



NephroCAGE Federated Learning Infrastructure for Transatlantic Collaboration

Prof. Dr. Ali Sunyaev

Professor at KIT and Director at AIFB

Montréal, August 2nd, 2023

Critical Information Infrastructures Research Group



We study internet technologies—their design, use, and symbiosis with our society. Our research work accounts for the multifaceted use contexts of digital technologies with research on human behavior affecting information systems and vice versa.

To learn more, visit our website: <https://cii.aifb.kit.edu/>



Our Project Team

M. Sc. Konstantin Pandl



- Research associate at KIT since 2019
- M. Sc. in electrical engineering and information technology
- Research interests: machine learning, distributed systems

M. Sc. Florian Leiser



- Research associate at the KIT since 2021
- M.Sc. in information systems
- Research interests: expert decision-making, informed ML, federated learning

Dr. Scott Thiebes



- Research associate with since 2014
- M.Sc. In information systems in 2014
- Research interests: health information systems, digital health, trustworthy AI and privacy

Prof. Dr. Ali Sunyaev

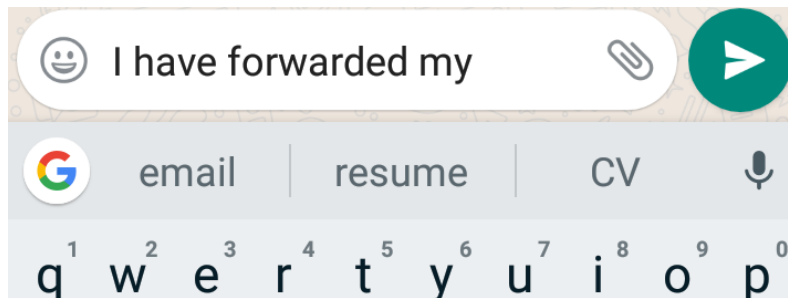


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What is Federated Learning?

Introduced by Google in 2017

Initial use case: high-quality, Machine Learning (ML)-based word suggestions for the Android keyboard



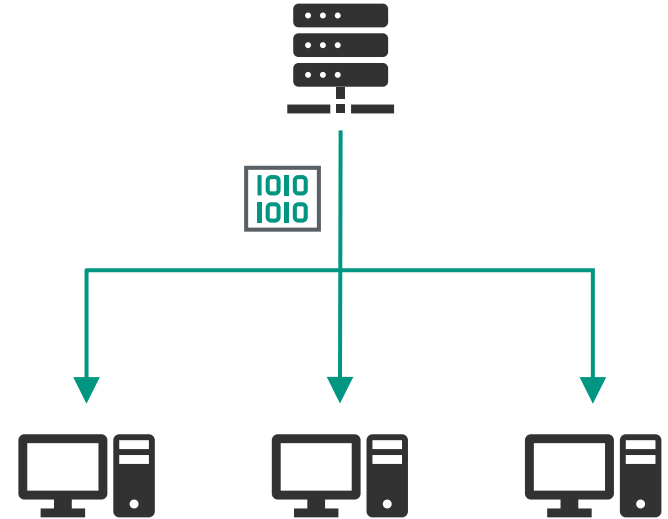
Problem:

