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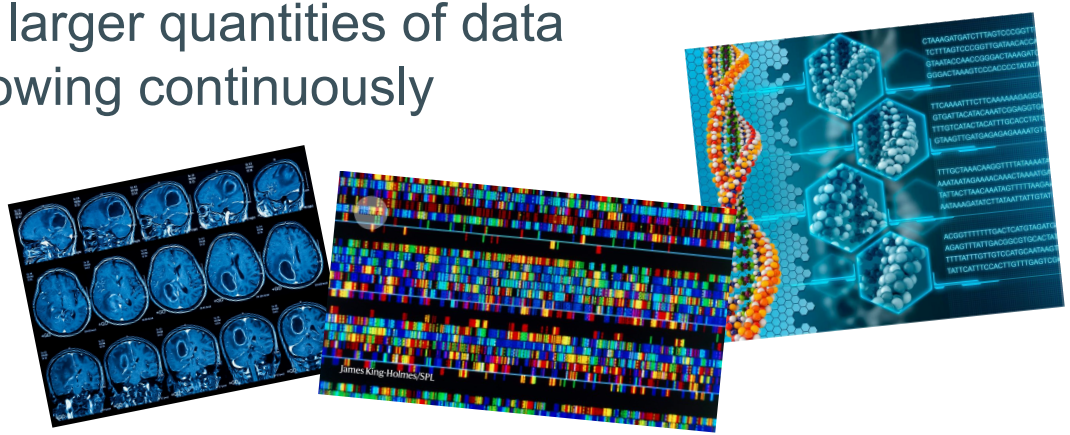
Julian Matschinske, M.Sc. Computer Science, UHH

Federated Learning - Introduction

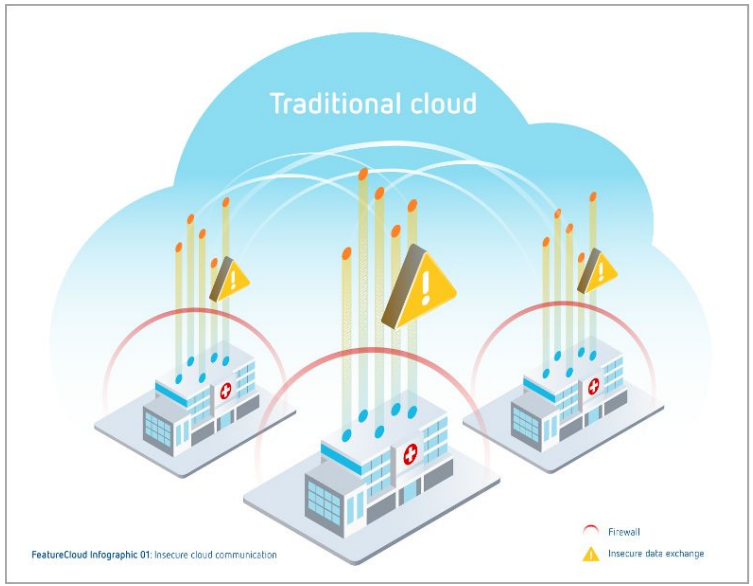
ISMB 2022, Federated Learning in Biomedicine (Tutorial)

Large-scale AI in Biomedicine

- Machine learning (ML) allows for classification and predictions in different domains
- Benefits hugely from larger quantities of data
- Amount of data is growing continuously



Large-scale AI in Biomedicine - Classical Approach



- Merge data into big datasets
- Train ML models on the whole set
- Share models with data contributors

