



[AI & Data Engineering session](#)

Architectural Foundations for Collaborative Machine Learning in Federated Data Spaces

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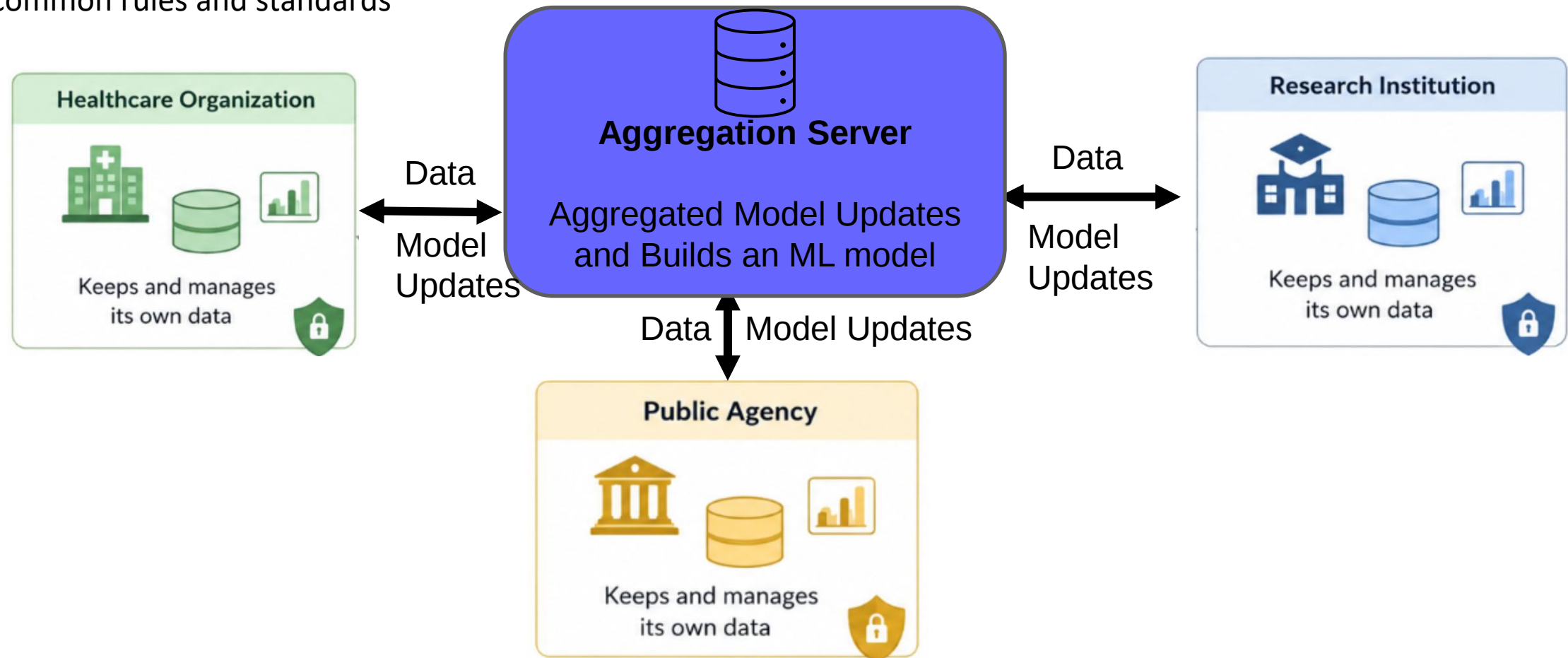
25 June 2026, Amsterdam, Netherlands



