

CER-VD et APDI Open Data



## Sharing without Sharing – Privacy-Conscious Decentralized Data Analytics

Prof. Jean-Pierre Hubaux (EPFL)

With gratitude to all the great colleagues and co-workers I have the privilege to collaborate with



7 October 2021



#### Use case for Swiss Personalized Oncology Project: federated analytics platform for research and molecular tumor board



## DPPH – Data Protection in Personalized Health

- 5 research groups across the ETH domain + SDSC (Swiss Data Science Center)
- Funding: 3 Millions CHFrs
- Duration: 3 years (4/2018 12/2021)
- Funding Program: ETH PHRT (Personalized Health and Related Technologies)

Strategic Focus Area Personalized Health and Related Technologies

#### Project goals:

EPEL

- Address the main privacy, security, scalability, and ethical challenges of data sharing for enabling effective P4 medicine
- Define an optimal balance between usability, scalability and data protection
- Deploy an appropriate set of computing tools



## DPPH/MedCo - A highly interdisciplinary team

#### Core team

#### Leadership team

![](_page_3_Picture_3.jpeg)

![](_page_3_Picture_4.jpeg)

![](_page_3_Picture_5.jpeg)

Dr. Francesco Marino Joao Sa (Senior SW developer, LDS) (SW developer, LDS)

Joao Sa

![](_page_3_Picture_8.jpeg)

Jules Fasquelle Nicolas Freundler (SW developer, CHUV) (SW developer, CHUV)

![](_page_3_Picture_10.jpeg)

#### **Hospital ambassadors**

![](_page_3_Picture_12.jpeg)

Prof. Alexandre Leichtle (Inselspital)

![](_page_3_Picture_14.jpeg)

Prof. Jacques Fellay (CHUV/EPFL)

![](_page_3_Picture_16.jpeg)

![](_page_3_Picture_17.jpeg)

Dr. David Cavin (HUG)

Solon Barraclough (HUG)

#### **SPO** ambassadors

![](_page_3_Picture_21.jpeg)

![](_page_3_Picture_22.jpeg)

![](_page_3_Picture_23.jpeg)

Prof. Olivier Michielin (CHUV)

lin Dr. Michel Cuendet (CHUV)

Dr. Sylvain Pradervand (CHUV)

## Unfolding

![](_page_4_Figure_1.jpeg)

![](_page_4_Figure_2.jpeg)

Strategic Focus Area

Personalized Health

(budget 3M CHF) EPFL DPPH and Related Technologies **ETH** zürich Data Protection in Dore

## MedCo in one slide...

- Distributed software platform for federated cohort exploration and analytics of clinical and genomic data
- •Co-developed by EPFL and CHUV EPFL
- Built on top of the i2b2 cohort explorer (i2b2 is used by 250+ hospitals worldwide)
- Relies on **advanced cryptographic techniques** → Multi-party homomorphic encryption (MHE)
- Code-reviewed and pen-tested by third-party industrial companies, compliant with hospitals' information security policies

Main functionalities

#### MedCo-Explore: cohort exploration

- Obtaining cohort sizes for clinical research studies based on inclusion/exclusion criteria,
- MedCo-Analysis: federated analytics
  - Survival analysis
  - ML training and testing (under development)

![](_page_5_Picture_13.jpeg)

![](_page_5_Picture_14.jpeg)

![](_page_5_Picture_15.jpeg)

![](_page_5_Picture_16.jpeg)

EPFL

## MedCo-Explore: cohort exploration/selection

![](_page_6_Picture_1.jpeg)

## MedCo-Analysis: distributed analytics

![](_page_7_Figure_1.jpeg)

#### Positioning of MedCo with respect to similar distributed platforms

|                  | Criteria \ Platform  | CLINERION<br>Real World Data Solutions | SHRINE<br>Dared Health Research Infernation Nativesk |     | VANTAGE | (F) | MedCO |
|------------------|--|--|--|-----|---------|-----|-------|
| Functionality    | Federated cohort exploration   | Yes                                    | Yes  | No  | No      | Yes | Yes   |
|                  | Federated analytics  | No                                     | No   | Yes | Yes     | Yes | Yes   |
| Privacy/Security | Protection of intermediate<br>results and distributed<br>computation | No                                     | No   | No  | No      | No  | Yes   |
|                  | Protection of end result from inference attacks                      | No                                     | Yes  | No  | No      | No  | Yes   |
|                  | Fine-grained role<br>management                                      | No                                     | No   | No  | No      | No  | Yes   |
| Usability        | Graphical user interface   | Yes                                    | Yes  | No  | No      | Yes | Yes   |
|                  | Public API   | No                                     | Yes  | Yes | Yes     | Yes | Yes   |
|                  | Service & support  | Yes                                    | No   | No  | No      | No  | Yes   |
|                  | Extensibility  | No                                     | Yes  | Yes | Yes     | Yes | Yes   |

