Pencil: Private and Extensible Collaborative Machine Learning without the Non-Colluding Assumption

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Overview

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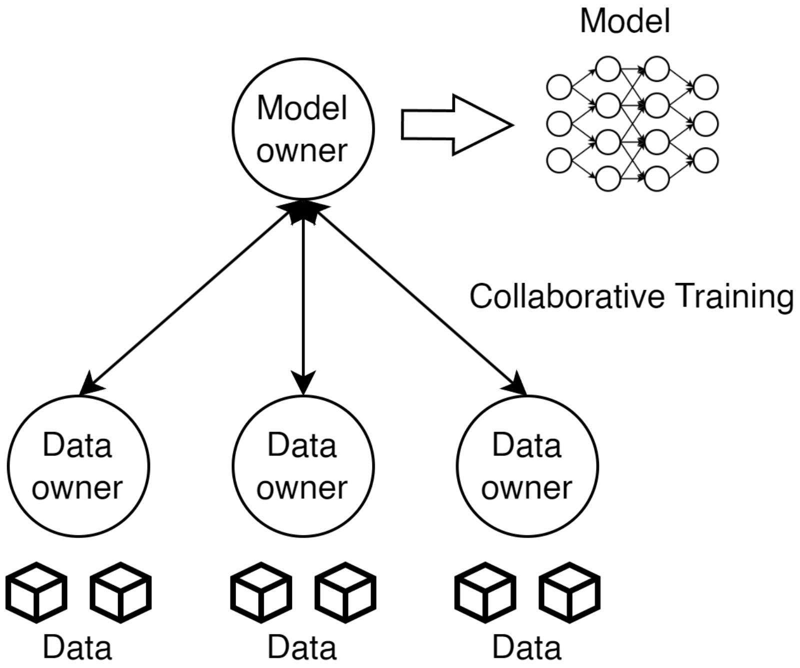
  - A Model Owner (MO) wishes to use the data of multiple Data Owners (DOes) to train a model.



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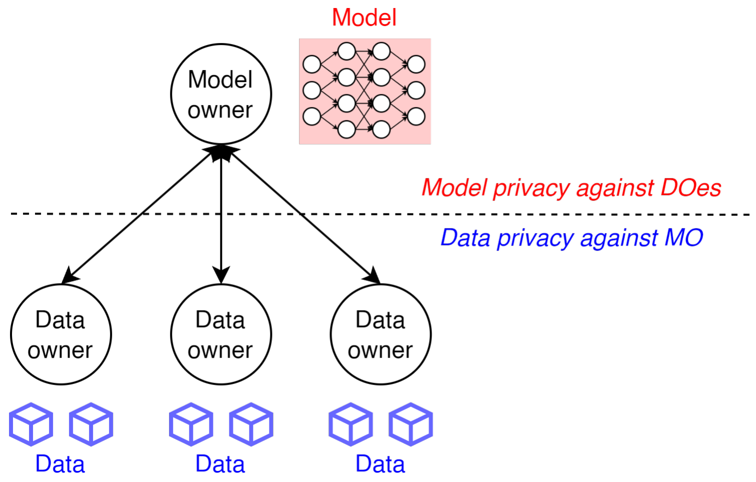

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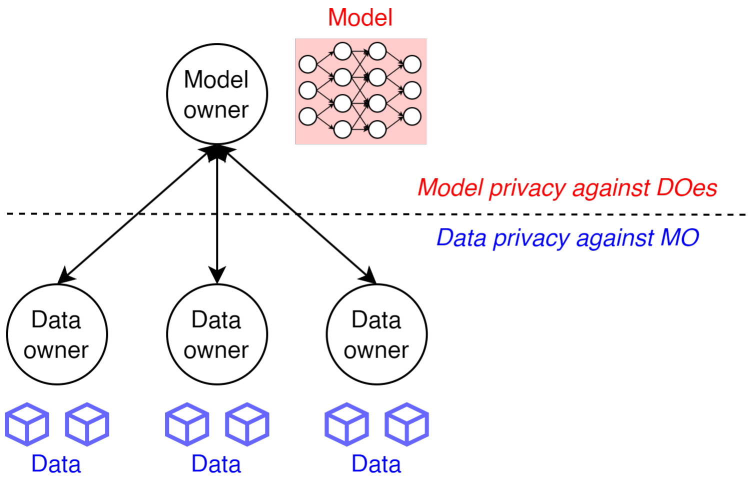

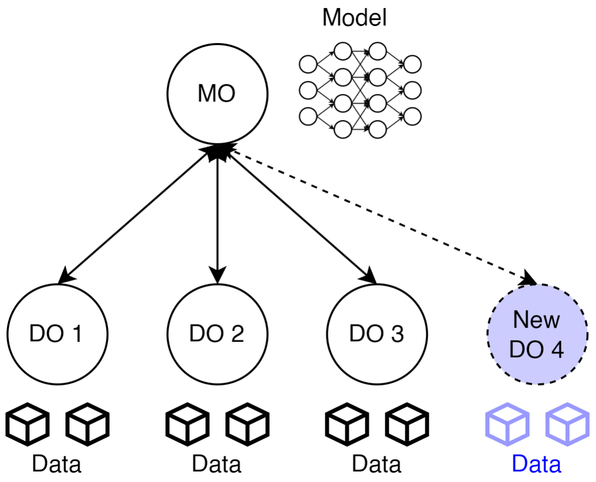

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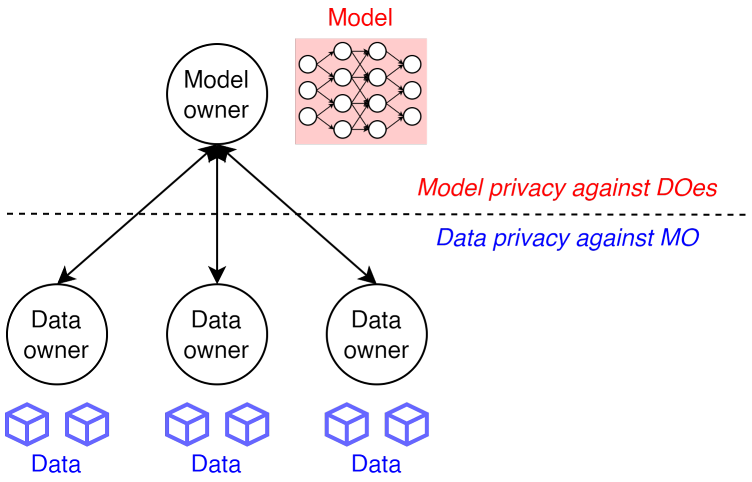
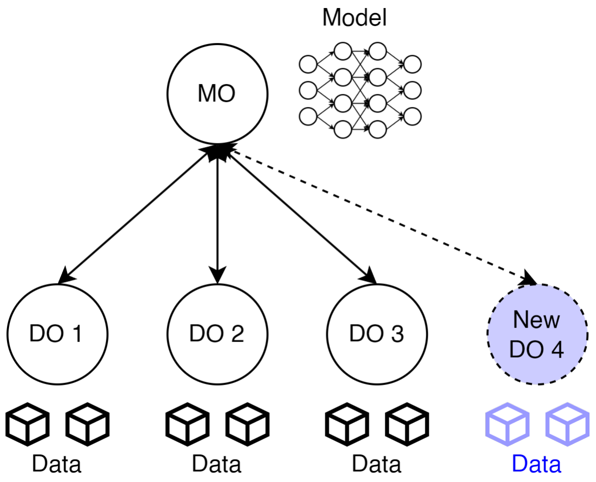
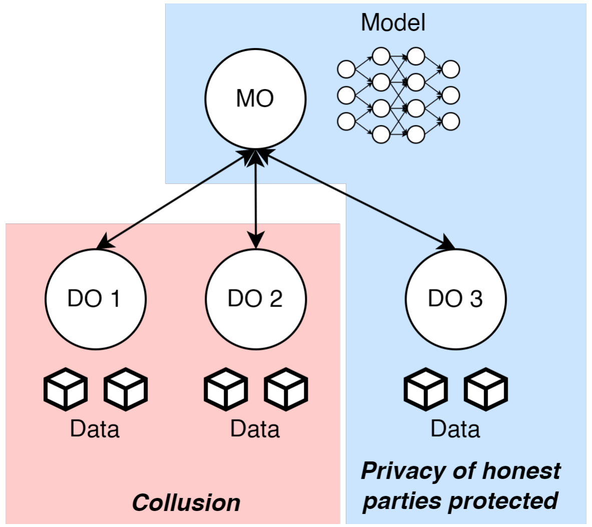
  4) **Against collusion** – Colluding parties should not have advantage to break privacy of other honest parties







