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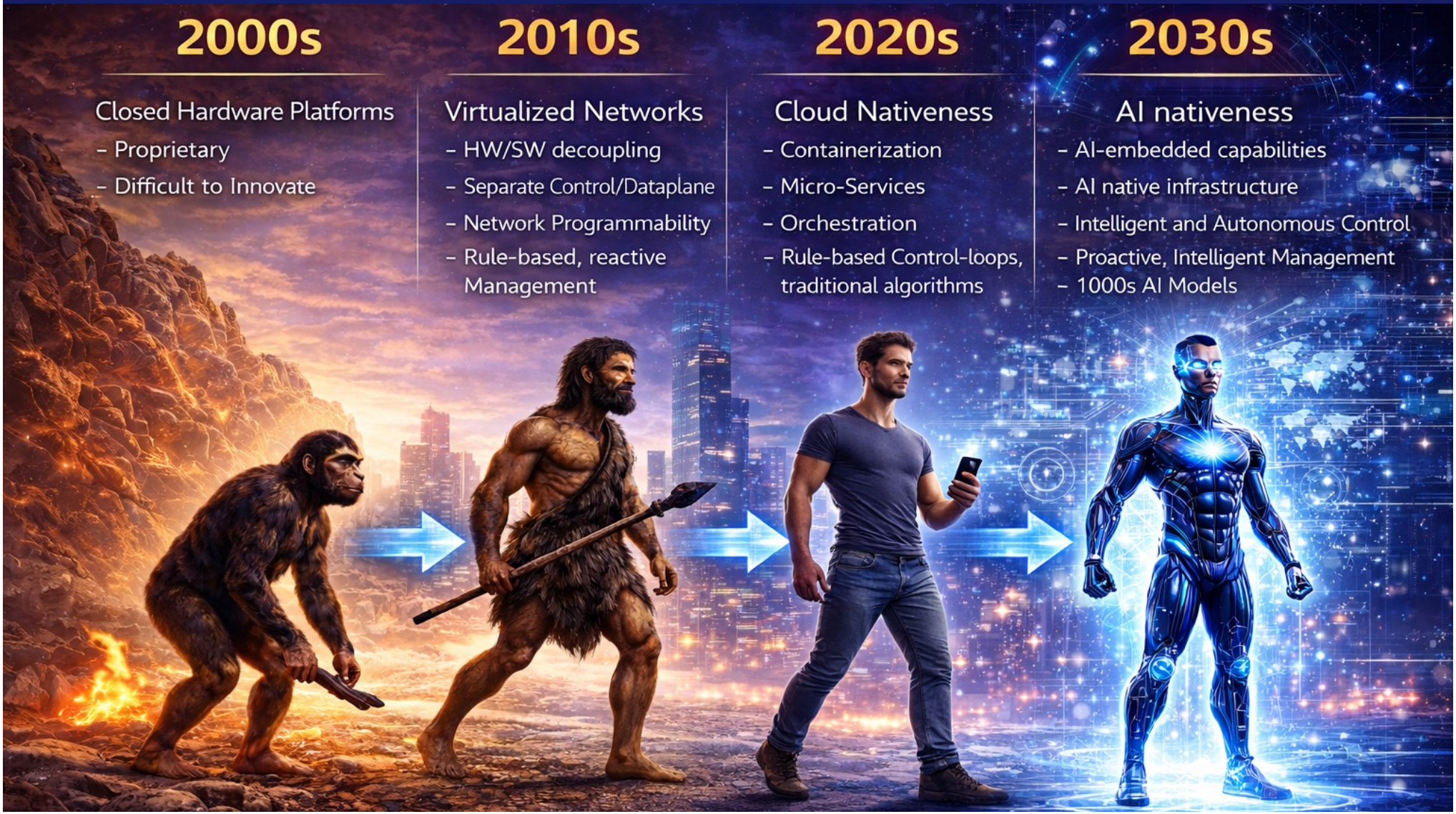
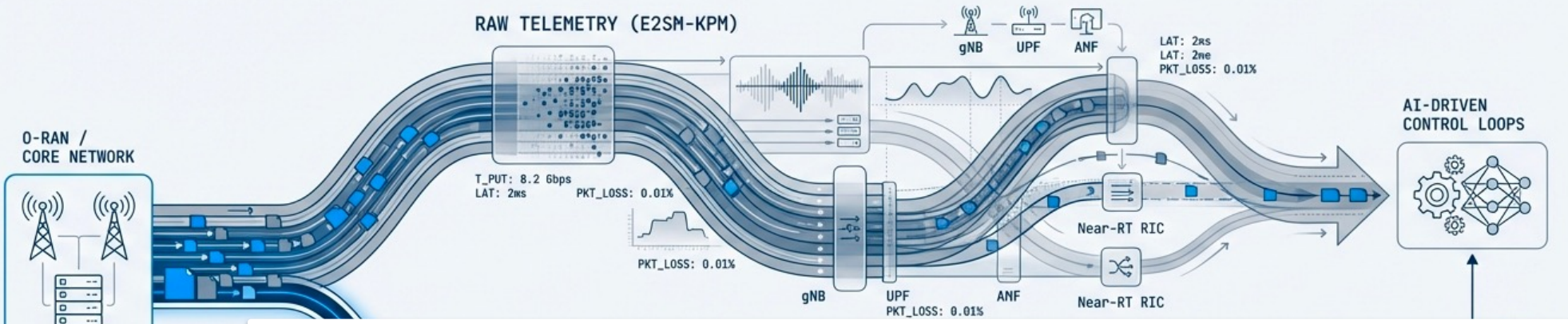
# Evolution of Telco Networks



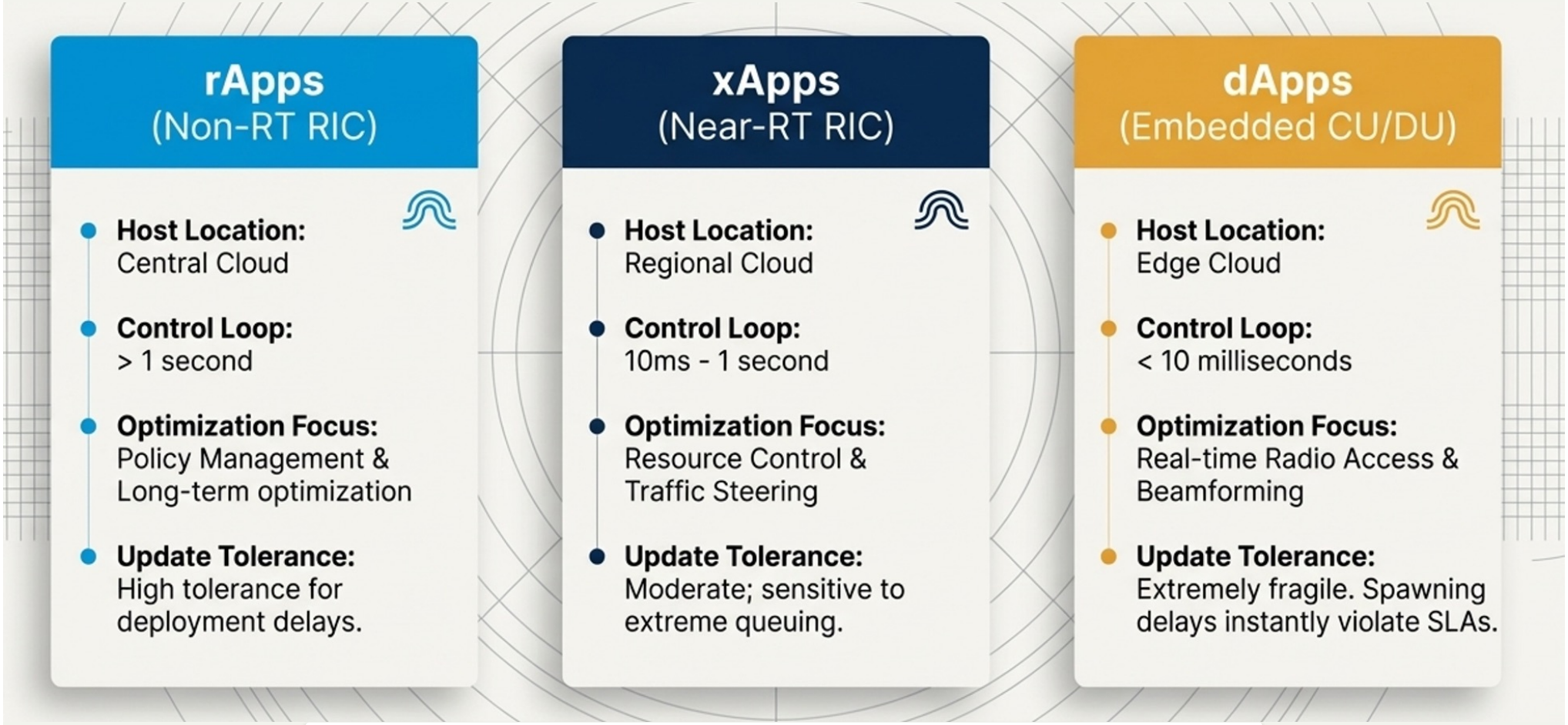
# Key Enablers for AI Nativeness

# Example: AI-Driven Network Management




- Most AI-Apps consume **telemetry** to **configure** network elements
- Configurations need to be **updated through AI Models**
- **Proactive Network Management requires Forecasting**
- Example of AI-based Timeseries Forecasting Apps
  - Traffic Demand,
  - Ressource Availability,
  - Anomaly Detection,
  - User Mobility ..

