HETAL: Efficient Privacy-preserving Transfer Learning with Homomorphic Encryption

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Solving privacy issues in machine learning

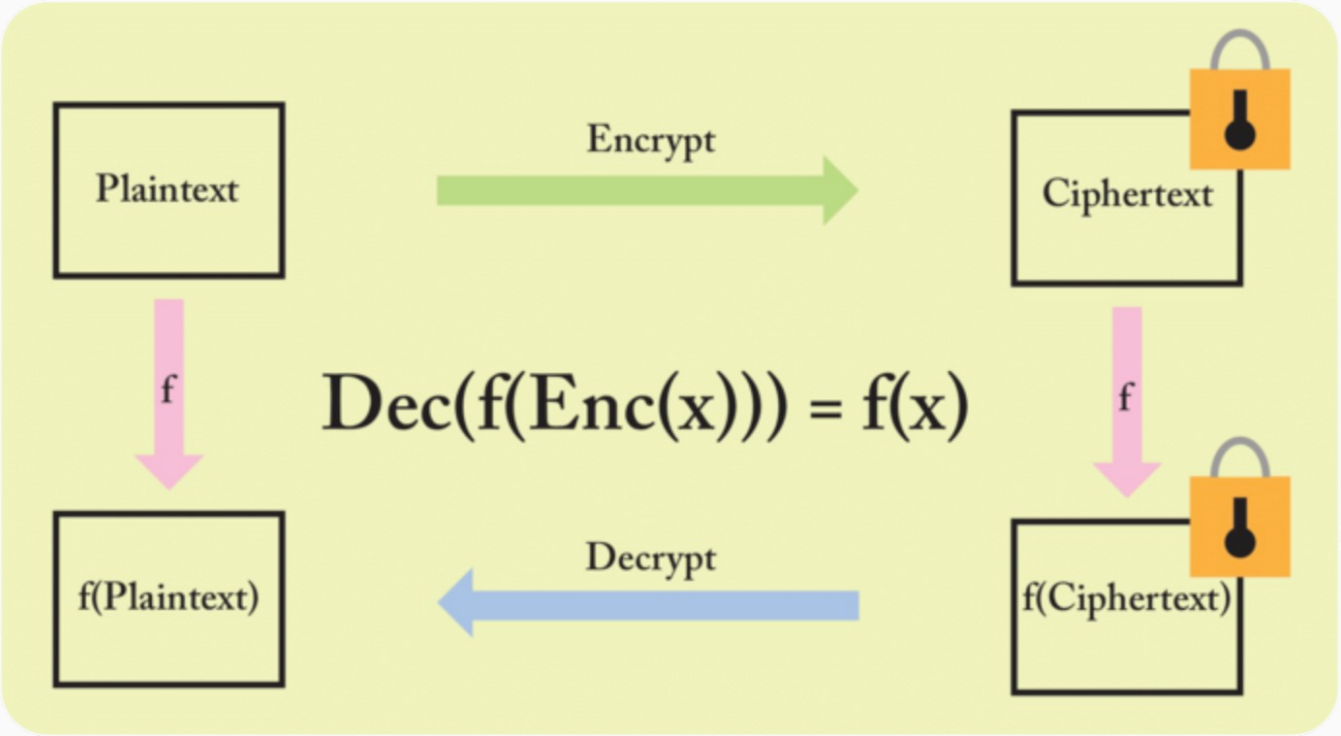
Question

How can we create / use machine learning models *without leaking private data?*

Privacy-preserving Machine Learning (PPML): prevent privacy leakage in machine learning. For example,

- Federated Learning
- Differential Privacy
- Trusted Excution Environment
- Secure Multi-Party Computation
- **Homomorphic Encryption**

Homomorphic Encryption (HE)



HE can perform computation on encrypted data *without having to decrypt it*.

Cheon-Kim-Kim-Song (CKKS) Scheme

- CKKS scheme supports unlimited number of SIMD operations over real and complex numbers, which is appropriate for machine learning applications
  - Addition / Multiplication
  - Rotation / Complex conjugation
  - Bootstrapping
- Lattice-based scheme, quantum-safe
- Needs to approximate non-polynomial functions

HE-based PPML

- Biggest challenge of HE: computationally expensive

Question

Can we make HE-based PPML practical?

