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SOTER: Guarding Black-box Inference for General Neural Networks at the Edge

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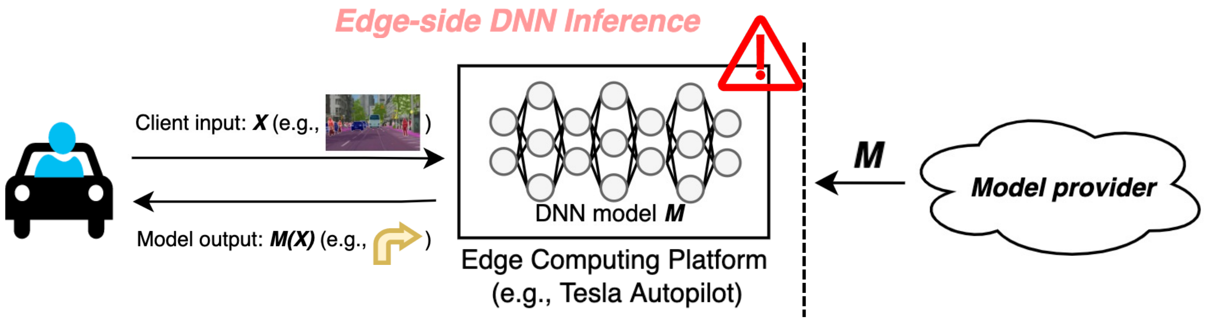
Background: Edge-side DNN Inference

- **Giant companies (e.g., Google) provide well-trained Deep Learning (DL) models to clients**
  - DL models, especially **Deep Neural Networks** (DNN), serve numerous mission-critical AI applications

Autonomous Driving	Home Monitoring	Virtual Assistance	Speech Recognition	…
TESLA	Sentry	Cortana	Google Cloud Speech API	…

  - Giant companies pay **substantial effort** to train **accurate** models, which are **private**

- **To provide high-quality (low-latency) services, DNN models are usually deployed on edge-side user devices**
  - Clients (i.e., users) run *edge-side DNN inference* to get real-time results



  - However, sensitive model parameters are exposed, and inference can be easily interfered at the untrusted edge!

- **In sum, edge-side inference requires low latency, high accuracy with confidentiality and integrity protection**

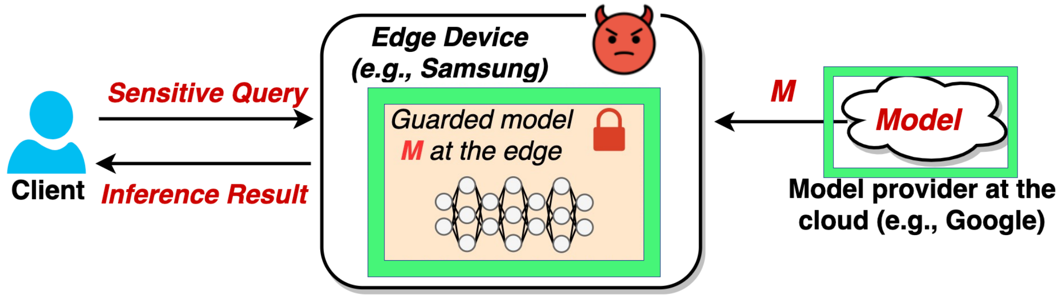
Background: Trusted CPU TEE & Untrusted GPU

- **Trusted Execution Environment (TEE) is promising to protect model confidentiality**
  - TEEs (e.g., Intel SGX, ARM TrustZone) provides **data confidentiality** and **code integrity** guarantees
  - TEEs are widely used to protect edge services
    - E.g., Samsung uses TrustZone to store *payment information;* Trustonic uses TEE to build IoT apps *with trusted-UI*
  - TEE-based inference systems are emerging (more details in page 4-5)

- **Edge-side TEEs are trusted, but edge-side GPUs are untrusted**
  - **CPU TEE does not support GPU, model providers cannot trust third-party GPUs**
    - Current **Trusted GPU**s either require extensive hardware modifications or support only hardware simulators
  - GPU is essential: Numerous edge devices have been integrated with GPU to accelerate edge intelligence
    - E.g., Apple's A15 chip equips *4-core GPU*; Samsung's new mobile processor Exynos2200 includes *AMD GPU*