Problem: Privacy regulation

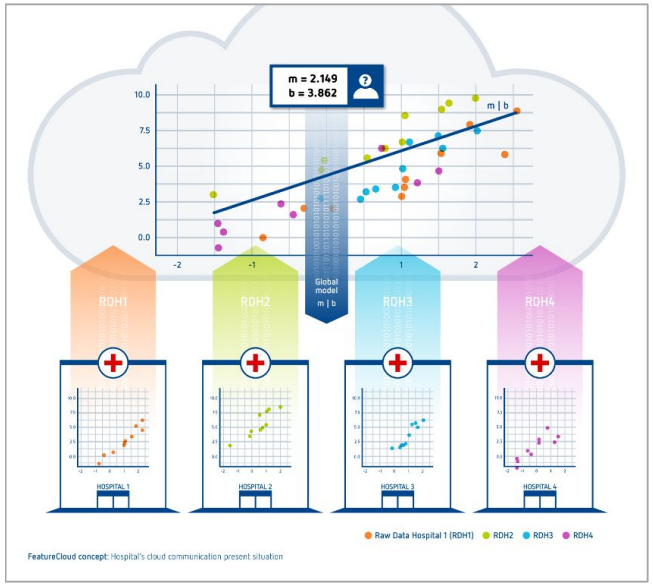
- General Data Protection Regulation (GDPR) and others
- Patients must have control over their data
- Data cannot leave the hospitals without big legal efforts

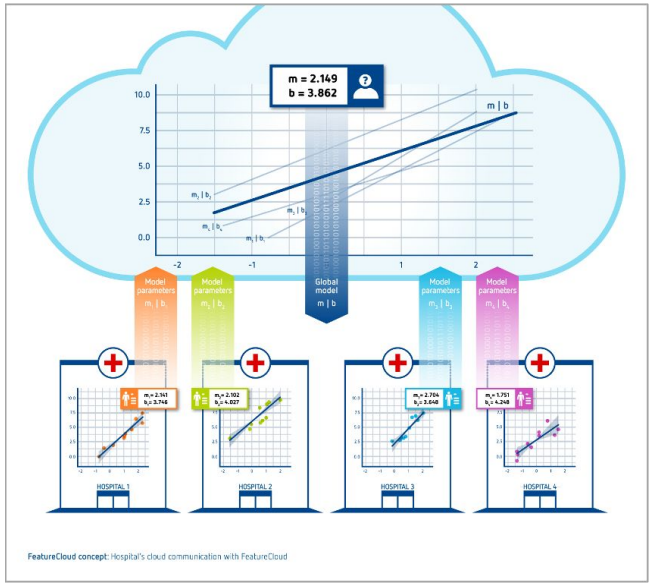
Idea: Federated Learning

- Data remains where is has been collected
- Split training between local training and global aggregation

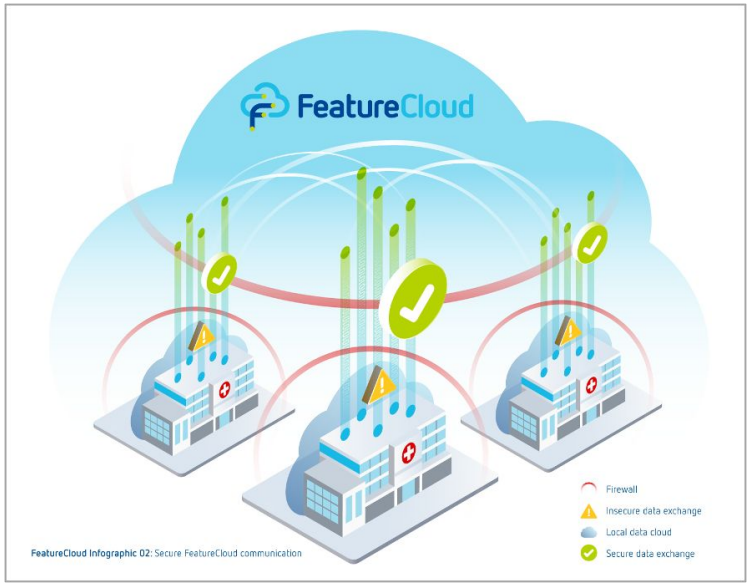
“Bring the model training to the data, not the other way round”

Large-scale AI in Biomedicine - Classical Approach





Federated Learning Platforms



- Isolate data
- Impose restrictions on communication
- Provide assistance for development of federated applications

What's the price?

