Partially Encrypted Machine Learning using Functional Encryption

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Table of Contents

Functional Encryption

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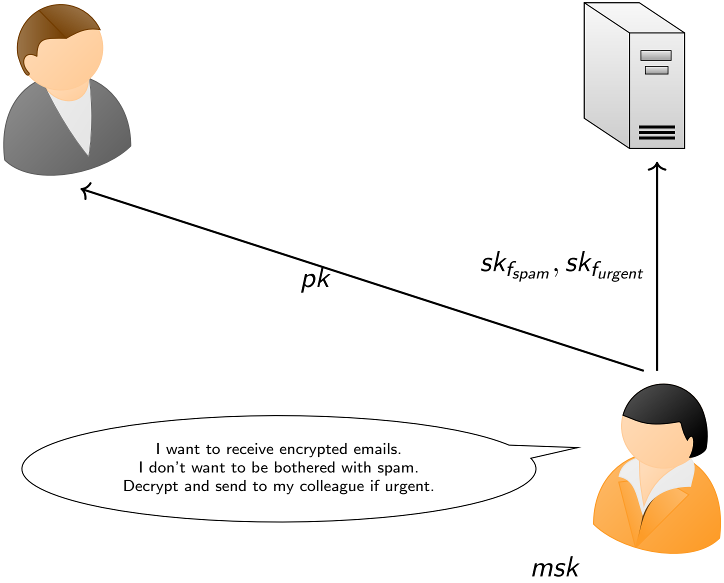
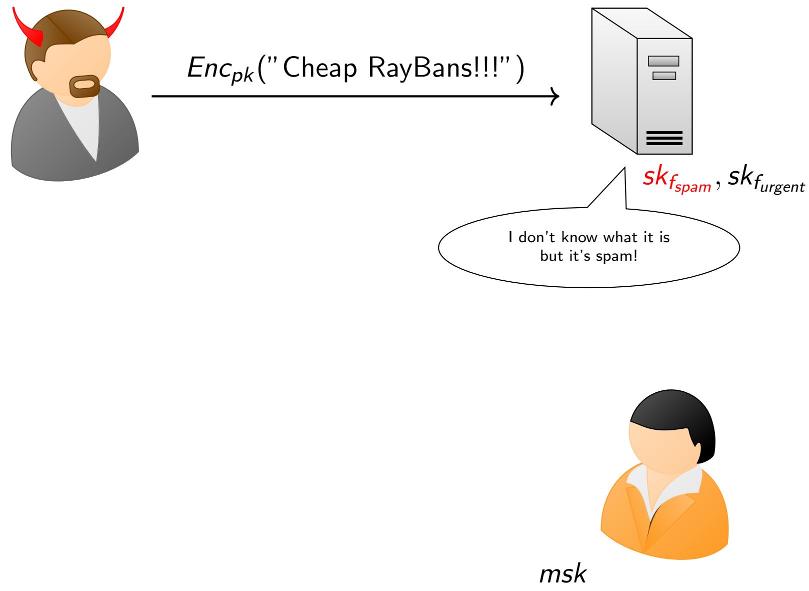
Functional Encryption: **A new paradigm**.
Get a *function* of the cleartext.
Function depends on the key.

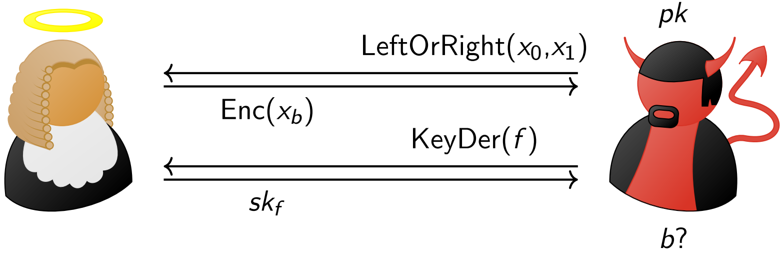
FE example


$sk_{f_{spam}}, sk_{f_{urgent}}$
pk
I want to receive encrypted emails.
I don't want to be bothered with spam.
Decrypt and send to my colleague if urgent.
msk

FE example


$Enc_{pk}(\text{"Cheap RayBans!!!"})$
pk
$sk_{f_{spam}}, sk_{f_{urgent}}$
I don't know what it is but it's spam!
msk

