Benchmarking Federated Learning in the SME Industry Context

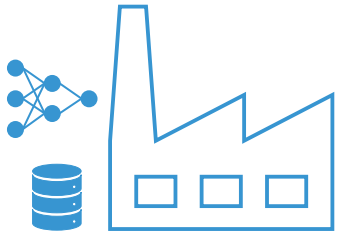
Evaluation concerning Privacy, Complexity and Performance with an Application to real-world Image Classification Problem

Anna Hensel, master's thesis

KARLSRUHE SERVICE RESEARCH INSTITUTE (KSRI)
INSTITUTE OF INFORMATION SYSTEMS AND MARKETING (IISM)

SMEs* often have related machine learning use cases, each facing several problems concerning classical ML


[7]



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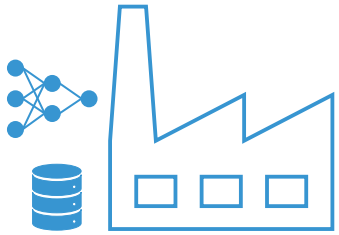
→ poor performance



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One model per company

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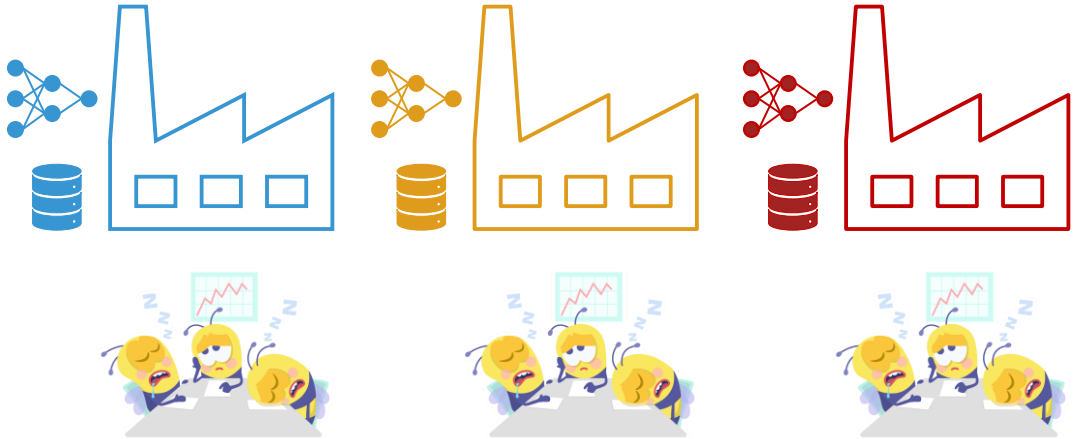

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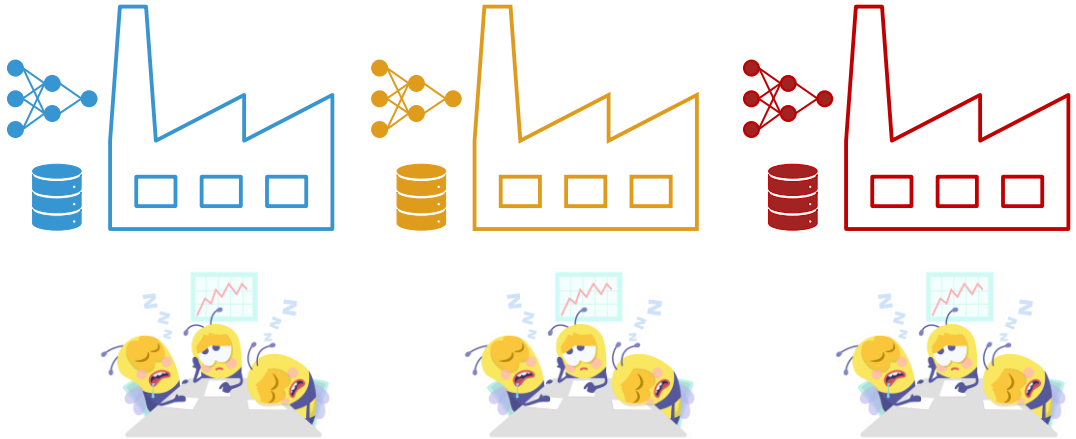
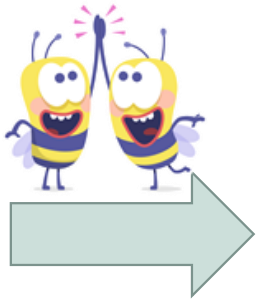
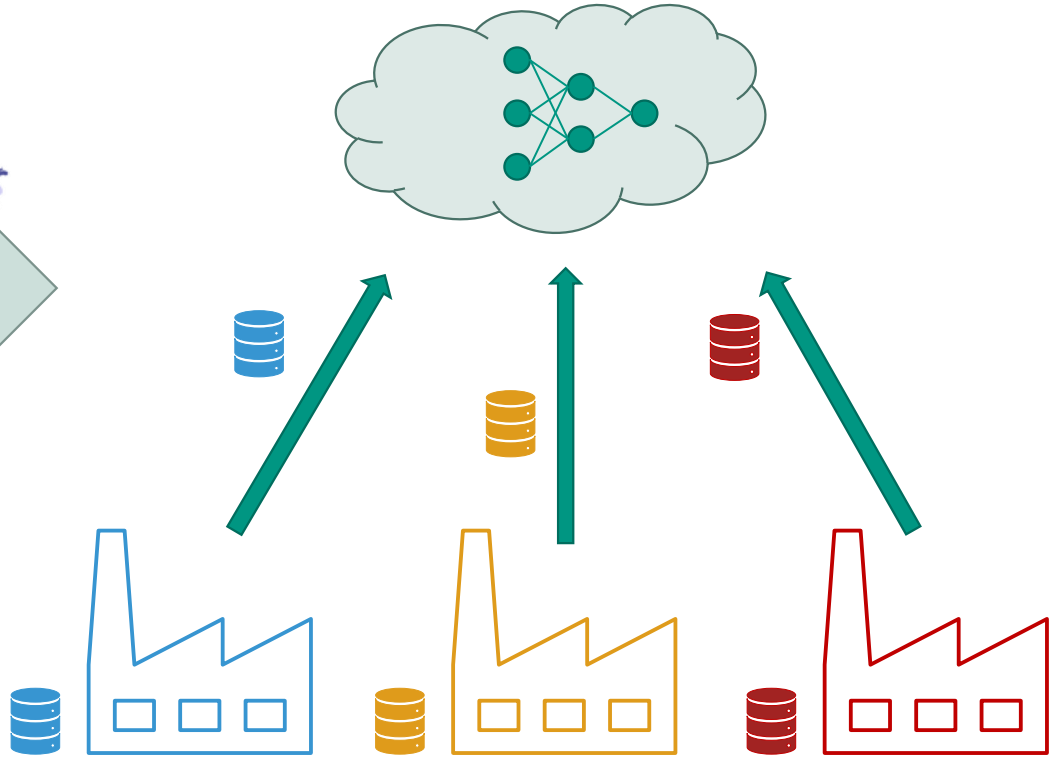




