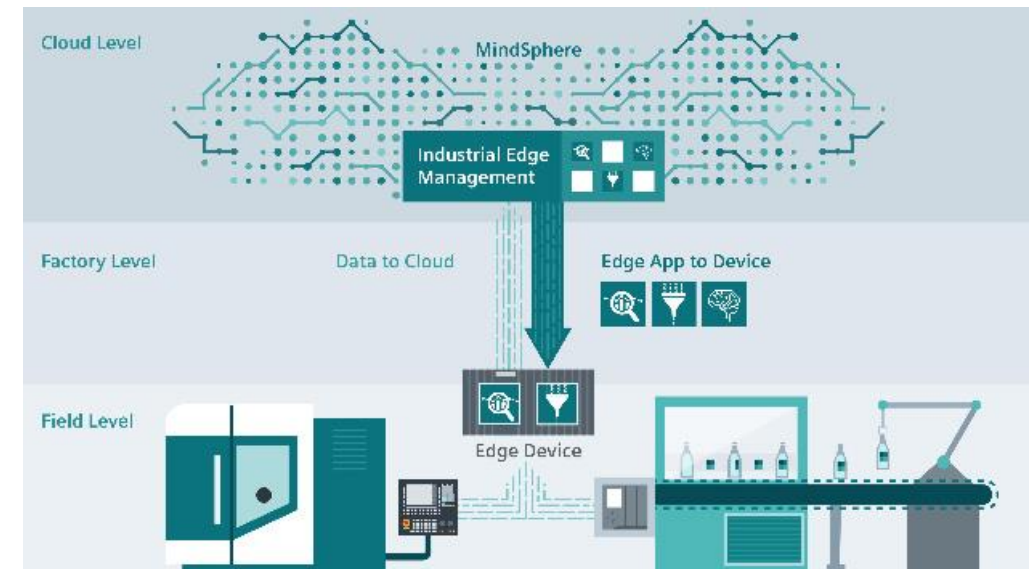
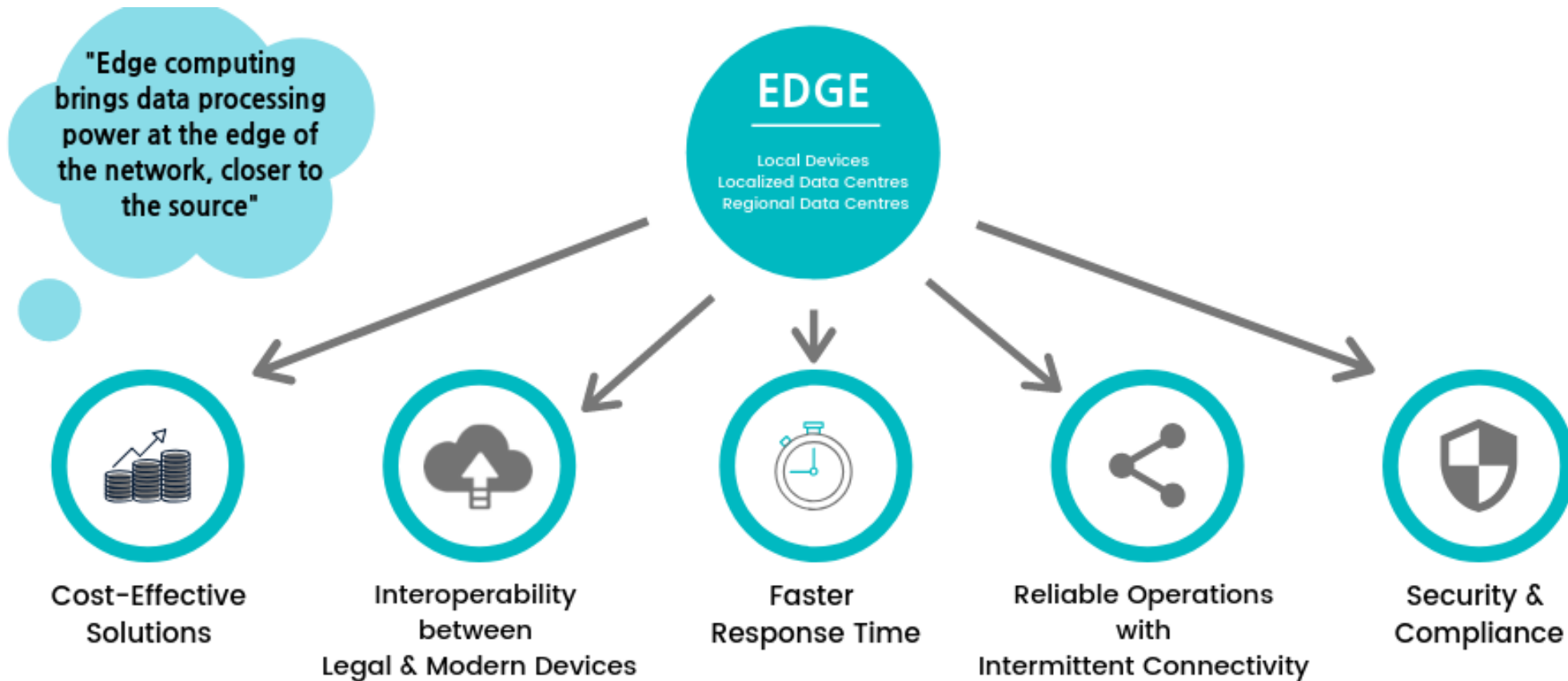


Edge Computing and AI for Industrial Applications – Outline

- What is Edge Computing?
- Managing AI Lifecycle
- Optimization of Models

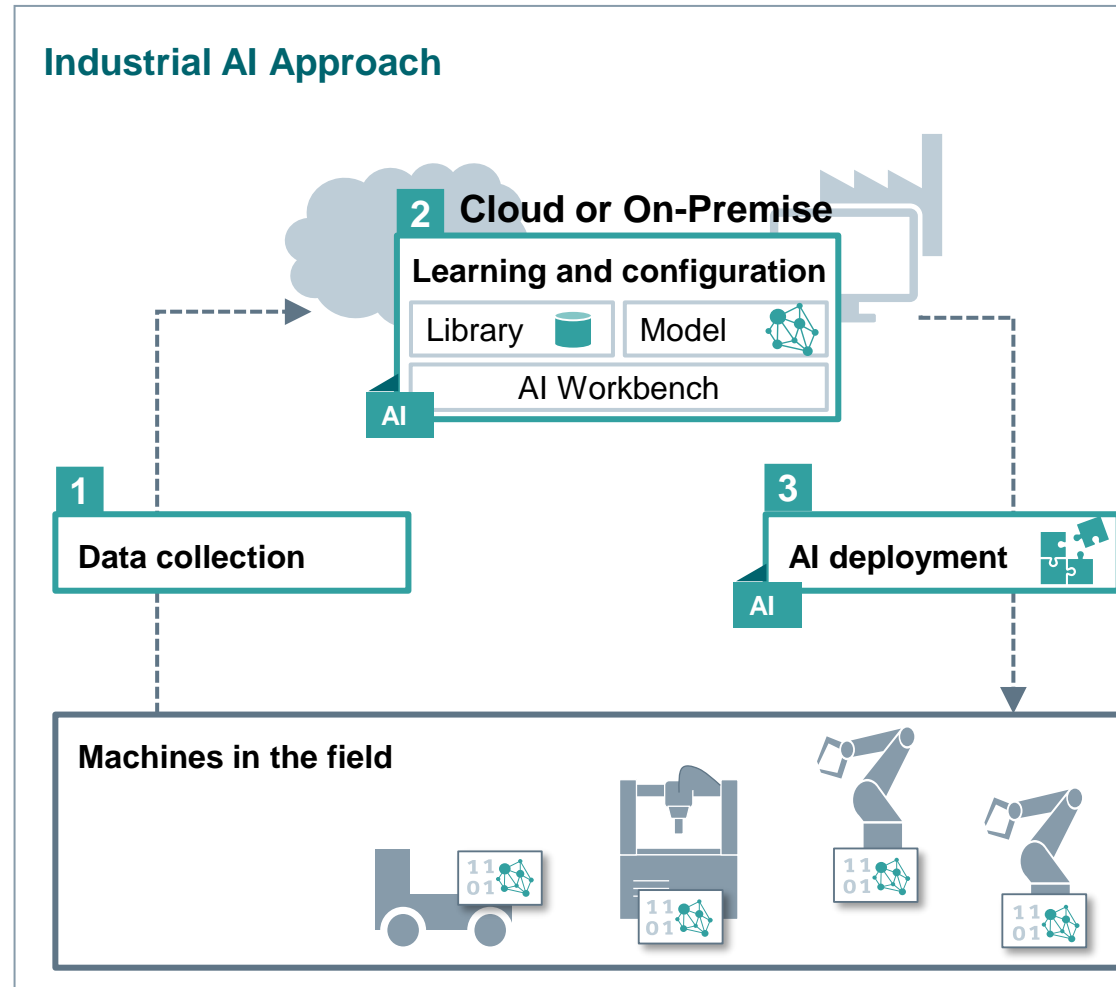


5 Key Benefits of Edge Computing



Artificial Intelligence in Industry

Vision for Industrial AI Approach



→ Requirements:

