Secure Machine Learning in the Cloud

Roland Hostettler, Subhrakanti Dey, Anders Ahlén

Division of Signals and Systems
Department of Electrical Engineering
Uppsala University

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Background

Machine learning

- Important in many industries (process, automotive, ...)
- Requires (sensitive) user/company data
- Can be computationally complex
- Can be implemented in the cloud
  - Scalable and flexible
  - Cost-efficient
  - Low-maintenance
  - Machine learning as a service (MLaaS)

Data security threats

- Industrial/governmental espionage
- User privacy and integrity
- Local legislation
- Data breaches or leaks

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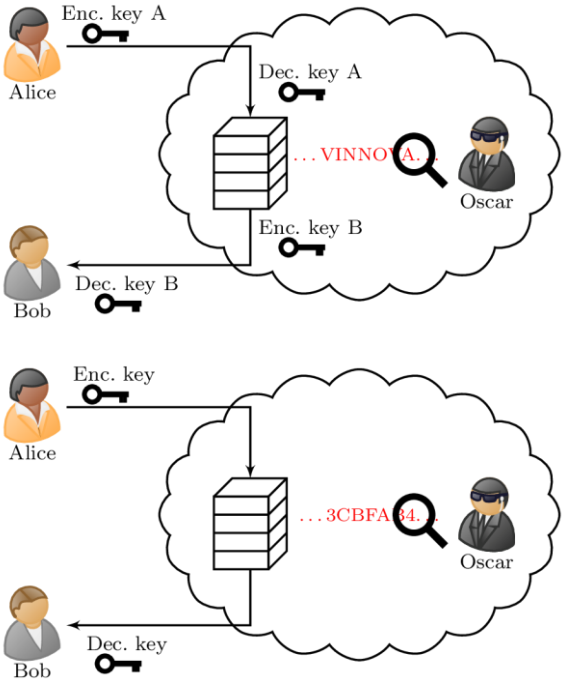
Project goals

1. Data security: Homomorphic encryption
    - Allows processing encrypted data without decrypting it
2. Privacy/integrity: Differential privacy
    - Ensures that individual data points can not be distinguished
3. Platform requirements and demonstration
    - Computational requirements, network/system architecture



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Homomorphic encryption

Homomorphic encryption:

$$f(x \circ y) = f(x) \circ f(y) \;\Leftrightarrow\; \mathrm{Enc}(x \circ y) = \mathrm{Enc}(x) \circ \mathrm{Enc}(y)$$

Fully homomorphic encryption (FHE):

- Supports addition and multiplication
- Computationally complex
- Limited to, e.g., integers or in number of consecutive operations (levels)

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Partially Homomorphic Encryption

- Supports limited types of operations (e.g., addition or multiplication)
- Computationally less complex
- Several schemes need to be combined or some operations need to be done in plain text

FHE: Cheon-Kim-Kim-Song scheme

- Fully homomorphic scheme
  - supports addition & multiplication
- Uses approximate arithmetic: $\mathrm{Enc}(x \circ y) \approx \mathrm{Enc}(x) \circ \mathrm{Enc}(y)$
- Leveled
  - Can be extended to support unlimited operations (bootstrapping)
- Complex functions can be implemented using polynomial approximations
  - Approximation must not exhaust the number of levels

Example: kNN using CKKS (1/2)

k-Nearest Neighbors (kNN):

- Simplistic approach for classification/prediction, based on finding k closest points to a test input
- Computational primitives:
  - Calculating the distance between data points (e.g., Euclidean distance)
  - Comparing distances and sorting
  - Weighted average / majority vote

Example: kNN using CKKS (2/2)

Some conclusions:

- Individual multiplications may be computationally complex (depending on the security parameters) but not a problem
- Approximation of functions using polynomials consumes many levels due to the multiplications
  - Good approximations often require high polynomial orders → consume many levels
  - Bootstrapping (refreshing the ciphertext) is expensive, and the main challenge is taking decisions and acting upon the mathematical output

Overview of results

- Understanding of HE and CKKS, their challenges and complexity
- Design studies for secure distributed computation network
- Implementation of PoC ongoing

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Partners and funding

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Collaboration Opportunities

- Research
- Industrial stakeholders
  - Use-cases
  - Reference group
- Verification and auditing

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