All data model



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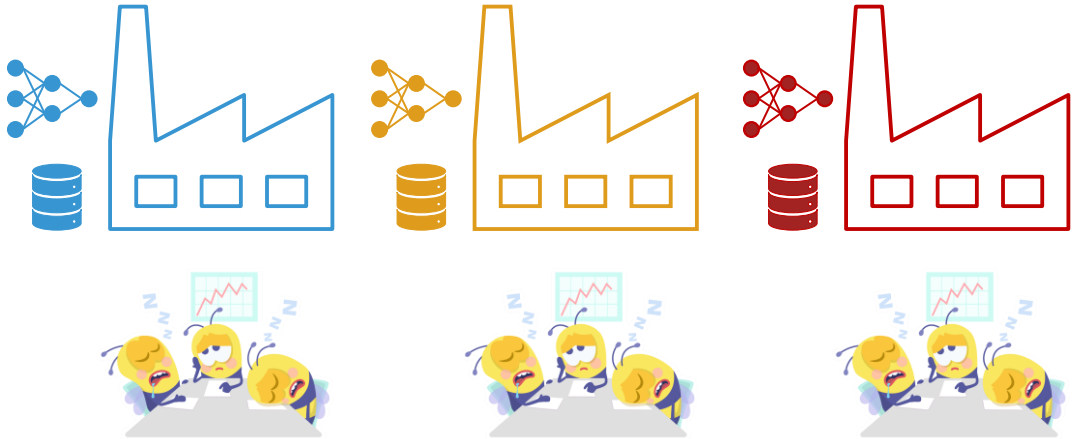

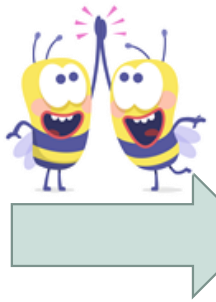

All data model

Huge privacy problem as companies data is sent to a central node

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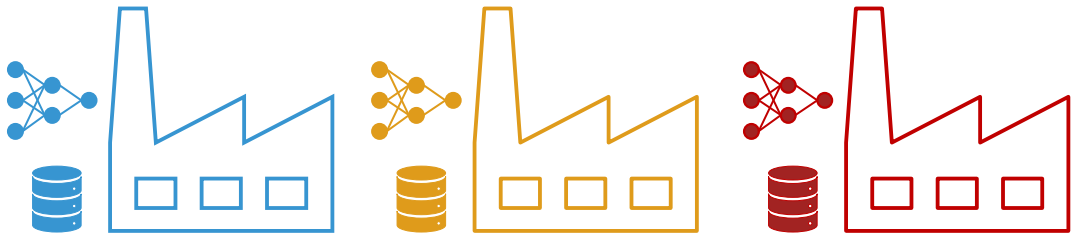
Federated learning allows for decentralized machine learning potentially mitigating privacy issues