HETAL

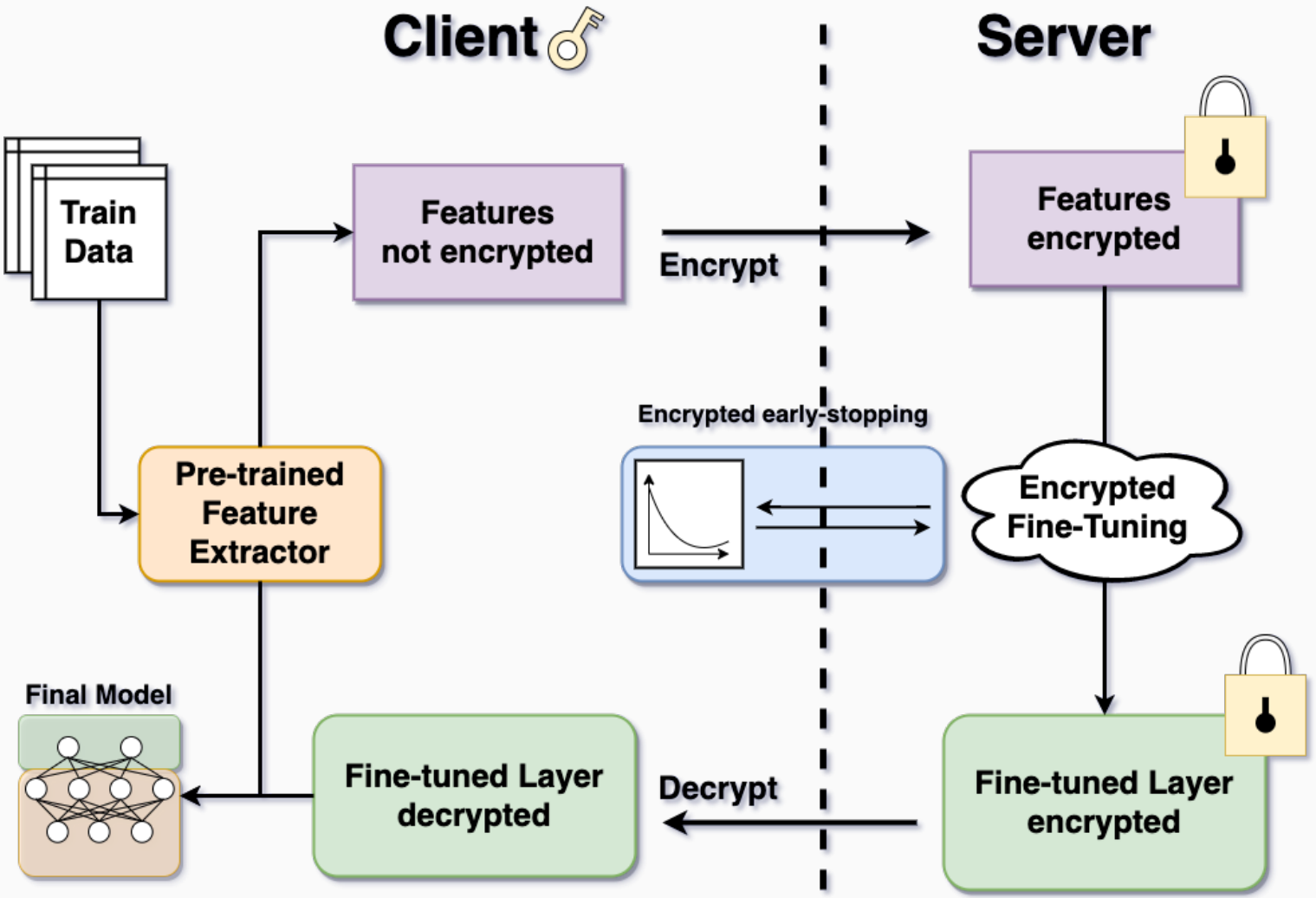


Figure 1: HETAL protocol

HETAL

- We propose **HETAL**, an efficient and practical **H**omomorphic **E**ncryption based **T**r**A**nsfer **L**earning algorithm for privacy-preserving transfer learning.
- Fine-tune classifiers with *encrypted* features extracted from pre-trained models
- *Encrypted early-stopping*
  - Simple communication protocol to determine whether to stop the training or not
- *Encrypted fine-tuning*
  - Softmax approximation on wide interval
  - Efficient encrypted matrix multiplication

Softmax approximation

- It is important to obtain good approximation on wide intervals, especially for training.
- We combine **domain extension** [1] and **normalization** (via comparison [2]) to approximate softmax on a wide range.
- We prove that approximation error is bounded by an explicit constant that does not depend on the domain extension index.
- Our softmax approximation covers inputs in range $[-128, 128]$ with estimated maximum / average errors of $\mathbf{0.0037} \sim \mathbf{0.0224}$ and $\mathbf{0.0022} \sim \mathbf{0.0046}$.
    - For input dimensions 3, 5, 7, and 10.