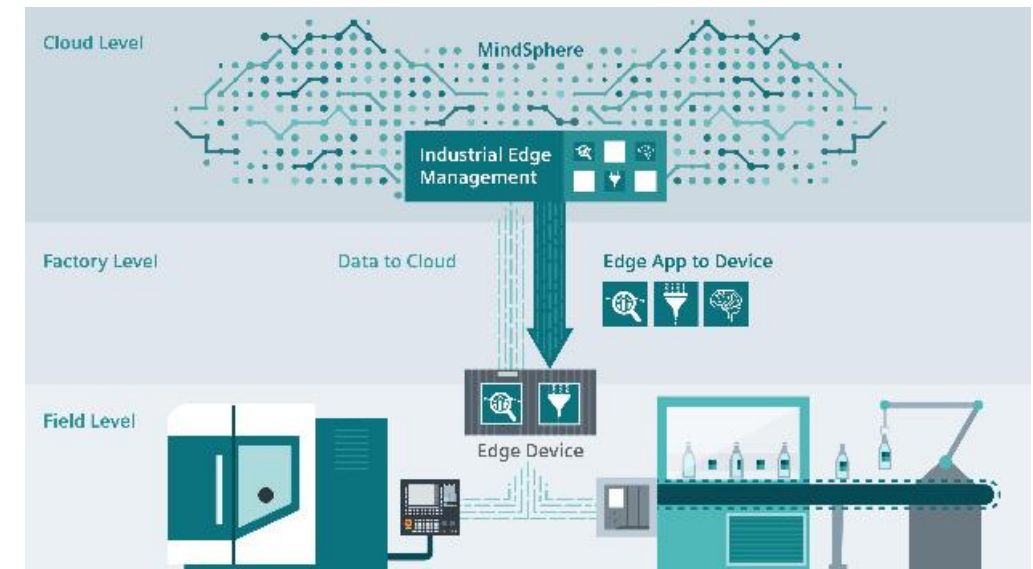
- 1. Data Collection:**
Data directly from machines
branch and process knowledge needed
labeling of data
- 2. Learning and configuration of AI Algorithm:**
Algorithm and training knowledge needed
Cloud or on-Premise
- 3. Deployment of AI:**
Industrial-suited Hardware required

→ Objective:

Automized Usage of AI Algorithms in an industrial environment

Edge Computing and AI for Industrial Applications – Outline

- What is Edge Computing?
- Managing AI Lifecycle
- Optimization of Models





Low-Code platform

Build apps faster for cloud, on-premise or hybrid infrastructure

IIoT as a service

Centralized compute & storage, with solutions, apps & services

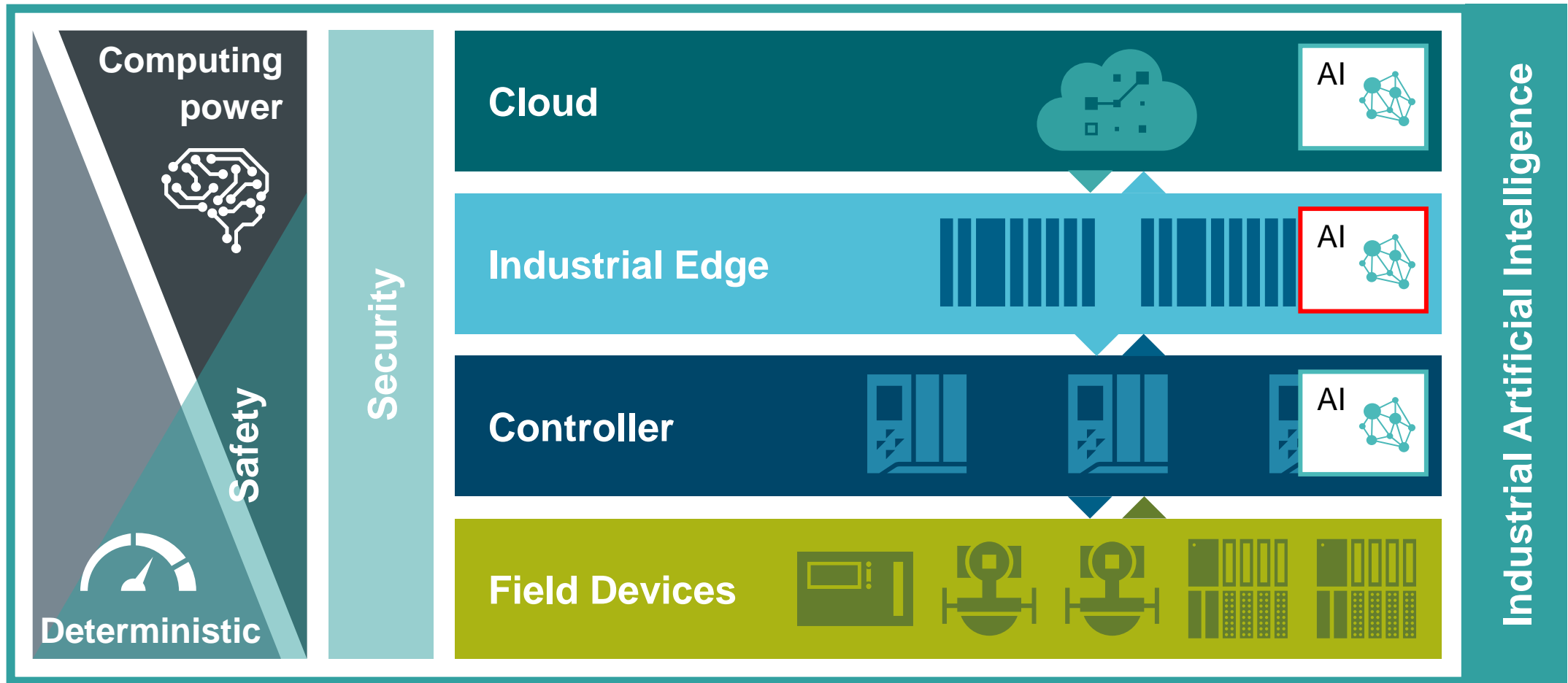
Edge Computing

Decentral compute & storage with device runtime, apps & management

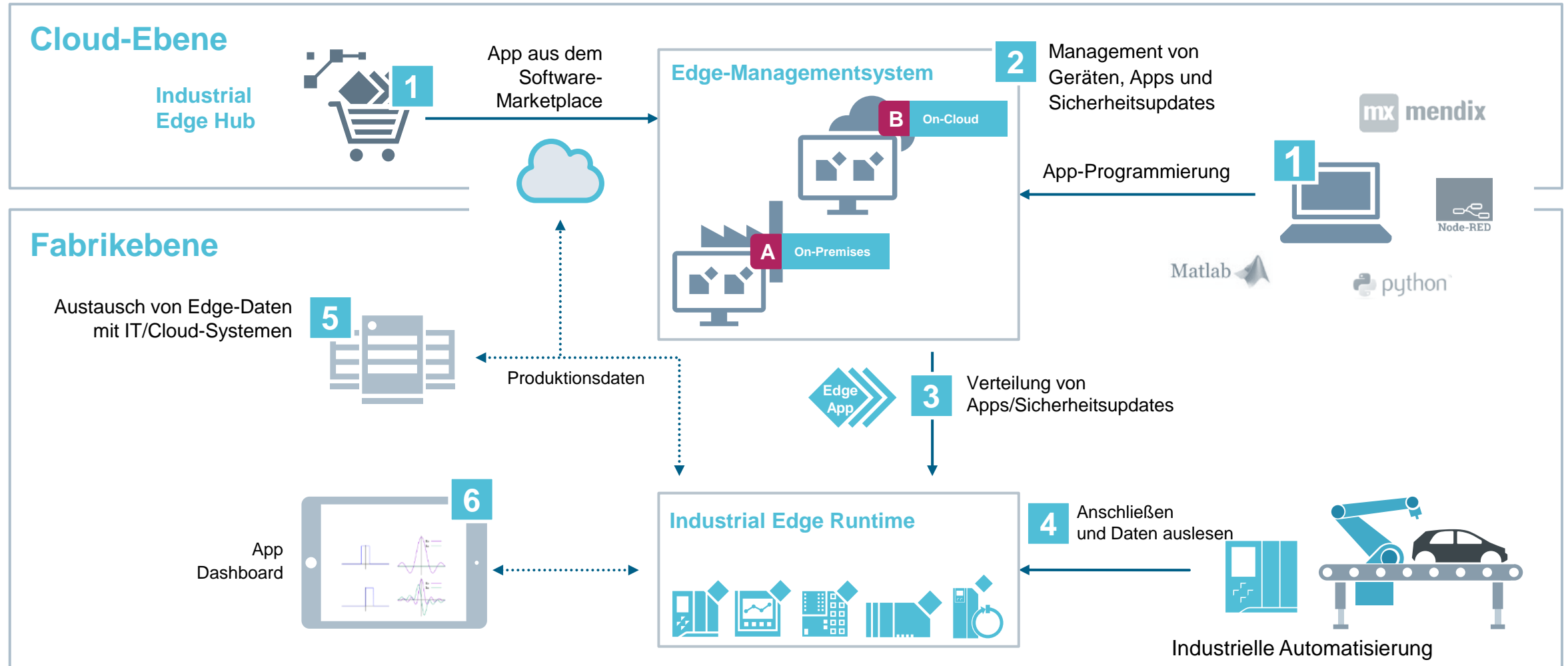
Field/Control

Automation runtime & engineering connectivity

Artificial Intelligence in Industry Platforms & Deployment



Siemens Industrial Edge Workflow



Additionally to devices by partners, Siemens provides a scalable industrial hardware to run Edge Applications

