**Privado: Practical and Secure DNN Inference**

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**Abstract**

Recently, cloud providers have extended support for trusted hardware primitives such as Intel SGX. Simultaneously, the field of deep learning is seeing enormous innovation and increase in adoption. In this paper, we therefore ask the question: "Can third-party cloud services use SGX to provide practical, yet secure DNN Inference-as-a-service?" Our work addresses the three main challenges that SGX-based DNN inferencing faces, namely, security, ease-of-use, and performance.

We first demonstrate that side-channel based attacks on DNN models are indeed possible. We show that, by observing access patterns, we can recover inputs to the DNN model. This motivates the need for Privado, a system we have designed for secure inference-as-a-service. Privado is input-oblivious: it transforms any deep learning framework written in C/C++ to be free of input-dependent access patterns. Privado is fully-automated and has a low TCB: with zero developer effort, given an ONNX description, it generates compact C code for the model which can run within SGX-enclaves. Privado has low performance overhead: we have used Privado with Torch, and have shown its overhead to be 20.77% on average on 10 contemporary networks.

**1 Introduction**

In recent years, deep neural networks (DNNs) have revolutionized machine-learning tasks such as image classification, speech recognition and language translation [1][2][3]. Today, the idea of applying DNNs to applications such as medical health prediction and financial modeling holds tremendous promise. Consider a medical health enterprise, Acme Corp., that has developed a state-of-the-art DNN-based model for identifying diseases from radiological images. Acme Corp. does not own its own cloud infrastructure, but wants to monetize this model by making it available to hospitals worldwide using a third-party cloud provider. Acme wants to keep the model parameters (i.e., weights and biases) private since it is precious intellectual property. On the other hand, hospitals want to keep their radiology data private given their privacy-sensitive nature. However, both Acme and its customers would still want to benefit from the cost-efficiencies of the cloud, and the functions it enables. Thus, a privacy-preserving deep learning inference service is critical for addressing such scenarios.

To protect code and data from compromised cloud software, cloud providers are extending support for trusted hardware primitives such as Intel SGX [4][5]. SGX supports hardware-isolated execution environments called enclaves that keep user-code and data private even from cloud administrators. Nevertheless, we are still far from realizing an end-to-end DNN inference service using SGX enclaves due to the following three challenges:

**Security.** Prior work has shown that enclave memory is susceptible to leakage via data access patterns [6][7][8][9]. However, it is not obvious that DNN model inference, that mostly uses matrix multiplications, is susceptible to such attacks. In Section 3 we motivate the need for data-oblivious DNN implementations within enclaves by demonstrating a first-of-its-kind attack, where an adversary can guess the input value simply based on the observable access patterns at specific layers of a model. Thus, we require the inference service to be resistant to such attacks.

**Ease-of-use.** Developing custom applications for enclaves is cumbersome. This is mainly because SGX does not provide system-call support, dynamic threading, etc. Thus, the inference code has to be carefully partitioned into inside-enclave and outside-enclave code. Moreover, programming tools and debuggers that run within SGX are very rudimentary. The alternative is to run entire applications that have been written for an insecure setting, unmodified, on entire operating systems and sandboxes that run within the enclave. Unfortunately, this results in a large trusted code-base [10][11] which compromises security of the application. Ideally, the service should re-
quire \textit{no custom programming} and yet, it should have a \textit{low trusted code-base (TCB)}.

\textbf{Performance.} Finally, the solution can be practical only if the performance overheads are “acceptably” low.

Unfortunately, previous research on secure DNN inference using SGX does not solve these challenges entirely. Prior work has either concentrated on customized algorithms and code that can fix access-based attacks at the cost of ease-of-use \cite{12}, or on solutions that are easy to use but do not protect against access-based attacks and have a high TCB \cite{13}. To make matters worse, these approaches have not been extensively evaluated on contemporary DNN models to ensure that performance overheads are indeed uniformly low. To this end, we present 	extsc{Privado}, a privacy-preserving DNN inference service that simultaneously provides obliviousness, low TCB, ease-of-use, and low performance overhead. To our knowledge, 	extsc{Privado} is the first system that targets and solves all these challenges.

We first address the security challenge. The key observation behind 	extsc{Privado}’s approach to data-obliviousness is that deep learning models predominantly have data-independent accesses, and very few data-dependent accesses (Section 4). Moreover, deep learning models exhibit very specific and regular data access patterns, and a simple yet efficient solution based on the CMOV instruction is sufficient to make the model parameters resistant to access-based attacks.\footnote{Similar to the threat model in previous work \cite{13,14,15}, we do not provide side-channel resistance to model structure such as the depth, neurons in each layer, etc.} 	extsc{Privado} uses a component we call the 	extsc{Privado-Converter} to automatically detect all such data-dependent access patterns in a given deep learning framework. It modifies them to become data-independent using CMOV. Our implementation of 	extsc{Privado} uses the Torch framework \cite{16}, however, our observations are independent of the framework and are applicable to deep learning algorithms in general.

