SHE: A Fast and Accurate Deep Neural Network for Encrypted Data

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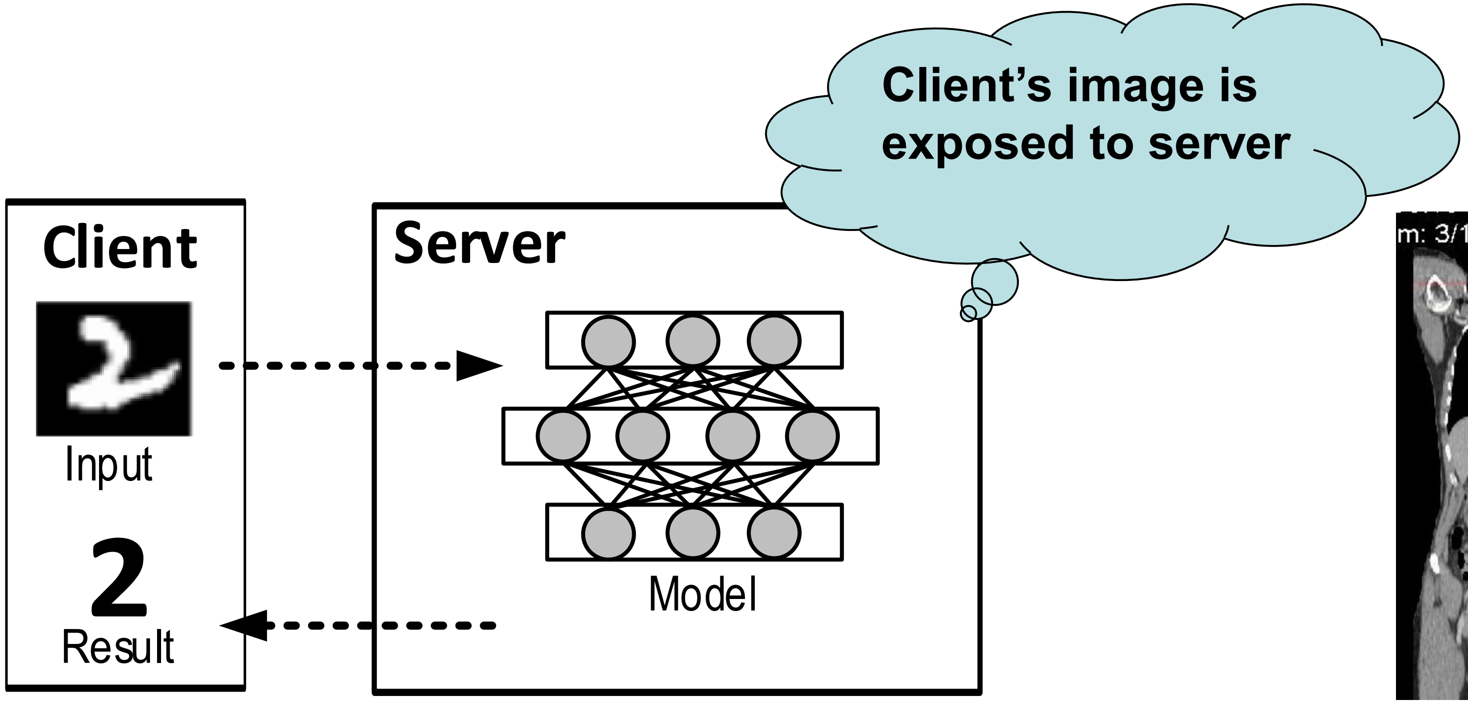
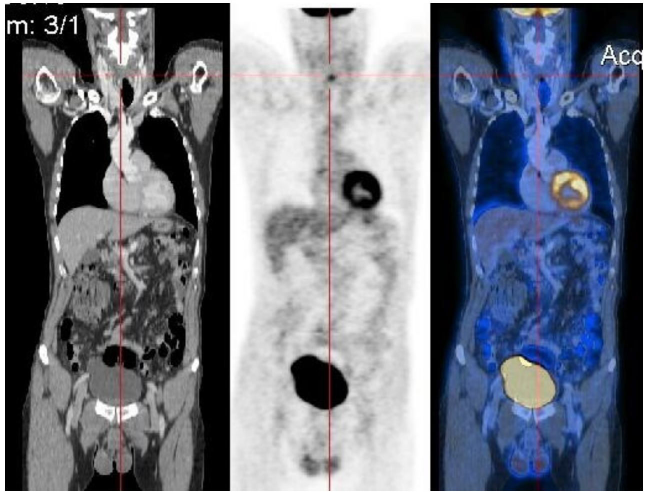
Outline

