

Confidential Truth Finding with Multi-Party Computation

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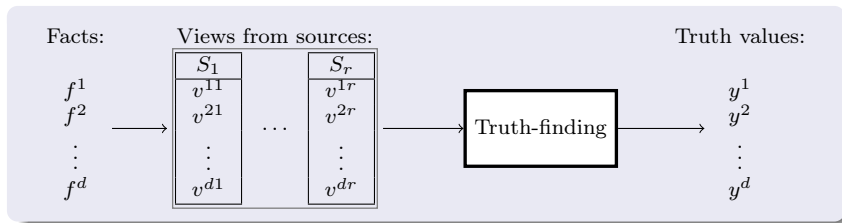
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Truth-finding with Disagreeing Sources

Let f^1, \dots, f^d be facts/queries.

Each of the r sources inputs their view $(v^{ij})_{i=1\dots d, j=1\dots r} \in \{-1, 0, 1\}^{d \times r}$ of each fact.

Truth values $(y^i)_{i \in \{1, \dots, d\}} \in [-1, 1]^d$

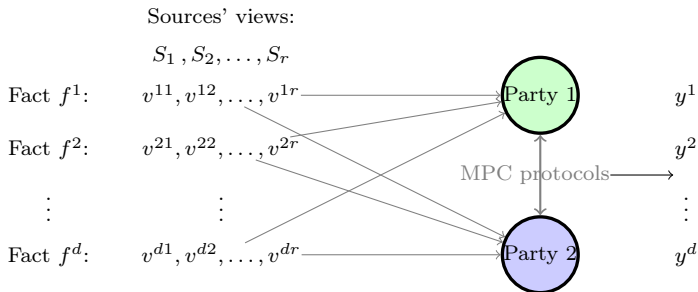


Truth-finding algorithms [YHY08] can be used to complete missing data.

Truth-finding on Confidential Views

Using **MPC** in truth-finding algorithms protects the views of the sources.

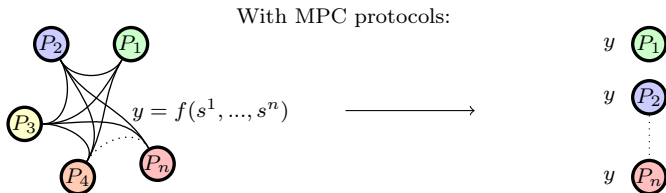
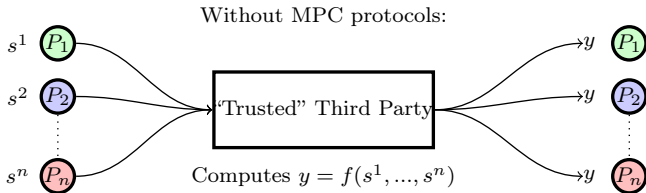
Asking each of the r sources for their view on d facts.



We compute $(y^i)_i \in [-1, 1]^d$ using **MPC** to protect $(v^{ij})_{i,j} \in \{-1, 0, 1\}^{d \times r}$.

Secure Multi-party Computation (MPC)

Let f be a public function.



Two-party Additive Secret-sharing

Let $l \in \mathbb{N}^*$, $\mathbb{Z}/2^l\mathbb{Z}$ a finite ring.

Two-party additive secret-sharing Π_{share} [MGW87]

Input: P_1 holds s^1

- 1 P_1 generates $s_2^1 \xleftarrow{\$} \mathbb{Z}/2^l\mathbb{Z}$
- 2 $s_1^1 \leftarrow s^1 - s_2^1 \pmod{2^l}$
- 3 P_1 sends s_2^1 to P_2

Notation: $[s^1]$ correspond to the shares s_1^1 and s_2^1 of s^1 .

Computing mod 2^l is crucial to keep the shares uniformly distributed in the ring.

Addition protocol

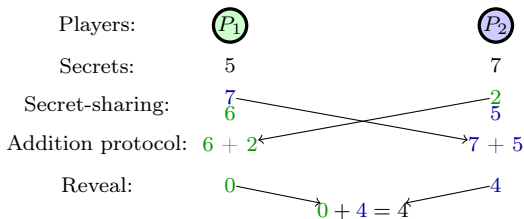
Two-party addition protocol Π_{add}

Input: P_i holds x_i, y_i for i in $\{1, 2\}$

Output: P_i holds z_i for i in $\{1, 2\}$ such that $z_1 + z_2 = x + y$

- 1 P_i computes $z_i \leftarrow x_i + y_i$ for i in $\{1, 2\}$

Example of the sum of two secrets modulo 8:

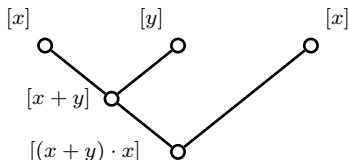


Arithmetic Circuit Evaluation in MPC

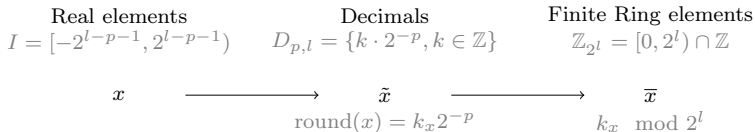
With $(x_1, x_2) \leftarrow [x]$ and $(y_1, y_2) \leftarrow [y]$ we can have:

- $(z_1, z_2) \leftarrow [x + y]$ with an addition protocol
- $(t_1, t_2) \leftarrow [xy]$ with a multiplication protocol [Bea91]

We can privately evaluate the arithmetic circuit of a function
 $f : (x, y) \rightarrow (x + y) \cdot x$:



From Real Elements to Finite Ring Elements [MZ17]



Example for $l = 2, p = 1$:

$I = [-1, 1)$	$D_{1,2} = \{-1, -0.5, 0, 0.5\}$	$\mathbb{Z}/2^2\mathbb{Z} = \{0, 1, 2, 3\}$
-1	$\widetilde{-1} = -1 = -2 \cdot 2^{-1}$	$\overline{-1} = -2 \bmod 2^2 = 2$
-0.5	$\widetilde{-0.5} = -0.5 = -1 \cdot 2^{-1}$	$\overline{-0.5} = -1 \bmod 2^2 = 3$
0.6	$\widetilde{0.6} = 0.5 = 1 \cdot 2^{-1}$	$\overline{0.6} = 1 \bmod 2^2 = 1$

For simplicity, we omit the bar.

Computing Real Functions in the Finite Ring

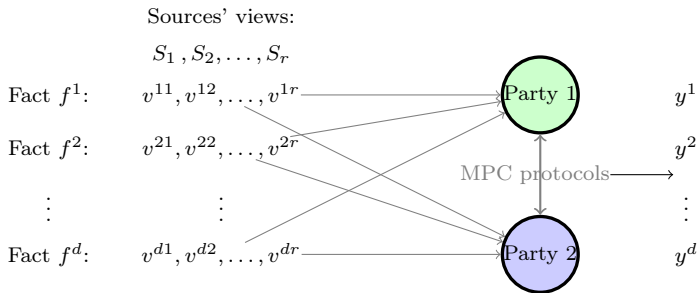
We compute the arithmetic circuits of real functions using Π_{add} and Π_{mult} .

Example: For a positive secret $[x]$ compute $[\frac{1}{x}]$ in MPC [Kno+21].

- 1 Define the function $g(y) = x - \frac{1}{y}$
- 2 Use Newton-Rapshon iterations to find the root x of g because $g(\frac{1}{x}) = 0$
- 3 The sequence is defined as follows: $y_{n+1} = y_n^2 x + 2y_n$

Truth-finding Security Model

- There are d binary facts f^1, \dots, f^d
- For $i \in \{1, \dots, d\}, j \in \{1, \dots, r\}$, source j answers $v^{ij} \in \{-1, 0, 1\}$ to f^i
- A truth-finding algorithm returns a truth value $y^i \in [-1, 1]$ for each fact f^i



A Truth-finding Algorithm: Cosine

Simplified version of Cosine [Gal+10]

Input: The answers $(v^{ij})_{i,j}$ **Output:** The truth values $(y^i)_i$

- 1 Initialize truth values $(y^i) \leftarrow 1$
- 2 For a number of iterations do:
 - 1 For every source j :

$$\theta^j \leftarrow \frac{\sum_{i, v^{ij}=1} y^i - \sum_{i, v^{ij}=-1} y^i}{\sqrt{\left(\sum_{i, v^{ij} \neq 0} v^{ij} \right) \left(\sum_{i, v^{ij} \neq 0} (y^i)^2 \right)}}$$

- 2 For every fact f^j :

$$y^i \leftarrow \frac{\sum_{j, v^{ij}=1} (\theta^j)^3 - \sum_{j, v^{ij}=-1} (\theta^j)^3}{\sum_{j, v^{ij} \neq 0} (\theta^j)^3}$$

