IBM Research

HybridAlpha: An Efficient Approach for Privacy-Preserving Federated Learning

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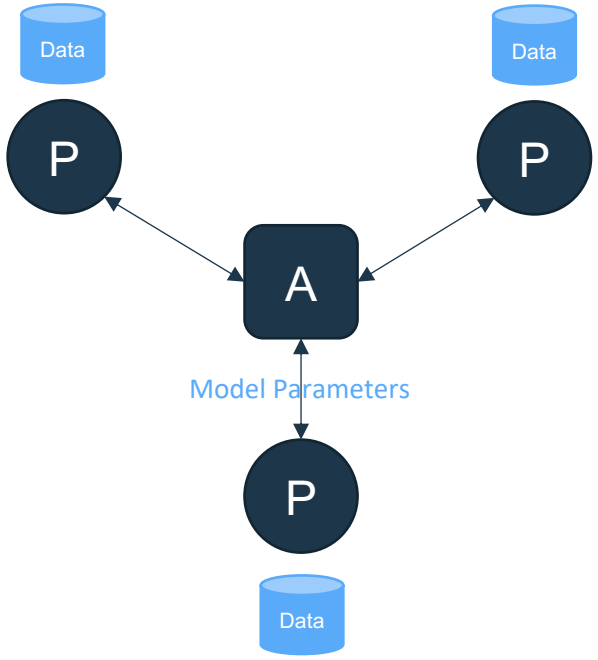
Federated Learning - Overview

How it works:

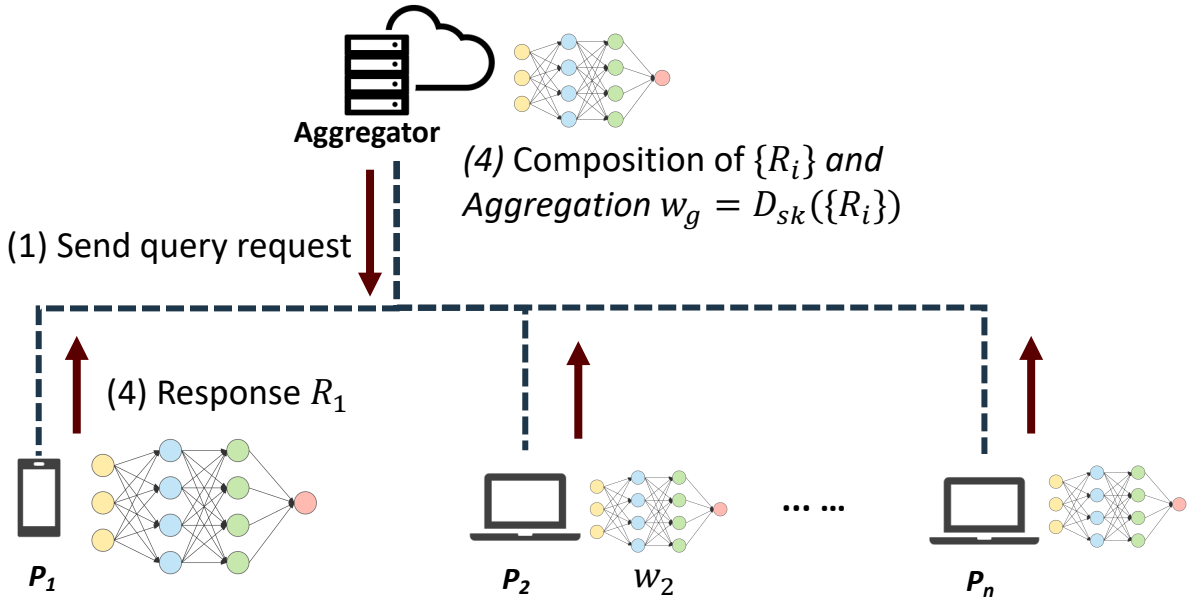
- Parties (P) collaboratively train a ML model, keeping training data to themselves
- Models are trained locally, within each party
- Local models' parameters from parties are merged and distributed to parties, at the end or after each epoch
- Different topologies used in different trust models, often using an Aggregator (A)



Privacy Issues of Federated Learning

- privacy leakage of model output
- privacy disclosure of aggregation computation

Hybrid Approach to Federated Learning



(2) Train locally and generate model w_1

(3) $\mathrm{R}_1 = E_{pk_1}\left(w_1 + \frac{noise}{N}\right)$

Overview of existing FL framework

Privacy Issues of Federated Learning

- privacy leakage of model output
- privacy disclosure of aggregation computation

Current approaches

- combines secure multi-party computation (SMC) and differential privacy (DP) through reduced noise