SIEMENS
Ingenuity for life



1 S7-1500 TM MFP

2 IPC127E

3 IOT2050

4 RuggedCom APE

5 IPC227E

6 IPC427E

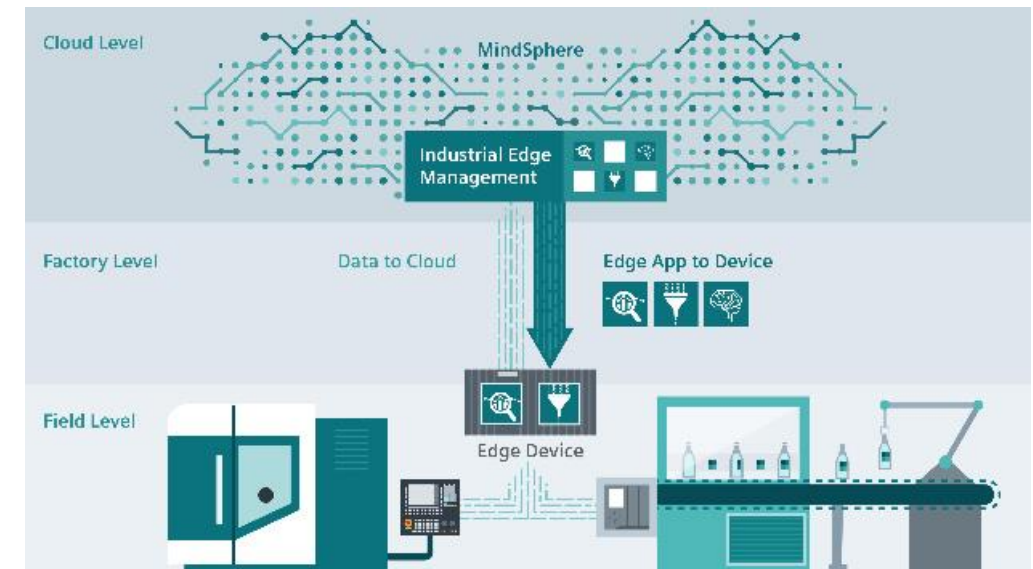
7 IPC6x7E

Available / Available mid-term

Potential future development

Edge Computing and AI for Industrial Applications – Outline

- What is Edge Computing?
- Managing AI Lifecycle
- Optimization of Models

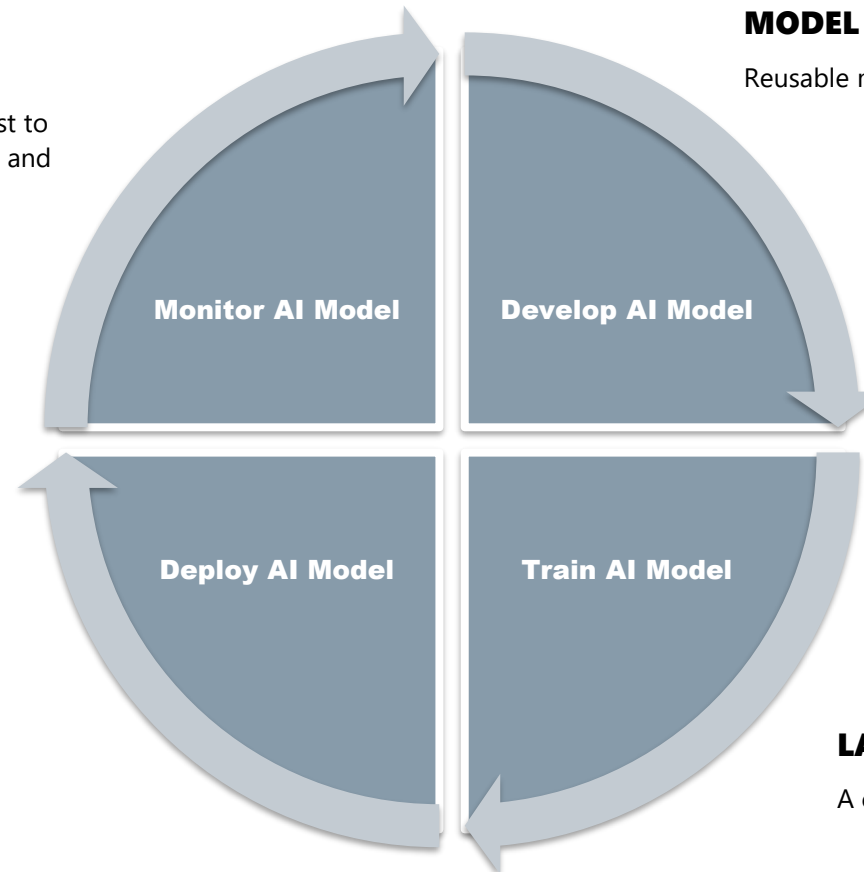


EXPERT VIEW

An interface that empowers a data scientist to quickly reason about system performance and failures

