SYNTHEMA + ERN-EuroBloodNet

Joint Training Programme on Synthetic Data Generation in SCD and AML

Funded by the European Union

SYNTHEMA - Secure Federated Learning via P2P Secure Multi Party Computation

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Netcompany

#1

Webinar 2: Regulatory on Medical Devices, AI Act, Privacy-Preserving and Ethical Considerations

15/05/2025

Privacy in Federated Learning

Siloed Data Centres

- For **data and AI-driven health innovation acceleration**, rise **of Federated Learning**
- Particularly needed in **clinical contexts, heavily regulated** for personal/ sensitive data protection and privacy guarantees (GDPR, EHDS, data protection regulations, etc.)

Privacy in FL

- FL enhances **privacy and data protection by design**
- **No need to share data**, as algorithms move to data

Privacy Issues in FL

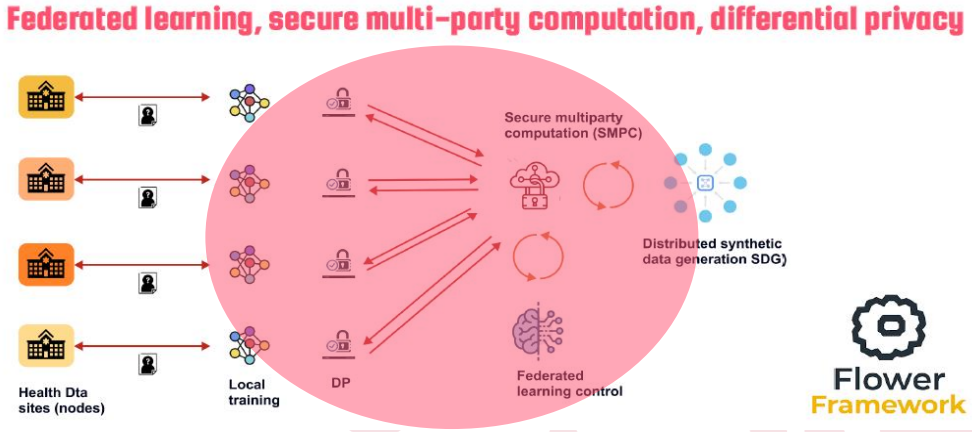
- FL susceptible to **data leakage** or **inference attacks** during **network communication** for **model updates & aggregation**
  - Membership attacks, gradient leakage, etc. (*)
- **Centralized aggregation**: single point of trust – what if aggregation server **not trusted**?

(*) J. Geiping et. al., "*Inverting Gradients - How easy is it to break privacy in federated learning*", 34th Conference on Neural Information Processing Systems (NeurIPS 2020), Vancouver, Canada, 2020

PETs: Secure Multi-Party Computation (SMPC) Protocols to the Rescue

- Computation of functions (i.e. computation of the **model learned parameters**) over **shared secrets held** by **different peers without revealing** them directly
  - **Privacy-preserving aggregation of model updates**

- **Key properties:**
  - **Privacy**: No party learns others' raw secrets
  - **Correctness**: Mathematical guarantees that computation is performed faithfully
  - **Robustness**: provides guarantees even with some malicious participants

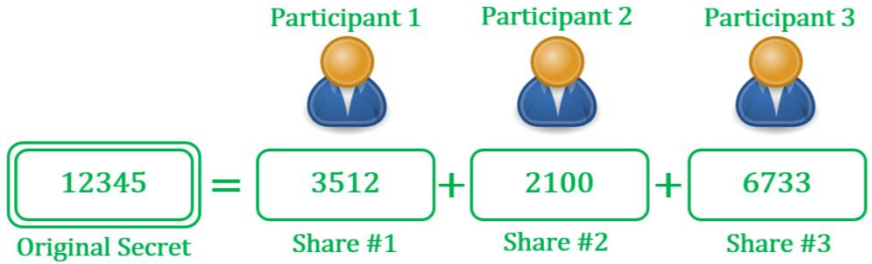


C. Zhao et al, "*Secure Multi-Party Computation: Theory, practice and applications*", Elsevier Information Sciences, Vol. 476, 2019, pp. 357-372.

Figure from Webinar 1 – F. Alvarez, "Infrastructure for SDG in ERN-EuroBloodNet"

SMPC Protocol Implementation

- **Additive secret sharing**
  - A cryptographic technique that **divides a secret value** into **multiple parts** (**shares**)
  - **Each share** of the original secret is **distributed to several participants**, ensuring that **control over the secret value is shared** and not held by a single entity.