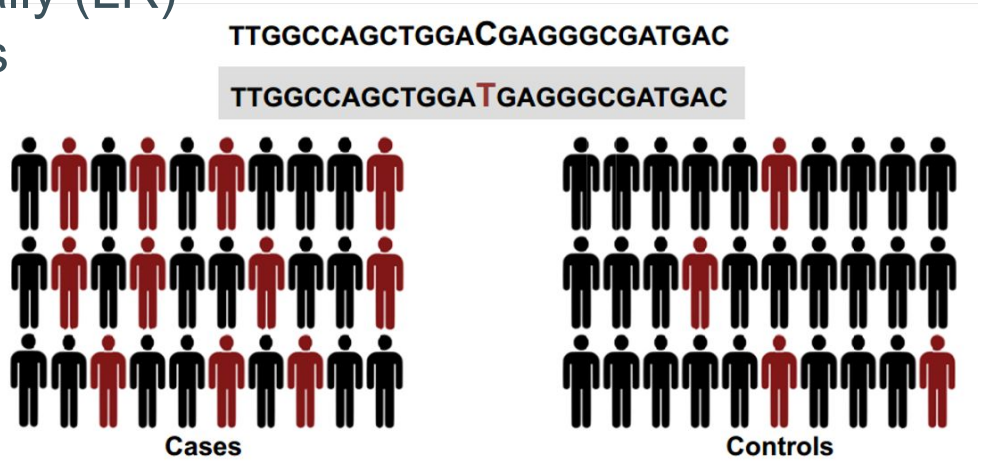
- Loss of performance due to communication overhead
- Loss of accuracy (in most cases) due to higher difficulty of generalization
- Less control over data quality

Is Federated Learning privacy-preserving?

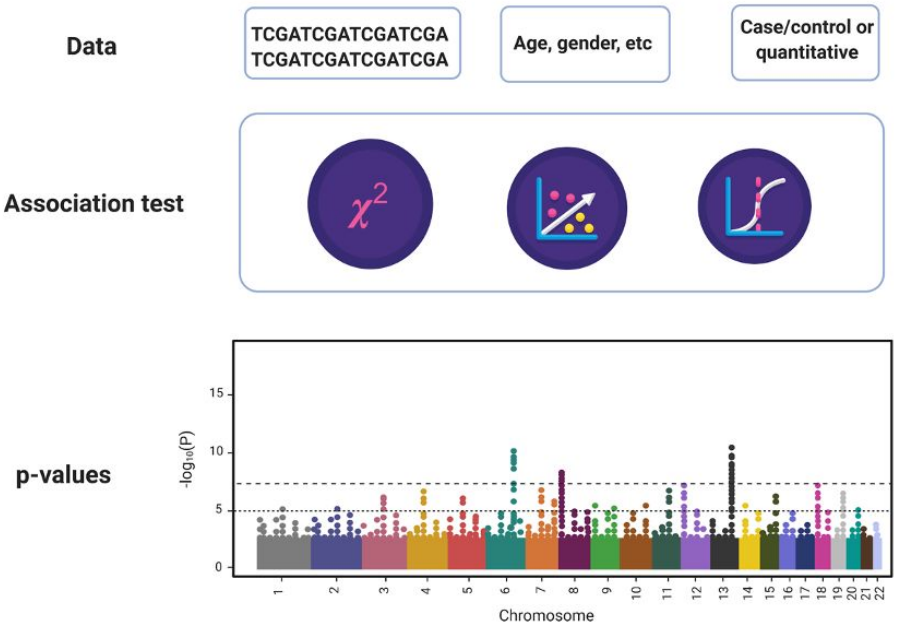
- Depends on the method and the data
- Privacy leaks can still occur (e.g., due to overfitting)
- But: huge improvement over sharing raw data
- Can be enhanced with additional techniques
  - Differential privacy
  - Secure multiparty computation
  - Homomorphic encryption

Application example: GWAS

- Case/control studies on SNP data
- Each SNP examined individually (LR)
- Find SNPs related to diseases