Federated data spaces & collaborative ML



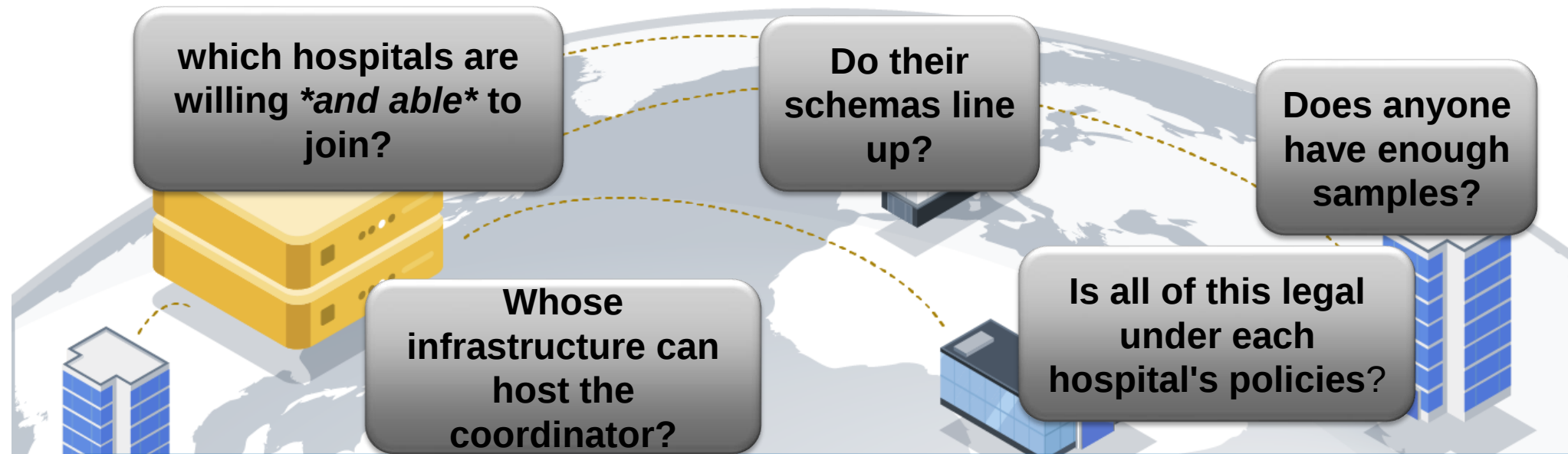
Federated Data Spaces: Collaborative environments where multiple organizations share and access data using common rules and standards



How it actually works today



Imagine **five hospitals** (H_1 – H_5) want to collaboratively train a diagnostic model on chest X-rays.



Textbook FL:

The hospitals **agree on a single FL paradigm** (say, FedAvg).

All will participate, have compatible data, and can exchange model weights.

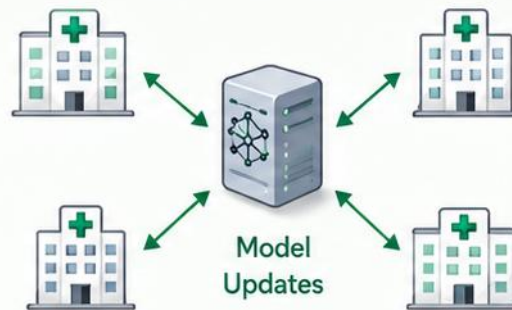
(Usually) A central orchestrator coordinates rounds.

→. You just plug in Flower or TensorFlow Federated, and run.

Example scenarios

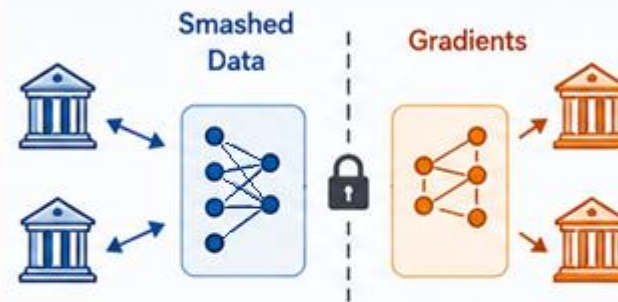


(A) Cross-hospital Federated Learning



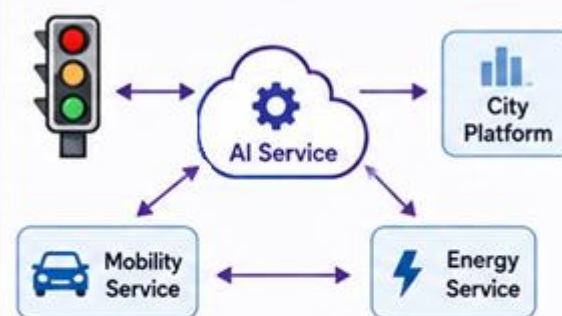
- Regulatory constraints
- Heterogeneous clients
- Changing availability

(B) Split Learning in a Financial Data Space



- Model and data confidentiality
- Locality constraints
- This layer stays on this infrastructure