1. MLaaS and Data Privacy
2. Secure MLaaS
3. Our work
4. Conclusion

Machine Learning as a Service(MLaaS)



MLaaS



Private data

MLaaS needs to protect client's data privacy

Homomorphic Encryption

- Homomorphism
  - Addictive homomorphism: F(a+b)=F(a)+F(b)
  - Multiplicative homomorphism: F(a*b)=F(a)*F(b)
- Homomorphic Encryption: let **F()** is an encryption **Enc()**
  - Addition on ciphertext:
    Enc(a+b)=Enc(a)+Enc(b)
  - Multiplication on ciphertext:

    Enc(a*b)=Enc(a)*Enc(b)

Secure addition example

Task : Server helps client compute (15=5+10) but server dose not know the number 5 and 10.

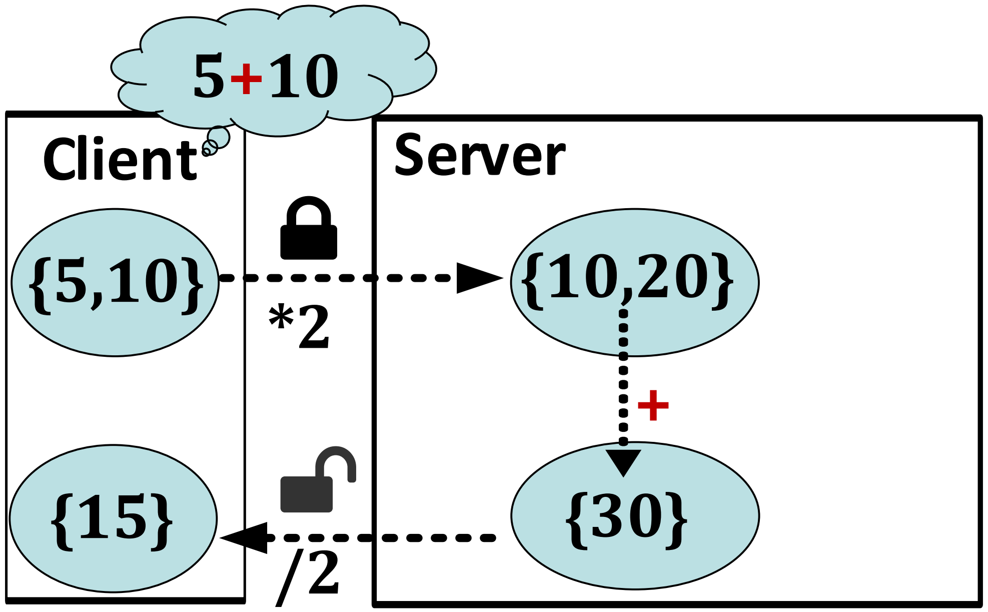
Solution: addition on ciphertext:

Let encryption function Enc(x)=2*x; decryption function Dec(x)=x/2;