Additive secret sharing
Image courtesy of geeksforgeeks.org

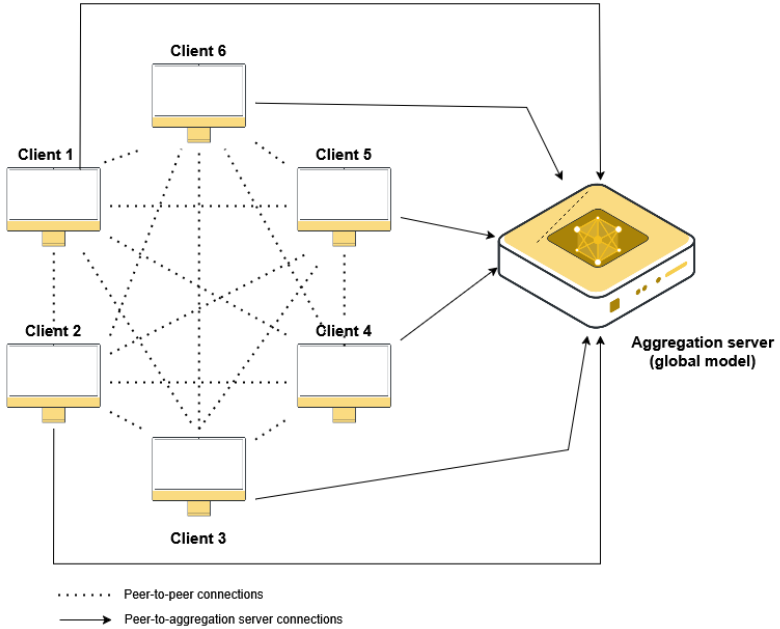
Issues with conventional SMPC-FL Implementations

- Each client **communicates directly** with the **Aggregation Server** after local client model training to **share model parameters**
    - Hence, most SMPC - Federated Learning implementations rely on **a centralized or semi-trusted aggregator**
    - This introduces a **single point of failure** and a **trust bottleneck**
    - It further exposes the system to **insider threats, collusion,** or **node compromise**.

Novel P2P SMPC Protocol within Flower FL framework (*)

- Leverages **additive secret sharing** and **peer-to-peer (P2P) message passing <u>across peers</u>** to construct a **<u>fully decentralized aggregation protocol</u>** compatible with existing FL workflows

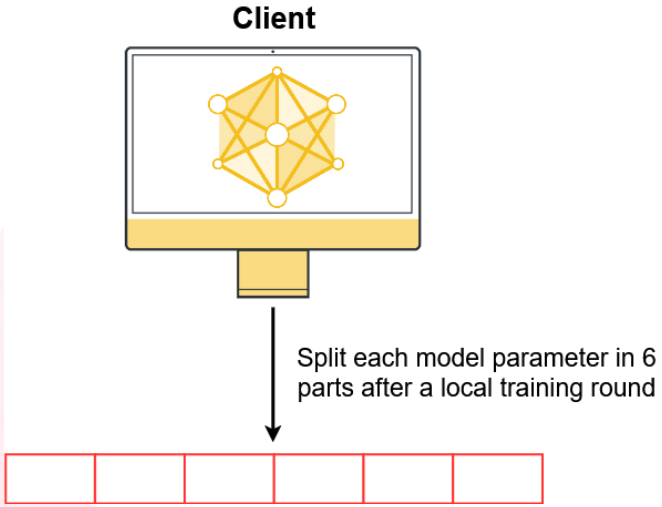
- **Each client** contributes to computation by **securely exchanging and combining secret shares** (i.e. the model learned parameters) **with its peers** and not only the Aggregation Server