(C) Distributed Inference across Smart-city Services

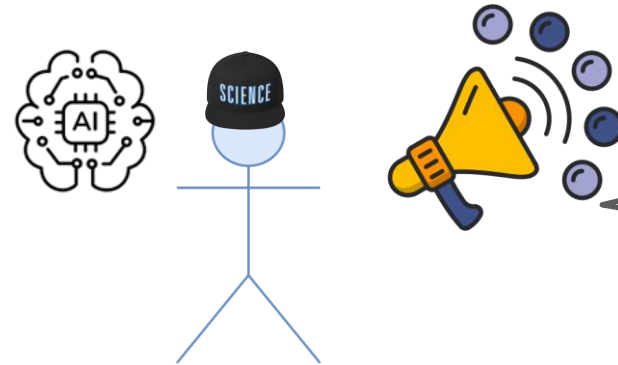


- Service composition
- Legal flows between services
- QoS

Shared Concerns

Discovery · Intent · Feasibility · Negotiation · Orchestration · Execution · Policy Enforcement

A broader vision

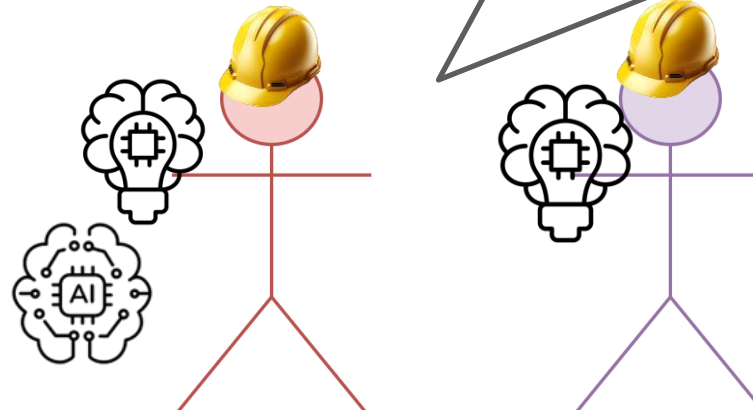


Hey everyone I am creating a Predictive Model for Water Flow , can anyone contribute?

I have some water flow sensors but I would like to train on a wider scope of data



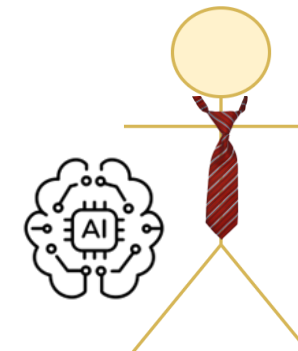
We cannot give our precious water flow sensor (data), but we can give you model training on our data



I do not care about your model, nor you can train with my resources



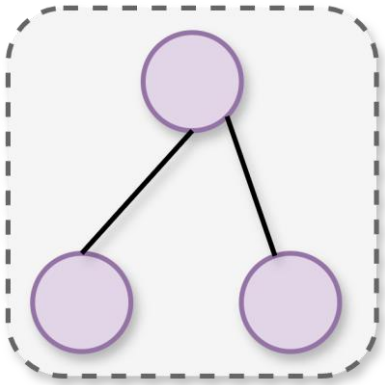
I cannot give you my data, but I would like the resulting model please



