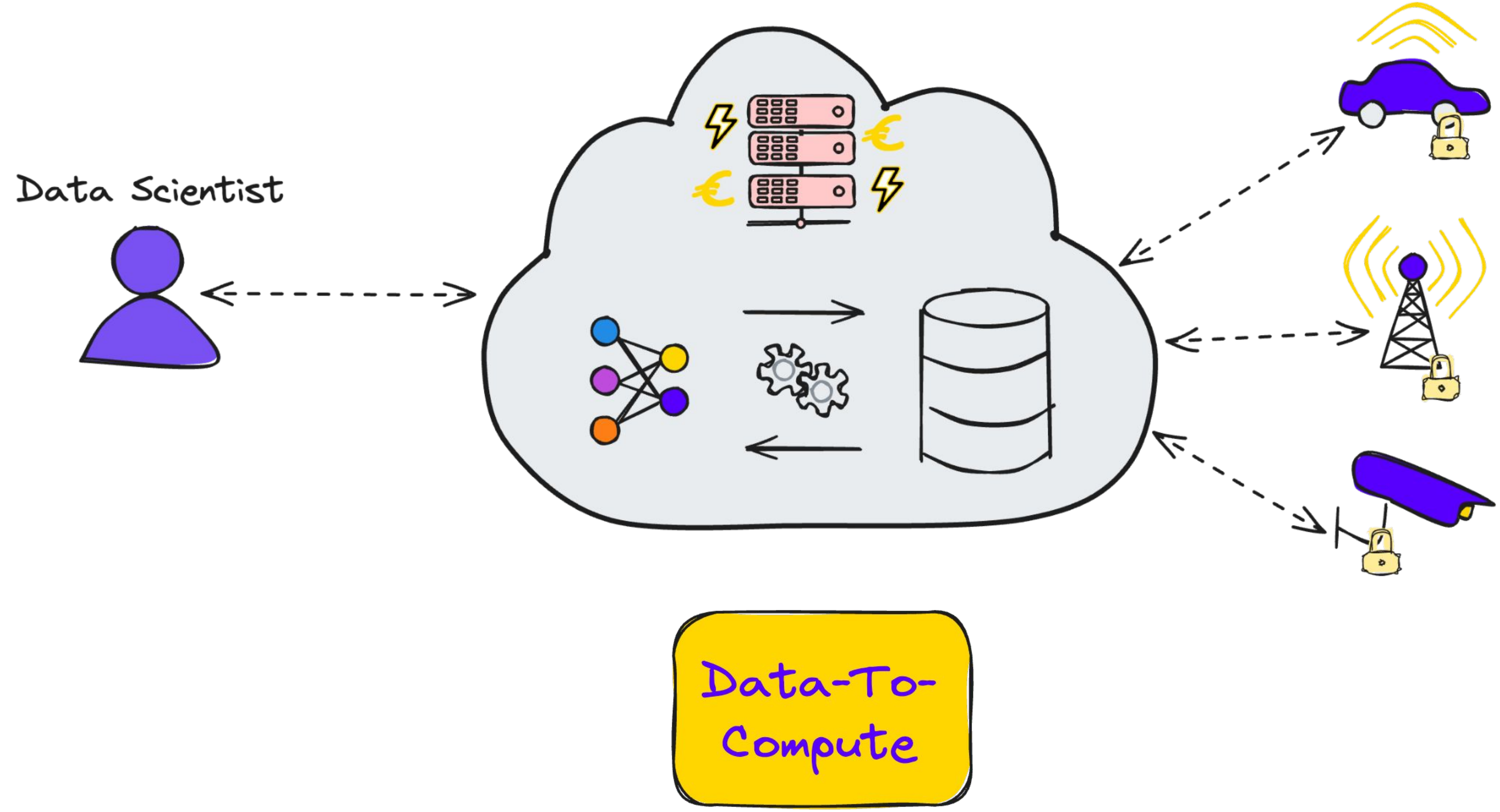
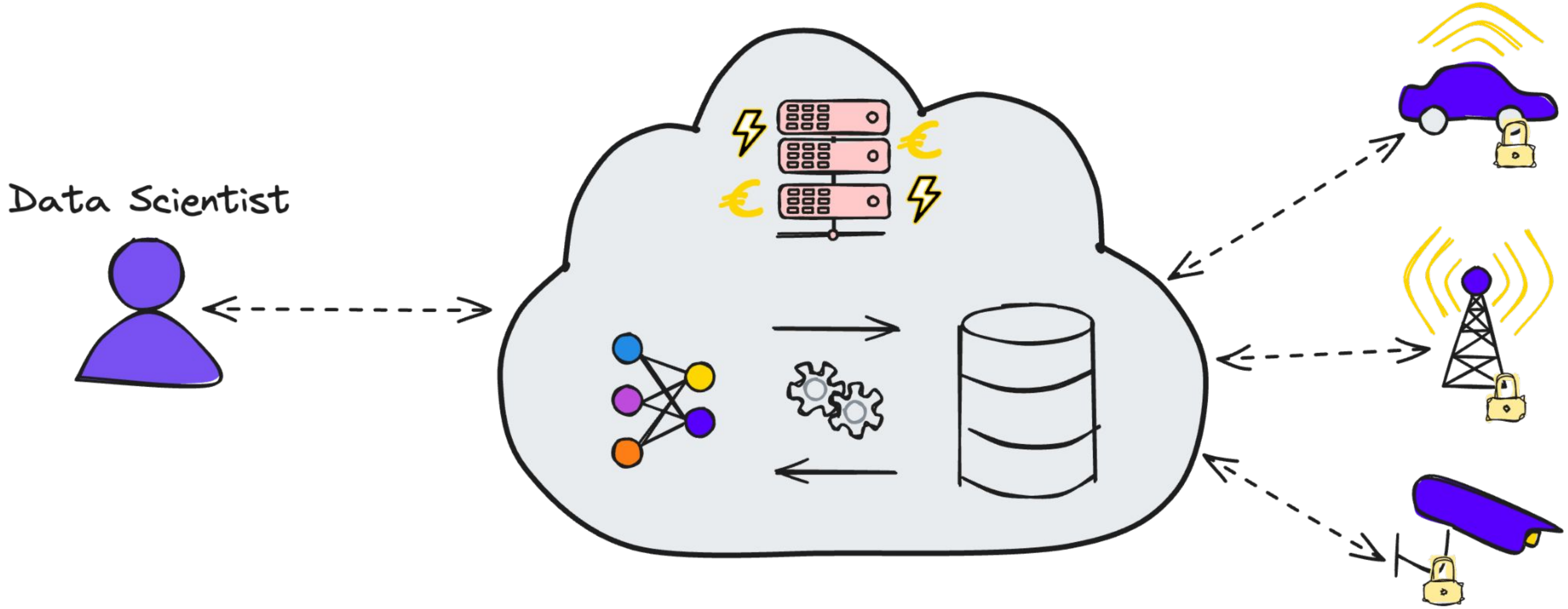
Embedded and Collaborative AI in the era of Decentralized Data

