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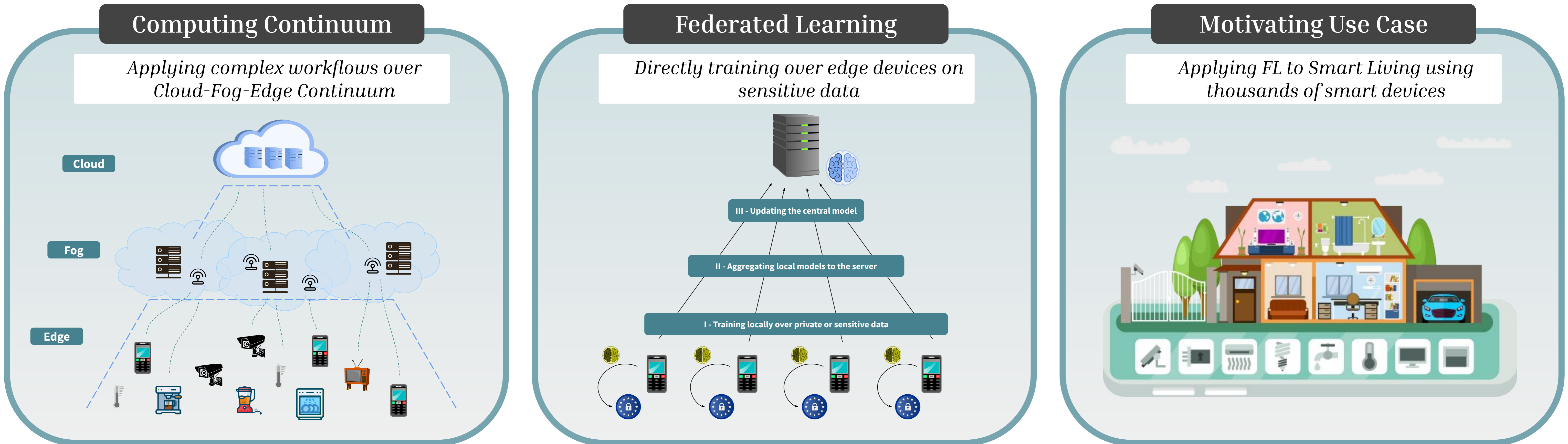
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Supporting Efficient Workflow Deployment of Federated Learning Systems on the Computing Continuum

