A Generic Hybrid 2PC Framework with Application to Private Inference of Unmodified Neural Networks (Extended Abstract)

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Overview

Introduction

Secure Two-Party Computation (2PC)

- compute functionalities $f(x_1, x_2) = (y_1, y_2)$ among distrusting parties
- each party P_i learns only their own input and output.

Example: *Private Inference* for Image Classification

- service provider's trained model and client's image stay private
- only client learns classification result

Our Contributions

Generic 2PC

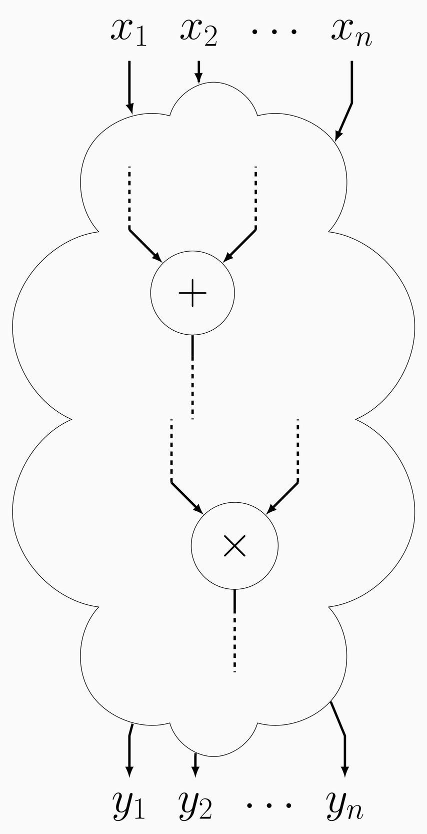
- first 2PC framework with *five different protocols* and *all conversions*
- new protocol *optimization* and conversions
- integration into the recent MOTION [BDST20] framework

Private Inference for Neural Networks

- using *standard MPC techniques* without modifying the networks
- implement common operations as specialized building blocks
- with performance
  - better than using generic 2PC protocols for circuits
  - comparable to recent, highly optimized works
- support for the *Open Neural Network Exchange (ONNX)* file format
  $\Longrightarrow$ *interoperability with deep learning frameworks used in industry*

Five Generic 2PC Protocols

- to evaluate Boolean and arithmetic circuits with semi-honest security
- $\langle x\rangle^S = (\langle x\rangle_1^S, \langle x\rangle_2^S)$ denotes a sharing of value x with protocol S



Yao's Garbled Circuits – Y

- with FreeXOR and Half-Gates optimizations
- $\langle x\rangle^Y = \big((k^0, \Delta), k^0 \oplus x \cdot \Delta\big)$ over $\{0,1\}$

Goldreich-Micali-Wigderson (GMW) – A, B

- $\langle x\rangle^B = (x^1, x^2)$ s. t. $x = x^1 \oplus x^2$ over $\{0,1\}$
- $\langle x\rangle^A = (x^1, x^2)$ s. t. $x = x^1 + x^2$ over $\mathbb{Z}_{2^\ell}$

ABY2.0 [PSSY21] Secret Sharing – α, β

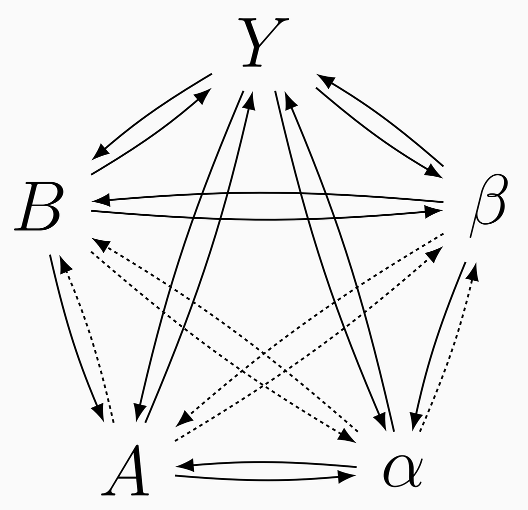
- $\langle x\rangle^\beta = (\Delta_x; \langle \delta_x\rangle^B)$ s. t. $\Delta_x = x \oplus \delta_x$ over $\{0,1\}$
- $\langle x\rangle^\alpha = (\Delta_x; \langle \delta_x\rangle^A)$ s. t. $\Delta_x = x + \delta_x$ over $\mathbb{Z}_{2^\ell}$

Auxiliary Protocols and Preprocessing

- based on Oblivious Transfer

Conversion Protocols

Conversions Between All Five Protocols



- change representation of shared values
- evaluation of hybrid circuits combining Boolean and arithmetic components
- 14 direct (⟶), 6 as composition (⋯►)
- based on protocols from ABY [DSZ15], ABY2.0 [PSSY21], and MOTION [BDST20], with improvements

