Reinforcement learning for particle accelerators

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Jan Kaiser, Chenran Xu

Trends and challenges of frontier accelerators

Denser beams for higher luminosity and brilliance

- Complex beam dynamics
- Complex accelerator design and operation

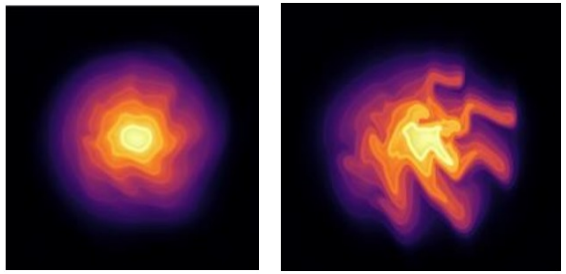


Image: KIT

Larger circular colliders for higher energies

- Orders of magnitude more signals
- Machine protection limits

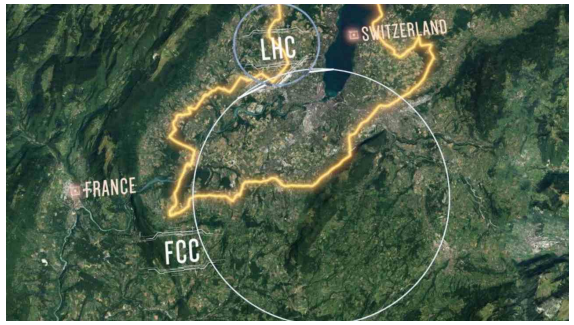


Image: CERN

Compact plasma accelerators with higher gradients

- Tight tolerances
- High-quality beams required

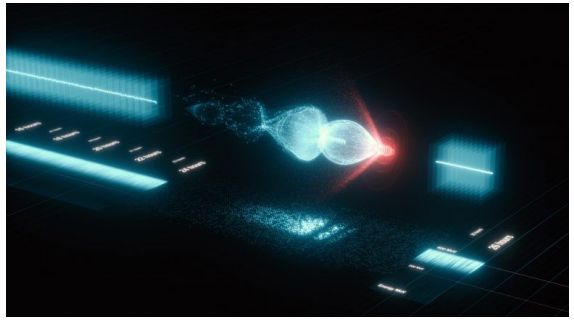
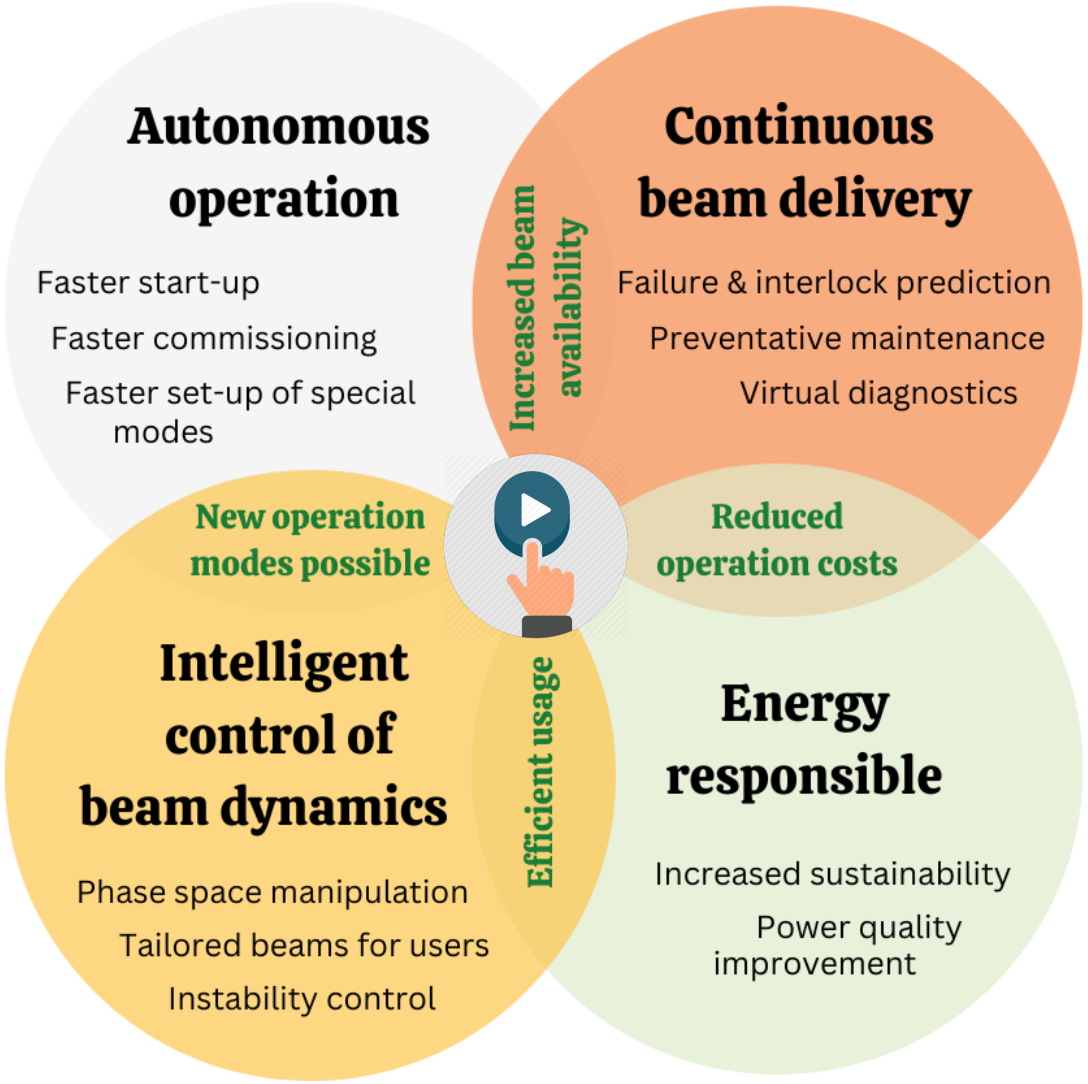


Image: DESY

FLS2023-TH3D3

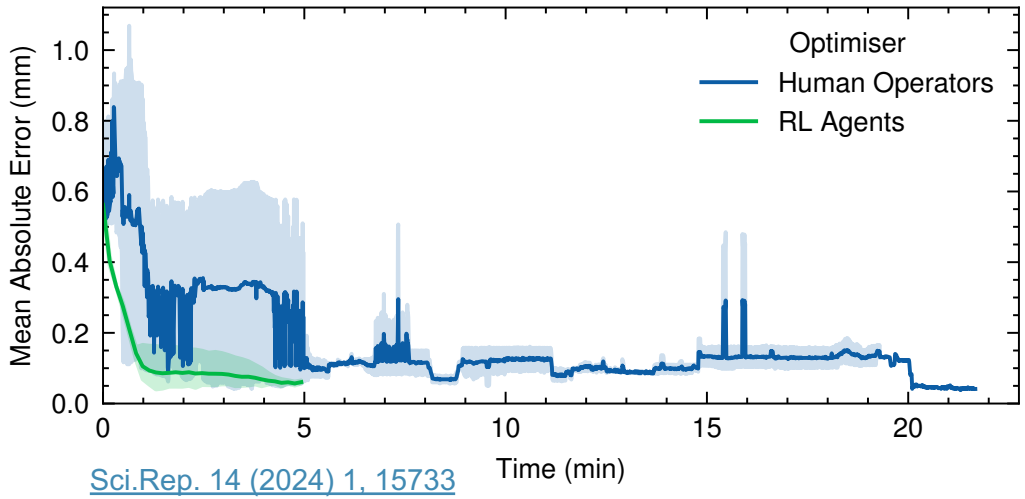
A vision for future accelerators, driven by ML