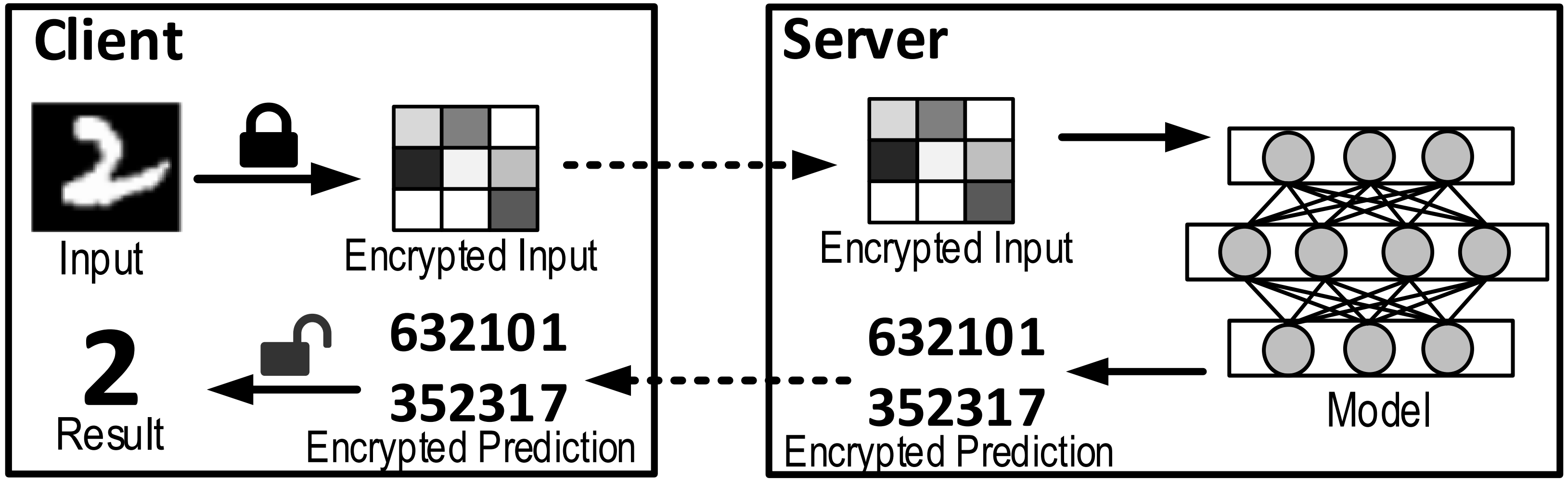
1. Encryption: Enc(5)=10; Enc(10)=20.

2. Addition:
   Enc(5+10)=Enc(5)+Enc(10) =30;

3. Decryption:
   Dec(Enc(5+10))=30/2=15



HE enables secure MLaaS



Secure MLaaS

- 1. Encrypts input
- 2. Uploads encrypted input
- 3. Performs inference on encrypted data
- 4. Downloads encrypted prediction
- 5. Decrypts encrypted prediction

Problems

- HE only supports linear operations
  - **Addictive homomorphism** ($F(a+b)=F(a)+F(b)$)
  - **Multiplicative homomorphism** ($F(a*b)=F(a)*F(b)$)

- Deep Neural Network (DNN)
  - **Linear operations** (Convolution Layer, Dense Layer)
  - **Non-linear Operations** (Activation functions, Max Pooling)

How to process non-linear operations?