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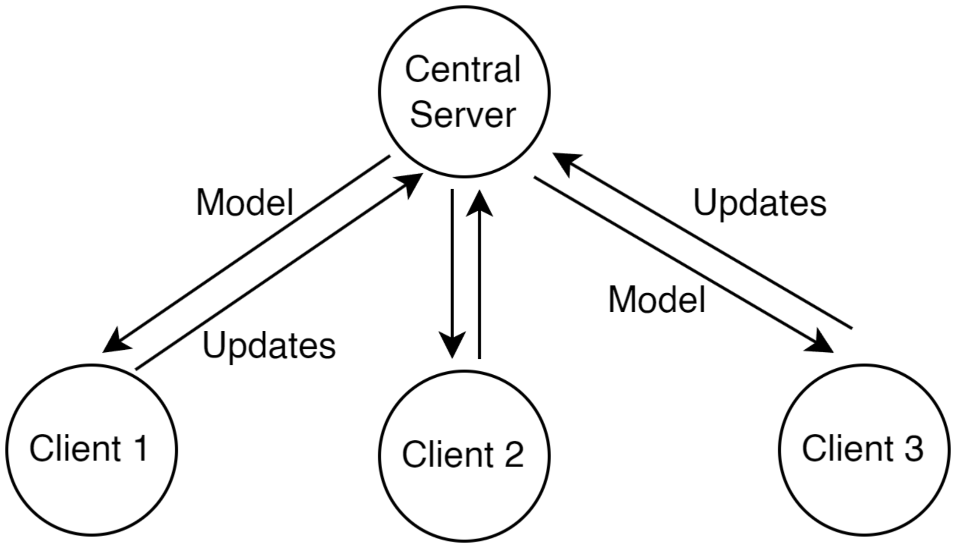
- Federated Learning
  - In every iteration, Server (MO) distributes the model to Clients (DOes).
  - Clients train with local data and upload the updates for aggregation.



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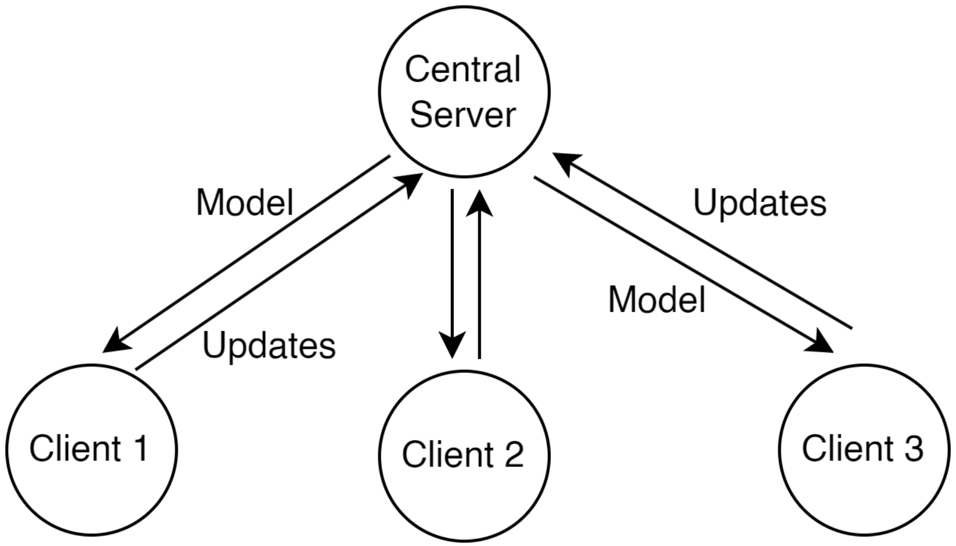

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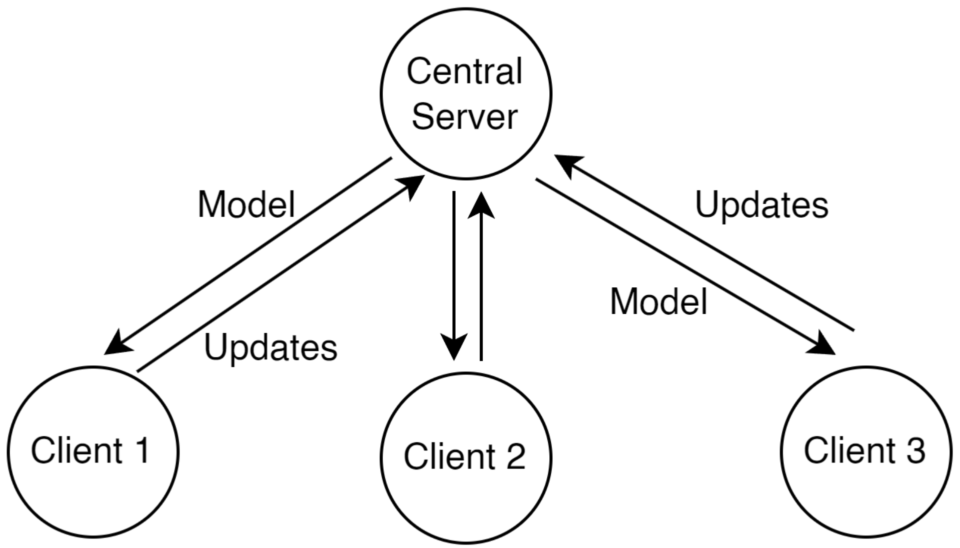

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Cons

- The model privacy isn't protected at all!

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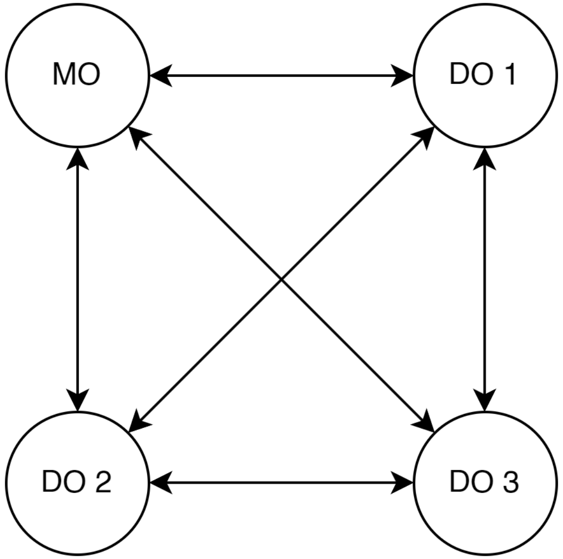
  - MO and DOes participate in n-party computation as servers.



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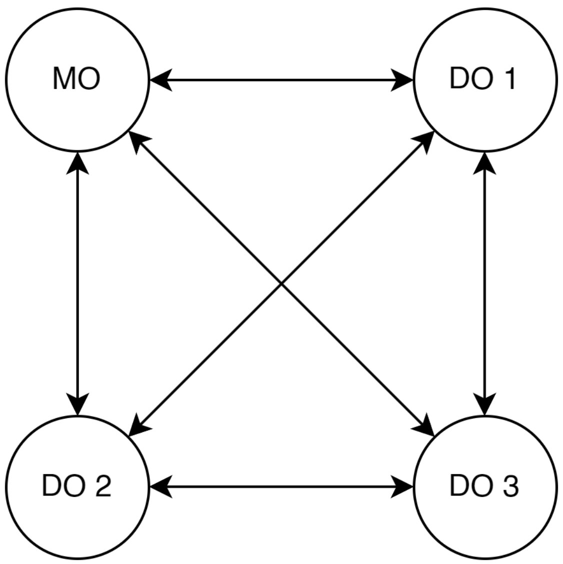

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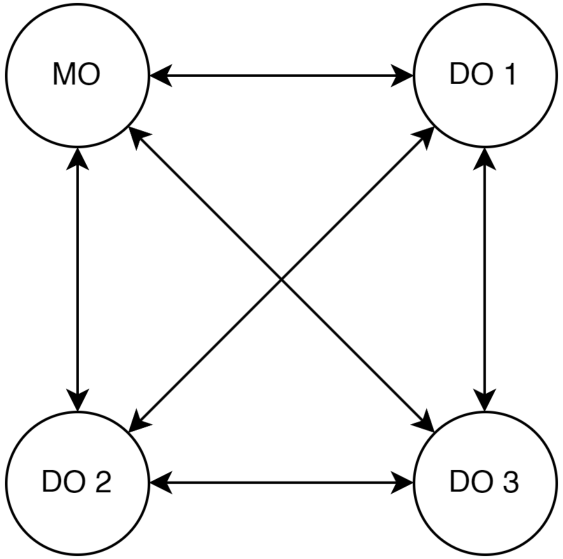