ML process typically runs on a large data set in the cloud

Keyboard inputs are too sensitive to share them with a cloud server

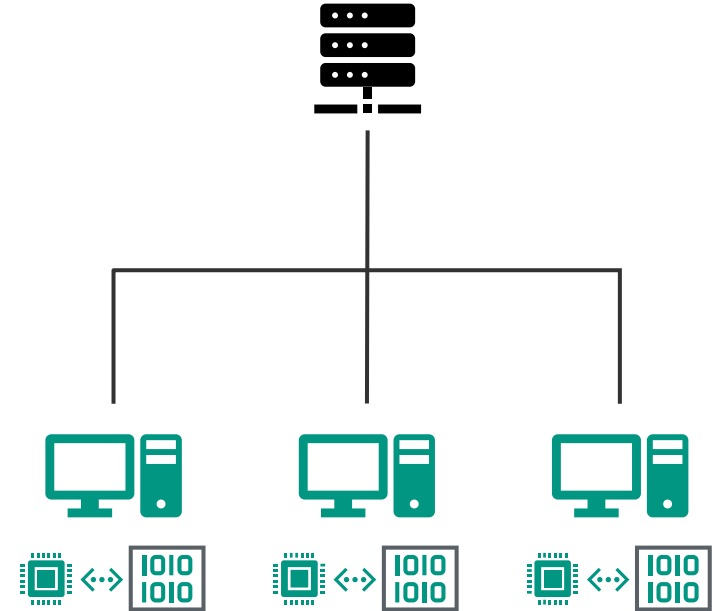
Procedure of (Centralized) Federated Learning

- 1 Central server broadcasts the model to all clients
- 2 Clients train the model with their local data
- 3 Clients send their updated model back to the server
- 4 Central server aggregates model updates and generates an updated model



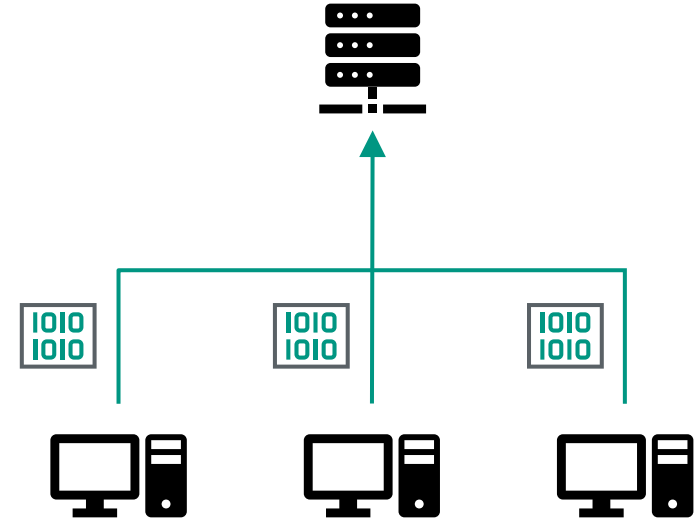
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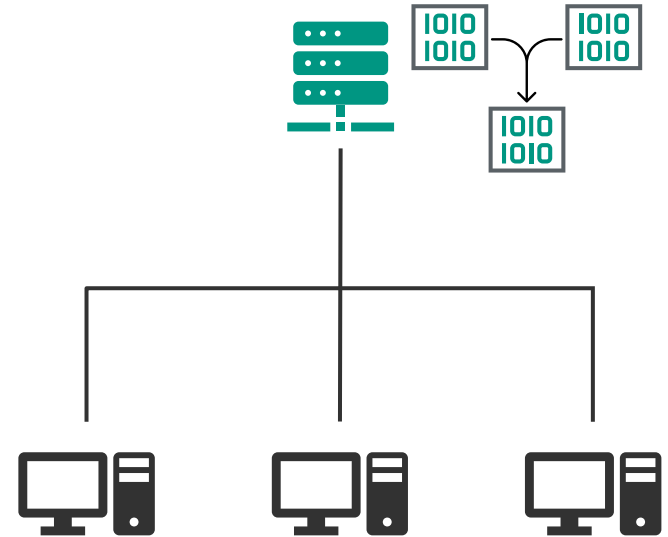
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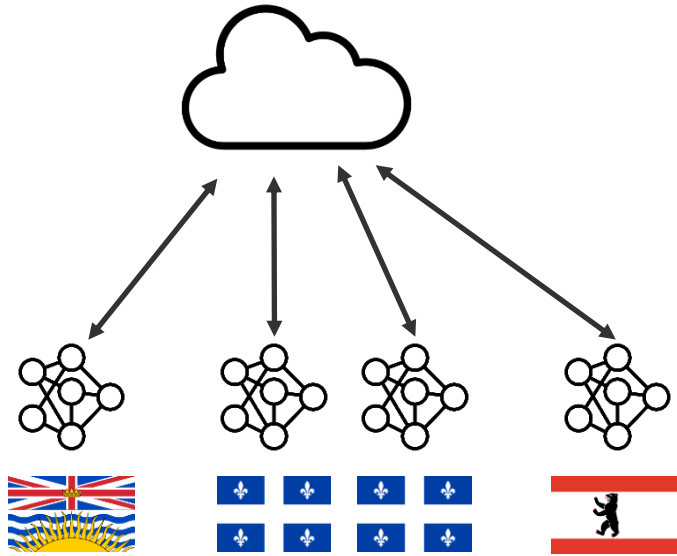