# GDPR legal compliance: partial aggregates are not personal data anymore, they are anonymous

![](_page_9_Picture_1.jpeg)

#### Published on 25.2.2021 in Vol 23, No 2 (2021): February

Preprints (earlier versions) of this paper are available at https://preprints.jmir.org/preprint/25120, first published October 19, 2020.

![](_page_9_Picture_4.jpeg)

#### Revolutionizing Medical Data Sharing Using Advanced Privacy-Enhancing Technologies: Technical, Legal, and Ethical Synthesis

James Scheibner <sup>1, 2</sup> <sup>(D)</sup>; Jean Louis Raisaro <sup>3, 4</sup> <sup>(D)</sup>; Juan Ramón Troncoso-Pastoriza <sup>5</sup> <sup>(D)</sup>; Marcello Ienca <sup>1</sup> <sup>(D)</sup>; Jacques Fellay <sup>3, 6, 7</sup> <sup>(D)</sup>; Effy Vayena <sup>1</sup> <sup>(D)</sup>; Jean-Pierre Hubaux <sup>5</sup> <sup>(D)</sup>

## Legal qualification of data processed through MedCo

![](_page_10_Figure_1.jpeg)

- Data transferred/processed with MedCo can be considered anonymized data
- No need of bilateral data transfer agreements between institutions to perform federated analytics
- Patient consent not required for MedCo-Explore (out of scope of HRA)
- Patient consent might not be required for MedCo-Analysis (under some circumstances)

|                     | 1 : Local data        | 2 : Encrypted partial results | 3 : Encrypted full result | 4 : Decrypted full result  |
|---------------------|-----------------------|-------------------------------|---------------------------|--|
| Data status         | Individual-level data | Locally aggregated            | Globally aggregated       | Globally aggregated  |
| Legal qualification | Personal data         | Anonymized data               | Anonymized data           | Anonymized (if proper protection in place)<br>Personal data (if proper protection not in<br>place) |

## Data Protection Impact Assessment (DPIA) for multisite medical data analysis (June 2021)

#### Centralized approach with standard pseudonymization

| Threat                                    | Threat<br>likelihood | Threat impact | Risk   | Risk level |
|---|----------------------|---------------|--|------------|
| Unlawful access to the system             | Unlikely             | High          | Loss of data<br>confidentiality  | Moderate   |
| Malicious use of the system               | Possible             | High          | Loss of data<br>confidentiality  | High       |
| Loss of data                              | Unlikely             | Minor         | Loss of data integrity,<br>data unavailability   | Minor      |
| Data leak of<br>host/cloud                | Possible             | High          | Loss of data<br>confidentiality  | High       |
| Collusion of<br>host/cloud                | Possible             | High          | Loss of data<br>confidentiality  | High       |
| Corrupted or<br>malicious host/cloud      | Possible             | High          | Data unavailability, loss<br>of data integrity, loss of<br>data confidentiality, loss<br>of data correctness | High       |
| Unavailability of<br>host/cloud           | Possible             | Minor         | Data unavailability, loss of data correctness  | Moderate   |
| Re-identification/attri<br>bute inference | Possible             | High          | Loss of data<br>confidentiality  | High       |

#### Federated approach enhanced with MedCo

| Threat   | Measure<br>introduced<br>with MedCo | Threat<br>likelihood | Threat<br>Impact | Risk   | Risk level |
|--|-------------------------------------|----------------------|------------------|--|------------|
| Unlawful access to the system                  | 1                                   | Unlikely             | Minor            | Loss of data<br>confidentiality  | Low        |
| Malicious use of the system                    | 1, 2, 4, 10                         | Possible             | Minor            | Loss of data<br>confidentiality  | Low        |
| Loss of data                                   | 3, 5                                | Unlikely             | Minor            | Loss of data<br>integrity, data<br>unavailability  | Low        |
| Data leak                                      | 4, 5, 8, 9, 10                      | Unlikely             | Minor            | Loss of data<br>confidentiality  | Low        |
| Collusion<br>between nodes                     | 4, 9                                | Unlikely             | Moderate         | Loss of data<br>confidentiality  | Moderate   |
| Corrupted or<br>malicious nodes                | 2, 5, 6, 7, 8, 9                    | Unlikely             | Moderate         | Data unavailability,<br>loss of data<br>integrity, loss of<br>data confidentiality,<br>loss of data<br>correctness | Moderate   |
| Unavailability of of nodes                     | 6, 7                                | Possible             | Minor            | Data unavailability,<br>loss of data<br>correctness  | Moderate   |
| Re-identification<br>or attribute<br>inference | 1, 2, 4, 9, 10                      | Unlikely             | Minor            | Loss of data<br>confidentiality  | Low        |

