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Secure Classification as a Service

BACHELOR'S THESIS

Bachelor's degree programmes: Physics and Information & Computer Engineering

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Abstract

Abstract of your thesis (at most one page)

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Keywords: FHE, classification, neural network

Technologies: Microsoft SEAL (C++, nodejs), Tensorflow Keras, Numpy, xtensor, Docker, msgpack, React, Materialize, Nginx

Languages: C++, Python, JavaScript

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Introduction

Goal:

Background

2.1 Basics of Fully Homomorphic Encryption

Homomorphic Encryption (HE) makes it possible to operate on data without knowing it. One can distinguish three flavors of it, Partial-, Semi- and Fully Homomorphic Encryption (FHE).

- Brakerski/Fan-Vercauteren (BFV) scheme for integer arithmetic
- Brakerski-Gentry-Vaikuntanathan (BGV) scheme for integer arithmetic
- Cheon-Kim-Kim-Song (CKKS) scheme for real-number arithmetic
- Ducas-Micciancio (FHEW) and Chillotti-Gama-Georgieva-Izabachene (TFHE) schemes for Boolean circuit evaluation

2.1.1 Packing

FFT in CKKS! Polynom -> Vektor mit einer FFT Vektor -> Polynom mit einer IFFT

2.1.2 HE using RSA

With unpadded RSA, some arithmetic can be performed on the ciphertext - looking at the encrypted ciphertext $\mathcal{E}(m_1) = (m_1)^r \mod n$ of the message m_1 and m_2 respectively, the following holds:

$$\mathcal{E}(m_1) \cdot \mathcal{E}(m_2) = (m_1)^r (m_2)^r \mod n \tag{2.1}$$

$$= (m_1 m_2)^r \mod n \tag{2.2}$$

$$=\mathcal{E}(m_1 \cdot m_2) \tag{2.3}$$

The encryption therefore partially fulfills the properties of ring homomorphism, which in general is defined as follows:

Definition 2.1.1: Ring Homomorphism

Given two rings $(R, +, \cdot)$ and (S, \oplus, \otimes) , we call a mapping $\varphi : R \to S$ a ring homomorphism when it satisfies the following conditions:

$$\forall a, b \in R : \varphi(a+b) = \varphi(a) \oplus \varphi(b) \land \varphi(a \cdot b) = \varphi(a) \otimes \varphi(b)$$

2.1.3 Learning with Errors (LWE)

2.1.4 Ring-LWE

Learning with Errors on Rings (RLWE) how to get from LWE to RLWE

2.1.5 The BFV scheme

2.1.6 The CKKS scheme

The CKKS scheme allows us to perform approximate arithmetic on floating point numbers.

2.2 Machine Learning

Undoubtedly one of the most prevalent concepts in todays computing world, Machine Learning (ML) has shaped how computers think and how we interact with them significantly. As Shafi Goldwasser puts it, 'Machine Learning is somewhere in the intersection of Artificial Intelligence, Statistics and Theoretical Computer Science' (Goldwasser 2018).

Within the scope of this thesis, the basics of neural networks and associated learning methods shall be covered, limited to the category of supervised learning problems (as opposed to unsupervised learning problems). Supervised learning refers to the machine *training* an algorithm to match some input data (features) with corresponding output data (targets), often related to pattern recognition. The trained algorithm can then be utilised to match fresh input data with a prediction of the targets.

A popular subset of applications to ML are classification problems, predominantly image classification, which was not as easily possible before without a human eye due to the lack of computing power. Classification problems can be formulated quickly, the goal is to computationally categorize input data (for instance, images) into a predefined set of classes (for instance, cats and dogs). The primary concept behind Machine Learning is not at all new, linear regression was already employed by Gauss and Legendre in the early 19th century; the term 'Neural Network' was first used by McCulloch and Pitts in 1943. Much media attention was earned in the 2000-2010 decade when larger image classification problem became feasible with the increasing computational power of modern computers, up until the advent of Deep Learning (Bishop and Nasrabadi 2007).

2.2.1 Linear Regression?

Given an input vector $\mathbf{x} \in \mathbb{R}^n$, the goal of linear regression is to predict the value of a target $t \in \mathbb{R}$.

2.2.2 Gradient Descent?

2.2.3 The Backpropagation Algorithm

2.2.4 Multi-Layered Neural Networks

Matrix -> Activation Function

- Matrix Multiplication (Dense Layer)
- Convolutional Layer
- Sigmoid Activation
- Max Pooling

2.3 Post-Quantum Security

2.3.1 Shor's Algorithm

2.4 Demo

In this chapter, we provide some usage examples for glossaries and acronym lists with glossaries (section 2.5), bibliography and citations with biblatex (section 2.5), and more.