Requirements for Edge-side DNN Inference

➢ **Deployment scenario**



➢ **An *ideal* edge-side inference system should meet the following requirements:**

Performance

- ***Low latency:*** utilize co-located GPU accelerator to speed up model inference
- ***High accuracy***: retain the same accuracy as the original model

Security

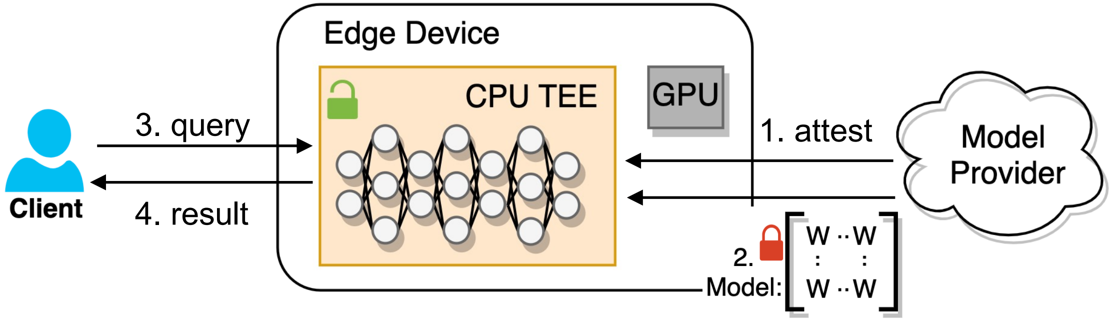
- ***Model confidentiality***: model parameters' plaintexts should be hidden
- ***Inference integrity:*** any attacks (e.g., malicious modifications) on inference results should be detected

Prior work: TEE-shielding Approach

- **Existing TEE-based inference systems include <u>*TEE-shielding*</u> *approach* and <u>*partition-based*</u> *approach***

- ***TEE-shielding* approach (e.g., MLCapsule [CVPR '21])**

  - ***How it works***



1. **Attest** to the TEE-equipped edge device
2. **Offload** and **decrypt** the encrypted model in an attested TEE enclave
3. **Take** client **input** to run inference purely inside the CPU TEE
4. **Return** the **inference** result back to the client

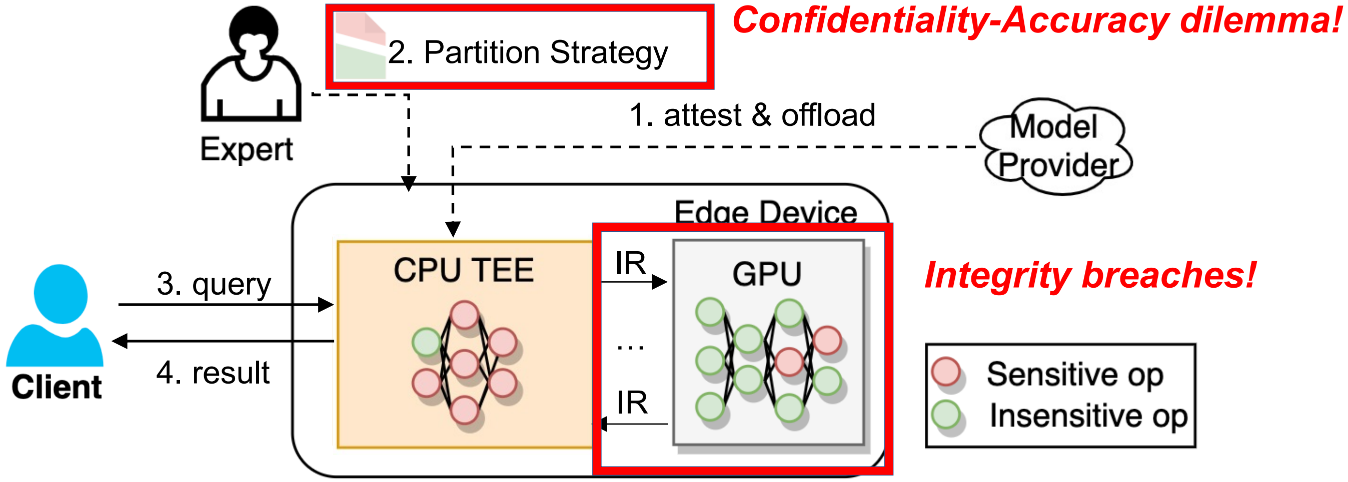
  - ***Advantages:*** Protect model confidentiality and inference integrity; Retain high accuracy

