Quantum Reinforcement Learning for Particle Beam Steering

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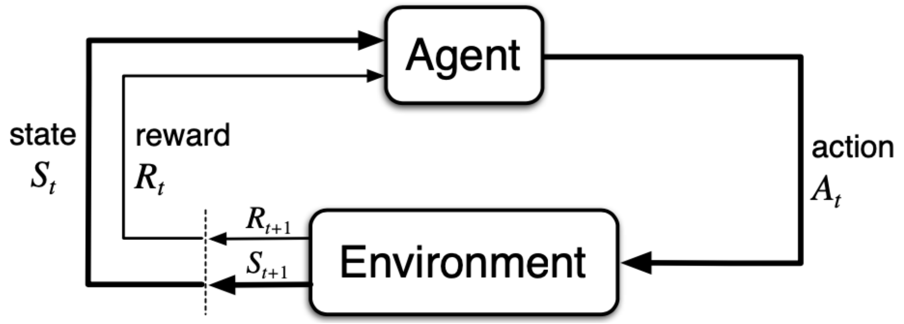
Introduction

Reinforcement learning (RL) in a nutshell



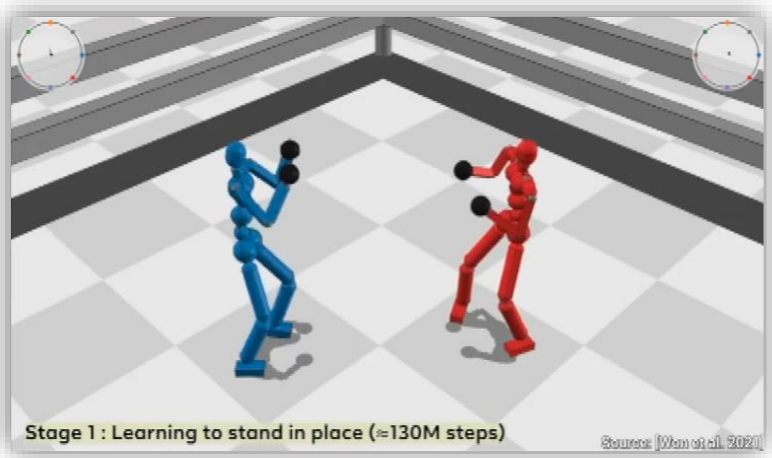
RL book: Sutton & Barto

Agent interacts with environment

- **Receives reward after every action**
- Learns through **trial-and-error**
- **Training sample:** $(s_t, a_t, r_t, s_{t+1}, d_t)$

Decision making

- Agent follows **policy π**: $S \to A$
- **Goal:** find optimal policy π^*
- **Optimal ⇔ maximizing return:** $G_t = \sum_k \gamma^k R_{t+k}$



https://www.youtube.com/watch?v=SsJ_AusntiU
https://www.youtube.com/watch?v=Lu56xVlZ40M
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Expected return can be estimated through ***value function $Q(s, a)$***

- Helps answering: **"Best action to take in given state?"**
- Not a priori known, but **can be learned iteratively**
- **Q-learning:** learn $Q(s, a)$ using **function approximator**
  - **DQN:** Deep Q-learning *(feed-forward neural network)*
  - **FERL:** Free energy based RL *(quantum Boltzmann machine)*

Introduction

FERL motivation

- **Free energy based RL**
  - Efficient for **high-dimensional spaces**
  - Q-function estimate: **free energy of coupled spin system**
  - **Spin system ⇔ quantum Boltzmann machine** (QBM)
- **Higher sample efficiency compared to classical deep Q-learning**
- Limiting here: **discrete state and action spaces**

Free energy-based reinforcement learning using a quantum processor

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Recent theoretical and experimental results suggest the possibility of using current and near-future quantum hardware in challenging sampling tasks. In this paper, we introduce free energy-based reinforcement learning (FERL) as an application of quantum hardware. We propose a method for processing a quantum annealer's measured qubit spin configurations in approximating the free energy of a quantum Boltzmann machine (QBM). We then apply this method to perform reinforcement learning on the grid-world problem using the D-Wave 2000Q quantum annealer. The experimental results show that our technique is a promising method for harnessing the power of quantum sampling in reinforcement learning tasks.

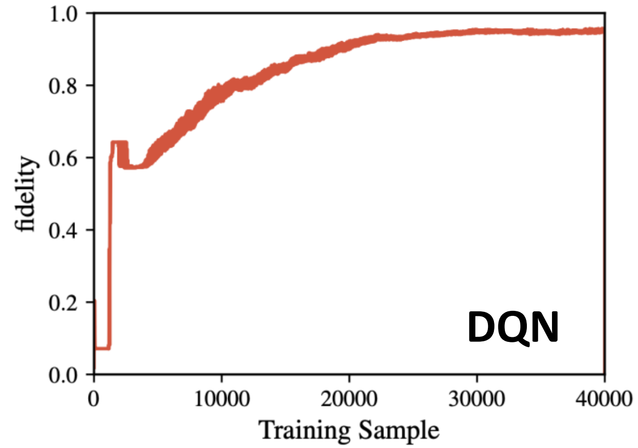
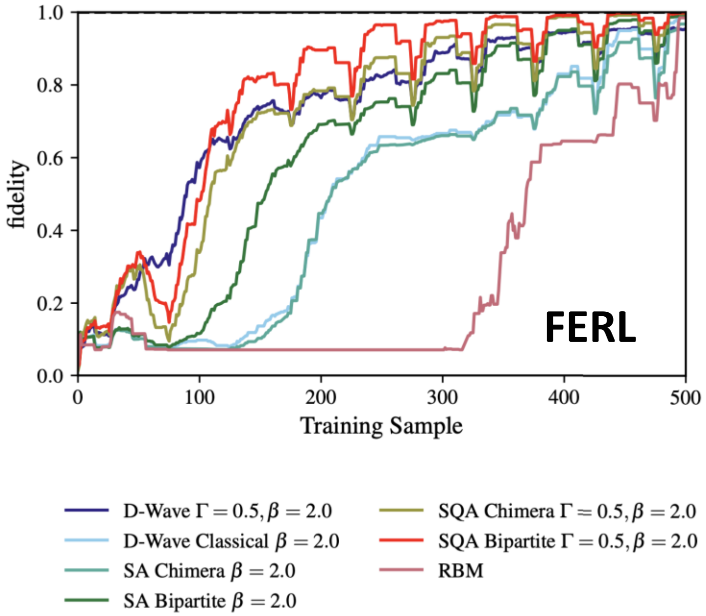


FIG. 4: The learning curve of a deep Q-network (DQN) with two hidden layers, each with eight hidden nodes, for the grid-world problem instance as shown in Fig. IV.



