DarKnight: A Data Privacy Scheme for Training and Inference of Deep Neural Networks

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Abstract

Protecting the privacy of input data is of growing importance as machine learning applications reach new application domains. Cloud companies are providing machine learning as a service to make it easier for data holders to create customized training and inference paradigms. In this paper, we provide a unified training and inference framework for large DNNs while protecting input privacy. Our approach called DarKnight relies on cooperative execution between GPUs and trusted execution environment (TEE) to train complex models. The cooperative execution allows DarKnight to exploit the computational power of GPUs to perform linear operations, while exploiting TEEs to protect input privacy. In particular, DarKnight uses a novel encoding to linearly combine multiple inputs along with an additive stream cipher noise to obfuscate the inputs. The proposed encoding process allows DarKnight to efficiently decode the computed data even as the model parameters continuously evolve during the backward propagation of DNN training. DarKnight further simplifies the encoding process for inference where the model parameters are unchanged. Unlike prior approaches, DarKnight does not need to store model parameters within the TEE memory thereby getting around the TEE’s limited secure memory limitations. By encoding and decoding multiple inputs during each iteration, DarKnight is well suited for current generation batch training process. We implement DarKnight on an Intel SGX enclave augmented with a GPU to demonstrate our new training capabilities.

1 Introduction

The need for protecting input privacy in machine learning (ML) is growing rapidly in many areas such as health care [1], autonomous vehicles [2], business [3], communication [4] and etc. In this paper we propose a novel methodology that offers data security to the data holders with privacy concerns. One of most prominent benefits of this work is that MLaaS engineer can easily utilize this framework to securely implement their desired DNNs in the cloud, without any model modifications. To achieve this goal, this work rely on Trusted Execution Environments (TEE) to provide a unified scheme for inference and training of large DNNs on private data. The primary challenge of using TEEs is that DNNs need powerful computational and memory resources while existing TEEs computational
power and memory space is very limited. Prior training schemes \[5,6\] secure the entire model within a TEE, thereby preventing large models from taking advantage of the TEE and also are unable to use ML accelerators such as GPUs. Prior inference schemes using TEE \[7,8,9,10\] exploit the fact that model parameters are fixed during inference to enable split execution between TEE and GPU. These schemes cannot be used for training since the parameters are constantly updated during the training process. Our approach, called DarKnight, is a unified platform designed for both training and inference of DNNs without revealing the input data to the MLaaS platforms. To the best of our knowledge this is the first work that uses a single enclave for training large DNNs and has a comparable performance with the fast GPUs.

DarKnight uses TEEs to linearly combine multiple inputs and then use an additive stream cipher noise to blind the input data before exposing it to the unguarded hardware. The scheme then uses a GPU to perform linear operations such as convolution and dense layer matrix multiplication on the coded input data for high performance. By restricting GPUs to perform only linear operations, DarKnight guarantees that computations on each input data can be decoded. By limiting TEEs to perform only data encoding and non-linear operations, DarKnight enables training large DNN models that exceed the size of TEE memory limitations. We design and implement DarKnight on an Intel SGX server equipped with GPU. We train VGG16, VGG19 and MobileNet as large DNN models, to demonstrate the efficacy of DarKnight. Furthermore, we perform several system-level optimization to reduce the memory utilization of the TEE.

The rest of the paper organizes as follow. In Section 2 we describe the problem setup and design objective. Section 3 explains the methodology for inference and training in addition to the challenges facing the proposed algorithm. The experimental results 4 are presented in section. In section 5 we draw the conclusion.

2 Background

2.1 Intel SGX

Trusted execution environments such as ARM TrustZone \[11\], Intel SGX \[12\] and Sanctum \[13\] provide an execution environment where computational integrity of user’s application is guaranteed by the hardware. For instance, using Intel SGX provides a limited amount of secure memory within an enclave which is protected from other processes, operating systems, hypervisors, and physical attacks. Users can write code to execute part of their application within an enclave while allowing other parts to be executed outside of an enclave. SGX has 128 MB as the enclave memory. In the case that the enclave application needs more space, a time consuming page eviction process is initiated. While some types of side channel attacks have been performed on SGX, Intel has been able to fix many of these attacks \[14,12,15,16,17,18,12\]. In this work we assume that computations performed within SGX are invisible to the outside entities. Instead DarKnight focuses on exploiting this feature to securely and efficiently perform inference and training.