  - ***Limitations:*** No GPU acceleration with extremely high inference latency (up to 36.1*X*) than insecure GPU inference

Prior work: Partition-based Approach

➢ **Partition-based approach (e.g., AegisDNN [RTSS '21], eNNclave [AISec '20])**

- ***How it works***



Sensitive segments **-> trusted-but-slow** CPU TEE

Insensitive segments (with ***plaintext*** or ***retrained* parameters**) -> untrusted-but-fast GPU

- ***Advantages:*** Low latency with GPU acceleration
- ***Limitations***: Incur either confidentiality loss or accuracy loss; Integrity breaches on partitioned model

Goals of Our Solution: SOTER

➢ **SOTER is a partition-based inference system that achieves all desired properties for edge-side DNN inference**

- **Accelerate** heavy-weight computation with GPU and **retain high accuracy** as the original model
- **Protect model confidentiality** by hiding all parameters' plaintexts
- **Detect integrity breaches** (e.g., malicious modifications) on inference results

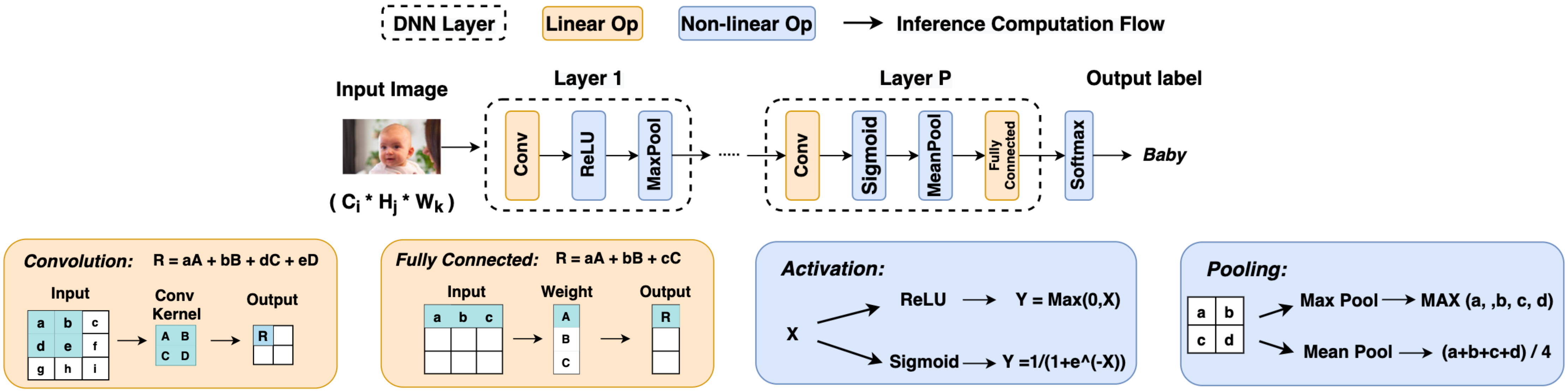
	GPU Acceleration	**No Accuracy Loss**	**Model Confidentiality**	**Inference Integrity**
MLCapsule	😐	😀	😀	😀
eNNclave	😀	😐	😀	😐
AegisDNN	😀	😀	😐	😐
SOTER	😀	😀	😀	😀

➢ **To achieve these goals, SOTER asks two questions:**

- ***Q1:*** *How can we utilize untrusted GPU for acceleration without sacrificing confidentiality or accuracy?*
- ***Q2:*** *How to efficiently detect integrity breaches outside the TEE?*

