



NephroCAGE Work Package 1 – Federated Learning Infrastructure

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Our project team

M. Sc. Konstantin Pandl



- Research associate at KIT since 2019
- M. Sc. in electrical engineering and information technology in 2018
- Research interests: machine learning, digital health, distributed systems

M. Sc. Scott Thiebes



- Research associate with Prof. Sunyaev since 2014
- M. Sc. in information systems in 2014
- Research interests: digital health, patient-centric health care, gamification

Prof. Dr. Ali Sunyaev

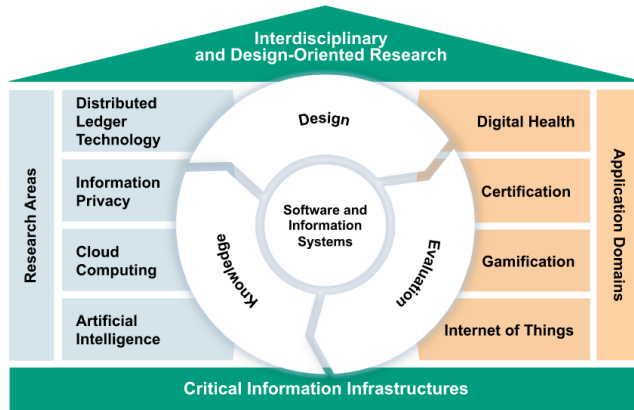


- Professor at KIT and director of the AIFB since 2018
- Previous professorships at the University of Cologne and Kassel
- Research interests: trustworthy artificial intelligence, innovative health IT solutions

Our research group and KIT

Our research group

- We study internet technologies – their design, their usage, and their symbiosis with our society.



Karlsruhe Institute of Technology

- Located in Karlsruhe, Germany
- One of the largest research and educational institutions in Germany, ca. 25k students and 10k employees
- Originated from the University of Karlsruhe founded in 1825

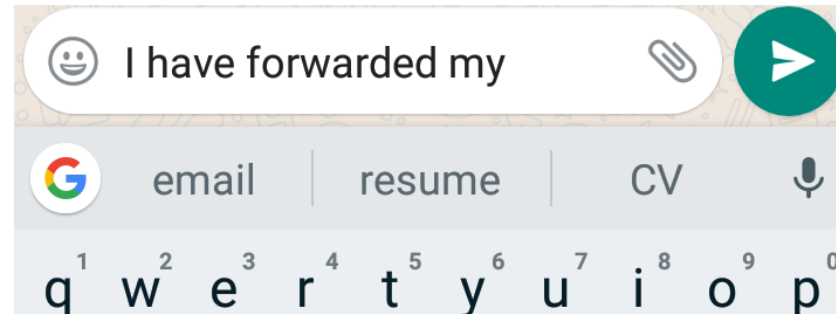


Goal of the work package

- Design a **federated learning infrastructure**, that
 - preserves the **confidentiality** of the training data
 - is based on blockchain / distributed ledger technology, and thus, **robust** and **auditable**
- **Develop** this infrastructure
- **Deploy** this infrastructure in the clinics
- **Evaluate** its utility

History of federated learning

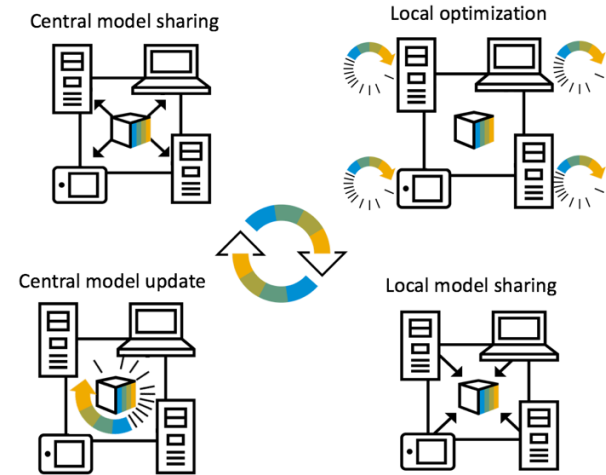
- Introduced by Google in 2017
- Initial use case: high-quality, machine learning (ML)-based word suggestions for the Android keyboard



- Problem: ML process typically runs on a large data set in the cloud, but keyboard inputs are too sensitive to share them with a cloud server
- Solution: federated learning