FLS2023-TH3D3

What is the path to true autonomous accelerators? (with continuous, robust, and safe control)

Maybe reinforcement learning



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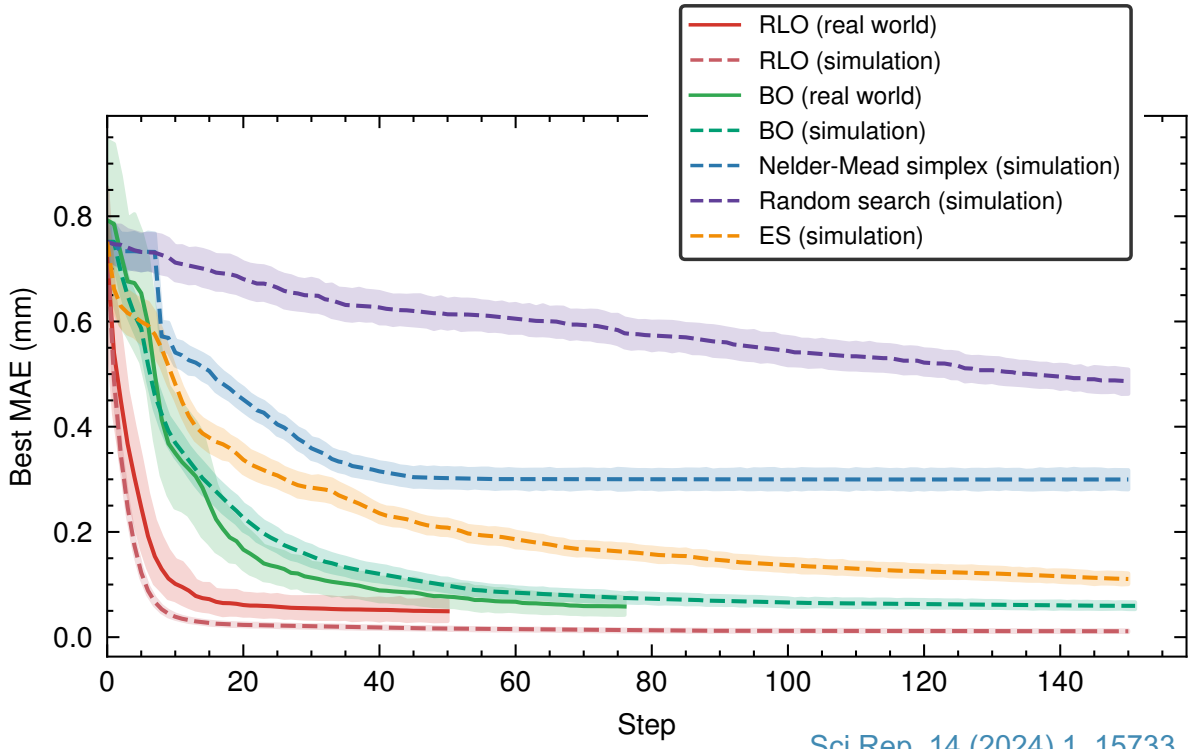
Why RL for particle accelerators?

Reinforcement learning can:

- **Adapt dynamically** to changing environments
- **Scale better** to high-dimensional problems than other methods
- Consider **delayed consequences**
- Perform **closed-loop control in real time**
- **Converge faster** than any other methods after training



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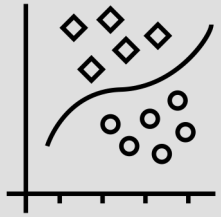
RL is a promising and powerful framework for adaptive, goal-directed behaviour in complex environments

MACHINE LEARNING

SUPERVISED LEARNING

Classification, prediction, forecasting

computer learns by example



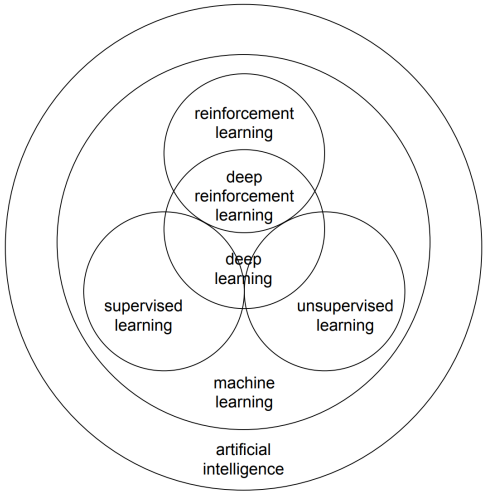
Spam detection
Weather forecasting
Housing prices prediction
Stock market prediction

UNSUPERVISED LEARNING

Segmentation of data

computer learns without prior information about the data

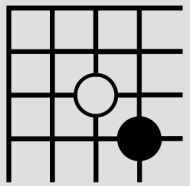
Medical diagnosis
Fraud (anomaly) detection
Market segmentation
Pattern recognition



REINFORCEMENT LEARNING

Real-time decisions

computer learns through trial and error



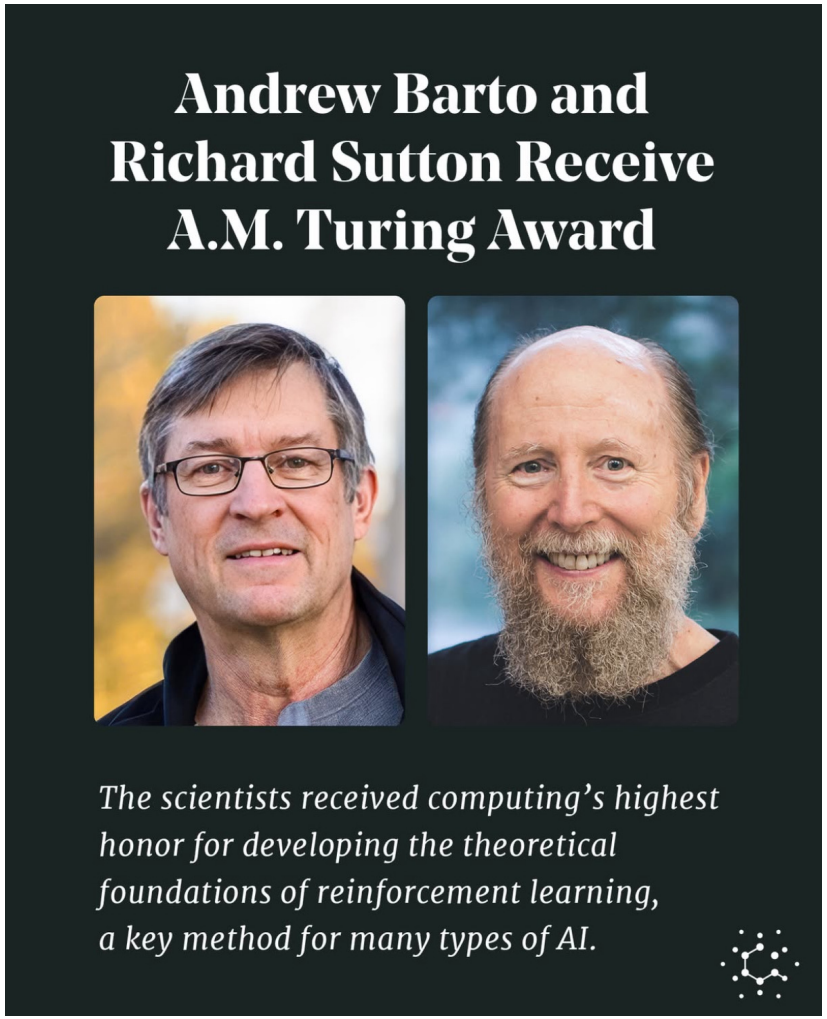
Self-driving cars
Make financial trades
Gaming (AlphaGo)
Robotics manipulation