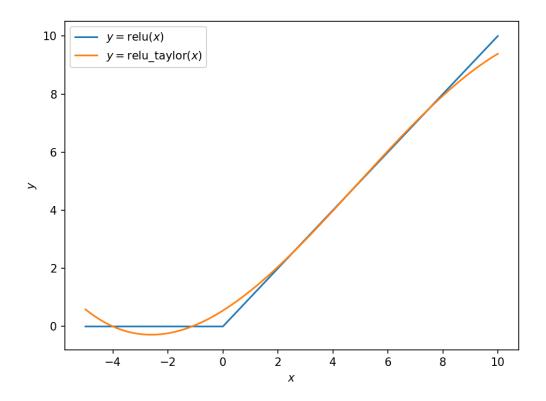


Figure 2.1: Comparison of the Relu activation function vs. its Taylor expansion

2.5 Notation and Acronyms

Symbols and acronyms are defined in the preamble, after loading the glossaries package, and used as follows.

In this chapter, we introduce the necessary background on the Advanced Encryption Standard (AES). We denote binary exclusive-or by \oplus .

This is an example of how to specify and cite a book Daemen and Rijmen 2002, a journal article Shannon 1949. AES is a block cipher defined by Daemen and Rijmen (2002).

Implementation

3.1 Chosen Software Architecture

In the given setting, the most accessible frontend is commonly a JavaScript web application.

To still make the classification run as quickly and efficiently as possible, a C++ binary runs in the backend providing an HTTP API to the frontend application. In order to allow for more flexibility of the HTTP server, the initial approach was to pipe requests through a dedicated web application framework with database access that would allow, for instance, user management next to the basic classification. However, the resulting communication and computation overhead, even when running with very efficient protocols such as ZeroMQ, was too high.

Extending the accessibility argument to reproducibility, Docker is a very solid choice (Nüst et al. 2020). To run the attached demo project, simply execute

```
docker-compose build docker-compose up
```

in the 'code' folder and point your browser to https://localhost.

3.1.1 Docker Multi-Stage Build

An enterprise-grade, scalable deployment is achieved by means of zero-dependency Alpine Linux images which contain nothing but compiled binaries and linked libraries.

3.2 The MNIST dataset

The MNIST dataset (LeCun and Cortes 1998) contains X train and Y test images with corresponding labels. In order to stick to the traditional feedforward technique with data represented in vector format, therefore it is common to reshape data from (28, 28) images (represented as grayscale values in a matrix) into a 784 element vector.

3.3 Matrix-Vector Multiplication

The dot product that is required as part of the neural network evaluation process needs to be implemented on SEAL ciphertexts as well.

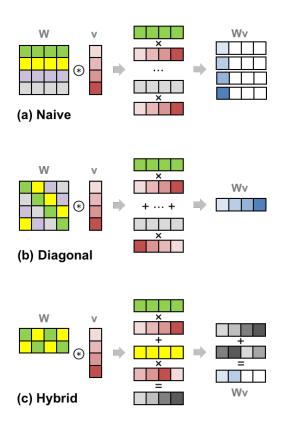


Figure 3.1: Different techniques to compute a dot product between a matrix and a vector, each having their up- and downsides.

There are multiple methods to achieve a syntactically correct dot product (matrix-vector multiplication) as described by Juvekar, Vaikuntanathan and Chandrakasan (2018) for square matrices.

- 1. Naive
- 2. Diagonal
- 3. Hybrid
- 4. Babystep-Giantstep

3.3.1 Adapting to non-square matrices

The weight matrices in the given classification setting are by no means square, on the contrary their output dimension tends to be much lower than the input dimension as the goal is to reduce it from $28^2 = 784$ to 10 overall.

However, that also means one cannot directly apply the diagonal method as described in the proceedings above. This 'flaw' can be mitigated by a simple zero-padding approach in order to make the matrix square, filling in zeros until the lower dimension reaches the higher one.

3.3.2 The Naive Method

Term by term, one can express a matrix-vector product as follows:

$$\{M\mathbf{x}\}_i = \sum_{j=1}^t M_{ij} x_j$$

3.3.3 The Diagonal Method

For the following, define

$$\operatorname{rot}_{j}: \mathbb{R}^{t} \mapsto \mathbb{R}^{t}, \ \{\operatorname{rot}_{j}(\mathbf{x})\}_{i} = x_{i+j}$$
$$\operatorname{diag}_{j}: \mathbb{R}^{t \times t} \mapsto \mathbb{R}^{t}, \ \{\operatorname{diag}_{j}(M)\}_{i} = M_{i,(i+j)}$$

with all indices $i, j \in \mathbb{Z}_t$ member of the cyclic quotient group $\mathbb{Z}_t := \mathbb{Z}/t\mathbb{Z}$ of all integers modulo t.