THE DATA SCIENCE LANDSCAPE: CLOUD-DRIVEN VALUE



THE DATA SCIENCE LANDSCAPE: CLOUD-DRIVEN VALUE

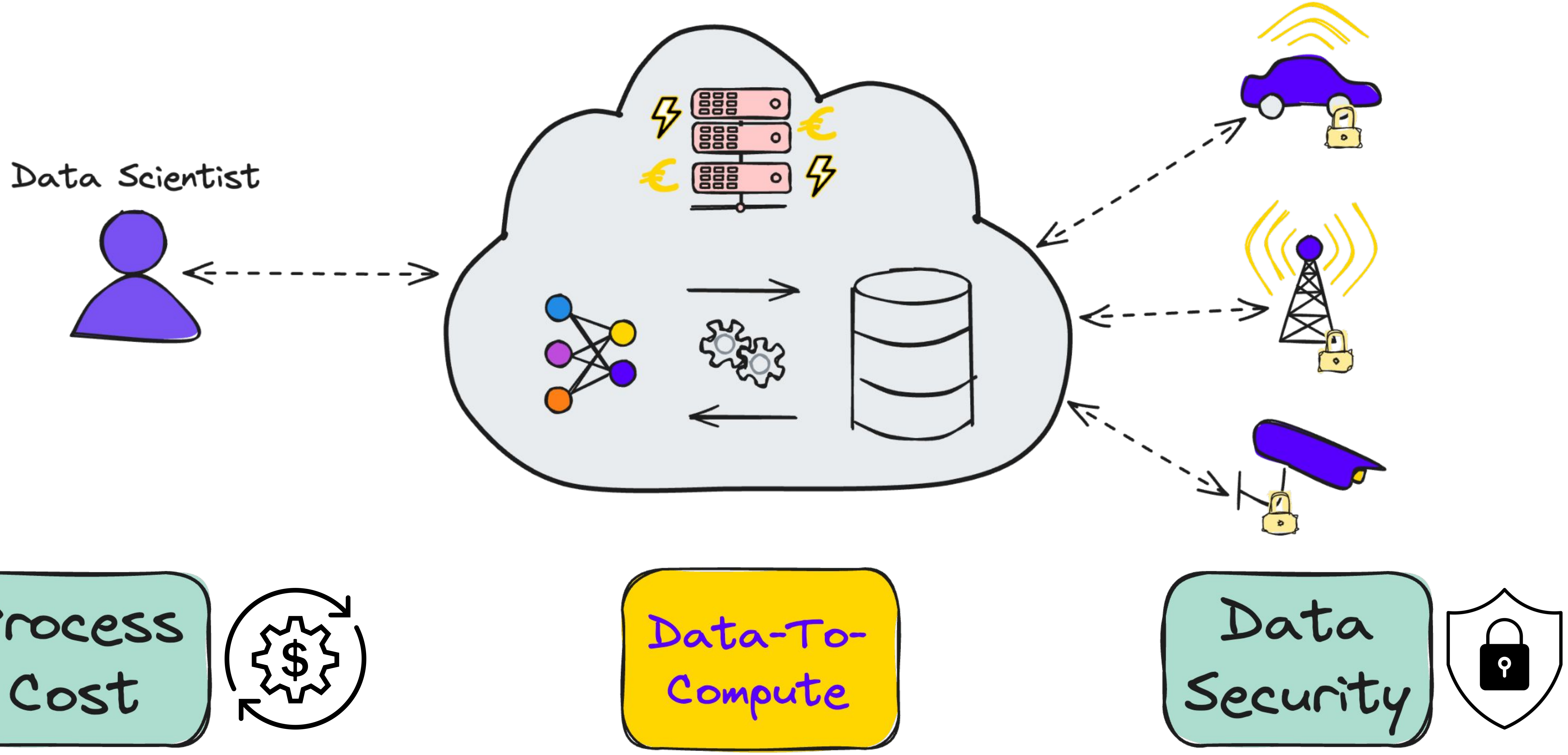


Data-To-Compute

Data Security

- Companies' **Sovereignty**
- User **Privacy** (GDPR)

THE DATA SCIENCE LANDSCAPE: CLOUD-DRIVEN VALUE

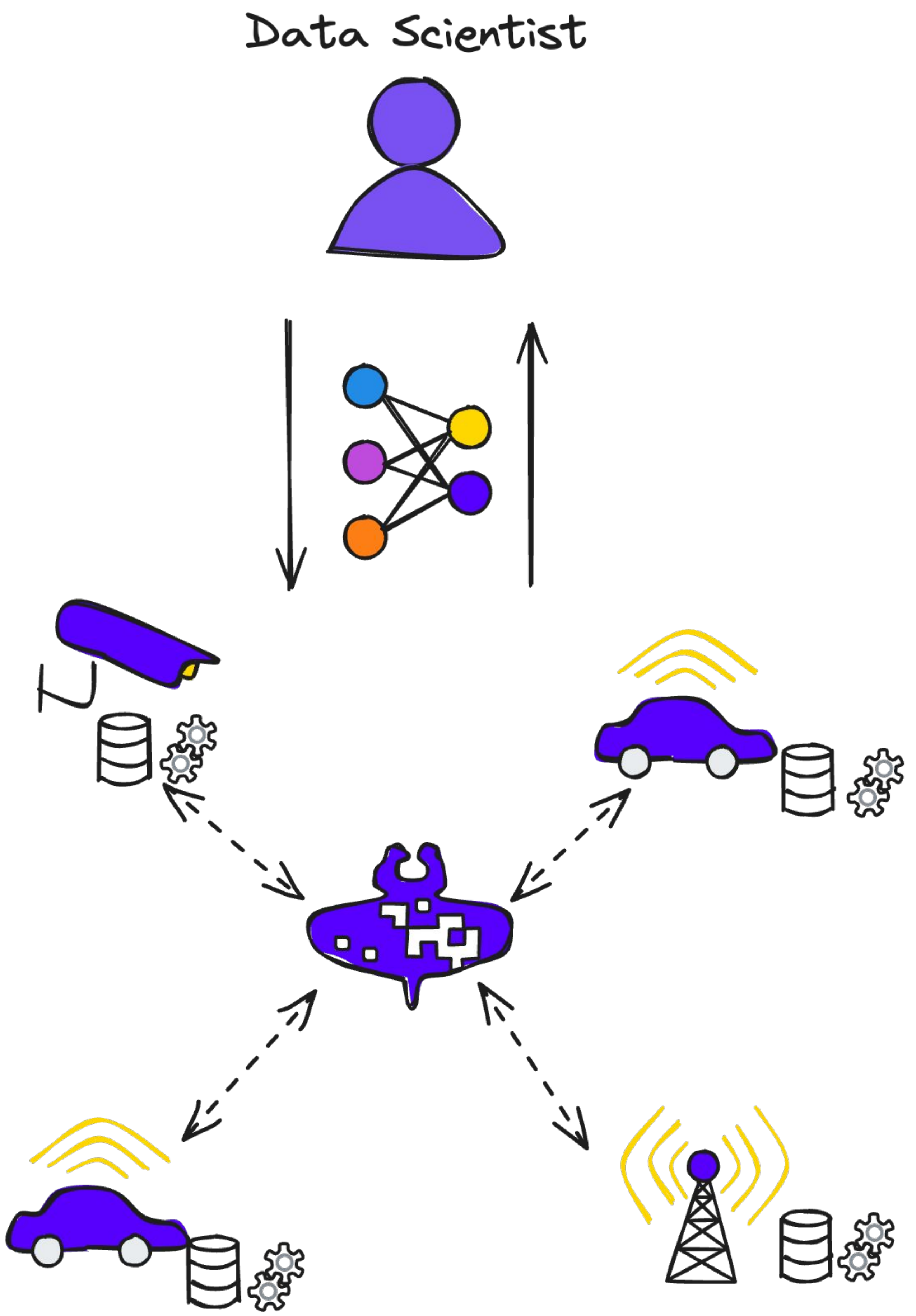


- **Financial** Cost
- **Environmental** Cost
- **Latency**

- Companies' **Sovereignty**
- User **Privacy** (GDPR)

REVOLUTIONIZING AI WITH COMPUTE-TO-DATA

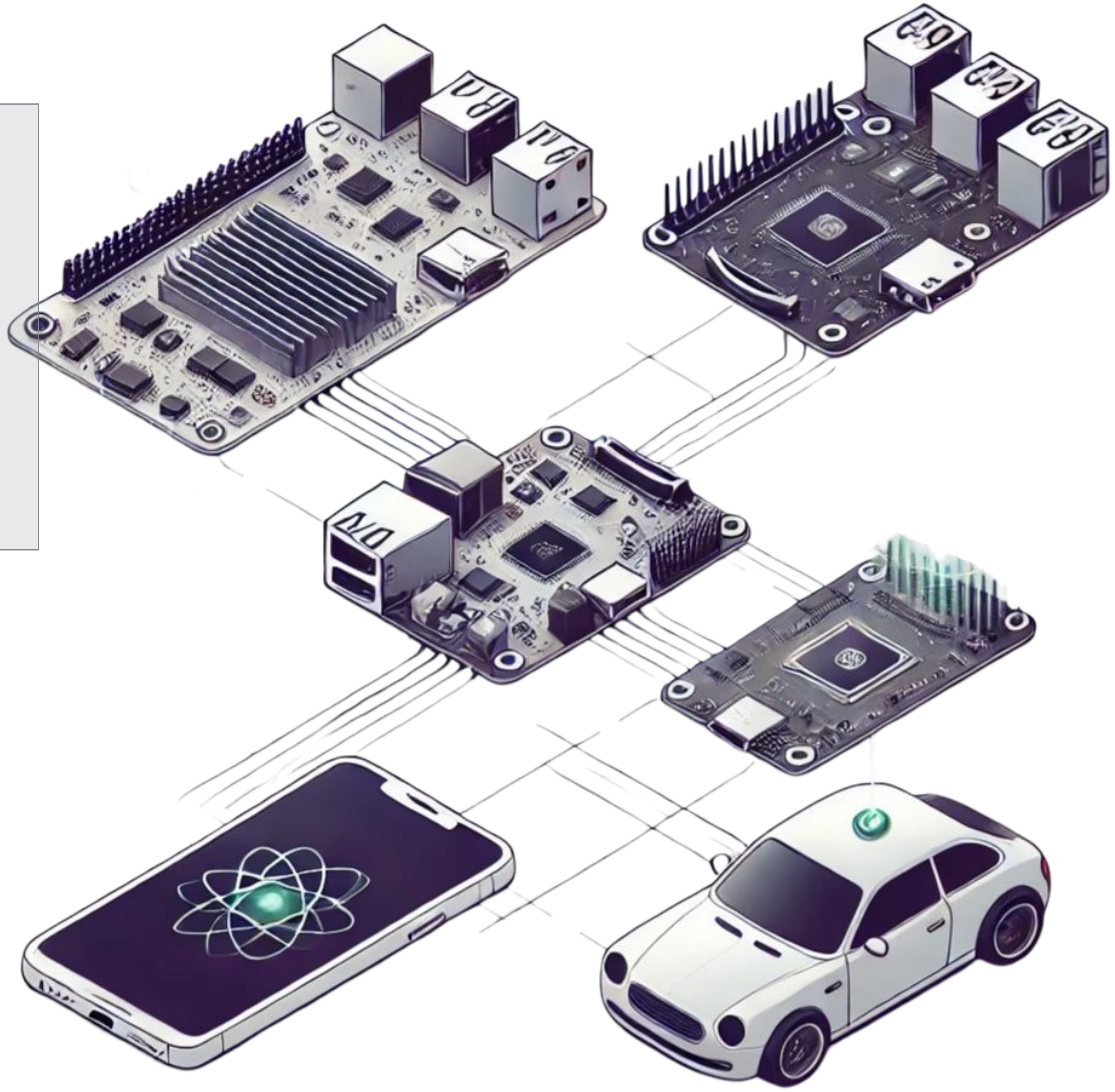
- Local Processing



REVOLUTIONIZING AI WITH COMPUTE-TO-DATA

- **Local Processing**

- **Empowered Embedded Devices:** Modern autonomous systems, including vehicles, leverage **enhanced onboard computing power**.