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[1] Cheon et al., *Efficient homomorphic evaluation on large intervals*, IEEE Transaction on Information Forensics and Security, 2022

[2] Cheon et al., *Efficient homomorphic comparison methods with optimal complexity*, International Conference on the Theory and Application of Cryptology and Information Security, 2020

Softmax approximation

Theorem

Let $p : \mathbb{R}^c \to \mathbb{R}^c$ *be an approximation of the softmax on* $[-R, R]^c$ *satisfying*

$$\|\mathrm{Softmax}(\mathbf{x}) - p(\mathbf{x})\|_\infty < \epsilon.$$

Then for $\mathbf{x} \in [-\frac{1}{2}L^n R, \frac{1}{2}L^n R]^c$*, we have*

$$\|\mathrm{Softmax}(\mathbf{x}) - p(D_n(\mathrm{Norm}(\mathbf{x})))\|_\infty < \beta + \epsilon,$$

where $\beta = \beta(\delta, c, r, L, d)$ *is a constant that depends only on* δ, c, r, L, d *(not on n). Here* D_n *is a domain extension polynomial and* Norm *is a normalization map.*

Encrypted matrix multiplication

- Matrix multiplication with HE: needs to implement using only additions, multiplications, rotations, and conjugations.
- We propose **DiagABT** and **DiagATB**, which are optimized matrix multiplication algorithms of the form $AB^\intercal$ and $A^\intercal B$.
- These algorithms are optimized with techniques including
  - off-diagonal masking
  - tiling
  - complexification
  - partial rotation