# AI-based App examples (some)




How to implement/update AI Models efficiently?

# AI-native stack in CNCF

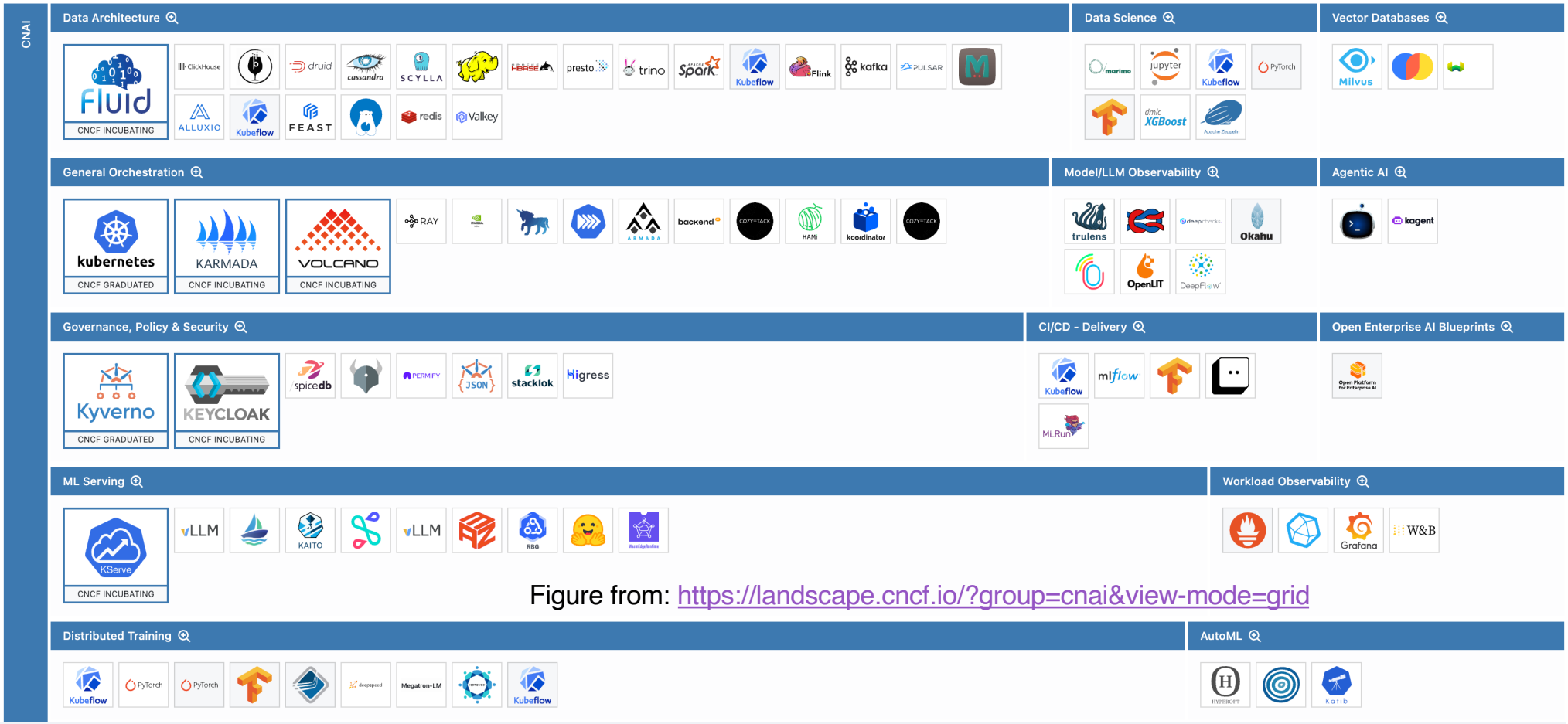
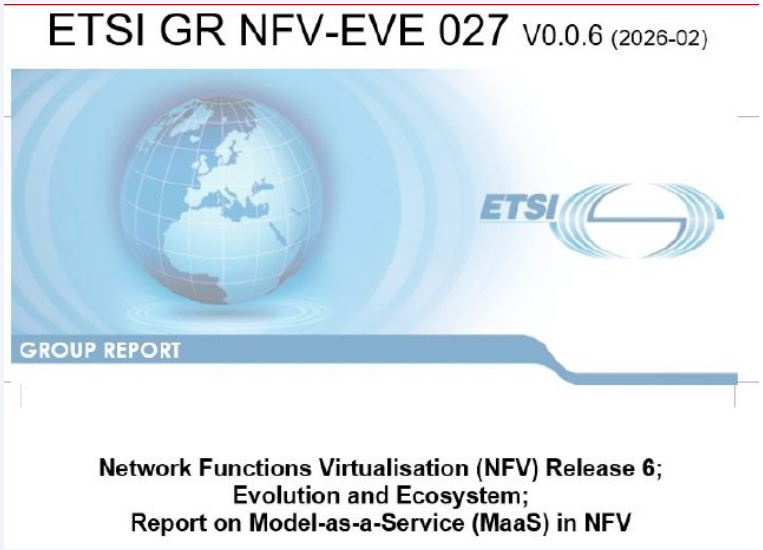



Figure from: https://landscape.cncf.io/?group=cnai&view-mode=grid

**Many generic tools → How to use them in Telco AI-native Networks?**

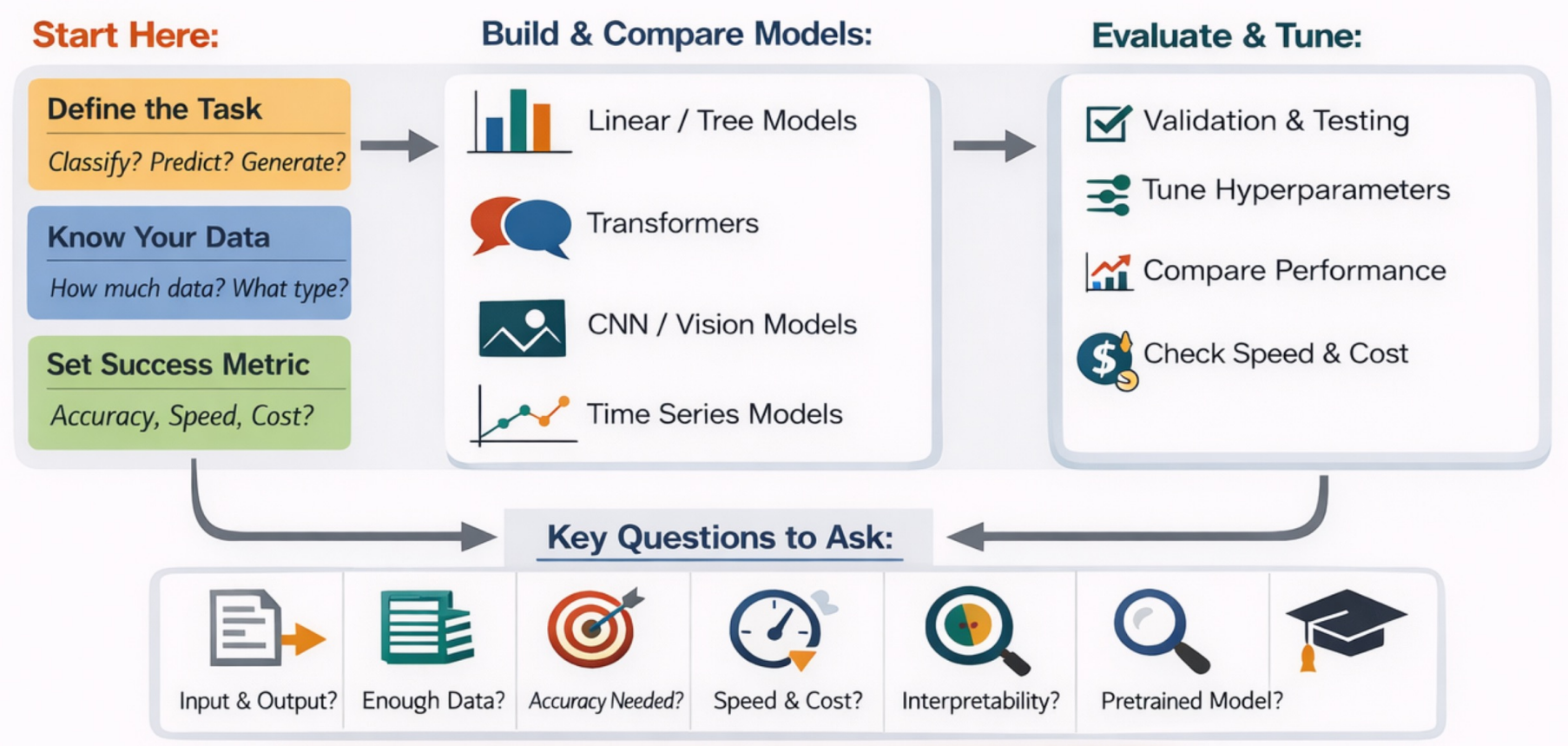
# (AI) Model as a Service

- **Model as a Service (MaaS)**:
  - make AI models repeatable, deployable, and consumable at scale
  - models are treated as managed assets
- **Automation** of the "**model pipeline**"
  - **AI Model Benchmarking**
    **→ which model fits my data and use-case best?**
    - Data preparation, Feature enrichment, Hyperparameters
    - Model Training, Model evaluation, Model versioning
  - **AI-Lifecycle Management**
    **→ when to re-train and redeploy AI model where?**
    - Deployment, monitoring
    - Dynamic updating → hard