Federated learning model



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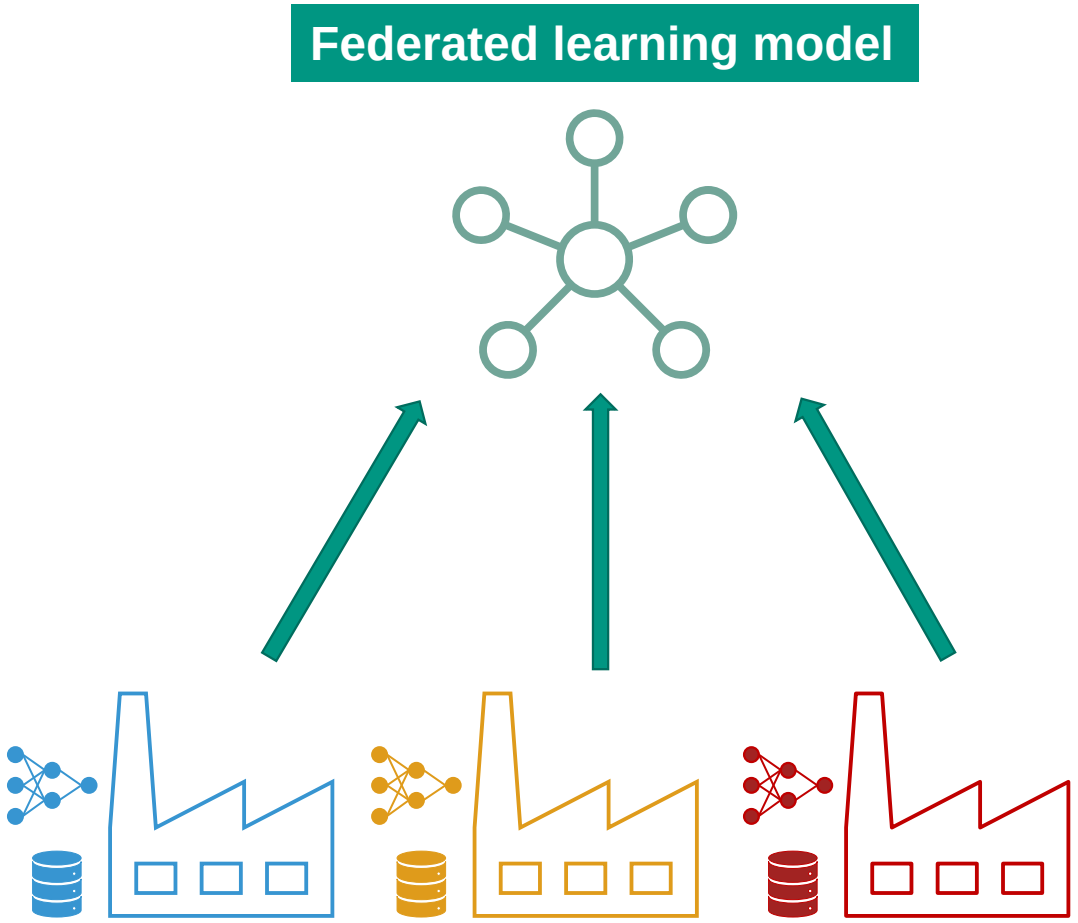

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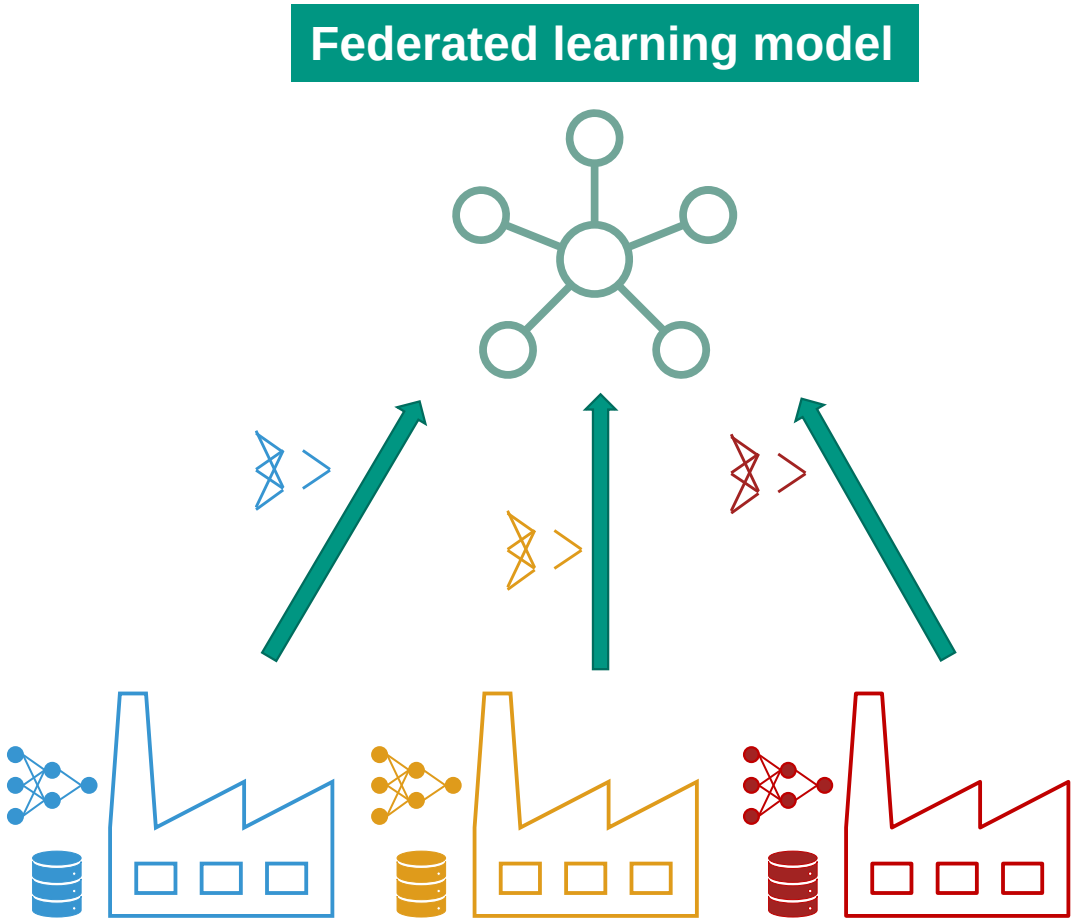