The DPIA was elaborated notably with the help of Valérie Junod and Sylvain Métille

## Feedback from EDÖB on MedCo DPIA

![](_page_12_Picture_1.jpeg)

Schweizerische Eidgenossenschaft Confédération suisse Confederazione Svizzera Confederaziun svizra

#### Federal Data Protection and Information Commissioner

"... the threat impact of most risks with the MedCo system shows to be clearly lower than with traditional systems. Since data processed within the Medco framework remain encrypted at rest and during computation, an attacker would cause little damage. As no entity has the full decryption key, it seems indeed unlikely that he could decrypt and abuse the stolen data. (...)"

13 September 2021

#### The "Holy Grail" for SPHN secure federated analytics: FAMHE

#### Truly Privacy-Preserving Federated Analytics for Precision Medicine with Multiparty Homomorphic Encryption

David Froelicher<sup>1</sup>, Juan R. Troncoso-Pastoriza<sup>1</sup>, Jean Louis Raisaro<sup>2,3</sup>, Michel A. Cuendet<sup>4</sup>, Joao Sa Sousa<sup>1</sup>, Hyunghoon Cho<sup>5</sup>, Bonnie Berger<sup>5,6,7</sup>, Jacques Fellay<sup>2,8</sup>, and Jean-Pierre Hubaux<sup>1,\*</sup>

<sup>1</sup>Laboratory for Data Security, EPFL, Lausanne, Switzerland <sup>2</sup>Precision Medicine Unit, Lausanne University Hospital, Lausanne, Switzerland <sup>3</sup>Data Science Group, Lausanne University Hospital, Lausanne, Switzerland <sup>4</sup>Precision Oncology Center, Lausanne University Hospital, Lausanne, Switzerland <sup>5</sup>Broad Institute of MIT and Harvard, Cambridge, Massachusetts, USA <sup>6</sup>Computer Science and AI Laboratory, MIT, Cambridge, Massachusetts, USA <sup>7</sup>Department of Mathematics, MIT, Cambridge, Massachusetts, USA <sup>8</sup>School of Life Sciences, EPFL, Lausanne, Switzerland <sup>\*</sup>jean-pierre.hubaux@epfl.ch

## Accepted for publication in Nature Communications $\rightarrow$ will appear on 11 October

https://doi.org/10.1101/2021.02.24.432489

- Idea: train and run ML models on decentralized datasets without "seeing" the data
- Initially CHUV + EPFL, then Broad Inst. + MIT researchers joined the effort

#### FAHME: Privacy-Preserving Federated Analytics for Precision Medicine with MHE - Survival curves (Kaplan-Meier)

![](_page_14_Figure_1.jpeg)

[Centralized] Samstein, R. M. et al. Tumor Mutational Load Predicts Survival after Immunotherapy across Multiple Cancer Types. Nat. genetics 51, 202–206 (2019).

[FAHME] Froelicher et al. Truly Privacy-Preserving Federated Analytics for Precision Medicine with Multiparty Homomorphic Encryption.

## FAHME: Privacy-Preserving Federated Analytics for Precision Medicine with MHE - GWAS

**Use case**: 1857 patients spread among 12 data providers.

*Original* = Centralized approach *FAMHE-GWAS* = Exact secure federated approach *FAMHE-FastGWAS* = Efficient

secure federated approach

*Meta-analysis* = distributed nonsecure non-iterative approach *Independent* = 1 DP alone

[Original approach] McLaren, P. J. et al. Polymorphisms of Large Effect Explain the Majority of the Host Genetic Contribution to Variation of HIV-1 Virus Load. Proc. Natl. Acad. Sci. 112, 14658– 14663 (2015).

[FAHME] Froelicher et al. Truly Privacy-Preserving Federated Analytics for Precision Medicine with Multiparty Homomorphic Encryption.