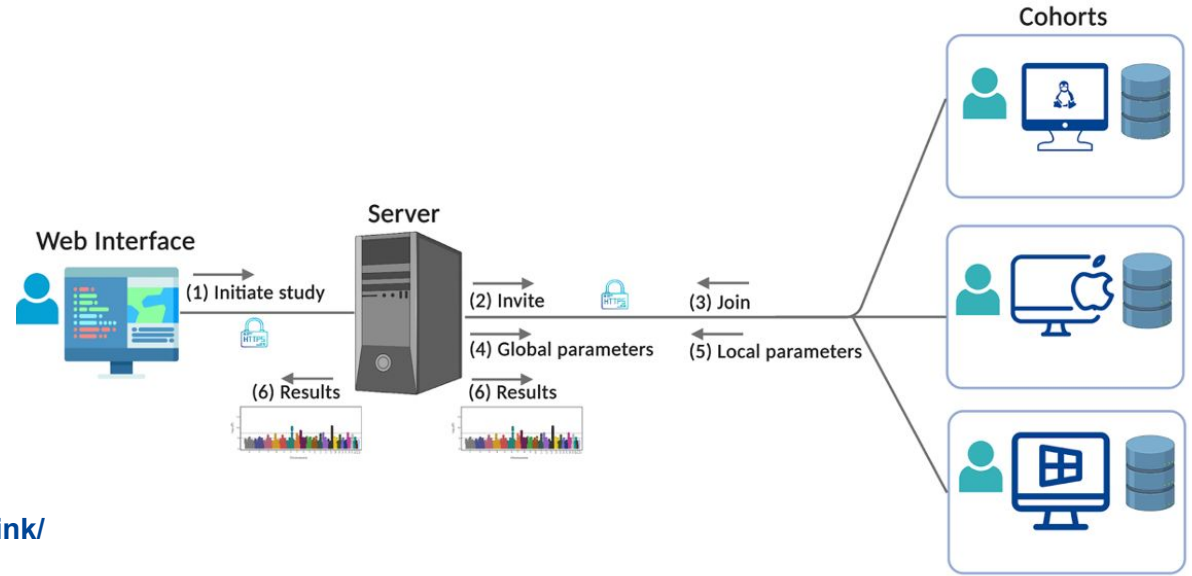


Application example: GWAS (Cont'd)



- Chi-square test
- Linear regression
- Logistic regression

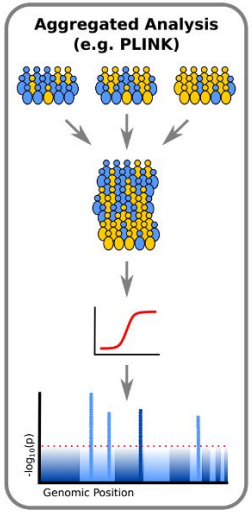
Application example: GWAS (Cont'd)



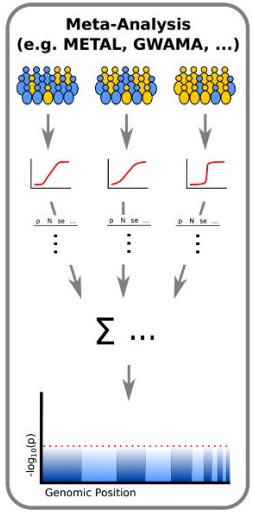
URL: **exbio.wzw.tum.de/splink/**

Reza Nasirigerdeh et al. (published in Genome Biology)

Application example: GWAS (Cont'd)



✗ Privacy-preserving
✓ Robust to imbalance



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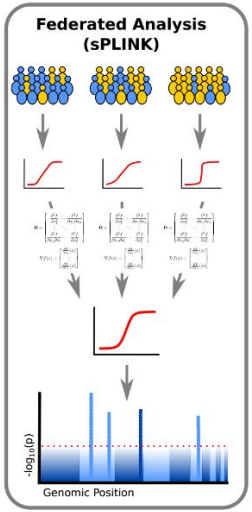