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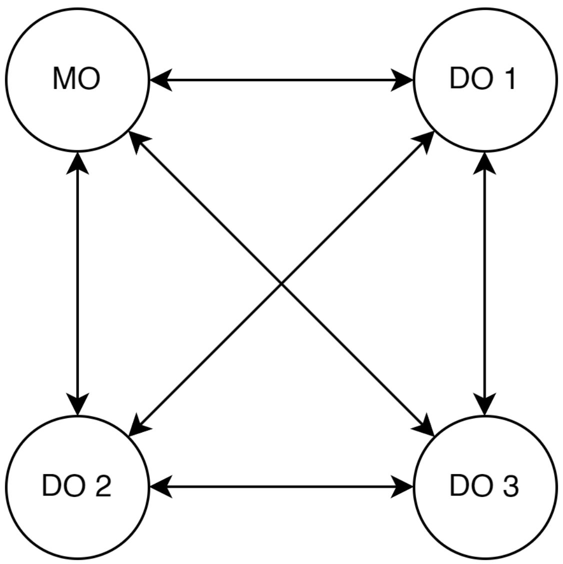

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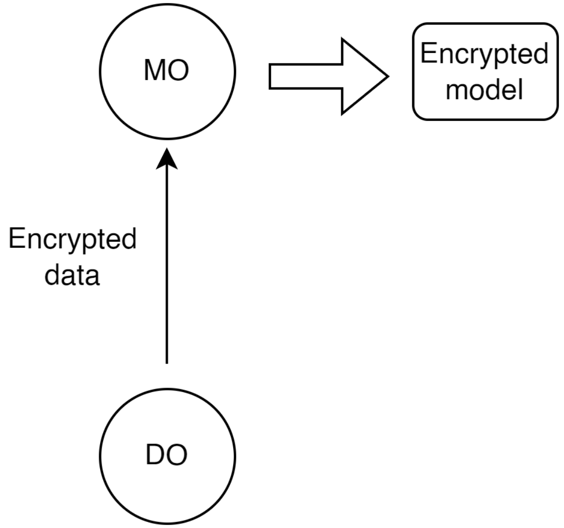
- Model (and data) privacy guaranteed.

Cons

- Not extensible: introducing new DOes requires new protocol design.
- Not secure against collusion
- Huge communication overhead.

Problems of prior works

- Pure Homomorphic Encryption (HE) Approaches
  - DO uploads encrypted data for training; MO obtains an encrypted model.



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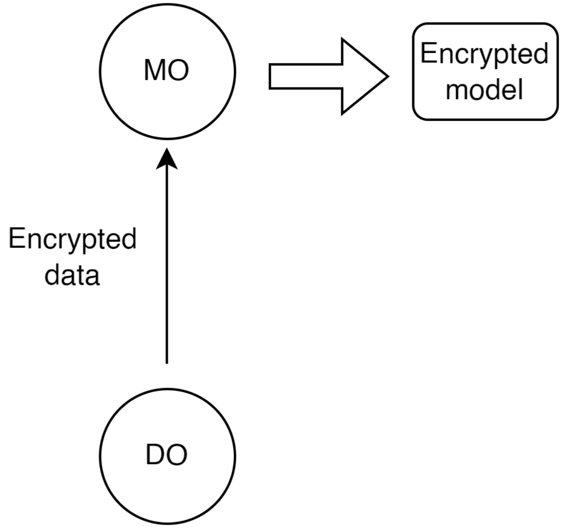

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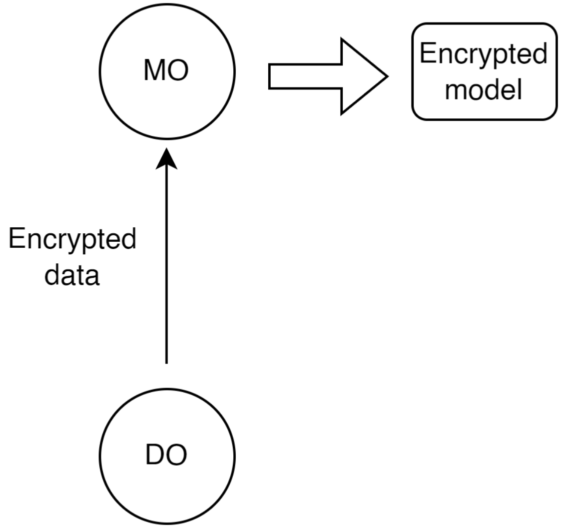

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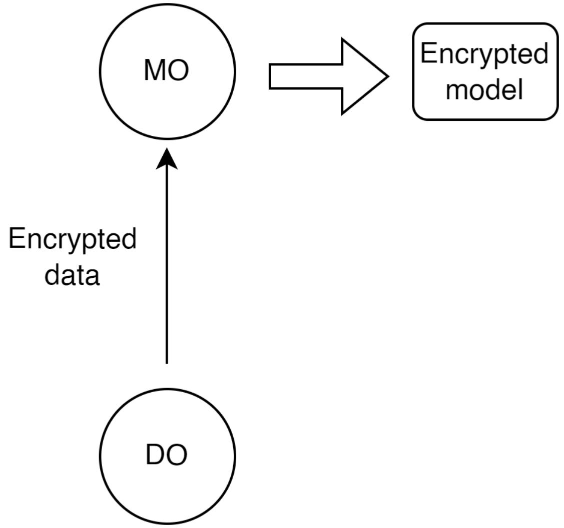

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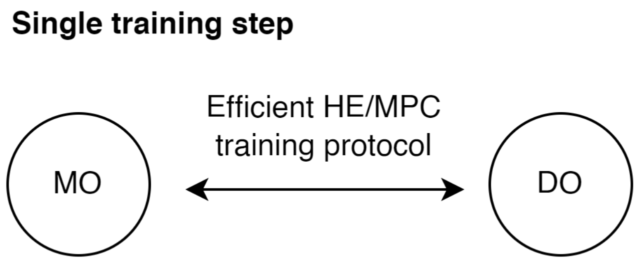
Cons
- Not extensible: only one DO!
- Heavy computation

Our solution

- 2-party training: HE + MPC
  - Data and model privacy guaranteed.



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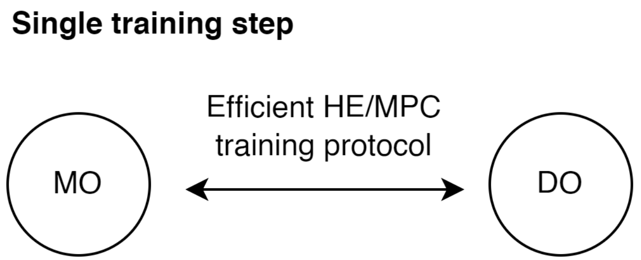

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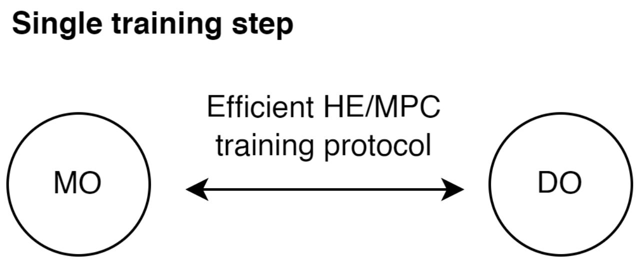

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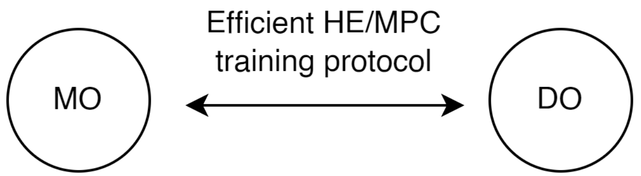
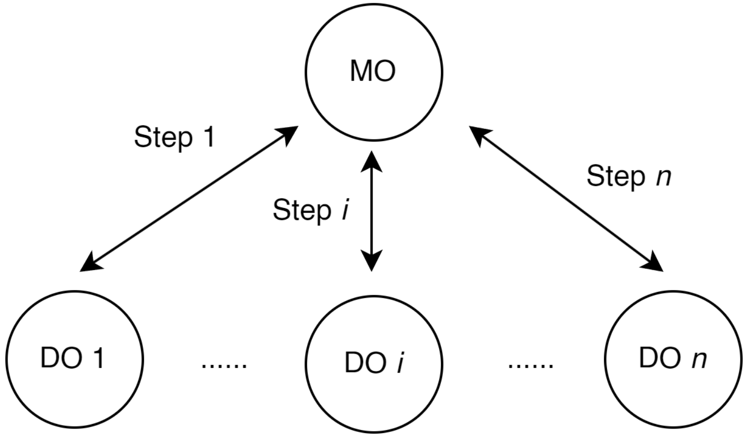
Single training step



Multiple steps across DOes



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  - Since no privacy leaks in 2-party, collusion could not break the privacy of any party.