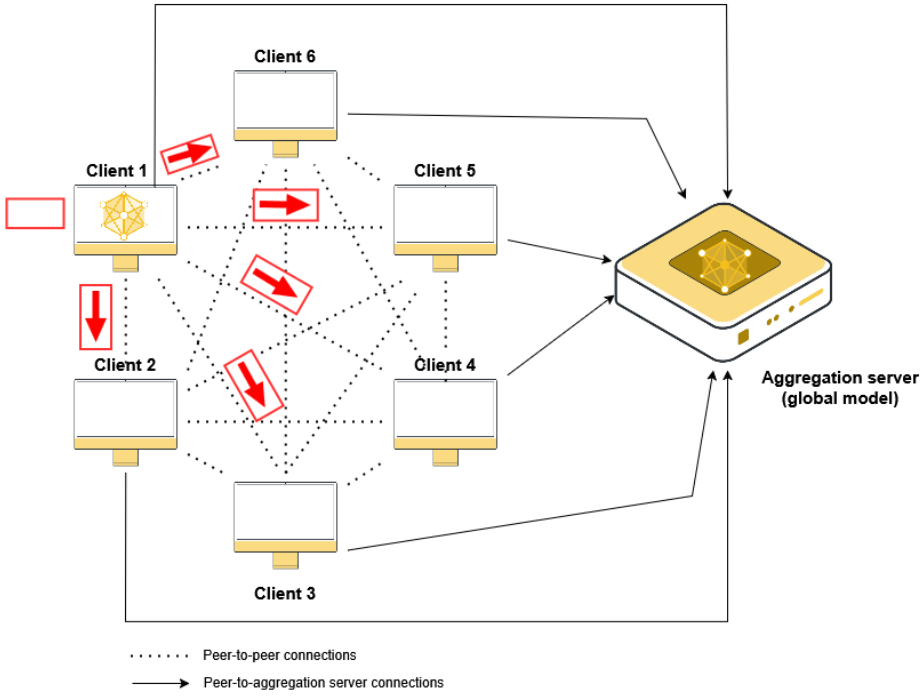
(*) P. Demetrakopoulos, T. Anagnostopoulos and S. Tsekeridou, "*Distributing trust: A P2P SMPC protocol for secure federated learning*," 2025 3rd International Conference on Foundation and Large Language Models (FLLM), Vienna, Austria, 2025, pp. 547-552, doi: 10.1109/FLLM67465.2025.11390879.
https://ieeexplore.ieee.org/document/11390879