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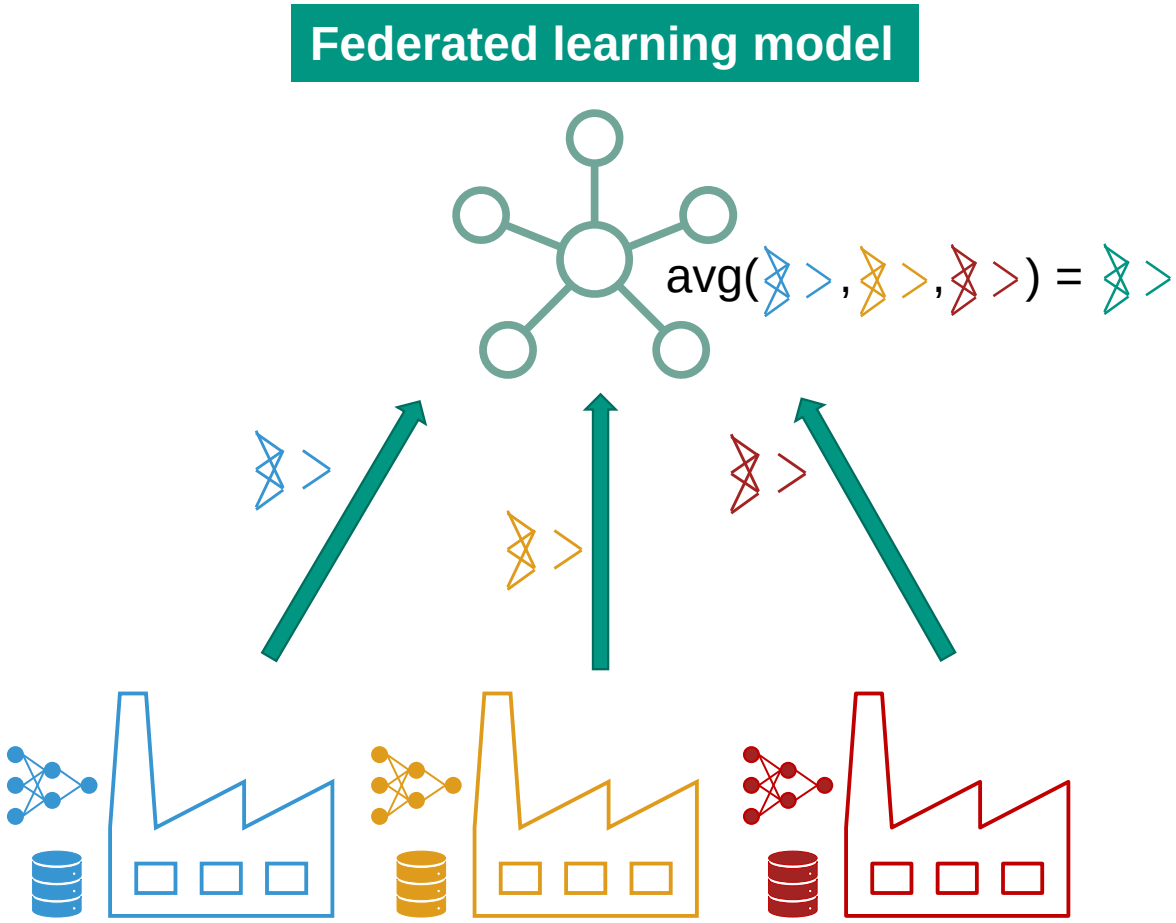