2.2 Related Work

There are a variety of approaches for protecting input privacy during DNN training and inference. We categorized these approaches in Table 1. These approaches can be classified as those that rely on homomorphic encryption (HE), multi-party computing (MPC), trusted execution environments (TEE), differential privacy (DiffP), and additive noise (Noise). In some of the works mentioned below a combination of forenamed techniques is used. Those works are assigned to a category that describes them best. These techniques can be applied either for inference or training. Homomorphic encryption techniques encrypt input data and then perform inference directly on encrypted data, albeit with significant performance penalty \[19,20,21,22\]. Secure multi-party computing is another approach, where multiple non-colluding servers may use custom data exchange protocols to protect input data \[23,24,28,29\]. However, this approach requires multiple servers to perform training or inference. An entirely orthogonal approach is to use differential privacy, which aims to guarantee the confidentiality of the user, if the output of the DNN for that user is exposed \[30,31,32\]. Additive Noise is another approach mostly used for inference. In this mechanism there is a trade-off between the privacy performance, computational complexity and, model accuracy \[25,26,27\]. Our idea relies on TEEs to perform private inference or training in a secure hardware \[5,6,7,8,9,10\]. In particular, TEE-based training solutions focus on holding the entire model within the TEE environment which
Table 1: Various Prior Works: Techniques Used and Their Applicability

| Inference/Training | MPC | TEE | DIIHP | Noise |
|--------------------|-----|-----|-------|-------|
| Inference          | FHME[19], MiniONN[20], CryptoNets[21], Gazelle[22] | SGXCMP[23], SecureML[24] | Mlcapsule[7], ObliviousTEE[8], P-TEE[9], Shalam[10] | Arden[25], NOffload[26], Shredder[27] |
| Training           | SecureML[23], SecureNN[26], ABY3[22] | MSP[5], Charon[6] | DiffP[30], Rappor[31], Apple[32], PP DNN[33] |

protects data and model from outside attackers. However, TEEs impose severe memory and compute limitations since the size of the model that fits within a TEE is quite small, thereby preventing large models from taking advantage of the TEE. Furthermore, most of the DNN training methods are currently performed on GPUs which do not support TEE.

In particular, Slalom [10] is an inference framework for protecting data privacy and integrity. Slalom uses the Intel SGX enclave to secure received input data \( x \) from a client, and blind input data with an additive stream cipher noise \( r \). The blinded data \( (x + r) \) is then sent to an untrusted accelerator where linear operations are performed. The computed data \( W \cdot (x + r) \) is then returned to the enclave which can decode the correct computational output \( W \cdot x \) by subtracting the precomputed \( W \cdot r \). Here \( W \) is the model parameter matrix. There are challenges towards the promise of Slalom.

First, Slalom cannot be used for training, since it precomputes \( W \cdot r \) offline and performs simple subtraction operation to decode the output \( W \cdot x \). Precomputing the blinding factors is not possible during training since the model parameters \( W \) are updated after every batch. Computing \( W \cdot r \) inside the SGX after every batch also defeats the purpose of offloading the computations. Even in inference, securely storing multiple instances of \( r \)'s and their corresponding \( W \cdot r \)'s within the enclave memory, occupies a substantial amount of memory for large DNNs. On the other hand, storing an encrypted version of these values outside the enclave memory, leads to significant encryption and decryption costs, as these values are needed after each linear operation.

3 DarKnight

DarKnight supports both inference and training in a single framework. Figure 1 depicts the overall execution flow of DarKnight. A MLaaS cloud server has at least one SGX enclave and one GPU accelerator. Our goal is to rely on the GPU to perform computationally intensive operations while relying on SGX to protect input privacy. As such the initial model \( W \) that a user wants to train is loaded into the cloud server. (1) The training image set is encrypted using a mutually agreed keys with SGX. (2) SGX decrypt the image. (3) SGX calls DarKnight’s blinding mechanism to seal the data. (4) The blinded data is offloaded GPU for linear operation. (5) GPU performs linear operations and returns the data back to SGX. (6) SGX decodes the received computation using DarKnight’s decoding strategy and performs activation to get the next layer’s hidden feature map. This process is repeated both for forward and backward propagation for each layer. The only difference between training and inference is the blinding and unblinding strategy. DarKnight designs a novel blinding strategy that can blind the weight updates and hidden feature maps which are computed with respect to a specific training input. While for inference the approach is simplified.