Limitation of current approaches

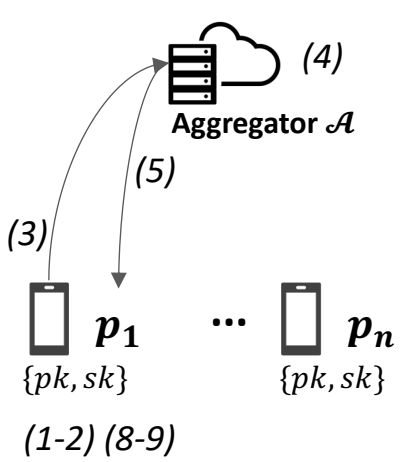
- very slow due to encryption algorithm used
- require multiple rounds of communication
- do not support dynamic participation: dropouts and new additions are not allowed without full system re-keying
- cannot prevent curious aggregators from getting partial decrypted data

Existing approaches V.S. Our approach

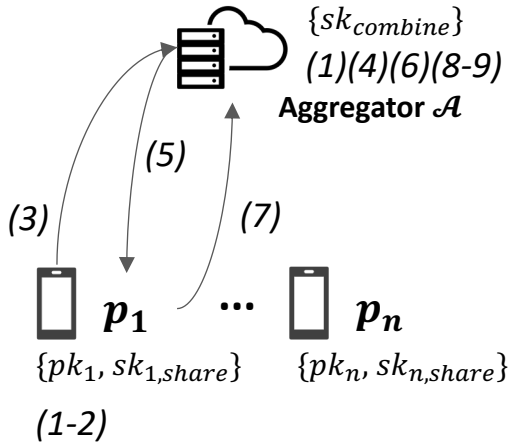
Comparison of privacy-preserving approaches in federated learning framework

	Threat Model		Privacy Guarantee		SMC	Features	
Proposed Approach	participant	aggregator	computation	output	type *	communication †	dynamic participants
Shokri and Shmatikov[36]	honest	honest	✗	✓	–	1 round	✓
PATE [31]	honest	honest	✗	✓	–	1 round	–
PySyft [34]	honest	HbC$^{\diamond}$	✓	✓	HE	2 rounds‡	–
Bonawitz et al. [6]	dishonest	HbC$^{\diamond}$	✓	✓	SS+AE	3 rounds‡	dropout
Truex et al. [38]	dishonest	HbC$^{\diamond}$	✓	✓	TP	3 rounds‡	✗
HybridAlpha (our work)	dishonest	HbC$^{\diamond}$	✓	✓	FE	1 round‡	dropout + addition

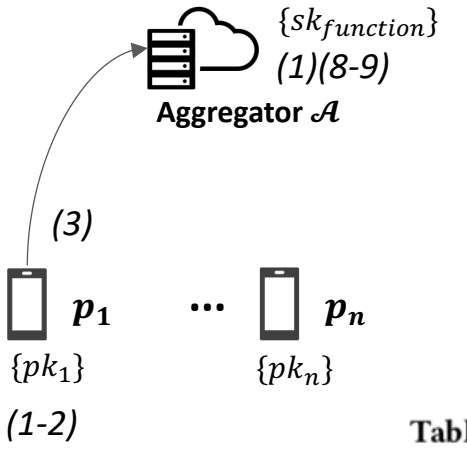
Comparison of SMC-based Secure Aggregation



P – SMC



TP – SMC



Our Approach

Steps of SMC aggregation

(1) key setup & local training
(2) encrypt model parameters c_{init}
(3) send c_{init} to $\mathcal{A}$
(4) combine cipher $c_{cmb} \leftarrow \{c_{init}\}$
(5) send back c_{cmb}
(6) partial decrypt $c_{part} \leftarrow c_{cmb}$
(7) send c_{part} to $\mathcal{A}$
(8) (combine) decryption
(9) update global model

Issues

- **Current SMC protocols are not efficient enough**
  - crypto efficiency (time)
  - communication steps
- **Lack of support for dynamic participants**

Table 2: The number of crypto-related operations required for each solution.