To address the ease-of-use challenge, 	extsc{Privado} uses the 	extsc{Privado-Generator} which takes as input models represented in the popular ONNX format \cite{17}, and automatically generates a minimal set of enclave-specific code and encrypted parameters for the model. There is no custom programming required. The server simply loads the auto-generated code for the model within an enclave where the model parameters are decrypted.

To reduce the TCB size, the 	extsc{Privado-generator} only includes files required for building the model instead of the entire DL framework (which has around 100,000 lines of code). Small TCB is amenable to analysis by various tools \cite{18,19}, ensuring that there are no exploits or inadvertent data leaks. This approach, we find, reduces the TCB size by 33.69%.

Finally, we address the performance challenge. We evaluated 	extsc{Privado} on 10 models used in real-world deep learning cloud services. Our evaluation shows that 	extsc{Privado} has 20.77% overhead on average for inference of Cifar10 and Imagenet images (Section 6).

In this paper, we make the following contributions.

- \textbf{Attack.} We demonstrate a concrete attack that can identify the class of encrypted inputs to the neural network models based on the access patterns observable in the intermediate layers (Section 3).
- \textbf{End-to-end Design.} Starting with an ONNX model, we show how our system can auto-generate data-oblivious code that can run seamlessly on SGX in the cloud with zero development effort for the cloud customer (Section 5).
- \textbf{Privado System.} We present 	extsc{Privado}, which incorporates the above-mentioned constructs into the Torch framework. 	extsc{Privado} converts Torch to replace data-dependent branches and it auto-generates minimal amount of Torch code from the ONNX model specification, thereby ensuring that the TCB size is small. Our evaluation in Section 6 shows that \textsc{Privado} incurs an average overhead of 20.77%.

2 Problem

In this section, we first outline the problem that \textsc{Privado} solves. We then describe our threat model. Finally, we outline the properties that \textsc{Privado} achieves.

2.1 Secure Inference-as-a-service

Neural network algorithms operate in two phases — training and inference. The training step uses a labeled dataset to generate \textit{model parameters} i.e., weights and biases such that the error between the true input class and the predicted class is minimum. Once a network is trained, the inference phase uses the model parameters to accurately predict the output class for any given input. We assume that the training happens a priori in a trusted environment while the inference is offered as a cloud service to benefit other users or for monetary gains. To ensure privacy guarantees, such a cloud-based inference service should a) protect the model parameters from the server and the users and b) protect the users’ inputs from the server.

Figure 1 shows the entities involved in such an inference service: the \textit{cloud provider}, the \textit{model owner}, and multiple \textit{model users}. The cloud provider supports trusted hardware primitives such as Intel SGX. SGX-enabled CPUs create isolated execution environments called \textit{enclaves} in which all data are encrypted. SGX-enabled CPUs also remotely attest the code executing within the enclaves to ensure its integrity \cite{20}.
Figure 1: A secure inference-as-a-service setting. The model owner uploads the model binary and the encrypted parameters to an SGX-enabled cloud provider. The model users send the encrypted inputs for inference and receive encrypted outputs.

The model owner first uploads the model binary and attests the code executing inside the enclave. After a successful attestation, the model owner establishes a secure channel with the enclave and sends the encrypted model parameters to the enclave. These parameters are decrypted only inside the trusted processor package.

After the trusted inference enclave is set up, a model user remotely attests the enclave and establishes a secure channel to it. It then sends encrypted input data on this channel. The cloud provider runs the model owner’s binary on the model users’ input, and sends back an encrypted output, or class, to the model user. Throughout the process, the untrusted cloud software learns nothing about the model parameters (property of the model owner) or the input/predicted output (property of the model user). Further, the model owner learns nothing about the model users input/output and the model user learns nothing about the model parameters.

2.2 Threat Model

The cloud provider is untrusted since an adversary can exploit bugs in the cloud software stack and get privileged access to the entire system. Although SGX prevents direct access to the enclave memory region, an adversary can learn significant information about the sensitive data via side-channels, specifically the access patterns. For example, the adversary can monitor the system call interface to learn the enclave’s access patterns to the storage disks and trace network packets. In addition, the adversary can perform page-faults and cache-channel attacks to learn the execution flow within the enclaves. A strong adversary can also snoop over the address bus to learn the memory access patterns of the enclave.