Reinforcement learning 🧠

More than machine learning

Psychology (classical conditioning)
Neuroscience (reward system)
Economics (game theory)
Mathematics (operations research)
Engineering (optimal control, planning)

Reinforcement learning



Quanta Magazine

What we understand today as RL (established in the 1980s) inherits concepts from:

- **Trial-and-error learning**
  Behavioural basis 🧠
  Learning emerges through repeated interaction, reward feedback, and adaptation

- **Optimal control**
  Mathematical framework 📐
  Markov decision processes (MDPs), Markov property, Bellman equation, partially observable MDPs (POMDPs), value function, policy function, dynamic programming

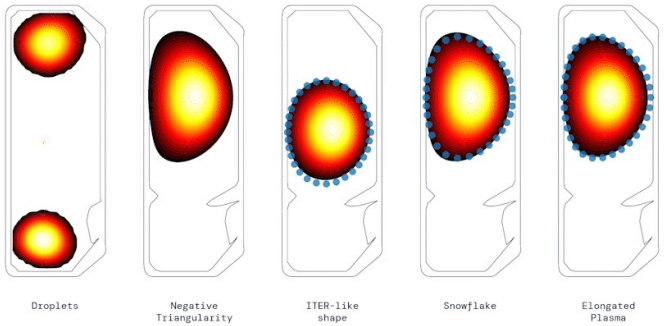
- **Temporal difference learning**
  Adaptability and scalability 🔁
  Enables prediction and learning from partial experiences

So, what can RL do *in practice*? 🧐

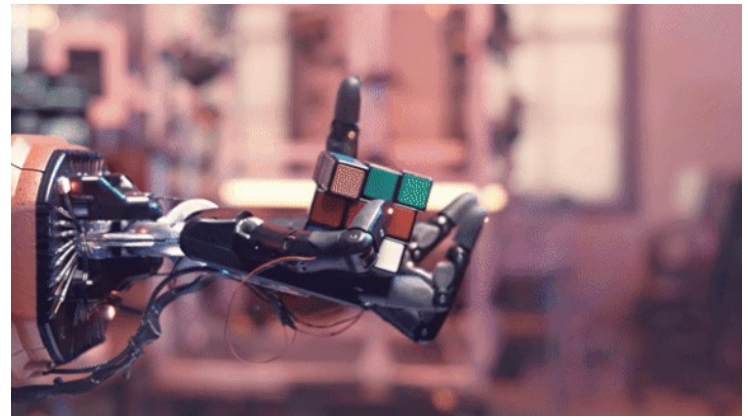
Modern RL = **deep RL**, which allows sequential decision making in continuous and infinite environments thanks to function approximation with deep neural networks.

Control the plasma in a tokamak fusion reactor

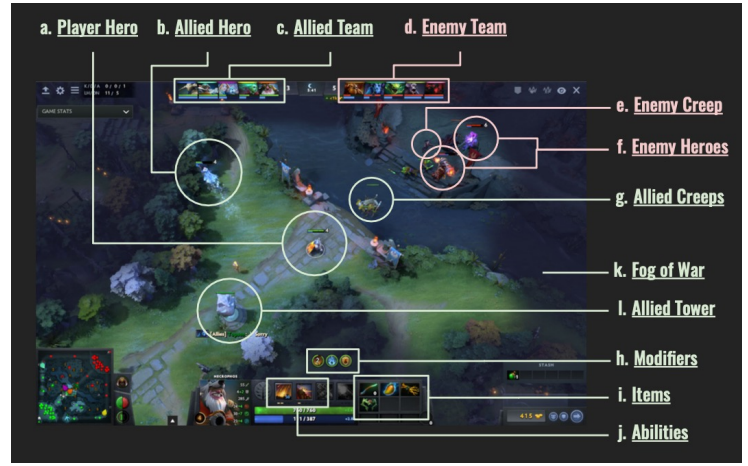
https://arxiv.org/abs/1707.02286



https://www.deepmind.com/publications/playing-atari-with-deep-reinforcement-learning

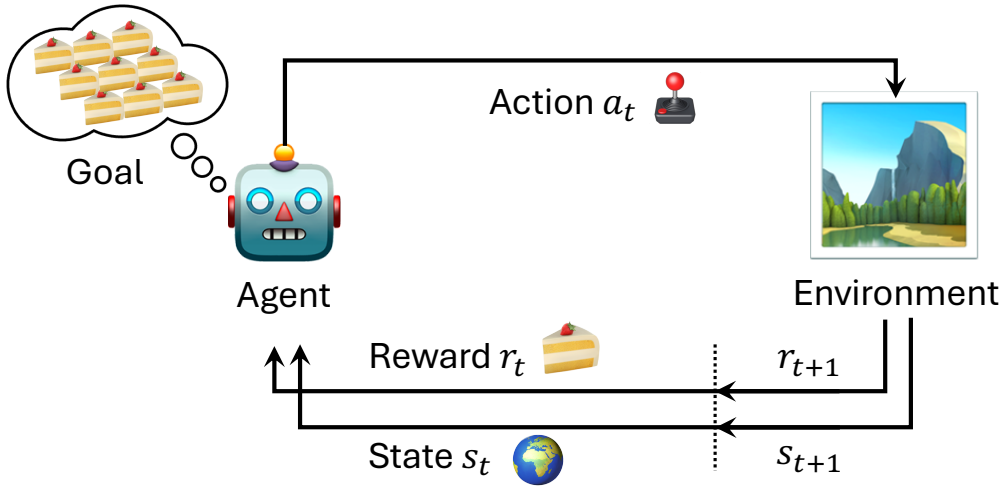


https://openai.com/index/solving-rubiks-cube/

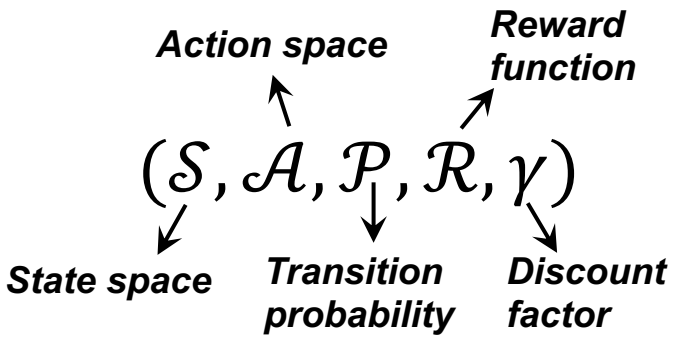


https://openai.com/index/openai-five/

RL in a nutshell



An agent (algorithm) learns through trial-and-error by interacting with a dynamic environment



Stochastic decision making is modelled by Markov decision processes (MDPs), a 5-tuple

Agent

1. Executes **action** a_t ***free-will***
2. Receives **observation** s_t ***perception***
3. Receives scalar **reward** r_t ***motivation***

Reward

Scalar feedback signal r_t that indicates how well the agent is doing at step t

Cumulative reward (return) $G_t(\tau) = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$ $\gamma \in [0, 1)$

Goal

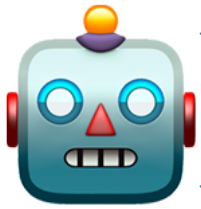
Maximisation of cumulative reward G_t through selected actions

Simple concept from which intelligent behaviour emerges

"Reward is enough" by Silver et al. (2021)

RL in a nutshell

How does the agent "learn"?



