HE-MAN
Homomorphically Encrypted MAchine learning with oNnx models

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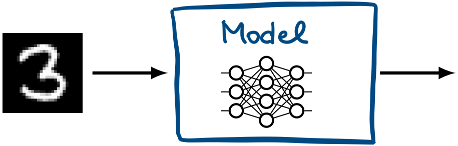
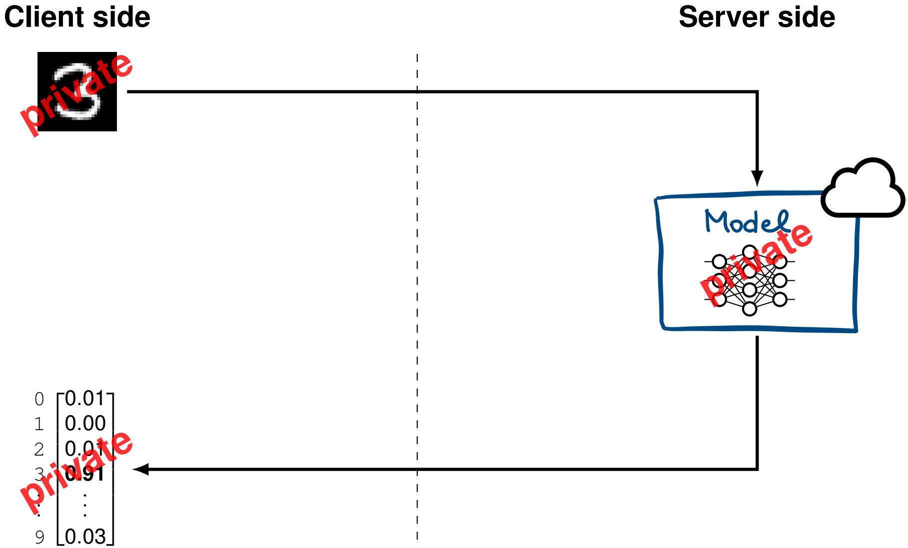
Machine Learning Services

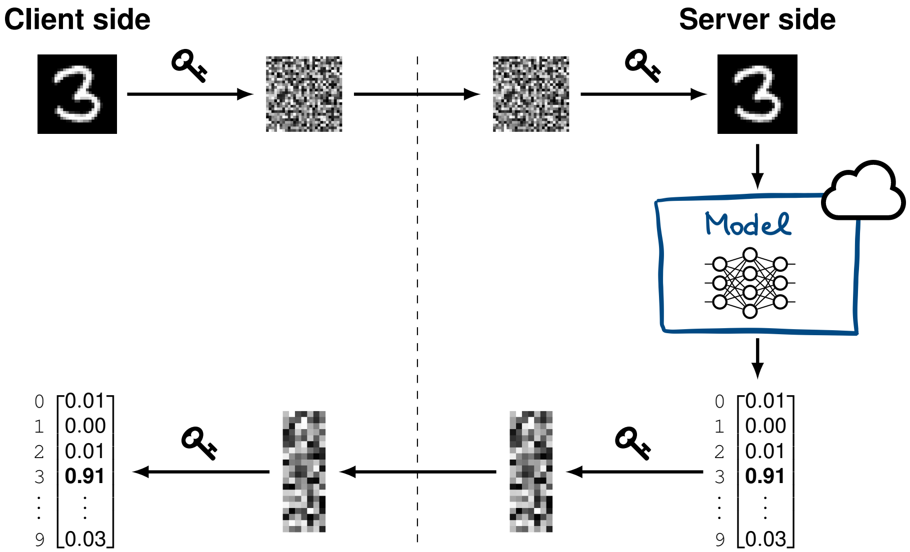


$$\begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \end{array} \begin{bmatrix} 0.01 \\ 0.00 \\ 0.01 \\ \mathbf{0.91} \\ 0.00 \\ 0.02 \\ 0.01 \\ 0.00 \\ 0.01 \\ 0.03 \end{bmatrix}$$