SYSTEM AGNOSTIC

Common runtime for cloud and edge



MODEL TEMPLATES

Reusable model artefacts

CONTINUOUS INTEGRATION

Testing and delivering new models and features through an automated pipeline

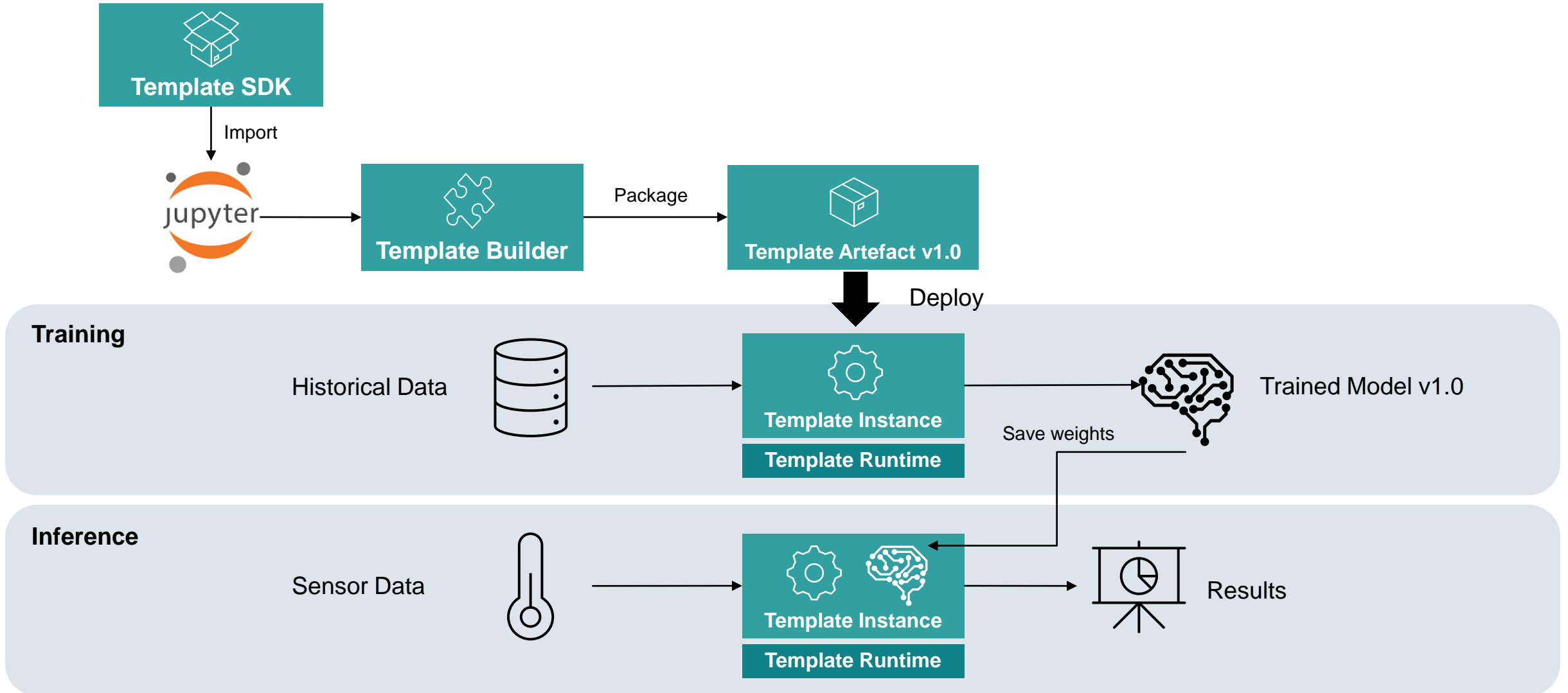
LABELLING UI

A convenient tool suite for labelling ML data

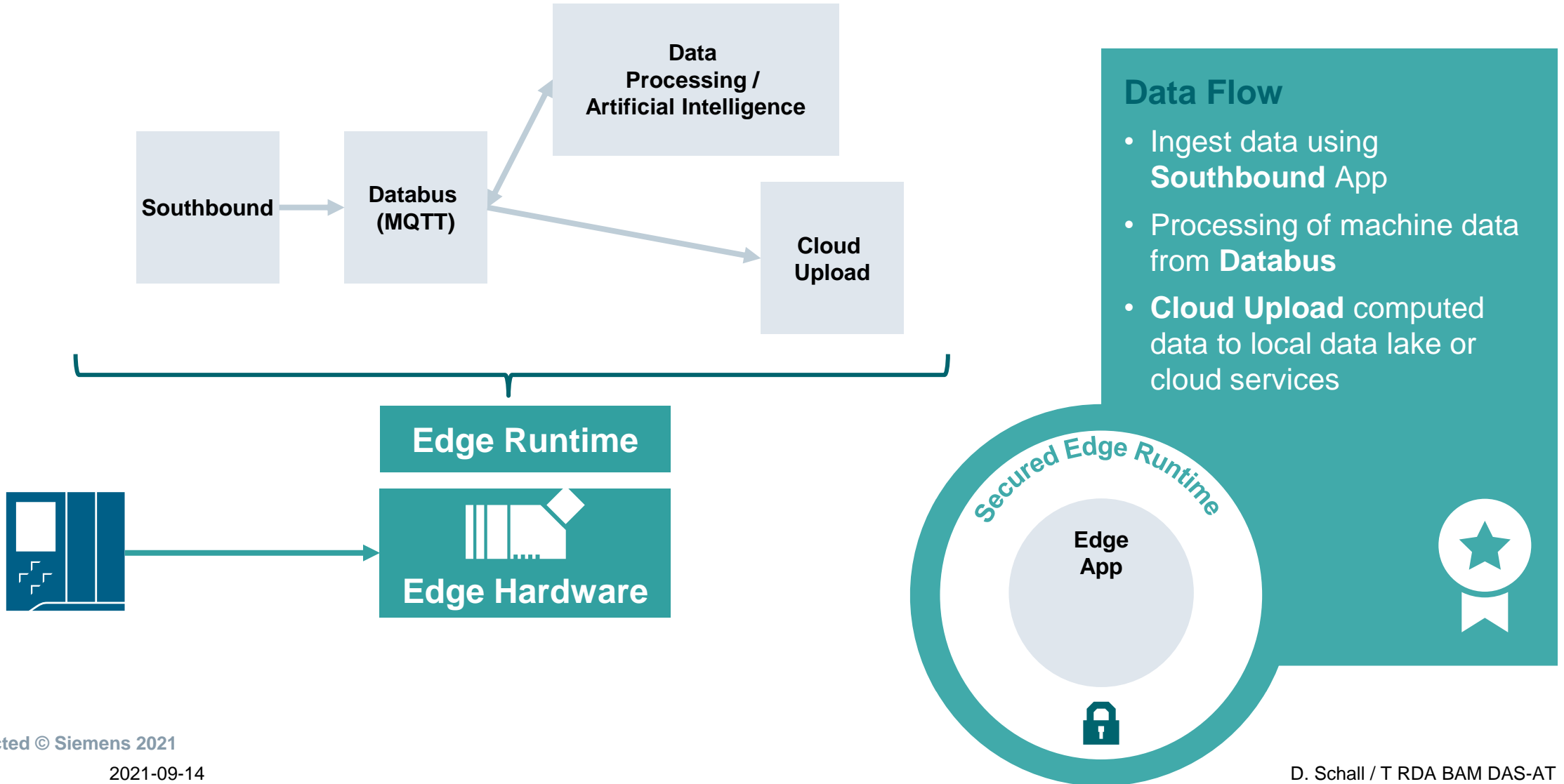
MODEL MANAGEMENT

An integrated transparent system management interface

AI Templates - Workflow

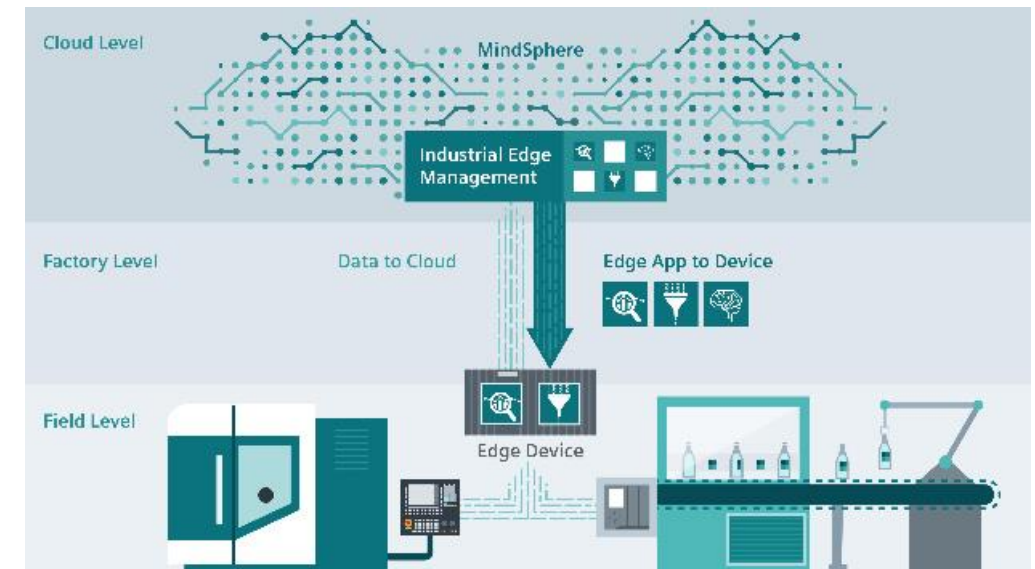


Industrial Edge Example Edge AI App



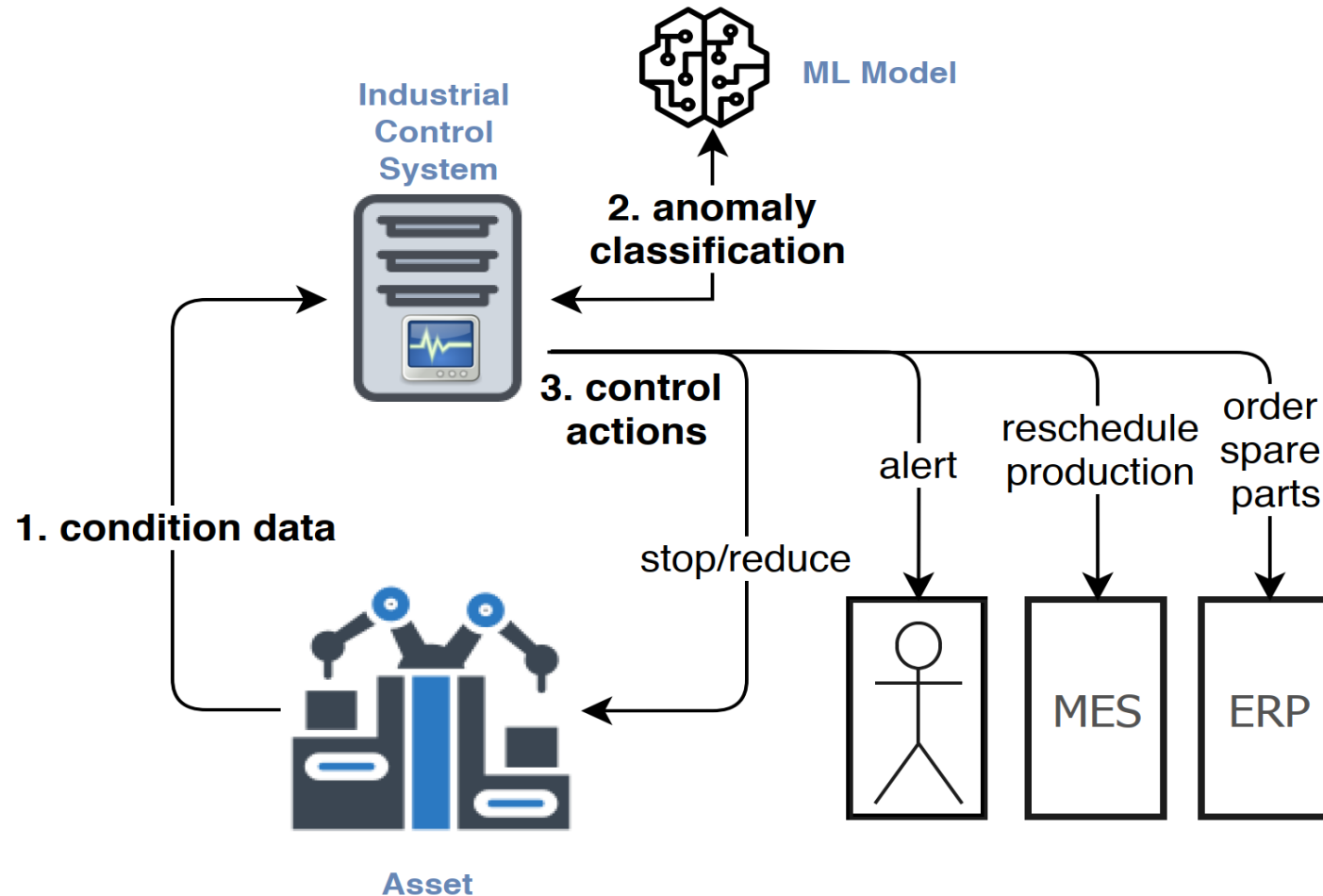
Edge Computing and AI for Industrial Applications – Outline

- What is Edge Computing?
- Managing AI Lifecycle
- Optimization of Models



Motivation – Machine Learning Models in Industrial Environments

Example: Anomaly classification based on asset data:



Problem Statement

- How can a machine learning model be improved with limited access to training data?
(e.g., How can anomaly classification be improved if little to no anomalies occurred in the past?)

Possible Solution

Access data from other users/customers

Problem

Potentially sensitive data cannot be disclosed to third parties

Consequences

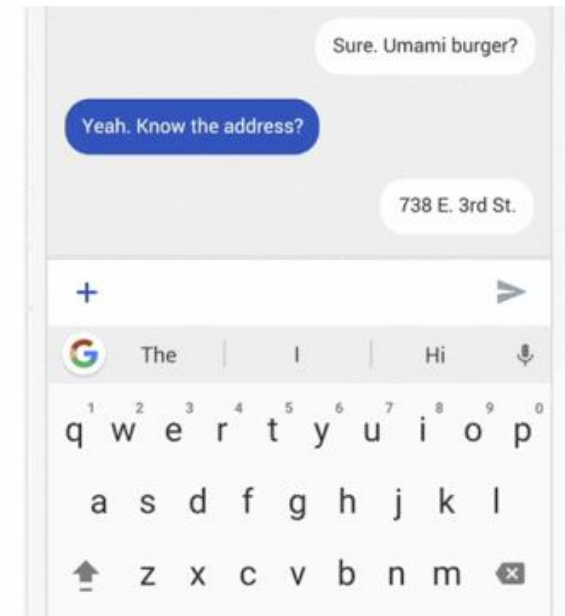
poor performance of ML model
costly experiments to collect training data