What behaviours perform well in this environment?

Policy: agent's behaviour function (how it picks its actions)

$$\pi : \mathcal{S} \rightarrow \mathcal{A}$$

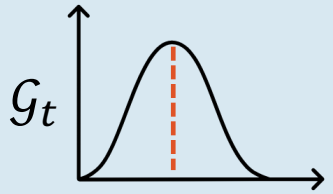
$$\pi(s) = a$$

$$\pi(a|s) = \mathbb{P}[a|s]$$

Estimate the utility of taking actions in particular states of the environment (evaluation of the policy)

Value function: how good each state and/or action are

$\mathcal{V}^{\pi}$= state-value function $\quad$ $\mathcal{Q}^{\pi}$ = action-value function



$\mathcal{V}^{\pi}, \mathcal{Q}^{\pi}$ are an estimation of where the return distribution is centered

- **Prediction**: evaluate the future given a policy
- **Control**: optimise the future (find the best policy)

$$\boldsymbol{\pi^* = \arg\max_{\pi} \mathbb{E}_{\pi}[\mathcal{G}_t]}$$

where π^* is the optimal policy

RL in a nutshell How does the agent "learn"?

At every time step t:

1. **The agent is in state s_t**
2. **The agent selects an action $a_t \sim \pi(a|s)$**

   This action is chosen based on the agent's current policy π, which may prioritise actions that maximise expected future reward, e.g.:

$$a_t = \arg\max_a Q^\pi(s_t, a)$$

3. **The environment returns:**
   - Next state s_{t+1}
   - Reward r_t
4. **The agent learns from the experience (s_t, a_t, r_t, s_{t+1})**

   Value-based methods: update value estimates (assess value of action)

   Policy-based methods: directly improve the policy (how to act)

Types of learning

Online: data is actively collected during training

Offline: learns from a fixed dataset (supervised learning)

Simulation-based: training in a virtual or simulated environment

Experiment-based: direct interaction with a real-world system

On-policy: policy is updated from data collected by the current version of the policy

Off-policy: can learn from data generated by a different policy

Main challenges of RL deployment

Policy and value functions are approximated by deep neural networks (DNNs)

$$\max_{\theta} J(\pi_\theta) = \max_{\theta} \mathbb{E}_{\pi_\theta}[G_t] \qquad \theta \leftarrow \theta + \alpha \nabla J(\pi_\theta)|_\theta$$

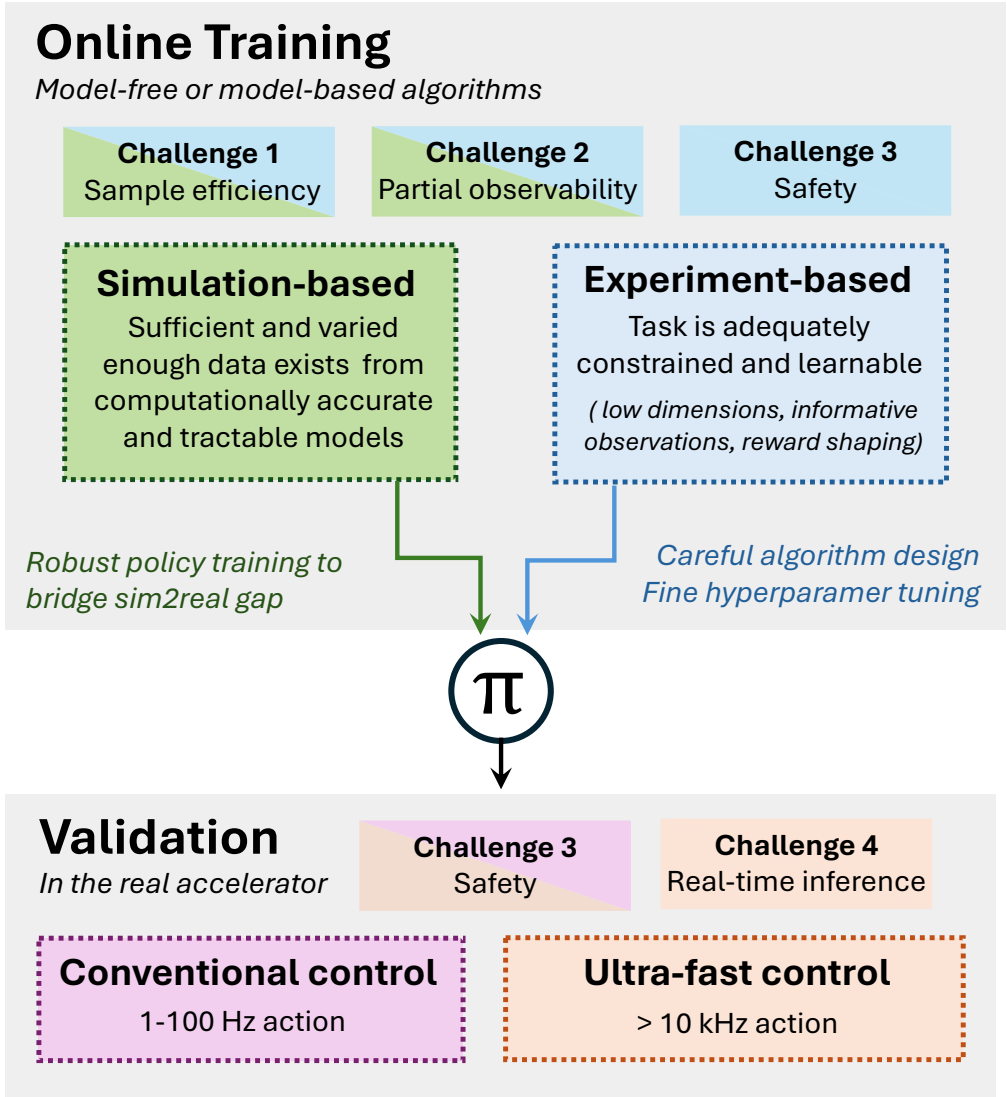
Generalisation capabilities

→ quantity and quality of data

No real **convergence** guarantees

Training instability due to:

- Bootstrapped value targets
- Function approximation bias (net. architecture, weight initialization, training dynamics)
- Hyperparameter sensitivity (high variance in performance across random seeds)