Scope and assumptions. We focus on hiding access patterns in neural network models because, as we show in the attack we describe in Section 3, they can leak information about user inputs. We do not protect against leakage via timing channels. Similar to previous work, we allow the server to learn the hyper-parameters of the model such as the number of layers and the number of neurons in each layer; these do not leak information about the sensitive inputs. However, defending against adversarial attacks based on model-inversion, membership inference or detecting adversarial samples is outside the scope of this work.

Further, we assume that the cloud provider always responds to the model users, and does not perform denial-of-service attacks on the model users. This is a rational assumption because denying service harms the reputation of the cloud provider and hinders monetization of the model. Last, we assume that all the SGX guarantees are preserved i.e., there is no hardware backdoor present in the processor package and the SGX keys are not compromised.

2.3 PRIVADO Properties

PRIVADO satisfies the following properties that we feel are necessary to create a practical, secure inference service.

- **Input-Obliviousness**: PRIVADO ensures oblivious access patterns during execution of the inference phase as it eliminates all input-dependent branch statements present in the deep learning framework.
- **Low-TCB**: In PRIVADO, the trusted code base for any model includes the smallest possible subset of the entire deep learning framework.
- **Zero Developer Effort**: With PRIVADO, users need not write custom SGX-specific code. Any machine learning scientist can use PRIVADO out of the box.
- **Expressiveness**: PRIVADO supports inference on state-of-the-art neural network models that contain complex combinations of linear and non-linear layers with parameters that range up to tens of millions.
- **Backward Compatibility**: Since it accepts ONNX as input, PRIVADO supports inference for models that have been trained in the past using any of the existing deep learning frameworks (e.g., Caffe2, Tensorflow, PyTorch, CNTK) and saved in the ONNX format.
- **Performance**: Lastly, PRIVADO has low performance overhead across all the different models that we have evaluated, executed on different input datasets.
3 Side-channel based Attack

In this section, we describe an attack using which an adversary can indeed learn significant information about encrypted input data by merely observing access patterns at a single layer in a DNN.

To illustrate the attack, we use a 4-layered fully-connected neural network model and the MNIST dataset \[24\]. MNIST is a collection of 32×32-pixel black and white images of handwritten digits (0-9). We show that, by performing model inference and observing its access patterns, an adversary can distinguish between different input digits.

**DNN Architecture.** The number of neurons in each of the 4 layers are 1024, 500, 50, and 10 respectively. The first layer contains 1024 neurons to capture the 32×32 pixels of the input images and the last layer has 10 neurons representing 0-9 classes. We have trained the NN to achieve 99% accuracy. Each hidden layer is fully-connected followed by a rectified linear activation function (ReLU) layer. ReLU is a commonly used activation function to train accurate models. Therefore, the output of each layer is:

\[ y_i = \text{ReLU}(W_iX_i - 1 + b_i) \]  

where \( i \) is the current layer and \( W, b \) and \( X \) are the weights, biases and the input values respectively.

**Leakage-prone Layer.** The ReLU function in equation (1) is represented as \( \max(0, x) \) which is implemented as the code below.

```python
1
2
if (input < 0) then:
    input = 0;
```

The function simply activates the neurons with values greater than zero and deactivates others. Consequently, the memory access pattern differs for every input based on whether the branch is executed or not. Thus, by simply observing access patterns, the adversary can learn which neurons get activated for any given input.

**Setup.** For the attack, we assume the adversary can observe the access patterns for any number of inputs to the model. For simplicity, we demonstrate the attack for input images of digit 1 and 4, but it is applicable to all the 10 digits. For each digit, the adversary provides approximately 1000 input queries to the model.

**Attack Results.** Figure 2 shows activated neurons in the third layer of our NN, for the two digits, as observed by the adversary. The x-axis represents the 50 neurons in the third layer and the y-axis represents the percentage of 1000 images that activated the neuron, for each digit.

Key to this attack is the observation that one digit activates a specific combination of neurons more than the other. For example, the digit 4 activates neurons 6, 7 and 24 (indicated with arrows over the solid line) about 10% more than digit 1 does. Similarly, digit 1 activates neurons 25, 34, 40 and 44 (indicated with arrows over the dotted line) significantly more than digit 4. We found similar differences to hold across other sets of input images as well.

Consequently, when an honest model user sends the cloud an encrypted image, the adversary, by observing access patterns, can correlate the results with the above observed patterns and thereby estimate the input with a probability that is significantly better than random. Therefore, this attack shows that the adversary can distinguish between encrypted inputs and even predict the class of an input image by observing their access patterns.

4 Sources of Leakage in DNNs

Leakage via access patterns is an important concern when using SGX for designing privacy-preserving systems. Recently, researchers have proposed Oblivious RAM based solutions for SGX to eliminate leakage for arbitrary read-write patterns \[25, 26\]. However, these solutions incur significant performance overhead, making them impractical for a DNN inference service \[27, 28\].

