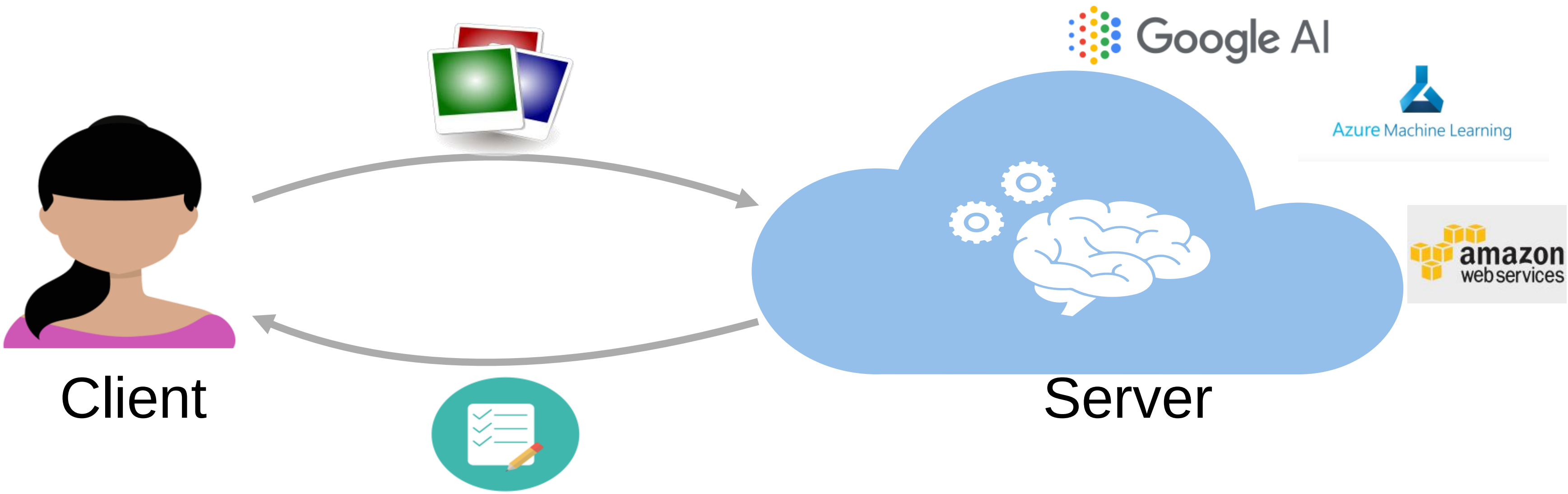
Privacy-preserving federated learning for healthcare