Security definitions



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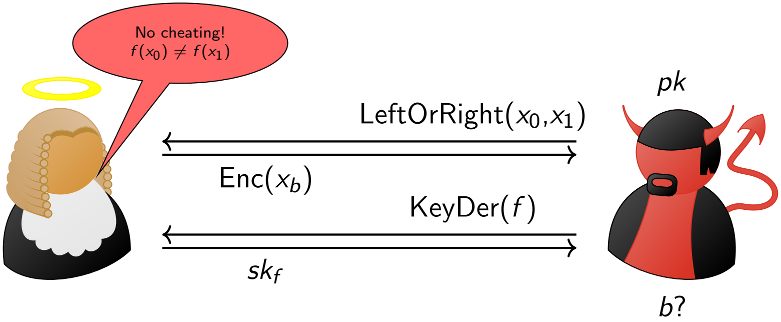

Table of Contents

Our contributions

- New Quadratic FE scheme;
- Python Implementation;
- Methodology for Thinking About Privacy in FE-ML;
- New Dataset;
- Collateral Learning Framework for Training Models in FE-ML.

Table of Contents

A New FE Scheme for Quadratic Forms

- Key $sk_{\mathbf{Q}}$ gets you $\vec{x}^T \mathbf{Q} \vec{x}$ from $Enc(\vec{x})$;
- Decryption $1.5\times$ faster than State-of-the-Art;
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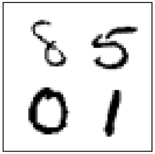
- All group-based computational FE schemes require a discrete logarithm;
- Must ensure output has reasonably small entropy;
- All DLOGs are in base g_T!
- We precompute tweaked Giant step of BSGS and store for reuse.

A Simple Model



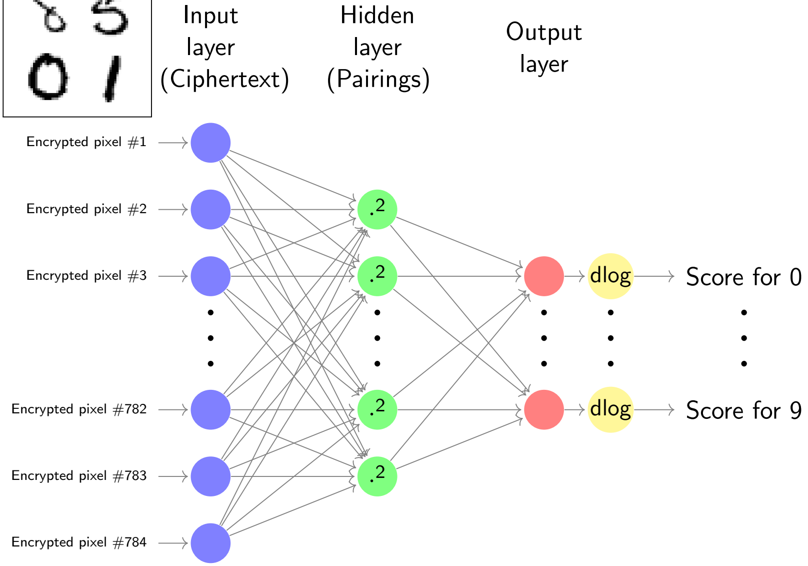


Table of Contents

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But your notion of privacy depends on the distributions on the $\vec{x}$'s.
10 scalars actually give a lot of information: [CFLS18] mount good recovery attacks.

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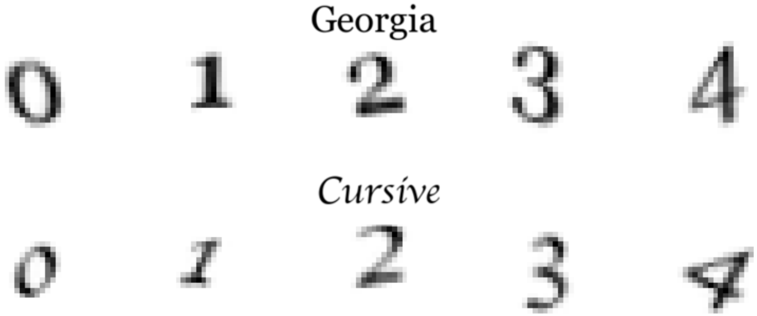
We can draw inspiration from the cryptographic notion of indistinguishibility.