Challenge 1: sample efficiency

Sample efficiency ↗
Training cost ↘

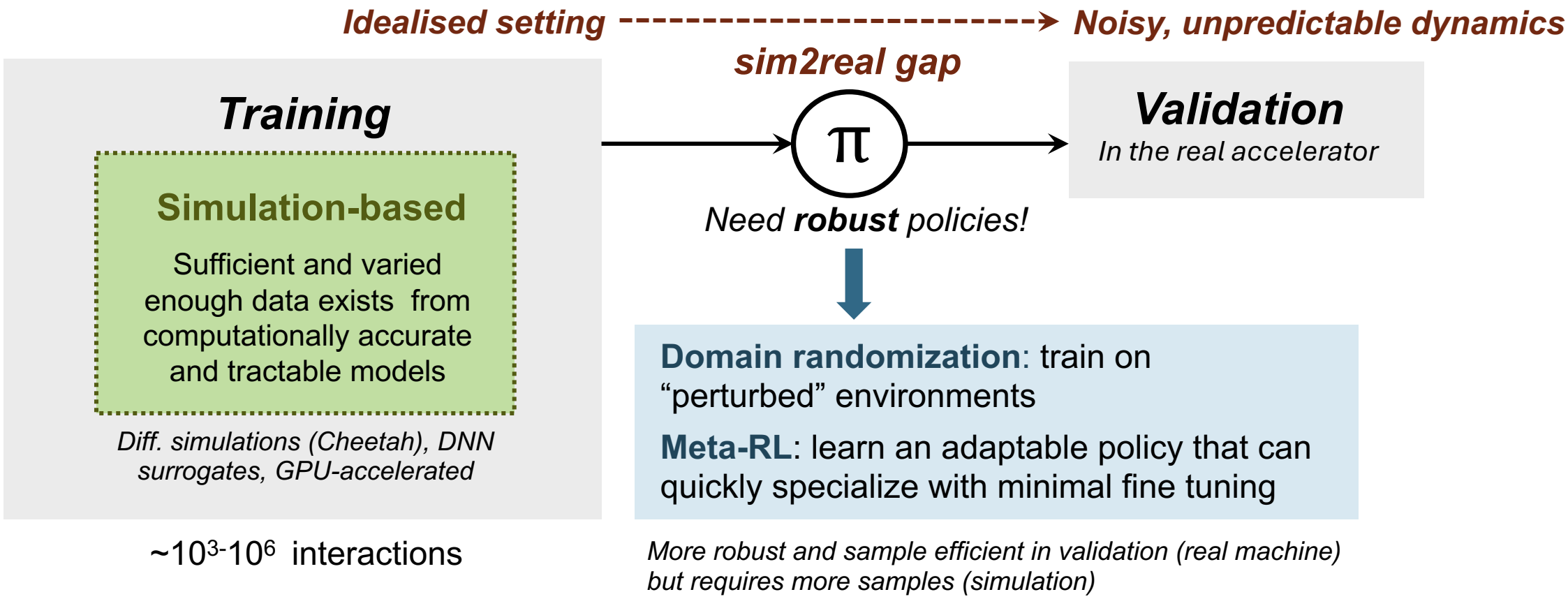
Sample efficiency: number of interactions with the environment required to achieve a certain level of performance during the decision-making process

	✅	❌
Model-free, on-policy *Policy gradient: REINFORCE* *Actor-critic: PPO, A2C*	▪ *Simple implementation* ▪ *Good for continuous action*	▪ *Poor sample efficiency* ▪ *Large variance if unclipped*
Model-free, off-policy, value based *DQN*	▪ *Sample efficient* ▪ *Efficient in discrete envs*	▪ *Unstable (function appr.)* ▪ *Limited to discrete or low-dimensions*
Model-free, off-policy, actor-critic *DDPG, TD3, SAC*	▪ *Sample efficient* ▪ *Good for continuous action* ▪ *Stable*	▪ *Hard to tune* ▪ *Hyperparameter sensitivity* ▪ *Overestimation bias*
Model-based RL	*Very high sample efficiency*	*Model is hard to train, complex to tune, brittle & sensitive*

?

Challenge 1: sample efficiency

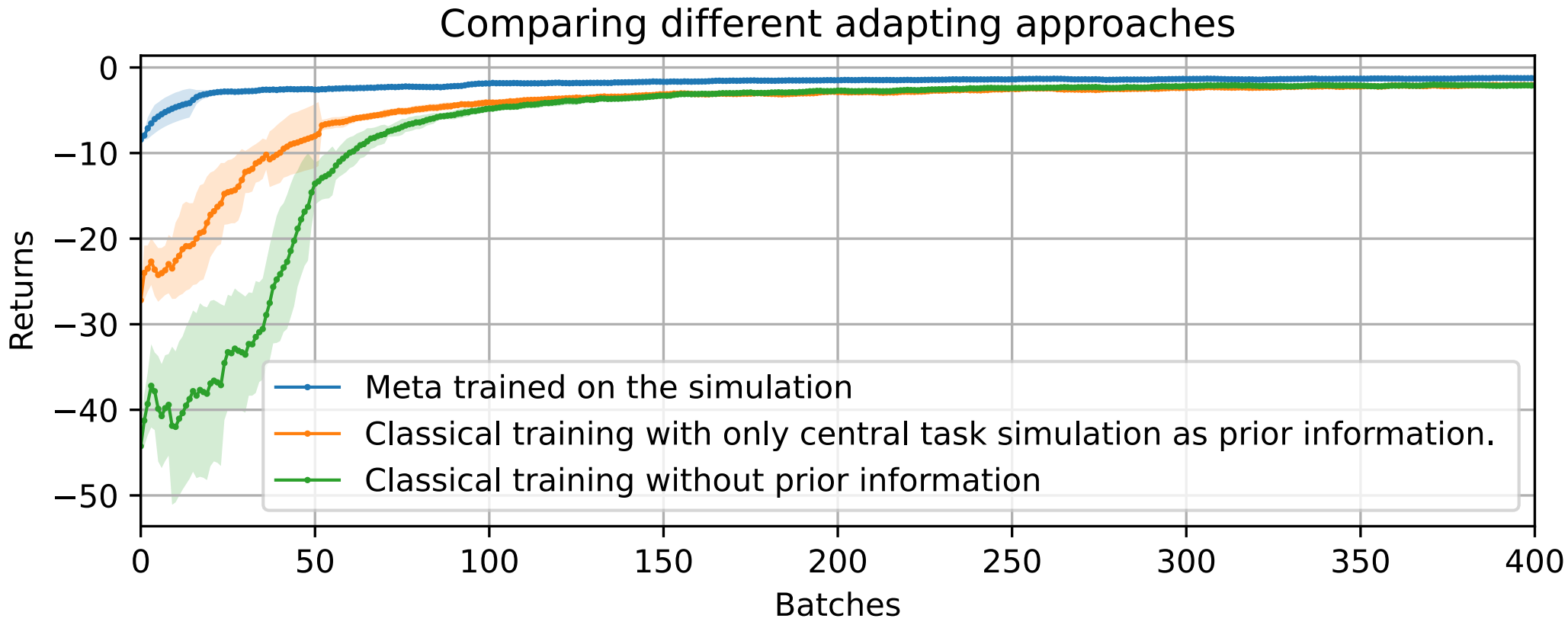
How does this play in practice?



Challenge 1: sample efficiency

How does this play in practice?

Beam steering task at AWAKE beamline
10 H dipoles, 10 V dipoles, 10 BPMs → ideal trajectory