Recap DNN Model Architecture

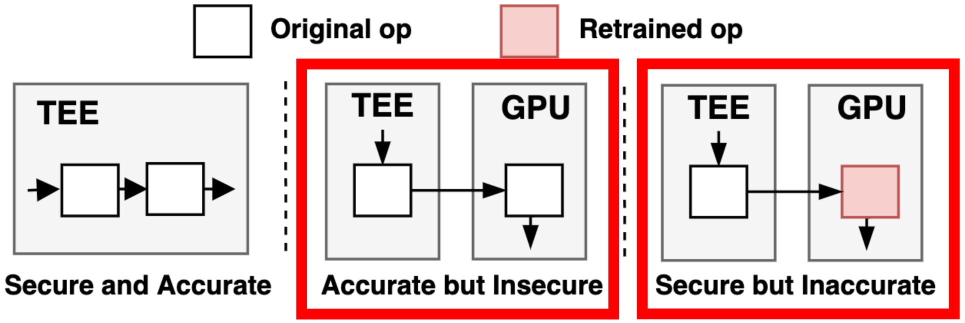
- **Recap DNN model architecture**



- **Associativity of common DNN operators:** (μ^-1 * μ) F(X) = μ^-1 F(μ X)
  - All linear operators (e.g., Conv, FC) satisfy associativity property and they represent a major fraction of model computation
  - Some non-linear operators (e.g., ReLU) are *scale-invariant* and satisfy this property under specific constraints
    - *E.g., ReLU: F*(*x*) = *Max*{0, *X*} is *scale-invariant* when ***μ*** **> 0**, i.e., $\boxed{F(\mu x) = Max\{0, \mu X\} = \mu F(X)}$

Bridging the Confidentiality-Accuracy Gap (Q1)

- **Confidentiality-accuracy dilemma**

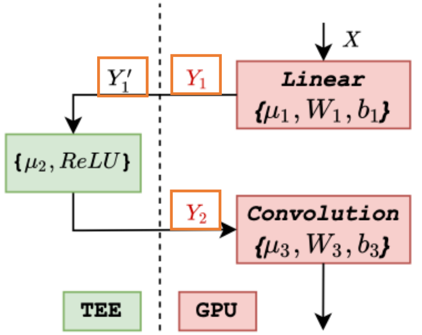


- **SOTER's key weapon: the general associativity property of common inference operators**

sensitive! (μ^-1 * μ) F(X) = μ^-1 F(μ X) insensitive -> GPU

sensitive -> TEE

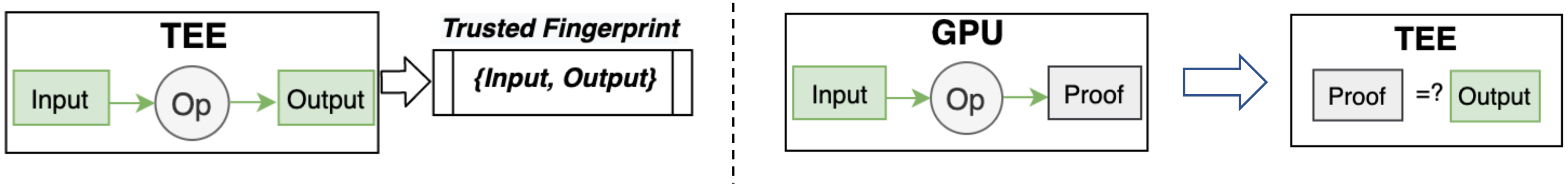
- **Major workflow**
  - **Step 1:** Automatically profile an encrypted model in TEE
  - **Step 2:** Morph a portion of associative operators' parameters with *hidden scalars*
  - **Step 3:** Partition morphed operators to run on GPU
  - **Step 4:** Execute operators in order, transmit IRs between kernels, restore execution results with hidden scalars in TEE



$$Y_1 = \mu_1(W_1 * X + b_1)$$
$$Y_1' = Y_1 * \mu^{-1} = W_1 * X + b_1$$
$$Y_2 = \mu_2 * ReLU(Y_1')$$
$$= 0 \Leftarrow if\ Y_1' \le 0$$
$$= \mu_2 * (W_1 * X + b_1) \Leftarrow if\ Y_1' > 0$$