Federated Learning

Federated Learning enables clients

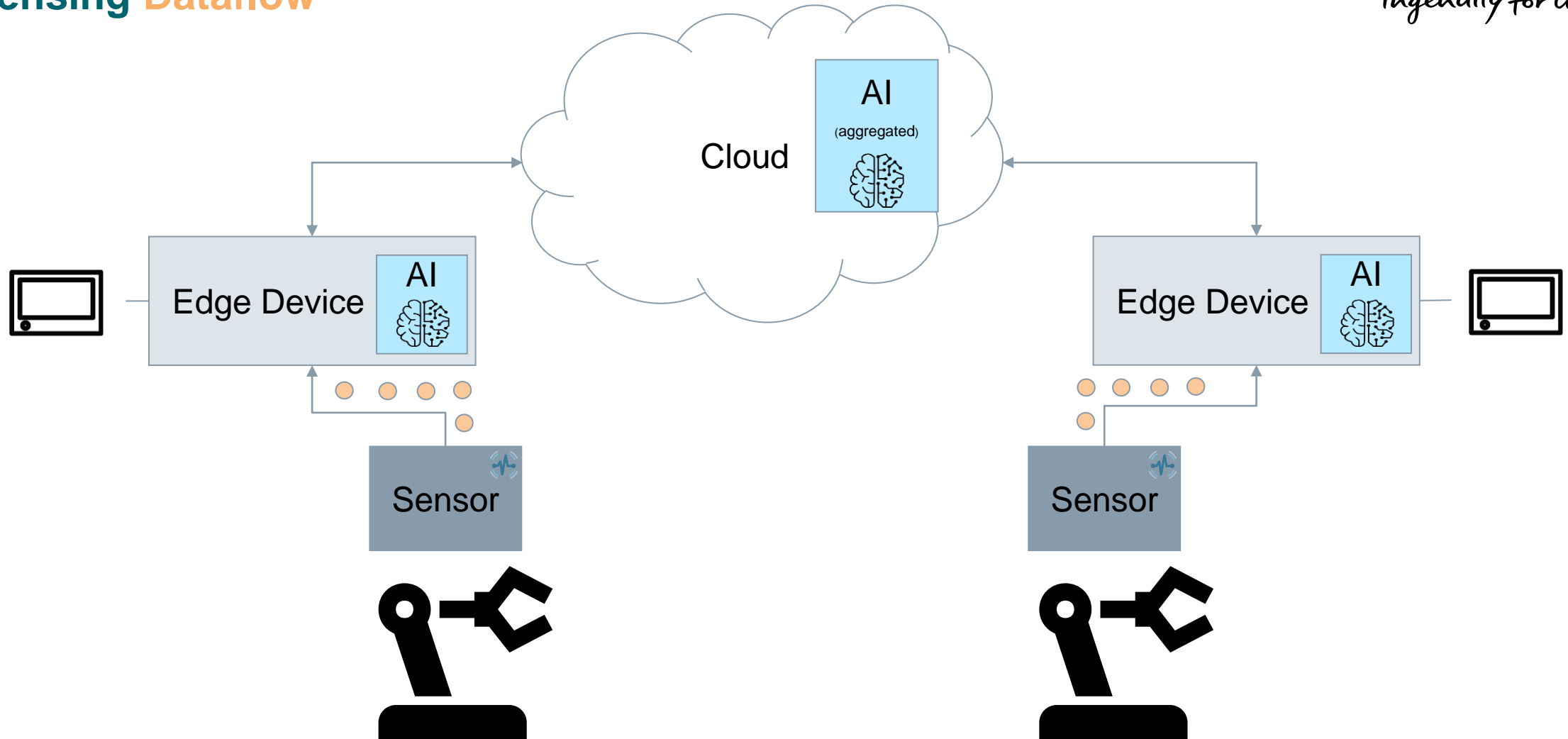
- to **collaboratively learn a shared prediction model**
- while **keeping** all the **training data on device**,
- decoupling the ability to do machine learning from the need to store the data in the cloud [1].

Initial Use Case: Gboard on Android (2017, beta)

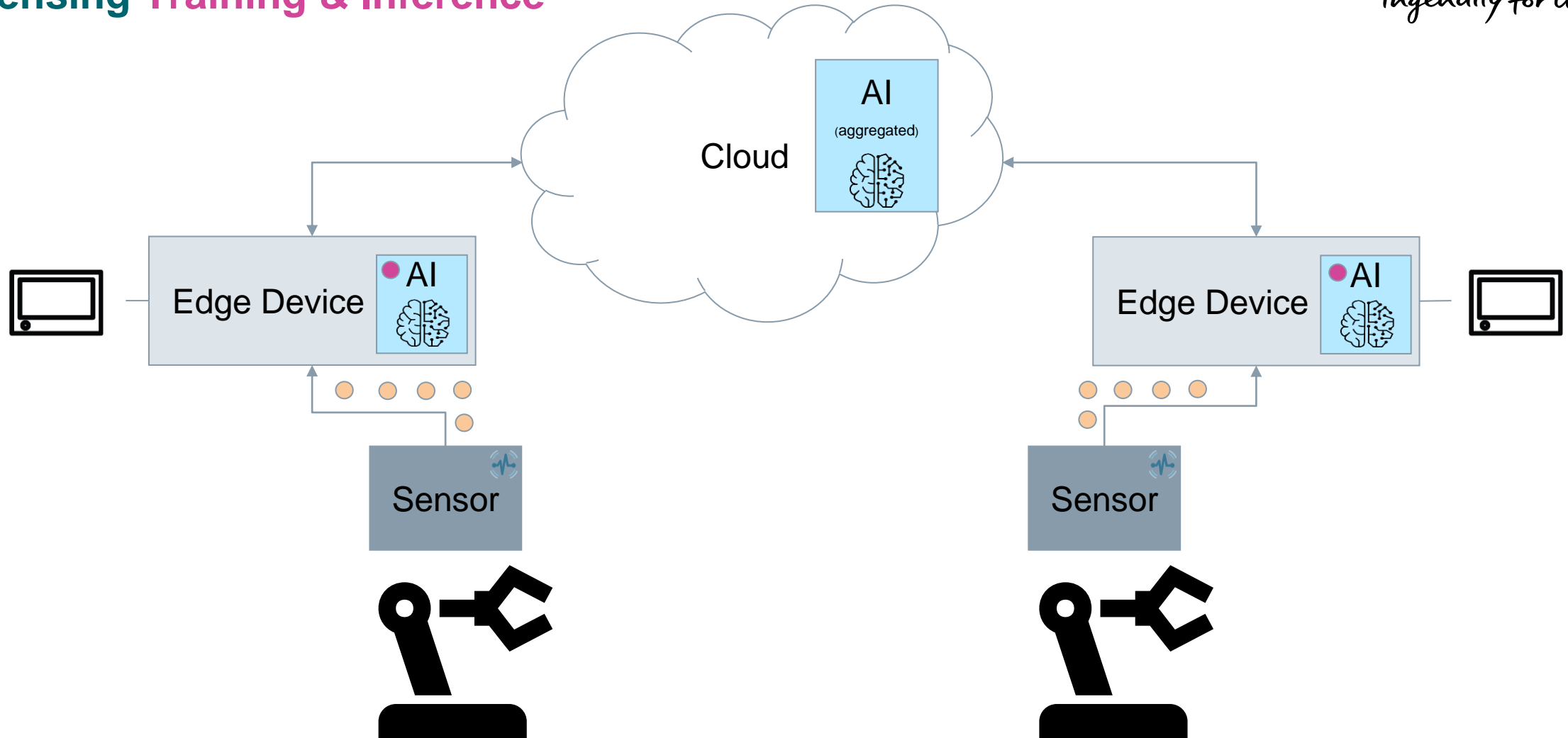


[1] <https://ai.googleblog.com/2017/04/federated-learning-collaborative.html>

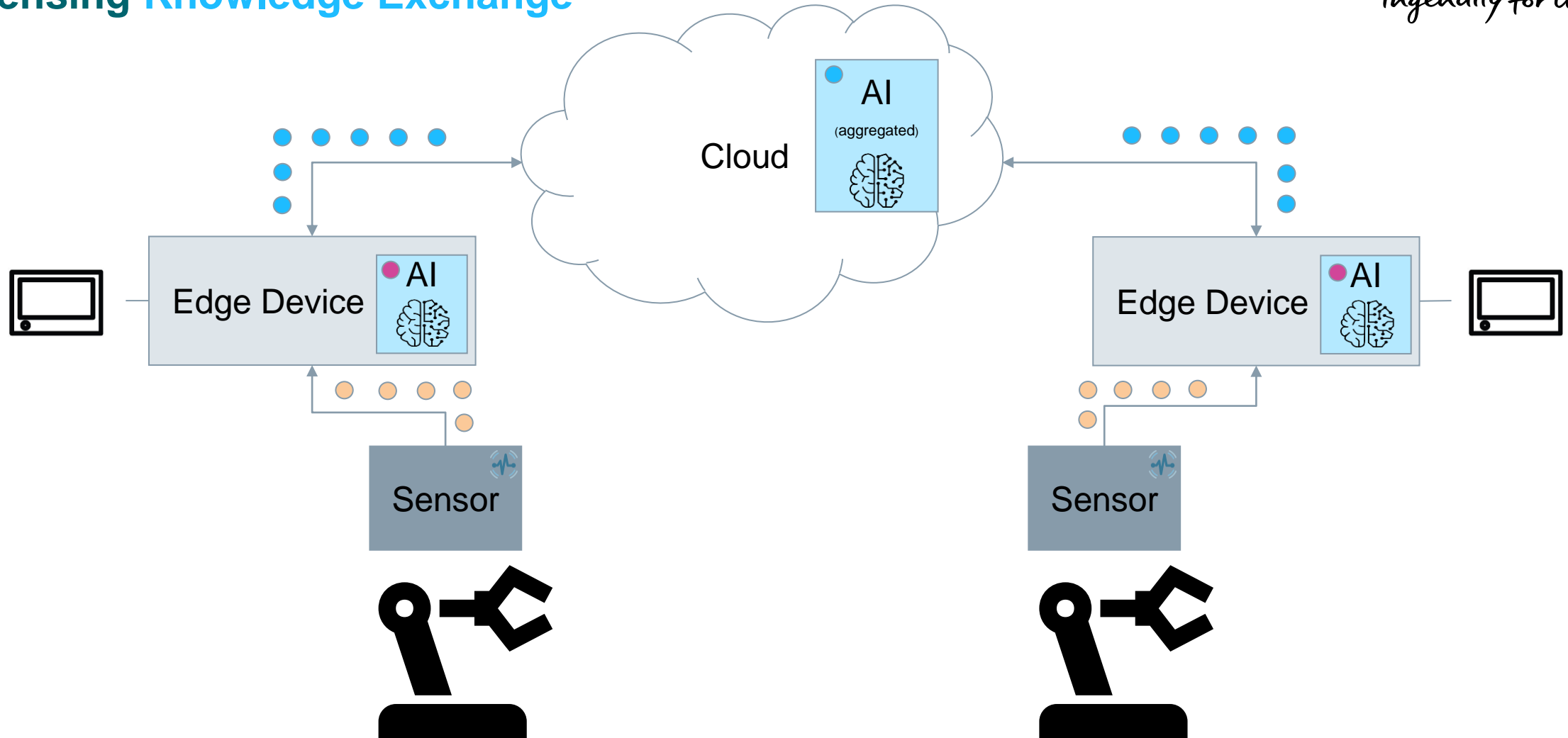
Motivating Federated Learning (FL) Scenario: Vibration-sensing **Dataflow**



Motivating Federated Learning (FL) Scenario: Vibration-sensing **Training & Inference**



Motivating Federated Learning (FL) Scenario: Vibration-sensing Knowledge Exchange



- **Federated Averaging**

Algorithm averaging models retrieved from local clients

- **Secure Aggregation**

Protocol ensuring that a server can only decrypt the average update if a large number of users have participated.