Melek Önen

January 2022, AI4Health

Machine Learning as a Service

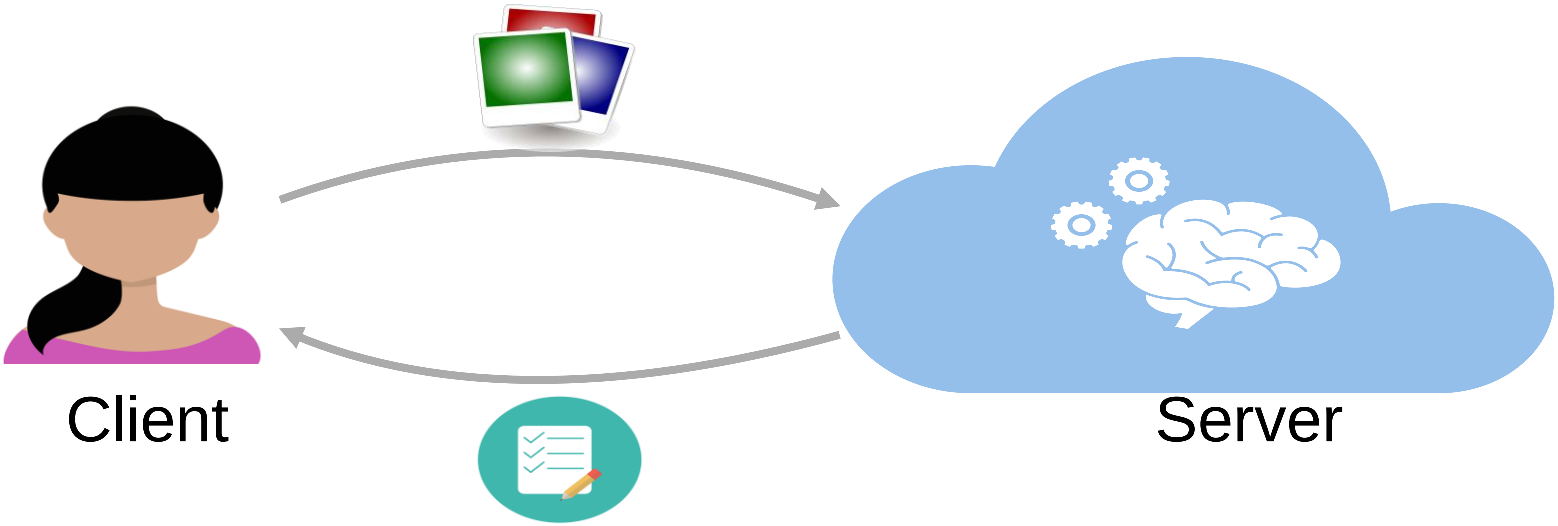


Performance

No need for ML knowledge

Cost reduction

Sensitive and confidential data



- Sensitive personal data
- Corporate data (IP)

- Intellectual property

- Legal restrictions

Data Protection - Tools

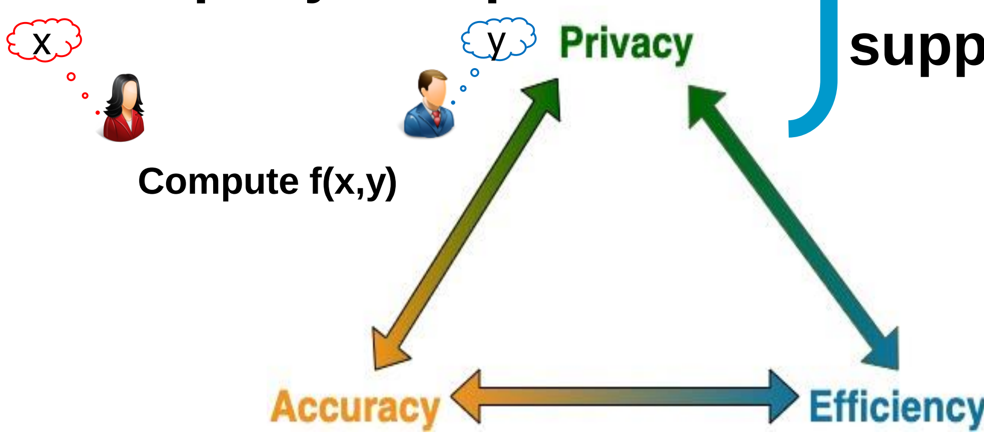
Traditional crypto → **not adapted**

Advanced crypto

Homomorphic Encryption

$$Enc(m_1) \blacklozenge Enc(m_2) = Enc(m_1 \spadesuit m_2)$$

Secure Multiparty Computation



- Additional overhead

- Only, some operations are supported

Homomorphic encryption

$$Encrypt(m_1)\ op1\ Encrypt(m_2) = Encrypt(m_1 op2\ m_2)$$

Partially HE

Support one operation only

Somewhat HE

Support arbitrary + and limited number of x

Fully HE

Support any function

El Gamal Cryptosystem

- $KeyGen(1^n)$
  - $SK: x$
  - $PK: \{p, g, g^x mod\ p\}$
- $Encryption(g^x, m)$
  - Choose $r \leftarrow Z_N^*$
  - Output $c = (c_1, c_2) = (g^r, m(g^x)^r)$
- $Decryption(x, c)$
  - $Compute\ c_1^x$
  - Output $m = \frac{c_2}{c_1^x}$

El Gamal Homomorphism

- $c = (c_1, c_2) = (g^r, m(g^x)^r),\ c' = (c_1', c_2') = (g^{r\prime}, m'(g^x)^{r\prime})$