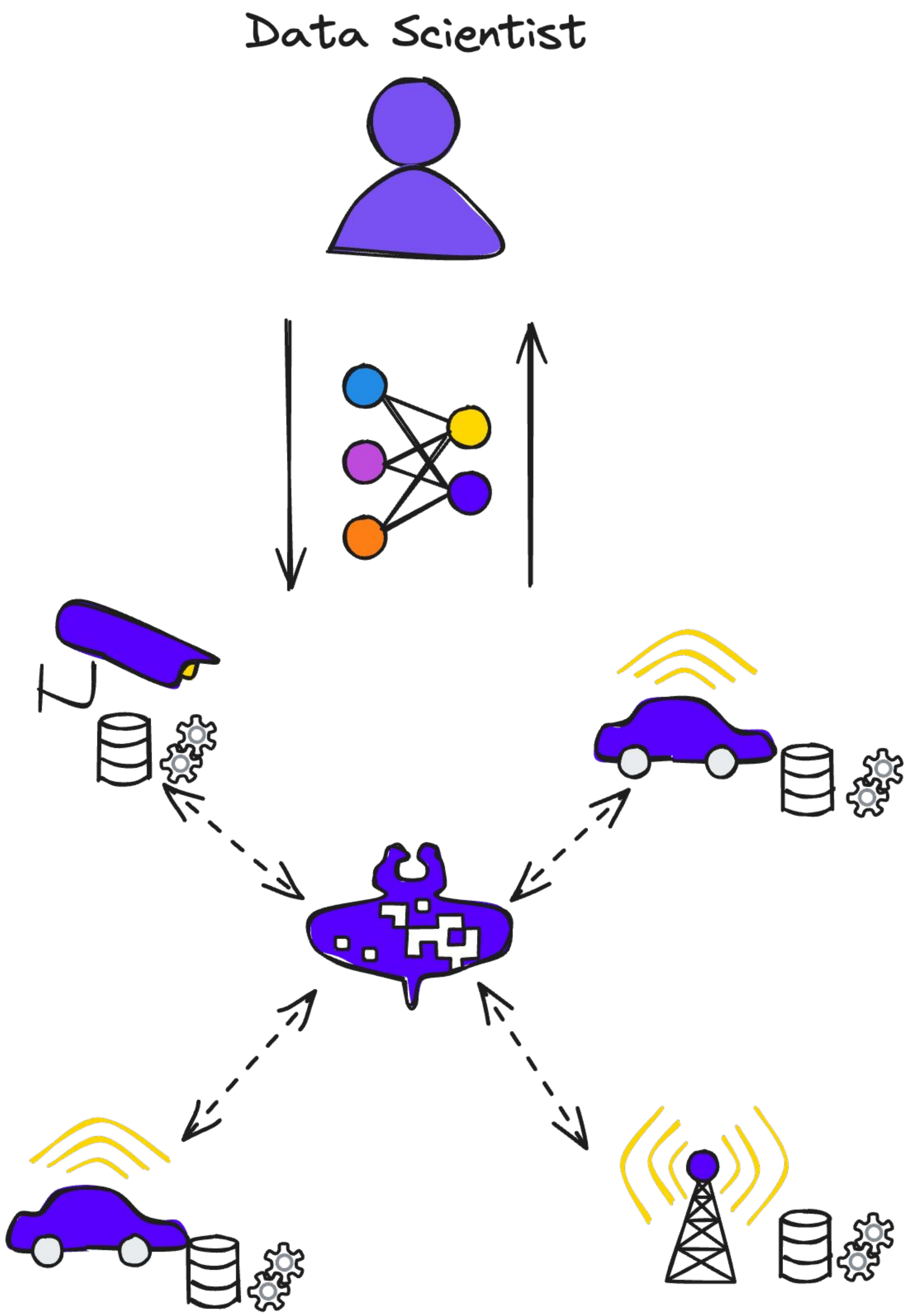


REVOLUTIONIZING AI WITH COMPUTE-TO-DATA

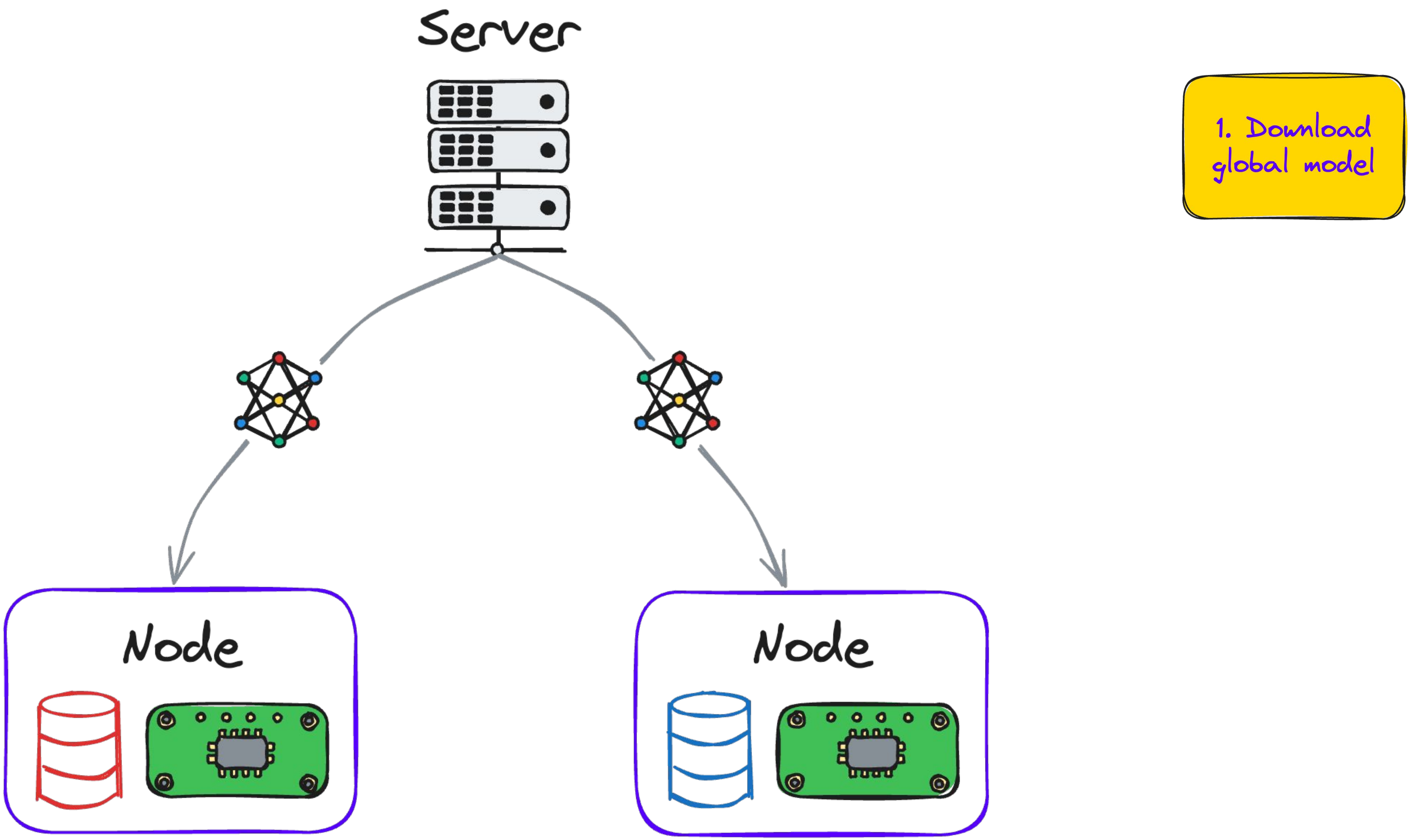
- **Local Processing**

- **Empowered Embedded Devices:** Modern autonomous systems, including vehicles, leverage **enhanced onboard computing power**.