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Context

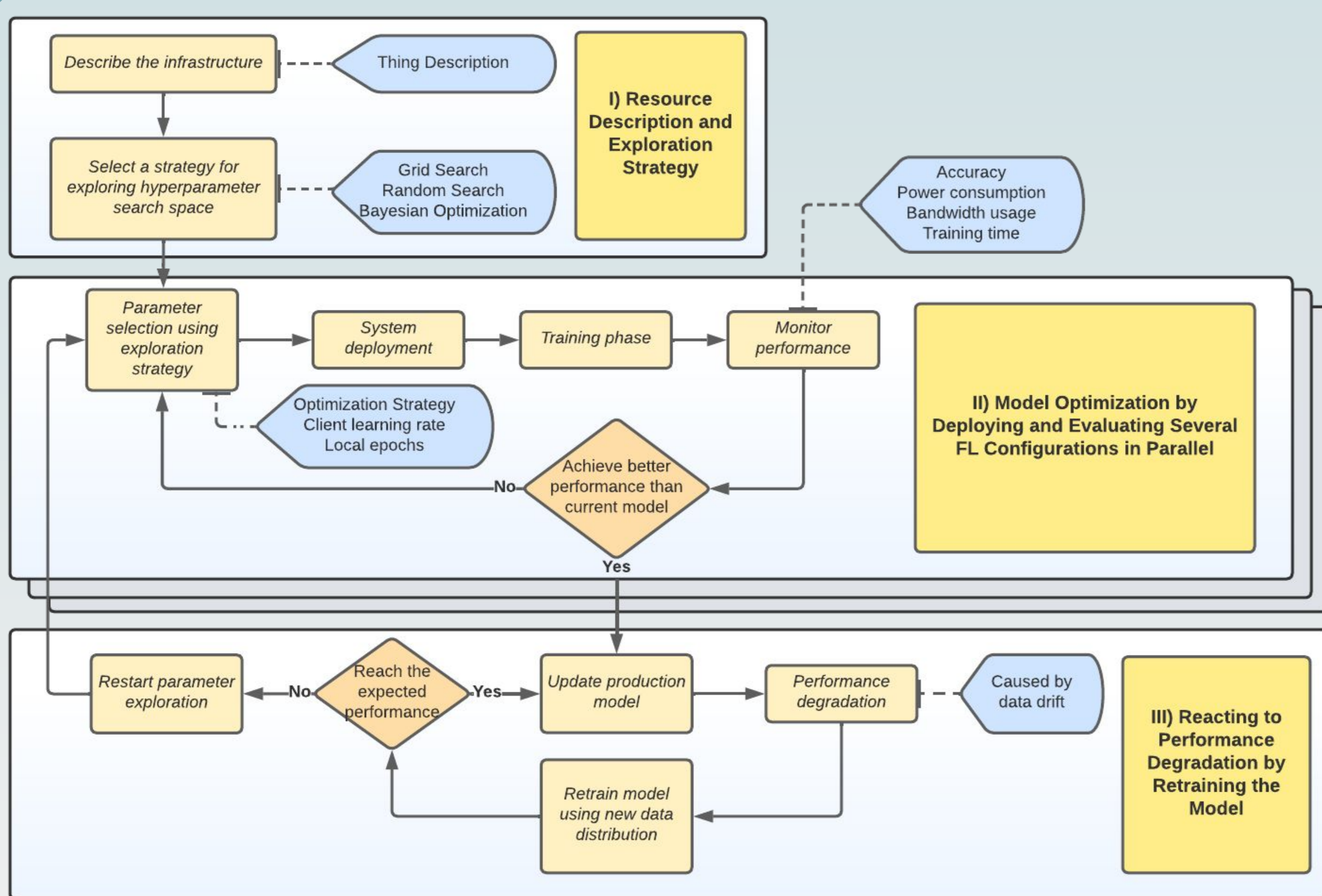


Problems

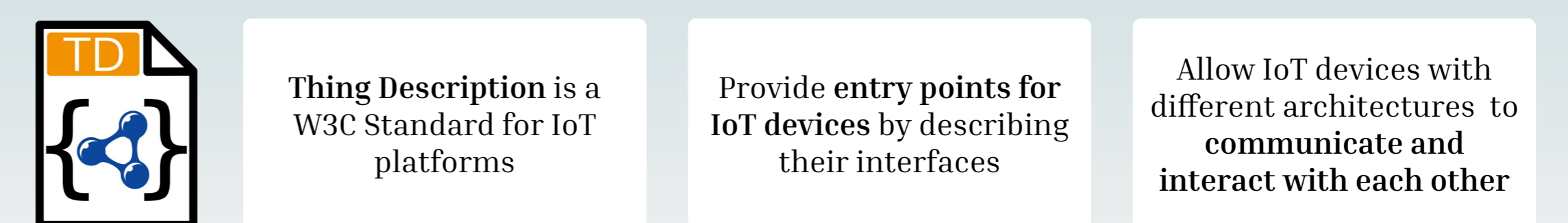
- Heterogeneous devices**: IoT objects relying on different architectures require extra efforts to be supported in a same application (supporting different standards)
- Hyperparameter tuning**: Federated Learning introduces several additional hyperparameters in contrasts with standard ML, requiring deeper optimization
- Inconsistent performance**: Devices with very different usage result in data drift and inconsistent performance of the model among clients