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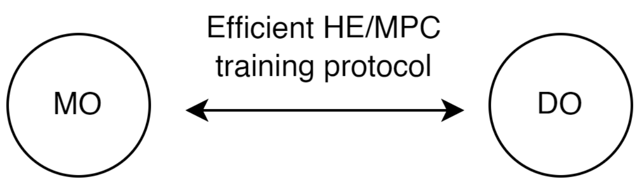

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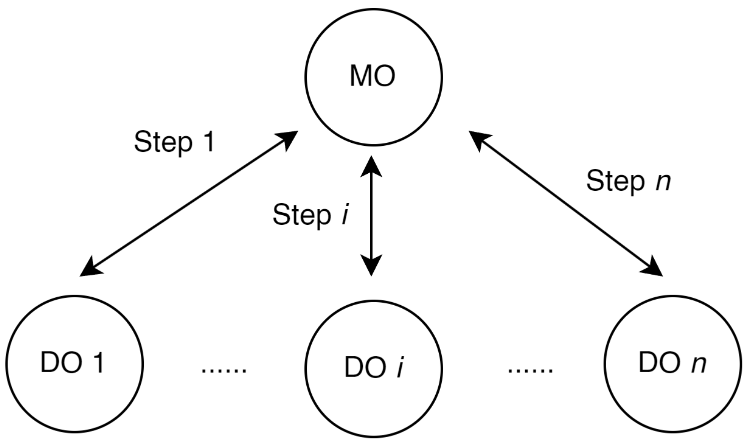

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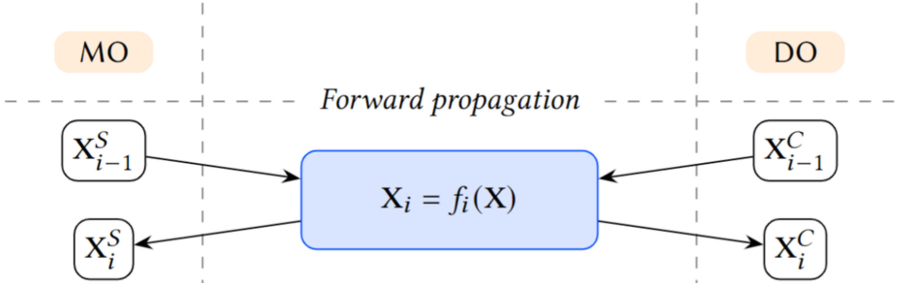

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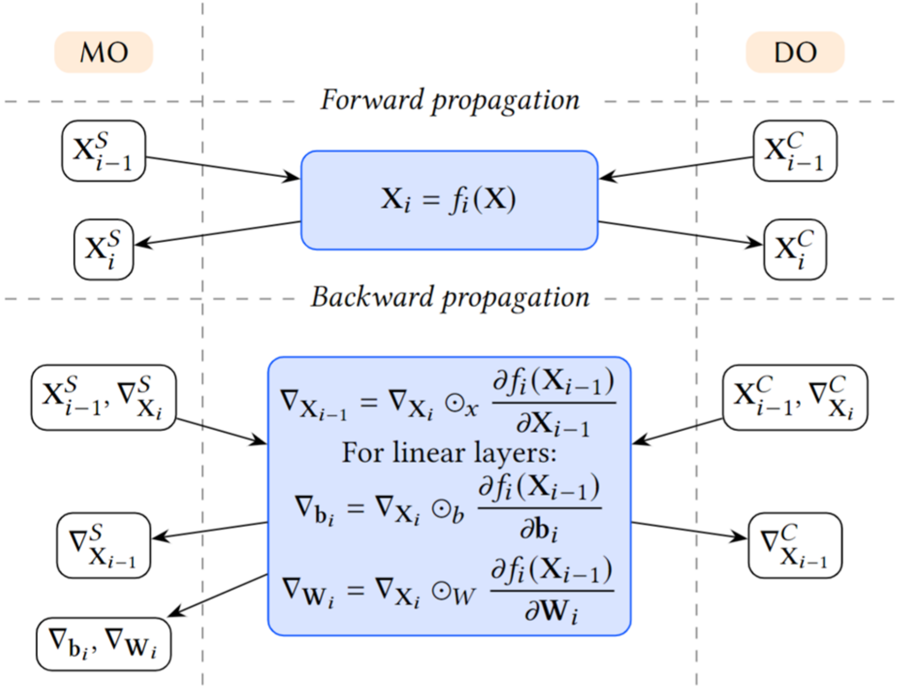

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  - … but the weight gradients are given to the MO.

$$\nabla_{\mathbf{b}_i} = \nabla_{\mathbf{X}_i} \odot_b \frac{\partial f_i(\mathbf{X}_{i-1}; \mathbf{W}_i, \mathbf{b}_i)}{\partial \mathbf{b}_i}$$

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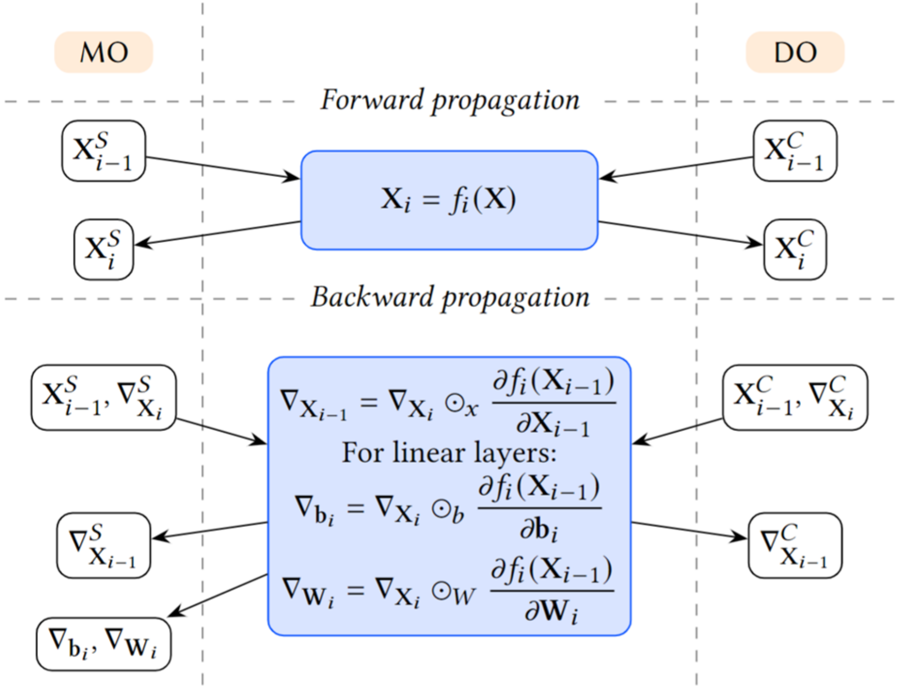

Training: Linear layers = HE

- Forward propagation
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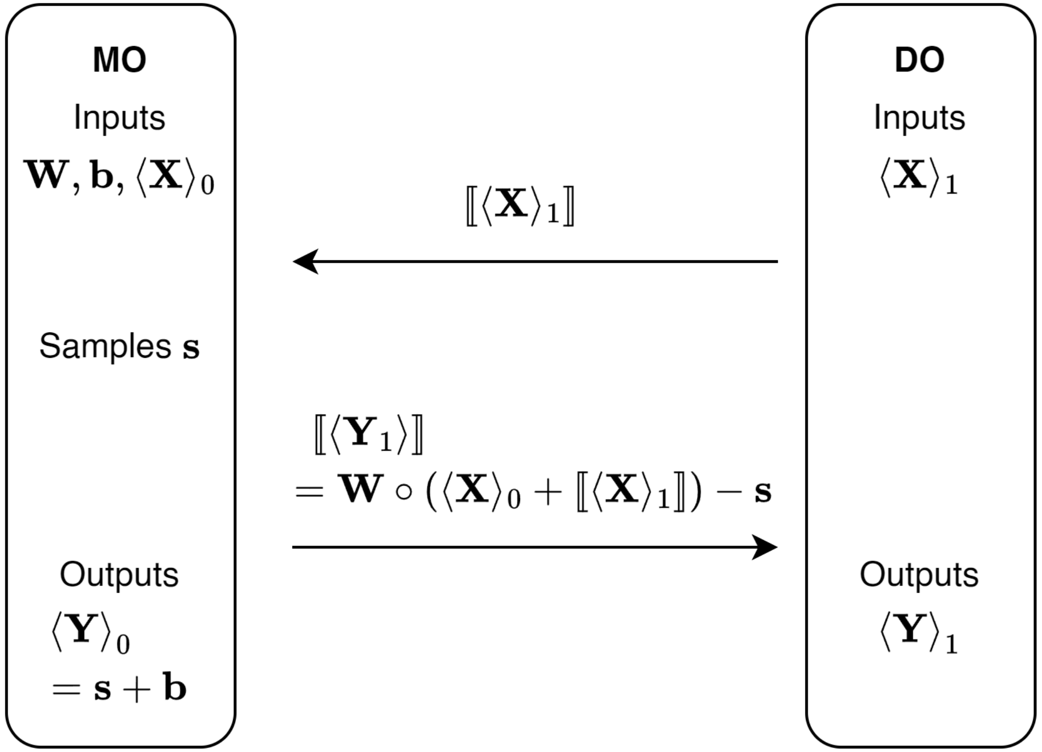