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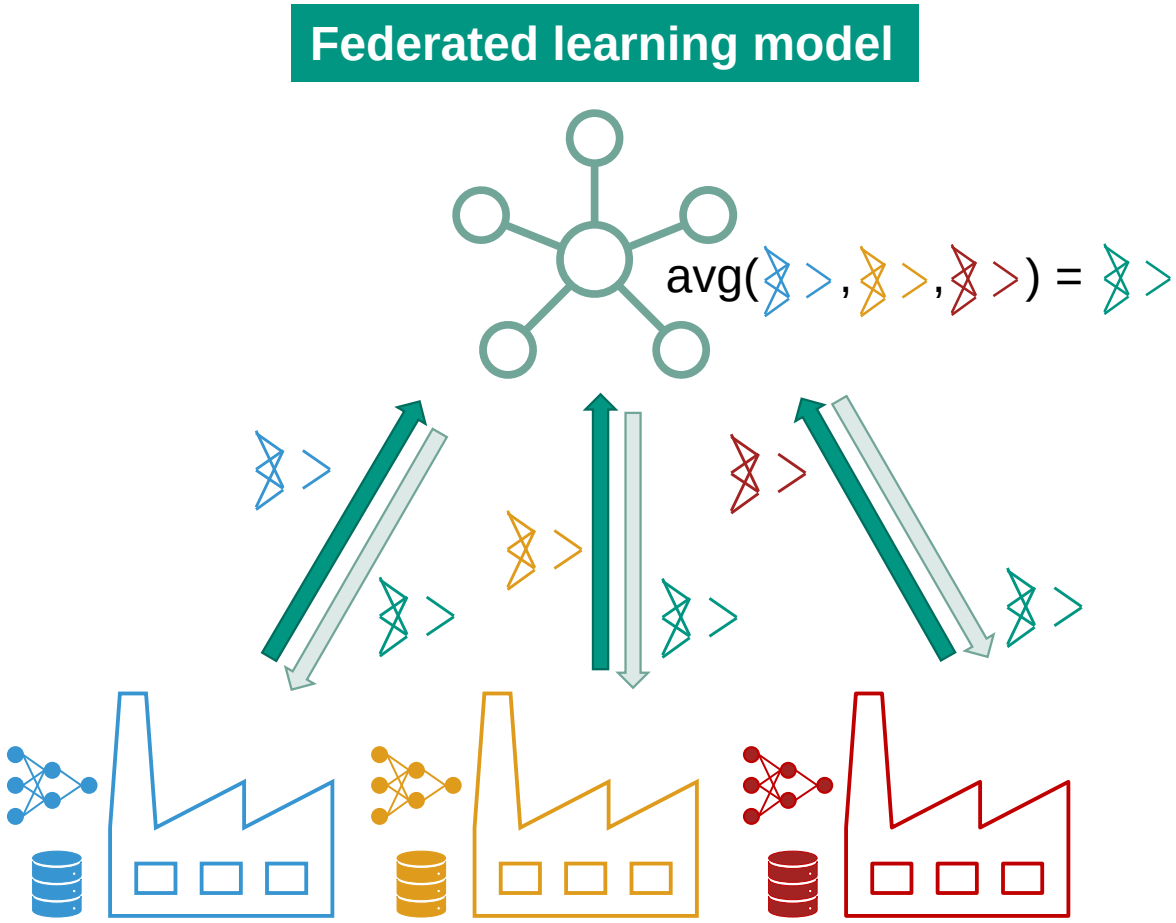

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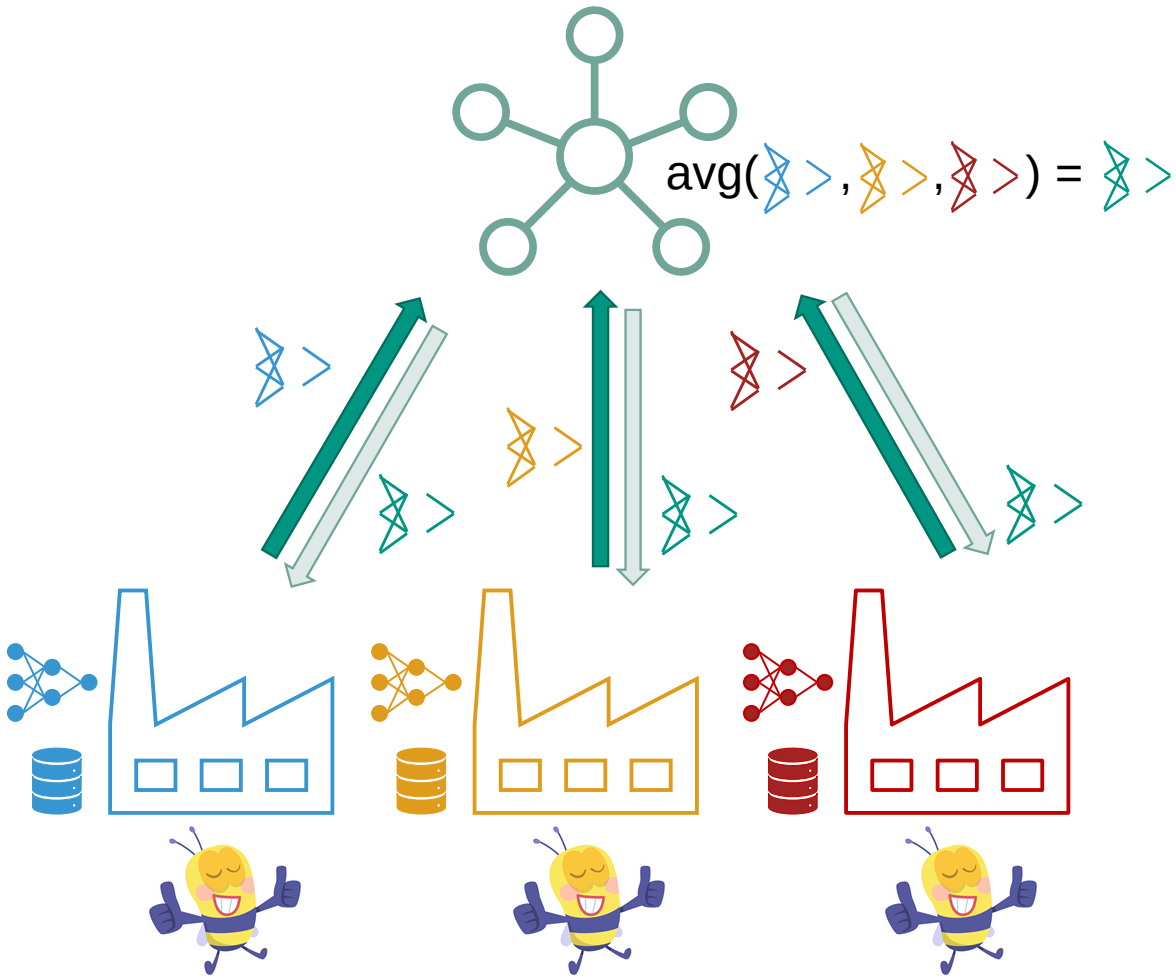