DarKnight enables training and inference on very large models as its unique blinding strategy does not need to store the model parameters \( W \) within secure memory. Instead only a few scalars need to be protected, thereby allowing efficient training of large DNN models with multiple images as we explain below:

3.1 Privacy in Inference

In this section we start with DarKnight’s inference strategy. We consider a trained DNN, represented by model parameters \( W \) with \( L \) layers, which is performing inference on input \( x_0 \), which must be protected. At a layer \( l \) the inference process computes \( y_l = \langle W_l, x_l \rangle \), where \( \langle \cdot, \cdot \rangle \) corresponds to the bilinear operation at that layer (e.g. matrix product, convolution, etc.). After the linear operation an activation function \( g(\cdot) \) creates the next layer input \( x_{l+1} = g(y_l) \). Within this context, DarKnight first receives a set of \( K \) inputs \( x_0^{(1)}, \ldots, x_0^{(K)} \) for a batch inference from a client. Our goal is to
perform linear calculations of \( y_0^{(1)} = \langle \mathbf{W}_0 \cdot \bar{x}_0^{(1)} \rangle, \ldots, y_0^{(K)} = \langle \mathbf{W}_0 \cdot \bar{x}_0^{(K)} \rangle \) on the GPU without exposing the inputs to the GPU. Note that the subscript 0 in all these variables refers to the values of the first layer. As of this point, we will drop the subscript for a more clear notation. The blinding and unblinding strategy is similar for the rest of the layers.

**Key Insight:** The main idea behind DarKnight’s privacy protection scheme is the fact that our multiplication operator is bilinear. Thus, instead of asking the GPU to calculate \( \langle \mathbf{W}, \bar{x}^{(i)} \rangle \), which exposes the inputs, DarKnight blinds multiple inputs by combining them linearly plus a random noise vector with sufficient power. Due to the bilinear property any linear operation on \( K \) blinded inputs can be recovered if there are \( K \) different linear computations performed.

**DarKnight Blinding:** More specifically, DarKnight creates \( K + 1 \) inputs \( \bar{x}^{(1)}, \ldots, \bar{x}^{(K)} \), as follows,

\[
\begin{align*}
    \bar{x}^{(1)} &= \alpha_{1,1} x^{(1)} + \cdots + \alpha_{1,K} x^{(K)} + \alpha_{1,(K+1)} \mathbf{r} \\
    \vdots & \\
    \bar{x}^{(K+1)} &= \alpha_{(K+1),1} x^{(1)} + \cdots + \alpha_{(K+1),K} x^{(K)} + \alpha_{(K+1),(K+1)} \mathbf{r}
\end{align*}
\]

(1)

The scalars \( \alpha_{i,j} \)'s and the noise vector \( \mathbf{r} \) are randomly generated, such that the variance of the noise is sufficiently larger than the inputs (See remarks below for more details). We gather the scalars \( \alpha_{i,j} \)'s in the the matrix \( \mathbf{A} \). And we assume that \( \mathbf{A} \) is secured in enclave memory and is invisible to an adversary. Hence, by revealing the values \( \bar{x}^{(i)} \)'s to the external hardware, we do not expose the inputs \( x^{(i)} \)'s.

The blinded data \( \bar{x}^{(i)} \)'s are sent to the GPU which performs the following computations: \( \bar{y}^{(1)} = \langle \mathbf{W}, \bar{x}^{(1)} \rangle \ldots \bar{y}^{(K+1)} = \langle \mathbf{W}, \bar{x}^{(K+1)} \rangle \).