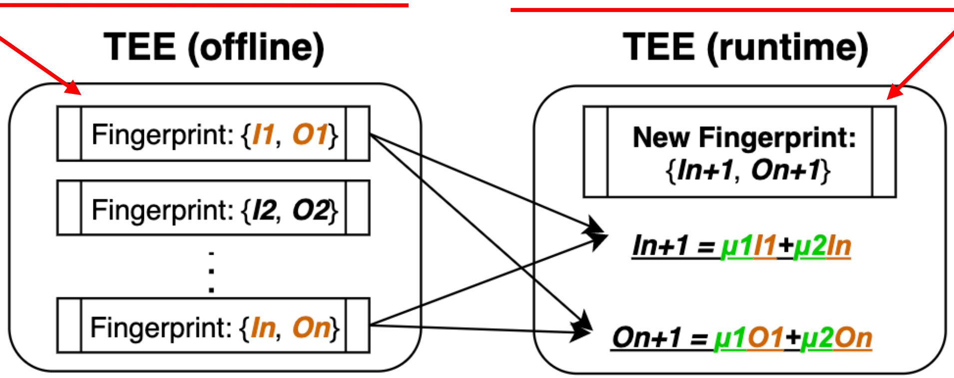
Detecting Integrity Breaches (Q2)

- **Partition-based system *inevitably* open access to integrity breaches outside the TEE**
- **Detect integrity breaches: a straw man *Trusted Fingerprint* (TF) re-computing approach**



- **Key challenge: Obliviousness-timeliness dilemma**
  - If we use fixed TF, the adversary can easily observe and bypass the TF detection
  - If generate new TF as regular user input in CPU TEE, TFs become oblivious to observe, but TF generation (in CPU TEE) becomes the performance bottleneck, leading to slow detection
- **SOTER solves the challenge using the same associativity observation from confidentiality protection**
  - Associativity variant: If F(X1) = Y1; F(X2)=Y2; …; F(Xn)=Yn, then F(μ1X1+ μ2X2+…+ μnXn)= μ1Y1+ μ2Y2+…+ μnYn

Step 1:
Prepare ***cornerstone TFs*** in the preprocessing phase



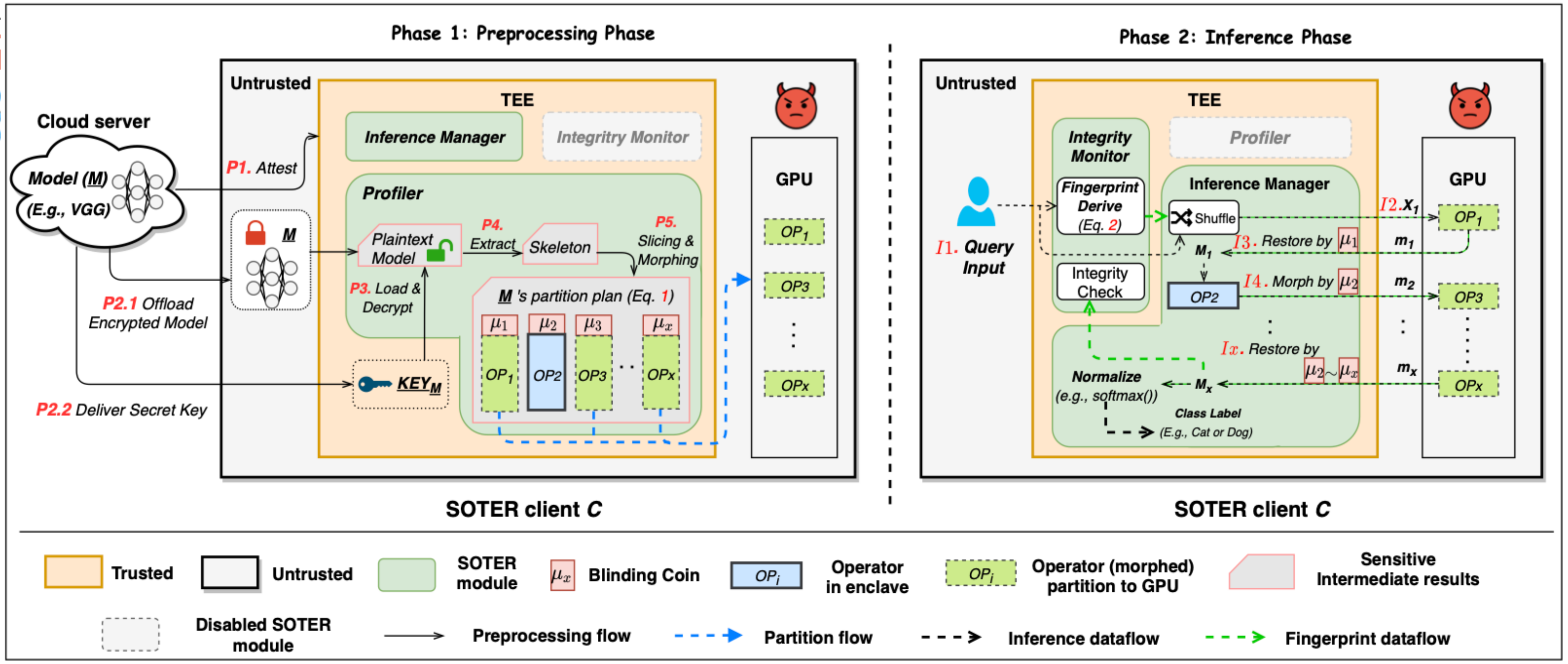
Step 2:
Generate new ***scalars*** and use the ***associativity variant*** to efficiently produce new TFs