✓ Privacy-preserving
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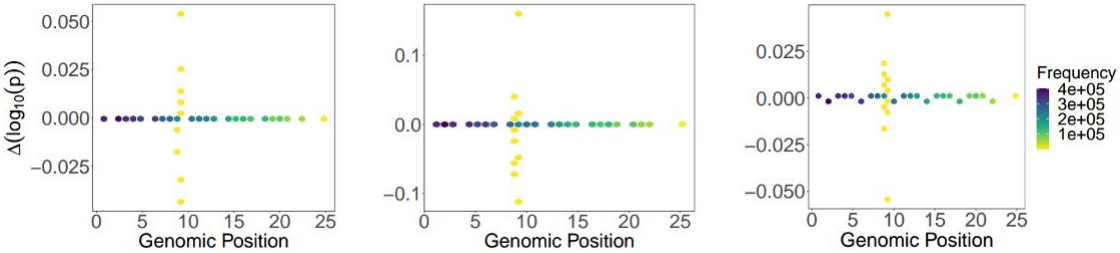
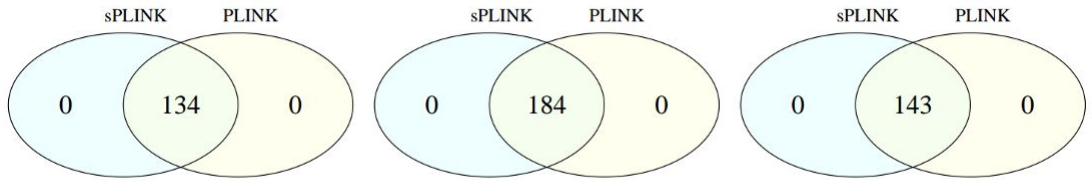
Application example: GWAS (Cont'd)



a) Logistic regression **b)** Linear regression **c)** Chi-square test



d) Logistic regression **e)** Linear regression **f)** Chi-square test

Other examples

Flimma

Differential expression analysis based on the limma voom pipeline

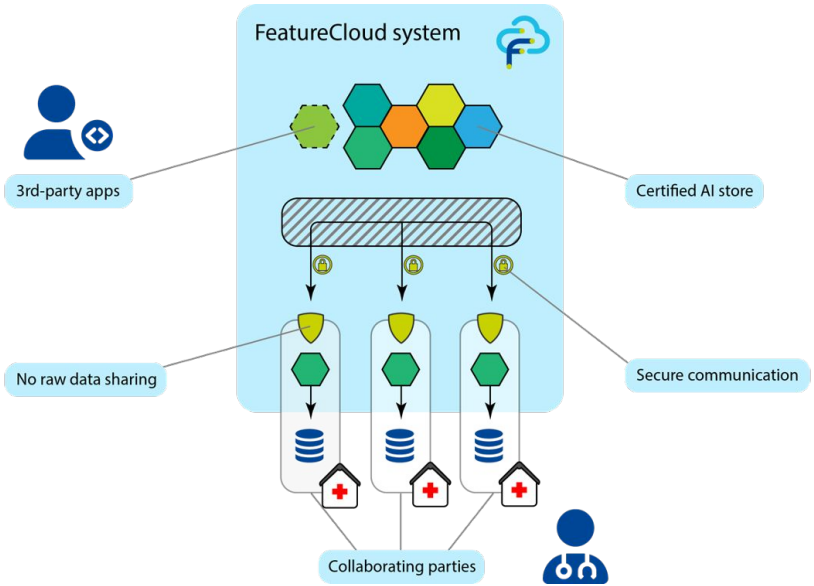
URL: **exbio.wzw.tum.de/flimma/** | *Olga Zolotareva et al.* (published in Genome Biology)