By customizing our solution to the specifics of how memory is accessed in DNN algorithms, we believe the overhead of making DNN inference data-oblivious can be significantly reduced. We make two key observations. First, the vast majority of computations in DNNs involve linear layers (fully connected or convolution layers) that exhibit only deterministic accesses, i.e., the memory access patterns do not vary based on the input. Second, cer-
tain types of DNN layers, such as ReLU or max-pool, exhibit input-dependent accesses, i.e., their memory access patterns can vary depending on the input (as we show in Section 3). However, even in layers that exhibit input-dependent accesses, the accesses are of a very specific type: either a given memory location is accessed, or no memory locations are accessed. We call these assign-or-nothing patterns.

We discuss these observations in detail for layers that are commonly used in popular neural networks and later confirm them empirically in our evaluation.

4.1 Linear & Batch Normalization Layers

In neural networks, such as multilayer perceptrons (MLPs) and convolutional networks (CNNs) the dominant part of the computation can be represented as a matrix-multiplication between the weights and the inputs to each layer. In fact, over 90% of computation in many modern networks are attributed to the convolution operation \( \mathbf{w} \cdot \mathbf{x} \). Similarly, recurrent networks (RNNs, LSTMs) are also dominated by matrix multiplications. Matrix multiplication involves performing the same operation, irrespective of input values. This makes their access patterns input-independent.

Batch Normalization is another popular layer used in modern DNNs. Batch normalization, at inference time, simply adjusts the input value by the expected mean and variance of the population (computed during training). Thus, batch normalization does not perform any input dependent access.

4.2 Activation Layers

Activation layers are important in neural networks for capturing the non-linear relationship between the input and the output values. Several activation functions are used in these networks to improve the accuracy of the models. Sigmoid and tanh are the most basic activation functions which are computed as \( \frac{1}{1+e^{-x}} \) and \( \frac{2}{1+e^{-2x}} - 1 \) respectively. As seen from the formulas, neither function incurs any input-dependent access patterns. While RNNs still use tanh activations, the standard choice in recent MLPs and CNNs have been the ReLU activation.

ReLU defined as \( \max(0,x) \) uses an input-dependent conditional branch as we described in Section 3 and hence leaks information from its access patterns. Other variants of ReLU such as Leaky ReLU, Parameterized ReLU, Randomized ReLU and Exponential linear activations exhibit a similar access pattern.

Observe that there is no else condition. If the condition is true, the assignment statement executes, else, there is no assignment. This branch exhibits the assign-or-nothing pattern. Further, observe that the condition is sequentially executed for all the inputs (or indices). There is no branching based on array indices, and therefore no access patterns that are dependent on array indices.

4.3 Pooling Layers

It is common to use pooling layers after convolution layers to reduce the output size at each layer. Two popular variants of pooling layer are max-pool and mean-pool. Typically, a filter of size \( 2\times2 \) with a stride of 2 is applied to the input of this layer. The pooling function replaces each of the \( 2\times2 \) region in the input either with a mean or max of those values, thus reducing the output size by 75%.

As the mean-pool function simply computes an average of the values from the previous layer, it exhibits a deterministic access pattern irrespective of the actual input to the model. However, the max-pool variant selects the maximum value in this \( 2\times2 \) window and sets it as the output. Listing 1 shows the code that implements a max-pool operation. The input-dependent branch statement writes to the sensitive input location only if the condition is true. Again, there is no else condition. The loop terminating conditions are public values (2\( \times \)2) that do not leak information about the input. Hence, similar to the ReLU function, the max-pool operation exhibits an assign-or-nothing pattern.

4.4 Softmax Layer

Most of the networks conclude with a softmax layer that calculates the probability for each of the output classes. The softmax layer performs a deterministic computation of calculating a value corresponding to each output class. The class that has the highest value is then returned as the predicted class. Although the softmax layer is oblivious in itself, computing the maximum value among all the classes requires an input-dependent branch condition to find the max value, similar to the max-pool function. For this, a sequential comparison is performed over all the output values to find the class with the maximum probability. Again, this falls into the category of assign-or-nothing patterns.

4.5 Summary

The above analysis of all the common layers used in neural network algorithms shows that all the input-dependent access patterns can be categorized into assign-
Figure 3: This figure describes how the model owner generates the encrypted model and parameters using the PRIVADO-Converter and the PRIVADO-Generator.

or-nothing pattern. Moreover, the dominant computation cost (90+%) is matrix-multiplications that are input independent. Thus, a custom data-oblivious solution for DNNs that addresses only the input dependent access pattern is likely to have low overheads.