- Previous works: Polynomial approximation

  - **ReLU:** $Y = \max(x,0) \approx x^2 \approx 0.125x^2+0.25x+0.5$

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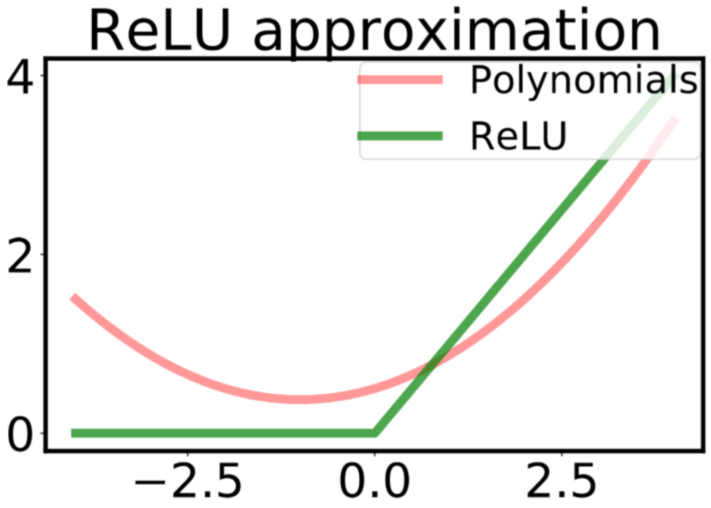
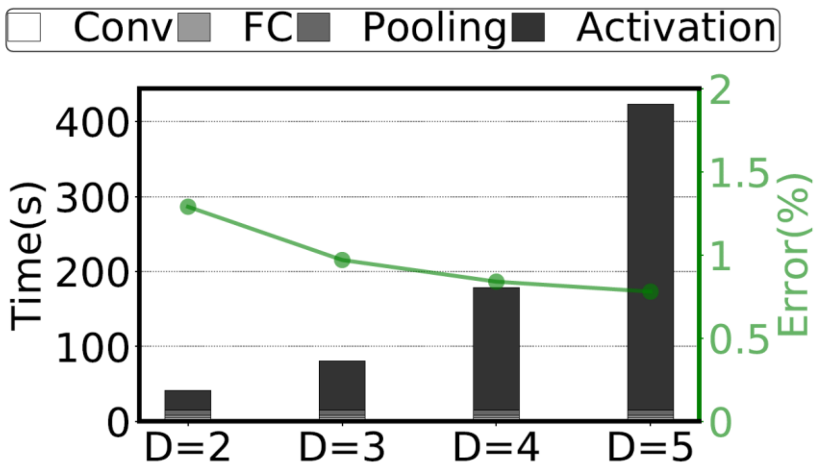
Motivation



1. Inaccurate approximation



2. Various-degrees approximation

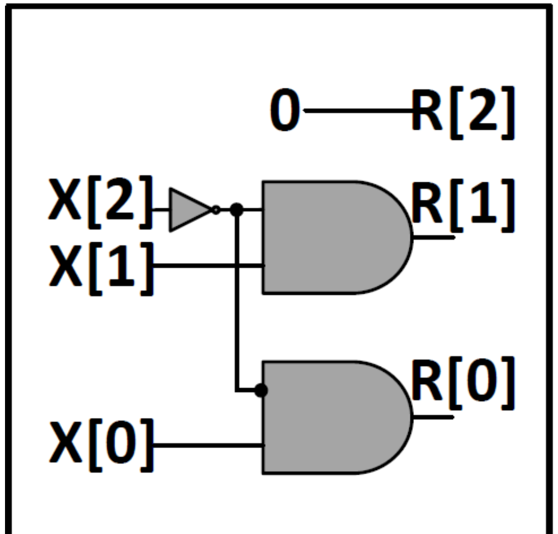
Executive summary

- **Need**: Fast and accurate deep Learning over encrypted data
- **Opportunities** to improve privacy-preserving deep learning by the co-design of Homomorphic Encryption scheme and neural network optimization:
  - Binary bits-operations-friendly TFHE encryption scheme
  - Shift-Accumulation based quantization for neural network
- **Problem**: Previous works stacked **multiple** & **inaccurate** ReLU activation and max pooling layers (Polynomials approximation):

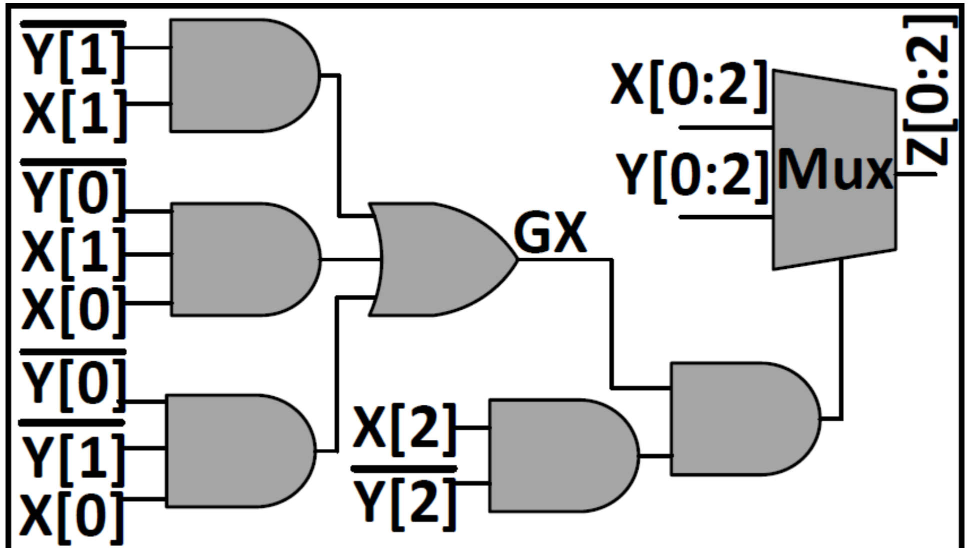
  Accuracy ↓ & overhead ↑ & shallow networks topology
- **Key Idea**: Directly implementing ReLU and max using TFHE [1]; Using cheap Shift-Accumulation to support deeper neural networks other than acceleration.
- **SHE**: Accuracy-lossless CNN, performance ↑76.12%, the first to support modern deep learning like AlexNet on ImageNet.