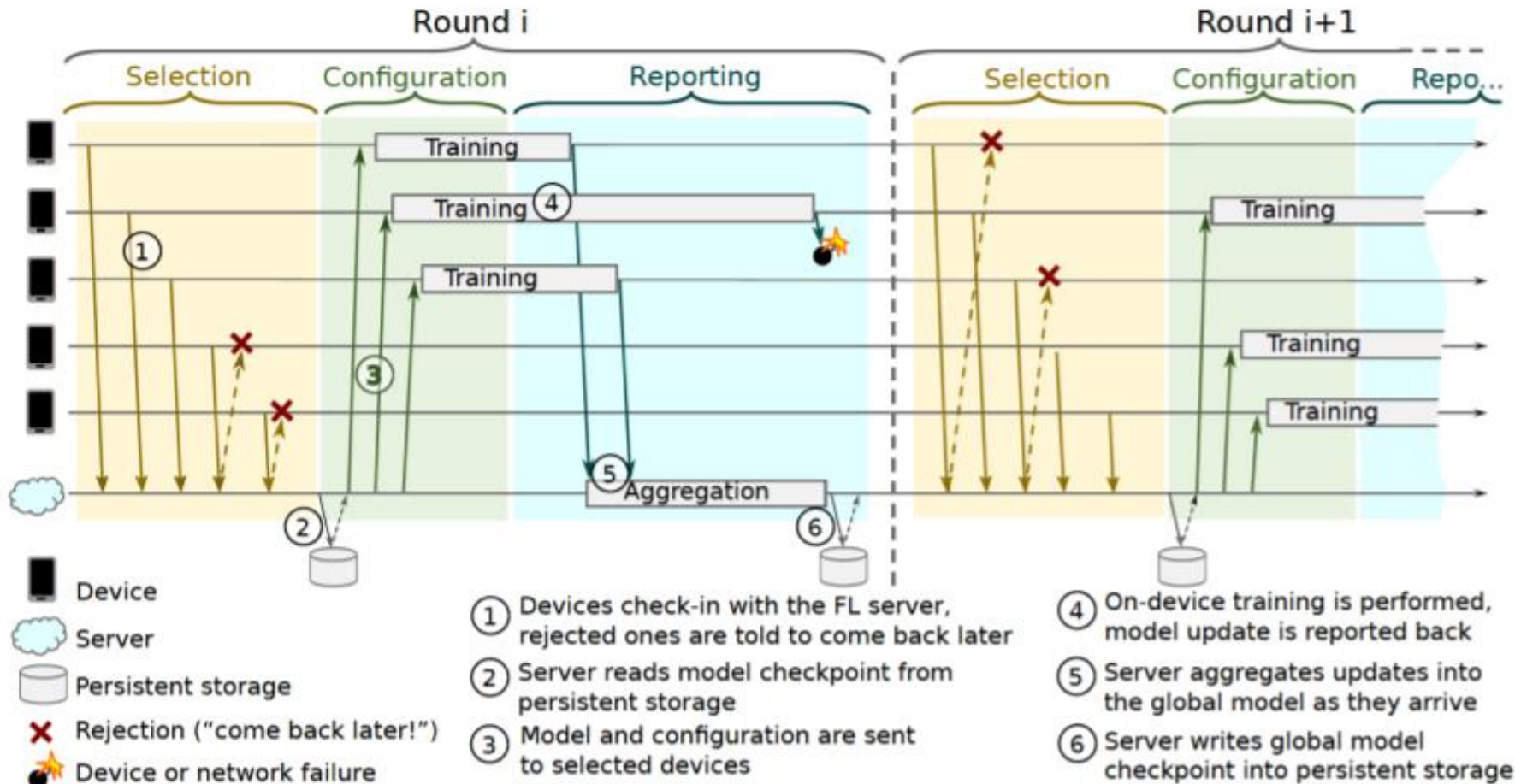
Algorithm 1 FederatedAveraging. The K clients are indexed by k ; B is the local minibatch size, E is the number of local epochs, and η is the learning rate.

Server executes:

```
initialize  $w_0$ 
for each round  $t = 1, 2, \dots$  do
   $m \leftarrow \max(C \cdot K, 1)$ 
   $S_t \leftarrow$  (random set of  $m$  clients)
  for each client  $k \in S_t$  in parallel do
     $w_{t+1}^k \leftarrow \text{ClientUpdate}(k, w_t)$ 
   $w_{t+1} \leftarrow \sum_{k=1}^K \frac{n_k}{n} w_{t+1}^k$ 
```

ClientUpdate(k, w): // Run on client k
 $\mathcal{B} \leftarrow$ (split \mathcal{P}_k into batches of size B)
for each local epoch i from 1 to E **do**
 for batch $b \in \mathcal{B}$ **do**
 $w \leftarrow w - \eta \nabla \ell(w; b)$
 return w to server

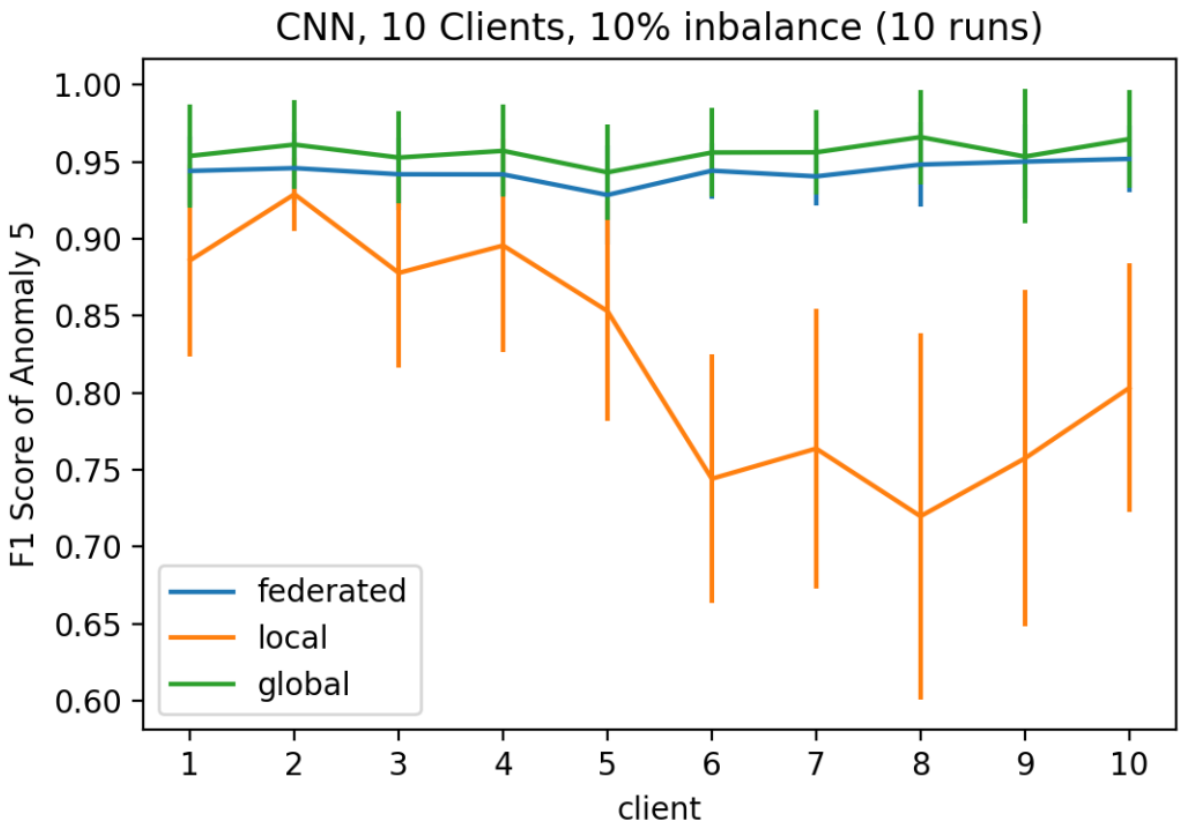
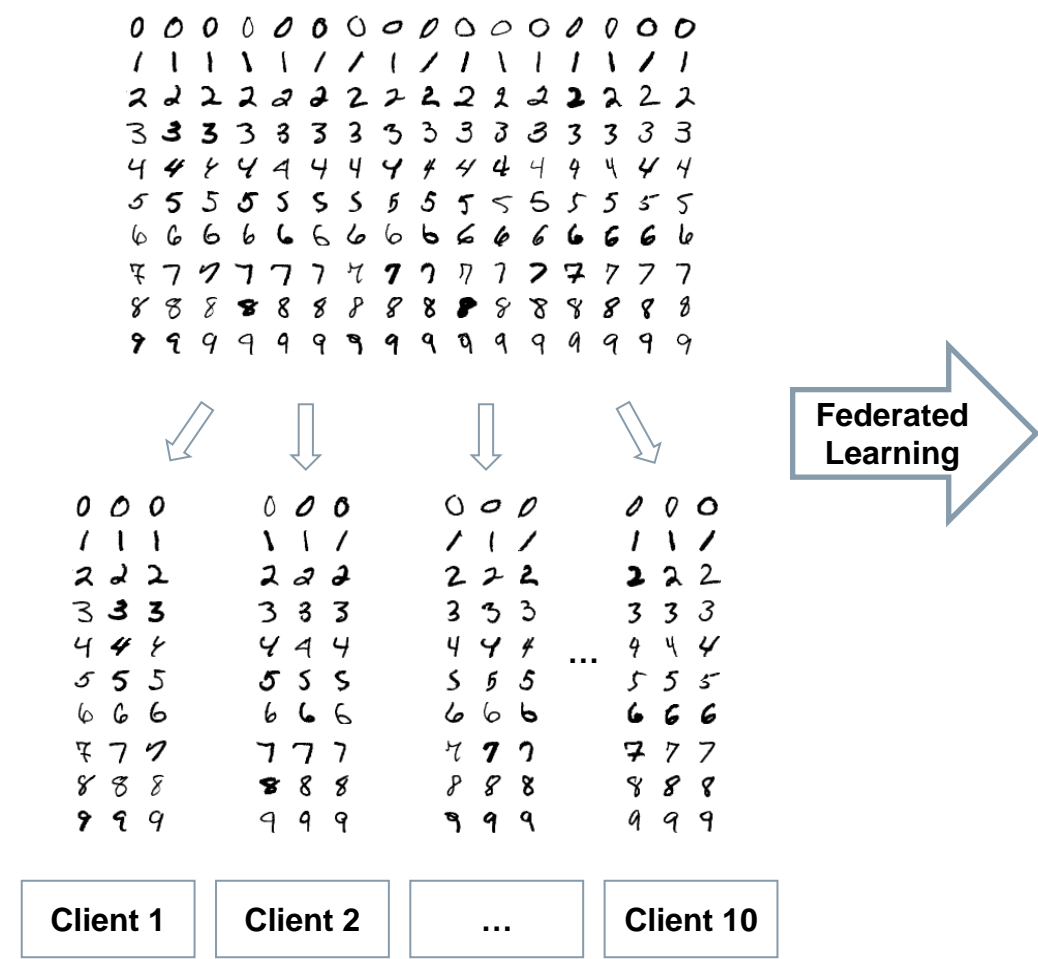
Federated Learning Protocol