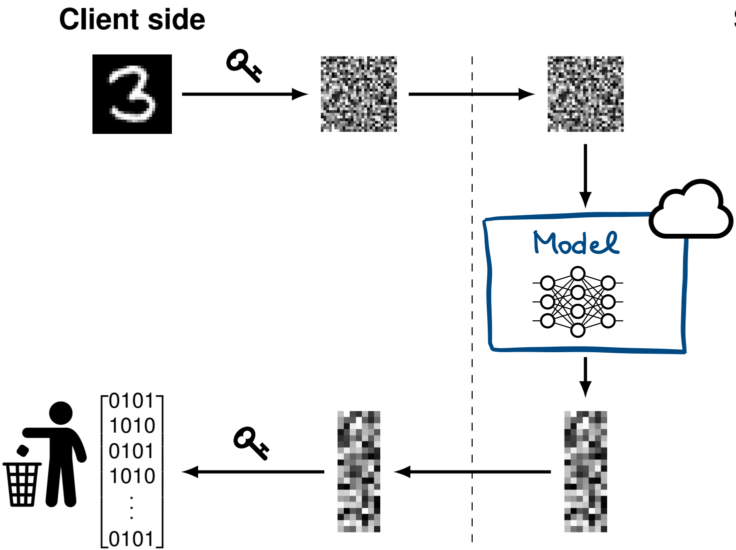
Machine Learning Services



Classical Cryptosystems



Classical Cryptosystems



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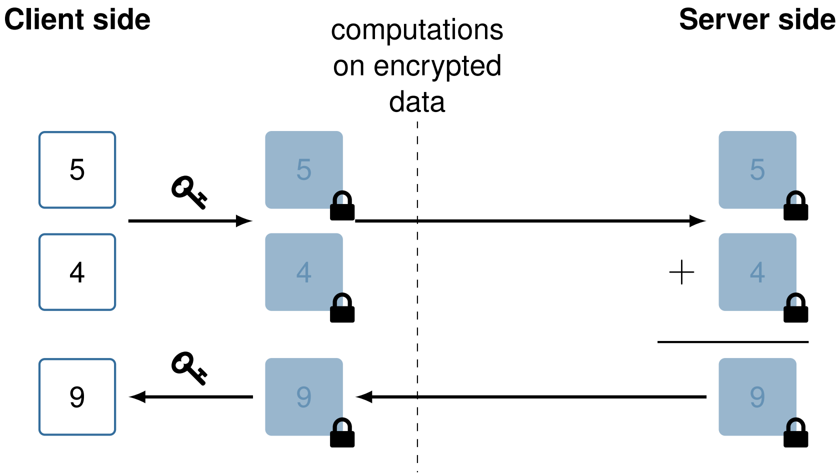
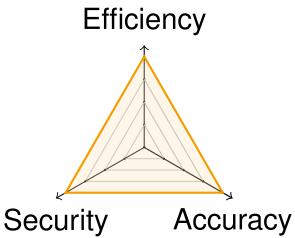
Fully Homomorphic Encryption (FHE)

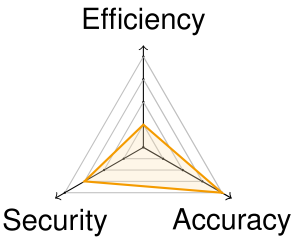


- $+$ <u>and</u> $\times \Rightarrow$ **Fully** Homomorphic Encryption (FHE)

Fully Homomorphic Encryption (FHE)



Ideal World

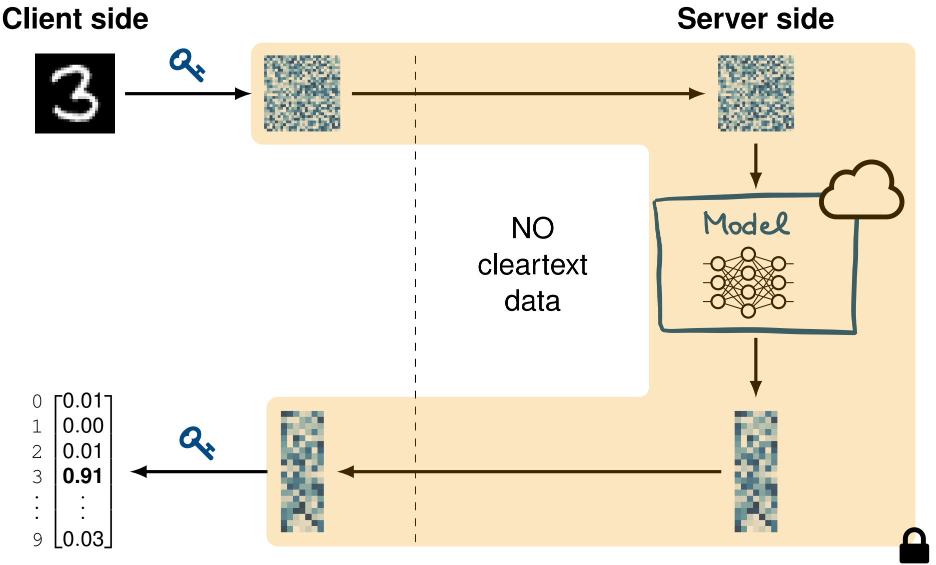


Real World

Further challenges:

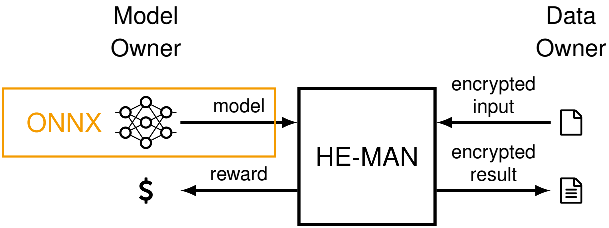
- FHE operations are orders of magnitude more complex
- Only additions and multiplications of ciphertexts are possible

Fully Homomorphic Encryption (FHE)