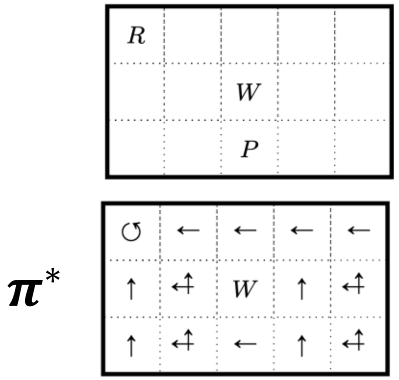


FIG. 3: (top) A 3×5 grid-world problem instance with one reward, one wall, and one penalty. (bottom) An optimal policy for this problem instance is a selection of directional arrows indicating movement directions.

https://arxiv.org/pdf/1706.00074.pdf

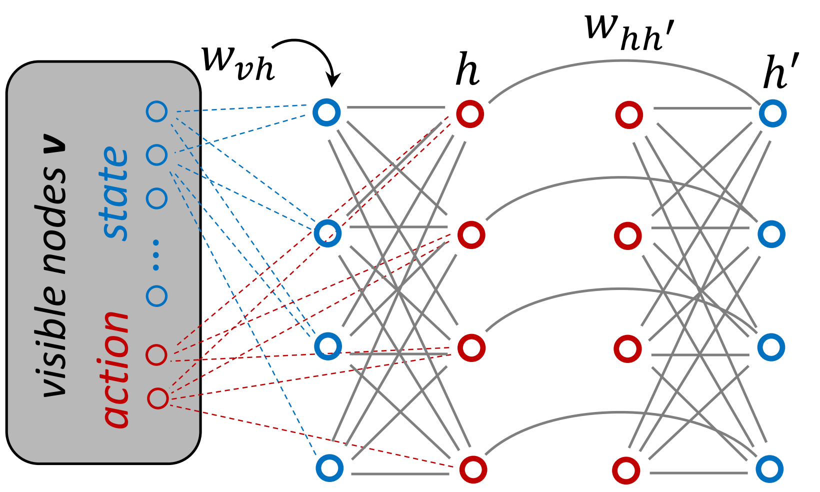
Introduction

QBM vs. DQN

FERL: QBM

- **Network of coupled, stochastic, binary units** *(e.g. qubits in spin up / down states)*
- $\boldsymbol{Q(s,a)}$ ≈ **negative free energy** of coupled spin system
- **Sampling ground-state** spin configuration using (simulated) **quantum annealing**
- **Implicit**

QBM

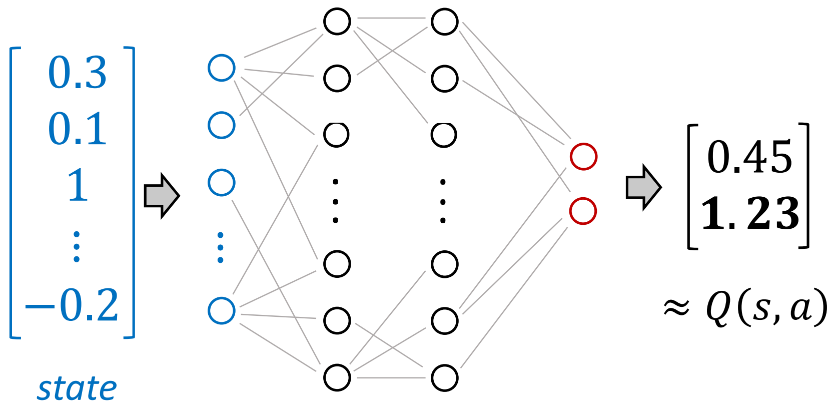


$$Q(s,a) \approx -F(\boldsymbol{v}) = -\langle H_{\boldsymbol{v}}^{\text{eff}} \rangle - \frac{1}{\beta}\sum_c \mathbb{P}(c|\boldsymbol{v}) \log \mathbb{P}(c|\boldsymbol{v})$$

Classical Q-learning: DQN

- **Feed-forward, dense neural network**
- **Explicit**

DQN



Project overview

Objectives

- **Implement FERL** using **simulated quantum annealing** and am **actual quantum annealer** (D-Wave)
- **Extend to continous state-action spaces** for real-world applications: **quantum actor-critic**
- **Compare quantum approach to classical RL** in terms of
  1) **Training efficiency** – *"# steps required to train agent"*
  2) **Descriptive power of QBM** – *"# weights needed"*

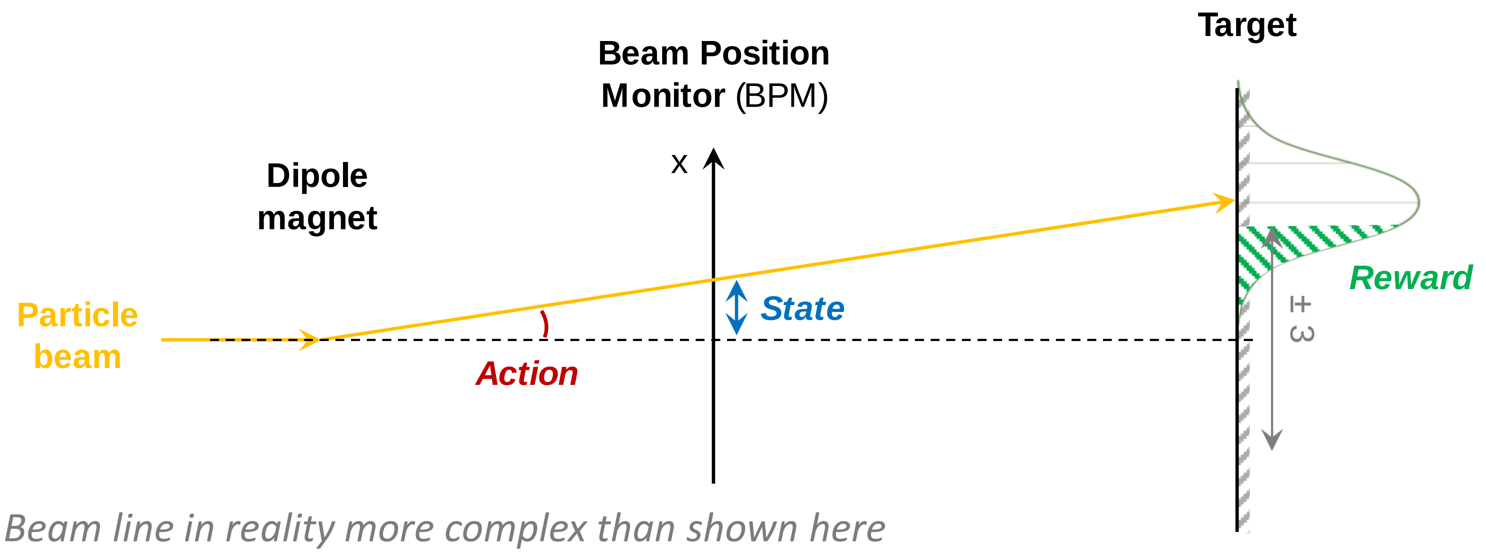
Use case I: Q-learning on 1D beam steering model *(simulated environment)*

Use case II: quantum actor-critic on 10D AWAKE beam line *(simulated and real environment)*

Use case I: Q-learning on 1D beam steering

Environment

- **OpenAI gym template**
- **Action:** deflection angle *(Discrete)*
- **State:** beam position *(continous)*
- **Reward:** integrated beam intensity on target