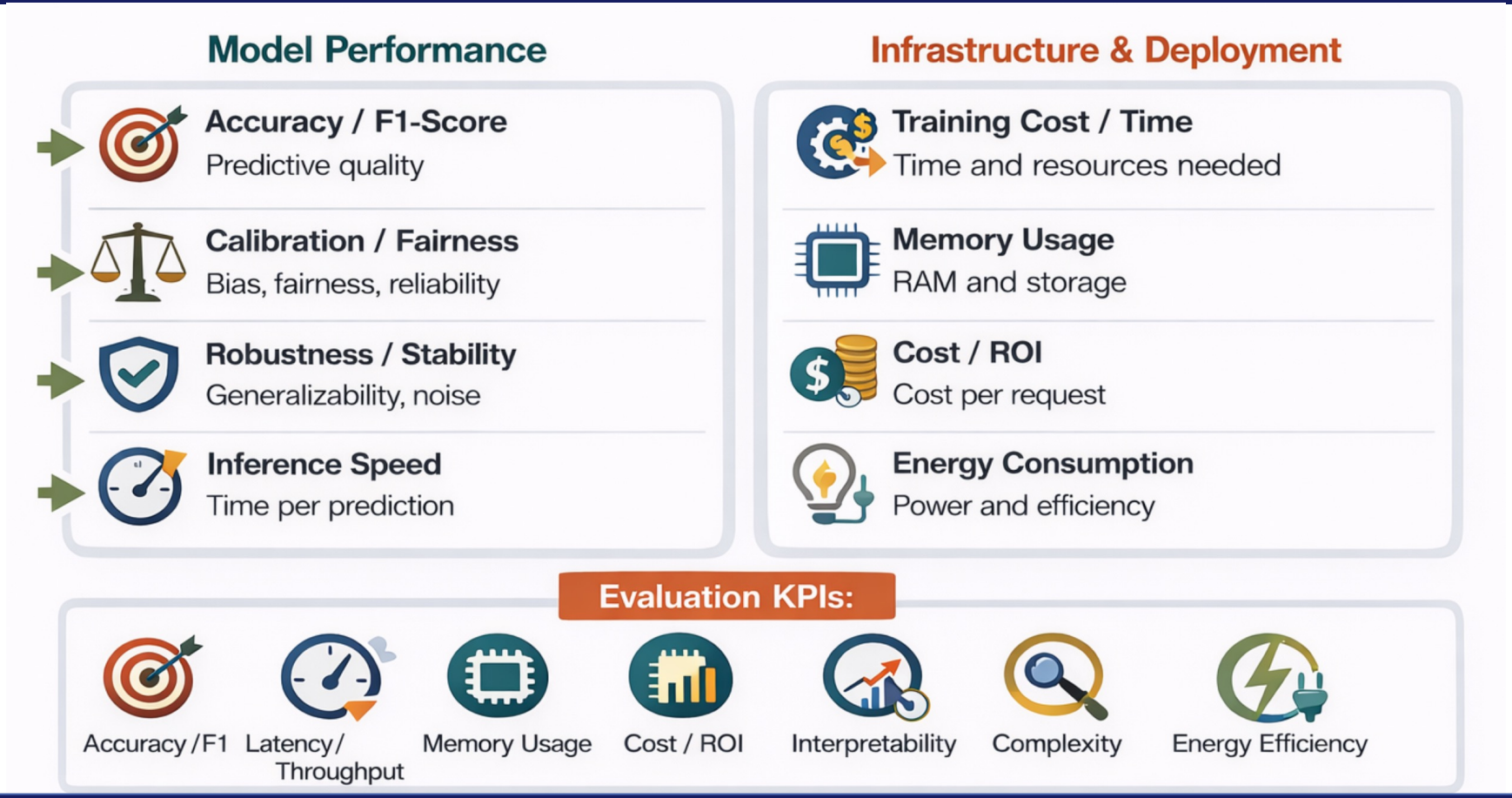

- **Typical capabilities**
  - High-performance inference service (quantization, pruning, runtime optimization, …)
  - Privacy-preserving learning → Federated and Split Learning support
  - Integration with AI Agents

# The Pain of finding a good AI-Model




Good Model? Need to benchmark several ones on your dataset → Need to implement basic blocks for each AI-Model → Labour intensive → Automate!

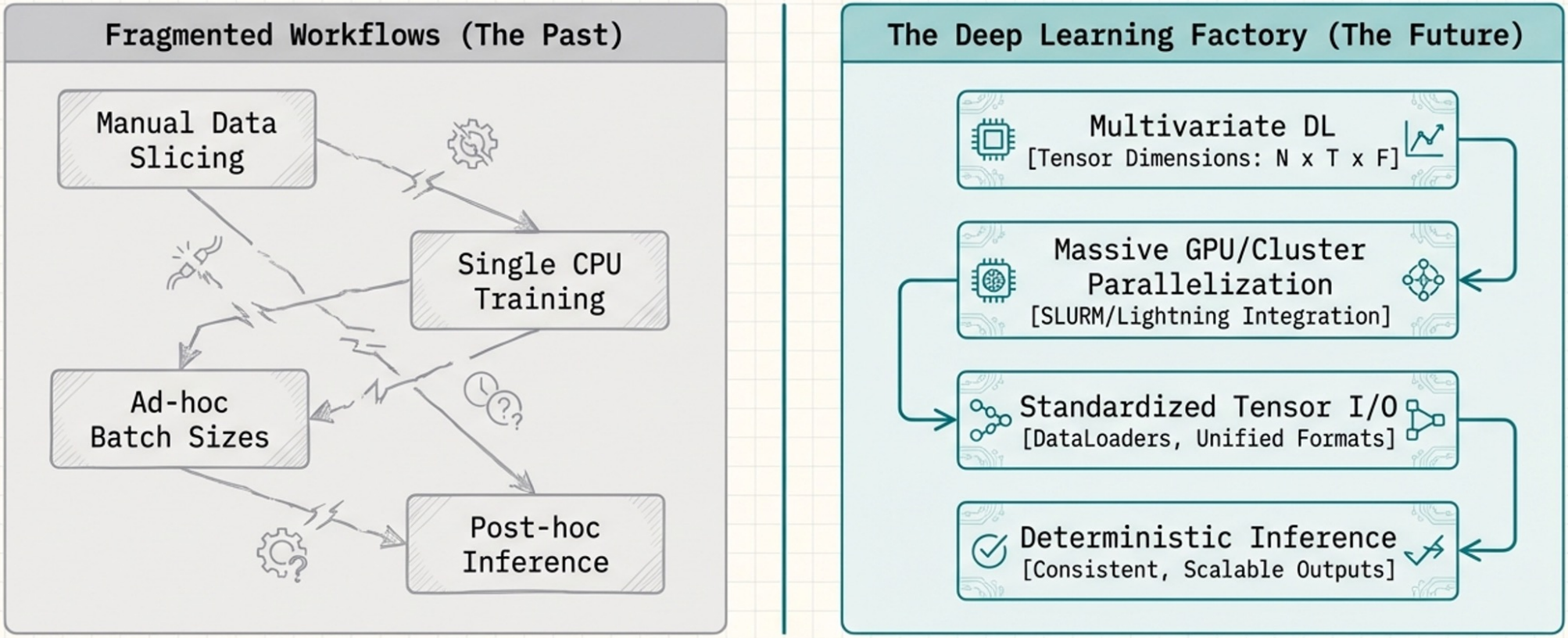
# Key Factors to Consider when Choosing an AI Model




Need to consider infrastructure KPIs for optimal deployment decisions!