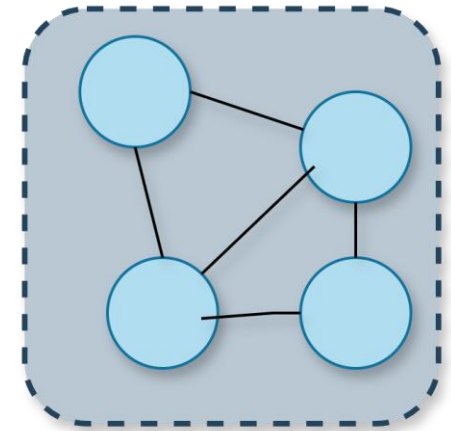
Architecture overview



Federated Data Space A

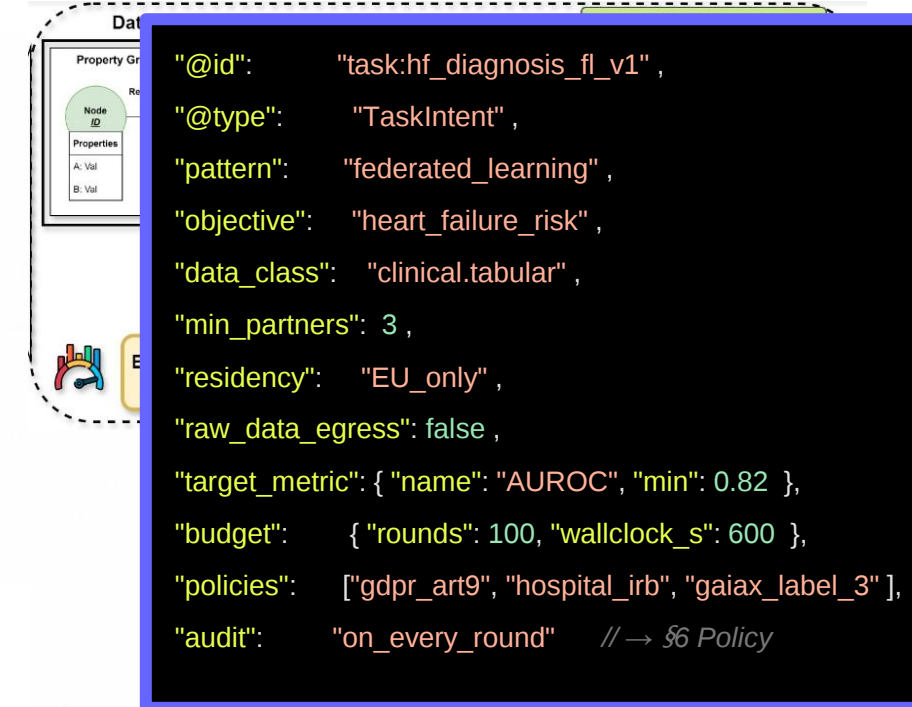
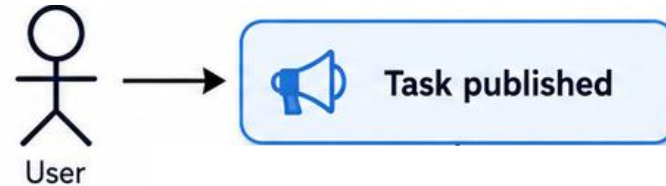


Federated Data Space B



Jointly Perform a Collaborative ML Task (Training, Inference)

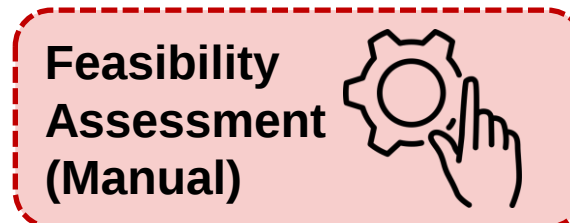
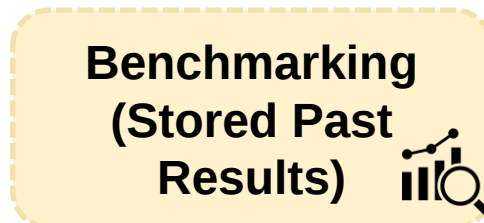
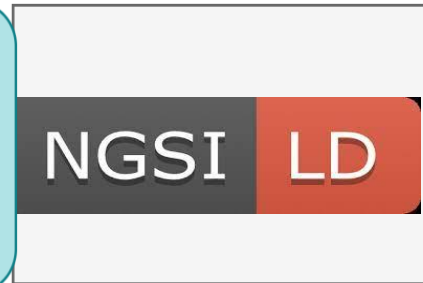
Collaboration Lifecycle