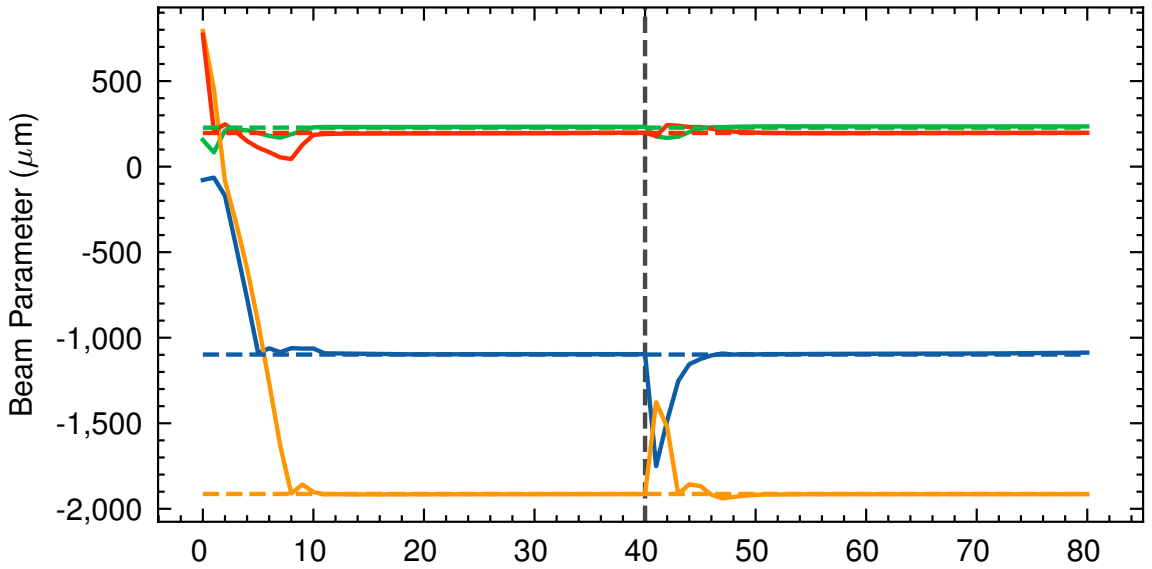
Towards few-shot reinforcement learning in particle accelerator control, *JACoW* IPAC2024 (2024) TUPS60

Robustness & sample efficiency

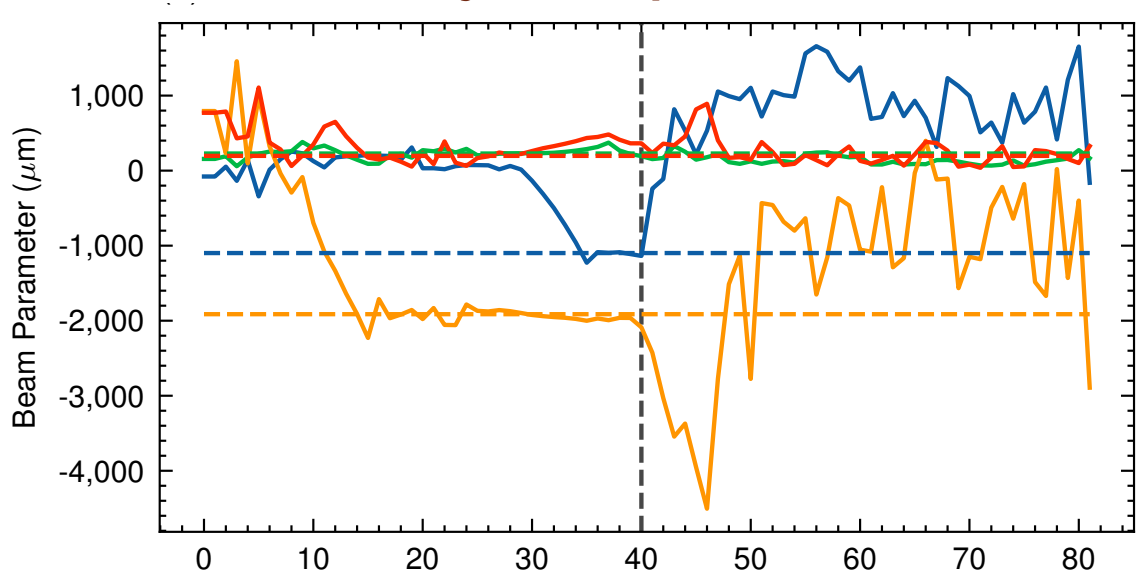
How does this play in practice?

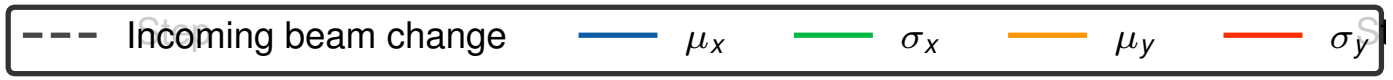
Beam steering and focusing task at ARES linear accelerator
3 quadrupoles, 2 correctors → target beam size and position on a screen
Recovery from sudden change in incoming beam

Reinforcement learning (with DR)



Bayesian optimisation





Reinforcement learning-trained optimisers and Bayesian optimisation for online particle accelerator tuning, *Sci.Rep.* 14 (2024) 1, 15733

Challenge 1: sample efficiency

How does this play in practice?

Training

Experiment-based

Task is adequately constrained and learnable

(low dimensions, informative observations, reward shaping)

Very rare! Only a handful of cases

FERMI, AWAKE, Linac4, KARA

- ~10^3 real-world interactions required for training
- Low-dimensional action and observation spaces
- Dense reward
- Very sensitive to hyperparameter choices
- Hard to find dedicated beamtime
- Safety concerns

"Basic reinforcement learning techniques to control the intensity of a seeded free-electron laser", Electronics, vol. 9, no. 5, 2020
"Model-free and Bayesian ensembling model-based deep reinforcement learning for particle accelerator control demonstrated on the FERMI FEL", arXiv:2012.09737, 2022.
"Sample-efficient reinforcement learning for CERN accelerator control", Phys. Rev. Accel. Beams, vol. 23, no. 12, p. 124 801, 2020.
"Preliminary results on the reinforcement learning-based control of the microbunching instability" IPAC2024-TUPS61

Challenge 2: partial observability

Fully observable environments

The agent directly observes the true state of the environment, which includes everything relevant

state of the agent (belief)

$$\mathcal{O}_t = \mathcal{S}_t^a = \mathcal{S}_t^e$$

observation

true state of the environment

Partially observable environments

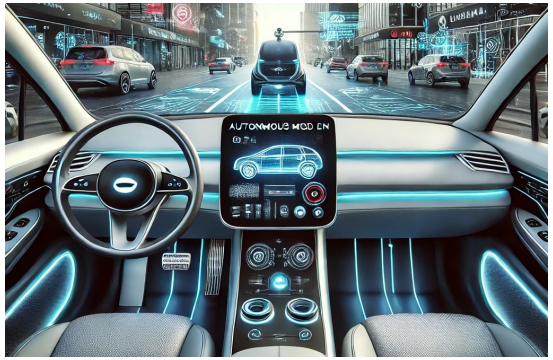
The agent receives partial observations and must create its own state representation

$$\mathcal{O}_t \neq \mathcal{S}_t^a \neq \mathcal{S}_t^e$$

partial, noisy, filtered

Stacking recent observations to approximate motion

Example: autonomous driving



$\mathcal{S}_t^e$: we know all cars exact positions, road friction, weather conditions, etc.

$\mathcal{O}_t$: pixels from cameras, GPS signal, lidar?
what the agent can “sense”

$\mathcal{S}_t^a$: estimated positions and speeds based on past observations
what the agent ”believes” the environment is

Challenge 2: partial observability

Ideal setting

State fully observable

- MDP (finite, discrete)
- Model known
- Value function exact
- Optimal policy computable

We can completely solve the control problem and find the **optimal policy π^***

vs

Real world

State partially observable

- POMDP (infinite, continuous)
- Model unknown or learned
- Value function approximated
- Policy approximated

We just want **good-enough policies** that are robust, generalizable, sample-efficient, and safe

Challenge 2: partial observability

Ideal setting

State fully observable

- MDP (finite, discrete)
- Model known
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vs

Real world

State partially observable

- POMDP (infinite, continuous)
- Model unknown or learned
- Value function approximated
- Policy approximated

Classical dynamic programming

- Bellman equations + greedy action.
- Policy evaluation, policy improvement, value iteration.
- Non-tractable for large state and action spaces.