**Example:** If two model have similar accuracy, pick the one with lower energy consumption

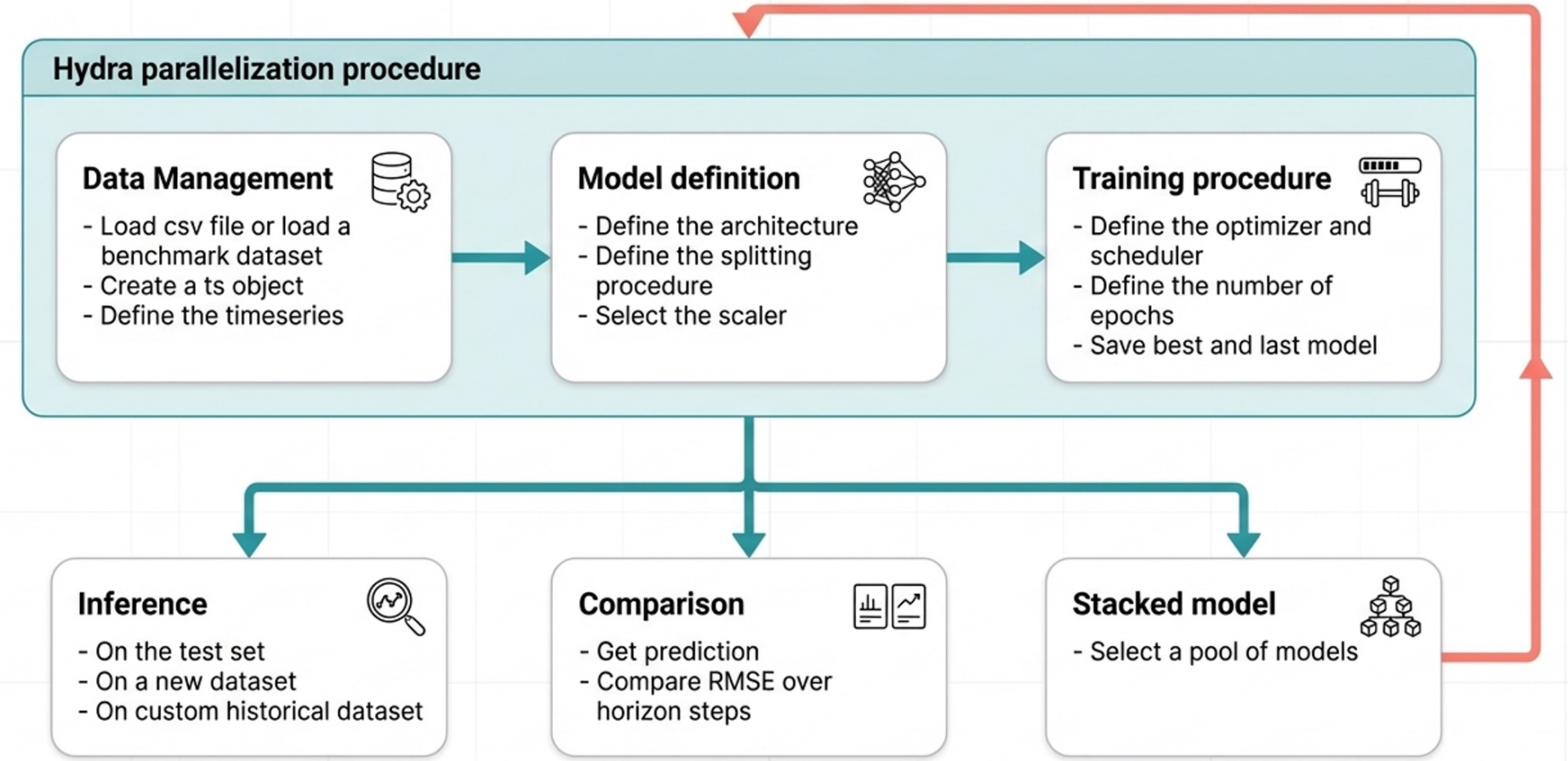
# The Reality of ML Model Development and Benchmarking




AI-based Models demand infrastructure built natively for Deep Learning, PyTorch Lightning, SLURM/K8S to automate ML Model benchmarking at Scale

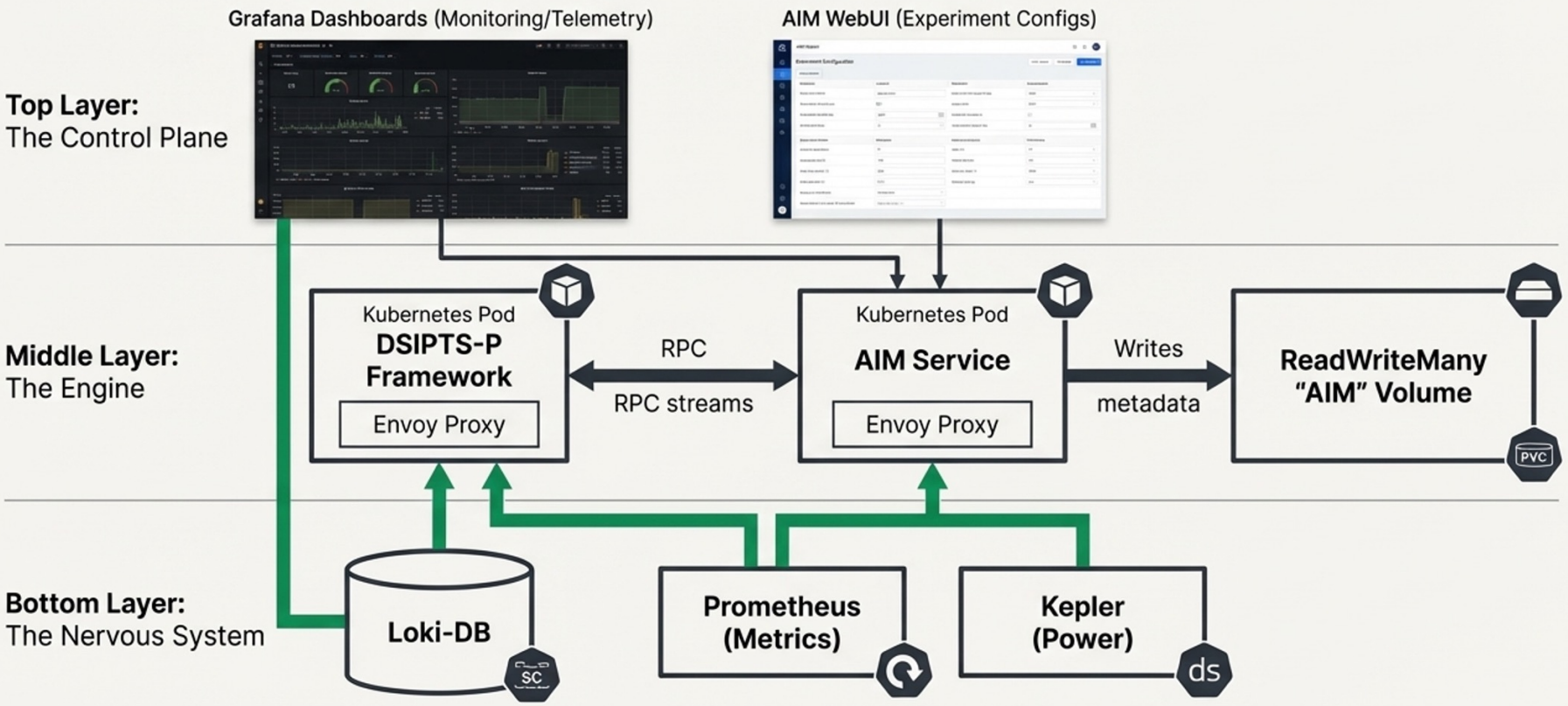
# Key Requirements for AI Model Benchmarking as a Service

# ML Model Development Automation




Whole Pipeline automated → Only YAML files/GUI for configuration
Automated training, versioning, inference and KPI scoring of diverse ML-Models

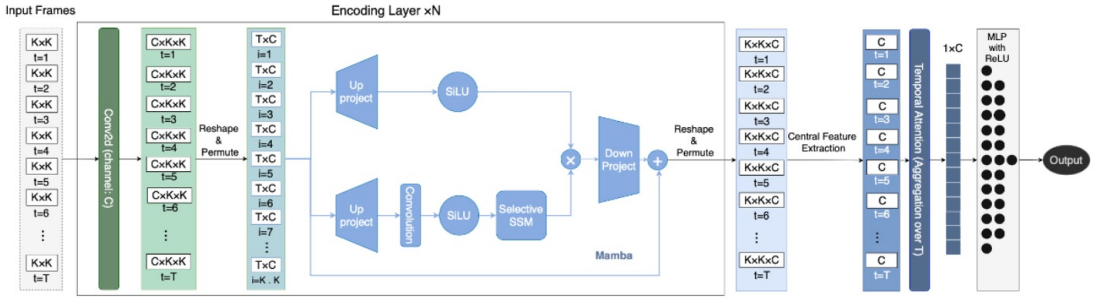
# AI Model Benchmarking Framework Architecture

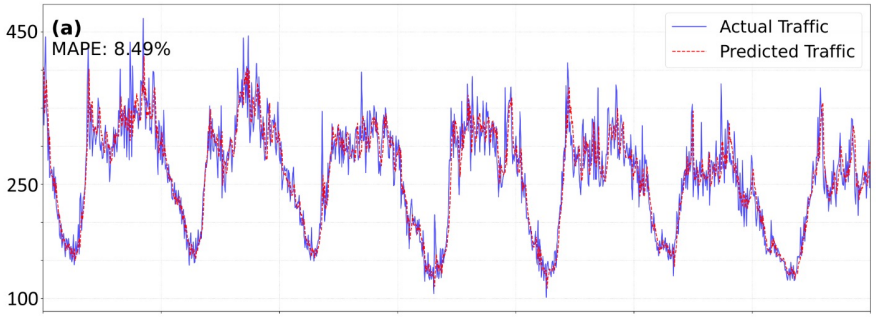


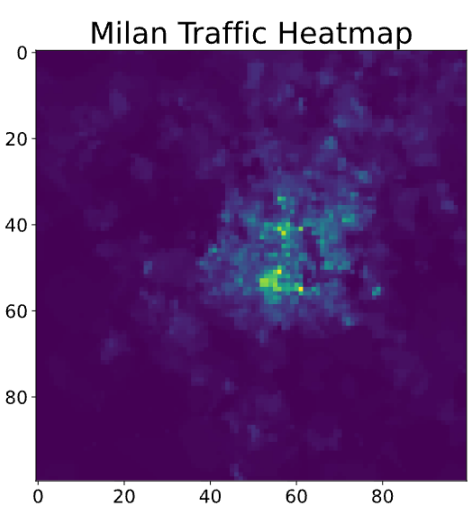

K8S Integration can launch training and inference on different hardware to compare performance vs. energy consumption (through Kepler)