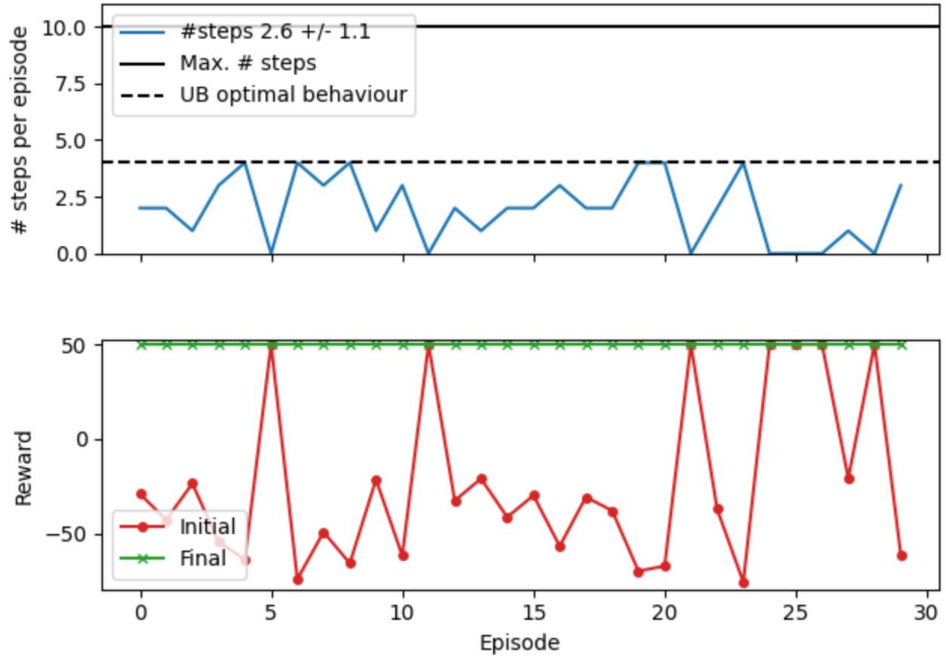


Beam line in reality more complex than shown here

Use case I: Q-learning on 1D beam steering

First successes with simulator and D-Wave quantum annealer

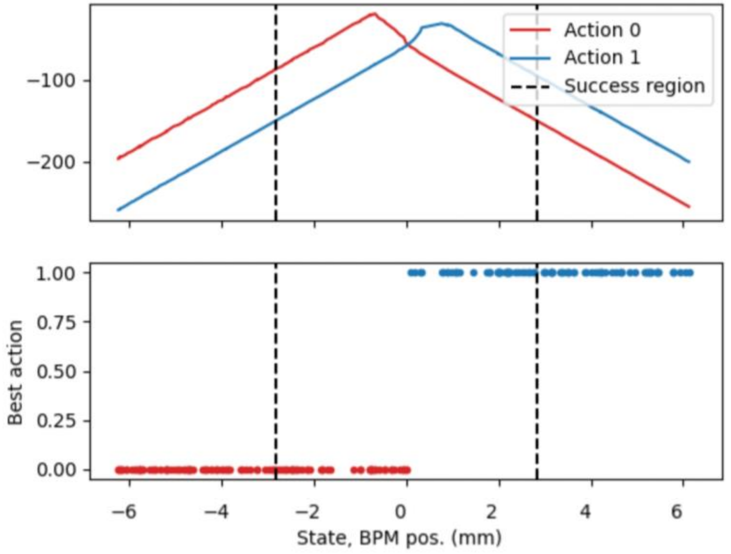
D-Wave training *and* evaluation



- **First success on D-Wave 2000Q: FERL works!**
- **Training** on hardware and with simulator **equally efficient**
- **Using same hyperparameters:** very helpful to optimize with simulator and then run on real hardware