Towards Federated Learning at Scale: System Design:

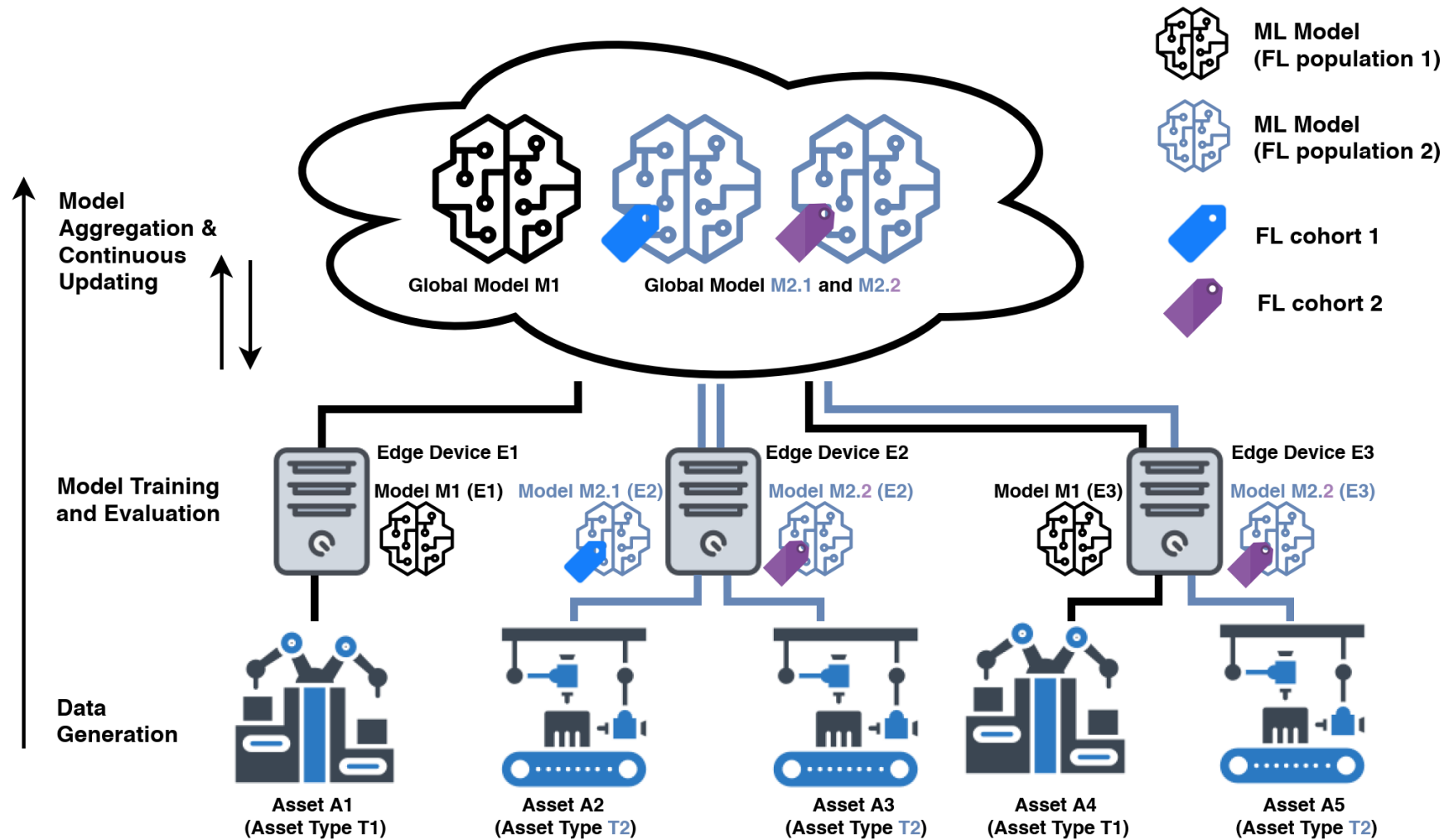
<https://arxiv.org/pdf/1902.01046.pdf>

Proof of Concept – MNIST Image Data



Federated Learning with 10 Clients on MNIST Dataset
(Source: Markus Kittel, Denis Krompass (CT RDA BAM MIC-DE))

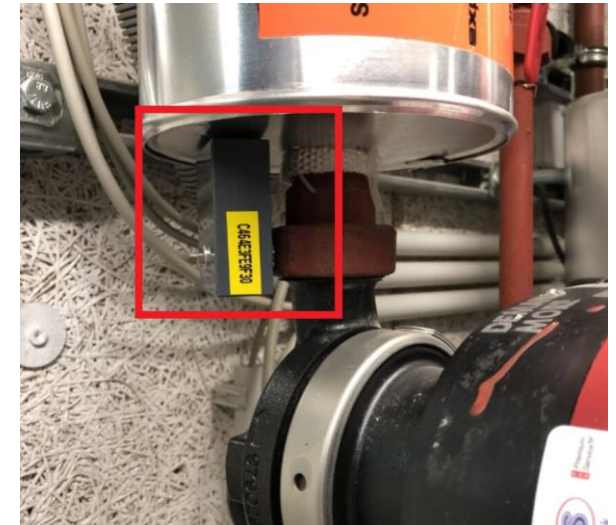
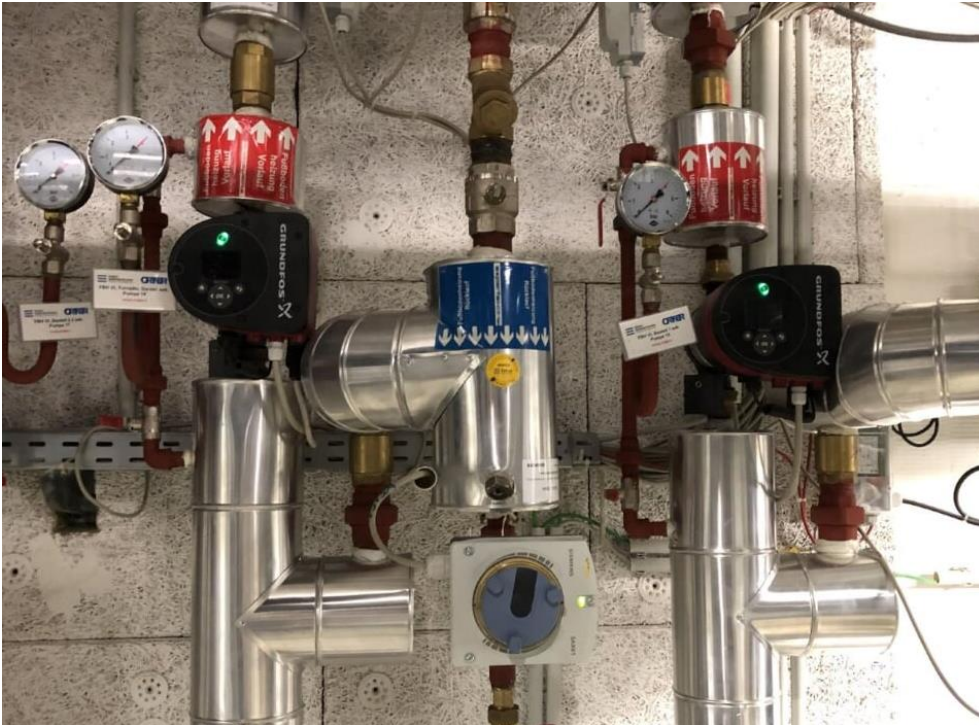
Industrial Federated Learning (IFL)



Hiesl, Thomas & Schall, Daniel & Kemnitz, Jana & Schulte, Stefan. (2020). Industrial Federated Learning – Requirements and System Design. 10.1007/978-3-030-51999-5_4.