SOTER: In a Nutshell

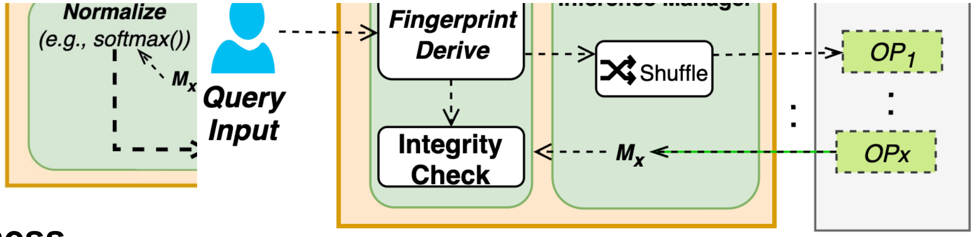
- By using **the same associativity weapon**, **three key modules** run in two phases to collectively provide low latency, high accuracy, model confidentiality, and integrity protection

SOTER Profiler

SOTER architecture



- The ***Profiler*** and ***Inference Manager*** module speeds up model inference with untrusted GPU while protecting parameters' plaintexts
  - Automatically profile and formulate partition plans
  - **Hide partitioned operators' parameters with secret blinding coins**



- The ***Integrity Monitor*** module check partitioned GPU operators' execution results to detect any integrity breaches
  - Top-W operator reserving
  - **Efficiently generate new trusted fingerprints at runtime for obliviousness**

Implementation and Evaluation

- **Implementation Details**
  - Implemented on PyTorch and Graphene-SGX, extensible to any imperative Deep Learning frameworks and TEE codebase
  - Adopted a **two-phase design** for offline preprocessing and online inference
  - Designed a **Morph-Then-Restore protocol** for cooperative executions between kernels (TEE & GPU)
  - Designed a **periodical upgrading mechanism** to prevent chosen plaintext attacks
  - Designed an **on-demand operator prefetching mechanism** to reduce TEE memory footprints

- **Baseline secure inference systems**
  - MLCapsule [CVPR ’21]
  - AegisDNN [RTSS ’21]
  - eNNclave [AISec ’20]

  (The above blue optimization is also incorporated in the three baselines)

- **Evaluation settings in our dedicated cluster**
  - Dell R430 server with 2.60GHZ Intel E3-1280 V6 CPU, 64GB memory, and SGX hardware support
  - A GPU farm with Nvidia 2080Ti GPUs, each GPU had 11GB physical memory
  - Evaluated on VGG19, Alexnet, Resnet152, Densenet121, Multi Layer Perception, and Transformer