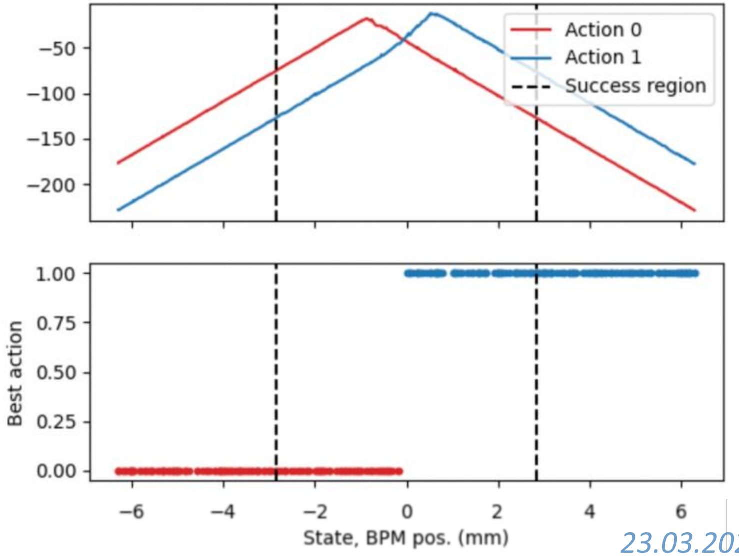
Trained with simulator

120 steps, batch size: 10



Trained on D-Wave quantum annealer

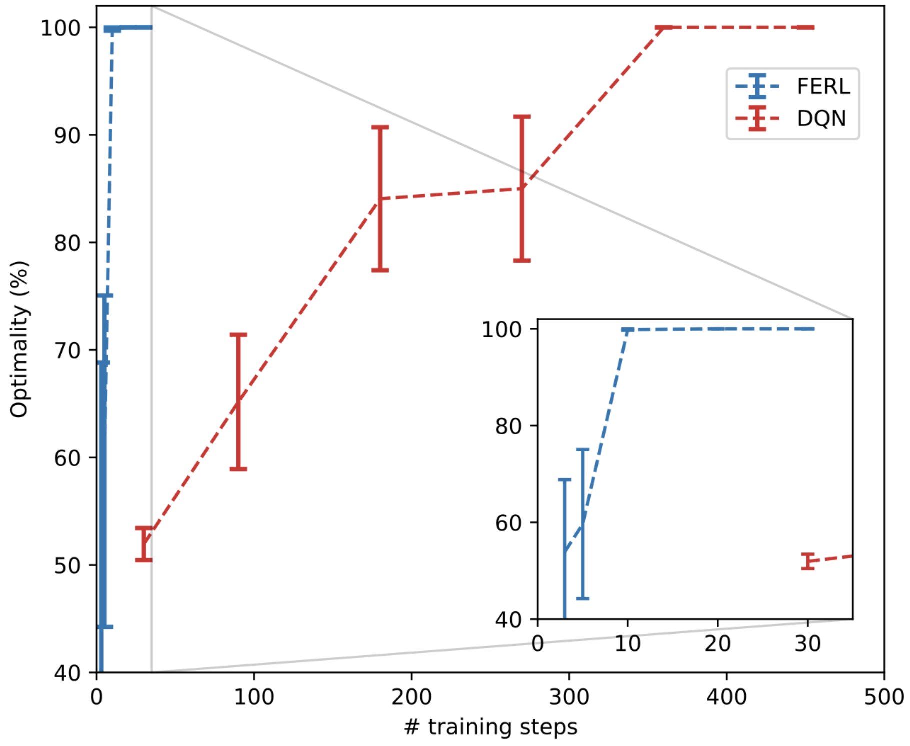
~120 steps, batch size: 7



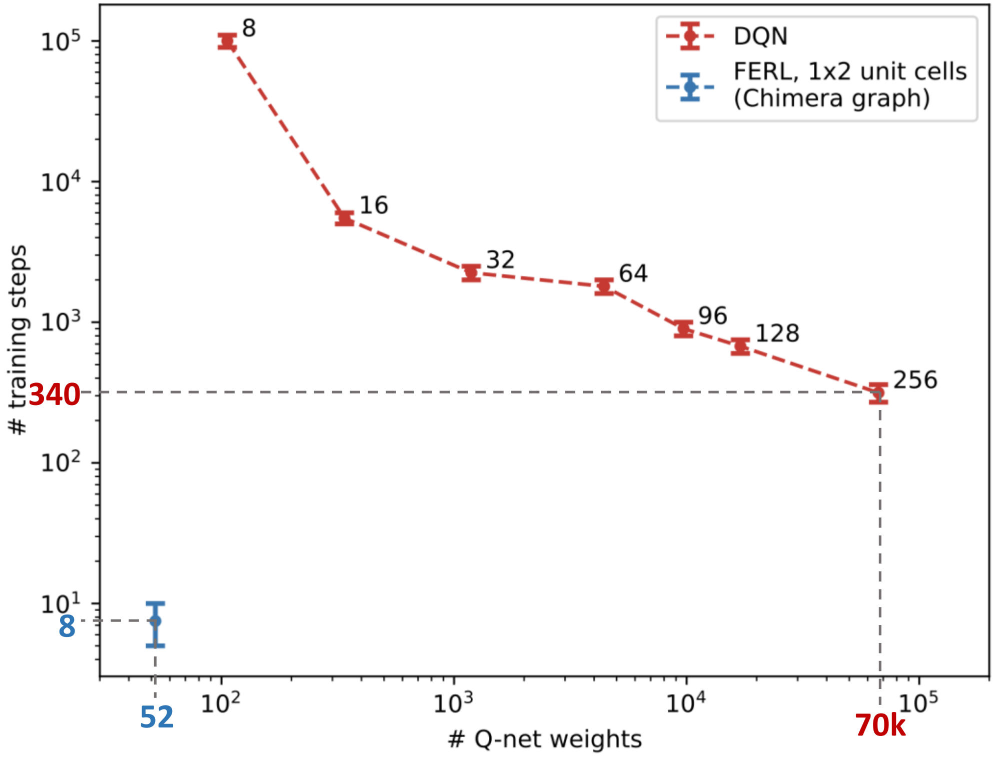
Use case I: Q-learning on 1D beam steering

Training efficiency & descriptive power

Training efficiency



Training efficiency vs. # Q-net / QBM weights



- **Optimality metric:** "in what fraction of possible states does agent take the right decision"
- **Training efficiency:** FERL massively outperforms classical Q-learning *(8±2 vs. 320±40 steps)*
- **Descriptive power:** QBM can reach high performance with **much fewer weights** than DQN (*52 vs. ~70k*)

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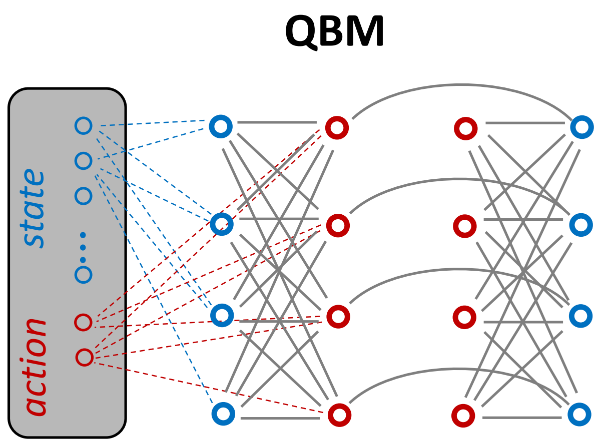
Use case I: Q-learning on 1D beam steering model *(simulated environment)*

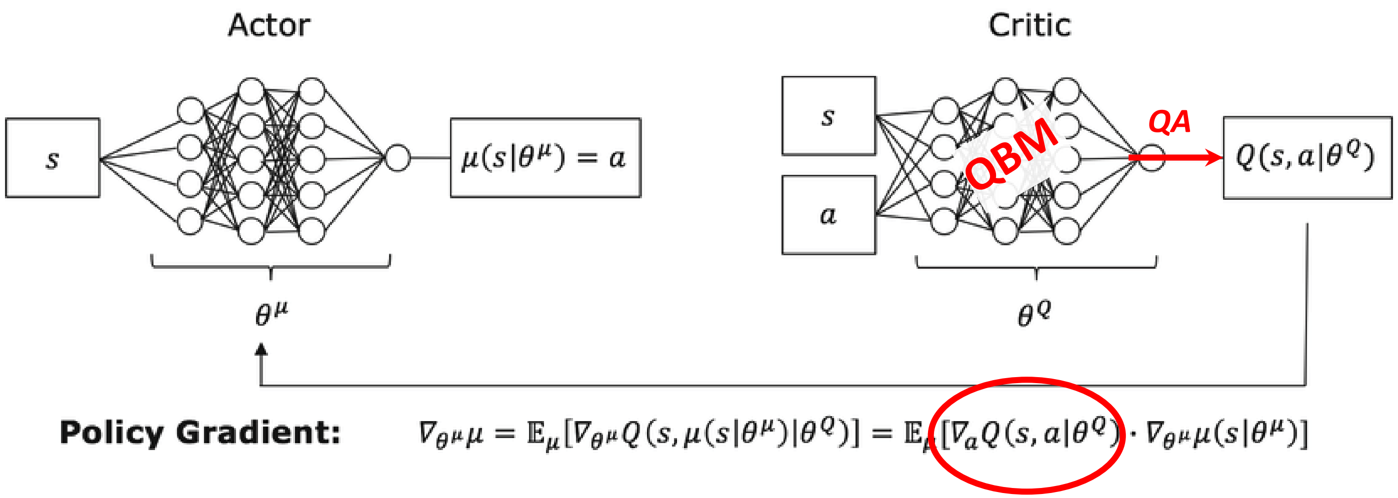
Use case II: quantum actor-critic on 10D AWAKE beam line *(simulated and real environment)*

Developing the quantum actor-critic

Quantum DDPG

- **FERL for continous state-action spaces to tackle real-world problems:** inspired by classical actor-critic methods
- **Why use FERL in combination with classical policy network?**
  - **QBM has ideal structure** to replace classical critic
  - Can we benefit from **high training efficiency of QBM** (?!)
    Intuitively: if critic learns faster, should be beneficial for actor training