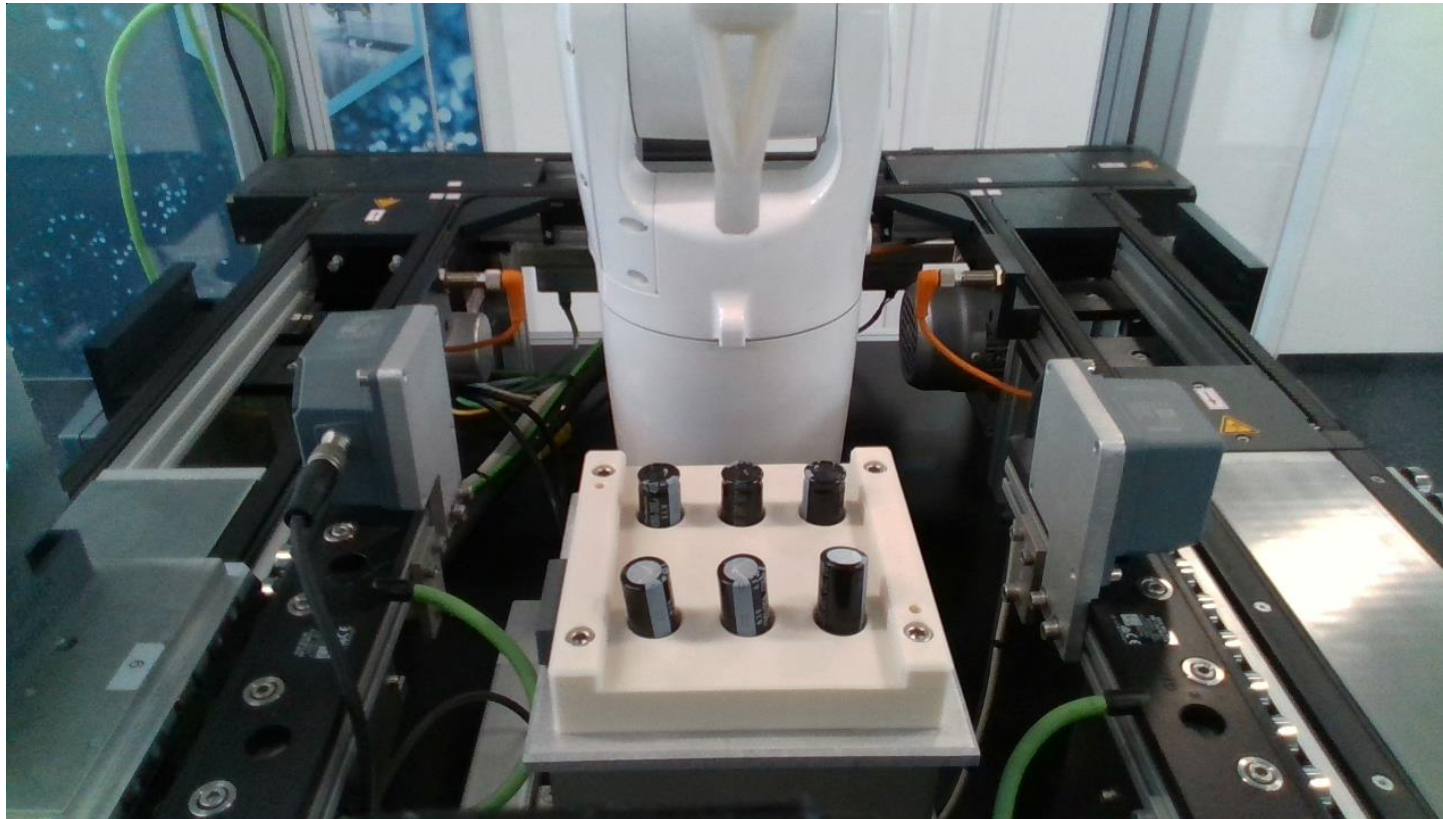
Use Case - Building Technologies: Circulation pump models - Aspern Smart City Research (ASCR)

- Vibration Data → Model building (e.g., for condition monitoring) → Federated Learning

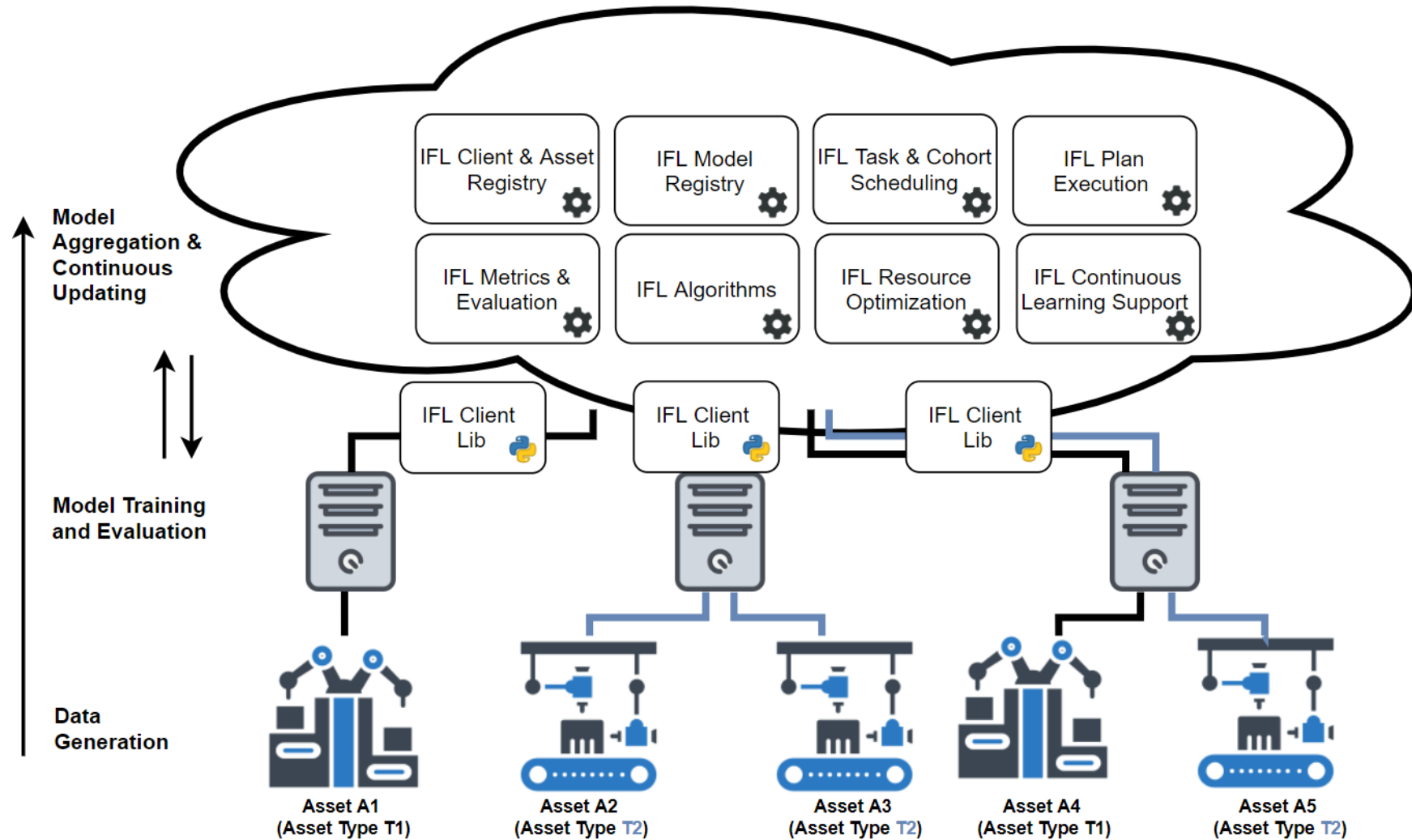


Use Case – Digilab Image-based Anomaly Detection

- Images of capacitors → Anomaly detection models → Federation



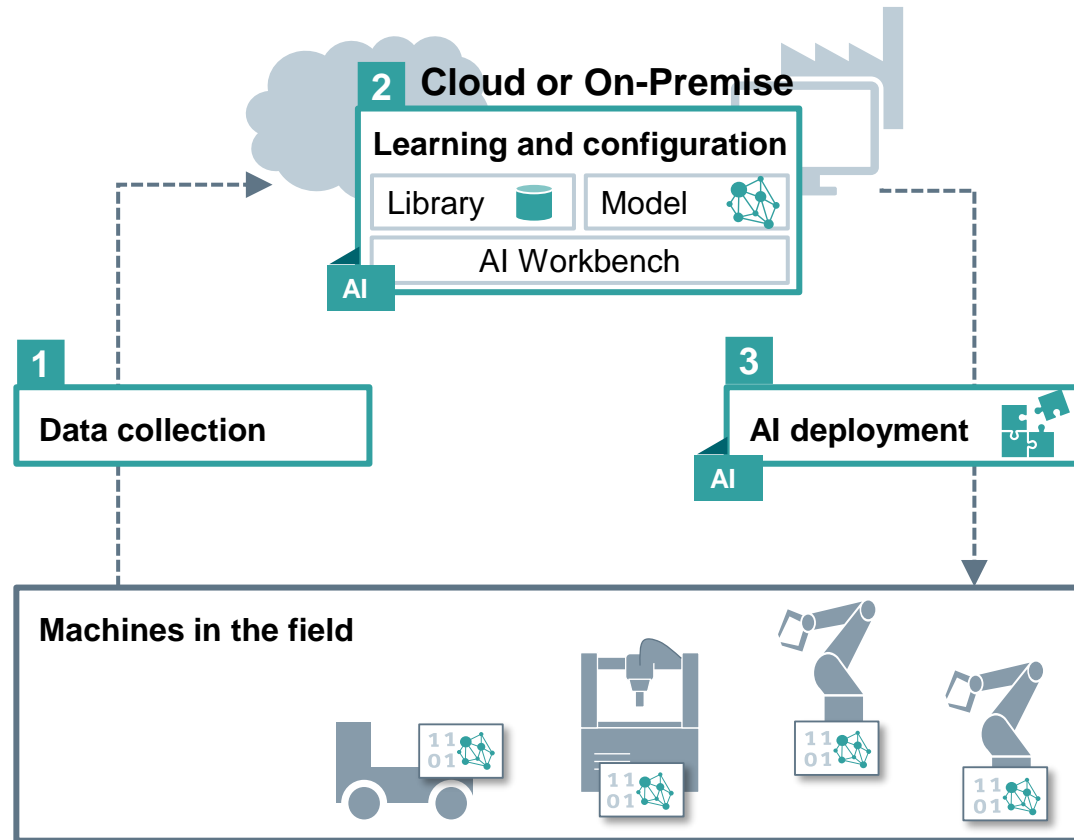
IFL System – Building Blocks



Artificial Intelligence in Industry

Recap and challenges for configuration technologies

Industrial AI Approach



→ Challenges:

- 1. Data Collection:**
Configuring different data sources
Semantic understanding of data points
- 2. Learning and configuration of AI Algorithm:**
Configuration and optimization of AI models
Configuration of AI pipeline
- 3. Deployment of AI:**
HW selection
Automatic deployment

Thank you!



Dr. Daniel Schall

Head of Research Group

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