- Local training and model sharing preserves **privacy**
- Enables joint use of data of several companies → unlocks **performance** potential
- **Complexity** due to model sharing and update communication

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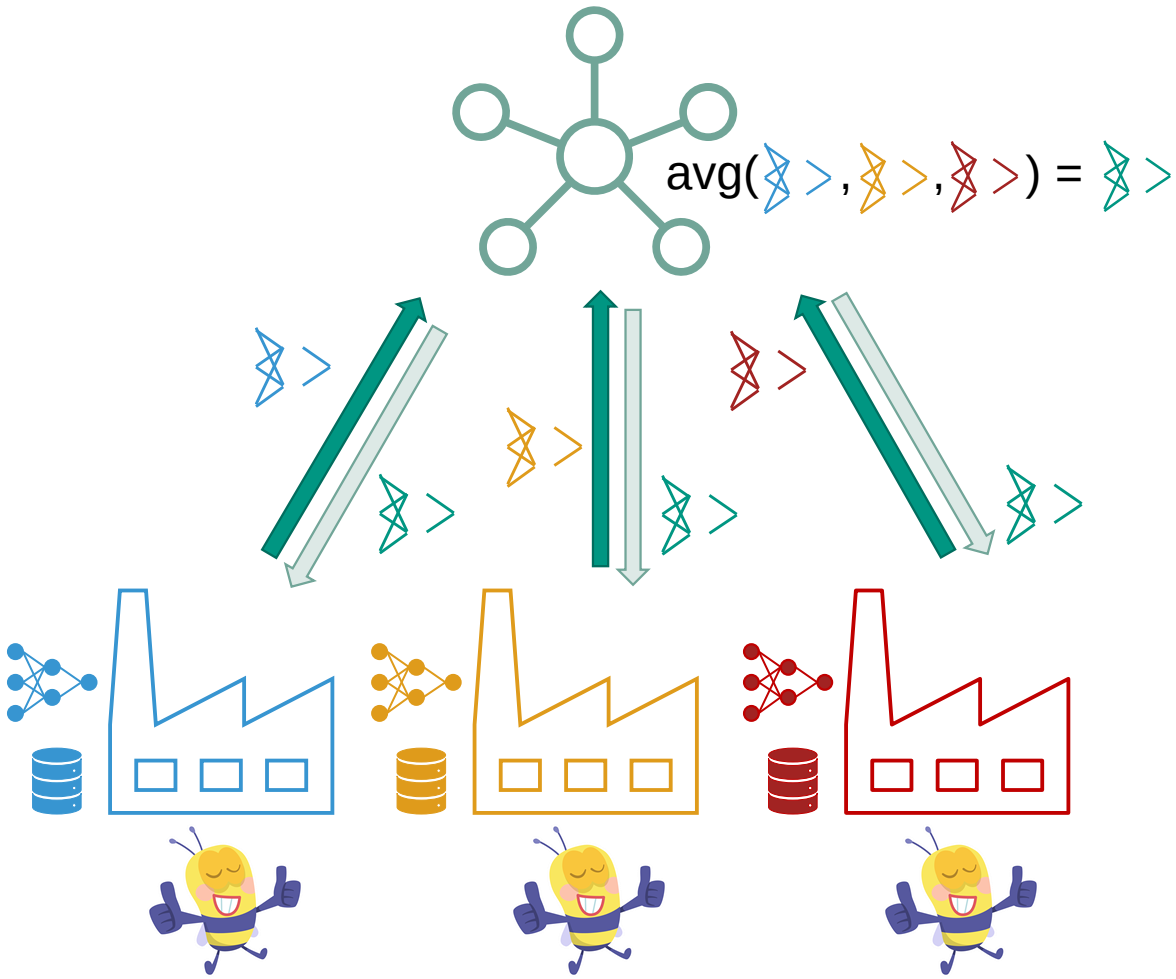

Research Questions and Contributions:

1. Under what conditions is federated learning (not) useful for SMEs in an industrial context?

2. How does federated learning compare to *one model per company* and *all data model*? What do SMEs need to consider in terms of *privacy*, *complexity* and *performance*?

3. Implementation of a benchmarking pipeline to empirically investigate and simulate federated learning in relation to *one model per company* and *all data model*.

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Privacy, complexity and performance are important dimensions for the evaluation of federated learning use cases for SMEs

Privacy

Complexity

Performance

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Privacy

⊕ One model per company

Federated learning

⊖ All data model

Complexity

Performance

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Critical aspects:

- Company sends weights to central node [2]
- Weights reflect company data

→ Adversarial attacks from “malicious client” or “malicious server” possible [8]
  - Sample reconstruction
  - Information inference

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Computational Complexity

Organizational Complexity

Implementation Complexity

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- Number of communication rounds [2] / iterations / communicated bits [5] not relevant in SME setting as much less clients

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- FL: setting up network complexity, contracts, legal issues, sharing costs, …
- The more companies the harder to organize

Implementation Complexity

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- FL: reduced/shared modelling complexity
- One model per company: set up and implement own model