Encrypted matrix multiplication

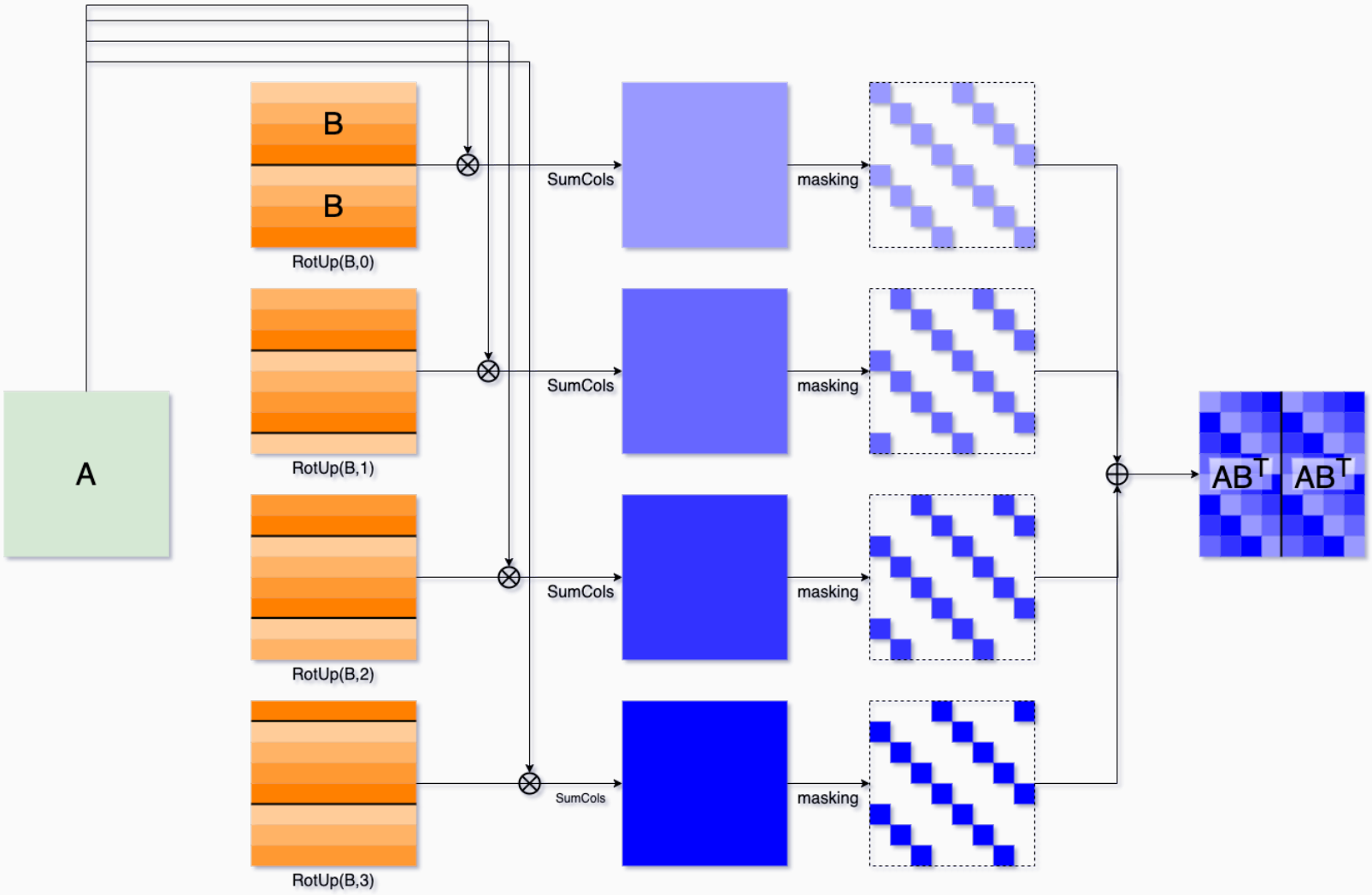

Figure 2: DiagABT algorithm for $A \in \mathbb{R}^{8\times 8}$ and $B \in \mathbb{R}^{4\times 8}$

Encrypted matrix multplication

Our matrix multiplication algorithms show **1.8 to 324 times** speed up compared to baseline algorithms.

(a, b, c)	$AB^\intercal$ $(A \in \mathbb{R}^{a\times b}, B \in \mathbb{R}^{c\times b})$					$A^\intercal B$ $(A \in \mathbb{R}^{a\times c}, B \in \mathbb{R}^{a\times b})$				
	(Jin et al.)*	ColMajor†	DiagABT	Speedup		(Jin et al.)*	RowMajor†	DiagATB	Speedup	
$(128, 128, 4)$	0.8192	0.1104	**0.0601**	13.63	1.84	10.0352	0.1171	**0.0415**	241.81	2.82
$(256, 256, 8)$	3.2768	0.3203	**0.1211**	27.06	2.64	40.1408	0.3167	**0.1239**	323.98	2.56
$(512, 769, 4)$	4.9216	0.7609	**0.1223**	40.24	6.22	60.2896	0.7176	**0.3343**	180.35	2.15
$(1024, 769, 8)$	9.8432	3.0428	**0.3710**	26.53	8.20	120.5792	2.8546	**1.2558**	96.02	2.27
$(2048, 769, 16)$	19.6864	12.6251	**1.2376**	15.91	10.20	241.1584	11.8220	**4.9970**	48.26	2.37

Table 1: Comparison with baseline matrix multiplication algorithms.

* Jin et al., *Secure transfer learning for machine fault diagnosis under different operating conditions*, International Conference on Provable Security, 2020

† Crockett, *A low-depth homomorphic circuit for logistic regression model training*, Workshop on Encrypted Computing & Applied Homomorphic Cryptography, 2020

Results

With CryptoLab's HEaaN library and a single NVIDIA Ampere A40 GPU, we fine-tune classifiers with encrypted features **in an hour** with **at most 0.51% accuracy drop**.

dataset	encrypted		not encrypted		
	Running time		ACC (a)	ACC (b)	ACC loss ((b) - (a))
	Total (s)	Time / Iter (s)			
MNIST	3442.29	9.46	96.73%	97.24%	0.51%
CIFAR-10	3114.30	15.72	96.57%	96.62%	0.05%
Face Mask Detection	566.72	4.29	95.46%	95.46%	0.00%
DermaMNIST	1136.99	7.06	76.06%	76.01%	-0.05%
SNIPS	1264.27	6.95	95.00%	94.43%	-0.57%

Table 2: Transfer learning results on 5 benchmark datasets.

Summary

- We present an efficient HE-based transfer learning algorithm called HETAL.
- Efficiency of HETAL is based on two main components:
  - Highly precise softmax approximation algorithm with wide domain of approximation;
  - Efficient encrypted matrix multiplication algorithms, DiagABT and DiagATB.
- We trained classifiers with encrypted features extracted from five real-world datasets via pre-trained transformers in an hour.

Are we done?

NO!

- Much efficient matrix multiplication
  - Low-level optimizations with advanced HE techniques (e.g. HERMES [3])
  - Better implementation (e.g. Multi-GPU)
- Other types of classifiers (tree-based models, MLP, ...)
- Real-world applications

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[3] Bae et al., *HERMES: Efficient Ring Packing using MLWE Ciphertexts and Application to Transciphering*, Crypto 2023

AutoFHE

HETAL will be integrated into CryptoLab's new product,

AutoFHE