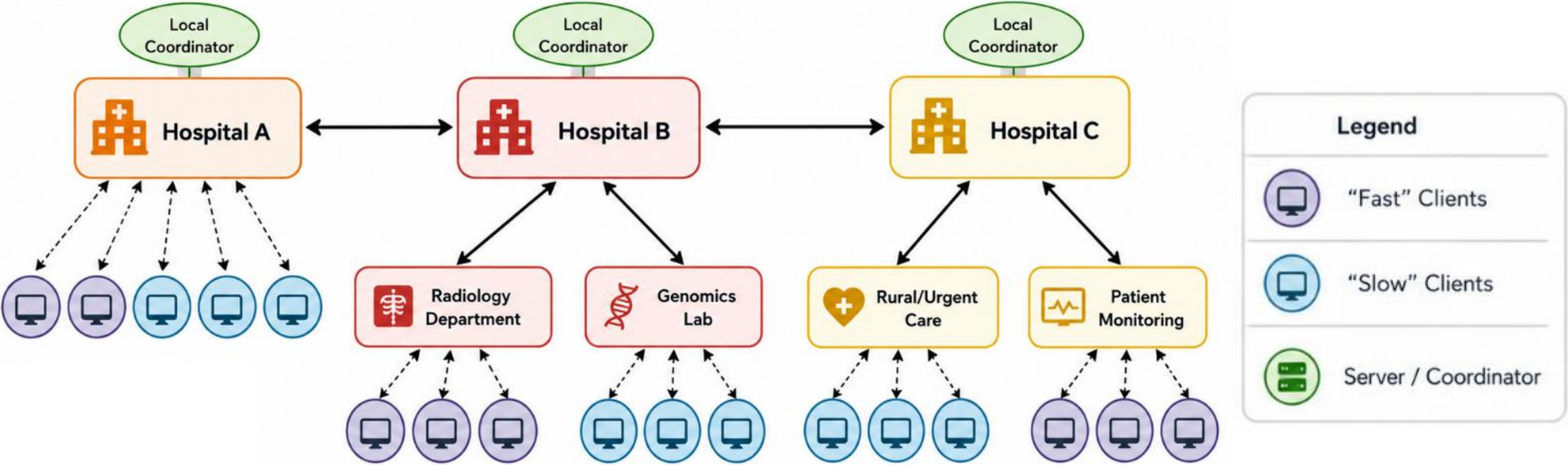
Prototype



Distributed Knowledge Base

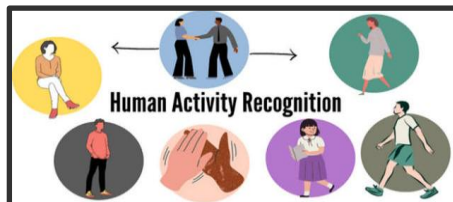
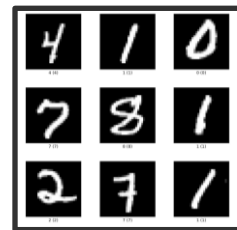
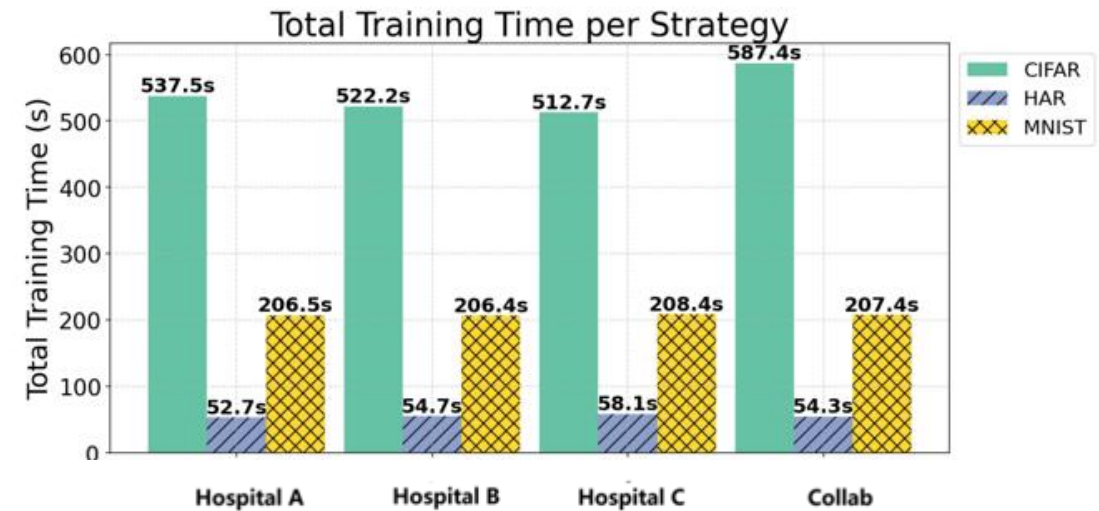
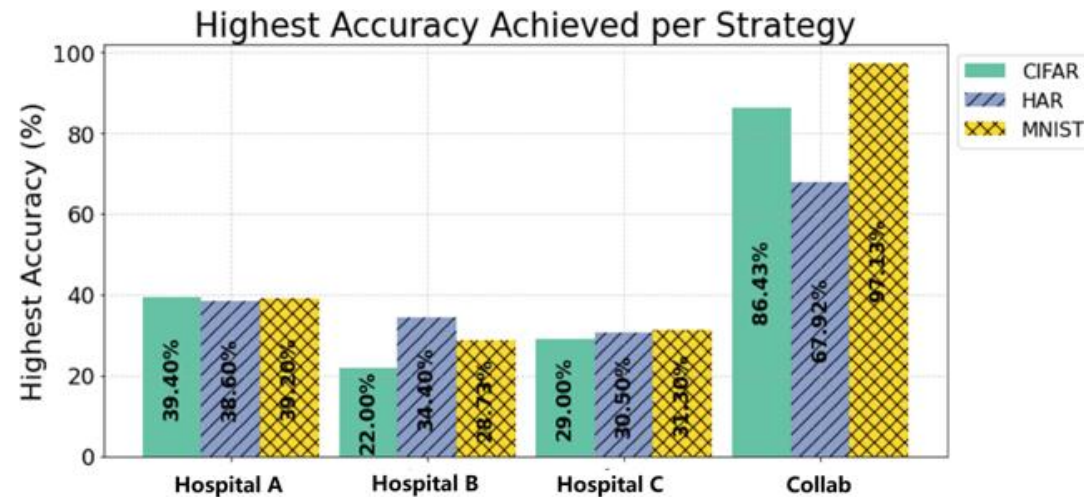