Our work SHE

- **SHE**
  - Supports **accuracy-lossless** ReLU and Max → **Accurate**
  - TFHE scheme



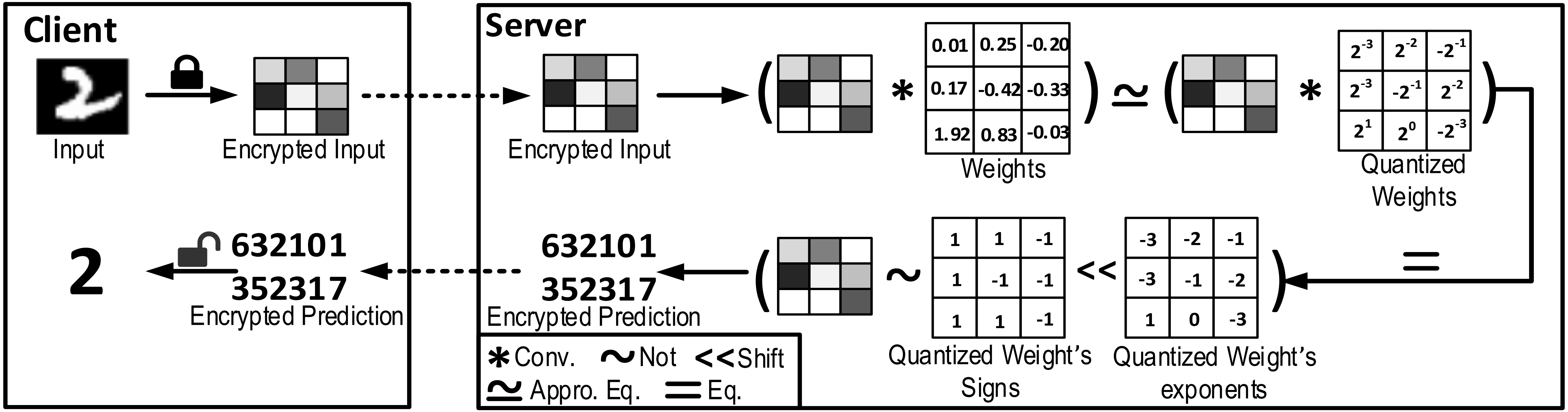
3-bit ReLU

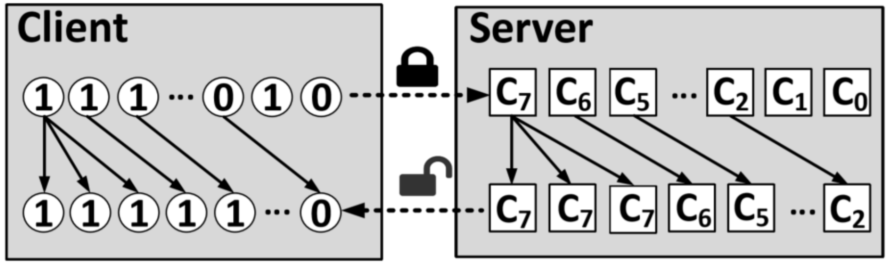


3-bit Max

Our work SHE

- **SHE**
  - Logarithmic Quantization: Convolution to Shift-Accumulation → **Fast**





Very Cheap shift operations

Thank you!