HE-MAN

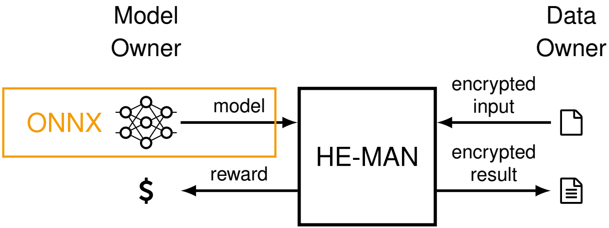
High-level architecture



Previous work

- FHE-implementation of specific NNs [BGBE19]
- Individual ML framework support: TensorFlow [RRK+20], PyTorch [KVH+21]

HE-MAN
High-level architecture



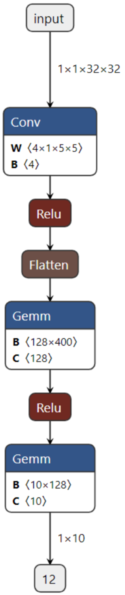
Why ONNX?

- Format definition
- Framework independence
- Broad language support

ONNX in HE-MAN

So far implemented

- AddOperator
- AveragePoolOperator
- ConstantOperator
- ConvOperator
- FlattenOperator
- GemmOperator
- MatMulOperator
- MulOperator
- PadOperator
- ReluOperator
- ReshapeOperator
- SubOperator



Evaluation

- Performance
  - Classification accuracy
  - Latency
- Handwritten digit classification
  - MNIST

- Face recognition
  - LFW (Labeled Faces in the Wild)

Results

Dataset	baseline	HE-MAN-Concrete		HE-MAN-TenSEAL	
Network	accuracy	accuracy	latency	accuracy	latency
MNIST					
CryptoNets	**.975**	**.968**	279 s	.924	8 s
LeNet-5	**.991**	**.984**	1672 s	.789	237 s
LFW					
MobileFaceNets (classifier)	**.990**	.970	69 s	**.972**	208 s

Key Result: accuracy on par with plaintext result, at increased runtime

Conclusion

HE-MAN

- Neural network inference on homomorphically encrypted data
- Preserves privacy of model and data
- Accuracies close to cleartext results
- Broad model support via ONNX format

Future work:

- Full ONNX operator set implementation

Thank you!

https://github.com/smile-ffg/he-man-concrete

https://github.com/smile-ffg/he-man-tenseal

Paper:

https://arxiv.org/abs/2302.08260

References I

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Low latency privacy preserving inference.
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[KVH+21] Brian Knott, Shobha Venkataraman, Awni Hannun, Shubho Sengupta, Mark Ibrahim, and Laurens van der Maaten.
Crypten: Secure multi-party computation meets machine learning.
In M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan, editors, *Advances in Neural Information Processing Systems*, volume 34, pages 4961–4973. Curran Associates, Inc., 2021.

[RRK+20] Deevashwer Rathee, Mayank Rathee, Nishant Kumar, Nishanth Chandran, Divya Gupta, Aseem Rastogi, and Rahul Sharma.
Cryptflow2: Practical 2-party secure inference.
In *Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security*, CCS '20, page 325–342, New York, NY, USA, 2020. Association for Computing Machinery.

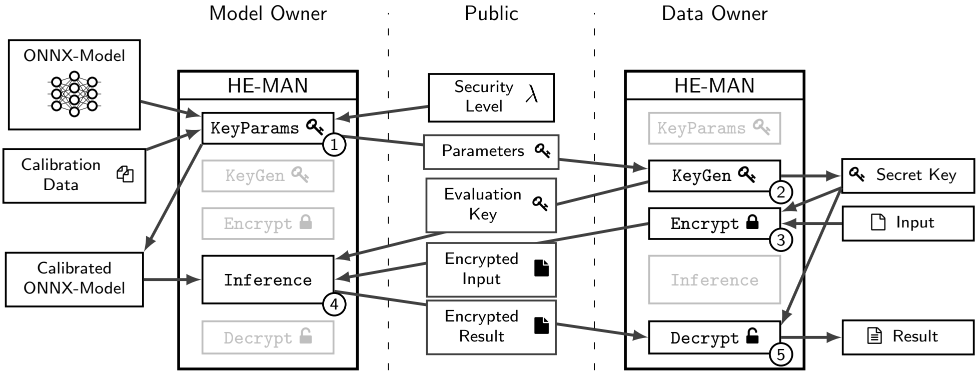
RSA

Encrypt: $c = m^e \mod N$

$$\prod_i c_i = \prod_i m_i^e = \left(\prod_i m_i\right)^e \mod N$$

$$\sum_i c_i = \sum_i m_i^e \neq \left(\sum_i m_i\right)^e \mod N$$

HE-MAN Architecture



Crypto Parameters in FHE

TenSEAL

		$\log_2 q$		
N	$\log_2 N$	$\lambda = 128$	$\lambda = 192$	$\lambda = 256$
2048	11	54	37	29
4096	12	109	75	58
8192	13	218	152	118
16384	14	438	300	237
32768	15	881	600	476