Modern RL (deep RL)

- One sample does not return the true expected value (noisy reward).
- The same action does not always lead to the same next state.
- We don't know the true state (only observed).

Challenge 2: partial observability

Ideal setting

State fully observable

- MDP (finite, discrete)
- Model known
- Value function exact
- Optimal policy computable

vs

Real world

State partially observable

- POMDP (infinite, continuous)
- Model unknown or learned
- Value function approximated
- Policy approximated

Partial observability will always be a challenge in particle accelerator deployment, but can be mitigated with:

- Frequent and informative observations
- Memory (e.g., recurrent architectures) or a learned model
- Well-structured state representation
- Low-frequency decision making

Challenge 3: safety

Exploration vs exploitation dilemma:

We want to learn the **optimal behaviour** and for that we need to behave non-optimally to **explore** the state-action space.

→ ***Hard safety*** cannot be ensured in high-dimensional continuous state spaces!

Hard safety in RL, especially during exploration, is an active area of research

Soft safety can be implemented:

- Shielding
- Reward shaping
- Uncertainty-aware planning

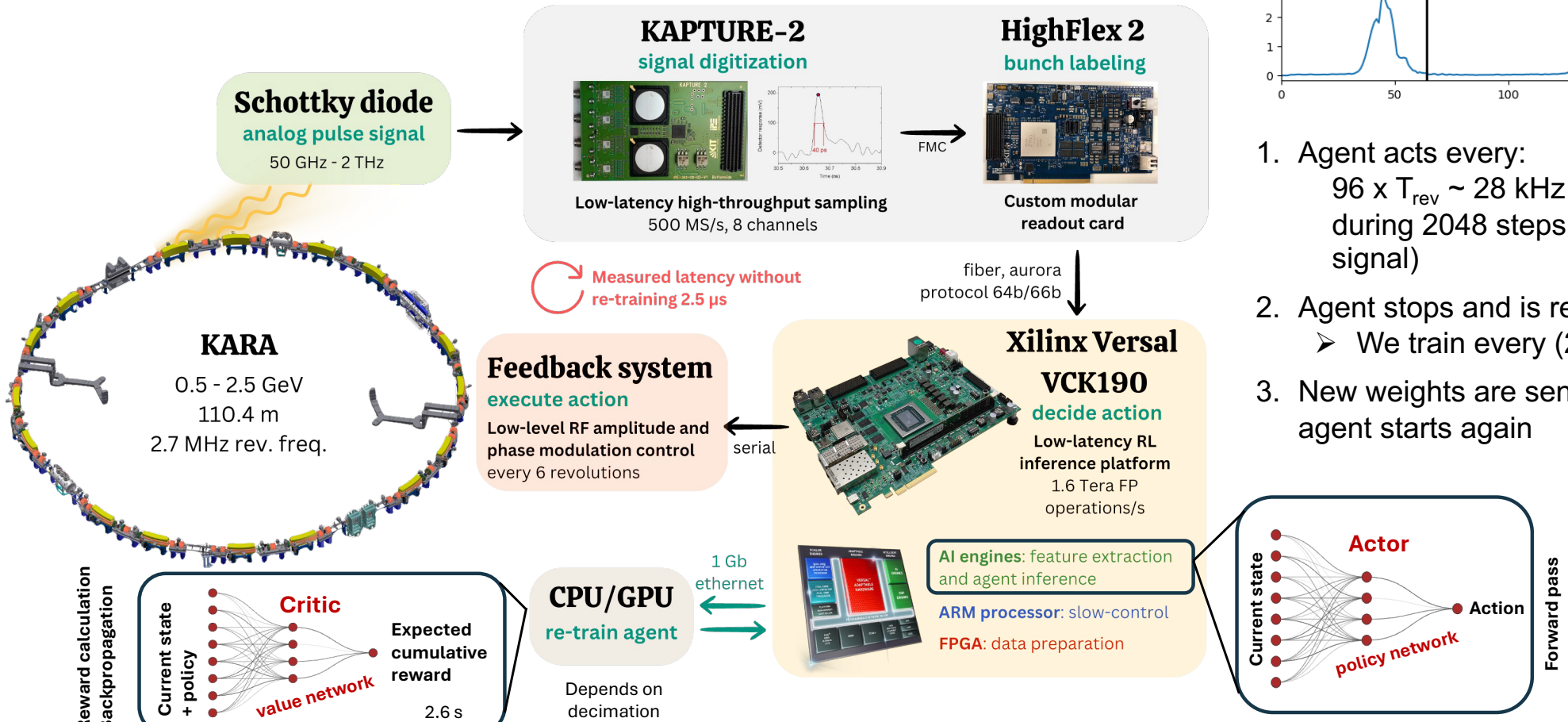
Trade-offs between safety, optimality, and sample efficiency.

My recommendation: do experiment-based training only in safe machines (low energy, electrons) or have an excellent interlock system.

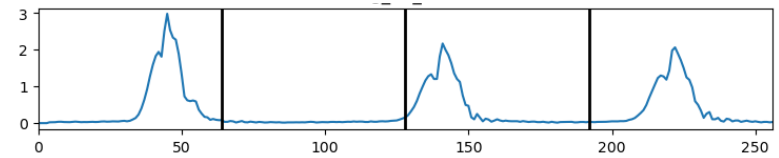
Challenge 4: real-time inference

Control of the microbunching instability

- Revolution frequency: 2.7 MHz (T_{rev} = 370 ns)
- Synchrotron frequency: 7-9 kHz (T_{sync} = 110-143 μs)
- → 300-400 T_{rev} ~ T_{sync}



Circular buffer of last 64 THz signal samples (decimated)