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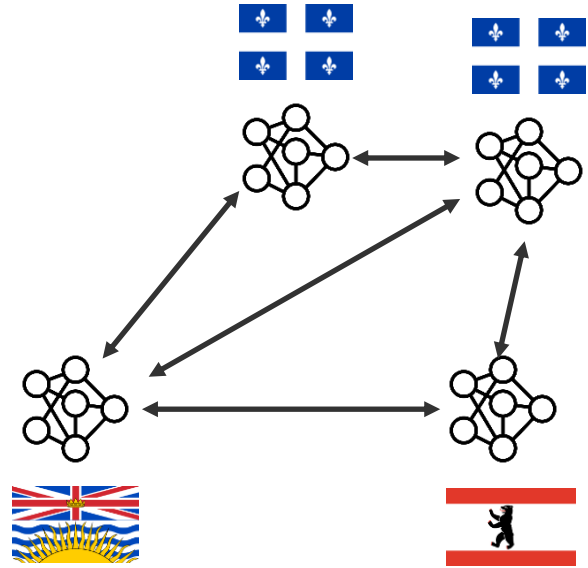
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Centralized and Decentralized Learning Infrastructure



Low failure safety, low transparency, raises model ownership questions

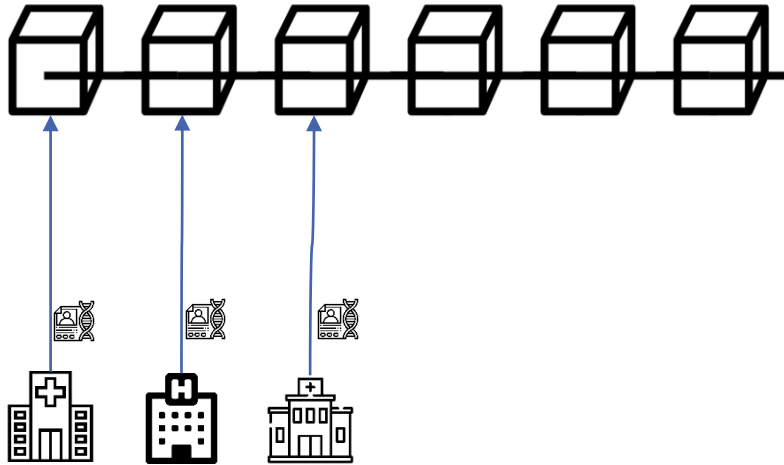


Higher failure safety, high transparency and auditability, but higher network/storage cost

Introducing DLT

Contents of each block:

- Sending Institution (as hash)
- Message content
- Transmission fee



Two-Server Setup

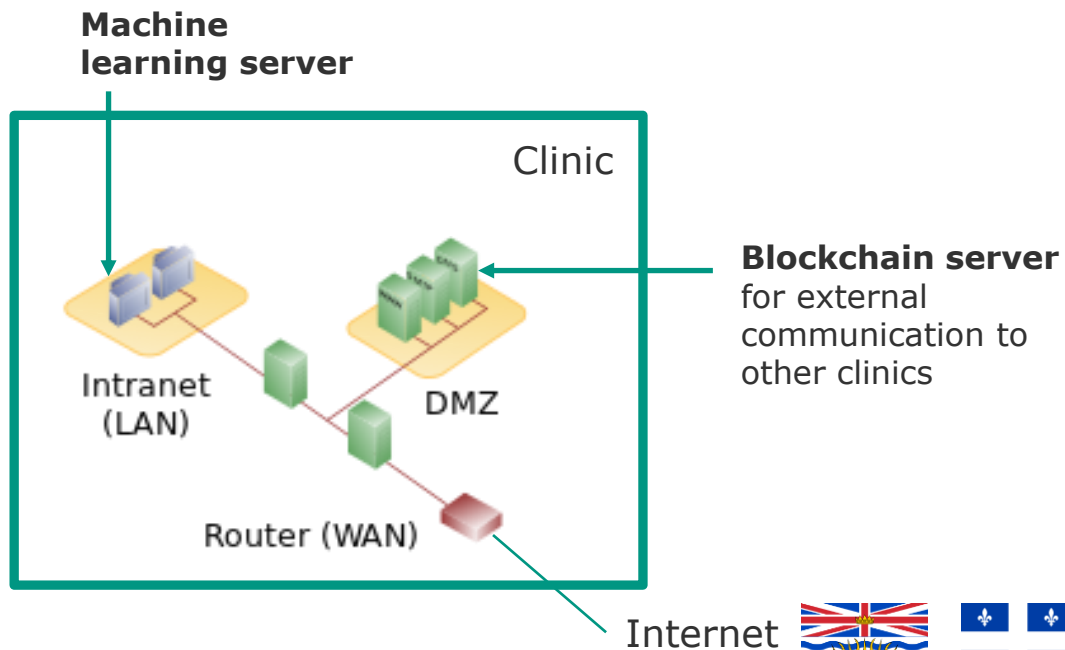
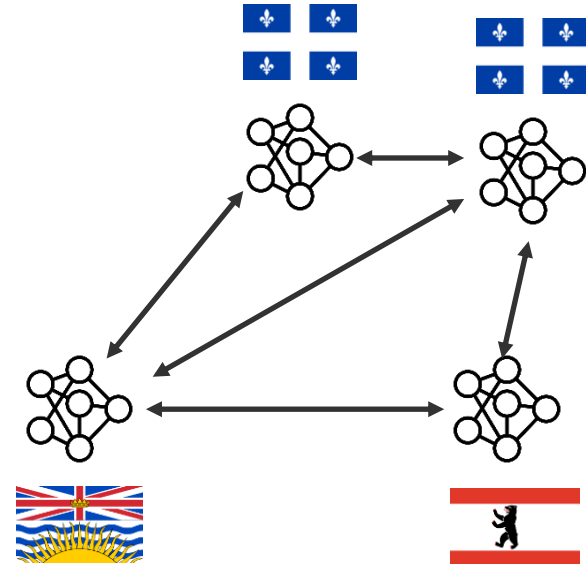


Image source:
https://commons.wikimedia.org/wiki/File%3ADMZ_network_diagram_2_firewall.svg

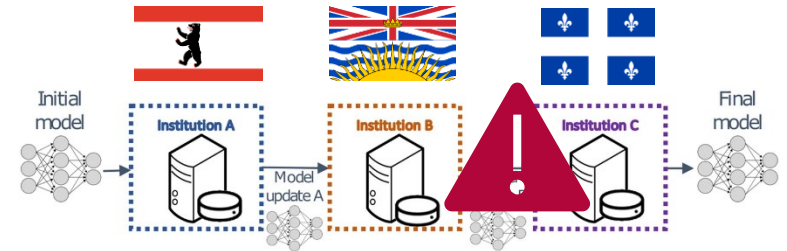
Decentralized Federated Learning Infrastructure