Communication	TP-SMC	P-SMC	HybridAlpha *
Step (1)	n	n	$n + m$
Step (3)	$n \times m$	$n \times m$	$n \times m$
Step (5)	$m \times t$	$n \times m$	-
Step (7)	$t \times m$	-	-
TOTAL	$2mt + mn + n$	$2mn + n$	$mn + m + n$

Functional Encryption in a Nutshell

- In functional encryption for inner-product, a third-party authority that
  - generates the public key pk for encryptor to encrypt vector $\boldsymbol{x} = [\boldsymbol{x_1}, \ldots, \boldsymbol{x_n}]$
  - generates functional private key $sk_{f,y}$ that is corresponding to a vector $\boldsymbol{y}$ for the decryptor

- From now on, let us assume, there is **a trusted third party other than aggregator** to be involved in the federated learning

Functional Encryption for Inner-product [*]

$$f(\boldsymbol{x}, \boldsymbol{y}) = \sum x_i y_i$$

$$D_{sk}\left(f\left(E_{pk}(x_1, \ldots, x_n)\right), \boldsymbol{y}\right) = \sum x_i y_i$$

without learning $x_1, \ldots, x_n$

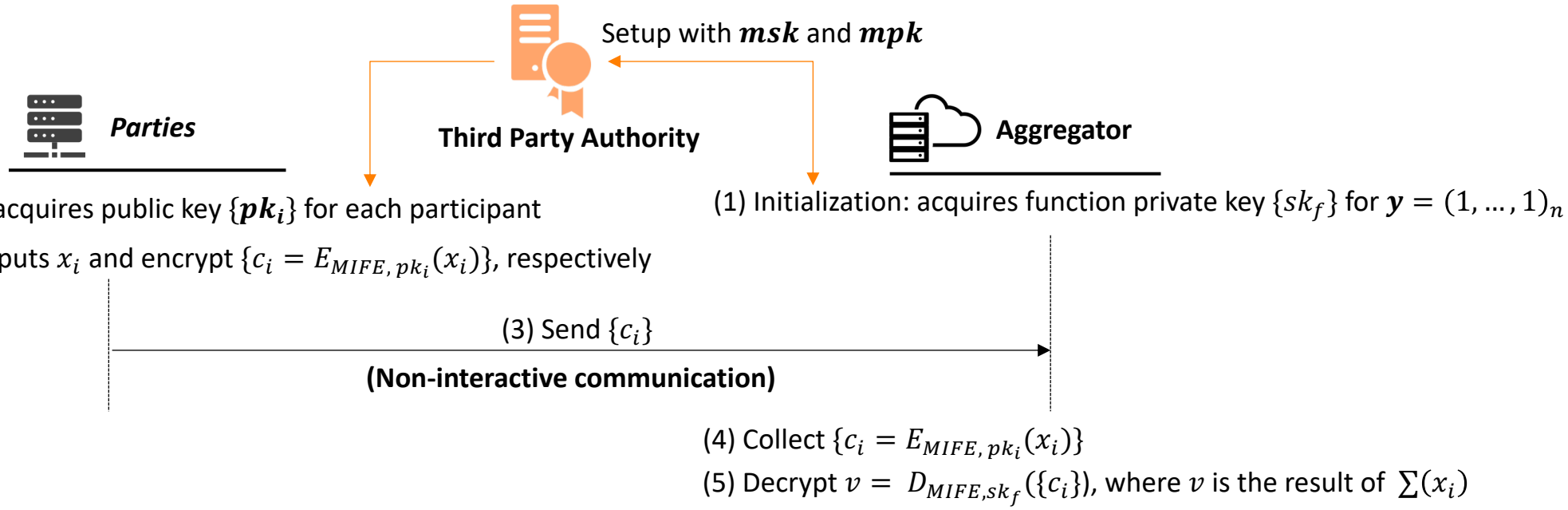
$x_1, \ldots, x_n$ can be from one single source or multiple sources

[*] Abdalla, Michel, Florian Bourse, Angelo De Caro, and David Pointcheval. "Simple functional encryption schemes for inner products." In *IACR PKC*, pp. 733-751. Springer, Berlin, Heidelberg, 2015.

Non-interactive Secure Computation

secure multi-party aggregation computation

- **Parties** $P = (p_1, \dots, p_i, \dots, p_n)$, each party p_i has input x_i
- **Aggregator** acquire $\sum(x_i)$ without learning specific x_i of p_i



Constructed from **Multiple-input Functional Encryption (MIFE)**[*]

[*] Abdalla, Michel, Dario Catalano, Dario Fiore, Romain Gay, and Bogdan Ursu. "Multi-input functional encryption for inner products: function-hiding realizations and constructions without pairings." In CRYPTO 2018.