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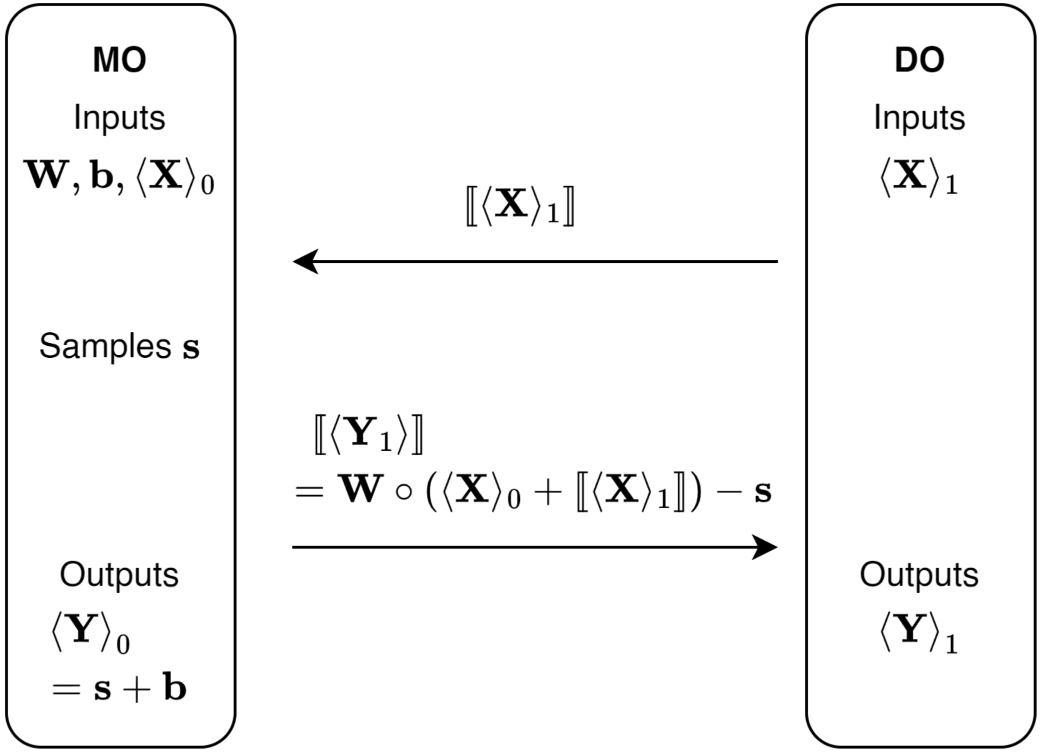
  - 2-round protocol with HE
  - As a general solution, this algorithm does not specify how $\mathbf{W} \circ [\![\mathbf{X}]\!]$ is evaluated.
  - Our implementation uses batched polynomial encoding, but other methods (e.g. Gazelle's encoding) could be used.



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  - Gradient of W, given to MO

Training: Linear layers = HE

- For gradient of W, it is the product of two secret-shared values

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(no need for cipher-cipher multiplication)

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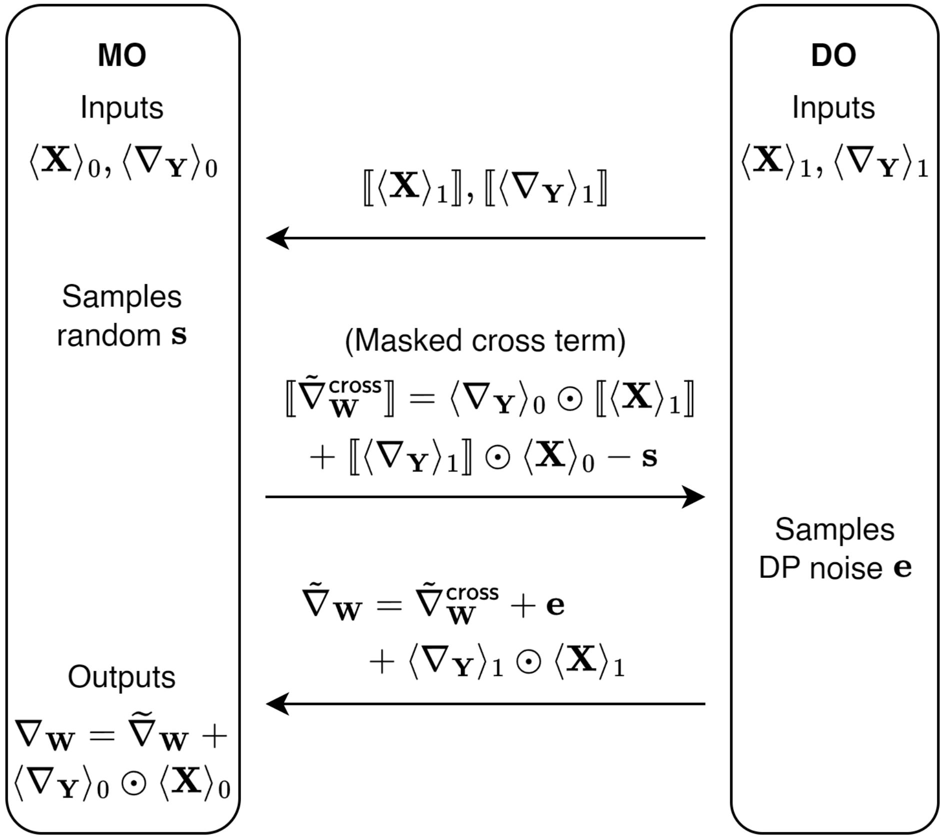

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- Example: $\mathrm{ReLU}(x) = \mathrm{DReLU}(x) \cdot x$
  - DReLU => secure comparison protocol
  - Boolean-arithmetic multiplication => OT-based multiplexing

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- First, let's consider a fixed u and variable v's.

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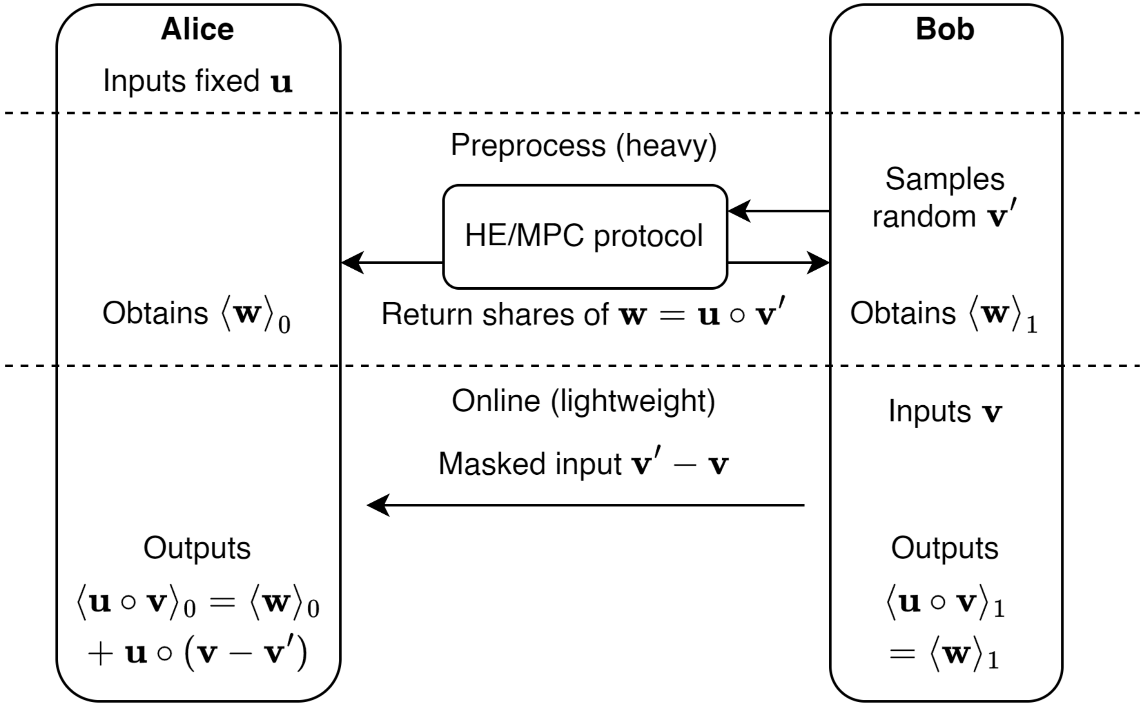