Partea

Time-to-event studies

URL: **exbio.wzw.tum.de/partea/** | *Julian Späth et al.*

Platform example: FeatureCloud

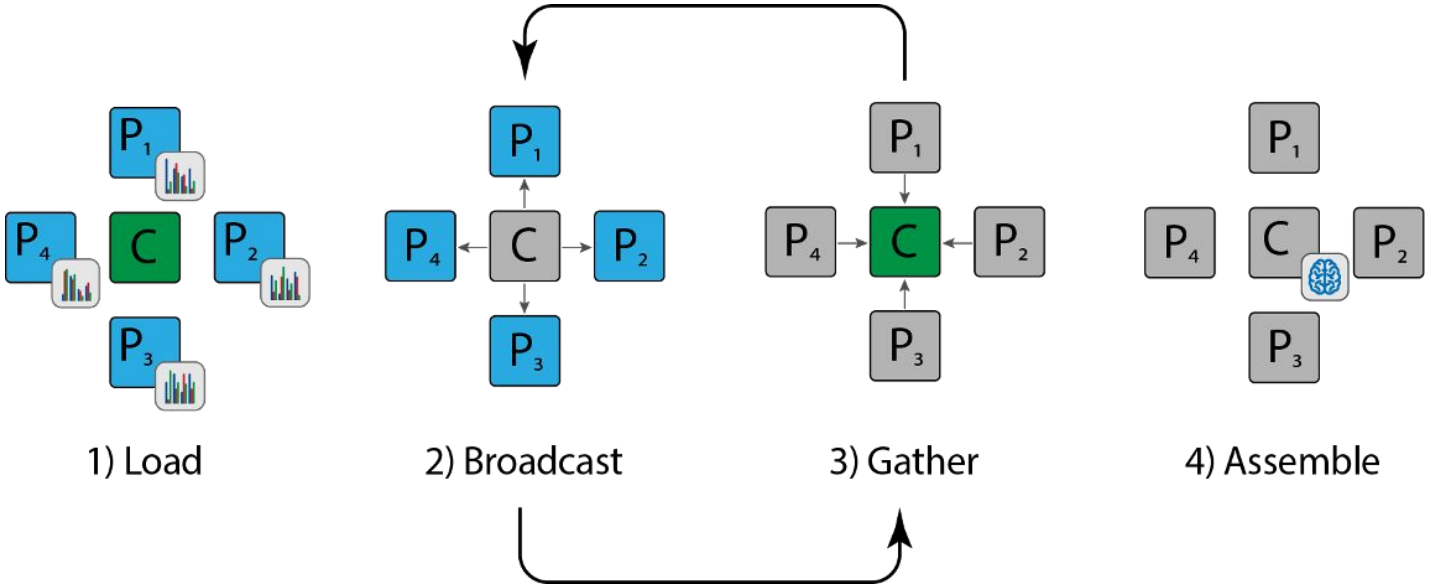


- Increase convenience for developers (including testing and deployment)
- Increase trust in apps (certification, consent management)
- Create a community (developers, researchers, patients)

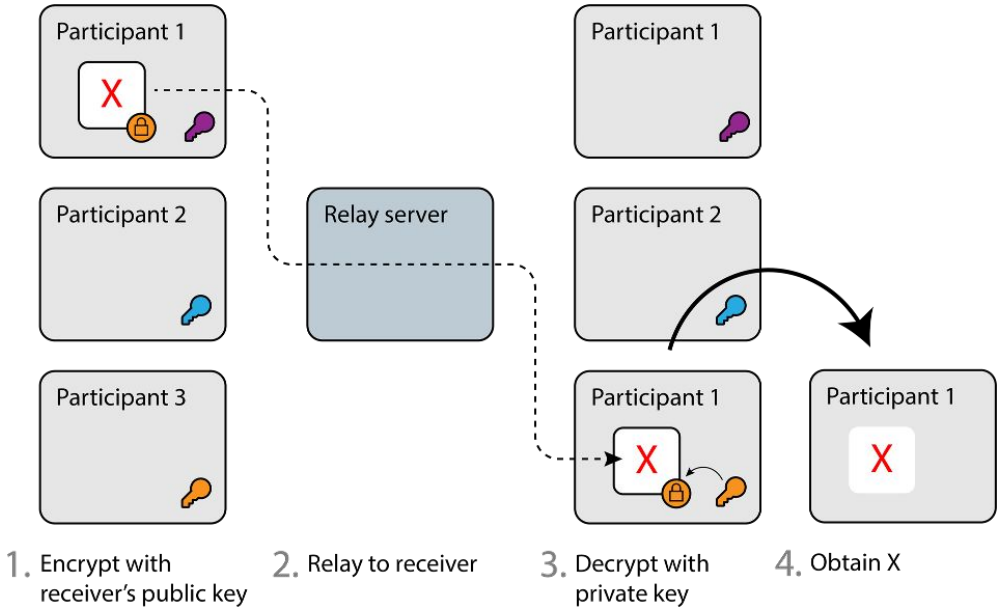
App communication

- Star-based federated learning
  - Gather-broadcast
- Peer-to-peer
- Secure multi-party computation

Star-based communication



Peer-to-peer communication



Continuous vs. discrete models

- Continuous models can usually be federated ‘straightforward’
  - Gradient descent
  - Federated average
  - One or multiple interactions