Threat Model

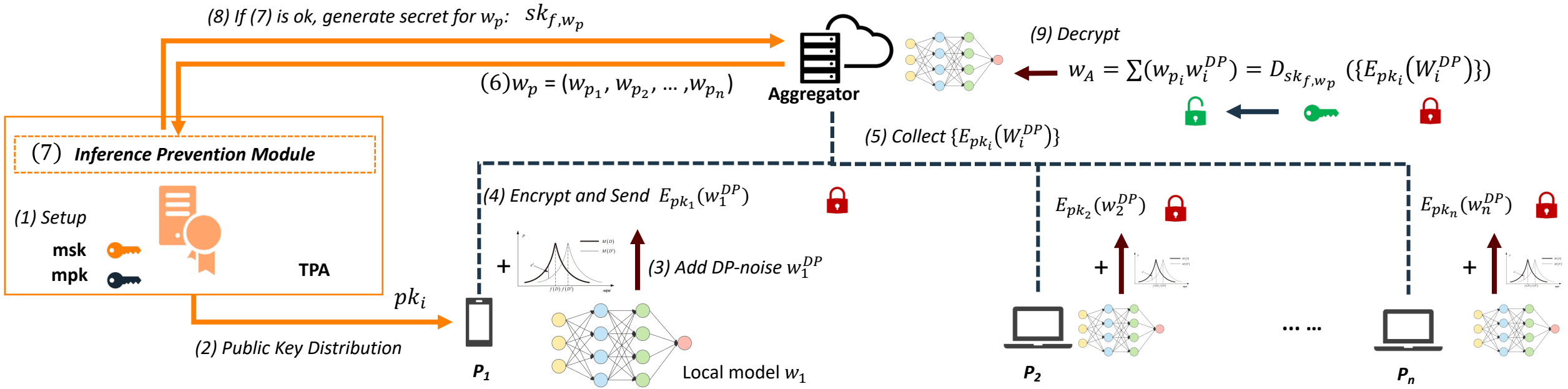
- A trusted third party (TPA) that distributes keys
- An honest but curious aggregator, and the aggregator may collude with dishonest parties
- Parties may try to infer data from other participants through the final model or during the federated learning process

Third Party Authority

Aggregator

Parties

Overview of HybridAlpha



Hybrid Approach

- differential privacy + noise reduction through SMC
- privacy guarantee: model output / aggregation

Efficiency Improvement

- Efficient encryption/decryption algorithm
- Non-interactive secure computation

Support Dynamic Participants

- Randomly drop out / join in

Inference Prevention Module

- *Threshold t* helps detect and stop attacks from curious aggregators and colluding participants, *t* defines a threshold on the number of non-colluding participants

- For example, if $t = 3$, the module filters the following suspicious weight vector w_p*:*
  - infers one party's model update:
    - *<0,0,0,1>*
    - *<0.0009,0.009,0,1>*
    - *<1>*
  - *exclude honest parties' model update:*
    - *<1,1,0,0>*

- *t* has an impact on the number of dropouts allowed by the system
  - Mainly, it helps set up the minimum quorum of participants replying to the system

Algorithm 2: Inference prevention filter

Input: $\mathbf{w}_p$:=A weighted vector to be inspected for inference attacks; t:= threshold of minimum number of dropouts and expected number of non-colluding participants

1 **function** *inference-prevention-filter*($\mathbf{w}_p, t$)
2 $c_{nz} \leftarrow$ count the non-zero element in $\mathbf{w}_p$;
3 **if** $c_{nz} < t$ **then return** "invalid w_p" ;
4 **foreach** *non-zero* $w_{p_i} \in \mathbf{w}_p$ **do**
5 **if** $w_{p_i} \neq \frac{1}{c_{nz}}$ **then return** "invalid w_p";
6 **end**
7 forward $\mathbf{w}_p$ to the TPA;

Experimental Results

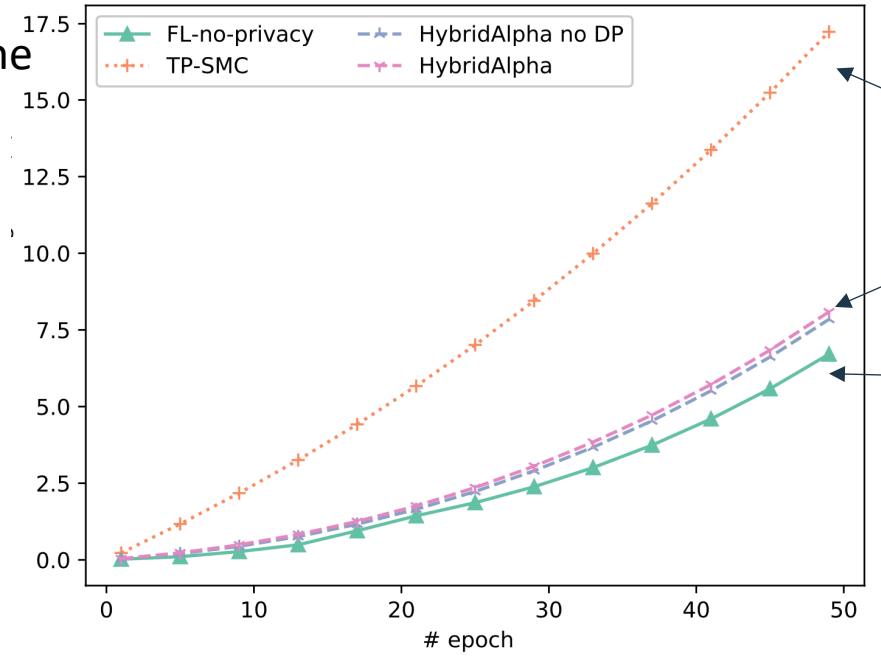
Cryptosystems Implementation
- Python + GMP/Charm-crypto library