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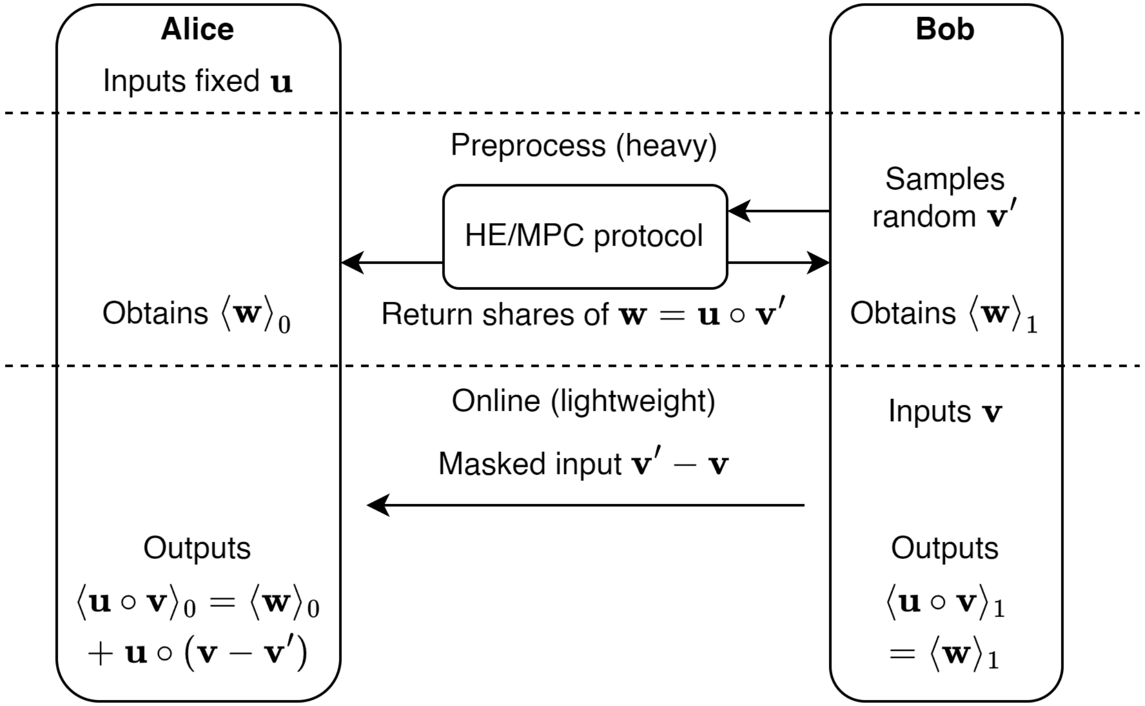

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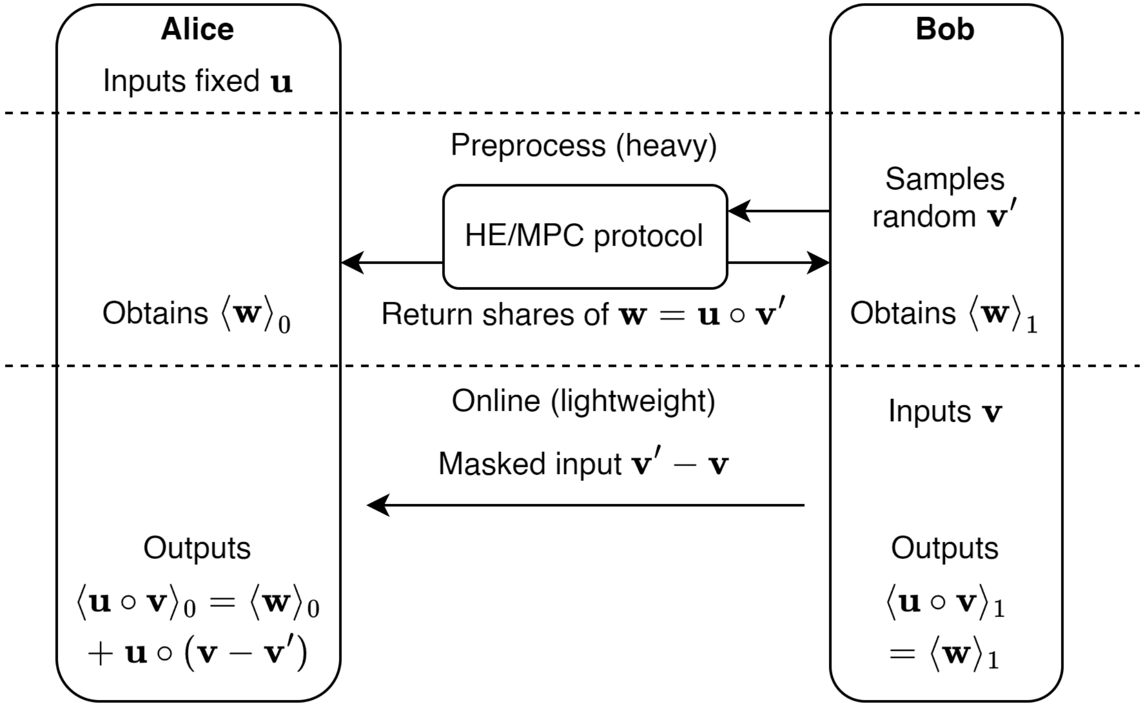

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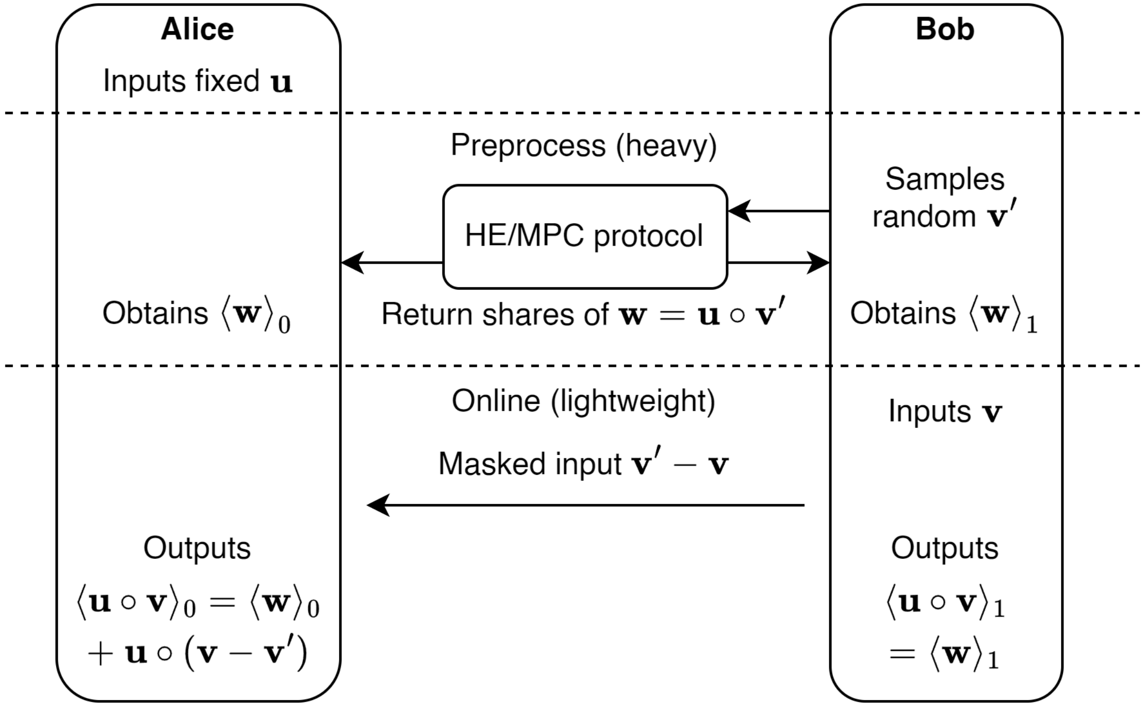

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- Total communication is not reduced, while total computation is even increased.