- $(c_1 c_1', c_2 c_2{}') = (g^{r+r'}, m.m' g^{(r+r')x}) = Encrption(g^x, mm')$

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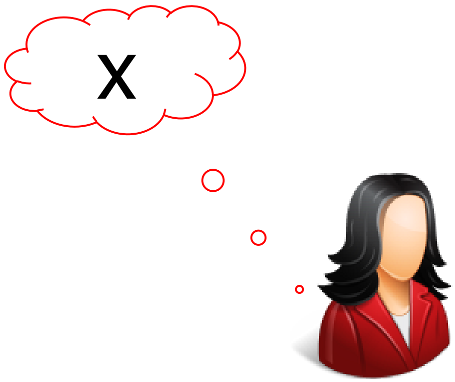
Homomorphic encryption

- **Partially homomorphic encryption**
  - Practical
  - Used for electronic voting, simple statistical operations
- **Somewhat homomorphic encryption**
  - Useful for low-degree polynomials
- **Fully Homomorphic Encryption**
  - Still not very practical
  - Ongoing research

Secure Two-party computation



Compute f(x,y)

leak no other information than what Ideal model leaks

Yao's GC

Arithmetic sharing

Boolean sharing

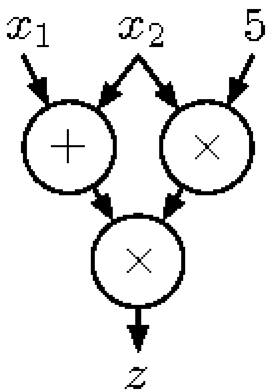
Yao's Secure Two-Party Computation

- **First secure two-party computation**

- **Problem**
  - Inputs: A: x; B: y;
  - Output: f(x,y)

- **Idea**
  - Represent f as a Boolean Circuit
  - Transform this circuit to a garbled circuit that hides all information but the output

2PC with Arithmetic circuits



$$z = (x_1 + x_2) \times (x_2 \times 5)$$

- **Arithmetic Circuit**
  - Addition gates
  - Multiplication gates

Secret sharing for addition gates [Ben-or et al.'88]

- **Goal: compute** $\mathrm{z} = x_A + x_B$
  - Secret share x_A
    - $x_A = x_{A1} + x_{A2}$
  - Secret share x_B
    - $x_B = x_{B1} + x_{B2}$
  - Send shares to two parties
    - P1:$x_{A1},\ x_{B1}$; P2:$x_{A2},\ x_{B2}$;
  - Compute sum
    - P1: $res1 = x_{A1} + x_{B1}$; P2: res2 = $x_{A2} + x_{B2}$;

  $\Rightarrow x_A + x_B = \mathrm{res1} + \mathrm{res2}$

$\Rightarrow$ **No communication needed!**

How to multiply?

- **Goal compute** $z = x_A . x_B$
  - Secret share x_A
    - $x_A = x_{A1} + x_{A2}$
  - Secret share x_B
    - $x_B = x_{B1} + x_{B2}$
  - Send shares to two parties
    - P1: $x_{A1},\ x_{B1}$; P2: $x_{A2},\ x_{B2}$;
  - Compute multiplication
    - P1: $res1 = x_{A1}.x_{B1}$; P2: res2 = $x_{A2}.x_{B2}$;

$\Rightarrow x_A . x_B \neq \mathrm{res1}.\mathrm{res2}$

$\Rightarrow x_A . x_B = (x_{A1} + x_{A2})(x_{B1} + x_{B2})$

How to compute this?

$$= x_{A1}x_{B1} + x_{A2}x_{B2} + x_{A1}x_{B2} + x_{A2}x_{B1}$$

Beaver triplets

- **Let $c = ab$ and let secret share and obtain** $[a], [b], [c]$
- **Secret share x_A and x_B**
- **Compute**
  - Construct $e = x_A + a;\ d = x_B + b$; from [a], [b], $[x_A]$, $[x_B]$
  - $[z] = [x_A . x_B] = [c] + e[x_B] + d[x_A] - ed$

$\Rightarrow$ **Pre-processing and storage needed**

$\Rightarrow$ **1-round communication**

2 Party Computation - Summary

- **2 different methods**
  - Yao's GC
  - 2-PC through arithmetic sharing
- **Assumption**
  - Semi-honest parties
- **Open questions**
  - From 2PC to multi-party computation
  - From semi-honest to malicious adversaries