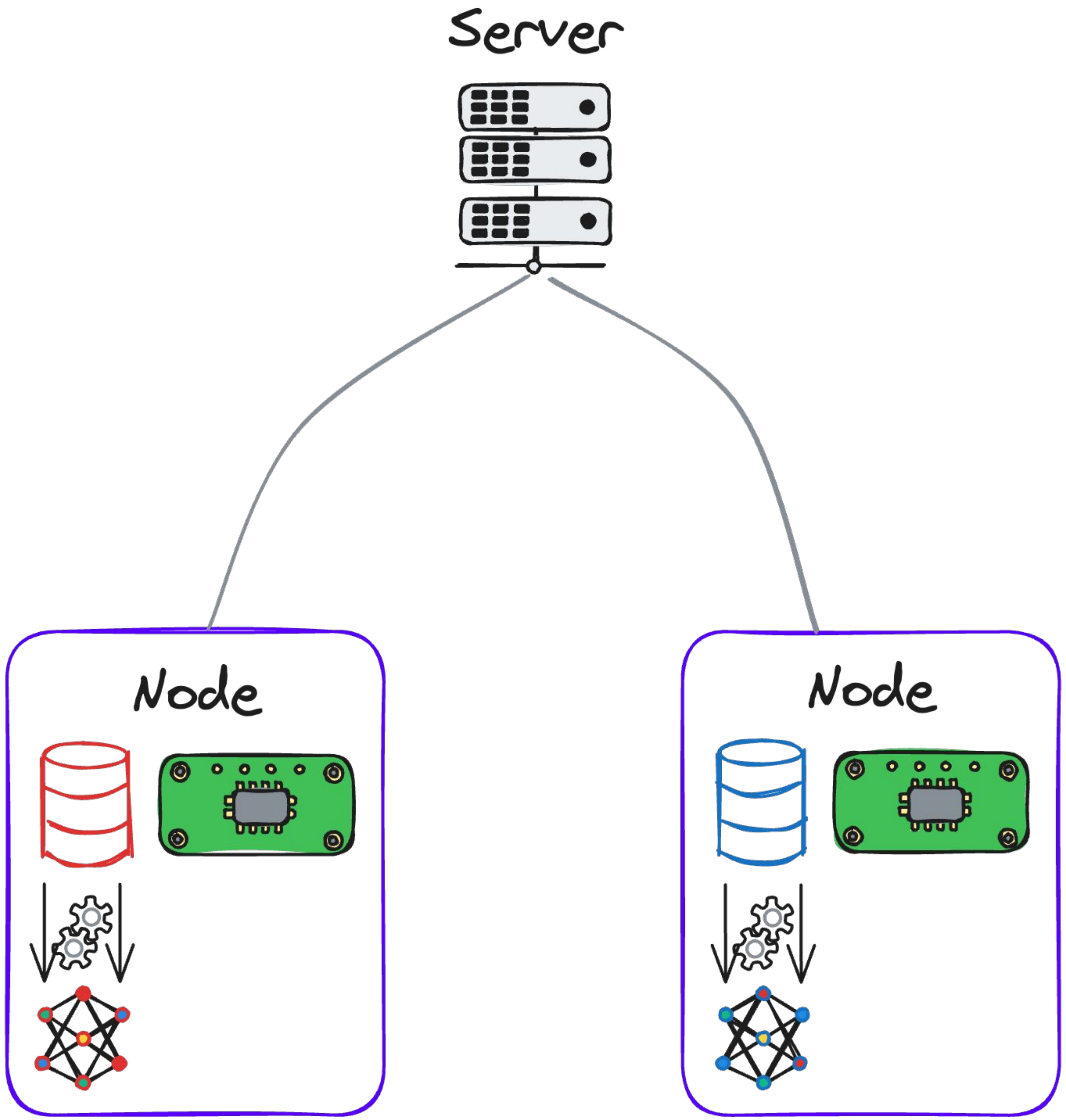
- **Collaborative Algorithms:** Harnessing **decentralized** and **federated learning** to enable real-time collaboration across devices.



