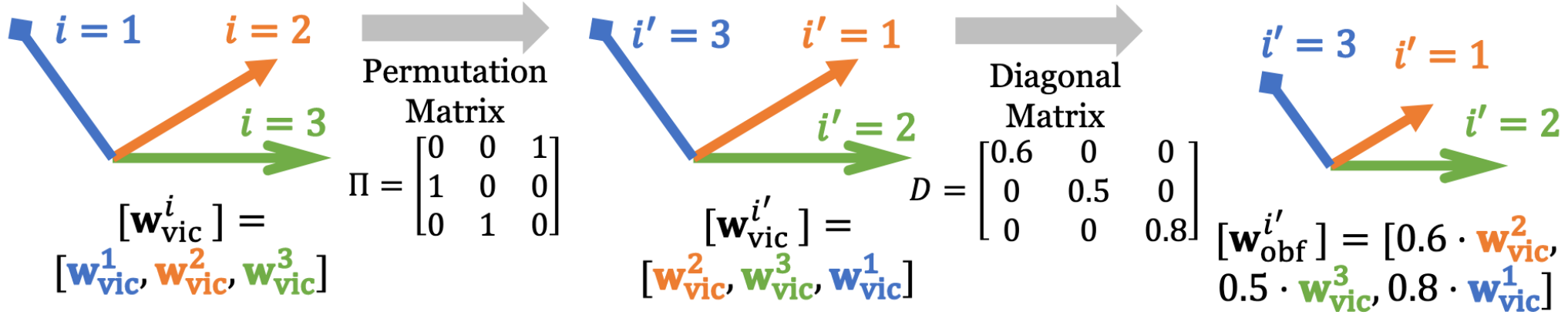


Figure: Wang, Pengli, et al. "Game of Arrows: On the ({In-) Security} of Weight Obfuscation for {On-Device}{TEE-Shielded}{LLM} Partition Algorithms." *USENIX Security 2025*

Details on Encryption

- **Alternative Strategy:**
- **GroupCover (ICML 2024):** Applies **matrix–vector** (or small matrix–matrix) multiplication within each group of weight vectors (slightly slower)
- **ArrowCloak (USENIX Security 2024):** Intentionally perturb the direction
- **O2Splitter (ACNS 2025):** Add Gaussian Noise with Differential Privacy (DP) guarantee (seeded with a secret key).

GroupCover [82]	ICML'24	$g(W_{\text{vic}}) = [A_1 W^{(1)}, \cdots, A_k W^{(k)}] \cdot \Pi,$ $g^{-1}(Y_{\text{obf}}) = ([A_1^{-1} Y_{\text{obf}}^{(1)}, \cdots, A_k^{-1} Y_{\text{obf}}^{(k)}]) \cdot \Pi^{-1}$
ARROWCLOAK	-	$g(W_{\text{vic}}) = (W_{\text{vic}} \cdot D_1 + \mathbf{v} \cdot \mathbf{1}_n \cdot D_2) \cdot \Pi$ $g^{-1}(Y_{\text{obf}}) = Y_{\text{obf}} \cdot \Pi^{-1} \cdot D_1^{-1} - X \cdot \mathbf{v} \cdot \mathbf{1}_n \cdot D_2 \cdot D_1^{-1}.$

Zhang, Zheng, et al. "Groupcover: a secure, efficient and scalable inference framework for on-device model protection based on tees." *ICML 2024*
Sun, Yulian, et al. "Obfuscation for Deep Neural Networks Against Model Extraction: Attack Taxonomy and Defense Optimization." *ACNS 2025*

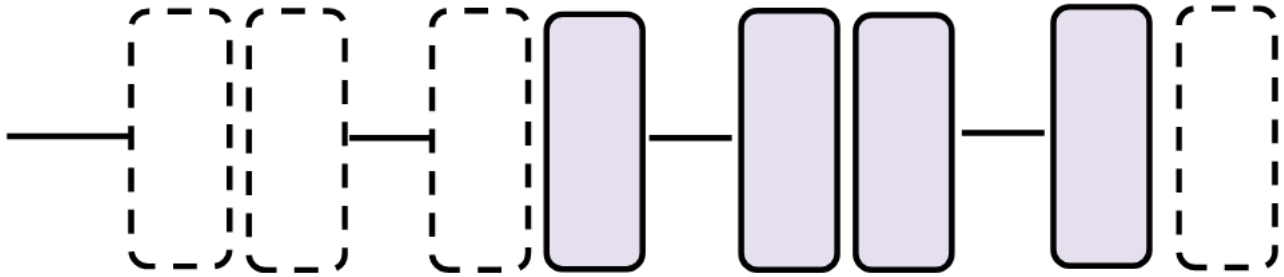
Details on Encryption

- **Which layers to encrypt?** 🤔
- Short answer: does not matter for robustness when the number >= 2
- Previous search: protect earlier layers (concept formation and feature extraction) first
- In our scheme: a simple greedy search for higher accuracy degradation or even random selection would bring similar good results.
- **Left as future work:** less weights (better efficiency) and good robustness
- E.g. An extreme: Corelocker locks 5% weights at neuron-level
- Caveats: Broken later by identifying these weights and fine-tune only on them

Wang, Zihan, et al. “Corelocker: Neuron-level usage control.” *IEEE Security and Privacy (SP)* 2024
Sun, Yulian, et al. "Obfuscation for Deep Neural Networks Against Model Extraction: Attack Taxonomy and Defense Optimization." *ACNS 2025*

Theoretical Outlook

- **Okay. The results look fine. But why does it work by encrypting a subset of the weights?**
- Findings: though when encrypting >=2 layers, which 2 (or more) does not matter very much, when encrypting the first layer, earlier layers tend to be more effective in locking the accuracy
- **Why?** Transformers have residual connections
  - Some layers hardly change the representation of the input in later layers
  - Enables layer pruning in transformers!



Prune a whole layer without affecting outputs

Qiao, Kangyu, et al. "IG-Pruning: Input-Guided Block Pruning for Large Language Models." EMNLP 2025.

Theoretical Outlook

- **Okay. The results look fine. But why does it work by encrypting a subset of the weights?**
- Findings: though when encrypting >=2 layers, which 2 (or more) does not matter very much, when encrypting the first layer, earlier layers tend to be more effective in locking the accuracy
- **Why?** Transformers have residual connections
  - Some layers hardly change the representation of the input in later layers
  - Enables layer pruning in transformers!
- **Hand-wavy**: when multiple layers are encrypted with independent random keys, their **perturbations propagate and compound** toward a predictable “noise distribution”
  - >=2 layers would be too much that the representation shifts off the region later layers recognize, and they effectively see OOD inputs.