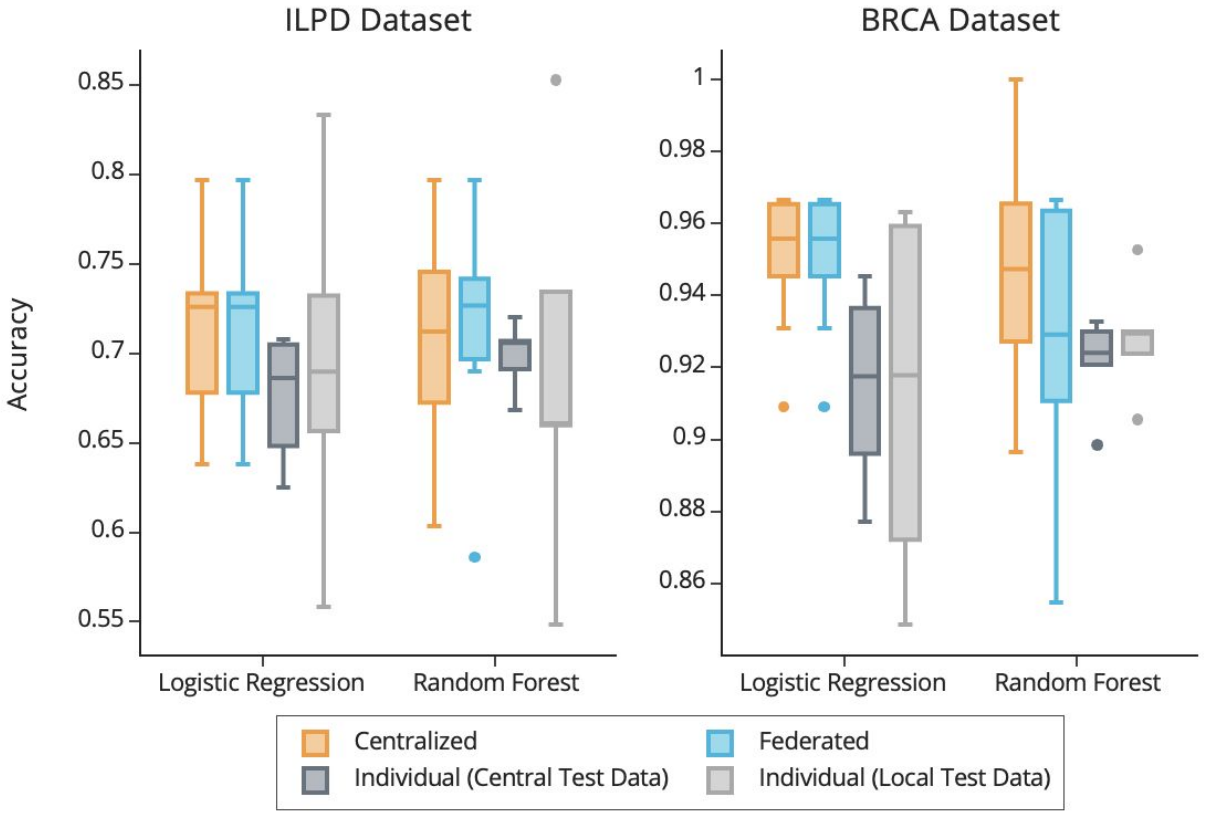
- Discrete models are more difficult
  - Example: Decision tree
  - Possible solutions: Ensemble techniques

Example: Random forest

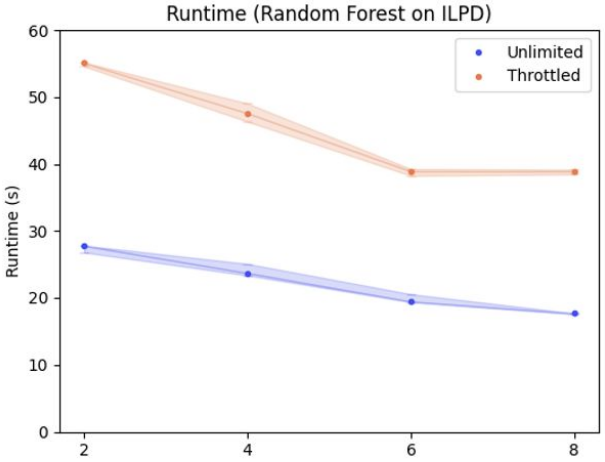
- Train decision trees using bootstrapping on each site
- Transmit models and merge into big ensemble → Random Forest