HOW TO TRAIN A MODEL ON DECENTRALIZED DATA: FEDERATED LEARNING



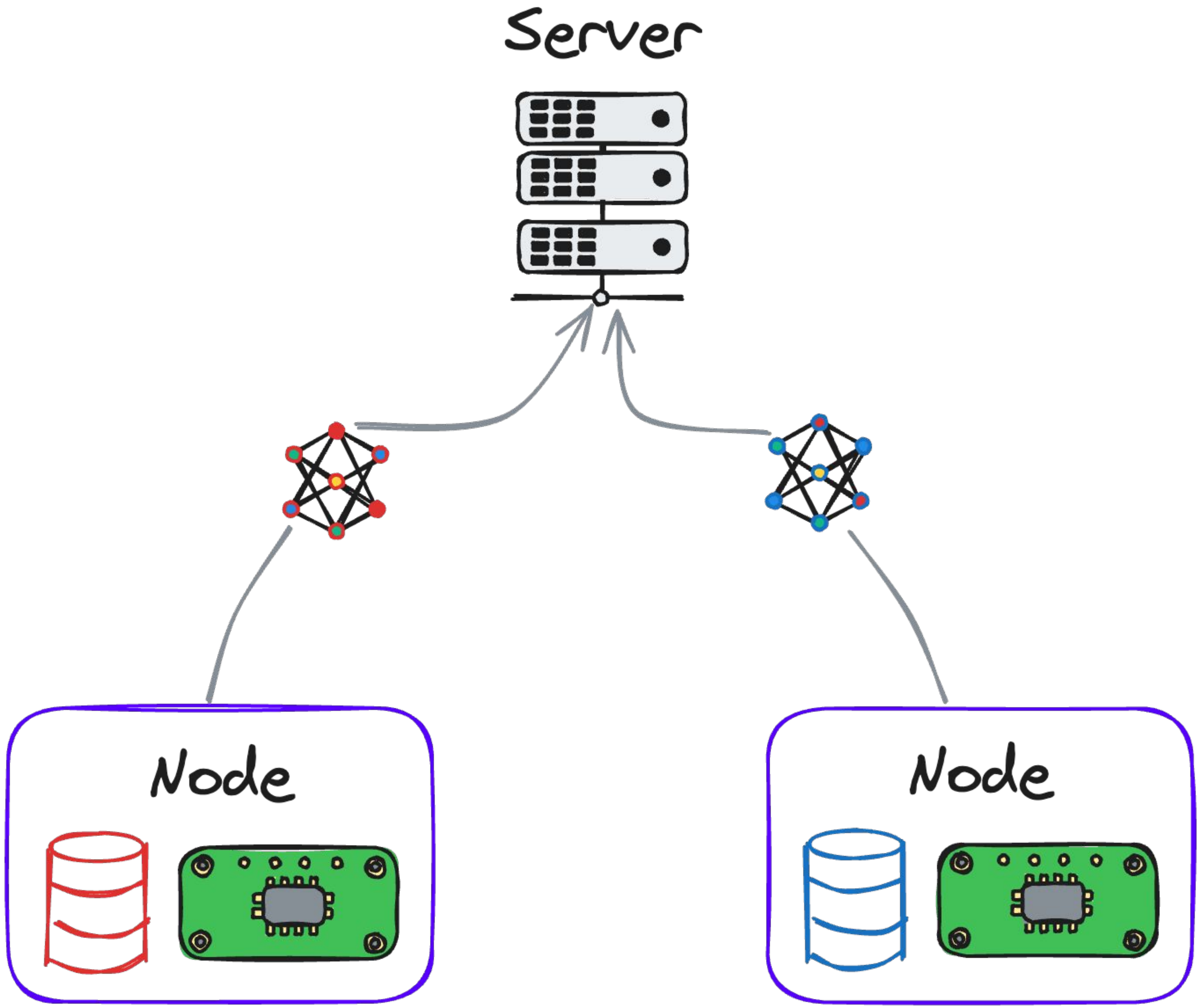
HOW TO TRAIN A MODEL ON DECENTRALIZED DATA: FEDERATED LEARNING



1. Download global model

2. Update model with local data

HOW TO TRAIN A MODEL ON DECENTRALIZED DATA: FEDERATED LEARNING

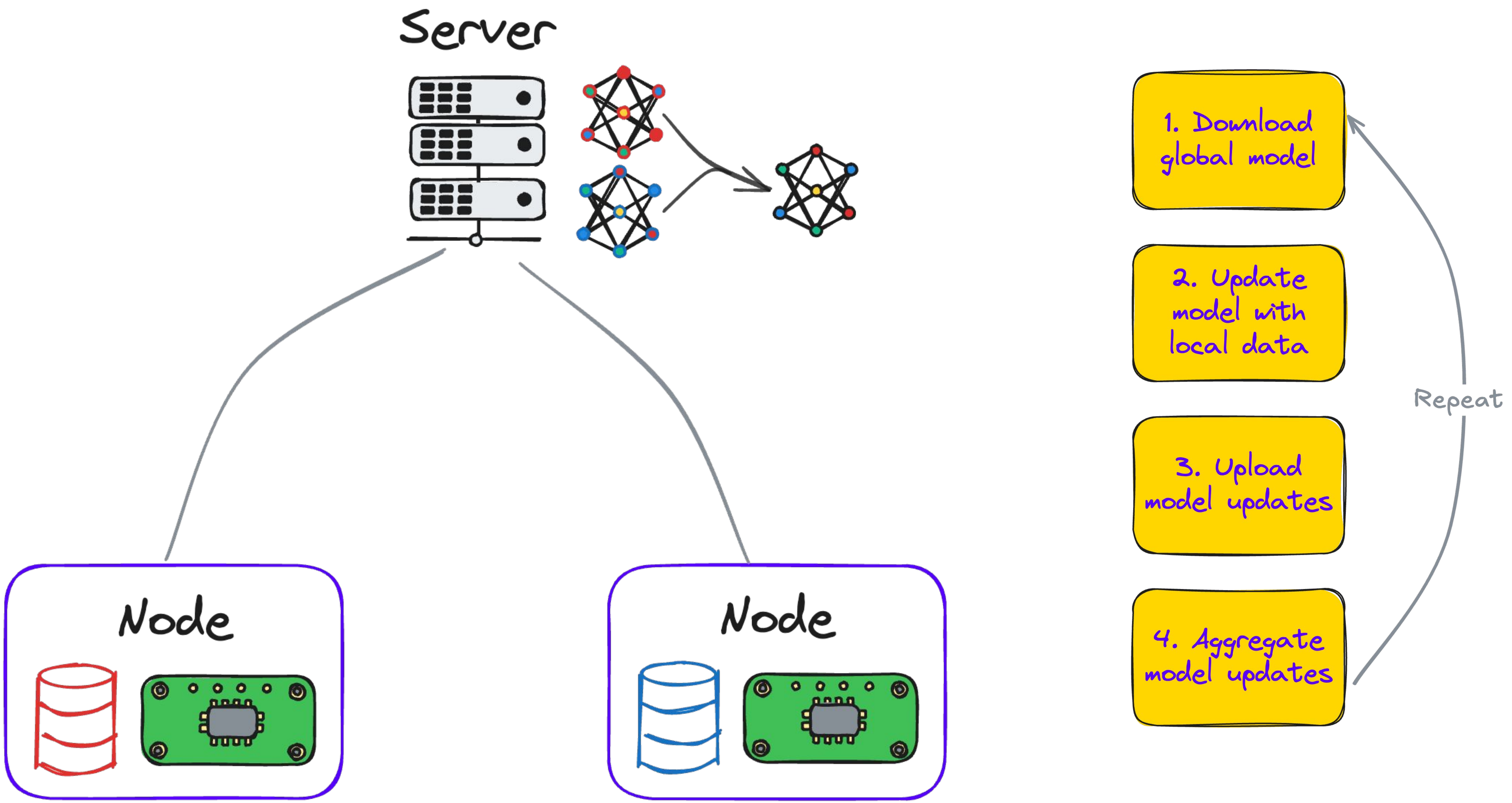


1. Download global model

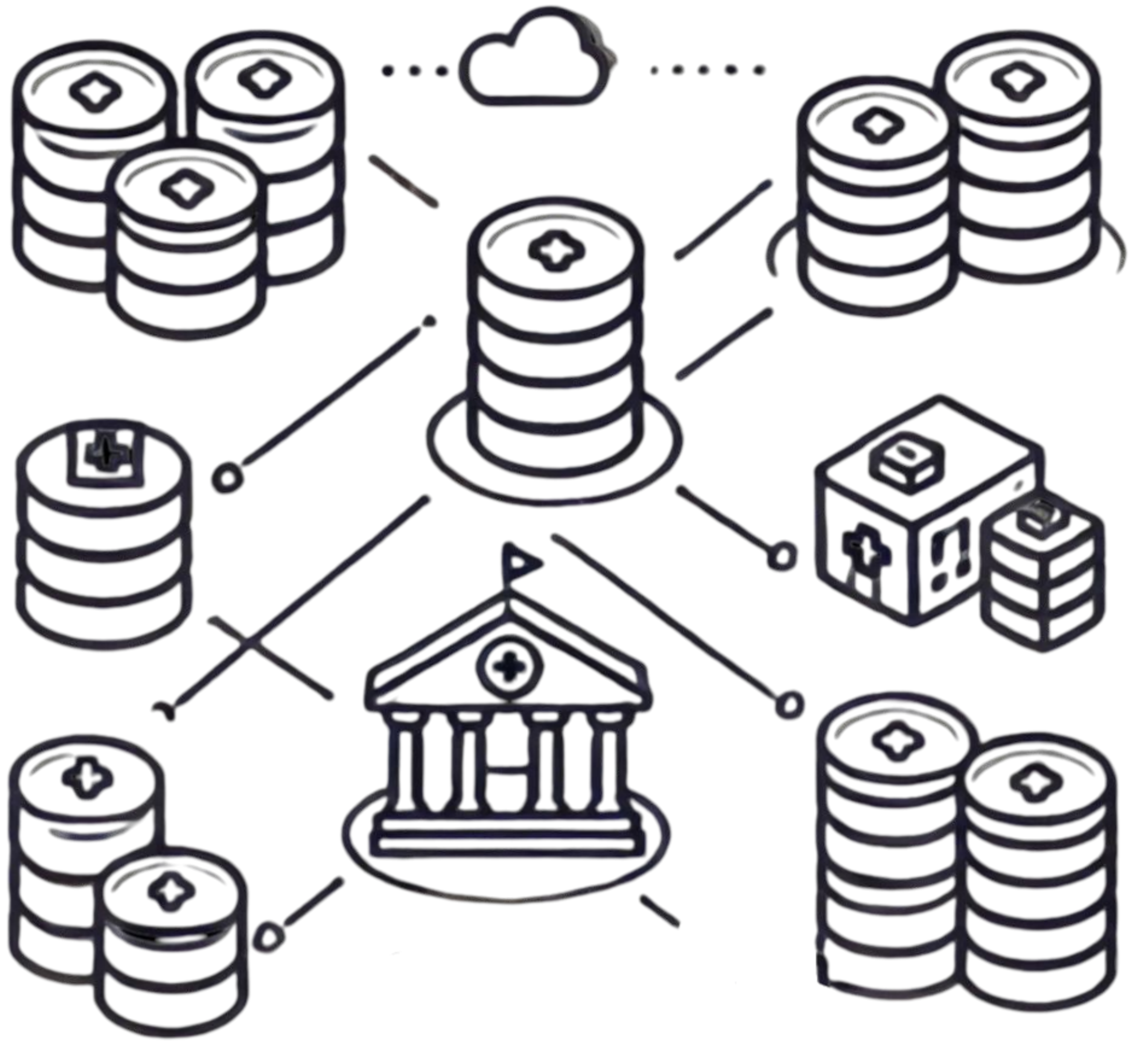
2. Update model with local data

3. Upload model updates

HOW TO TRAIN A MODEL ON DECENTRALIZED DATA: FEDERATED LEARNING



FROM SILO TO DEVICES: THE DIFFERENT DECENTRALIZED SETTINGS

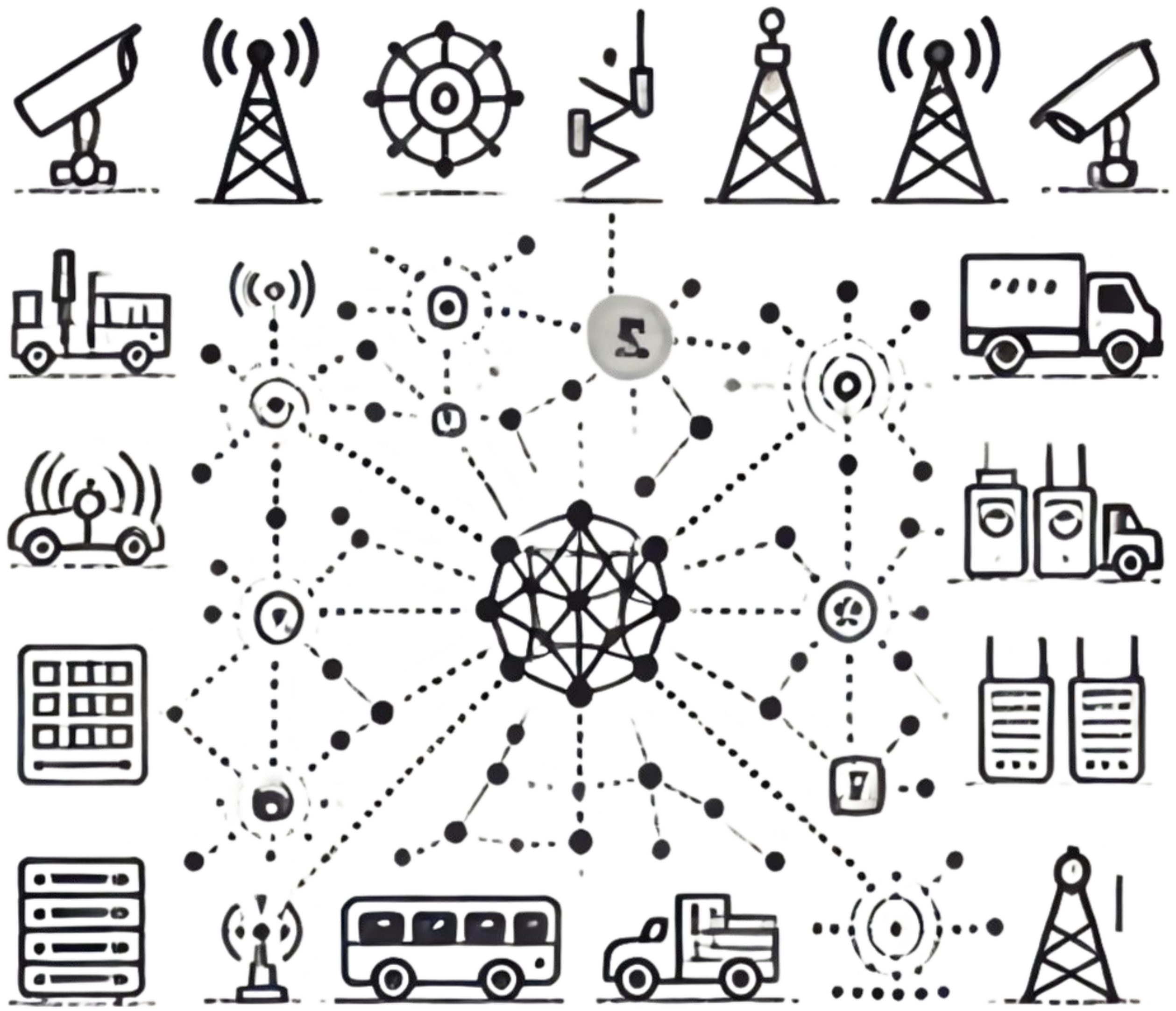


Characteristics of **Cross-Silo FL:**

- Small number of clients (organizations)
- Large computational resources
- High reliability and availability of clients

Characteristics of **Cross-Device FL:**

- Large number of clients (devices)
- Limited computational resources per device
- Potential for variability in device availability and network connectivity