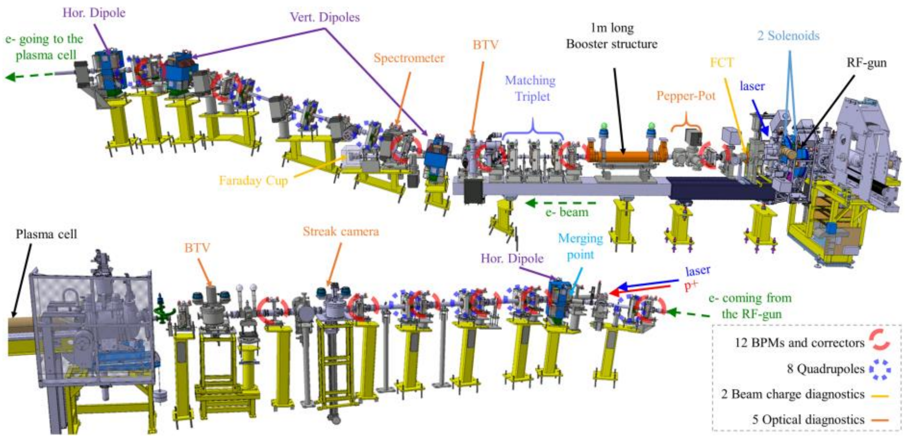


Main challenge

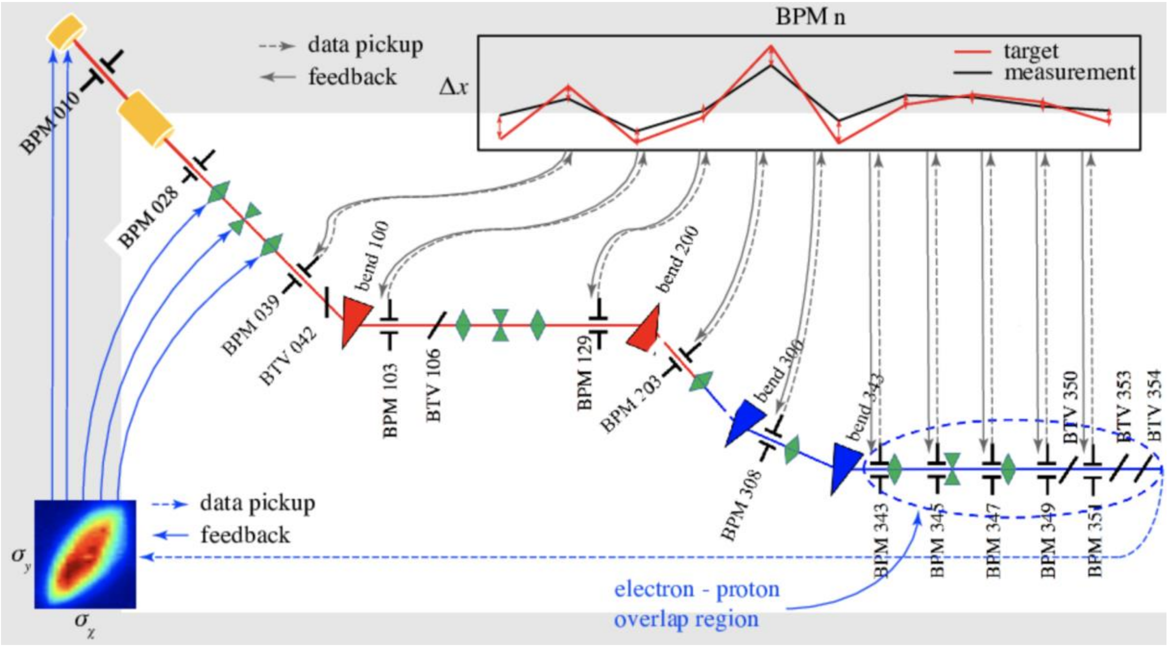
- Calculating derivative of critic wrt. action $\nabla_a Q(s,a|\theta^Q)$
- Numerical (finite difference) or semi-analytical derivative options

Use case II: Q-learning on 10D AWAKE beam line

Environment



- **AWAKE electron beam line**
  https://gitlab.cern.ch/be-op-ml-optimization/envs/awake
- **OpenAI gym template**
- **Action:** deflection angles at 10 correctors *(continous)*
- **State:** beam positions at 10 BPMs *(continuous)*
- **Reward:** negative rms from 10 BPMs

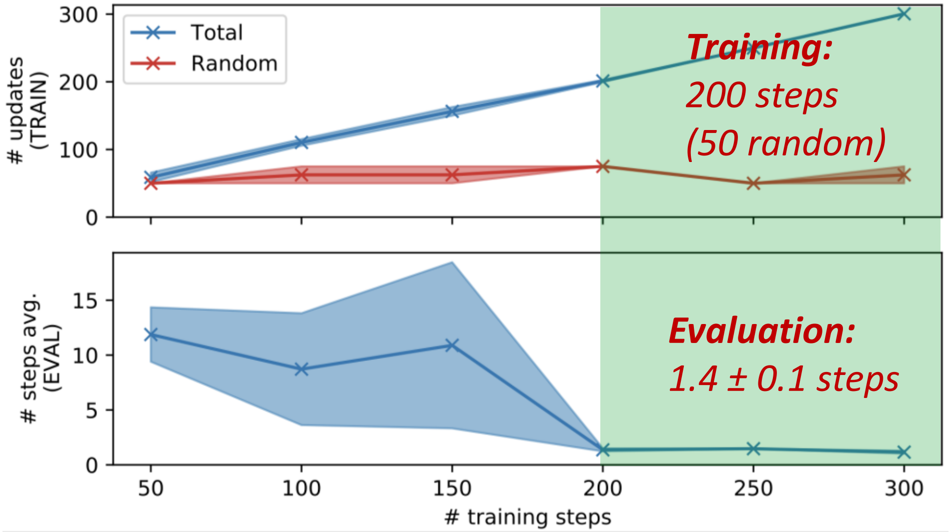


Credits: A. Scheinker

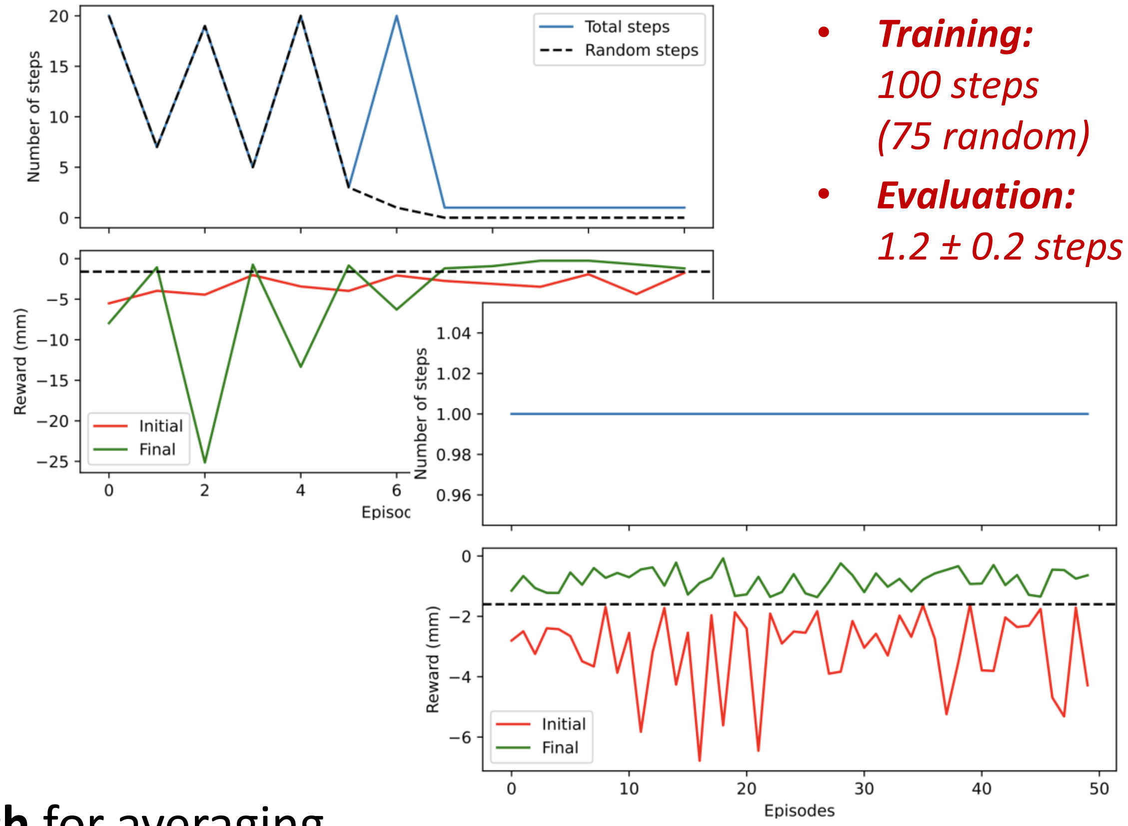
Use case II: Q-learning on 10D AWAKE beam line