Explaining the P2P SMPC Protocol – Assumption: 6 clients

Step 1: Client splits parameters after local training round in 6 parts

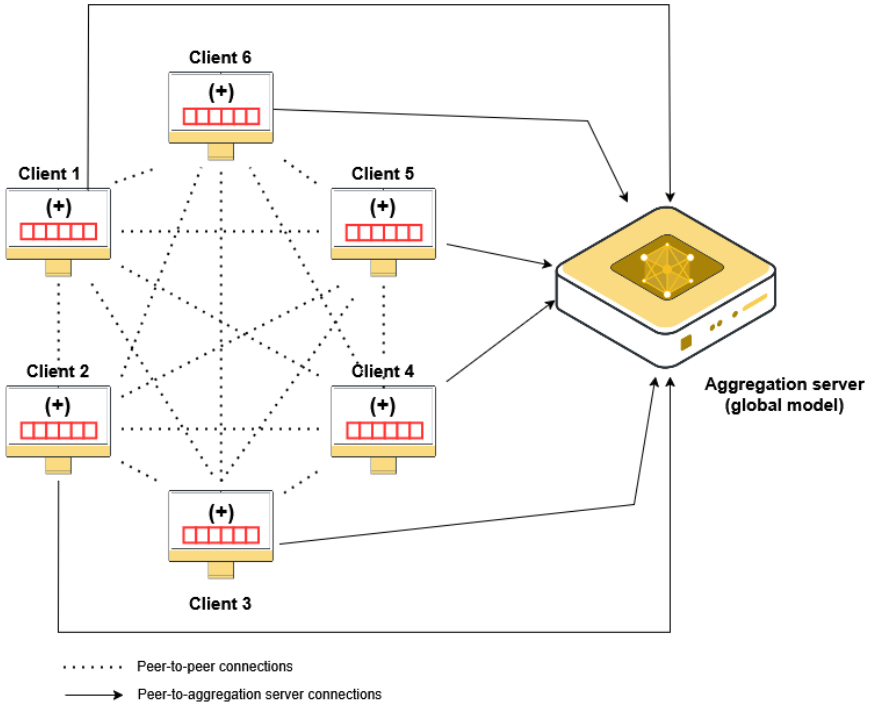


Step 2: clients distribute shares to all other clients in P2P mode

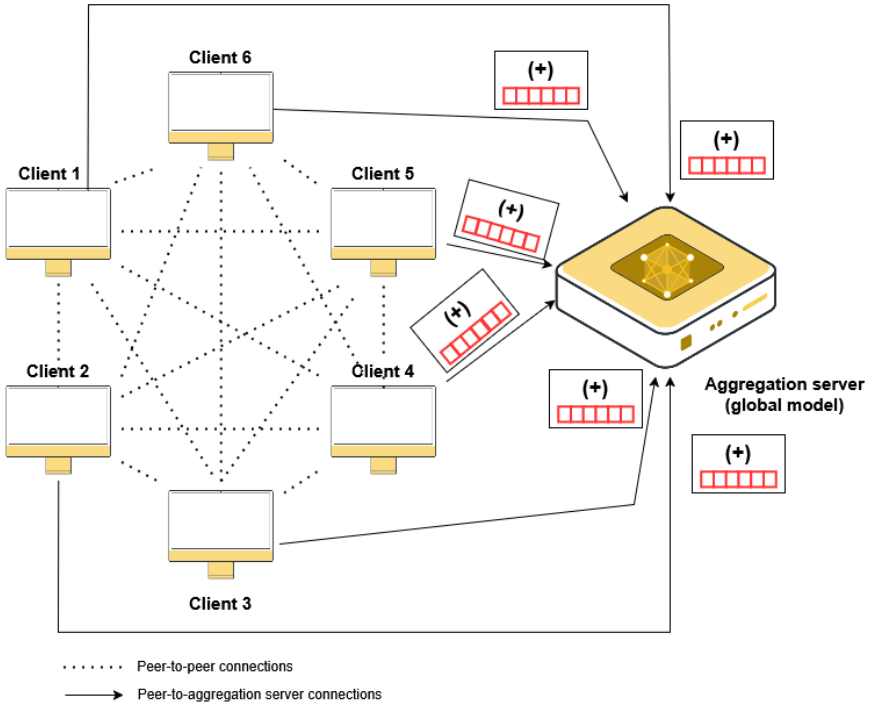


Explaining the P2P SMPC Protocol

Step 3: Each client holds one share per parameter from other peers. Local aggregation performed at each client

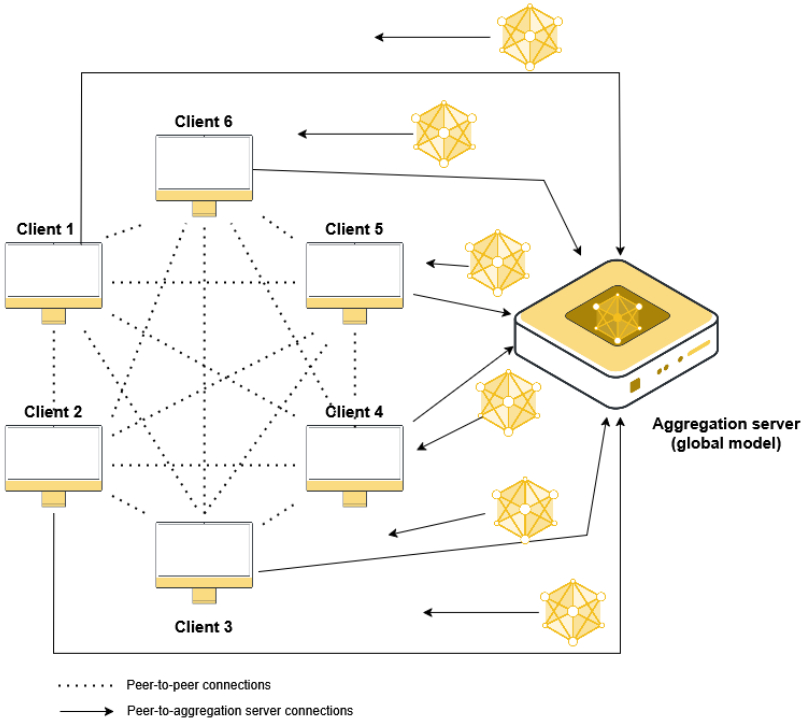


Step 4: Clients send locally aggregated parameters to the Central Aggregation Server

