

garbled neural networks are practical

...according to

marshall ball

columbia university

brent carmer

galois inc

tal malkin

columbia university

mike rosulek

oregon state university

nichole schimanski

galois inc

private classifier



ML classification as service

usually only **weights** are private
black-box reconstruction of weights!

private classifier

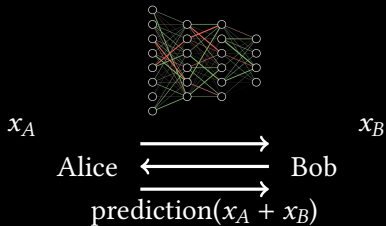


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vs.

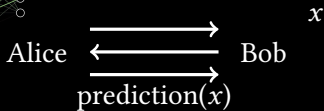
public classifier



e.g., spam filtering on secret shared data

less to hide \implies (potentially) cheaper

private classifier

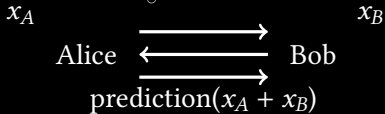
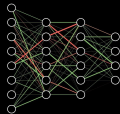


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In this work: **both**

FHE

- + low communication
- + low round complexity
- high computation
- low-depth only

secret-sharing

- + low communication
- high round complexity

garbled circuits

- + low round complexity
- + good for boolean
- bad for arithmetic

FHE

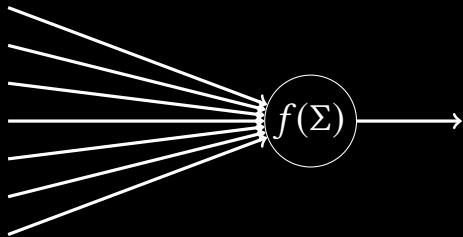
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conventional wisdom:

NN are mostly arithmetic operations \implies GC is a bad fit

outline of this work

Garbling scheme of Ball-Malkin-Rosulek-2016

- ▶ very efficient for arithmetic operations
- ▶ inefficient for comparisons, etc

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Improvements to BMR16 garbling techniques

- ▶ targeting common NN activation functions
- ▶ **approximate** activations \Rightarrow accuracy-efficiency tradeoff

Implementation @ github.com/GaloisInc/fancy-garbling

- ▶ TensorFlow model support

XONN

Sadegh Riazi, Samragh, Chen, Laine, Lauter, Koushanfar

ours

garbled circuit NN evaluation

binarized NN : $\{0, 1\}$ signals

requires retraining

comparable performance

garbled circuit NN evaluation

discretized NN : $\{0, \dots, N\}$ signals

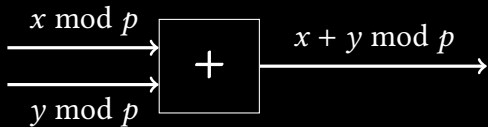
can discretize existing NN

comparable performance

future work \implies combine techniques, retrain NN with smaller discretization

circuit model for Ball-Malkin-Rosulek-16 garbling

free addition:

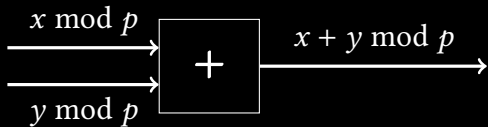


free to garble

(\Rightarrow free multiplication by constant)

circuit model for Ball-Malkin-Rosulek-16 garbling

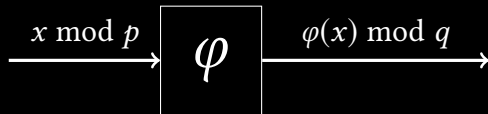
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free to garble

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unary/projection gates:

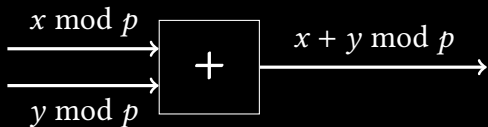


arbitrary $\varphi : \mathbb{Z}_p \rightarrow \mathbb{Z}_q$

cost to garble: $p - 1$ ciphertexts
(moduli should remain small)

circuit model for Ball-Malkin-Rosulek-16 garbling

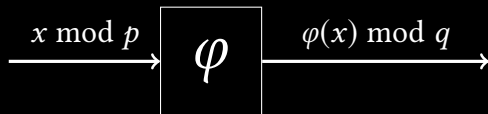
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[BMR16] construct multiplication, high-fan-in boolean, etc from these building blocks

residue representation:

$$[[x]]_{\text{crt}} = \left(x \bmod p_1, x \bmod p_2, \dots, x \bmod p_k \right)$$

addition mod $\prod_i p_i$: free ✓

multiplication mod $\prod_i p_i$: cheap: $O(\sum_i p_i)$ ✓

other things (comparisons, etc): **expensive**

residue representation:

$$\llbracket x \rrbracket_{\text{crt}} = \left(x \bmod p_1, x \bmod p_2, \dots, x \bmod p_k \right)$$