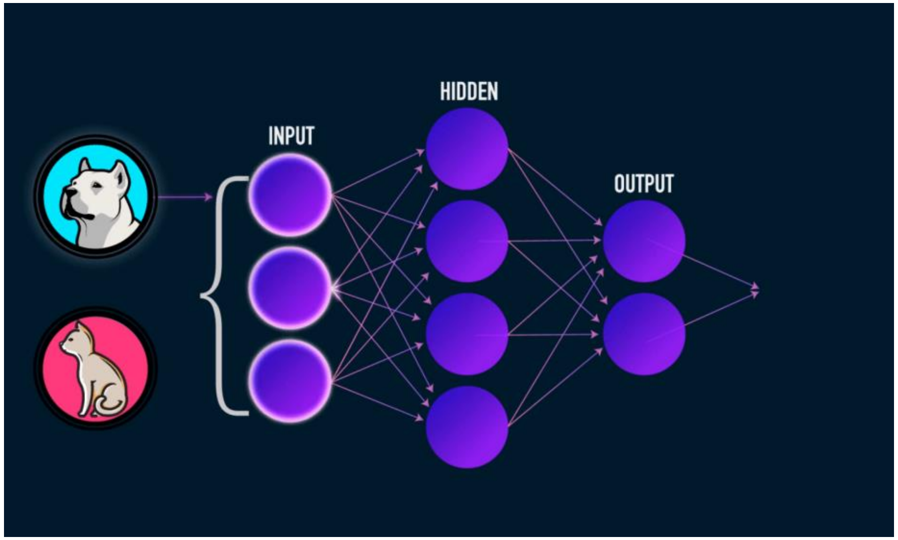
HE vs. 2PC

HE
Non-interactive
Only linear operations
Expensive in computation cost
No communication cost

2PC
Interactive - Client is involved
Linear and nonlinear operations
Efficient in computation cost
Expensive in communication cost

Artificial Neural Networks

Supervised machine learning technique



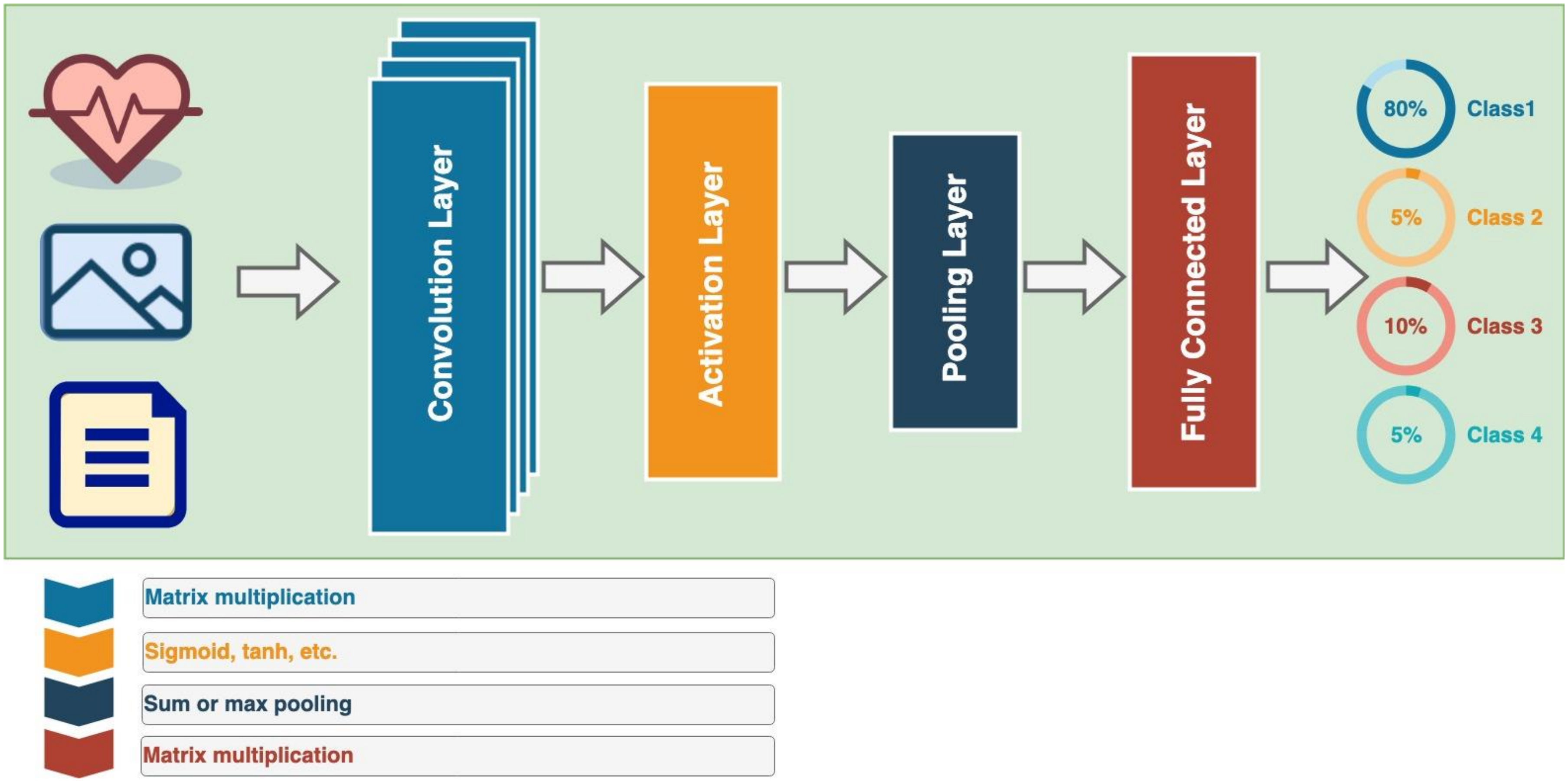
Two phases:

- Training
- Classification

NN layers:

- Activation layer
- Pooling layer
- Fully-connected layer
- Convolution layer (optional)

Neural Networks - Architecture



Privacy preserving NN Classification

Use Advanced cryptographic techniques

- Homomorphic encryption, Secure 2PC

Challenge : Privacy vs. Performance

- Additional overhead (Computation, memory & bandwidth)
- Complex operations (sigmoid, tanh, etc.)
- Real numbers (vs. integers with PETs)

Goal

- Reduce NN complexity
- Approximate complex operations $\Rightarrow$ Use low degree polynomials
- Approximate real numbers $\Rightarrow$ Use integers

Privacy preserving NN Classification

Use Advanced cryptographic techniques

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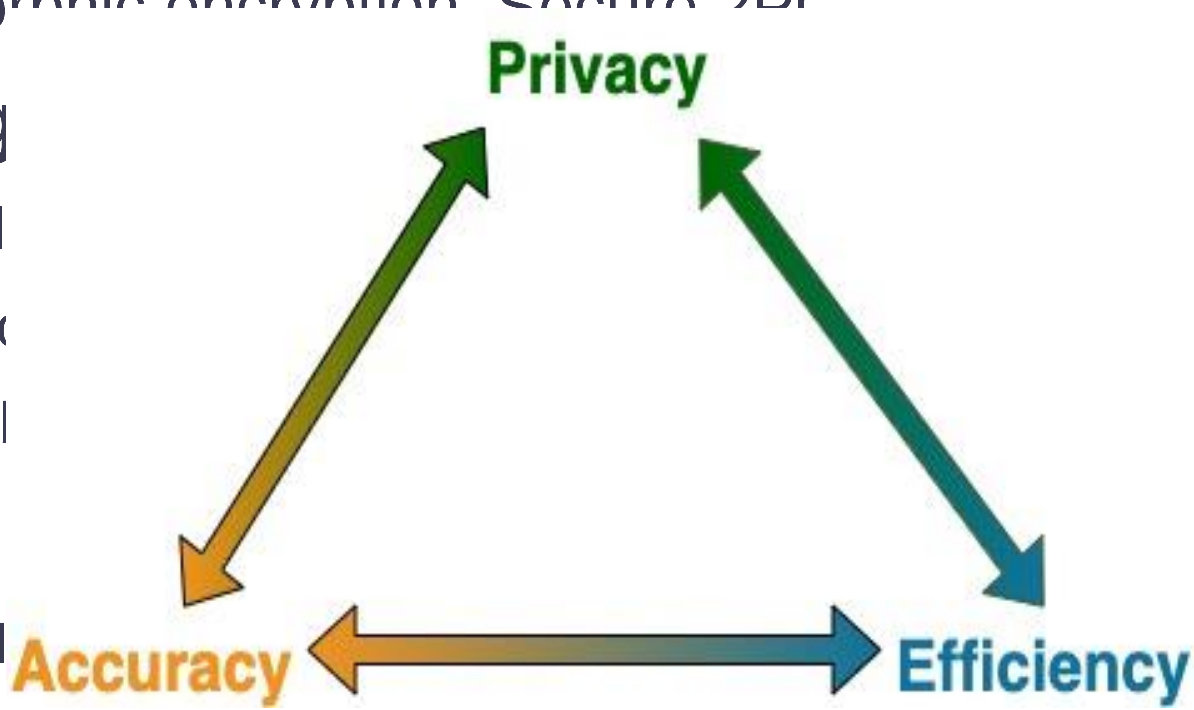
Challeng