5 PRIVADO Design

In this section, we present an overview and the design details of PRIVADO. PRIVADO consists of PRIVADO-Generator and PRIVADO-Converter that are trusted.

5.1 Overview

The model owner generates an inference model for the PRIVADO system using two steps (Figure 3). In Step 1, the model owner uses PRIVADO-Converter to transform the deep learning framework to be input-oblivious. In our prototype, we have designed PRIVADO-Converter to transform the popular Torch library. This is a one-time process for any given framework. PRIVADO-Converter identifies all the assign-or-nothing patterns in the DNN framework and replaces them with the input-oblivious CMOV instruction. We discuss our CMOV based solution in detail in Section 5.2.

In Step 2, the model owner uses PRIVADO-Generator to generate the model binary. PRIVADO-Generator takes as input the ONNX representation of the model, the input-oblivious DNN framework that Step 1 generated, required SGX libraries, and an encryption key. It outputs an enclave-executable model binary and the encrypted model parameters. ONNX is an open neural network exchange format that is supported by several existing deep learning frameworks (e.g., Caffe2, Tensorflow, CNTK and others). The design details of PRIVADO-Generator are mentioned in Section 5.3. Finally, the model owner uploads the model binary to the cloud provider to host it as an inference service, as discussed in Section 2.1.

5.2 PRIVADO-Converter

In this section, we outline how PRIVADO-Converter identifies input-dependent conditions and makes them oblivious.

Identifying Input-dependent Branches. DNN frameworks consist of libraries that the model uses to construct the final model binary. PRIVADO-Converter’s first step is to analyze all source-code of these libraries and identify all branches. To do this, it traverses the AST of each function in the library and reports all conditional statements such as if-else, input-dependent loop guards, and ternary operations. PRIVADO then performs an interprocedural data flow analysis to identify all the input-dependent variables. Finally, it then collects all the variables that are involved in each conditional statement and selects only the ones that are input-dependent.

Next, PRIVADO-Converter categorizes the input-dependent conditional statements into public and private input-dependent branches. Specifically, we whitelist all the branches that use purely public input, i.e., hyper-parameters such as network size, input size, etc. PRIVADO-Converter performs data-flow analysis to check if any of the branches use private input-dependent variables. It marks all such branches that can potentially leak user’s private data. Listing 1 shows one such branch in the Torch library implementation of the Max-pool layer, where the variables val and maxval used in the if-else condition on Line 4 are derived from the input. val and maxval are activation values of neurons that are provided as input to the pooling layer.

Our automated analysis provides us with a candidate list of private input-dependent branches, i.e., branches that may potentially leak inputs. We study a sampled set of the branches flagged by our analysis and observe that all of them adhere to the assign-or-nothing pattern. We do a best-effort source code analysis using a compiler pass to identify well-known branching constructs such as loops, if-else, and ternary operators. It is possible that our analysis may miss some branches (e.g., inline assembly code). In cases where we do not statically detect a branch in the library, our dynamic monitoring mechanism can flag such new branches whenever it observes that the execution traces of different inputs are deviating. To this end, we further empirically cross-check our branch analysis by comparing dynamic execution traces of the library for multiple inputs in our evaluation. Our results confirm that our analysis detects all the
branches involved in the network implementations that we test PRIVADO on (See Section 6.6). Thus, the static analysis combined with our dynamic monitoring ensures completeness of our branch analysis.

```
1 void THNN_SpatialDilatedMaxFooling_updateOutput_frame
2 {...} {
3  ...
4  if (val > maxval)
5    maxval = val;
6  ...
7  /* set output to local max */
8  *op = maxval;
```

Listing 1: Example of an input-dependent branch.

Using CMOV for Obliviousness. We use CMOV in a way similar to previous-work [34]. CMOV is an x86 instruction that accepts a condition, a source operand, and a destination operand. If the condition is satisfied, it moves the source operand to the destination. The important thing to note is that the CMOV instruction is oblivious when both the source and the destination operands are in registers: it does not cause any memory accesses, irrespective of the condition.

Let us consider the (simplified) branch code in Listing 2 that follows the assign-or-nothing pattern.

```
1 if (x < y)
2  x = y;
```

Listing 2: Branch patterns observed by PRIVADO.

PRIVADO-Converter automatically modifies all occurrences of such branches in the DNN library with equivalent code that uses CMOV with registers. Listing 3 shows how PRIVADO-Converter replaces the code shown in Listing 2 with a functionally equivalent oblivious code.

```
1// if (x < y) x = y;
2 mov eax, x
3 mov ebx, y
4 cmp eax, ebx
5 movl eax, ebx
6 mov x, eax
```

Listing 3: Oblivious Code using cmovl for the less than operator in PRIVADO.