![](_page_15_Figure_7.jpeg)

(b) FAMHE-GWAS

(c) Meta-analysis Approach

![](_page_15_Figure_10.jpeg)

![](_page_15_Figure_11.jpeg)

![](_page_15_Figure_12.jpeg)

## FAHME: Genome-wide association study

**Default**: 1857 patients spread among 12 data providers.

- $\rightarrow$  scale in all dimensions
  - a. With the number of data providers
  - b. With the number of patients
  - c. With the number of variants

![](_page_16_Figure_6.jpeg)

![](_page_17_Figure_1.jpeg)

![](_page_17_Figure_2.jpeg)

Tune Insight

![](_page_18_Picture_0.jpeg)

#### Tune Insight secures pre-seed round from Wingman Ventures

22.09.2021

#### > FINANCING

More news about

![](_page_18_Picture_5.jpeg)

![](_page_18_Picture_6.jpeg)

Tune Insight B2B software enables organizations to make better decisions by collaborating securely on their sensitive data to extract collective insights. Incubated at the EPFL Laboratory for Data Security, with a deployment in Swiss university hospitals and customer-funded projects in the insurance and cybersecurity businesses, Tune Insight will use the funds to accelerate product development, strengthen the team, and onboard more customers.

![](_page_18_Picture_8.jpeg)

## Conclusion

Achievements:

- We have solved the problem of GDPR-compliant federated analytics for medical data
- We provide MedCo, a fundamental building block for SPHN and beyond
- In September 2021, SPHN gave green light for further experimental deployments of MedCo
- Worldwide leading project on secure, privacy-conscious medical data sharing
- Solution for economic viability beyond 2021: Tune Insight

#### Ongoing and future steps:

- Assessment by CER-VD and APDI
- Transfer of people and know-how from EPFL to Tune Insight
- Further deployments in Swiss hospitals and beyond

## Back-up slides

## **Ethics Committees**

![](_page_21_Figure_2.jpeg)

- Very slow, manpower-hungry and tedious process to check the proposed data-protection measures
- Need to obtain informed consent; diversity of consent forms
- Ethics committees make an on-paper *a priori* evaluation, with little control on what happens afterwards
- Risk of "race to the bottom": the researchers that obtain permissions to see more data will extract more value → competitive advantage

![](_page_21_Picture_7.jpeg)

![](_page_22_Picture_0.jpeg)

#### ñļį>ή ЕЙ́ĮРЖ, О ήįĮЕх Ү́ФѾ.‡ЬРĮ uРЖΎСѾФ"!

![](_page_22_Figure_2.jpeg)

![](_page_22_Figure_3.jpeg)

#### Project contract(s)\*

- Project-specific developments
- Health-specific platform modules

#### CLA contract\*

- Third party developed modules
- Security/privacy certification by U
- Potential platform
   Integration by U

#### Use license contract

- Support
- Maintenance
- Updates
- Upgrades (new ML functionalities)

Third Party: Non-Tune Insight and non-EPFL developers of platform modules. Examples: CHUV, Insel,...

Third Party Module: Statistical computation modules that are registered and deployed on top of the platform, but not certified or coded by Tune Insight.

![](_page_23_Figure_0.jpeg)

#### FAHME: Privacy-Preserving Federated Analytics for Precision Medicine with MHE - Survival curves (Kaplan-Meier)

![](_page_24_Figure_1.jpeg)

[Centralized] Samstein, R. M. et al. Tumor Mutational Load Predicts Survival after Immunotherapy across Multiple Cancer Types. Nat. genetics 51, 202–206 (2019).

[FAHME] Froelicher et al. Truly Privacy-Preserving Federated Analytics for Precision Medicine with Multiparty Homomorphic Encryption.

## FAHME: Privacy-Preserving Federated Analytics for Precision Medicine with MHE - GWAS

![](_page_25_Figure_1.jpeg)

[Original approach] McLaren, P. J. et al. Polymorphisms of Large Effect Explain the Majority of the Host Genetic Contribution to Variation of HIV-1 Virus Load. Proc. Natl. Acad. Sci. 112, 14658– 14663 (2015).

[FAHME] Froelicher et al. Truly Privacy-Preserving Federated Analytics for Precision Medicine with Multiparty Homomorphic Encryption.