- Additional ... n)
- Complex ...
- Real numl



Goal

- Reduce N
- Approximate complex operations $\Rightarrow$ Use low degree polynomials
- Approximate real numbers $\Rightarrow$ Use integers

Approximation of NN layers

- Convolution layer
  - Matrix multiplications $\Rightarrow$ No need for approximation
- Activation layer
  - Most common approach: $\boldsymbol{x^2}$ and ReLU
- Pooling layer
  - Sum or average
- Fully Connected layer
  - Matrix multiplications $\Rightarrow$ No need for approximation
- Real numbers
  - Most common approach: Multiplying with 10^n

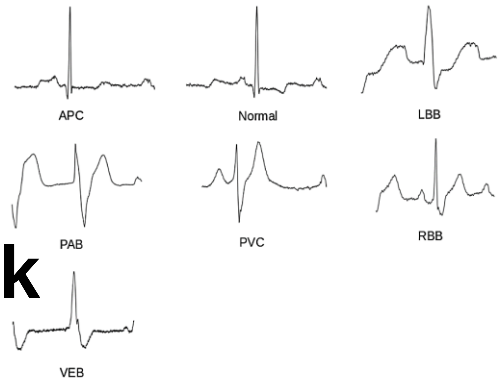
PAC: Pp Arrhythmia Classification

[FPS 2019]

NN based ECG analysis

2PC based NN classifier

- Low degree polynomials for activation functions
- Approximation of real numbers
- PCA for size reduction



Performance results with PhysioBank

- 96.34% accuracy
- 1 sec prediction time in real environment

PAC in batches

- Efficient solution for real scenarios

What about federated learning for healthcare?

EPIONE Team– Marco Lorenzi
- Development of the **FedBioMed platform**
- Development of the interface, adaptation of the central infrastructure to the project algorithms, installation of the "client" software infrastructure

https://fedbiomed.gitlabpages.inria.fr/

Antoine Lacassagne
CENTRE DE LUTTE CONTRE LE CANCER
unicancer NICE

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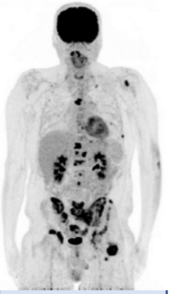
10 Comprehensive Cancer Centers
- Definition of a multi-center AI clinical project
- Structuring and storage of the database in a local client application (harmonization of formats and structuring)
- Hospitals transmit only the parameters of the learning model



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Security and privacy for emerging technologies such as Big Data or IoT

3iA Côte d'Azur
Interdisciplinary Institute for Artificial Intelligence

Objective at the end of the project
a functional platform, open to the project's partner hospitals, versatile

