Multi-Party Replicated Secret Sharing over a Ring with Applications to Privacy-Preserving Machine Learning

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Secure multi-party computation – multiple participants jointly evaluate a function on secret inputs



- No information is disclosed other than the output
- Replaces a trusted third party
- *n* parties with corruption threshold *t*
- Many applications

- Shamir secret sharing over field \mathbb{F}_p
 - Frequent modular reduction
 - Doesn't work over a ring
- Replicated secret sharing (RSS) over ring ${\cal R}$
 - Efficient
 - Easy to conceptualize
 - Good performance-security trade-off
 - Built-in type compatibility (uint32_t and uint64_t)
- Setting: semi-honest, honest majority (t < n/2)

- RSS framework for *n* parties over a ring (arbitrary and \mathbb{Z}_{2^k})
- Quantized neural network optimizations
- Extensive benchmarks against field implementation and state-of-the-art

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- Split x into $\binom{n}{t}$ shares, distribute $\binom{n-1}{t}$ shares per party - e.g. For 5 parties: 10 total shares, 6 per party
- $-[x]_k \implies$ secret shared private value over \mathbb{Z}_{2^k}
- Building blocks can be done over any ring (multiplication, reconstruction, input)
- Random bit generation RandBit [DEF⁺19] vs. edaBit [EGK⁺20]
- Composite protocols (over \mathbb{Z}_{2^k}):
 - $\begin{array}{ll} & [a_{k-1}]_k \leftarrow \mathsf{MSB}([a]_k) & [\mathsf{CDH10}, \mathsf{DEF}^+19] \\ & [a/2^m]_k \leftarrow \mathsf{TruncPr}([a]_k, m) & [\mathsf{DEK20}] \\ & [a]_{k'} \leftarrow \mathsf{Convert}([a]_k, k, k') & [\mathsf{DEF}^+19, \operatorname{BitDec}([a_k])] \end{array}$

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Quantized neural networks

- Neural network, but smaller ($\mathbb{R} \to 8\text{-bit}$ integers)
- Weights, inputs, biases have scales (m) and zero points (z)

$$y = \sum_{i=1}^{N} x_i w_i + b \implies \bar{y} \approx z_3 + \frac{m_1 m_2}{m_3} \cdot \sum_{i=1}^{N} ((\bar{x}_i - z_1) \cdot (\bar{w}_i - z_2) + \bar{b})$$

and "clamp" \bar{y} to $0 \leq \bar{y} \leq 255$

- Certain activation functions can be incorporated into m_3, z_3 for free (e.g. ReLU6)
- [DEK20]'s procedure: fixed-point multiplication, followed by truncation and clamp result

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Problem

Uses k = 72 to accommodate for the 63-bit truncation.

Solution

Fold scales into clamping operation, and compute a much smaller truncation at the end of each layer.

- "Rearranging" terms:

$$0 \leq \left(\bar{y} = \frac{m_3}{m_1 m_2} z_3 + \sum_{i=1}^{N} \left((\bar{x}_i - z_1) \cdot (\bar{w}_i - z_2) + \bar{b} \right) \right) \leq \frac{255 m_3}{m_1 m_2},$$

- Bitlength will grow \implies truncate down to 8 bits.
- Lowers ring size by over a factor of two! $(72\rightarrow30)^{*}$
- Updated model parameters can be distributed by the model owner
- No impact on accuracy

^{*}Theoretically can be lowered further

Summary of results

 RSS offers compelling advantages over field-based equivalents for 3, 5, 7 parties (10-33× improvement)



Multi-Party RSS over a Ring

Summary of results

 On-par performance with 3PC ring frameworks in (quantized) neural network applications (MobileNets)

		Ours				MP-SPDZ Z _{2^k} , [DEK20]			
	α	0.25	0.5	0.75	1.0	0.25	0.5	0.75	1.0
ρ	128	3.19	6.47	9.92	13.3	3.19	6.26	9.88	14.0
	160	4.94	10.0	15.1	20.7	4.15	8.17	13.6	19.3
	192	7.17	14.3	22.0	29.7	5.00	11.0	17.8	26.7
	224	9.71	19.9	30.0	40.9	6.57	14.1	23.1	34.9

Table: 3PC quantized MobileNets

- Future work:
 - Integration to the PICCO compiler [ZSB13]
 - Floating point compatibility [RBS⁺22, ABZS13]

Thank you!

Questions?

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Image: A matrix

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References



M. Aliasgari, M. Blanton, Y. Zhang, and A. Steele.

Secure computation on floating point numbers.

In Network and Distributed System Security Symposium (NDSS), 2013.

O. Catrina and S. De Hoogh.

Improved primitives for secure multiparty integer computation.

In International Conference on Security and Cryptography for Networks (SCN), pages 182–199, 2010.

I. Damgård, D. Escudero, T. Frederiksen, M. Keller, P. Scholl, and N. Volgushev. New primitives for actively-secure MPC over rings with applications to private machine learning.

In IEEE Symposium on Security and Privacy, pages 1102–1120, 2019.

A. Dalskov, D. Escudero, and M. Keller.

Secure evaluation of quantized neural networks.

Proceedings on Privacy Enhancing Technologies (PoPETs), 2020(4):355–375, 2020.

D. Escudero, S. Ghosh, M. Keller, R. Rachuri, and P. Scholl. Improved primitives for MPC over mixed arithmetic-binary circuits. In *Advances in Cryptology – CRYPTO*, pages 823–852, 2020.

- D. Rathee, A. Bhattacharya, R. Sharma, D. Gupta, N. Chandran, and A. Rastogi.
 SecFloat: Accurate floating-point meets secure 2-party computation.
 In *IEEE Symposium on Security and Privacy*, pages 1553–1553, 2022.
- Y. Zhang, A. Steele, and M. Blanton.

PICCO: A general-purpose compiler for private distributed computation. In ACM Conference on Computer and Communications Security (CCS), pages 813–826, 2013.