Evaluation Questions

- **How is SOTER's end-to-end performance compared to baselines?**
- **How is SOTER's confidentiality protection compared to baselines?**
- **Are SOTER's trusted fingerprint oblivious to the adversary outside the TEE?**
- **How sensitive is SOTER's performance to different partition ratio?**

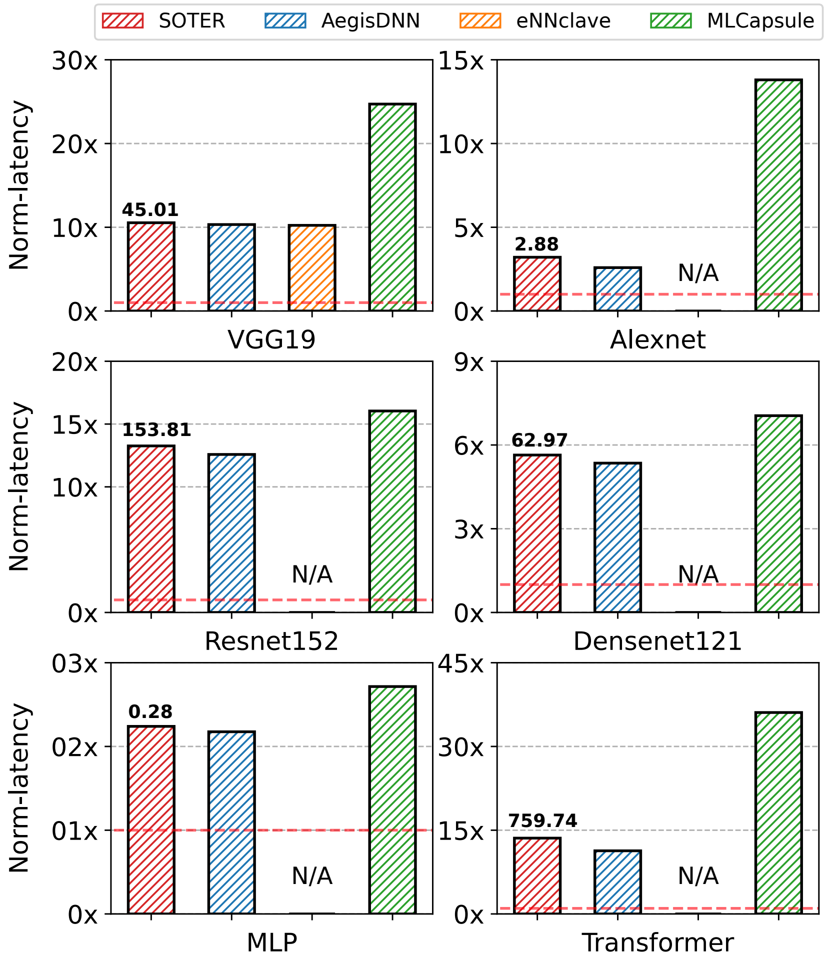
End-to-end performance

➢ **Figure 1 shows the inference latency (normalized to insecure GPU inference, red dotted line) compared to three baselines (SOTA TEE-shielding and partition-based approach) running six prevalent DNN models**

- SOTER achieved **1.21*X* ~ 4.29*X* lower inference latency** than TEE-shielding MLCapsule
- SOTER enforced **integrity protection**, with only 1.03*X* ~ 1.27*X* higher inference latency than partition-based AegisDNN

SOTER's inference results (in milliseconds)						
Model	**MLP**	**AN**	**VGG**	**RN**	**DN**	**TF**
P1: CPU (TEE)	0.19	1.65	25.38	92.18	41.65	439.52
P2: GPU	0.05	0.71	14.24	33.97	13.71	204.93
P3: Kernel Switch	0.01	0.18	0.83	25.98	5.6	41.52
P4: Integrity Check	0.03	0.34	4.56	14.75	6.02	73.77
End-to-end (P1+P2+P3+P4)	0.28	2.88	45.01	153.88	62.97	759.74

Figure 1



Security Evaluation

➢ (**Confidentiality**) Even if SOTER completely hides partitioned operators' plaintexts, an adversary may still conduct ***model stealing attacks*** to train a ***substitute model (SM)***