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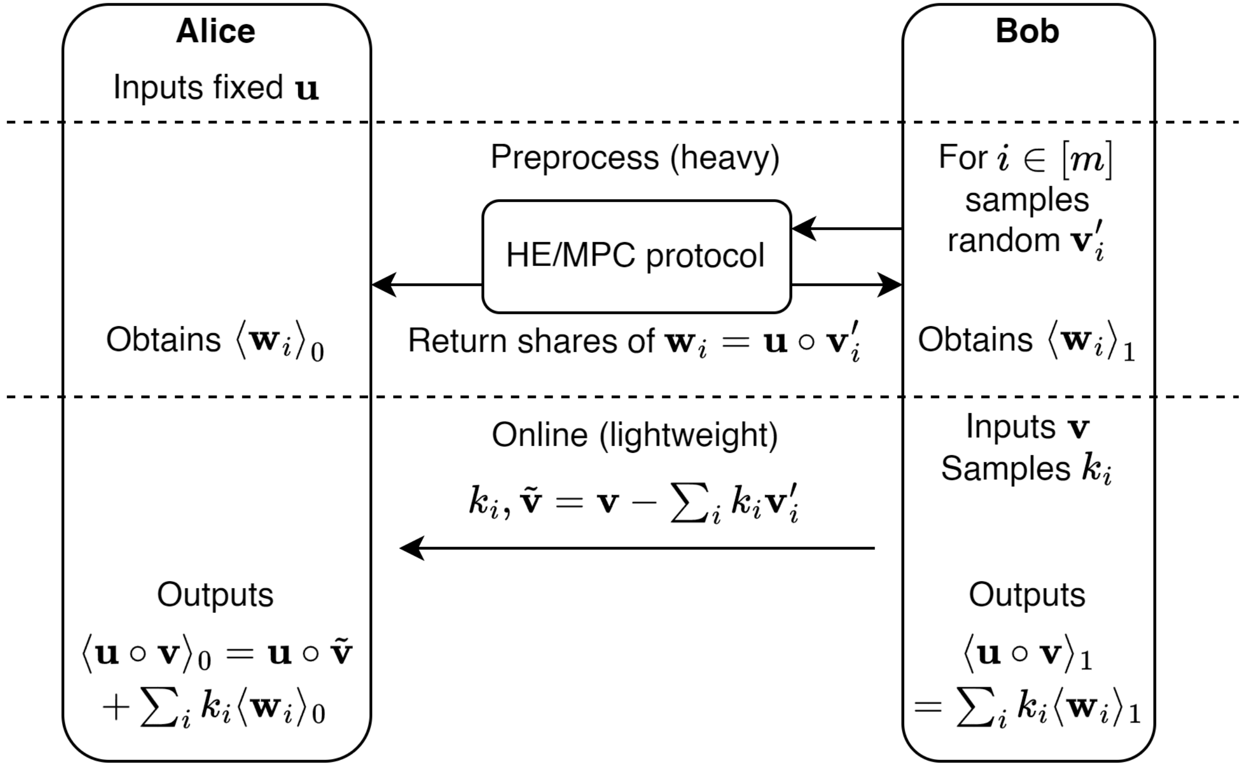

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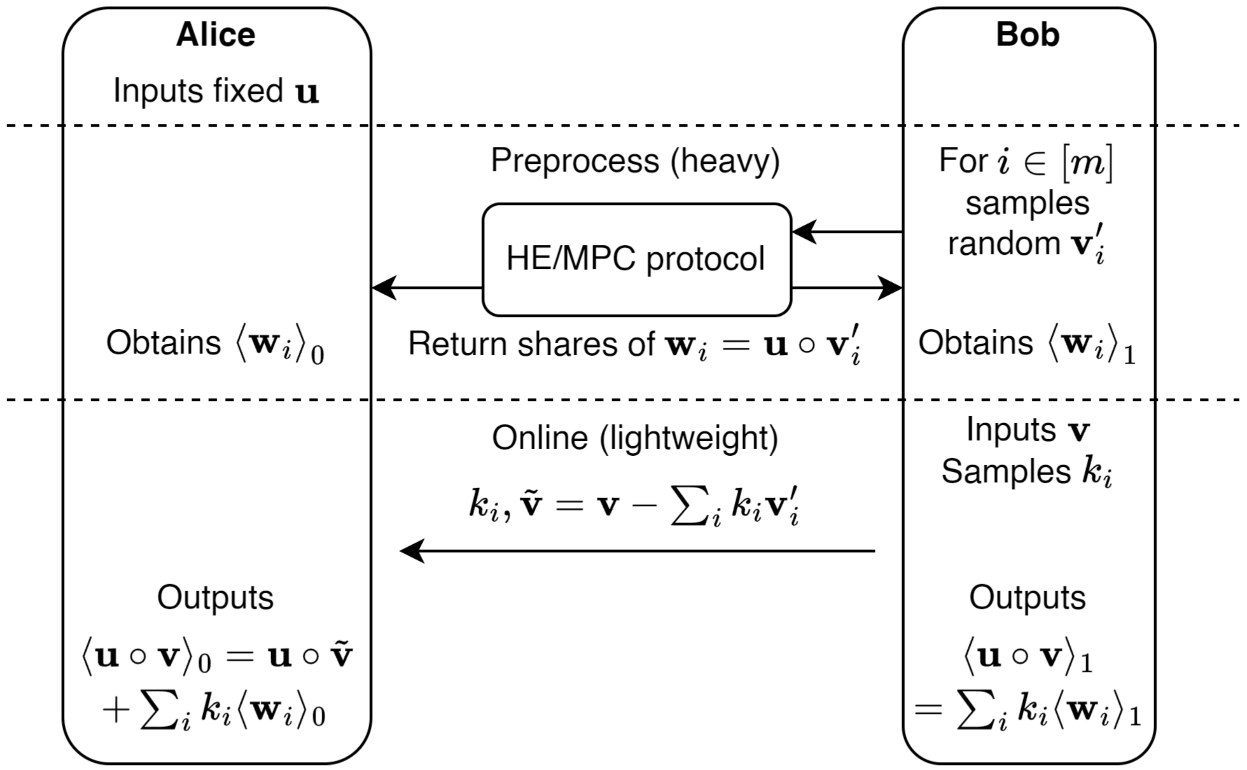
  - Bob samples m random v_i''s to conduct preprocessing.
  - Reuse the shares $\langle w_i \rangle$ for multiple online executions



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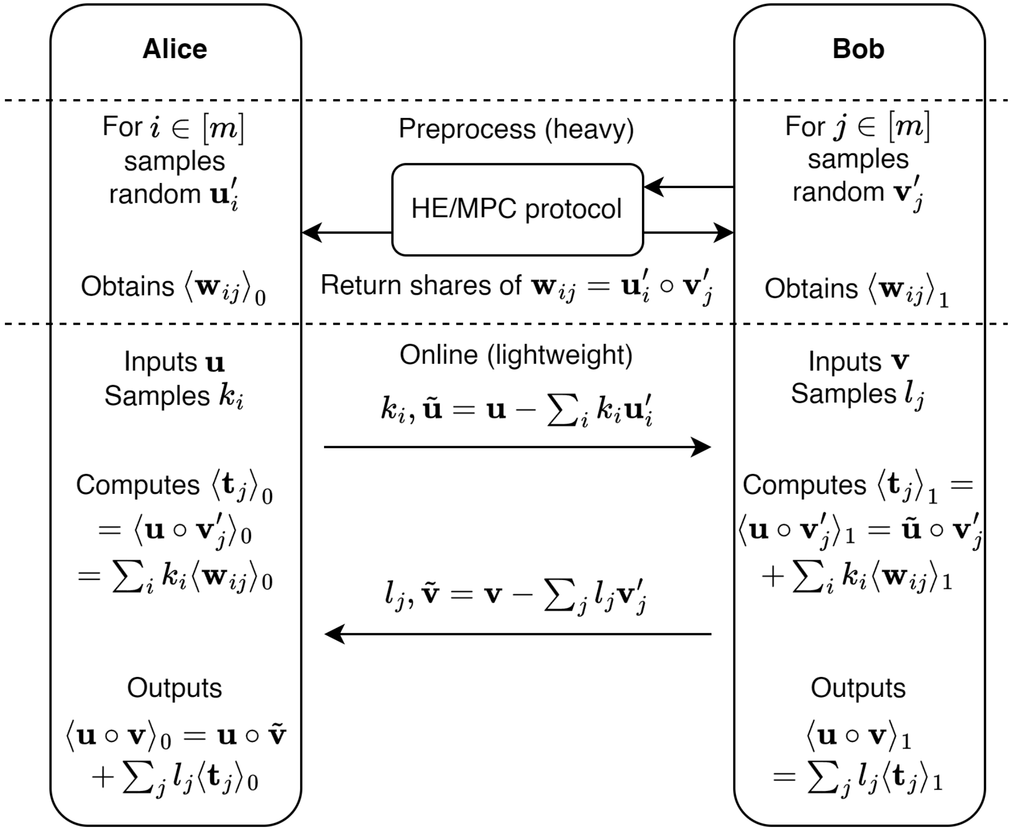