**DarKnight Unblinding:** The \( K + 1 \) outputs \( \bar{y}^{(i)} \) returned from the GPU must be deblinded to extract the original results \( y^{(i)} \). These value can be extracted as follows,

\[
\begin{align*}
    \mathbf{Y} = \begin{bmatrix} \mathbf{W} \cdot [\bar{x}^{(1)}, \ldots, \bar{x}^{(K+1)}] \end{bmatrix} = \begin{bmatrix} \mathbf{W} \cdot [x^{(1)}, \ldots, x^{(K)}, \mathbf{r}] \end{bmatrix} \cdot \mathbf{A} \Rightarrow \mathbf{Y} = \mathbf{Y} \cdot \mathbf{A}^{-1}
\end{align*}
\]

(2)

**Few remarks** are in place (1) Unlike prior works DarKnight does not need to store \( \mathbf{W} \cdot \mathbf{r} \) within the enclave memory thereby significantly enhancing our ability to infer with much larger models. (2) The size of the matrix \( \mathbf{A} \) that is secured is proportional to the number of inputs that are blinded together rather than the model size \( \mathbf{W} \), which is several orders of magnitude larger. (3) The values of the matrix \( \mathbf{A} \) can be computed offline in the pre-processing phase for performance improvement. We also prefer to choose a matrix \( \mathbf{A} \), with a condition number close to one, so that our blinding and unblinding algorithm remains numerically stable. For this purpose, orthogonal matrices serves us the best. (4) The process of deblinding \( K \) inputs with one additive stream cipher requires \( K + 1 \) computations. During deblinding we extract \( \mathbf{W} \cdot \mathbf{r} \), but that value is just dropped. Thus DarKnight trades \( 1/K \) additional computations in order to eliminate the need to secure very large model parameters.

**Selection of \( K \):** Selecting larger \( K \) (number of images that are batch inferred) decreases the overhead of one additional noise related computation. However, increasing the size of \( K \) requires blinding multiple images within an enclave. Our analysis indicates we can merge and process up to four images from ImageNet dataset at the same time without exceeding current SGX memory limitations. This result is shown in Figure 2a. Thus we need one extra linear computation for every four images.
inference requests.

**The noise vector:** Here, we proposed a simple version of the DarKnight that shares one noise vector \( r \), among all the equations. This is sufficient to blind the inputs in each equations. But a more complicated version of the DarKnight is explained in the Appendix, that uses multiple noises in each equation in a way to decrease the mutual information between the equations \((\square)\) (in case the attacker knows the underlying blinding method).

### 3.2 Privacy in Training

Model training places a significant burden on DarKnight’s input obfuscation scheme used for inference. In the training setting, the model parameters, \( \mathbf{W} \), are updated each time a batch is processed. For a model with \( L \) layers which is being trained with a batch of \( K \) inputs, the model parameters \( \mathbf{W}_l \) at layer \( l \) are updated using the well known SGD process as:

\[
\mathbf{W}_l^{\text{new}} = \mathbf{W}_l^{\text{old}} - \eta \times \nabla \mathbf{W}_l, \quad \nabla \mathbf{W}_l = \frac{1}{K} \sum_{i=1}^{K} \langle \delta_l^{(i)}, \mathbf{x}_l^{(i)} \rangle
\]

(3)

Here \( \eta \) is the learning rate, and \( \delta_l^{(i)} \) is the gradient of the loss for the \( i \)-th point in the training batch, with respect to the output of layer \( l \). DarKnight must protect \( \mathbf{x}_l^{(i)} \) for each layer of the DNN when the layer’s linear operations (convolution, matrix multiplication) are outsourced to a GPU. Recall that the decoding process for inference exploited the invariant property of model parameter for any given input such that \( \langle \mathbf{W} \cdot [\bar{x}^{(1)}, \ldots, \bar{x}^{(k+1)}] \rangle = \langle \mathbf{W} \cdot [\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(k)}, \mathbf{r}] \rangle \cdot \mathbf{A} \). However, during the training process, we have different \( \delta_l^{(i)} \) for each input \( \mathbf{x}_l^{(i)} \). Thus, decoding the \( \langle \delta_l^{(i)}, \mathbf{x}_l^{(i)} \rangle \) from obfuscated inputs \( \langle \delta_l^{(i)} \rangle \) is a non-trivial challenge.

**Key Insight:** The key insight is that while training a batch of inputs it is not necessary to compute the \( \langle \delta_l^{(i)}, \mathbf{x}_l^{(i)} \rangle \) for each input \( \mathbf{x}_l^{(i)} \). Instead the training process only needs to compute cumulative parameter updates for the entire batch of inputs. Hence, what is necessary to compute is the entire \( \nabla \mathbf{W}_l \) which is a summation over multiple inputs in the batch.