Improvements to ABY [DSZ15] and ABY2.0 [PSSY21]

- security parameter κ, bit length ℓ

$B \to A$: using shared bits

	setup	online	
	comm.	comm.	rounds
ABY	$\ell\kappa$	$\ell^2/2+\ell$	2
this	$\ell\kappa + \ell^2/2$	2ℓ	1

$Y \to A$: *without* online comm.

	setup	online	
	comm.	comm.	rounds
ABY	$\ell\kappa$	$\ell^2/2+\ell$	2
this	$(2\ell-1)\kappa+\ell$	0	0

$\beta \to \alpha$: optimized setup phase

	setup comm.
ABY2.0	$\ell\kappa + \ell^2$
this	$(\ell-1)\kappa + \ell^2/2 - \ell/2$

Optimized setup for mixed products

- $\langle b\cdot n\rangle^A \leftarrow \langle b\rangle^B \cdot \langle n\rangle^A$
- $\langle b\cdot n\rangle^\alpha \leftarrow \langle b\rangle^\beta \cdot \langle n\rangle^\alpha$
- $\langle b_1\cdot b_2\rangle^\alpha \leftarrow \langle b_1\rangle^\beta \cdot \langle b_2\rangle^\beta$

ABY [DSZ15] vs. ABY2.0 [PSSY21]

Multiplications / ANDs / Matrix Products / Convolutions

Online Communication

- GMW: linear in *input* size
- ABY2.0: linear in *output* size

Setup Phase

- GMW: batched generation of Beaver triples $(\langle a\rangle^A, \langle b\rangle^A, \langle a\cdot b\rangle^A)$
- ABY2.0: function-dependent setup $\Longrightarrow$ SIMD even more important

Conversions

- newer conversions improve on original ABY [DSZ15] protocols
- ABY: $A/B \to Y$: 2 rounds, $Y \to A/B$: no communication
- ABY2.0: $\alpha/\beta \leftrightarrow Y$: both 1 round

$\Longrightarrow$ same overall round complexity when alternating A/α and Y

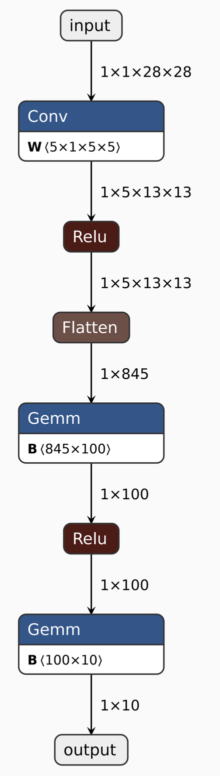
Neural Networks

- many batched operations $\Longrightarrow$ reduces disadvantage of ABY2.0 setup
- ABY2.0 clearly better for ReLU

Neural Network Building Blocks

Idea

- exploit high-level structure of networks, and do not compile to circuits
- use generic protocols, but implement them in a optimized way
- do not change the networks' architectures