Defining Security for FE-ML



Collateral Learning

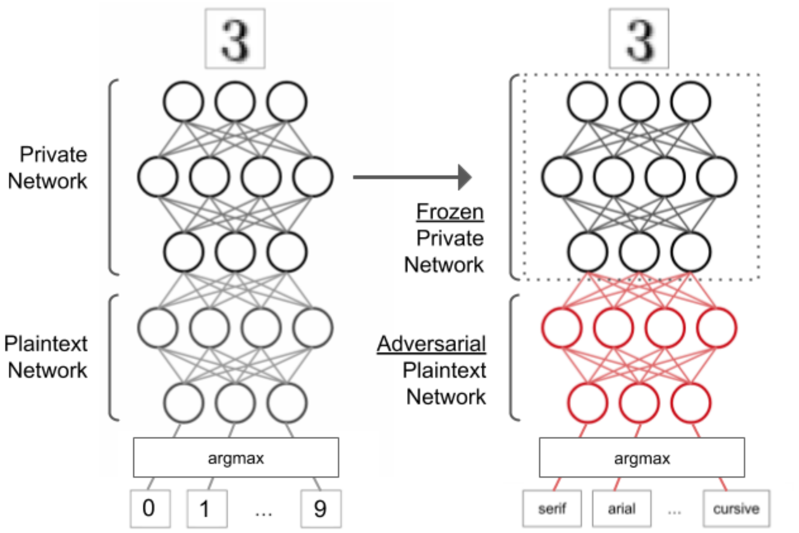


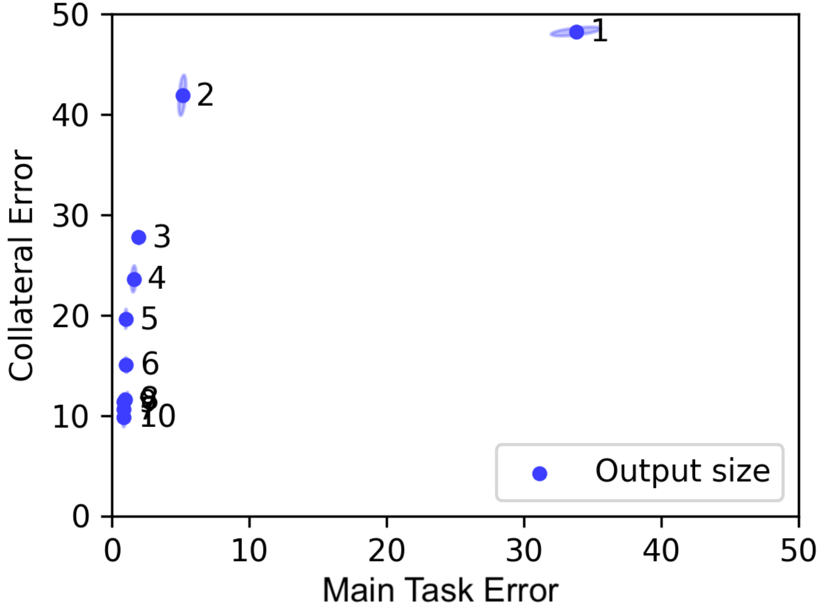
Table of Contents

Implementation

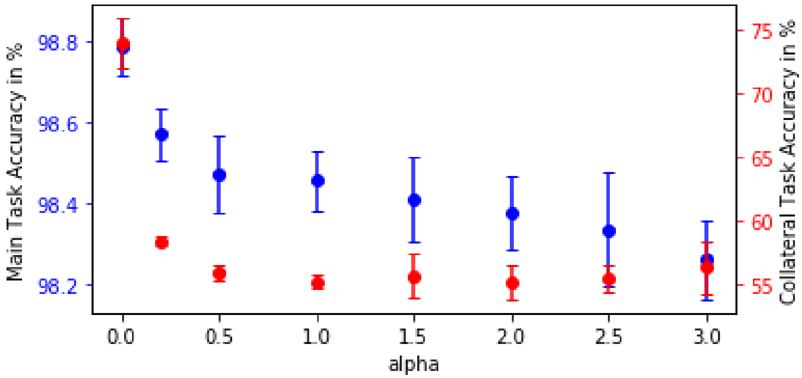
We provide a Python implementation using Charm with PBC.
We use a database for precomputed discrete logarithms.

Functional key generation	0.094s
Encryption time	12.1s
Evaluation time	2.97s
Discrete logarithms time	0.024s

Results: Influence of Output Size



Results: Influence of Adversarial Parameter



Open problems

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- Trusting models.

Recap: Our contributions

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