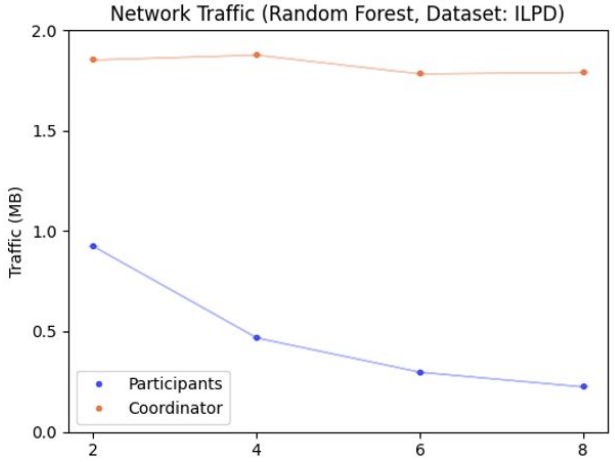
Federated Random Forests can improve local performance of predictive models for various healthcare applications, Anne-Christin Hauschild, Marta Lemanczyk, Julian Matschinske, et al., Bioinformatics, Volume 38, Issue 8, 15 April 2022, Pages 2278–2286

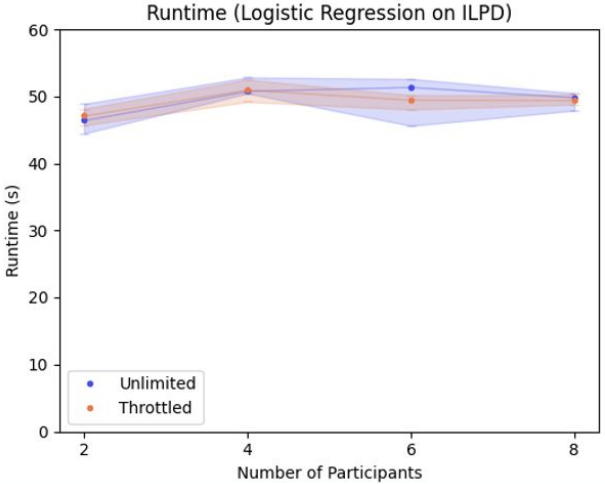
Evaluation

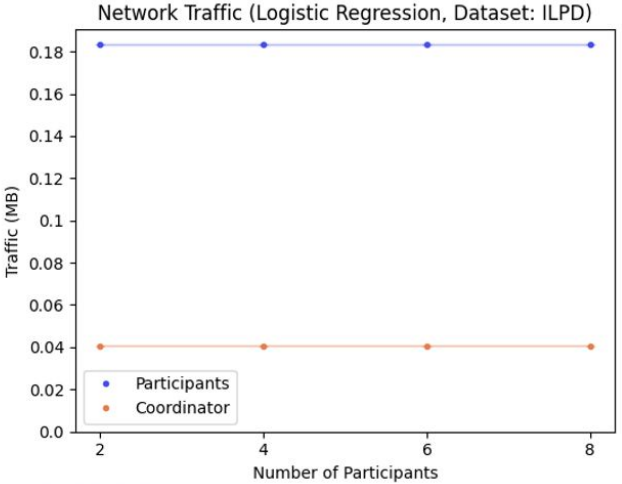

ILPD Dataset
BRCA Dataset
Accuracy
0.85
0.8
0.75
0.7
0.65
0.6
0.55
1
0.98
0.96
0.94
0.92
0.9
0.88
0.86
Logistic Regression
Random Forest
Logistic Regression
Random Forest
Centralized
Federated
Individual (Central Test Data)
Individual (Local Test Data)

Evaluation


Runtime (Random Forest on ILPD)
Runtime (s)
Unlimited
Throttled


Network Traffic (Random Forest, Dataset: ILPD)
Traffic (MB)
Participants
Coordinator


Runtime (Logistic Regression on ILPD)
Runtime (s)
Unlimited
Throttled
Number of Participants


Network Traffic (Logistic Regression, Dataset: ILPD)
Traffic (MB)
Participants
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Thank you!

→ **Questions, comments, thoughts?**