Our Proposal

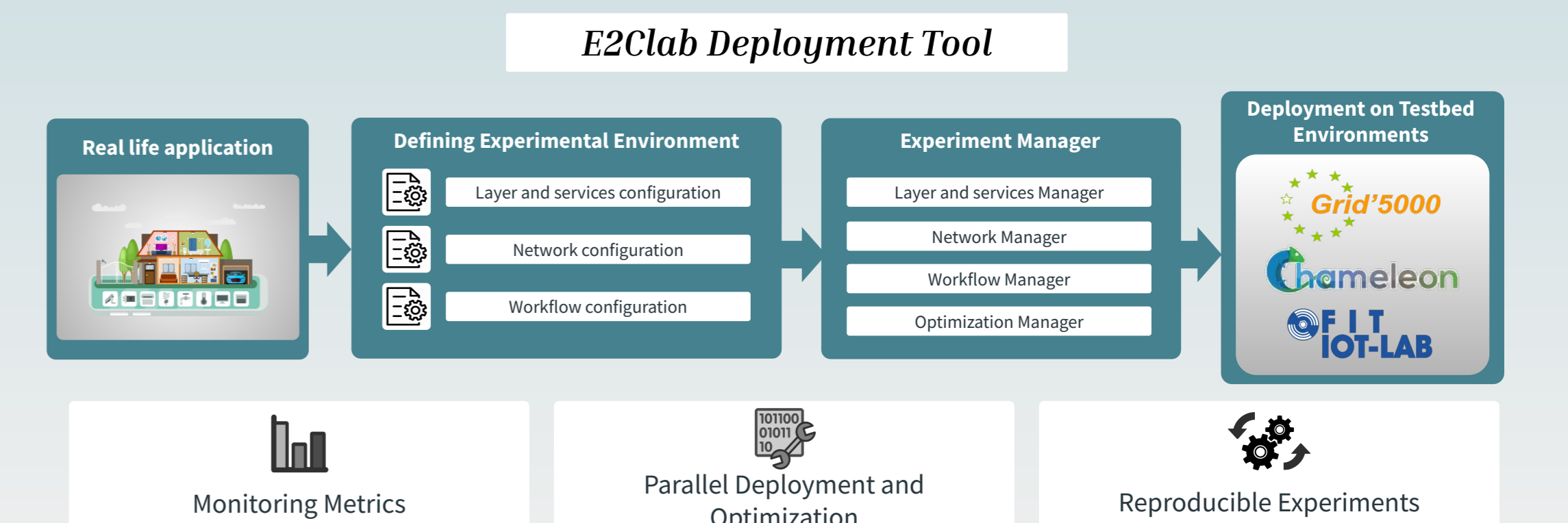
A Workflow for Efficient FL Deployment and Model Optimization



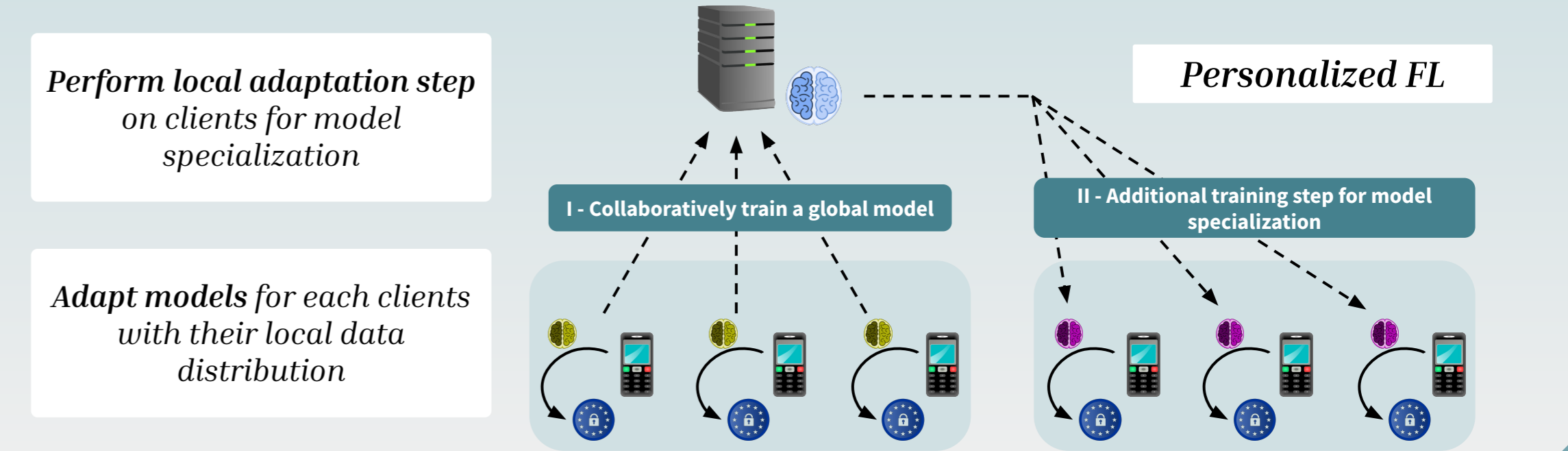
How to improve interoperability across IoT platforms ?



