Privacy Preserving Neural Network Classification

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Privacy goals in PAPAYA

PAPAYA Objectives

Privacy by Design

- **PP analytics**: **Neural Networks (NN),** clustering, statistics

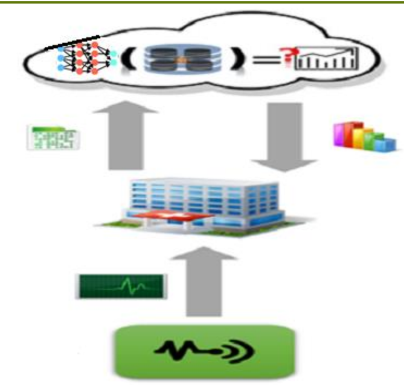
Different Settings

- One data owner vs. multiple data owners
- One querier vs. multiple queriers

Use Cases

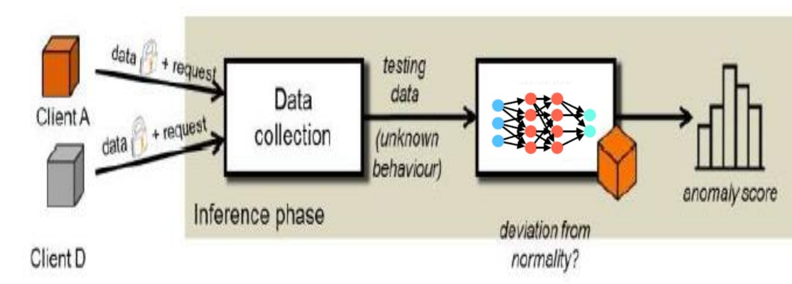
healthcare

Arrhythmia Detection



mobile and phone usage

Threat Detection



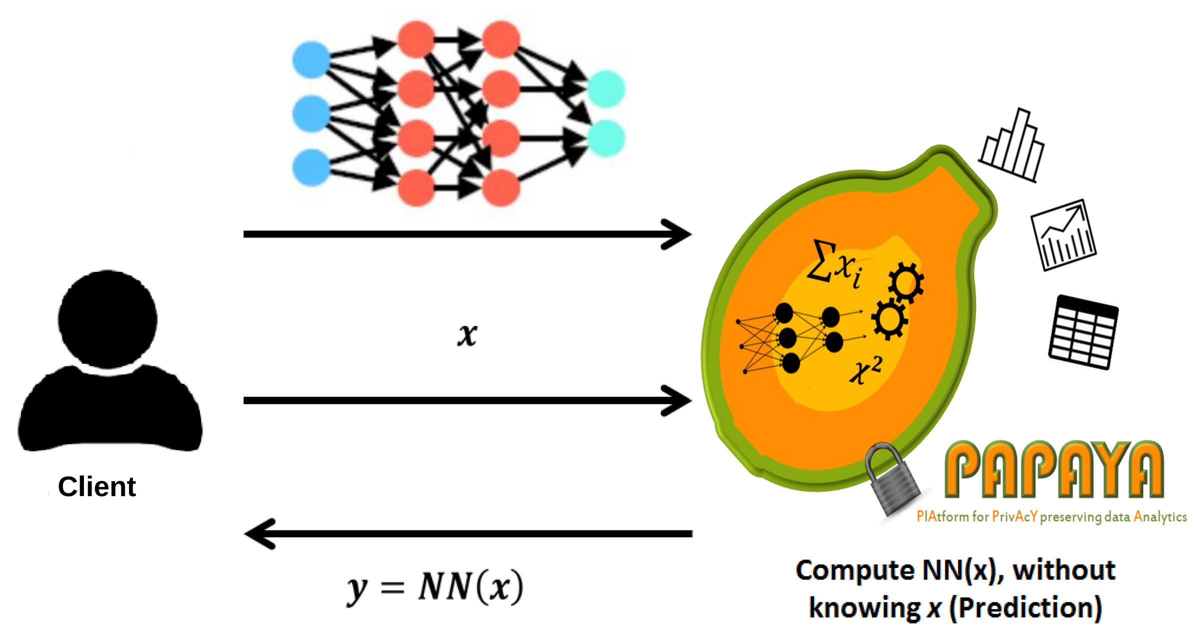
Analytics example – Neural Network classification

NN Layers and Operations

- **Input Layer**
- **Hidden Layer**

 - Convolutional layer (matrix multiplications)
 - Activation layer (sigmoid, tanh, etc.)
 - Pooling layer
 - Fully connected layer

- **Output Layer** (softmax, etc.)