THE CHALLENGES OF COMPUTE-TO-DATA

Algorithmic Customization in Federated Learning:

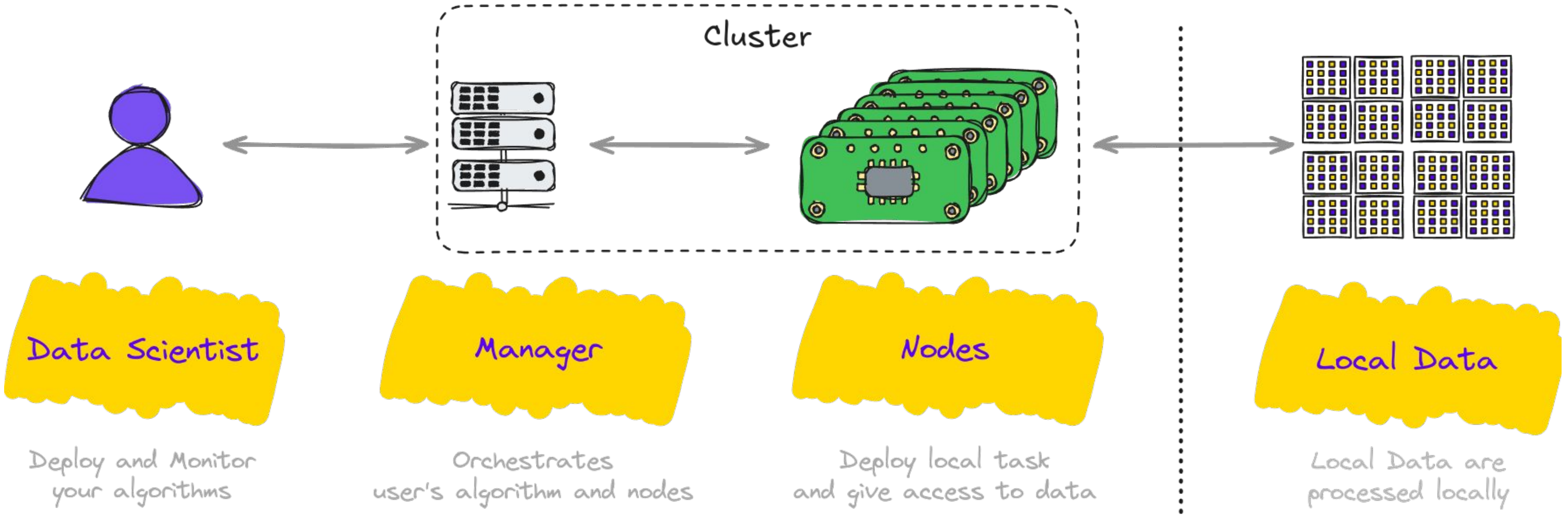
- Handling **heterogeneous** and non-IID **data** distributions.
- Designing **lightweight AI models** for resource-constrained devices (frugal AI).
- **Optimizing communications**: reducing model size and adjusting frequency of updates.
- **Ensuring privacy** and protection against **reverse attacks** from model parameters.
- Transitioning Machine Learning innovations into Federated Learning (e.g., AutoML, ethical AI).

MLOps at the Edge: From Prototyping to Production

- **Managing heterogeneous systems**
- **Orchestrating availability** based on device **states**.
- **Ensuring secure** computations, communication, and data **traceability**.
- **Scaling** decentralized computations and communications across **platforms** and **protocols**.
- **Supporting flexibility** for continuous innovation and DevOps in algorithm deployment.