How to automatically deploy and monitor FL solutions ?



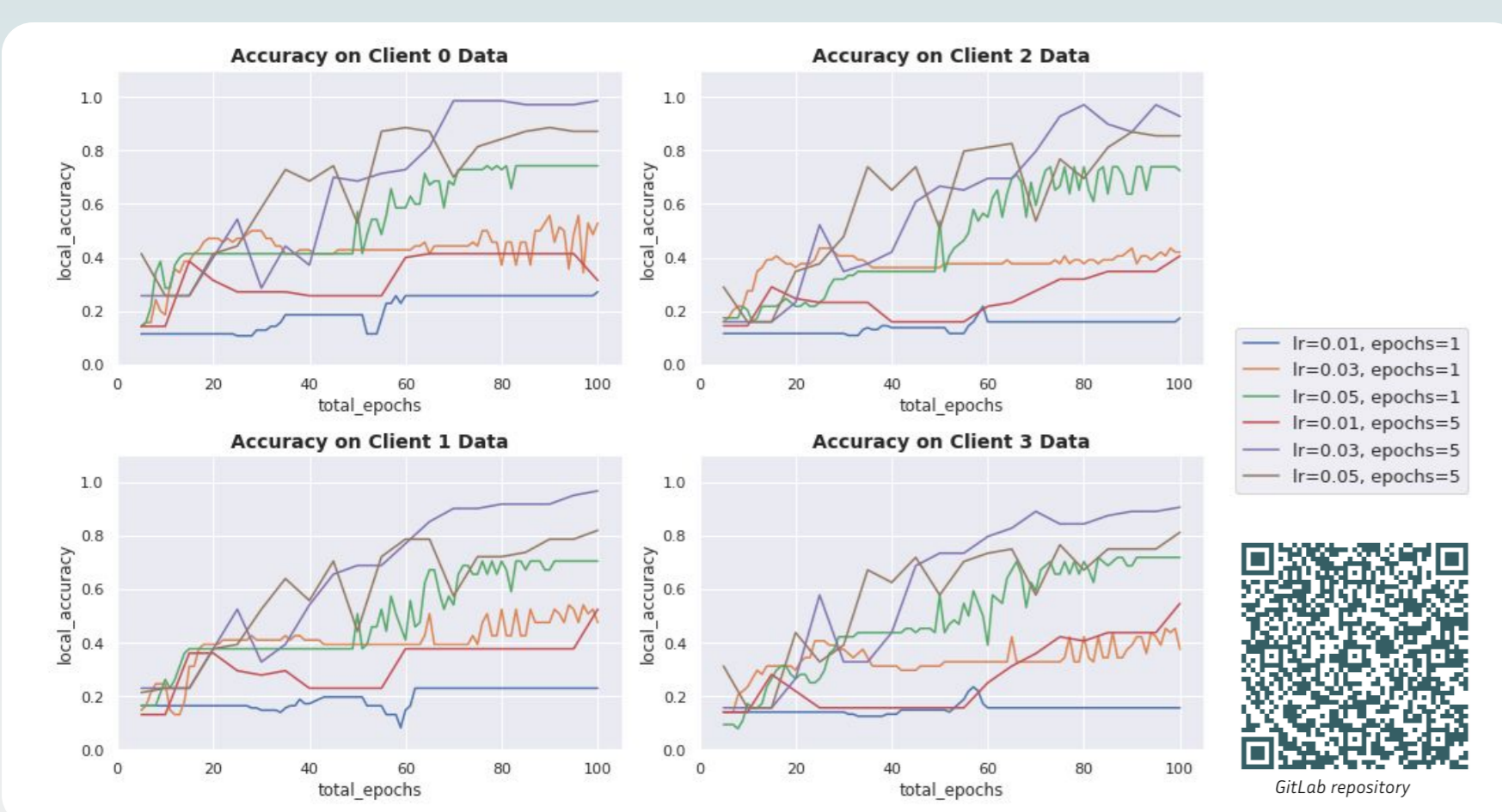
How to ensure good model performance on each client ?