Picture credit: Olivier Humbert

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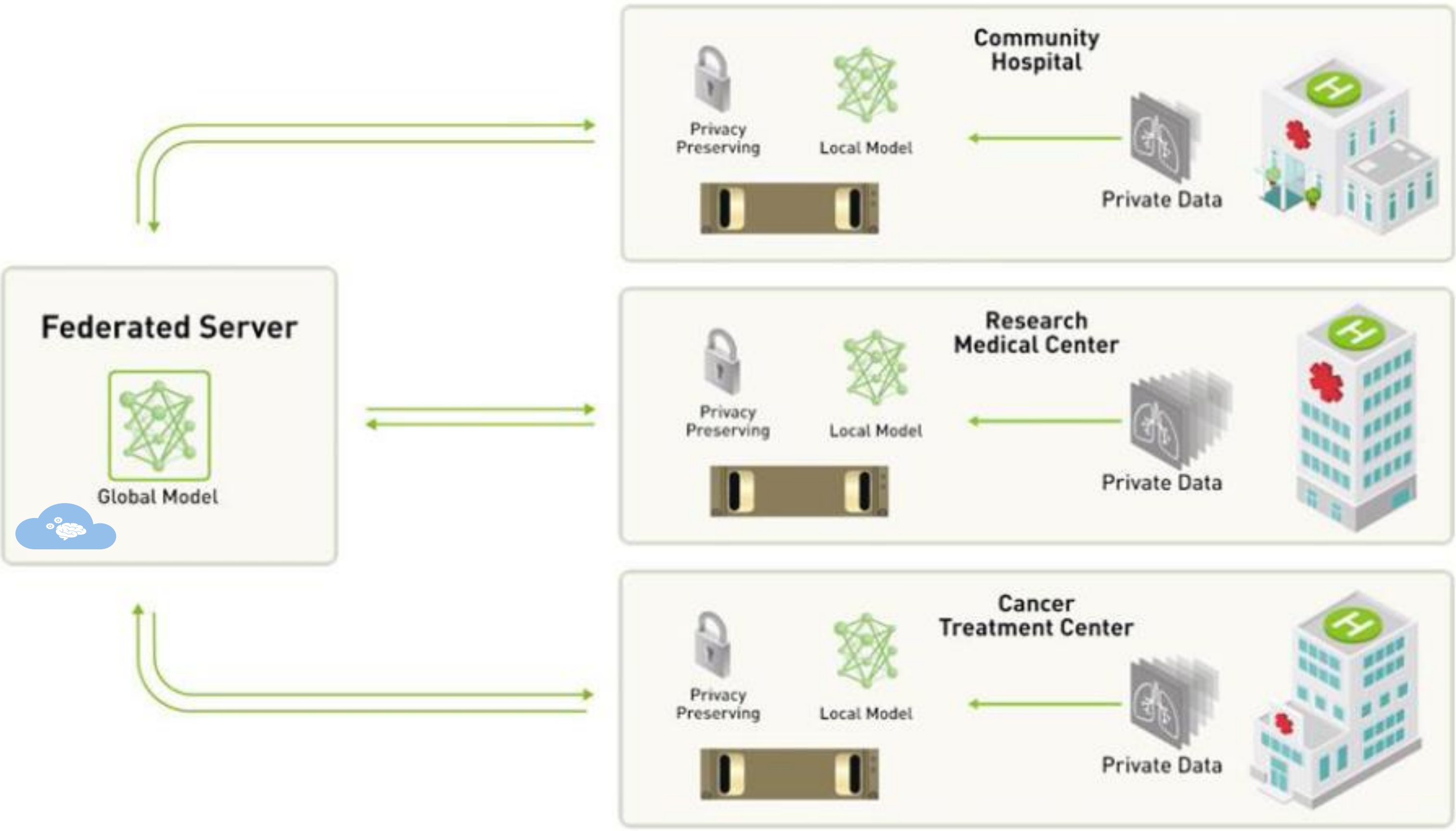

Picture credit: Olivier Humbert

Open questions

- **Multiple parties**
  - Need for a dedicated key management scheme?
  - Need for MPC with multiple parties?
  - Need for a new adversarial model (the more the risky?)?
- **Healthcare data**
  - Usually large datasets $\Rightarrow$ adds even more complexity
  - What about operations
  - More bandwitdh

Thank you!

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