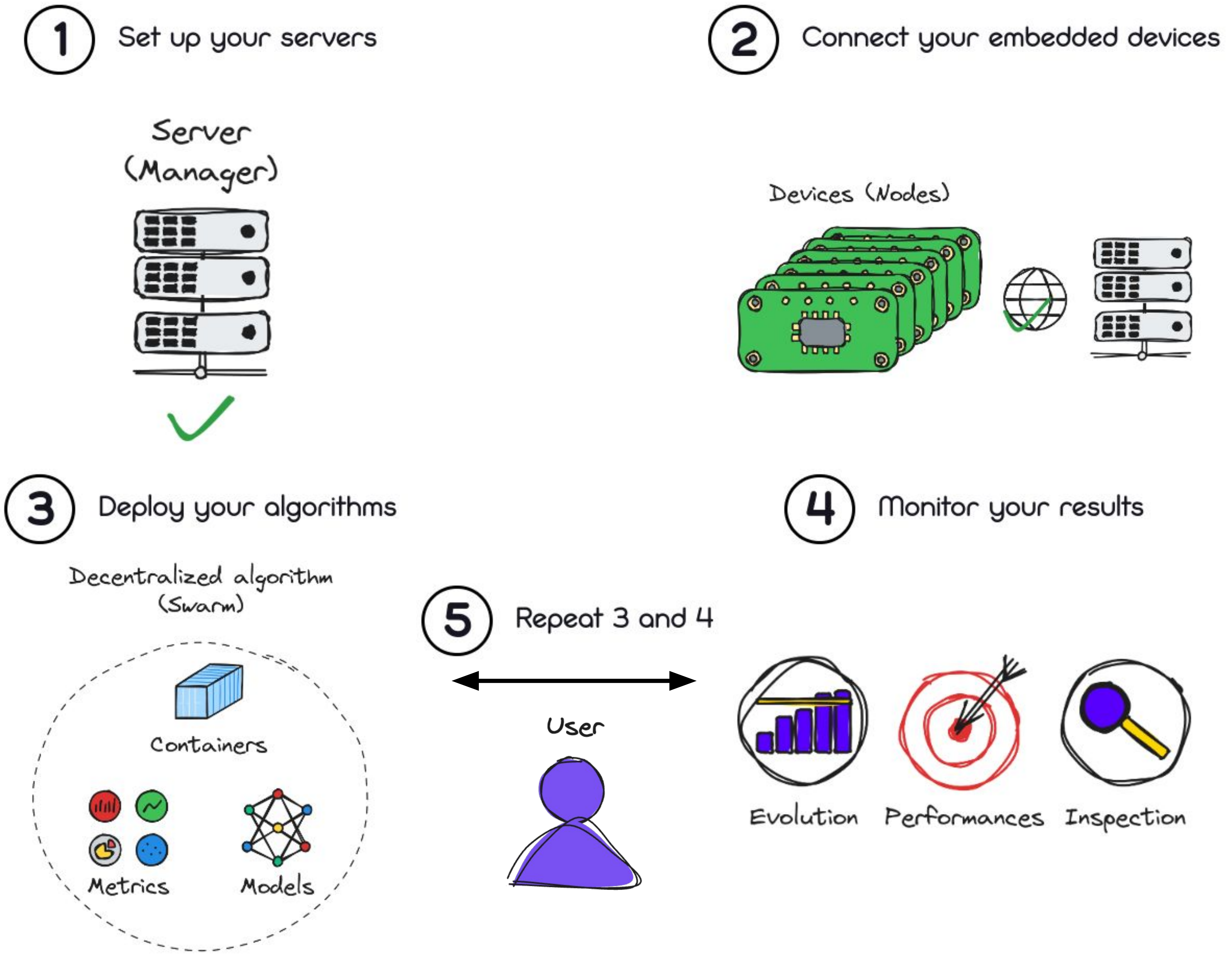
DEPLOY SOVEREIGN, SECURE, AND COST-EFFECTIVE AI SOLUTIONS

- Built-In Security
- Data Sovereignty
- Cost Optimization

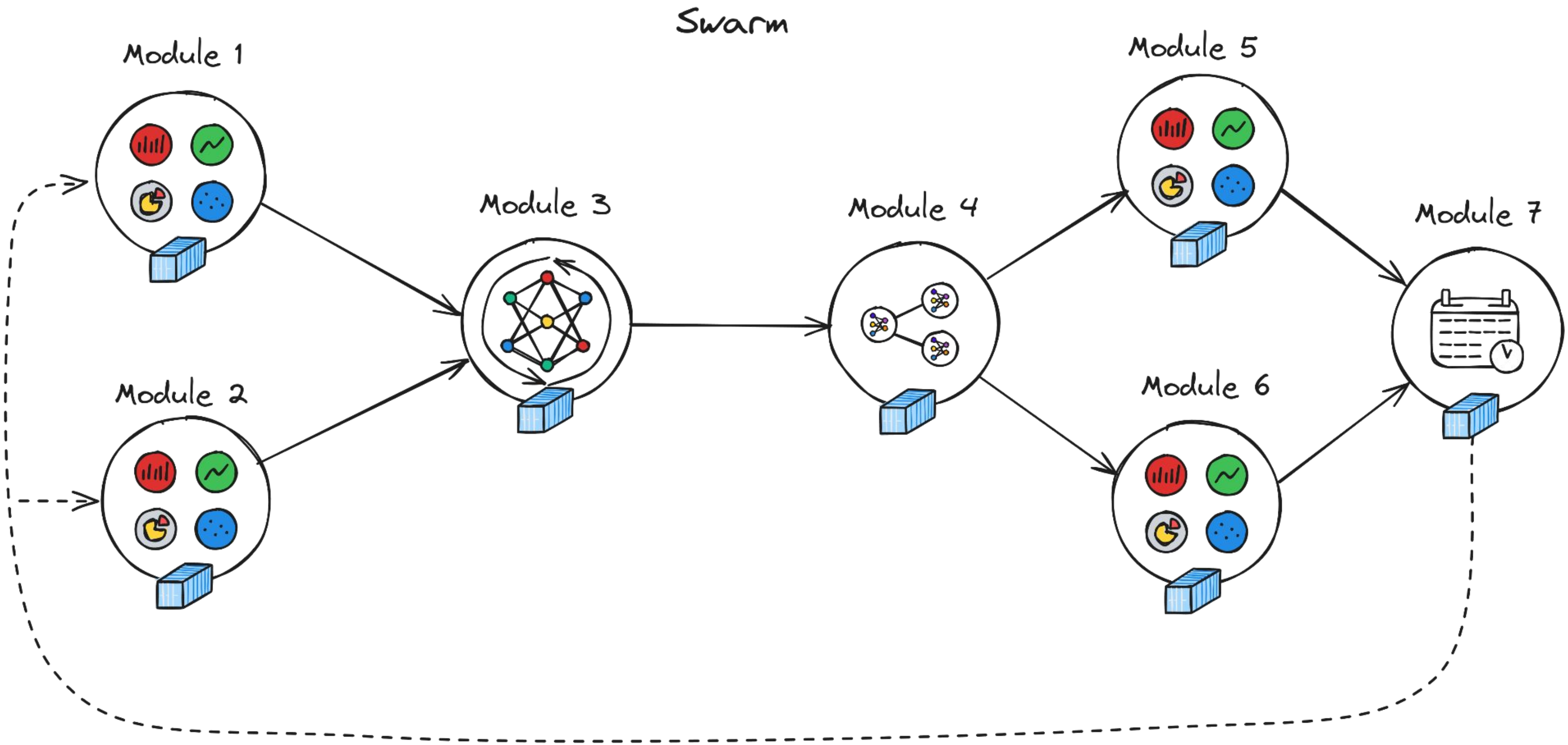


MANTA: SEAMLESS AI LIFECYCLE FROM PROTOTYPE TO PRODUCTION

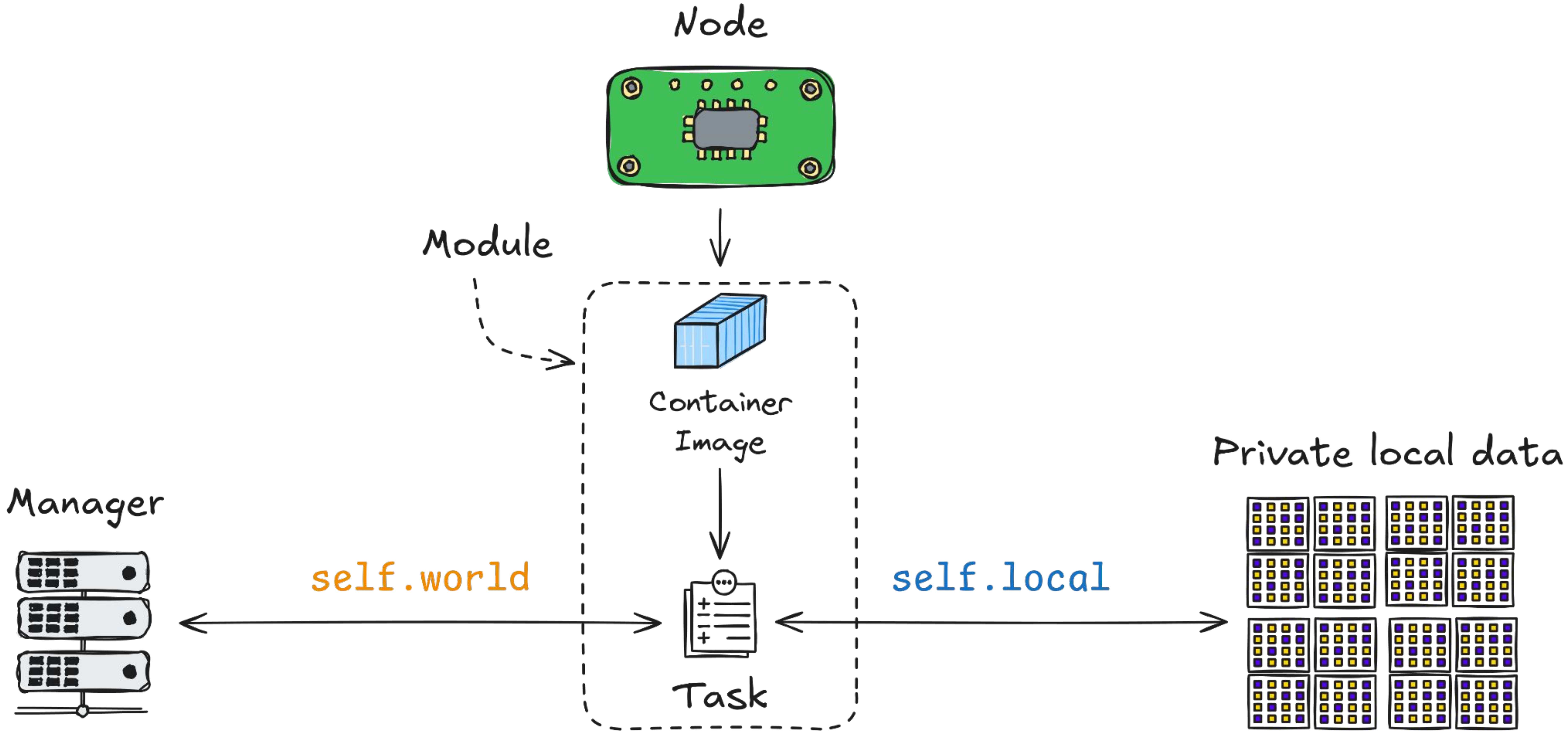
- **Optimize every stage of the AI lifecycle**
- **Reduced Latency** for real-time data processing
- **Data Traceability**
- **Unmatched Flexibility**



MANTA: DEPLOY YOUR DECENTRALIZED AND COLLABORATIVE ALGORITHMS

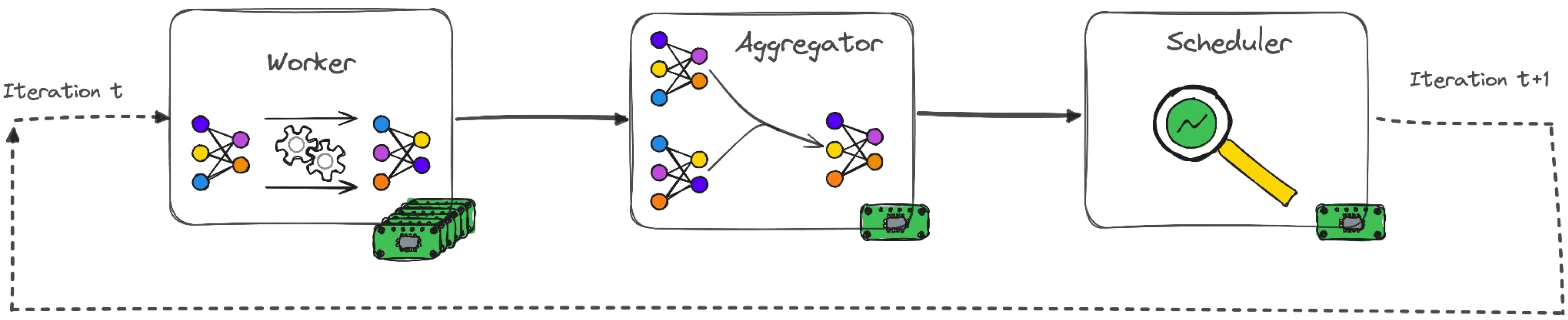


MANTA: DEVELOP YOUR MODULES



manta

TODAY'S DEMO: FEDERATED LEARNING ON YOUR COMPUTERS !