Classical vs. quantum actor-critic: training efficiency

Classical actor-critic



Quantum actor-critic

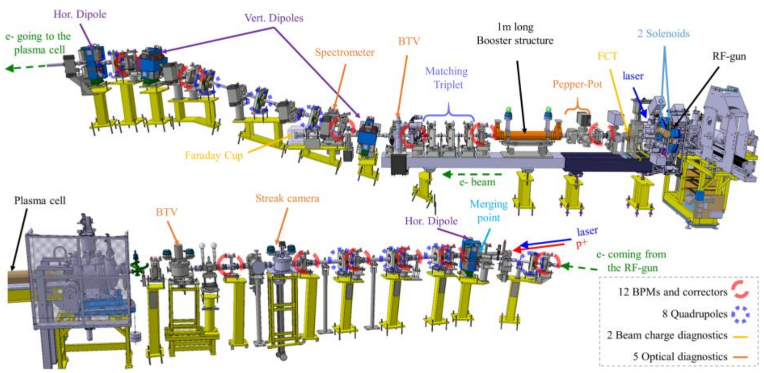


- ***Training:***
  100 steps
  (75 random)
- ***Evaluation:***
  1.2 ± 0.2 steps

- Running **5 trainings and evaluations from scratch** for averaging
- Showing current best performance, **yet to finish hyperparameter optimization** for both
- **Quantum actor-critic is ahead, but the race is still on …**

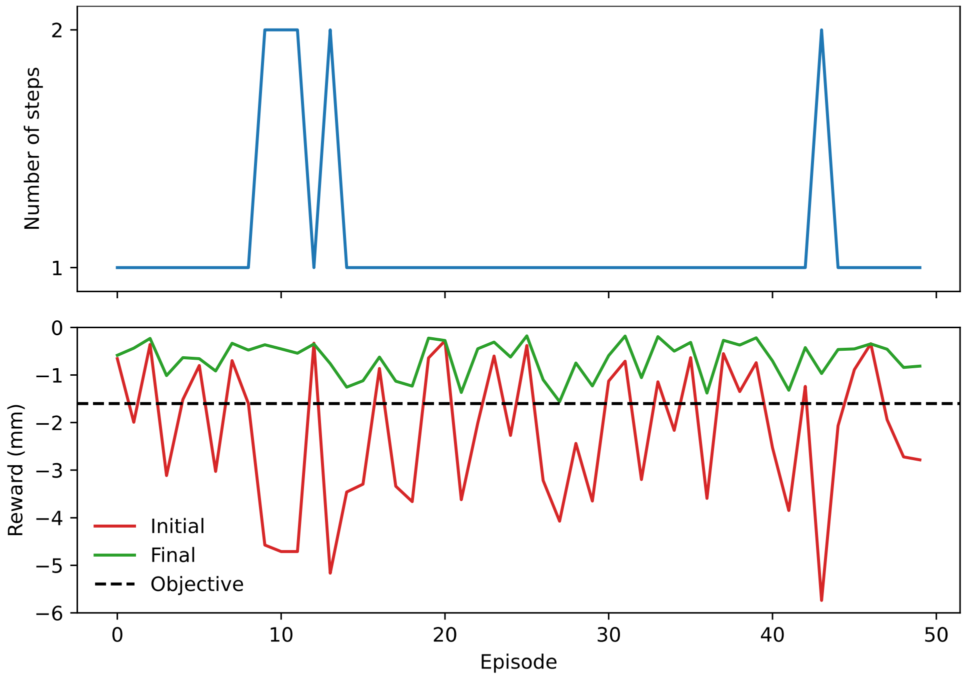
Use case II: Q-learning on 10D AWAKE beam line

Test on actual AWAKE beam line

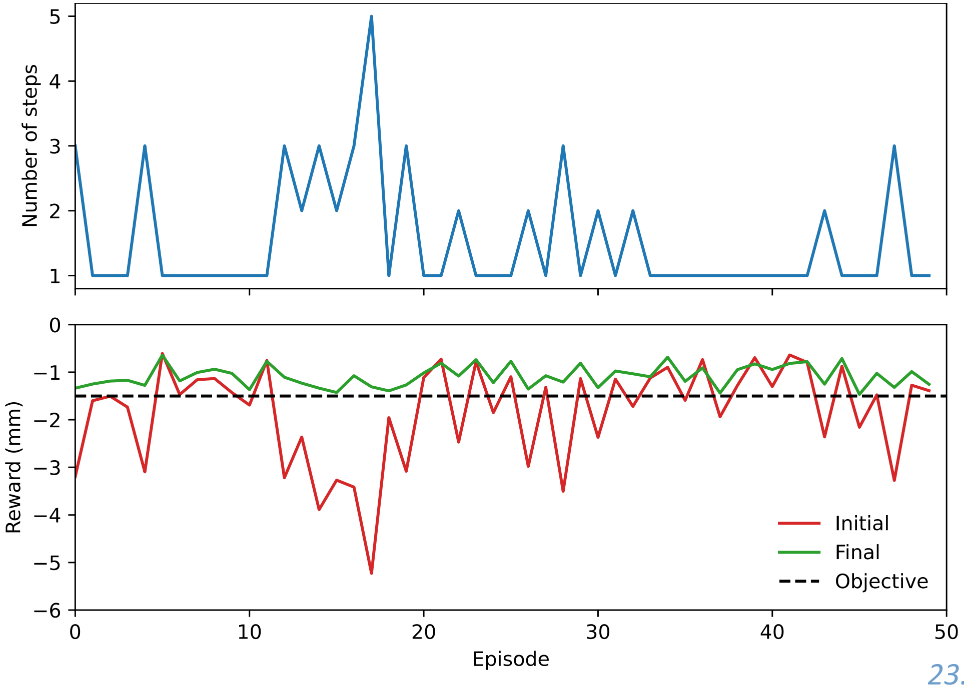


- **Trained and tested our quantum actor-critic agent** on *simulated* 10D AWAKE beam line
- **Deployment on *real* beam line => agent works successfully ☺ !**
  Even with 1 broken beam position monitor (BPM) …
- **Will redo with optimized agent and fixed BPM**

Evaluation on simulated beam line



Evaluation on real beam line



Summary

- **FERL works both with simulator and on quantum annealing hardware**
- **Developed new quantum actor-critic algorithm** that performs well and solves 10x10D **continuous state-action** problem both in **simulated and real environments**
- See **advantage** in terms of **sample efficiency *and* descriptive power** for all cases studied
- **More studies on D-Wave annealer planned**
- Attempt training in **more complex environment**

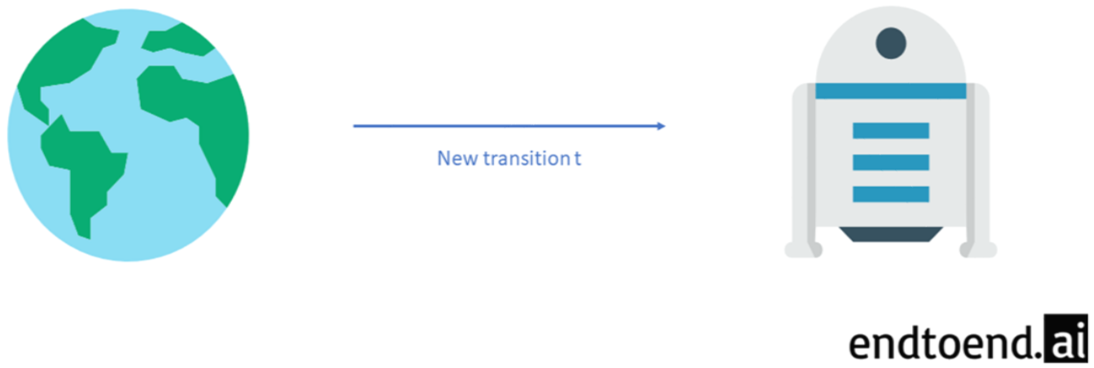
Thank you !