Privacy by Design Challenges

- **Privacy vs. efficiency**

 Deep NN ⇒ Significant overhead with cryptographic tools

- **Privacy vs. accuracy**

 Complex operations (sigmoid, softmax, etc.) ⇒ Not suitable to crypto tools

- **Real Numbers**

Privacy Preserving Neural Network Classification – Existing solutions

with Homomorphic Encryption [1]

- Non-interactive
- Only linear operations (eg. AF is approximated to x^2)
- Expensive in computation cost
- No communication cost

with Secure Two-party Computation [2]

- Interactive – Client is involved
- Linear operations and comparisons
- Efficient in computation cost
- Expensive in communication cost

Privacy Preserving Neural Network Classification: A Hybrid Solution

Hybrid Solution

Features

- Paillier for linear operations

 ⇒ Optimized computational overhead

 ⇒ Less computation time compared to [1]

- Paillier for x^2

 ⇒ New interactive protocol to compute x^2

- 2PC for comparison only (ReLU case)

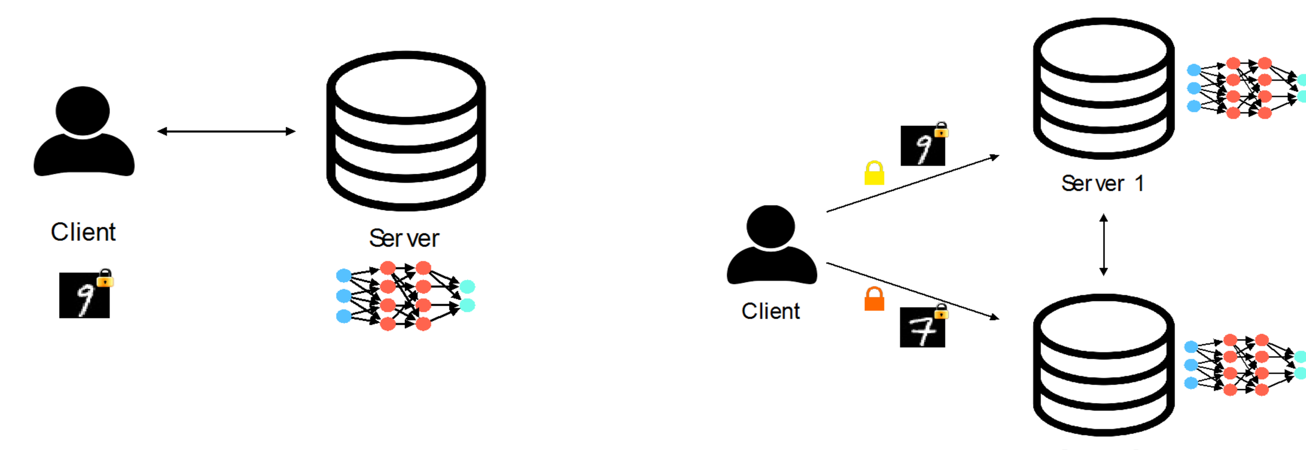
 ⇒ Optimized communication overhead

 ⇒ Less bandwidth usage compared to [2]

- Similar level of accuracy as in [1, 2]

Input
Convolution layer
Activation layer (x^2)
Pooling layer (avg)
Convolution layer
Pooling layer (avg)
Fully Connected layer
Activation layer (x^2)
Fully Connected layer
Output

Flexible solution: 2 settings



Results

- Computation cost 30-fold better than [1]
- Communication cost 27-fold better than [2]

Technique	Computation Cost (s)	Communication Cost (MB)
HE [1]	297	372.2
2PC [2]	1.2	47.6
Hybrid Solution	10	1.73

References:
[1] Gilad-Bachrach, Ran, et al. "Cryptonets: Applying neural networks to encrypted data with high throughput and accuracy." *International Conference on Machine Learning*. 2016.
[2] Liu, Jian, *et al. "Oblivious neural network predictions via minionn transformations." Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security. ACM, 2017.*

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