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Federated learning

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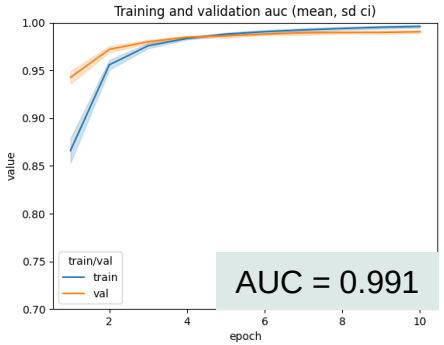
Performance measure to enable **comparability** between and within companies
- Accuracy [2, 6]
  - Threshold needed
  - Unbalancedness
- AUC [9]
  - Abstracts from balancedness
  - Quality of score (no threshold needed)

All data model

FL model per company

One model per company



- The all data model can be seen as an upper bound

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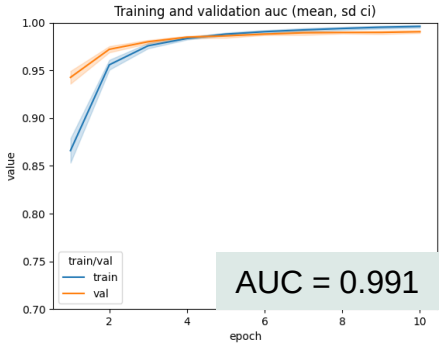
All data model



FL model per company

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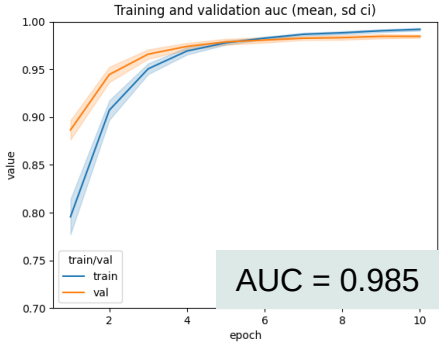
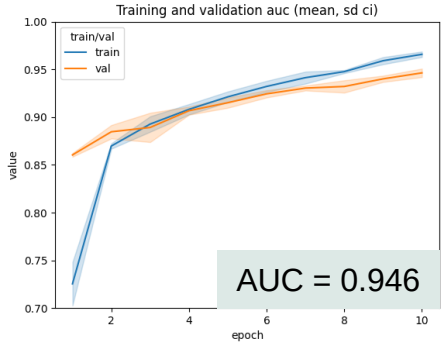
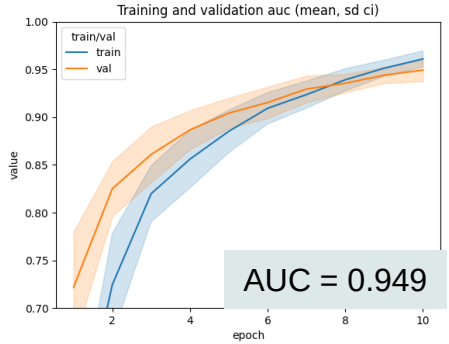


Company 1
50% of all data, balanced



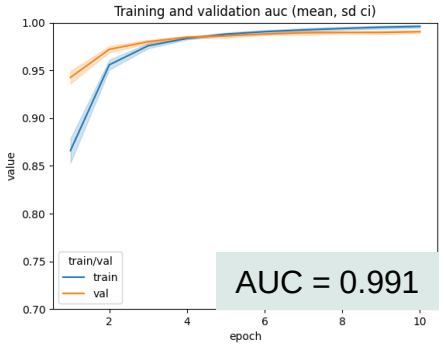
Company 2
25% of all data, unbalanced



Company 3
25% of all data, unbalanced

- The all data model can be seen as an upper bound
- One model per company can be seen as a lower bound

All data model



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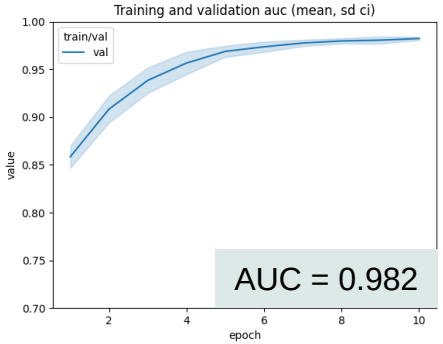

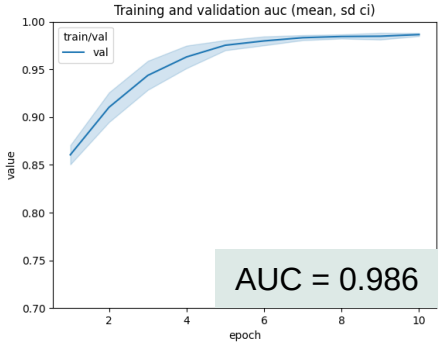

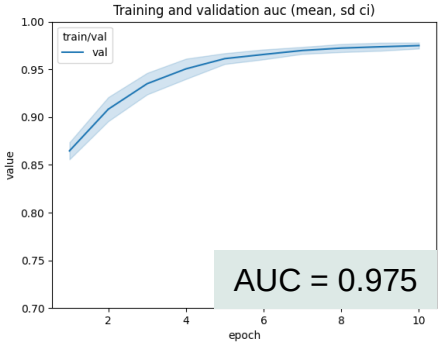

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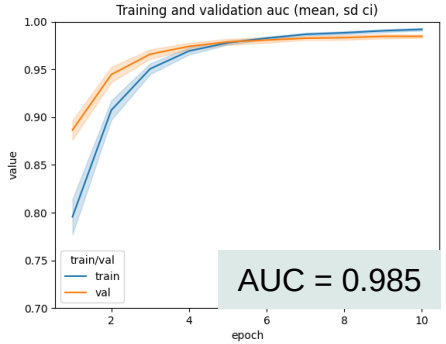