First, the code copies sensitive values \( x \) and \( y \) into registers. Then, the CMOV instruction does a register-to-register copy based on the output of the comparison instruction. Note that the adversary cannot observe the registers in the secure CPU package. Therefore, using CMOV instruction makes memory access patterns deterministic and oblivious. This ensures that after our transformation, the library does not leak any information. PRIVADO-Converter employs different conditional move instructions (e.g., CMOV, CMOVZ, CMOVE, CMOVBE, FCMOVBE) based on the specific instances of the branch patterns as well as the data types of the variables. Listing 4 shows the use of CMOV instructions to replace the leaky branch in the max-pool example in Listing 1.

```
1 float temp;
2 asm volatile("fld %2 \n"
3       "fld %3 \n"
4       "fcomi \n"
5       "fcmove %st(1), %st \n"
6       "fstp %0 \n"
7       "fstp %1 \n"
8       "mov %0(%maxval), %m(%maxval)"
9       "mov %0(%maxval), %m(%maxval)"
)
```

Listing 4: Using conditional move instructions to hide input-dependent branch in Listing 1.

Automated Transformation.

PRIVADO-Converter uses the LLVM compiler to perform a source-to-source transformation. In this way, all transformations to use CMOV are performed in an automated manner.

Our analysis ensures that the transformed code preserves the intended functionalitly of the algorithm. Since the number of branches which are transformed is relatively small, we manually check that the transformed code is functionally equivalent to the original code. We also empirically verify this claim by ensuring that the accuracies of the models are preserved after PRIVADO-Converter’s transformation.

5.3 PRIVADO-Generator

The PRIVADO-Generator performs outputs an enclave-executable model and encrypted parameters from a given ONNX representation of a trained model. The ONNX format has both the model configuration details such as the layers, neurons and the actual weights and bias values stored in the same file.

Generating Enclave-specific Code. For a given model, PRIVADO-Generator generates two pieces of code: one runs inside the enclave, and the other runs outside. In addition, it generates an “.edl” file which defines specific ecalls (entry calls to the enclave) and ocalls (exit calls from the enclave). PRIVADO-Generator defines two key ecalls: initialize() initializes the parameters of the model, and infer(image) performs inference on encrypted images. It defines only one ocall, predict(), which returns the model’s (encrypted) predicted class. PRIVADO-Generator generates inside-enclave functions by parsing the ONNX model and converting the ONNX operators to corresponding Torch function calls. For example, some ONNX operators have an equivalent function in Torch (ReLU’s equivalent is THNN_FloatThreshold_updateOutput()) while other operations, like grouped convolution, require composing multiple Torch functions in a for-loop. The non-enclave code deals with creating and initializing the
enclave, waiting on a socket to receive encrypted images from a client, calling the ecall to perform inference, and returning the ocall-predicted class to the client.

Reducing TCB. PRIVADO-Generator reduces the TCB by trimming the Torch library to only the bare-minimum set of files required to compile a given model. Once it identifies all layers in the ONNX model, it includes and compiles only the necessary Torch files from the math and the NN libraries. This step excludes irrelevant library code and thereby reduces the trusted code-base.

Encrypting Parameters. The model weights and parameters are encrypted in AES-CTR mode using the encryption key. The model owner shares the encryption key over a secure channel to the enclave that executes the model binary.

6 Evaluation

In this section, we first provide a brief outline of the PRIVADO implementation. Next, we state our evaluation goals. Finally, we describe the results of our evaluation.

6.1 Implementation

Our PRIVADO prototype is built upon the Torch DNN framework. PRIVADO-Converter is implemented as an LLVM source-to-source transformation and has 1437 lines of C code while PRIVADO-Generator has 1700 lines of C++ code. PRIVADO-Generator uses the AES-CTR encryption from the sgx-crypto library for encryption. We use Intel SGX SDKv.2 for Linux and compile with GCCv5.4 with -02 optimization flag.

6.2 Evaluation Goals

Our evaluation answers the following questions:

- **Ease-of-use.** How easy is it to use PRIVADO to generate secure versions of multiple state-of-the-art models?
- **Performance.** How much overhead does PRIVADO add, compared to baseline (insecure) inference?
- **Lowering TCB.** By how much does PRIVADO reduce the trusted-code base?
- **Obliviousness.** Are the generated models oblivious?