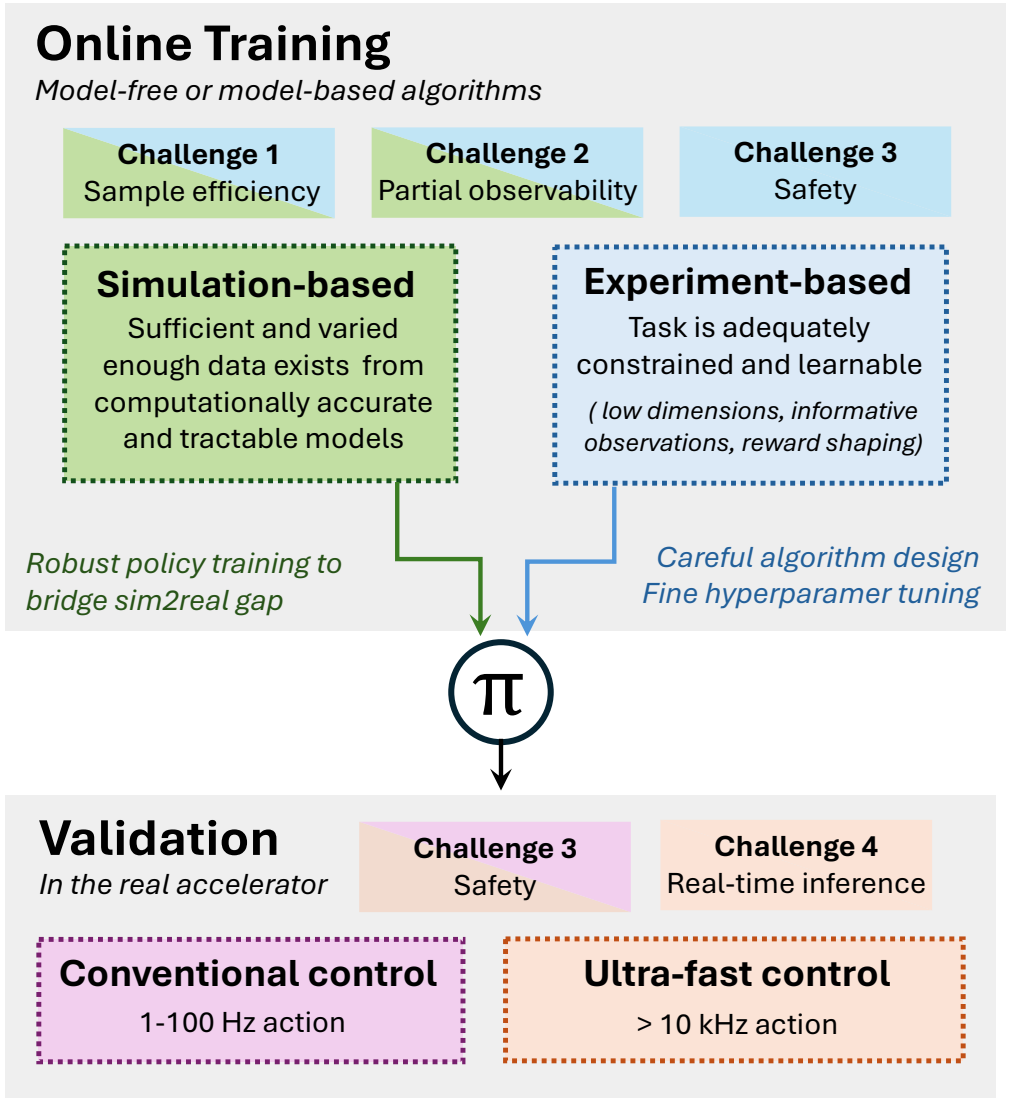


1. Agent acts every:
   96 x T_{rev} ~ 28 kHz ~ 0.25 x T_{sync} ~ 36 μs during 2048 steps (samples of decimated signal)
2. Agent stops and is re-trained in a CPU (~2.6 s)
   - ➢ We train every (2048 x 96) T_{rev} = 509 T_{sync}
3. New weights are sent to Versal board and agent starts again

Doctoral thesis L. Scomparin

Main challenges of RL deployment

In particle accelerators



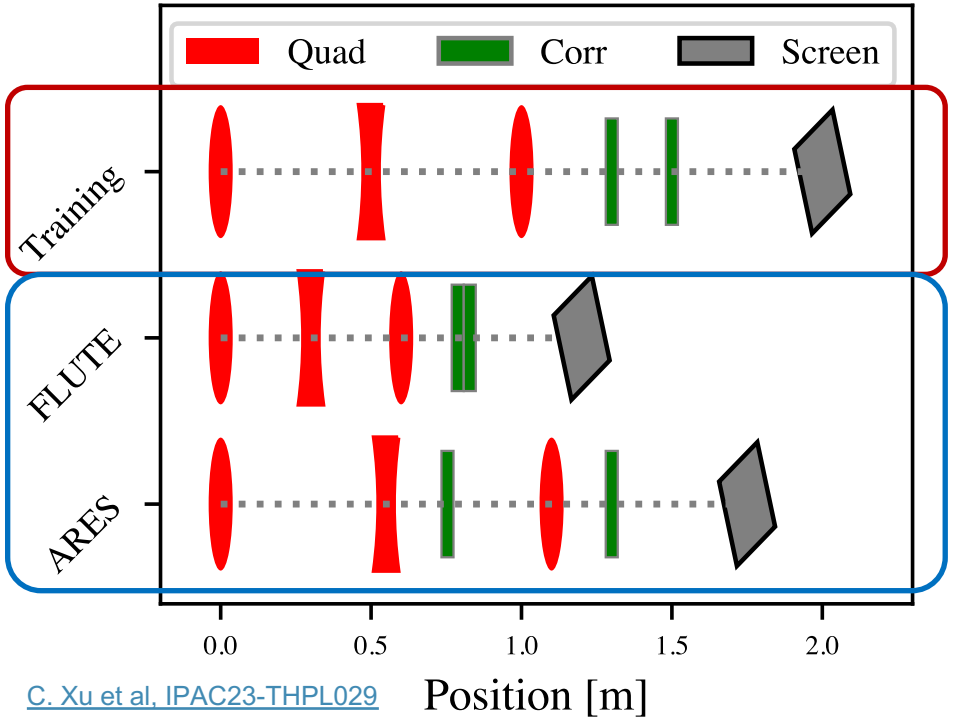
RL is a promising and powerful framework for adaptive, goal-directed behaviour in complex environments…

…that requires careful design!

Can it be an intelligent accelerator co-pilot? 🤖

Future directions

Lattice-agnostic RL



C. Xu et al, IPAC23-THPL029

Used during training, with randomized positions but following order (=DR)

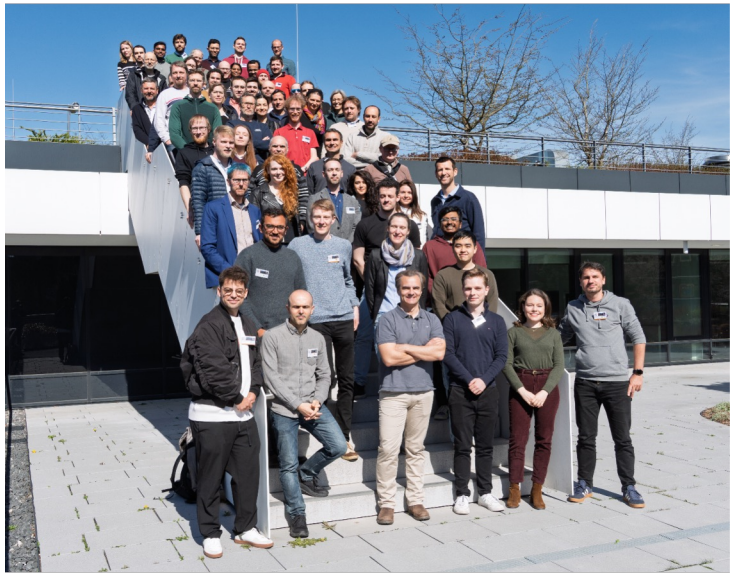
Test lattices
Re-training with new lattice only 2% of the original training samples

Multi agent RL, hierarchical RL, explainable RL, more model-based RL

The Reinforcement Learning for Autonomous Accelerators Collaboration

Join our Discord

Yearly targeted workshops



RL4AA'25 at DESY

Github: https://github.com/RL4AA

Discord: https://discord.gg/rudtJaeW

Website: https://rl4aa.github.io/

Youtube: https://www.youtube.com/@RL4AACollaboration

Paper: DOI:10.18429/JACoW-IPAC2024-TUPS62

Annika Eichler, Christian Contreras, Christian Hespe, Simon Hirlaender, Jan Kaiser, Sabrina Pochaba, Borja Rodriguez Mateos, Andrea Santamaria Garcia, Chenran Xu

Next year RL4AA'26 workshop:

University of Liverpool (25th – 27th April 2026)

Thank you for your attention!

What questions do you have for me?

A more detailed talk: https://doi.org/10.5281/zenodo.12649046

RL resources:

- Sutton & Barto book
- Reinforcement learning lectures by David Silver
- https://spinningup.openai.com/en/latest/

Some of our research:

- https://doi.org/10.1038/s41598-024-66263-y
- https://doi.org/10.1103/PhysRevAccelBeams.27.054601
- https://arxiv.org/abs/2409.16177
- https://doi.org/10.1007/978-3-031-65993-5_21

Get the paper

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