3.3.4 The Hybrid Method

3.3.5 The Babystep-Giantstep Optimization

Since Galois rotations are the most computationally intensive operations in most cryptographic schemes used today (Dobraunig et al. 2021), they take a large toll on the efficiency. In order to reduce the number of rotations required, one can make use of the *Babystep-Giantstep* optimization as described in Halevi and Shoup 2018, which works as follows:

Theorem 3.3.1: Babystep-Giantstep Optimization

Given a matrix $M \in \mathbb{R}^{t \times t}$ and a vector $\mathbf{x} \in \mathbb{R}^t$, with $t = t_1 \cdot t_2$ split into two BSGS parameters $t_1, t_2 \in \mathbb{N}$ and

$$\operatorname{diag}_{i}'(M) = \operatorname{rot}_{-\lfloor i/t_1 \rfloor \cdot t_1}(\operatorname{diag}_{i}(M))$$

, one can express a matrix-vector multiplication as follows:

$$M\mathbf{x} = \sum_{k=0}^{t_2-1} \operatorname{rot}_{(kt_1)} \left(\sum_{j=0}^{t_1-1} \operatorname{diag}'_{(kt_1+j)}(M) \cdot \operatorname{rot}_j(\mathbf{x}) \right)$$
(3.1)

where \cdot denotes an element-wise multiplication of two vectors.

Proof. Babystep-Giantstep Optimization

$$\left\{ M\mathbf{x} \right\}_{i} \stackrel{?}{=} \left\{ \sum_{k=0}^{t_{2}-1} \operatorname{rot}_{(kt_{1})} \left(\sum_{j=0}^{t_{1}-1} \operatorname{diag}'_{(kt_{1}+j)}(M) \cdot \operatorname{rot}_{j}(\mathbf{x}) \right) \right\}_{i} = \sum_{k=0}^{t_{2}-1} a_{i+kt_{1}}$$

with

$$a_i = \sum_{j=0}^{t_1 - 1} b_{ij} x_{i+j}$$

with

$$b_{ii} = 1$$

3.4 Polynomial Evaluation

From the implementation perspective, there are three properties to watch out for when working with SEAL ciphertexts:

1. Scale (retrieved using x.scale())

Scale has nothing to do with noise. "Scale out of bounds" can appear even if noise is extremely low. Although repeated multiplication of a ciphertext by a plaintext will slowly increase the noise, it is not the reason why you see "scale out of bounds". "Scale out of bounds" error specifically means that the scale of a ciphertext or plaintext is larger than the product of all elements in coeff_modulus. If you perform multiplications without rescaling, you can quickly see this error. The more rescaling you perform, the less elements will be left in coeff_modulus. Even if you managed to have the same scale in a ciphertext after every multiplication and rescale, eventually the coeff_modulus can be too small to accommodate another multiplication.

Can be adjusted with: evaluator.rescale_inplace()

- 2. Encryption Parameters (retrieved using x.parms_id())
 Can be adjusted with: evaluator.mod_switch_to_inplace()
- 3. Ciphertext Size (retrieved using x.size())
 Can be adjusted with: evaluator.relinearize_inplace()

Multiplication Each time one multiplies two ciphertexts, the scales multiply (logarithmically, they add up, i.e. the bits are added together). The chain index reduces by 1. The chain index of an encoded ciphertext depends on the coeff moduli. There must be enough bits remaining to perform the multiplication, namely log2(scale) bits.

Addition The scales must be the same, but luckily they will not change.

3.5 Transparent Ciphertext

The problem is that you are subtracting a ciphertext from itself. This kind of operation results in a ciphertext that is identically zero; this is called a transparent ciphertext. Such a transparent ciphertext is not considered to be valid because the ciphertext reveals its underlying plaintext to anyone who sees it, even if they don't have the secret key. By default SEAL throws an exception when such a situation is encountered to protect you from a problem you may not have noticed. If you truly know what you are doing and want to enable the creation of transparent ciphertexts, you can configure SEAL [...]. (Laine 2020)

'transparent ciphertexts (a.k.a. ciphertexts whose second polynomial is zero) are malformed and do not need the secret key to decrypt'

Results

- 4.1 Performance / Runtime Benchmarks
- 4.2 Communication Overhead
- 4.3 Accuracy

Conclusion

Notation

 \oplus exclusive-or (XOR)

9

Acronyms

AES	Advanced Encryption Standard	(
FHE	Fully Homomorphic Encryption	(
HE	Homomorphic Encryption	6
ML	Machine Learning	8

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