6.3 Ease-of-use

In our experiments, we used PRIVADO-Generator on 10 state-of-the-art neural network models specified in ONNX. We select these models based on the differences in their depth (or the number of layers), parameter sizes, training dataset and accuracy. PRIVADO-Generator successfully transformed all these trained models from their given ONNX format to SGX-enabled code within just a few seconds. No custom-coding was required. We chose networks that achieve good accuracy on two popular dataset for images: Cifar-10 [35] and ImageNet [36]. LeNet uses the least number of parameters (62K), and AlexNet uses the highest number (61.1M). The number of layers in these models range from 12 (LeNet), all the way to 910 (DenseNet).

| Models  | No. of Layers | No. of Param. | Dataset  | Acc. (%) | Top 1/Top 5 |
|---------|---------------|---------------|----------|----------|-------------|
| LeNet   | 12            | 62 K          | Cifar-10 | 74.6     |             |
| VGG19   | 55            | 20.0 M        | Cifar-10 | 92.6     |             |
| Wideresnet | 93          | 36.5 M        | Cifar-10 | 95.8     |             |
| Resnet29 | 102          | 34.5 M        | Cifar-10 | 94.7     |             |
| Resnet110 | 552          | 1.70 M        | Cifar-10 | 93.5     |             |
| AlexNet | 19            | 61.1 M        | ImageNet | 80.3     |             |
| Squeezenet | 65          | 1.20 M        | ImageNet | 80.3     |             |
| Resnet50 | 176          | 25.6 M        | ImageNet | 93.6     |             |
| Inceptionv3 | 313          | 27.2 M        | ImageNet | 93.9     |             |
| DenseNet | 910           | 8.10 M        | ImageNet | 93.7     |             |

Table 1: Models evaluated with PRIVADO. Column 1 – 5 show the name of the model, the total number of layers, the number of parameters, the dataset and the accuracy respectively. We report Top 1 and Top 5 accuracy for Cifar-10 and ImageNet respectively.

6.4 Performance

Experimental Setup. We run all our experiments on a machine with 6th Generation Intel(R) Core(TM) i7-6700U processor, 64GB RAM and 8192 KB L3 cache with Ubuntu Desktop-16.04.3-LTS 64 bits and Linux kernel version 4.15.0-33-generic as the underlying operating system. The BIOS is configured to use the entire 128 MB for the creation of enclaves. All our measurements are averaged over 100 iterations and use a single core.

Methodology. For every model, we compute three execution time metrics. The baseline time measures standard versions of the model running outside SGX. The SGX time measures time to run the model within SGX, but with no obliviousness. The SGX+CMOV time measures time to run the model within SGX with added support for obliviousness. During each execution, we record statistics such as the enclave memory size, number of page-faults and input-dependent branches for each of the models. Table 2 shows the execution time for our benchmark models. PRIVADO incurs overhead between −27.4% and 90.4%. We believe these numbers are acceptable, given the additional security and privacy guarantees. We now describe several interesting results from our evaluation.
SGX-Enclaves improve efficiency for models that fit entirely in SGX memory. Surprisingly, our first finding is that some models, namely LeNet, VGG19, Resnet110 and Squeezenet, execute faster with PRIVADO than the baseline (negative overhead in Table 2). Note that these models are relatively small: they fit entirely within SGX memory (90 MB), and so do not incur page-fault overheads. Upon further analysis, we observed that these models run faster with SGX because the SGX SDK provides efficient implementation of some libc functions, such as malloc, as compared to standard libc used in the baseline execution.

Page-faults cause most of the overhead. For models that exceed the 90 MB SGX memory limit, we find that page-swapping between the enclave and outside memory (page-faults) contribute most of the performance overhead. To explain this, we use the metric, normalized page-faults per second (NPPS), in Table 2. This metric calculates the number of page-faults incurred inside SGX for one model inference, normalized by the baseline execution time. We observed that the performance overhead is highly correlated with the NPPS metric for all models. Among models that exceed 90MB, AlexNet has the highest NPPS (65245) and the highest overhead (90.4%) while Wideresnet has the lowest NPPS (5080) and lowest overhead (15.6%). These results suggest that for SGX inference, there are optimization opportunities in model design and implementation that can carefully minimize memory size and/or page faults.

Obliviousness is cheap for neural networks. Observe columns “SGX” and “SGX+CMOV” in Table 2. The former captures SGX overheads without obliviousness (including decryption of input which costs only about 84 and 313 microseconds for cifar-10 and imagenet images respectively), while the latter captures SGX overheads after adding obliviousness. We find that the overhead of adding obliviousness is a mere 1% on average for these ten DNN models. This observation confirms our claim that neural networks have relatively few input-dependent branches and that the bulk of the computation is access independent, and hence the cost of achieving obliviousness is nominal.