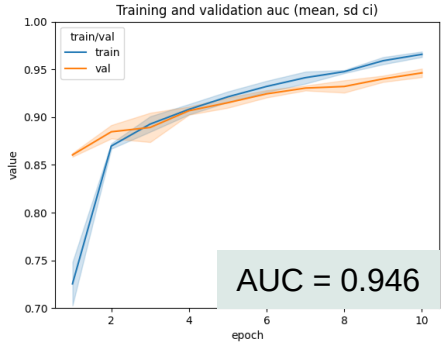

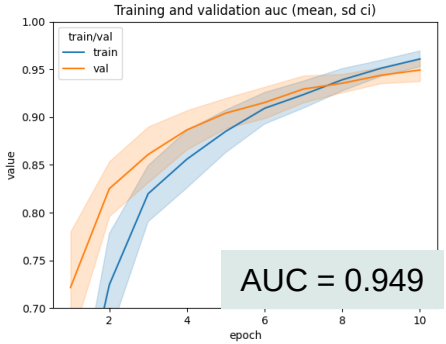

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Company 2
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Company 3
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- The all data model can be seen as an upper bound
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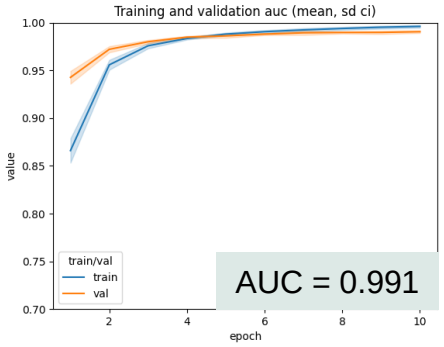
- Companies with insufficient data profit more from the federated model

All data model



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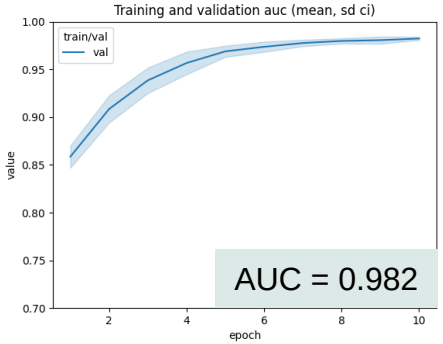

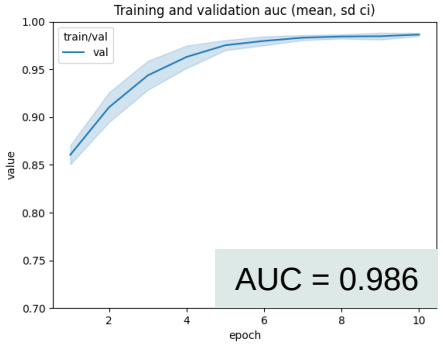

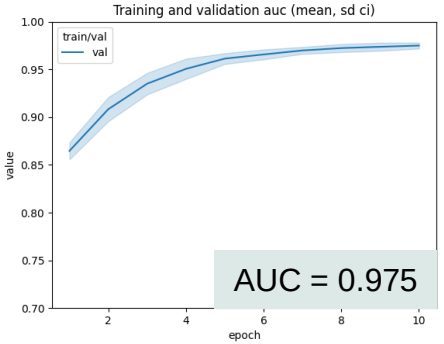

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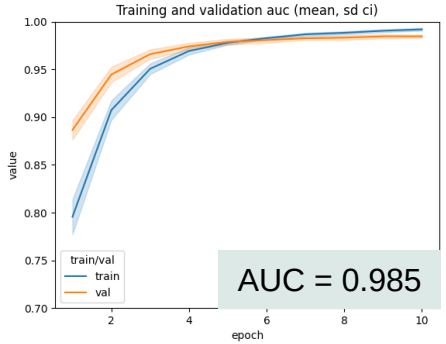

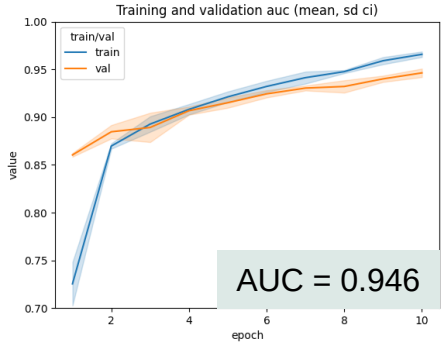

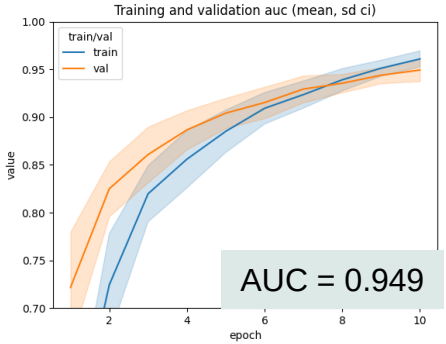

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- For companies with sufficient data there is little incentive to take part in FL setting

Discussion topics

Measuring Performance

Do you know an alternative measure to AUC which suits to my industry/SME setting?

Measuring Incentives

Idea: Shapley Value with AUC as contribution measure
Do you have experience with it?
How to interpret the result?

Measuring Complexity

What kind of complexity does really matter for SMEs regarding my setting?

Thank you for your attention!

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Sources

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