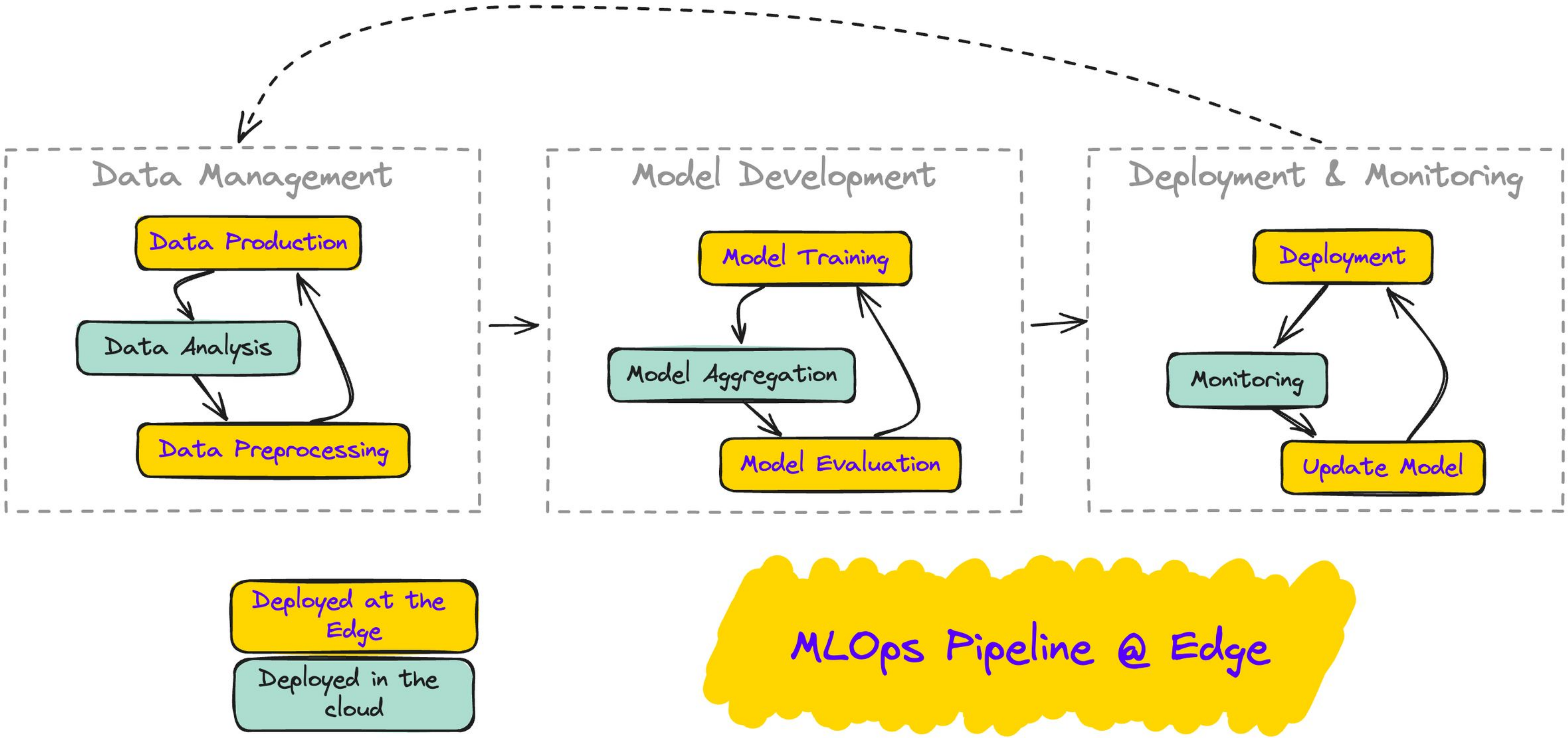
HUGO MIRALLES
CO-FOUNDER
www.linkedin.com/in/hugo-miralles
hugomiralles@manta-tech.io
+33 6 59 96 27 85

BENJAMIN BOURBON
CO-FOUNDER
www.linkedin.com/in/benjamin-bourbon
benjaminbourbon@manta-tech.io
+33 6 47 35 88 08

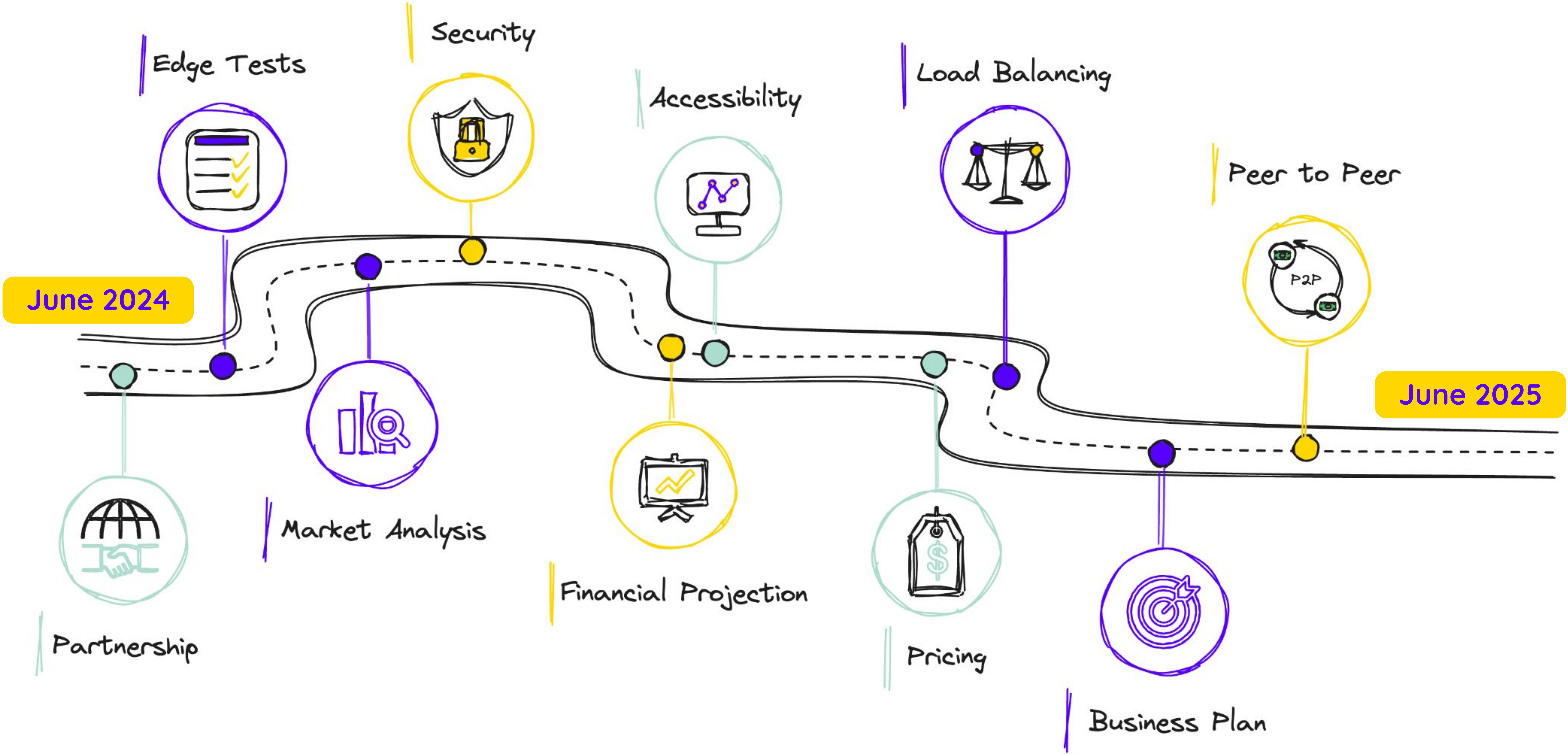
manta

Let’s try Federated Learning with Manta !

MLOPS @ EDGE : ENHANCING MARKET EFFICIENCY WITH MANTA



MANTA ROADMAP: FROM INNOVATION TO MARKET IMPACT



MARKET: NAVIGATING COMPETITIVE WATERS