linear combination, public weights: free ✓

linear combination, private weights: cheap: $O(\sum_i p_i)$ ✓

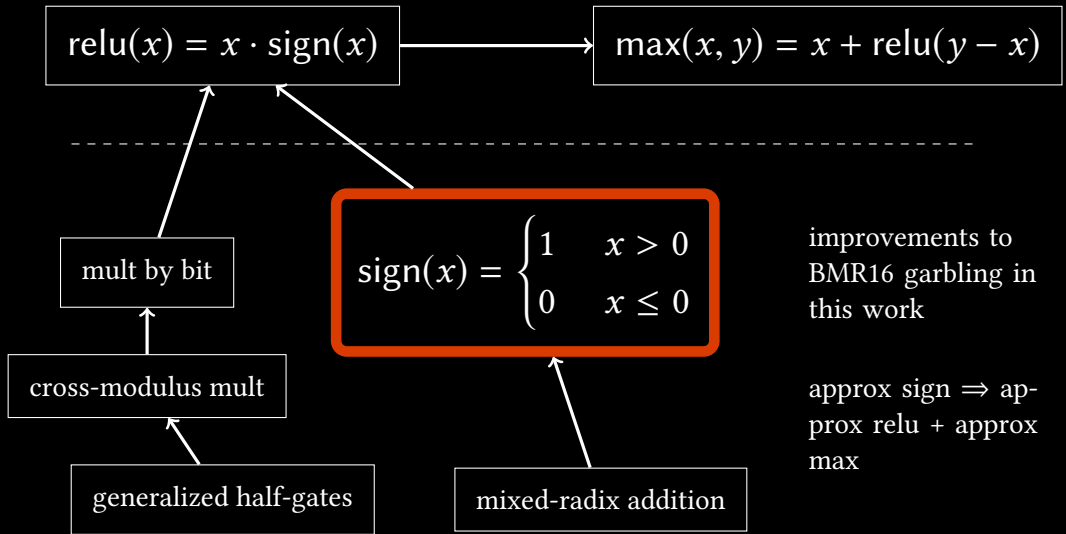
activation function, max-pooling, etc: expensive

$$\text{relu}(x) = x \cdot \text{sign}(x)$$



$$\max(x, y) = x + \text{relu}(y - x)$$

x is in residue representation



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$$[[x]]_{\text{crt}} = \left(\underbrace{x \bmod p_1, \dots, x \bmod p_k}_{x_1} \right)$$

$$\text{sign}(x) = \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases}$$

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our approach:

approximate fractions inside Σ

add fractions (ignore integer part)

check whether result $> 1/2$

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★ (non-free) binary adder circuit

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choice of “fixed-pt resolution”
affects **cost & accuracy**

# primes	$\prod_i p_i$	fixed-point resolution	correct	cost
7	$2^{19.0}$	$108360 = 86 \cdot 7 \cdot 6^2 \cdot 5$	$= 100\%$	637
		$10560 = 88 \cdot 6 \cdot 5 \cdot 4$	$\geq 99.99\%$	470
		$1200 = 60 \cdot 5 \cdot 4$	$\geq 99.9\%$	315
8	$2^{23.2}$	$1975680 = 98 \cdot 9 \cdot 8^2 \cdot 7 \cdot 5$	$= 100\%$	1078
		$107100 = 102 \cdot 7 \cdot 6 \cdot 5^2$	$\geq 99.999\%$	770
		$10920 = 78 \cdot 7 \cdot 5 \cdot 4$	$\geq 99.99\%$	574
		$1170 = 78 \cdot 5 \cdot 3$	$\geq 99.9\%$	385
9	$2^{27.7}$	$31933300 = 76 \cdot 7^5 \cdot 5^2$	$= 100\%$	1534
		$119700 = 114 \cdot 7 \cdot 6 \cdot 5^2$	$\geq 99.999\%$	933
		$12600 = 84 \cdot 6 \cdot 5^2$	$\geq 99.99\%$	696
		$1260 = 140 \cdot 9$	$\geq 99.9\%$	465
10	$2^{32.6}$	$791920800 = 202 \cdot 11^2 \cdot 6^4 \cdot 5^2$	$= 100\%$	2294
		$128520 = 102 \cdot 7 \cdot 6^2 \cdot 5$	$\geq 99.999\%$	1122
		$13440 = 112 \cdot 6 \cdot 5 \cdot 4$	$\geq 99.99\%$	843
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99.99% accuracy @ 33-50% cost

	weights	time (s)	comm (MB)	accuracy (%)
boolean garbling	private	>300	3407	96.8
ours	private	1.98	128	96.8

MNIST-A (128+128+10 neurons) @ 22-bit discretization

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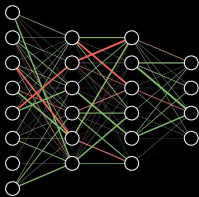
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ours (99.99% activation)	public	0.10	2.77	95.7
SecureML	private	4.88	-	93.1
MiniONN	private	1.04	47.6	97.6
Gazelle	private	0.03	0.5	-
XONN	private	0.13	4.29	97.6

MNIST-A (128+128+10 neurons) @ 22-bit discretization



garbled circuits are better than you thought

for arithmetic computations, NNs
... especially for NNs with public weights

approximate activation functions are great!

ia.cr/2019/338

github.com/GaloisInc/fancy-garbling