Experimental Environment
- 44 core Intel Xeon E5-2699 v4 platform with 384 GB of RAM
- CNN on MNIST dataset

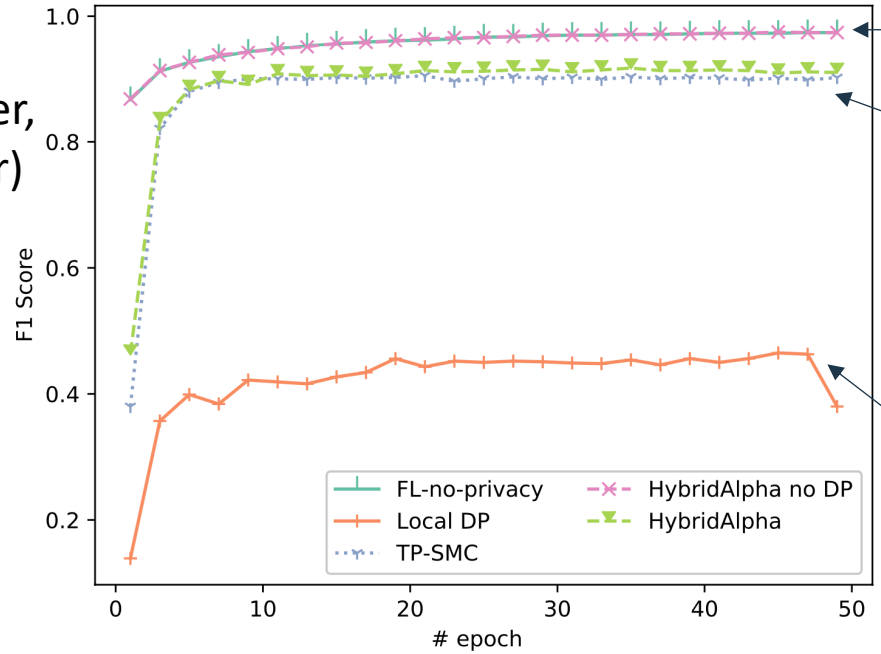
Baselines
- FL without DP/ FL local DP
- TP-SMC FL (DP)
- P-SMC FL (DP)

On average reduces
the training time by **68%**
the data transfer volume by **92%**
While providing
the **same model performance**
the **same privacy guarantees** as the existing solutions

Training time (hours)



F1 Score (the higher, the better)



Thank you! Questions?

Find our AI Security and Privacy Solutions team at:
https://resedit.watson.ibm.com/researcher/view_group.php?id=10276

References

[1] Keith Bonawitz, Vladimir Ivanov, Ben Kreuter, Antonio Marcedone, H Brendan McMahan, Sarvar Patel, Daniel Ramage, Aaron Segal, and Karn Seth. 2017. Practical secure aggregation for privacy-preserving machine learning. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security. ACM, ACM, 1175–1191.

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[3] Theo Ryffel, Andrew Trask, Morten Dahl, Bobby Wagner, Jason Mancuso, Daniel Rueckert, and Jonathan Passerat-Palmbach. 2018. A generic framework for privacy preserving deep learning. In Proceedings of Privacy Preserving Machine Learning Workshop with NeurIPS 2018.

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[5] Stacey Truex, Nathalie Baracaldo, Ali Anwar, Thomas Steinke, Heiko Ludwig, and Rui Zhang. 2018. A Hybrid Approach to Privacy-Preserving Federated Learning. arXiv preprint arXiv:1812.03224 (2018).

[6] Michel Abdalla, Dario Catalano, Dario Fiore, Romain Gay, and Bogdan Ursu. 2018. Multi-input functional encryption for inner products: function-hiding realizations and constructions without pairings. In Annual International Cryptology Conference. Springer, Springer, 597–627.