# Federated 2-factor authentication based on Switch-AAI or Switch edu-ID

- Federated authentication and authorization mechanism compatible with Switch-AAI (Shibboleth login procedure)
- Already used by Swiss hospitals and universities

![](_page_26_Figure_3.jpeg)

#### Positioning of MedCo with respect to similar distributed platforms

|                  | Criteria \ Platform  | CLINERION<br>Real World Data Solutions | SHRINE<br>Stored Health Research Information Network |     | VANTAGE | (P) | MedC |
|------------------|--|--|--|-----|---------|-----|------|
| Functionality    | Federated cohort exploration   | Yes                                    | Yes  | No  | No      | Yes | Yes  |
|                  | Federated analytics  | No                                     | No   | Yes | Yes     | Yes | Yes  |
| Privacy/Security | Protection of intermediate<br>results and distributed<br>computation | No                                     | No   | No  | No      | No  | Yes  |
|                  | Protection of end result from inference attacks                      | No                                     | Yes  | No  | No      | No  | Yes  |
|                  | Fine-grained role<br>management                                      | No                                     | No   | No  | No      | No  | Yes  |
| Usability        | Graphical user interface   | Yes                                    | Yes  | No  | No      | Yes | Yes  |
|                  | Public API   | No                                     | Yes  | Yes | Yes     | Yes | Yes  |
|                  | Service & support  | Yes                                    | No   | No  | No      | No  | Yes  |
|                  | Extensibility  | No                                     | Yes  | Yes | Yes     | Yes | Yes  |

## Clinerion

- + Already deployed in all Swiss university hospitals
- + Proven track record

## - Mainly designed for "patient recruitment" and pharmas' needs

- Rigid data model enabling queries across only 5 variables (diagnosis, procedures, labs, treatments, demographics)
- Customized ETL (hard to maintain without Clinerion support)
- Needs central trusted third-party
- Closed API (vendor lock-in) => expensive customizations, no extension or integration with other software components possible
- Limited to cohort exploration based on patient counts => no distributed analyitcs
- Lacks data protection guarantees for aggregated data leaving hospitals' IT infrastructure

## MedCo

- + Designed for "data recruitment" based on SPHN standards and hospitals needs
- + Fully integrated with i2b2, thus enabling distributed and privacy-preserving fine-grained queries for rich cohort exploration based on SPHN ontology and semantic interoperability standards
- + Open API and free license for academic and noncommercial purposes => extensible with new modules and improvements
- + Possibility to run distributed analytics (beyond patient counts) for hypotheses generation without compromising patients' privacy
- + Hospital IT security and legal compliance
- + State-of-the-art data protection technologies
- + Support by driver projects
- + Deployed and tested in 3 out of 5 Swiss university hospitals
- Not used in operational environments yet

#### What we have accomplished

- Shown that MedCo works, on data sets 1000 times larger than the ones currently used with Clinerion
- Addressed legal/ethical issues; produced the Data Privacy Impact Analysis (as requested by GDPR)
- Live tests by the NAB and HIT-STAG of MedCo for 3 weeks in May 2021; no feedback received so far
- Extensively demoed to the Swiss oncology community
- Thorough comparison with alternative solutions, including Clinerion
- Found the "Holy Grail" of secure federated analytics
- Traction from outside SPHN
  - Ophthalmology
  - UT Health (Houston), IKNL (Cancer Center, NL), Fondazione Maugeri (Pavia, I)
  - $\circ$  Cybersecurity, insurance  $\rightarrow$  launch of start-up Tune Insight

#### About medical data

- The current situation of medical data is appalling and is a worldwide embarrassment (lack of standards, poor quality, etc.)
- Switzerland is no exception, unfortunately
- It is not DPPH/MedCo mission to clean the mess
- But once MedCo is deployed, it will be an **incentive** for hospitals and clinics to work together → this should bootstrap a virtuous circle
- MedCo uses i2b2 to facilitate adoption

#### BioMed IT-MedCo-Hybrid for Swiss BioRef

![](_page_31_Figure_1.jpeg)

Credit: Alexander Leichtle and Harald Witte, Swiss BioRef, Insel

MedCo: Secure, Privacy-Conscious Federated Analytics Infrastructure for Precision Medicine

Was presented and demoed at multiple meetings of the Swiss Personalized Oncology (SPO) and Swiss Molecular Pathology Platform (SOCIBP) Projects

Attendees included:

Olivier Michielin (CHUV), Mohamed Ben Tires-Alj (USB), Marc Rubin (Insel), Christian Britschgi (USZ), Simon Haefliger (Insel), Sacha Rothschild (USZ), Pedros Tsantoulis (HUG), Andreas Wicki (USZ), Sylvain Pradervand (CHUV)

## What MedCo will bring to SPHN

![](_page_33_Figure_1.jpeg)

BioMedIT

![](_page_34_Picture_0.jpeg)

#### Federated Learning - Current Approaches

![](_page_34_Figure_3.jpeg)

- A. Gascón et al.. Privacy-preserving distributed linear regression on highdimensional data. PETS. 2017.