Pseudo-equality Test with Polynomial Evaluation

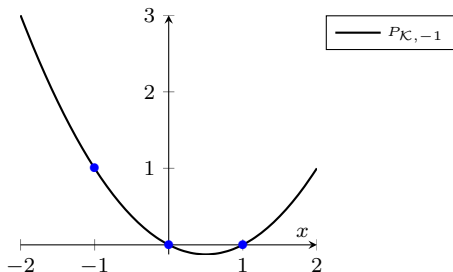
For a secret $[x]$ and a public element k we need:

$$[y] = \Pi_{\text{equal}}([x], k) \text{ with } y = \begin{cases} 1 & \text{if } x = k \\ 0 & \text{otherwise.} \end{cases}$$

For truth-finding algorithms, $k \in \mathcal{K} = \{-1, 0, 1\}$.

A classic equality test could be replaced by a degree-two polynomial $P_{\mathcal{K},k}$.

Examples for $k = -1$, $P_{\mathcal{K},-1}(x) = \frac{1}{2}(x^2 - x)$:



Alternative for the Secure Inverse Algorithm for Negative Values

Secure inverse algorithm [Kno+21]:

For a secret $[x]$

If $x > 0$, the inverse is computed as:

$$[y] = \Pi_{\text{inv}}([x]) \text{ with } y = \frac{1}{x}$$

If $x < 0$, the inverse is computed as:

$$[y] = \Pi_{\text{sign}}([x]) \cdot \Pi_{\text{inv}}(\Pi_{\text{abs}}([x])) \text{ with } y = \frac{\text{sign}(x)}{|x|} = \frac{1}{x}$$

If $x < 0$, we replace the sign computation with two multiplications:

$$[y] = [x] \cdot \Pi_{\text{inv}}([x] \cdot [x]) \text{ with } y = \frac{x}{x^2} = \frac{1}{x}$$

Results on Confidential Truth-finding

Cosine on MNIST
120 facts and 15 sources:

	Non-confidential	MPC with classic inverse	MPC with optimized inverse
Wall time	10^{-4} s	0.47 s	0.44 s
Accuracy	90%	90%	90%

Related solutions:

Reference	Algorithms
[Chi+16; NBK15]	Majority Voting
[Mia+15; Zhe+20; ZDW18]	Conflict Resolution on Heterogeneous Data (CRH) [Li+16]
[SSB23]	Cosine and 3-Estimates [Gal+10]

Conclusion:

Take home message:

Confidential truth-finding could be achieved with secret-sharing-based MPC

Contributions of the paper:

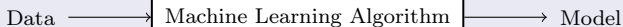
- MPC primitives for functions used in Truth-finding
- Arithmetic MPC protocols for the equality tests on finite sets

Future research:

- Truth-finding with differential privacy
- Truth-finding algorithm that protects the facts

Questions.

Machine Learning and Data



Examples of federated learning:

Data from banks → Fraud detection

Data from social media and eCommerce platforms → Marketing segmentation

Data from cars → Vehicle automation

Federated Learning with Confidential Data

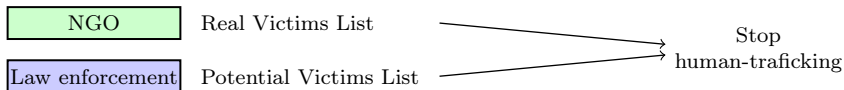
Constraints:

- Data is too confidential to be shared.
- Rules and regulations prevent sharing sensitive data.

Secure Multi-party Computation (MPC) allows computing the model output without revealing any participant's secret data input.

Example of MPC to fight human trafficking by Roseman Labs:

Sensitive data:



Truth Finding

- Truth-finding algorithms aim to know if a statement is correct or not
- They involve collecting sources answers to queries, and analyzing the answers
- These algorithms could be used to complete missing data

Given the answers to d queries from r sources: $(v^{ij})_{i=1\dots r, j=1\dots d}$

The algorithm outputs y^1, \dots, y^d the truth value of each of the d queries.

MPC-friendly Normalization Alternative

For a vector of secrets $([x^1], \dots, [x^n])$ we need:

$$([y^1], \dots, [y^n]) = \Pi_{\text{norm}}([x^1], \dots, [x^n]) \text{ with } y^i = \frac{x^i - \min_i x^i}{\max_i x^i - \min_i x^i}.$$

The goal is to scale the elements of the secret vector to $[0, 1]$ with less communication.

We apply a linear transformation $h(x) = 0.5x + 0.25$ instead of Π_{norm} :