Functional principle of federated learning

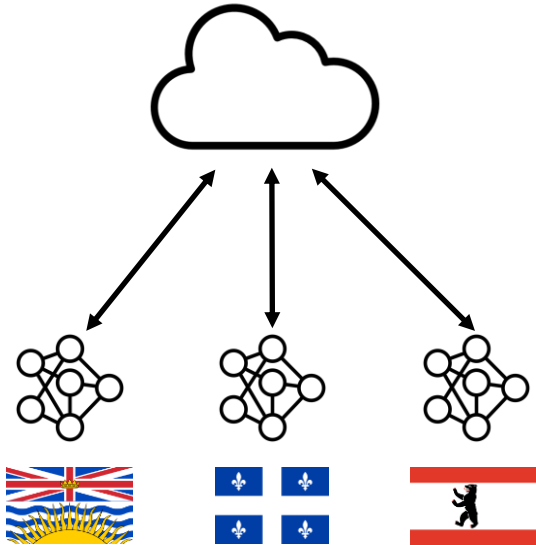
- Goal: ML across private data silos
- Key idea: train ML models on local data and only exchange ML models
- Process consists of repeated rounds, each round comprises 4 steps
- Central model update through averaging the local model parameters



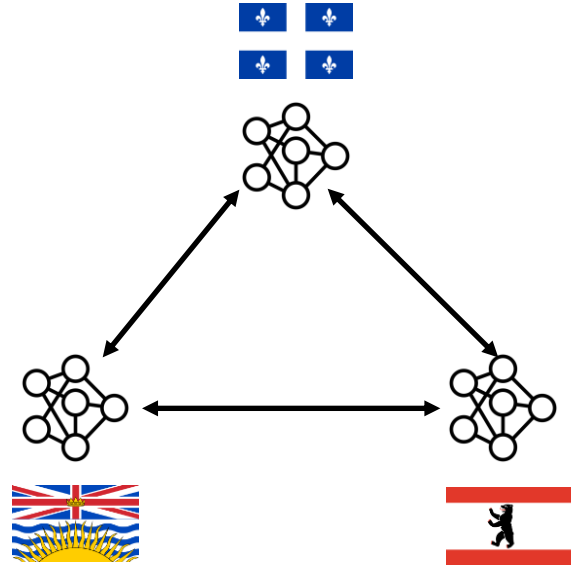
Procedure of a federated learning round

Image: <https://medium.com/sap-machine-learning-research/client-sided-differential-privacy-preserving-federated-learning-1fab5242d31b>

Centralized and decentralized federated learning



Low failure safety, low transparency, raises model ownership questions



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

Blockchain

- Originated with the emergence of Bitcoin, today a variety of different blockchain networks exist
- In the scope of our project: **private peer-to-peer network of institutions**
- Characteristics:
 - **Replicated** ledger (i.e., each institution stores a copy of the blockchain locally)
 - **Immutable** (i.e., data can be written but cannot be removed)
 - Each institution has **equal rights**
 - **Transparent** and, thus, **auditable**
- Goals in the project:
 - **Communication** between the institutions **through the blockchain**
 - **Store ML models** (or a representation such as hashes) on the blockchain ledger

Expected results of federated learning

- Highly anticipated
 - The federated ML model is trained on more data and, thus, performs better than locally trained models on a general test data set
- Potentially
 - The federated ML model may still perform worse on locally generated test data sets
 - The federated ML model is trained on more diverse data and, thus, performs better especially on minorities

Example model evaluation results (dice coefficient) —ProstateX challenge dataset

| | | ProstateX ($n = 343$) |
|----------------|------|-------------------------------------|
| Private models | NCI | $0.872 \pm 0.062^*$ |
| | SUNY | $0.838 \pm 0.043^*$ |
| | UCLA | $0.812 \pm 0.136^*$ |
| FL Model | | 0.889 ± 0.036 |

*Significantly lower than FL model ($P < .001$).

Sarma, K. V., Harmon, S., Sanford, T., Roth, H. R., Xu, Z., Tetreault, J., ... & Arnold, C. W. (2021). Federated learning improves site performance in multicenter deep learning without data sharing. *Journal of the American Medical Informatics Association*.



Thank you very much! Any questions?

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