(A **higher** accuracy/BLEU of SM means **more** confidentiality loss)

- SOTER achieved **stronger confidentiality** protection than AegisDNN
- SOTER achieved **the same strong confidentiality** protection as eNNclave while eNNclave sacrifices inference accuracy

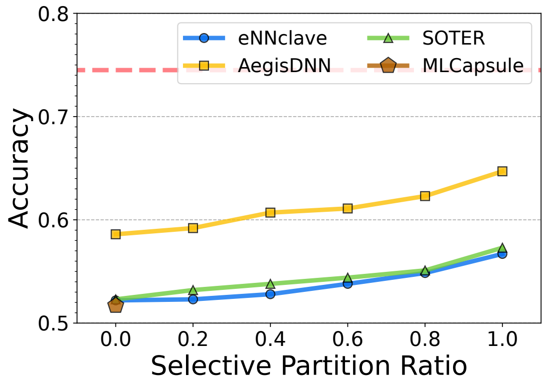


Figure 2.a (on VGG19)

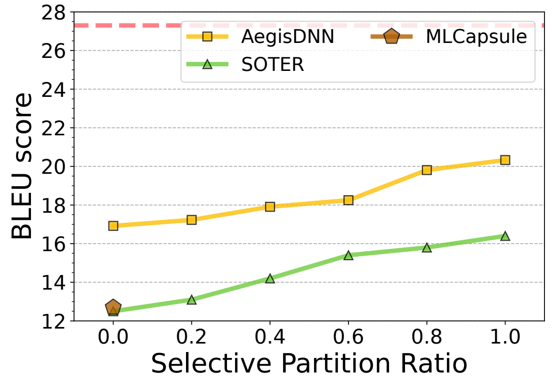


Figure 2.b (on Transformer)

➢ (**Integrity**) Compare SOTER's oblivious trusted fingerprint (Figure 3.a) with the straw man fixed trusted fingerprint approach (Figure 3.b)

- SOTER's fingerprints are **oblivious** to the adversary because the L2 distance distribution of fingerprints shares the same form of normal distribution as client's normal query input

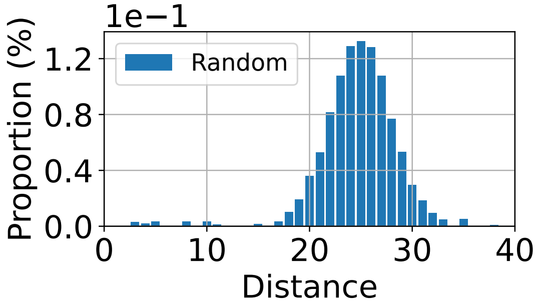


Figure 3.a (w oblivious TF)

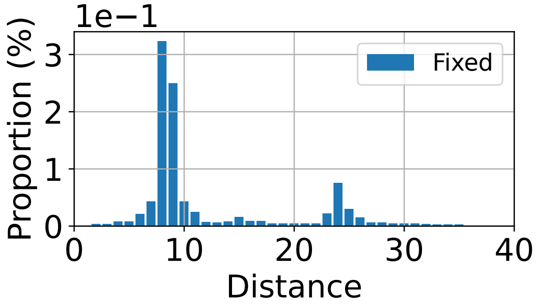


Figure 3.b (w/o oblivious TF)

Conclusion

- In this paper, we present SOTER, the first work that achieves **model confidentiality**, **low-latency** and **high-accuracy** with **integrity protection** for **general** neural network inference
  - Comparable **strong confidentiality** as TEE-shielding approach; Comparable **low latency** as partition-based approach; **High accuracy** same as insecure GPU inference; Overwhelming high probability of obliviously **detecting integrity breaches**
- These features encourage giant companies to develop powerful models and deploy them on third-party edge devices
- SOTER can also help with protecting models on untrusted cloud servers
- SOTER's future work is broad:
  - SOTER can integrate with emerging black-box defenses to further strengthen privacy guarantees
  - SOTER can be extended to multiple GPUs and TEEs for distributed model inference
- SOTER's artifact is available at https://github.com/hku-systems/SOTER

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