**DarKnight Blinding:** DarKnight exploits this insight to protect privacy without significantly increasing the encoding and decoding complexity of the blinding process. In particular DarKnight uses a new linear encoding scheme to combine inputs (covered by noise). As shown in (3), there are \( K \) inputs on which gradients are computed. Instead of calculating the \( K \) products in (3), DarKnight calculate the following \( K + 1 \) equations, in the backward propagation,

\[
\nabla \mathbf{W}_l = \sum_{j=1}^{K+1} \gamma_j \mathbf{E}_j, \quad \mathbf{E}_j = \left\langle \sum_{i=1}^{K} \alpha_{j,i} \delta_l^{(i)}, \sum_{i=1}^{K} \beta_{j,i} \mathbf{x}_l^{(i)} + \beta_{j,(K+1)} \mathbf{r} \right\rangle
\]

(4)

DarKnight selects \( \alpha_{j,i} \)'s, \( \beta_{j,i} \)'s and \( \gamma_i \)'s such that

\[
\mathbf{A}^\top \cdot \mathbf{\Gamma} \cdot \mathbf{B} = \begin{bmatrix}
1 & 0 & \ldots & 0 & 0 \\
0 & 1 & \ldots & 0 & 0 \\
\vdots & \ddots & \ddots & \ddots & \vdots \\
0 & \ldots & 0 & 1 & 0
\end{bmatrix}_{K \times (K+1)}
\]

(5)

Assuming batch size is equal to \( K \), the \( \alpha_{i,j} \) parameters used for scaling \( \delta \) values is gathered in the \( K + 1 \) by \( K \) matrix, \( \mathbf{A} \). \( \beta_{i,j} \)'s are gathered in the \( K + 1 \) by \( K + 1 \) matrix \( \mathbf{B} \), the scalar matrix with the same size for intermediate features and \( \gamma_i \)'s form the diagonal of a \( K + 1 \) by \( K + 1 \) matrix \( \mathbf{\Gamma} \), that gives us the proper parameters for efficient decoding.

**DarKnight Unblinding:** Given the constraint imposed on \( \alpha_{j,i} \)'s, \( \beta_{j,i} \)'s and \( \gamma_i \)'s the decoding process is trivially simple to extract \( \nabla \mathbf{W} \). It is easy to see that if the scalars \( \alpha_{i,j} \)'s, \( \beta_{i,j} \)'s and \( \gamma_i \)'s satisfy the relation \((\square)\), we will have

\[
\frac{1}{K} \sum_{j=1}^{K+1} \gamma_j \mathbf{E}_j = \frac{1}{K} \sum_{i=1}^{K} \langle \delta_l^{(i)}, \mathbf{x}_l^{(i)} \rangle = \nabla \mathbf{W}_l
\]

(6)
In other words, the unblinding process only involves calculating a linear combination of the equations in (4), which are calculated in the untrusted GPU and there is no need to compute each component individually. **DarKnight Training Complexity:** It is important to note that DarKnight’s training approach for blinding and unblinding is very simple. All the scaling parameters can be generated in the prepossessing phase and can be stored inside TEE. The size of the $\alpha$, $\delta$ and $\gamma$ matrices is just proportional to the square of the batch size that is being processed at one time. Even with a 8-64 batch size (commonly used in VGG training [34, 35]) these scaling values are substantially smaller than the model parameters $W$. Furthermore, even with a batch size of 8-64 the TEE may choose to process only a small subset of images, called a virtual batch, at a time. The size of the virtual batch is limited by the size of the SGX memory that must compute the $\bar{x}^{(i)}$, typically 4-8 images at a time. Thus the scaling parameters for blinding are quite small.

3.3 Extending DarKnight to Verify Data Integrity with Untrusted GPU

Apart from protecting privacy DarKnight can be extended easily to a scenario where the GPU hardware is not trusted. In this case the linear computations performed by the GPU must also be verified. In the interest of space we just provide an insight into how DarKnight can perform data integrity checks for inference. Similar extensions for training are also possible. Recall that DarKnight creates $K+1$ blinded inputs $\bar{x}^{(1)}, \ldots, \bar{x}^{(K+1)}$ for $K$ original inputs. To provide integrity DarKnight creates one additional linear combination of inputs $\bar{x}^{(K+2)}$ using the same approach as in Eq.1. This additional computation allows every output $y^{(i)}$ to be extracted by the SGX enclave by solving two different sets of linear equations. With this redundant equation, we can detect an error when the two ways to extract each $y^{(i)}$ does not match. In case an error is detected, the enclave may perform additional corrective action, such as executing on another GPU worker or perform additional redundant computations. But these actions are outside the scope of our current work.