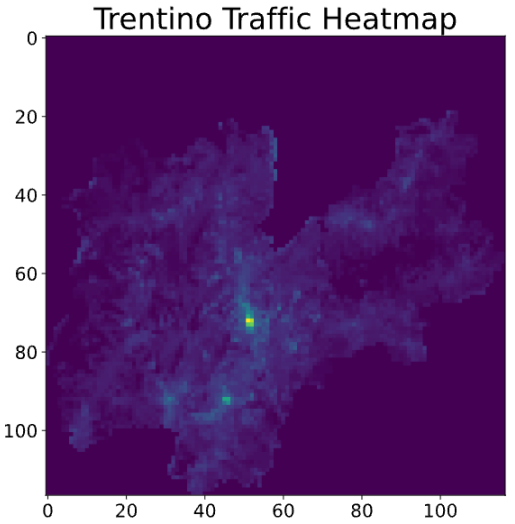
# Example: HiSTM - Complexity vs. Accuracy

| Model | MAE ↓ | RMSE ↓ | $R^2$ Score ↑ | SSIM ↑ |
|---|---|---|---|---|
| PatchTST | 20.231 | 45.235 | 0.5635 | 0.9187 |
| STN | 7.3908 | 16.8824 | 0.9546 | 0.9853 |
| VMRNN-B | 7.1659 | 19.0876 | 0.9420 | 0.9843 |
| PredRNN++ | 7.0000 | 19.1650 | 0.9425 | 0.9893 |
| xLSTM | 6.4672 | 15.0901 | 0.9637 | 0.9870 |
| VMRNN-D | 6.4151 | 16.3284 | 0.9575 | 0.9873 |
| STTRE | 5.5558 | 11.4426 | 0.9791 | 0.9917 |
| Autoformer | 5.5850 | 12.2750 | 0.9762 | 0.9920 |
| Informer | 5.4100 | 11.4600 | 0.9792 | 0.9922 |
| TimesNet | 5.3540 | 11.3270 | 0.9797 | 0.9922 |
| HiSTM | **5.2196** | **11.2476** | **0.9799** | **0.9925** |



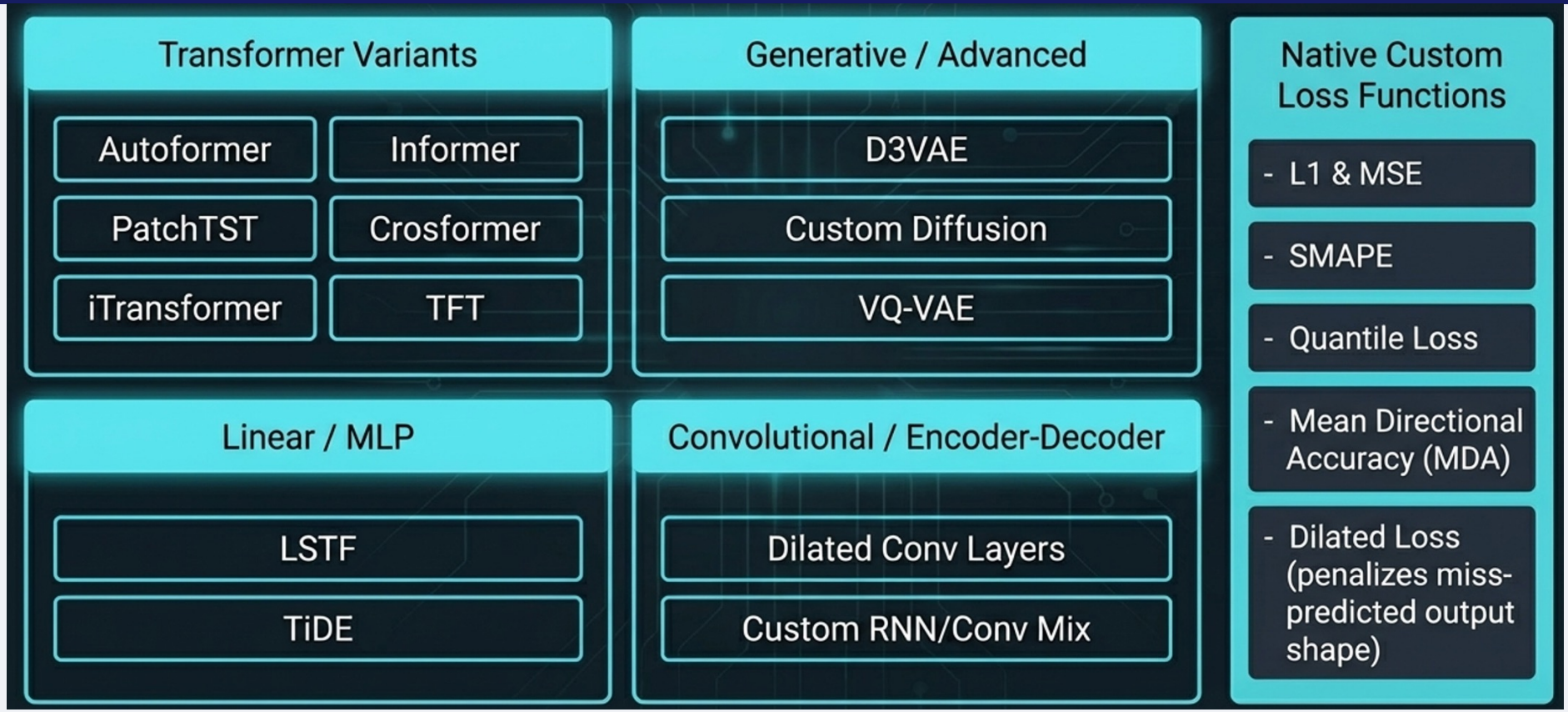




## Example Evaluation: Parameter Size vs Accuracy

# Supported Model Architectures (many more…)




Additional support for SplitLearning, Federated Learning, LSTM, xLSTM, Mamba, STNs, Bring your Own Model

# Massive Parallel Hardware Accel. Training/Inference Jobs

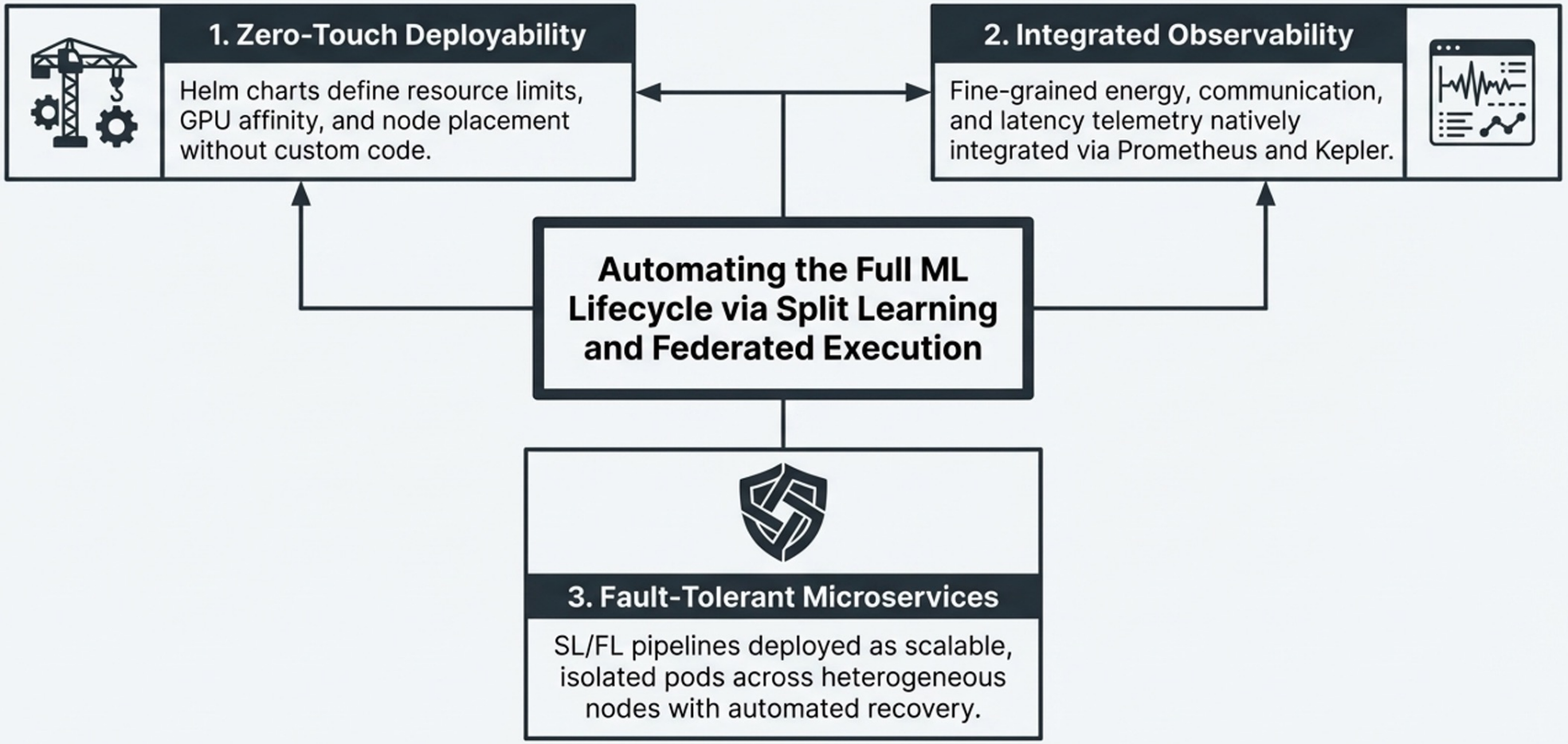

K8S/SLURM Integration: launch AI-model benchmarking jobs(trainig/inference) for 100s models on different hardware accelerators at scale