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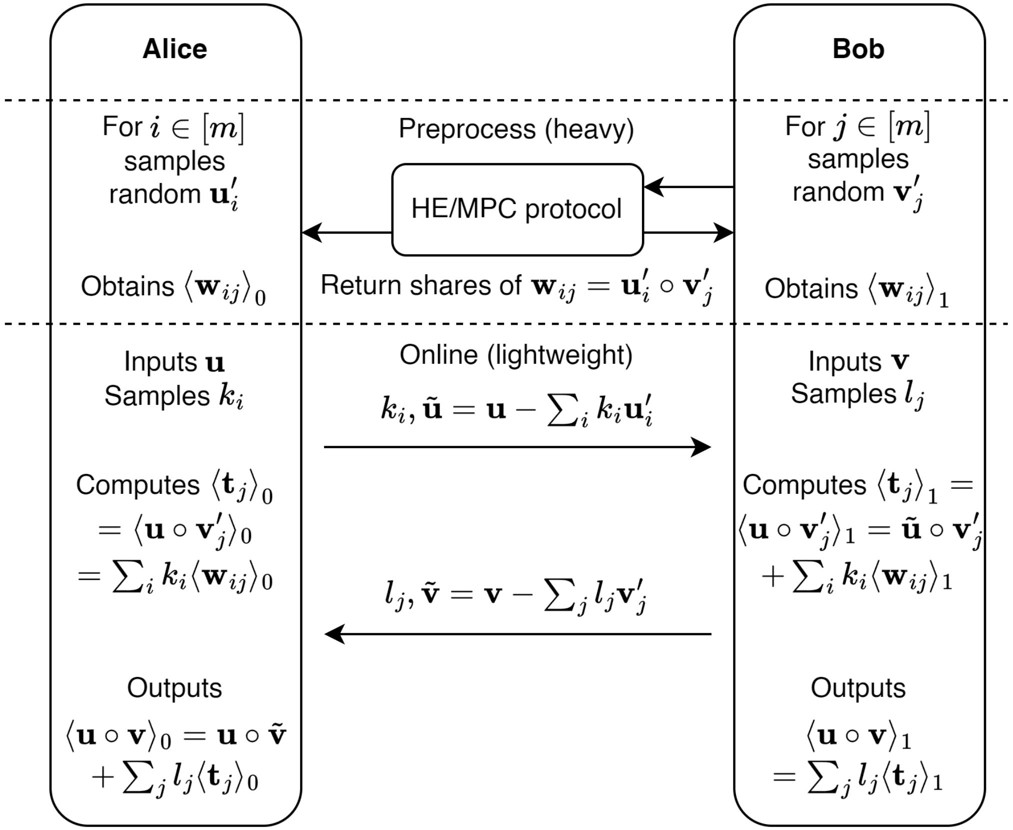
  - Traditional: T times HE/MPC evaluation of $\circ$
  - Ours: m^2 times of HE/MPC evaluation, regardless of T



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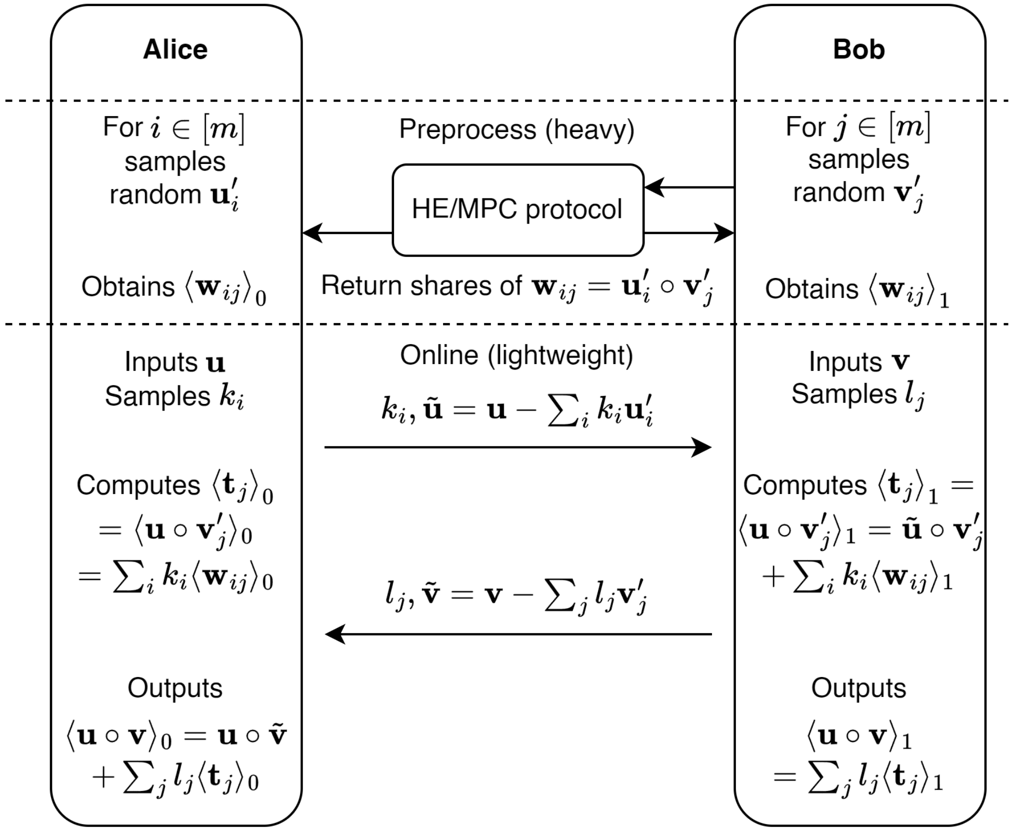
- Security analysis shows
  - To eliminate masks, an attacker would require at least $m + 1$ equations
  - Complexity of breaking one u or v is $O(2^{fm})$, f being the fixed-point precision



Evaluation: Training costs

Since the preprocessing technique introduces different security properties, we denote Pencil with or without it as Pencil and Pencil+ respectively.

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Scenario	Task	Model	Pencil			Pencil$^+$				
			Online			Preprocessing		Online		
			TP_{LAN}	TP_{WAN}	C	T_{prep}	C_{prep}	TP_{LAN}	TP_{WAN}	C
Train from scratch	MNIST	NN1	9.73×10^4	5.12×10^4	1.66	0.02	3.35	26.52×10^4	19.87×10^4	0.23
	MNIST	NN2	7.70×10^4	4.43×10^4	1.71	0.02	4.13	13.72×10^4	10.75×10^4	0.36
	CIFAR10	NN3	2.58×10^4	1.62×10^4	4.11	0.05	10.26	2.90×10^4	1.98×10^4	2.86
	CIFAR10	NN4	0.18×10^4	0.12×10^4	44.89	0.70	83.12	0.22×10^4	0.15×10^4	34.90
Transfer learning	CIFAR10	NN5	0.52×10^4	0.39×10^4	11.33	0.91	46.00	1.55×10^4	1.24×10^4	2.90
	CIFAR10	NN6	1.83×10^4	1.17×10^4	5.48	0.30	15.96	8.05×10^4	5.89×10^4	0.82

TABLE III: Training costs for different ML tasks. For the online phase, TP stands for the throughput (images/hour) of the training system, and subscript LAN, WAN indicate the network settings; C stands for the online communication (MB) per image. For Pencil$^+$, we also report the time (T_{prep}, hours) and communication (C_{prep}, GB) of preprocessing. Note that the preprocessing overhead is one-time overhead.

With Pencil+ and transfer learning, a model for CIFAR10 classification could be trained within 6.5 hours (10 epochs)

Evaluation: Training costs

Model	Throughput (10^4 img/h)				Comm. (MB/img)		
	[2]	[12]	P	P+	[12]	P	P+
2×128FC	0.7	0.11	9.7	29.3	552	1.7	0.2
3×128FC	0.6	0.10	8.1	18.9	658	2.2	0.3
2×512FC	0.2	0.03	2.6	13.2	3470	5.2	0.8

TABLE VII: Performance comparison with QUOTIENT [2] and Semi2k [12] in the 2 party setting. The models are represented as $n \times m$FC, as used by [2]. P represents Pencil and P^+ represents $Pencil^+$.

- Comparison with previous 2PC works shows improvements of up to 2 orders of magnitude.

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- Comparison with previous 2PC works shows improvements of up to 2 orders of magnitude.

Model	Throughput (10^3 img/h)			Comm. (per img)		
	[12]	Pencil	Pencil+	[12]	Pencil	Pencil+
2 parties	1.11	97	293	0.55GB	1.7MB	0.2MB
3 parties	0.61	97	293	2.58GB	1.7MB	0.2MB
4 parties	0.41	97	293	6.06GB	1.7MB	0.2MB
5 parties	0.07	97	293	57.69GB	1.7MB	0.2MB

TABLE VIII: Performance comparison with Semi2k [12] in multiple party setting.

- Unlike previous general n-PC frameworks, extending to multiple DOes does not introduce extra overhead for Pencil.

Thank you for listening!