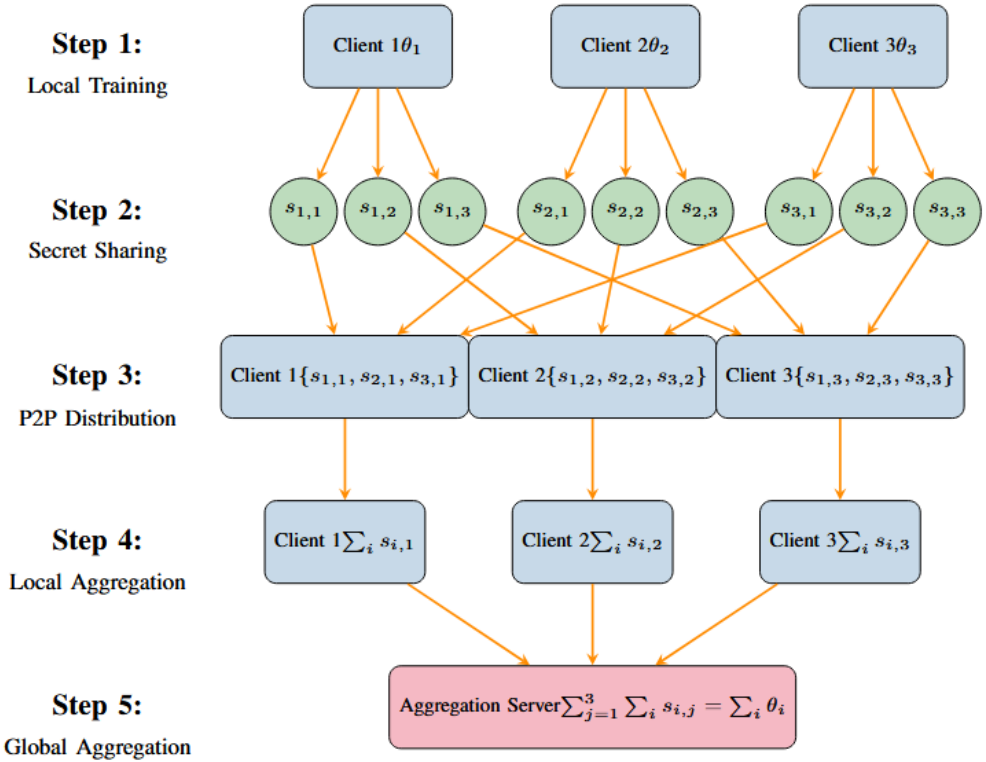


Explaining the P2P SMPC Protocol

Step 5: Aggregation server **aggregates all received local parameters**, computes **global model**, **sends it back to clients** and a **new training round** begins



Entire Process (3 clients)



Security and Privacy Guarantees

No individual share leaks model updates

- This protects the system from various kinds of attacks

Aggregation server **cannot infer the origin** (peer) of parameters

- Hence, it does **not need to be trusted / be semi-trusted**

Resilience to collusion

- Requires a **large number of compromised / malicious parties** to break security

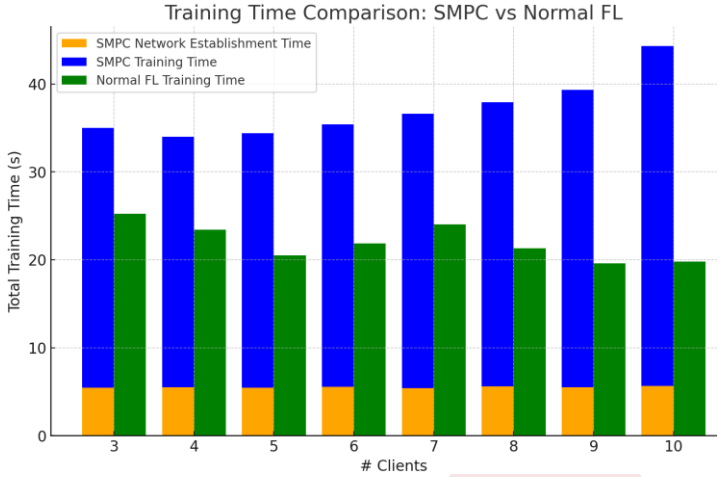
When combined with **differential privacy (as implemented in SYNTHEMA)**

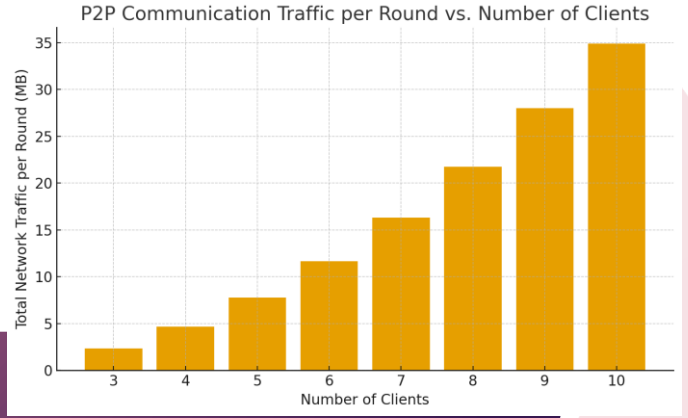
- **security and privacy** are significantly **enhanced**

Experimental Evaluation - Performance

- Two configurations:
  - **Standard FL**: Clients send plaintext model updates to centralized aggregator.
  - **P2P-SMPC FL**: Clients split model updates into additive secret shares, exchange them peer-to-peer, aggregate locally and send masked updates to centralized server.