# DSIPTS-P Federated and Split-Learning

| | Traditional Tools (Kubeflow, MLflow, PyTorch) | DSIPTS-P |
|---|---|---|
| Network-aware distributed learning | ○ | ● |
| GPU/Edge-aware pod placement | ◔ | ● |
| Real-time per-container energy telemetry | ○ | ● |
| Automated SL round recovery | ○ | ● |
| Declarative YAML edge-cloud configuration | ◔ | ● |

Recent extensions natively support Federated Learning and Split Learning (clients and servers are different training pods, connected through K8S network interfaces)

# DSIPTS-P Federated and Split-Learning




Khalid Ali, Phil Aupke, Andreas Kassler: DEMO: Distributed Edge & Split Learning for Energy-Aware Spatiotemporal Forecasting, to appear in IEEE Infocom 2026, Tokio, May 18, 2026.

# Infocom 2026 Demo

Scenario A

**Split Learning Optimization**

Balancing energy draw and end-to-end latency via dynamic model partition points.

Scenario B

**Resilience Under Chaos**

Surviving controlled network impairments, packet delays, and catastrophic pod failures.

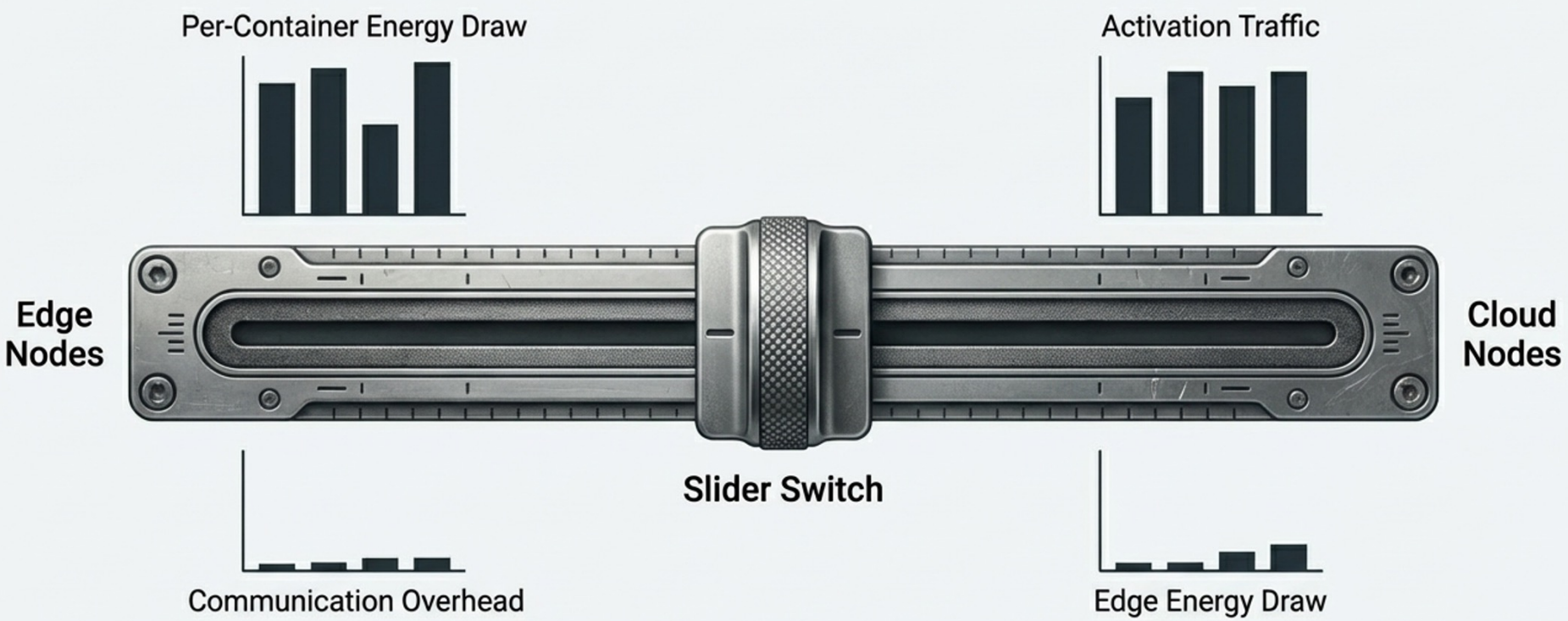
Scenario C

**Hardware Agility**

Seamless hot-swapping between CPU edge nodes and GPU cloud clusters with multi-model deployment.

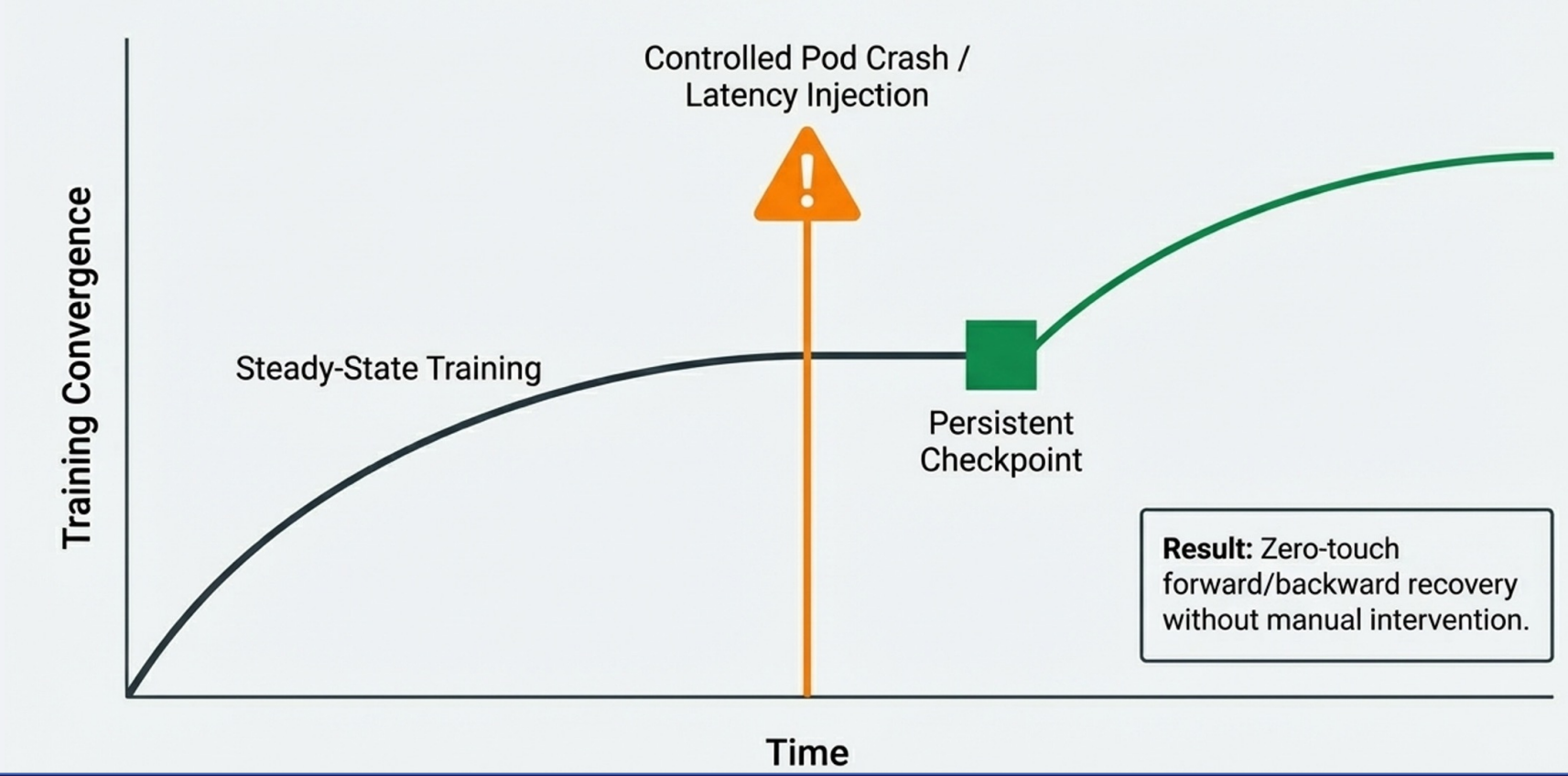
Target Environment: Real-world 5G base station traffic and gNB RB datasets