3.4 Random Noise and Quantization

The strength of random noise $r$ added by DarKnight provides strong privacy guarantees for both training and inference. However, strong noise may also obfuscate the original signal due to floating point errors, particularly with long running training iterations where the errors may accumulate. On one hand using a powerful random noise gives a more robust privacy guarantee and on the other hand, a strong noise requires a stricter quantization mechanism and consequently may affect the accuracy of training and inference. Quantized DNNs have been widely studied in recent years [36, 37, 38, 39, 40]. In this work we assume that either appropriate quantization is already performed or the random noise $r$ does not significantly accumulate the training errors. In the next section, we run some numerical experiments to evaluate the effect of additive noise to accuracy of inference and training.

4 Experiments

4.1 Setup

All the experiments ran on Intel(R) Coffee Lake E-2174G 3.80GHz processor. This server has 64 GB RAM and supports Intel Soft Guard Extension (SGX). The co-located GPU that is used for linear operations is Nvidia GeForce GTX 1080 Ti. In all of the following simulations, a single thread is performing the TEE’s functionality. Adding multiple threads has its complications especially because of the memory requirement for thread creation.

We used three different DNN models: VGG16 [41], VGG19 [41] and, MobileNet [42]. MobileNet’s goal is to design a small DNN which can be used on small devices and phones. Therefore, it replaces standard convolution with depth-wise convolution followed by point-wise convolution to reduce the number of linear operations. We used three well-known datasets for inference and training. one is CIFAR-10 [43] that has 50000 training images evenly distributed between 10 categories. Each 32x32 image stores three bytes of RGB for each pixel. CIFAR-100 [43] has 100 classes and each class contains 600 images. The other dataset is ImageNet [44] which is an image dataset designed based on WorldNet hierarchy with more than 1.2 million images and 1000 categories.
4.2 Results

For the sake of comparison we implement two baselines: one fully implemented on GPU and the other one is fully on SGX. For inference, we also compare our performance with Slalom [10] which is a privacy scheme that can only be used for inference. Needless to mention, the GPU version does not provide any security guarantee. For inference, we show how our model speeds up the execution time in both VGG16, VGG19 and MobileNet. Moreover, we examined the effect of different noise signals on the accuracy of inference. For training, first the effect of noise on the accuracy and convergence is analysed. Furthermore, The details of timing comparison of each operation is depicted for both forward and backward pass. Our source codes, GPU comparisons, and more results for more models and datasets are available at our github:

4.2.1 Inference

![Inference speedup comparison of different operations relative to DarKnight(1) for different virtual batch sizes for VGG16](image)

(a) Inference speedup comparison of different operations relative to DarKnight(1) for different virtual batch sizes for VGG16

![Inference speedup comparison with different implementations relative to SGX for VGG16, VGG19, and MobileNet](image)

(b) Inference speedup comparison with different implementations relative to SGX for VGG16, VGG19, and MobileNet

Figure 2: Inference execution time and speedup for ImageNet dataset of batch size 64 with Different models and configurations

Effect of Virtual Batch Size: Figure 2a demonstrates the effect of merging multiple images on the speedup of inference. As we explained in 2.1, the memory capacity of SGX is very limited and processing more data than the capacity of SGX cause performance degradation because of the complicated encryption and eviction procedure. DarKnight(k) denote a case of having a virtual batch size of k meaning that k input images combined and blinded with a noise signal. The X-axis shows the SGX operations and the Y-axis represents the speedup relative to the baseline of DarKnight(1) for each operation. As shown, combining more images up to a certain point, yields a speed up in all the operations. But by merging more than a certain number of images, the performance degrades significantly. The reason behind this observation is that after adding 4 images the available enclave memory is saturated. In the rest of the inference section we use DarKnight(4) which shows the most promising performance.