Backup

Introduction
How to learn from training samples

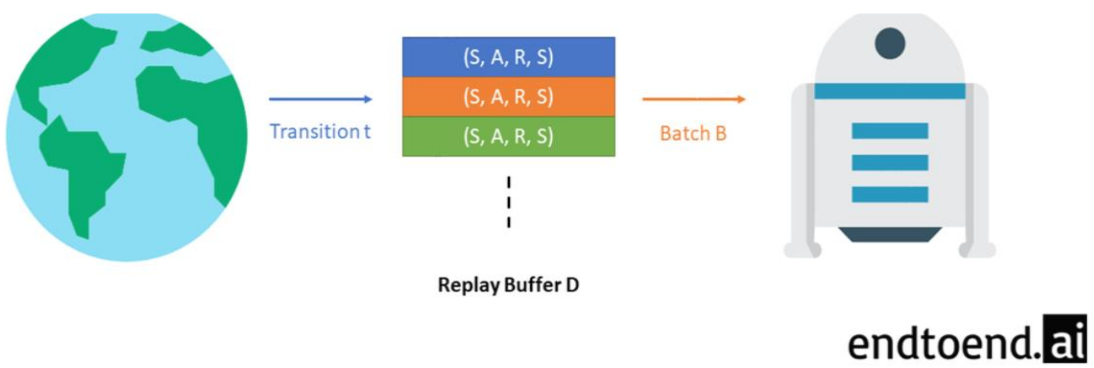
Online Learning

- Learn directly and only from **latest experience**
- Highly correlated data
- Agent learns from each interaction **once and discards** it immediately



Experience Replay

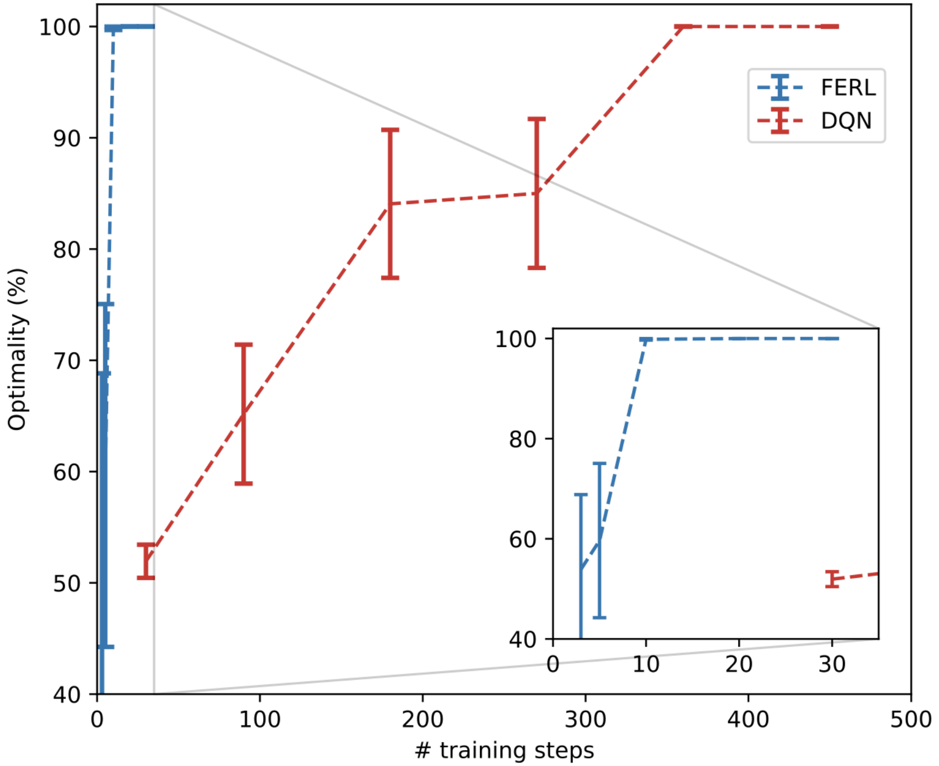
- Save transitions into **memory buffer**
- **Sample batch** from buffer to train agent on **multiple past training samples** at every step



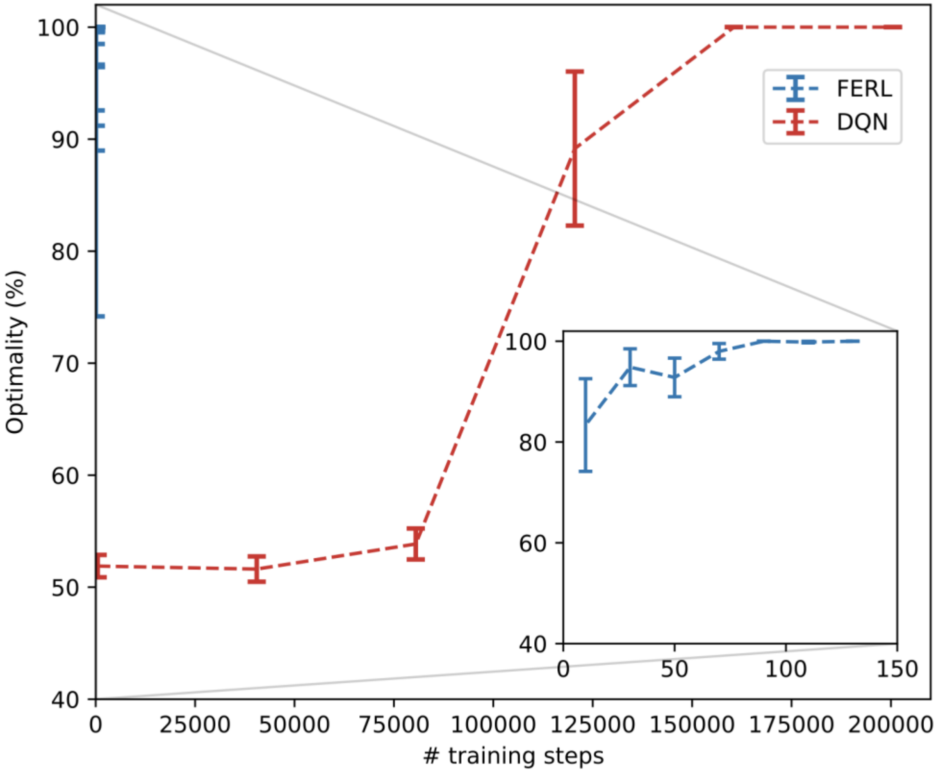
https://www.endtoend.ai/paper-unraveled/cer/