- Build Ethereum-based DLT
- Decentralized aggregation requires high synchronicity and therefore an organizing clients
- Without synchronicity multiple aggregation models could exist simultaneously



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- Institutional incremental learning avoids organization and allows institutions to train whenever new data is available

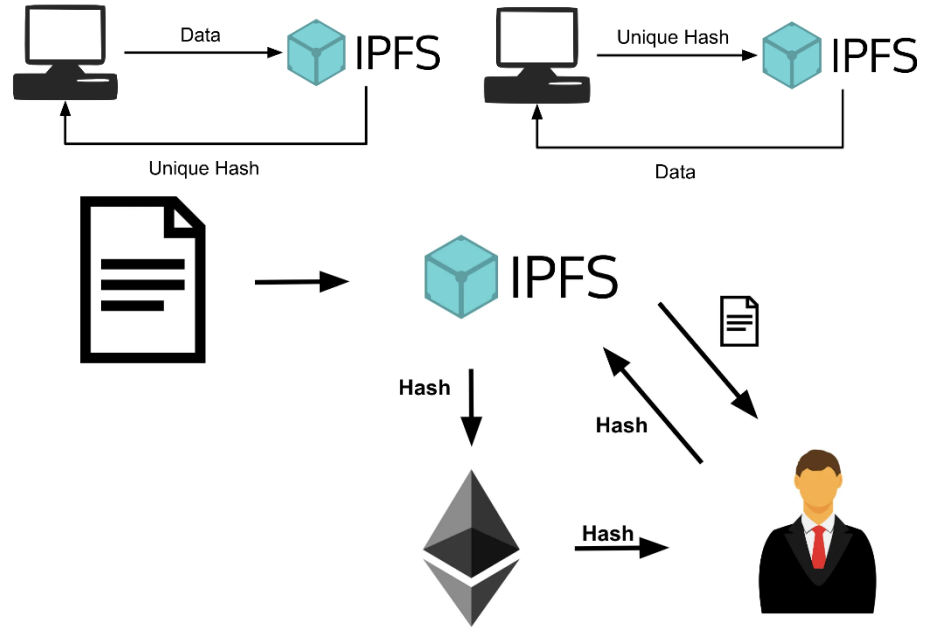


(c) Data-private Collaborative Learning using Institutional Incremental Learning

Image Source: Sheller, M.J., Edwards, B., Reina, G.A. *et al.* Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data. *Sci Rep* **10**, 12598 (2020). <https://doi.org/10.1038/s41598-020-69250-1>

IPNS as a peer-to-peer file sharing system

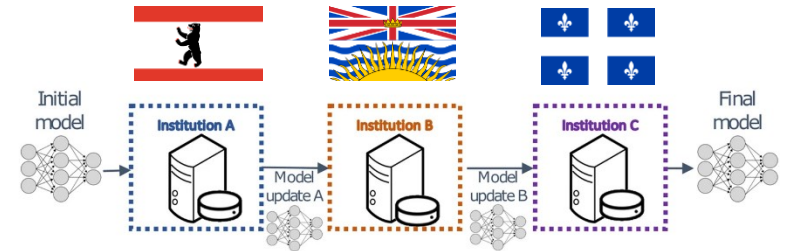
- First efforts were just changing transaction information in blockchain
- For further scalability, and to keep the blockchain lightweight, we implemented the InterPlanetary File System (IPFS)
- Runs on the blockchain server to retrieve files by hashes
- Extending with InterPlanetary Name System (IPNS) for updating (otherwise immutable) files
- We developed additional hashes indicating current training of model (reduced potential overlap to 15 seconds)



Images from: <https://medium.com/pinata/ethereum-and-ipfs-e816e12a3c59>

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Ongoing Research Efforts

KIT



Evaluate institutional incremental learning



Investigate different aggregation techniques



Identify drivers and inhibitors for FL adoption

Icons from <https://www.flaticon.com>



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