Inference Speedup: Figure 2b compares the speedup of the inference process for VGG16, VGG19 and MobileNet. The case of performing all the calculations on the SGX, using Slalom for inference, using Slalom with integrity, using DarKnight(4), and using DarKnight(3)+Integrity. A few remarks are in place. As observed in the figure, integrity increases the execution time, since we add some redundancy to the calculations to guarantee the integrity. We also observe 15-fold speedup, compared to the fully on SGX baseline, and 30% improvement compared to Slalom for VGG16. This advantage originates from two points. First, Slalom stores many random vectors, r<sub>i</sub>s, and their corresponding W<sub>i</sub> · r<sub>i</sub>. Therefore, it has less memory available for processing images and cannot simultaneously process the same amount of images as our model. To avoid storing the W<sub>i</sub> · r<sub>i</sub>s inside the SGX, they store the encrypted version of them in the unprotected memory. In each iteration, and in each layer, SGX has to go through the decryption procedure which has a substantial performance overhead. Moreover, they did not fully utilize the SGX memory, as they have to sequentially process one image at a time. For integrity checks Slalom uses Freivalds’ algorithm. However, their implementation only checks the integrity of convolution layers and dense layers integrity check are disregarded for simplicity. On the other hand, our implementation the integrity of all the linear operations including dense layers are checked. For integrity checks in our design we used the DarKnight(3) model in
which three images are linearly combined and covered by noise. The reason is that when integrity checks are added to the design, one extra equation is generated. In the other words, we will have 5 equations and 4 unknowns. We will have to simply make sure that the result derived from the first four are consistent with the fifth equation. In order to avoid memory overflow of SGX, it is beneficial to reduce the number of images from four to three, hence we use DarKnight(3) model. As depicted, our implementation of VGG16 with integrity has 45% performance improvement, compared to Slalom, while offering more robustness by checking the integrity of all linear layers.

The same is scheme is used for analyzing MobileNet behaviour. As mentioned in section 4.1 MobileNet reduced the amount of convolution computation and that is why we expect it to show less performance improvement using our method in relative to baseline. Although its speedup over baseline on SGX is less than VGG16, we still observe a 7.7x speedup, compared to SGX model, and 13% speedup over Slalom.

**Effect of Noise on Accuracy:** For our simulations, we use a random Gaussian vector with iid entries, \( \mathcal{N}(\mu, \sigma^2) \), as the noise vectors \( r_i \)'s. In Table 2 we investigated the effect of various means and variances for the noise, on the accuracy of the inference of VGG16, VGG19 and MobileNet. It is worth mentioning that the accuracy of the baseline (first row of the table) could be improved with different mechanisms, which is out of the scope of this work. While for a few of the noise signals a negligible accuracy loss are observed, for most of them, adding a noise signals cause no accuracy degradation. This arguments holds for VGG19 and MobileNet and also CIFAR-10 and CIFAR-100. The noise signals we applied here are orders of magnitude larger than dataset.

### Table 2: Effect of Different Noise Signals on the Accuracy of DarKnight Inference for VGG16, VGG19 and MobileNet on ImageNet with Batch-size = 64

| Noise     | VGG16 top1 Accuracy | VGG16 top5 Accuracy | VGG19 top1 Accuracy | VGG19 top5 Accuracy | MobileNet top1 Accuracy | MobileNet top5 Accuracy |
|-----------|---------------------|---------------------|--------------------|--------------------|-------------------------|-------------------------|
| Clean     | 63.36               | 84.14               | 63.35              | 84.39              | 64.17                   | 84.44                   |
| \(\mathcal{N}(4e3, 4e3)\) | 63.42               | 84.14               | 64.14              | 84.42              | 64.21                   | 84.64                   |
| \(\mathcal{N}(2e4, 4e3)\) | 63.37               | 84.23               | 64.10              | 84.49              | 64.10                   | 84.49                   |
| \(\mathcal{N}(1e4, 4e3)\) | 63.33               | 83.88               | 64.21              | 84.47              | 64.15                   | 84.18                   |
| \(\mathcal{N}(1e4, 5e3)\) | 63.49               | 84.00               | 64.33              | 84.71              | 64.08                   | 84.42                   |

4.2.2 Training

We used Intel Deep Neural Network Library (DNNL) for designing the DNN layers including the Convolution layer, ReLU, MaxPooling and, Dense layer. For evaluating training performance, two aspects are examined. One is the accuracy of training considering adding noise to the data and the other one is the execution time of training.