Part I: Q-learning on 1D beam steering
Sampling efficiency

Experience replay ON



Experience replay OFF



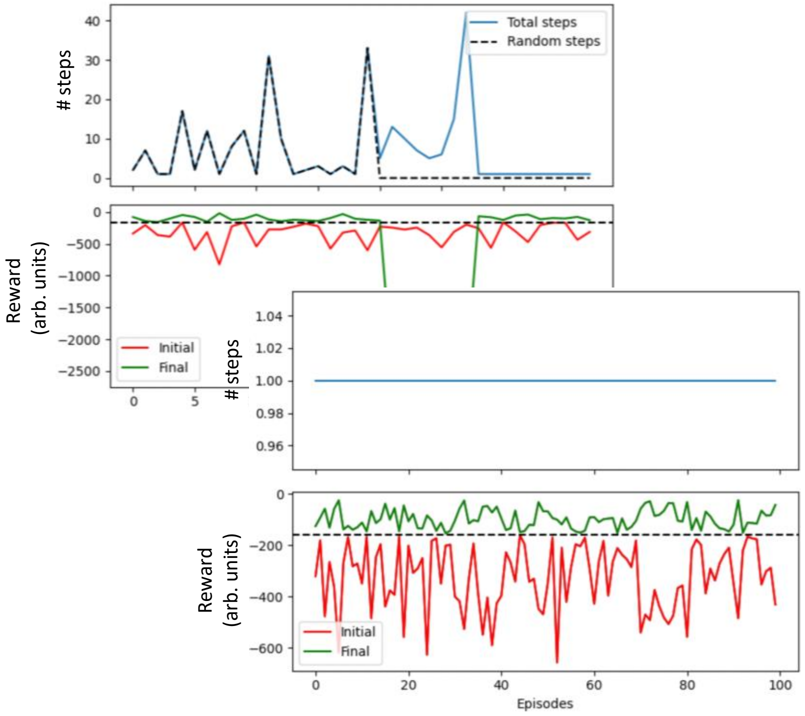
- **Optimality:** “in what fraction of possible states does agent take the right decision”
- **FERL massively outperforms classical DQN:** 10 vs. 360 steps (ER), 90 vs. 160’000 steps (no ER)
- **Required # weights** QBM vs. Q-net is also **completely different!**

Part II: Q-learning on 10D AWAKE beam line

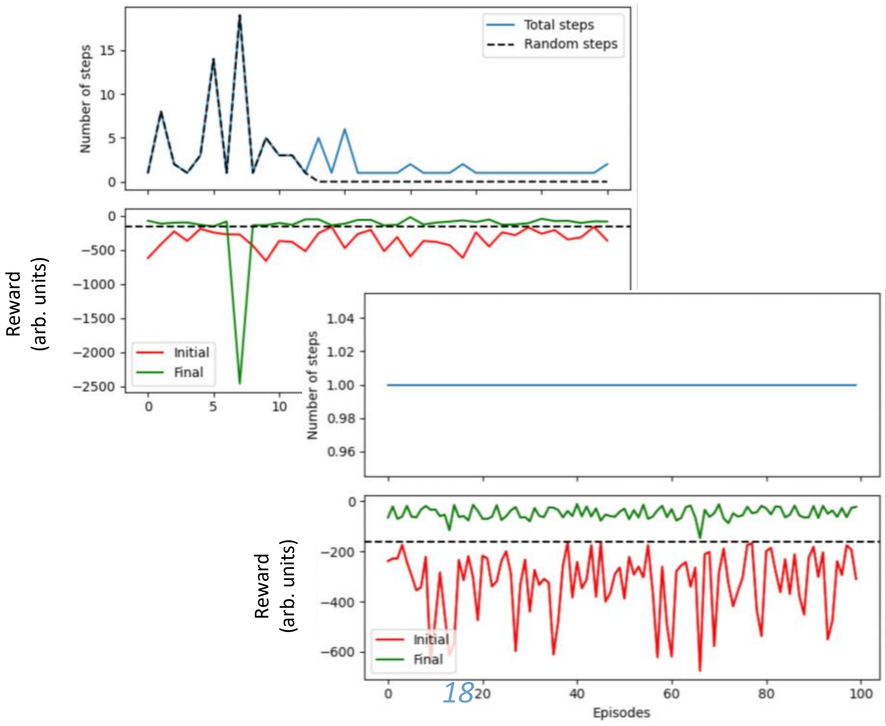
Quantum DDPG

- **Once issue fixed worked immediately really well ☺ !!!**
- **Every training is a success**, sometimes with a few more or less evaluation steps
- **QBM critic can be very small** and still produce good performance
- **Here: unoptimized. Hyperparameter optimization will bring performance well up …**

1x2 QBM: 300 + 110 steps

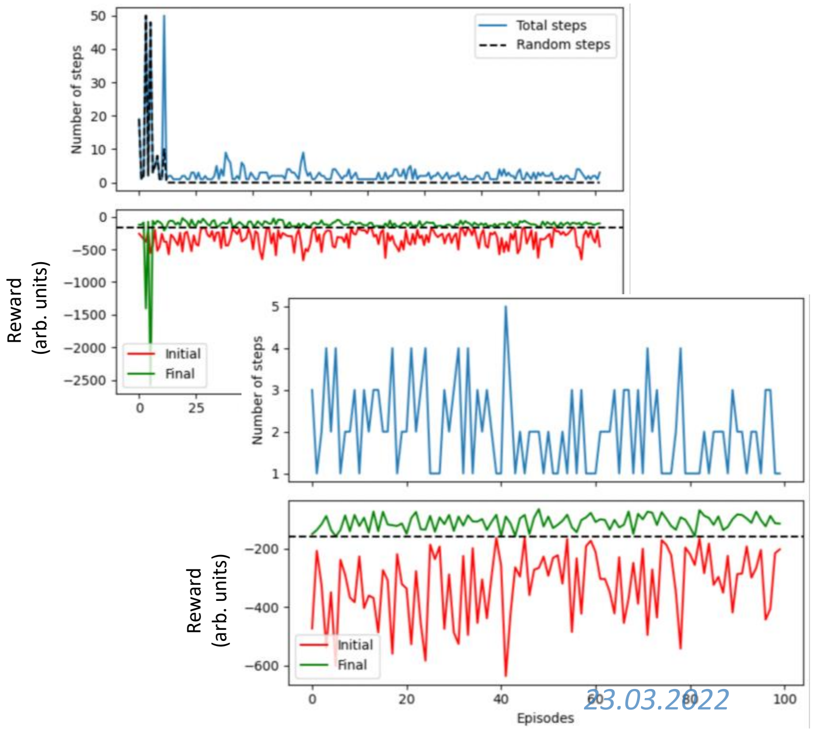


3x3 QBM: 150 + 35 steps



"Worst case"

3x3 QBM: 150 + 451 steps



Part II: Q-learning on 10D AWAKE beam line

Classical vs. quantum DDPG: # critic weights

- **Following numbers are valid for 6D env** *(yet to rerun for 10D env)*
- **Classical DDPG**
  - Best compromise between # training updates vs. # evaluation steps
  - Critic with: **400 x 300 x 1 nodes**, i.e. **123k+ weights** *(see backup)*
- **QBM**
  - Best performance to date with **4 x 4 unit cells, 8 qubits** each
  - **Not fully connected:** following D-Wave 2000Q Chimera topology
  - **Total number** of hidden-hidden (352) + visible-hidden (768) **weights: 1’120**

Factor 100 difference in # critic weights needed

actor networks are identical