Evaluation setup



Role	Instance Type	Family	Size	vCPUs	Memory (GiB)
Fast FL clients	c5.large	c5	large	2	4
Slow FL clients	t3.medium	t3	medium	2	4
FL server / aggregator	c5.xlarge	c5	xlarge	4	8

Some Results



$\approx 3\times$ accuracy lift on
CIFAR-10, at $< 10\%$
more wall-clock.

Conclusions & Future Work

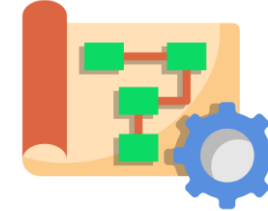


Key takeaways



- Cross-dataspace ML is mainly a coordination and architecture challenge.
- Six capabilities support the lifecycle: Discovery, Representation, Context, Feasibility, Orchestration, and Policy Enforcement.
- A Distributed Knowledge Base manages shared metadata, constraints, plans, context, and provenance.
- Collaboration can improve model accuracy while maintaining comparable training time.

Future work

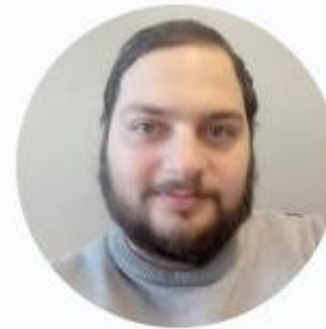


- Automate feasibility checks, and context interpretation.
- Evaluate the architecture at larger scale and under realistic network conditions.
- Support richer policies, metadata, and stricter constraints.
- Extend validation to split learning and distributed inference.
- Improve resilience to failures, malicious participants, and adversarial behaviour.

Thank you!



Thank you!



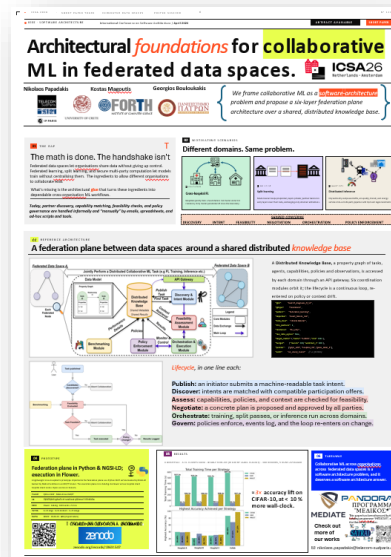
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