**Effect of Noise on Accuracy:** As depicted in Figure 3, the accuracy of training for different noise is measured during the first 200 epochs on VGG16 and VGG19. Figure 3a,b,c,d shows the accuracy of training for VGG16 on CIFAR-10 dataset. As demonstrated the accuracy after epoch 150 with some of noise signals is less than 0.001 and for some no accuracy degradation is observed. The same argument holds for CIFAR-100 as depicted in 3b. The same argument holds for VGG19.

**Training Execution Time:** Figure 4 demonstrates the speed of training using DarKnight relative to the baseline fully implemented on SGX for both forward pass and backward propagation. It breaks down the execution time spent in each category and shows the speedup we get per category.

![Figure 3: Training Accuracy of DarKnight in Different DNNs and Datasets](image-url)

(a) Training Accuracy of VGG16 for CIFAR-10 on VGG16; (b) Training Accuracy of VGG19 for CIFAR-10 on VGG19; (c) Training Accuracy of VGG16 for CIFAR-100 on VGG16; (d) Training Accuracy of VGG19 for CIFAR-100 on VGG19.

**Table 2:** Effect of Different Noise Signals on the Accuracy of DarKnight Inference for VGG16, VGG19 and MobileNet on ImageNet with Batch-size = 64.
of operations per image. For VGG16 for example, as shown for the baseline linear operation takes 0.85 and 0.99 of the execution time in forward and backward pass respectively. In forward pass the summation of blinding/unblinding and the linear operations reduces the linear operation time on SGX by 72% and hence the total execution time is cut by 70%. For backward propagation, this reduction is even higher since the total blinding/unblinding plus linear operation in DarkKnight takes only 10% of the time that baseline spent for its linear computation. As a result, DarKnight speeds up the backward propagation by more than 7 times. It is worth mentioning that, our implementation of ReLU takes longer than the baseline because some part of the unblinding function is fused to ReLU function for performance purposes. For VGG19 the same behaviour is observed.

![Graph showing speedup per image for one forward pass and backward propagation relative to baseline on VGG16 and ImageNet](image)

![Graph showing speedup per image for one forward pass and backward propagation relative to baseline on VGG19 and ImageNet](image)

Figure 4: Training Speedup of VGG16 and VGG19 on ImageNet

5 Conclusion

MLaaS has been attracted many data holders’ attention recently. One of the most important concerns of data owners is data privacy and computation integrity. In this work, we address these issues using Trusted Execution Environments (TEEs). This work utilizes TEEs to establish a solid baseline for both training and inference by minimizing the information leakage and increasing the robustness of the computation. To the best of our knowledge this is the first work that uses TEEs for training large DNNs while having a comparable performance with fast insecure hardware. We achieve a significant speedup by offloading the computationally expensive operations to the co-located GPU while keeping the non-linear operation inside the trusted hardware. For training, we preserve the privacy of the training points in standard SGD by linearly combining the training points and taking advantage of additive stream cipher noise. For training and inference, a novel encoding and decoding procedure is designed to reduce the overhead of blinding and unblinding functions which prepare the data for exposing it to the unguarded hardware.

Broader Impact

These days Machine learning has more applications than anytime before. The need for data privacy has been emerged especially now that smart homes, autonomous cars and, personal assistants have been taking over the world. These applications need to process stream of data flowing to them on real time. Since users do not want to reveal data about their personal lives, this real time data processing needs to preserve privacy.

The idea of input privacy using TEEs can be used by all the companies who offer MLaaS and all their costumers. This means that data holders can expose their private data to the secure part of the cloud without any privacy concerns. The cloud itself takes the responsibility of protecting the data when it needs to do a computationally expensive operations. Therefore, from data holder’s perspective they do not need any extra computation or communication power. On the other hand from MLaaS providers’ perspective, they do not need to design a different different cryptography method each time their costumers have a specific security requirement. The design time basically offloads to the TEE designer and once they finish the design, tons of applications can take advantage of it. This is
the first approach combining hardware and software to provide security and like every other area having hardware designed for a specific task can improve the performance significantly. Furthermore, MLaaS providers do not need to redesign the models or change any of the parameters for providing security.

One disadvantage is that if MLaaS uses a specific TEE to preserve privacy, there will be attacks targeted the TEE. Since the data is clean for the computations inside SGX, if an attacker is able to invade the TEE they have full access over raw data. Also they can modify the training data in a way that leads to noisy training.

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