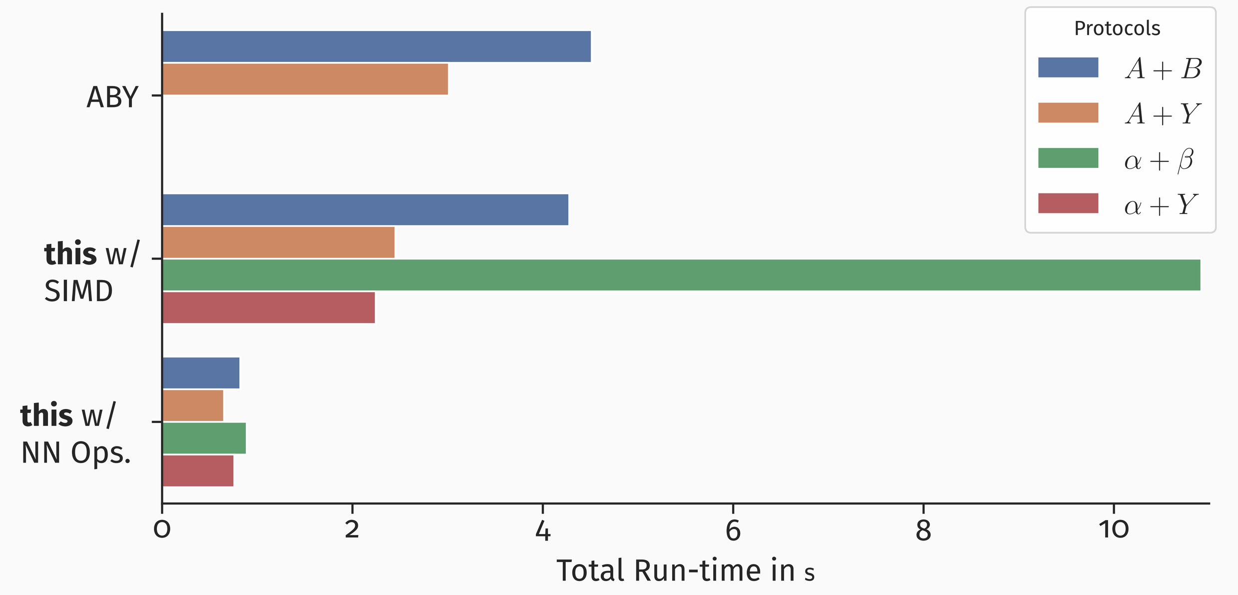
Currently Supported Tensor Operations

- fixed-point arithmetic with truncation by [MZ17]
- fully-connected and convolutional layers (A/α)
- ReLU (multiple variants $Y/B/\beta/A+B/\alpha+\beta$)
- MaxPool (using optimized circuits $Y/B/\beta$)
- AveragePool (A/α)

Neural Network Benchmarks

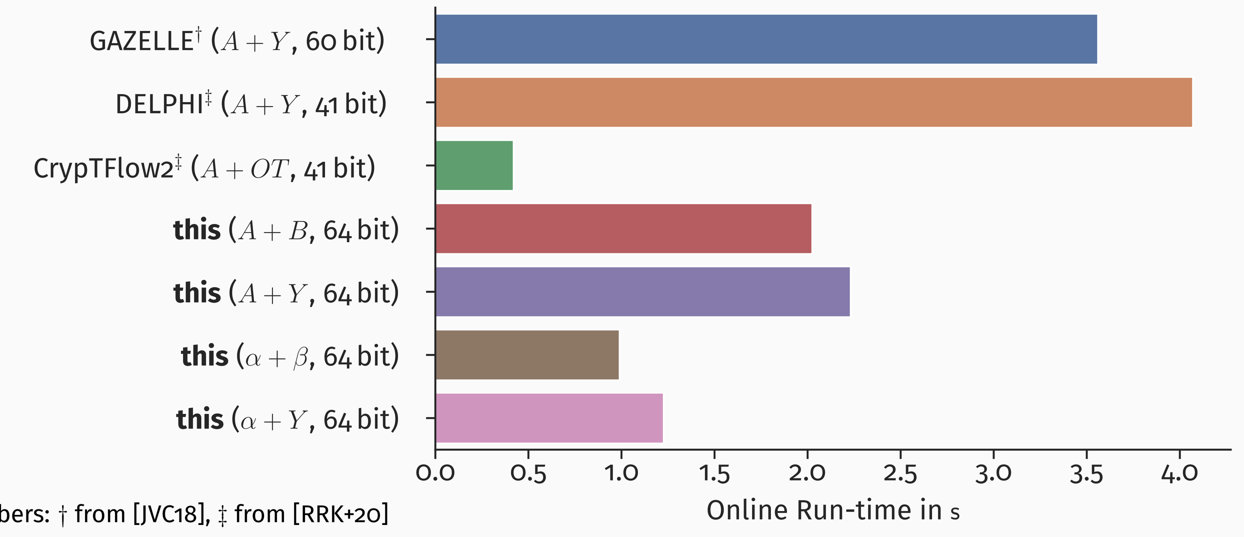
Small Network: MiniONN MNIST [LJLA17]

Neural Network Building Blocks vs. Generic 2PC for Hybrid Circuits



Larger Network: MiniONN CIFAR-10 [LJLA17]

Comparison with Prior and Concurrent Work [JVC18; MLS+20; RRK+20]



Numbers: † from [JVC18], ‡ from [RRK+20]

Extending the MOTION Framework ⇒ MOTION2NX

Extending and Improving the Framework

- implementation of the five generic 2PC protocols and conversions
- architectural improvements to increase flexibility and performance
  - cleaner interfaces, decoupled components
  - new system for asynchronous communication
  - executors allow for different execution strategies
- single instruction multiple data (SIMD) operations
- automatic collection of run-time statistics and metadata
- support for HyCC-generated [BDK+18] hybrid circuits

Support for Neural Networks

- secure tensor data types
- neural network building blocks
- parallelized tensor operations
- ONNX support for interoperability with PyTorch, TensorFlow, etc.

Open Source under an MIT License

- available on GitHub: `https://encrypto.de/code/MOTION2NX`

More Information

Extended Abstract

`https://encrypto.de/papers/BCS21PriMLNeurIPS.pdf`

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