# Scenario A



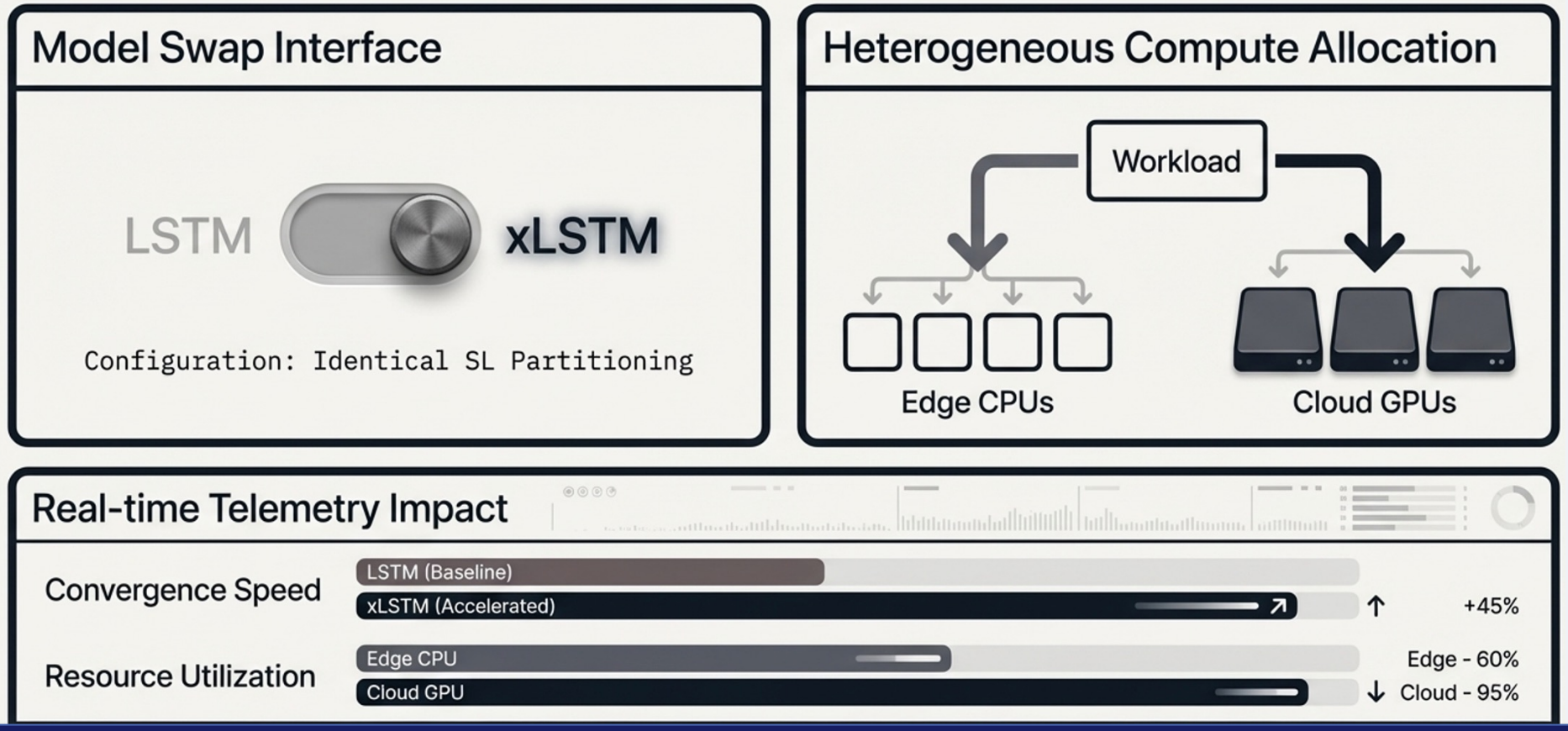

Through GUI, change SL partition points to explore tradeoffs between energy draw, communication overhead and accuracy

# Scenario B




Simple YAML file configuration inject faults in inter-pod communication to evaluate impact on convergence and inference time, crash recovery, etc.

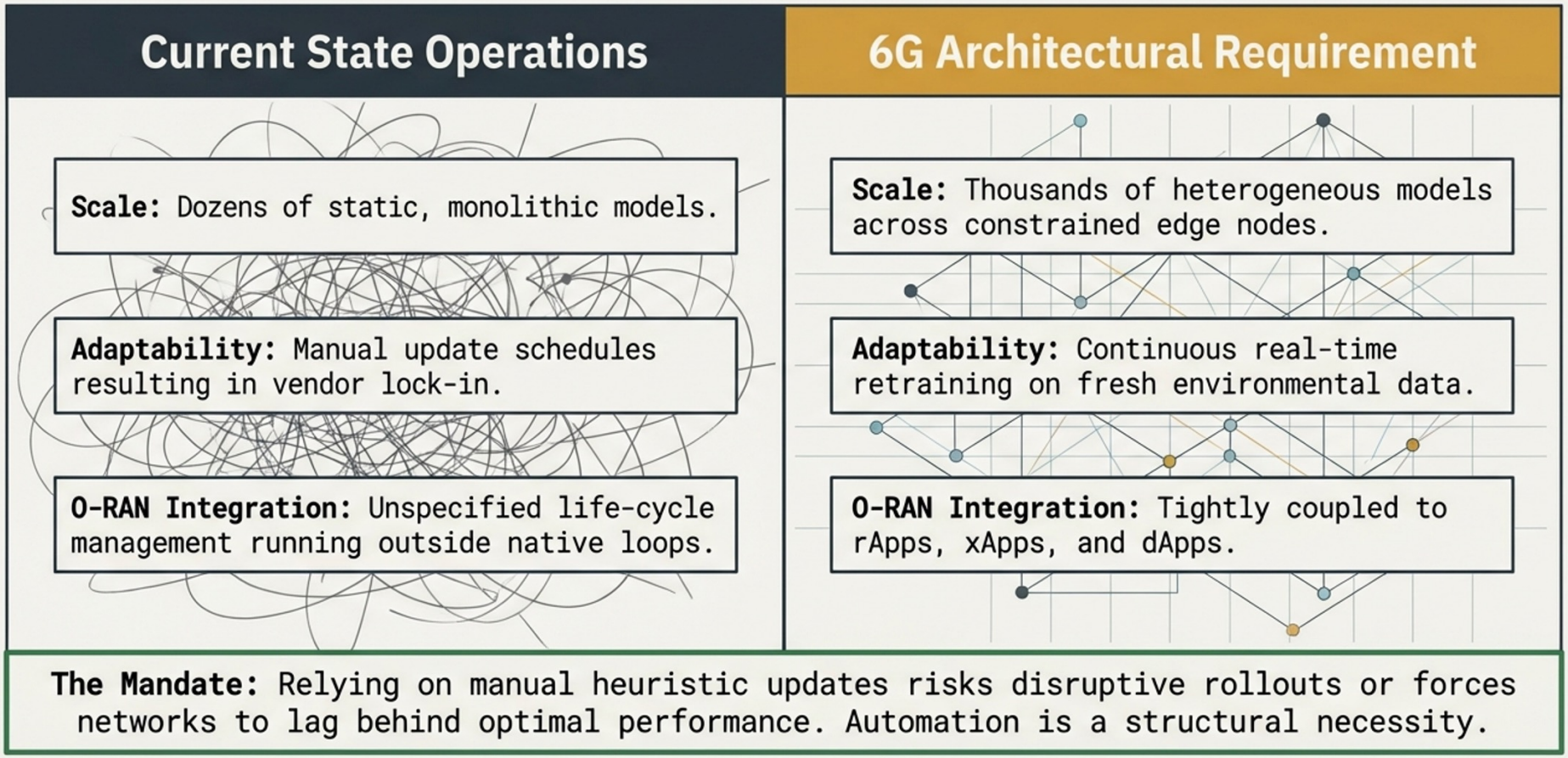
# Scenario C




Through GUI → compare performance of different ML-models in terms of convergence speed, resource utilization, GPU power, ….

# 6G MLOps Pitfall

## Now you found the best model using our Framework. Are we done?



# Why AI-model Update is hard in Telecom?

## Deployment examples

**Example 1**

### Traffic steering xApp

- Learns cell-load imbalance and hands over users **proactively**
- Needs **recalibration** after traffic mix, mobility, or topology changes

**Example 2**

### Energy-saving dApp / PRB slicing policy

- Turns carriers/features on-off or **reslices PRBs** under demand variation
- Needs **versioning** across sites and different gNB hardware

## Dynamically updating AI-Models is difficult

### 1. ML lifecycle complexity

- drift detection and retraining trigger
- hyperparameter search / model selection
- accuracy vs. latency vs. robustness after each new version