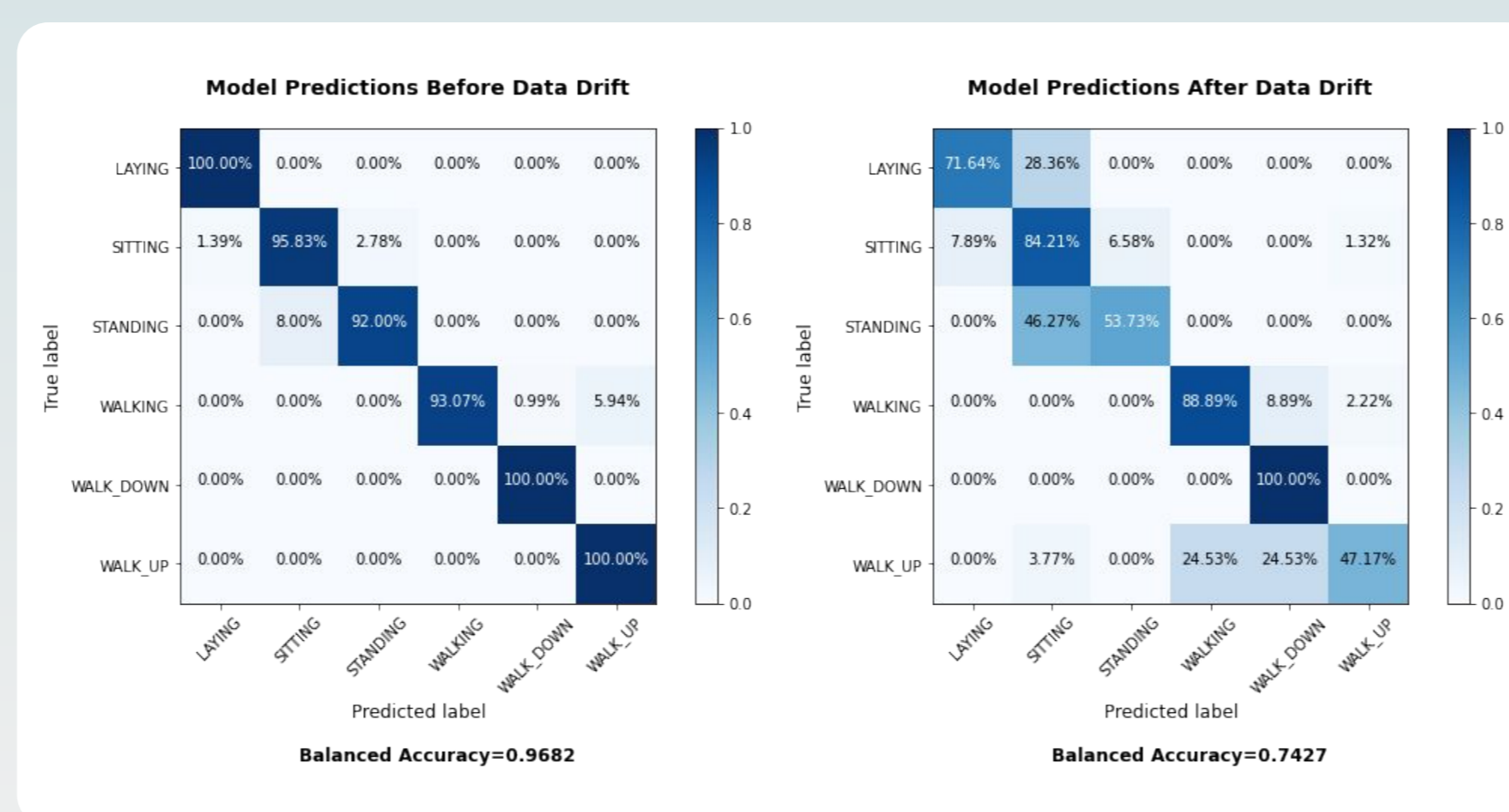
Early Results

Performing FL training over smartphone data from 8 users for recognition of Daily Living Activities

Impact of client learning rate and number of local epochs on training



Impact of data drift on model performance



Takeaways

We provided a solution to automatically deploy and optimize FL workloads in heterogeneous environments using formal description of the underlying infrastructure, hyperparameter optimization and model retraining in case of data drift.

Open Questions

How to determine which model is performing better considering several conflicting metrics and clients with different data distribution? (e.g optimizing energy consumption, accuracy of the model and bandwidth usage)

Considering constrained-devices, how often should models be trained? (minimizing battery usage of the device)