P. Mohassel and Y. Zhang. SecureML: A system for scalable privacy-preserving machine learning. In IEEE S&P, 2017.

http://www.datashield.ac.uk Personalized Health Train (PHT)

10

Aggregated data

#### (d) Differential Privacy Decentralized

![](_page_34_Figure_8.jpeg)

- M. Kim et al. "Secure and Differentially Private Logistic Regression for Horizontally Distributed Data," TIFS 2019 - M. Abadi et al. Deep learning with differential privacy. In ACM CCS. 2016.

- Chaudhuri and C. Monteleoni. Privacy-preserving logistic regression. In NIPS, 2009.

![](_page_35_Picture_0.jpeg)

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## Federated Learning - Current Approaches

![](_page_35_Figure_3.jpeg)

# (c) Decentralized

http://www.datashield.ac.uk Personalized Health Train (PHT)

#### (d) Differential Privacy Decentralized

![](_page_35_Figure_7.jpeg)

- M. Kim et al. "Secure and Differentially Private Logistic Regression for Horizontally Distributed Data," TIFS 2019
- M. Abadi et al. Deep learning with differential privacy. In ACM CCS, 2016.

- Chaudhuri and C. Monteleoni. Privacy-preserving logistic regression. In NIPS, 2009.

#### (d) Cryptographic (SMC, HE) Decentralized

![](_page_35_Picture_11.jpeg)

- A. Gascón et al.. Privacy-preserving distributed linear regression on highdimensional data. PETS, 2017.

P. Mohassel and Y. Zhang. SecureML: A system for scalable privacy-preserving machine learning. In IEEE S&P, 2017.

#### Our solution (Secure Multiparty Computation + Homomorphic Encryption) - Data Confidentiality - Not data outsourcing - Scale with #parties

- Exact results

![](_page_35_Figure_16.jpeg)

C. Mouchet, J. R. Troncoso-pastoriza, J.-P. Bossuat, and J. P. Hubaux. Multiparty homomorphic encryption: From theory to practice. PETS'21. https://eprint.iacr.org/2020/304, 2020.

#### Multi-Party Homomorphic Encryption (MHE) Efficient Functionalities

• Statistical computations (aggregations, histograms, moments,...)

Input Layer

 Machine learning/AI: Increasing set of models can be efficiently trained and evaluated with MHE

Hidden Laver

Generalized Linear Models (Represented as a simple neural network)

![](_page_36_Picture_4.jpeg)

Froelicher, J.R. Troncoso-Pastoriza, A. Pyrgelis, S. Sav, J.S. Sousa, J.-P. Bossuat, J.-P. Hubaux, "Scalable Privacy-Preserving Distributed Learning". PETS'21 https://arxiv.org/abs/2005.09532 **Deeper Neural Network** 

![](_page_36_Figure_7.jpeg)

Output Layer Boss

S. Sav, A. Pyrgelis, J.R. Troncoso-Pastoriza, J.-P. Bossuat, J.S. Sousa, J.-P. Hubaux, "POSEIDON: Privacy-Preserving Federated Neural Network Learning". NDSS'21 <u>https://arxiv.org/abs/2009.00349</u>

![](_page_37_Picture_0.jpeg)

## SPINDLE: Scalable Privacy-preservINg Distributed LEarning

Generic Secure Federated Learning that ensures **Data Confidentiality + Model Confidentiality by building on:** 

![](_page_37_Figure_3.jpeg)

![](_page_37_Figure_4.jpeg)

![](_page_37_Figure_5.jpeg)

EPFL

#### POSEIDON: Privacy-Preserving Federated Neural Network EPFL Learning

**Solution:** The data providers (DPs) collaborate to enable a joint gradient descent while protecting their privacy and **obtain a global and accurate model** 

![](_page_38_Figure_2.jpeg)

#### **Parameterization:**

Strong interdependencies between learning parameters and cryptographic parameters

## International collaborations

- GA4GH Data Security Work Stream
- MedCo now part of the i2b2 official community projects
- Prof. Shawn Murphy, HMS, and the ACT Network
- Broad Inst. + MIT

![](_page_39_Picture_6.jpeg)

![](_page_39_Picture_7.jpeg)