- Performance metrics:
  - **Model accuracy and loss** over training rounds
    - Comparable accuracy achieved by both
  - **Training time per training round** as the number of clients increases for both configurations
    - P2P-SMPC configuration: consistent increase in runtime with more clients, attributed to P2P exchange of shares and need for synchronization.
  - **Total network traffic per round** as number of clients increase.
    - Total amount of data exchanged across network grows approximately quadratically with number of clients





Flower

Collaboration with Flower Labs

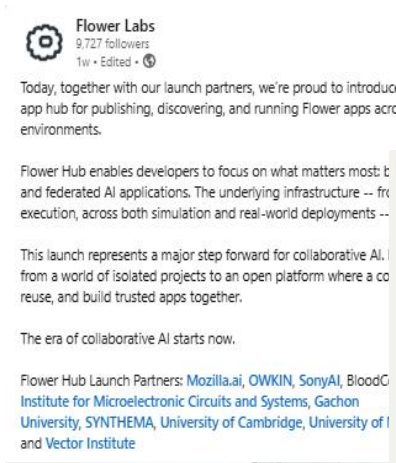
SYNTHEMA **Flower Next Pilot Application**

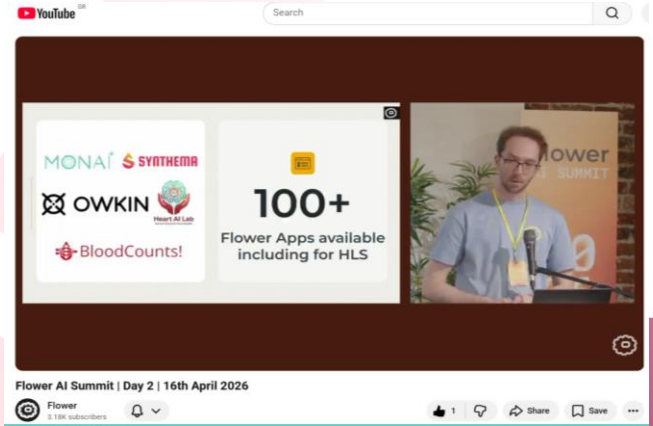
- started in January 2025

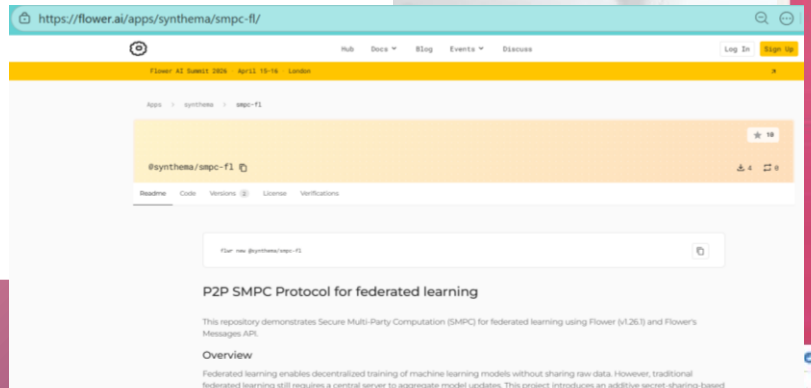
SYNTHEMA P2P SMPC Presentation at **Flower.AI Summit 2025**, London

SYNTHEMA **one of the early Flower Hub Launch partners**

- publishing the P2P open source SMPC App: @synthema/smpc-fl - Flower Hub







Other SYNTHEMA Related Work in PETs

- **Anonymization / Federated Anonymization** –Webinar 3 next Friday!

- SYNTHEMA as core use case and Netcompany as lead editor of **BDVA White Paper on Synthetic Data in Healthcare**
  - Healthcare - BDV Big Data Value Association

Thanks!

Any questions?

Keep in touch!

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