### 2. Deployability complexity

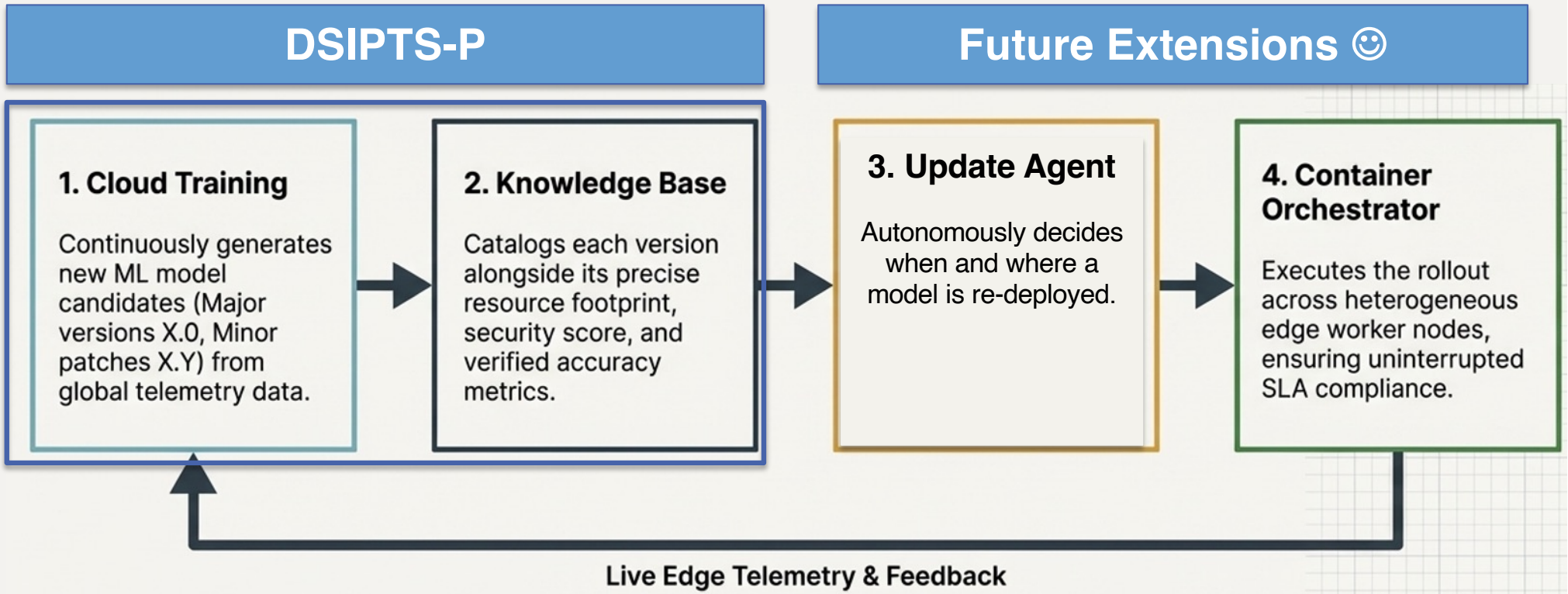
- low-downtime rollout, canary, rollback
- hardware-aware runtime choice (CPU/GPU/NPU, cloud/edge)
- energy-aware placement and inference optimization

### 3. Telecom integration complexity

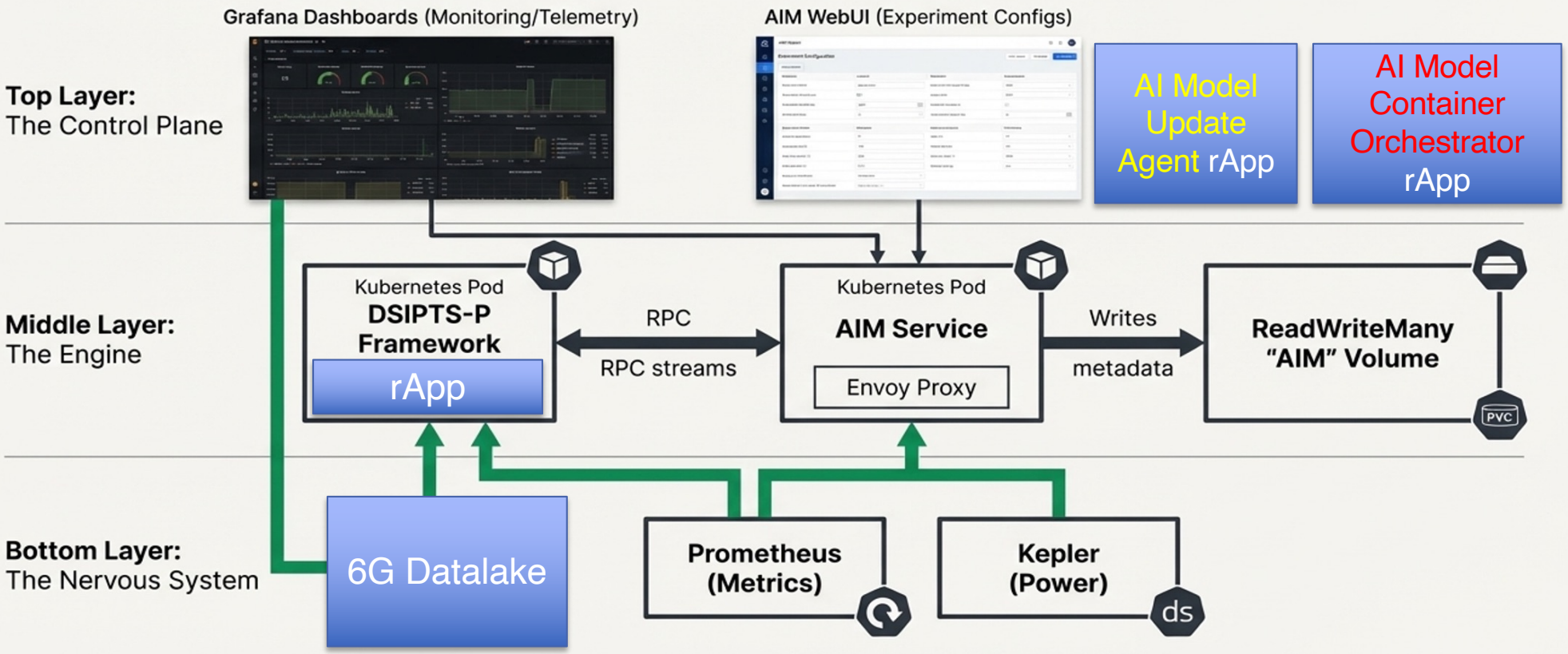
- where should it run: rApp, xApp, or dApp? On which node?
- which telemetry to subscribe to, from which data source / query IDs?
- which API calls close the loop, and what latency / compute budget is tolerated?

**The challenge is not only finding a good or better model - it is updating the right model, in the right place, at the right time with the right interfaces, without breaking the network operation.**

# 6G AI Model Benchmarking as a Service Framework



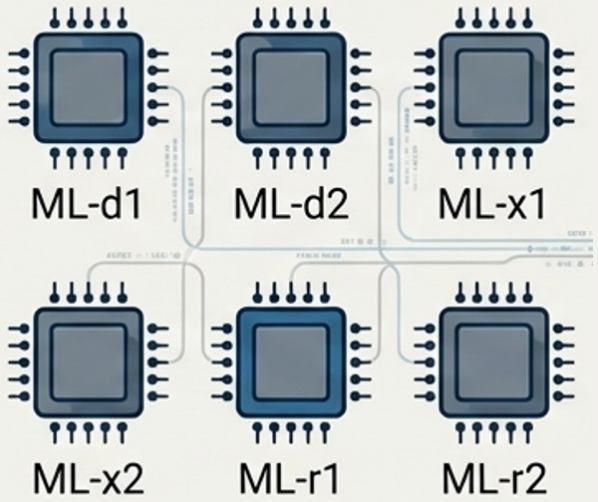
# AI Model Benchmarking Framework Architecture




AI Model Update agent decides when which models need updates
Container Orchestrator optimizes placement of AI model, wires it with 6G Telemetry
Those can be implemented through AI Agents for continuous reasoning

# Example: Model Repository

## The Models




## The Upgrades

- Major Versions:
  - +2% Accuracy | -2% Stability | -7% Service Time
- Minor Versions:
  - +0.1% Accuracy | -0.1% Stability

Update Agent: Decide when and where to update which AI-Apps: (1) Always Update (2) Never Update (3) Random (4) Server Load-based (5) Drift Detection Triggered

# Future Research Directions

**ML / MLOps research**

**Model quality optimization over time**

- drift detection, active retraining
- HPO / NAS / model selection
- compression and inference optimization
- benchmarking frameworks and experiment tracking

**Systems / cloud research**

**Reliable and efficient deployment**

- K8s orchestration, canaries, rollback
- hardware-aware scheduling and compilation
- Multi-KPI aware placement / autoscaling (energy, accuracy, latency)
- observability, fault tolerance, policy control

**Telecom / O-RAN research**

**Network-specific control integration**

- rApp/xApp/dApp placement and functional split
- telemetry subscriptions and data pipelines
- E2/Near-RT/Non-RT control APIs and loop timing
- per-use-case latency, compute, and SLA budgets

Existing solutions usually optimize one space or a pair of spaces
Telecom-grade continuous AI-model updating needs all three at once

# Summary

- Telco AI cloud needs AI Infra, AI Agents, MaaS, Digital Twin
- Finding a good model requires benchmarking at scale → HPC, K8s, AI Infra
- We provide a framework for automating AI model benchmarking and versioning at scale (incl. Split- and Federated Learning)
  - It can also be exposed for customers/users who want to train their own AI Algorithms, not necessarily related to Telco → Stock prices, Solar Power, …
- MLOps principles need to be integrated into 6G architecture for continuously updating to the best AI models
  - MLOps and Telco need to be integrated into coherent E2E framework
  - Can be done by AI Agent connected to dApps for model benchmarking, versioning, automatic deployment orchestration HPC required for massive loads of 1000 models retraining continuously

# Thank You!

- Have Questions? → kassler@ieee.org