Batching may be counter productive. Batching is typically used to improve inference performance, especially in GPUs. Figure 4 shows the execution time for inferring images in batches from 1 to 4 for the Squeezenet model.
As shown in Table 2, Squeezenet incurs a negative overhead for a single image as compared to the baseline execution. However, as the batchsize increases, we observe that the execution time for PRIVADO exceeds that of baseline by a factor of 3 images and onwards. Increase in batch size results in larger enclave memory size as the number of activations increases proportionately with batch size. For a batch size of three, Squeezenet memory usage exceeds 90 MB and the overhead switches from negative to positive. This result suggests the following rule of thumb: while performing inference in SGX enclaves, to minimize performance overhead, a smaller batch size that limits memory usage below 90 MB is essential.

6.5 Lowering TCB

A naive implementation of PRIVADO would require trusting the entire Torch math and NN libraries, which have approximately 30,000 lines of code. However, PRIVADO-Generator further lowers the TCB using the technique described in Section 5.3. To calculate the reduction in the trusted code base (TCB), we count the number of lines used to generate each of the 10 model binaries. The last column, “TCB Reduction”, in Table 2 shows the percentage reduction in TCB as compared to trusting the entire torch library of 30,000 lines for each model. On average, PRIVADO results in a 33.69% reduction in TCB for our benchmark models.

6.6 Obliviousness

PRIVADO-Converter transforms the program such that the execution trace is the same for all inputs. To empirically evaluate this claim, we trace all the instructions executed by the library and record them. To do this, we build a tracer using a custom PinTool based on a dynamic binary instrumentation tool called Pin [46]. Our tracer logs each instruction before it is executed, along with the memory address accessed (read/write) by the instruction. We run our models before and after using PRIVADO-Converter and log the execution traces for all the inputs in our dataset for checking obliviousness.

Figure 5 (a) shows a snippet of two execution traces of LeNet on two different inputs before applying PRIVADO-Converter. The left-hand side trace executes more instructions than the right-hand side trace. The adversary can thus distinguish between two inputs by merely observing such differences in the execution trace. This empirically reinstates that existing library implementations indeed leak input information.

Figure 5 (b) shows the trace after PRIVADO-Converter. The traces snippets are identical after our transformation. This confirms that PRIVADO-Converter fixed the branches which leaked information in Figure 5 (a). For each network in our evaluation, we collect such execution traces for all the input in the dataset and check if the traces deviate. We report that in our experiments, we do not detect any deviation. Hence, we confirm experimentally that we did not miss any branches for all the models in our evaluation thus achieving obliviousness.

7 Related Work

In this section, we discuss prior-work on secure neural-network inference using (a) cryptographic primitives such as homomorphic encryption (b) trusted hardware.

7.1 Cryptographic Primitives

CryptoNets [47] was the first to use homomorphic encryption to support neural network inference on encrypted data. Following CryptoNets, several other solutions such as DeepSecure [48], Minionn [49], SecureML [50], ABY3 [51], SecureNN [52], and Gazelle [53] have been proposed for secure neural network inference. These solutions use a combination of cryptographic primitives such as garbled circuits, secret-sharing, and fully homomorphic encryption. However, these solutions use heavy-weight cryptography and hence incur a significant performance overhead while limiting the ease of use thus making them difficult to adopt in practice. PRIVADO takes an orthogonal ap-
approach to these solutions and uses trusted hardware as the main underlying primitive.

7.2 Trusted Hardware

Ohrimenko et al. propose a customized oblivious solution for machine learning algorithms using SGX [12]. However, their work does not address the ease-of-use challenge. Recent work Myelin proposes the use of SGX primarily to secure the training process using differential privacy to achieve obliviousness guarantees [54]. PRIVADO, on the other hand, focuses on supporting end-to-end inference-as-a-service for a given trained model. Further, unlike PRIVADO, Myelin is not backward-compatible i.e., it cannot execute inference for models that are not trained using the Myelin framework. Our use of the popular Torch framework and ONNX along with automated tools for ensuring obliviousness with ease-of-use differentiates PRIVADO from previous work.

Hunt et al. proposed Chiron, a privacy-preserving machine learning service using the Theano library and SGX [13]. Chiron does not prevent leakage via access patterns which is a serious concern as shown in Section 3. Similarly, MLCapsule, a system for secure but offline deployment of ML as a service on the client side is susceptible to leakage of sensitive inputs via access patterns [14]. Finally, Slalom combines SGX and GPU for efficient execution of NN inference but also does not address access-pattern leakage [15].

8 Conclusion

We present PRIVADO a system which provides secure DNN inference. PRIVADO is input-oblivious, easy to use, requires no developer effort, has low TCB, and has low performance overheads. We implement PRIVADO on the Torch framework and demonstrate that PRIVADO is both practical and secure on 10 contemporary networks.

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