Quantum Reinforcement Learning for Beam Steering

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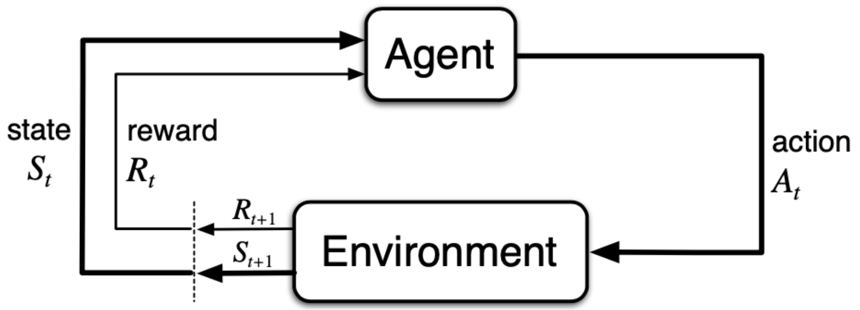
- **Motivation:** QBM vs DQN
- **Our project:** beam steering
- **Results:** DQN and QBM
- **Ongoing work:** QAOA and actor-critic

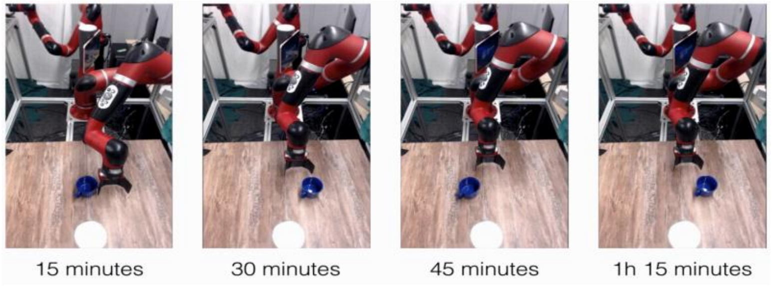
Reinforcement learning in a nutshell

RL book: Sutton & Barto



Agent interacts with environment

- **Receives reward after every action**
- Learns through **trial-and-error**



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Decision making

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

Expected return can be estimated through ***value function Q(s, a)***

- **"What's the best action to take in each state" => *greedy policy:*** *take action that maximizes Q(s,a)*
- **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)*
  - QBM-RL *(Quantum Boltzmann Machine)*

Motivation

- **Why using QBM for RL?**
  - **Free energy based RL** (FERL): efficient for high-dim. spaces (https://www.jmlr.org/papers/volume5/sallans04a/sallans04a.pdf)
  - **Higher sample efficiency over Deep Q-learning** (https://arxiv.org/pdf/1706.00074.pdf)
  - **Quantum RL:** an exciting combination ☺
- **Objective:** apply to one of our RL problems: beam steering

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.

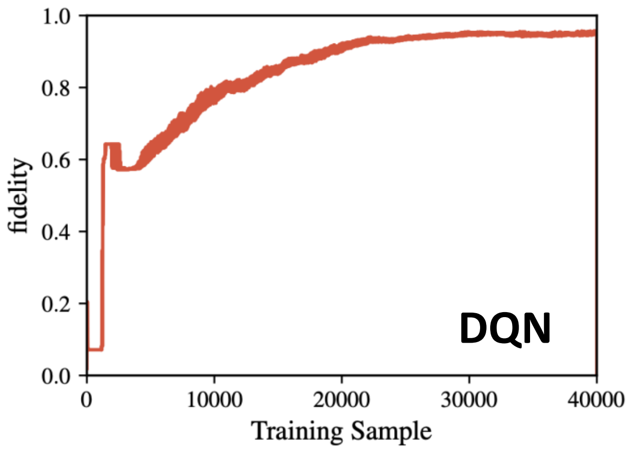
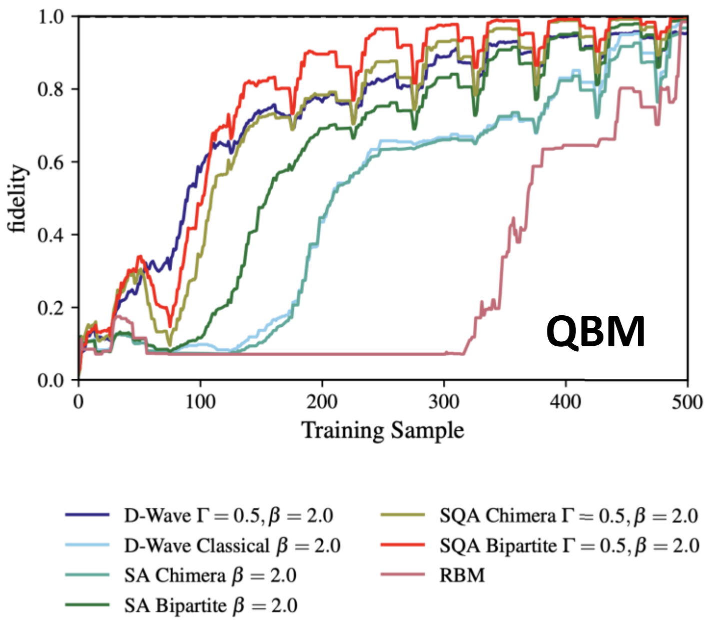


FIG. 4: The learning curve of a deep Q-network (DQN) with two hidden layers, each with eight hidden nodes, for the grid-world problem instance as shown in Fig. IV.



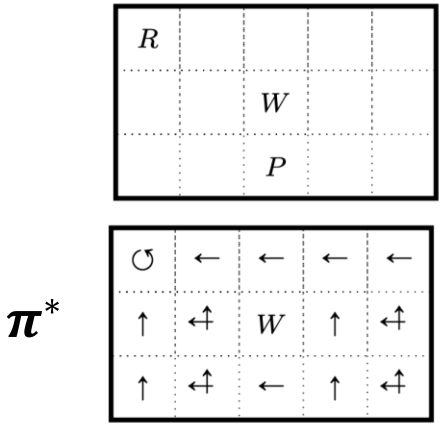


FIG. 3: (top) A 3×5 grid-world problem instance with one reward, one wall, and one penalty. (bottom) An optimal policy for this problem instance is a selection of directional arrows indicating movement directions.

Q-learning with QBM and DQN

FERL: clamped QBM

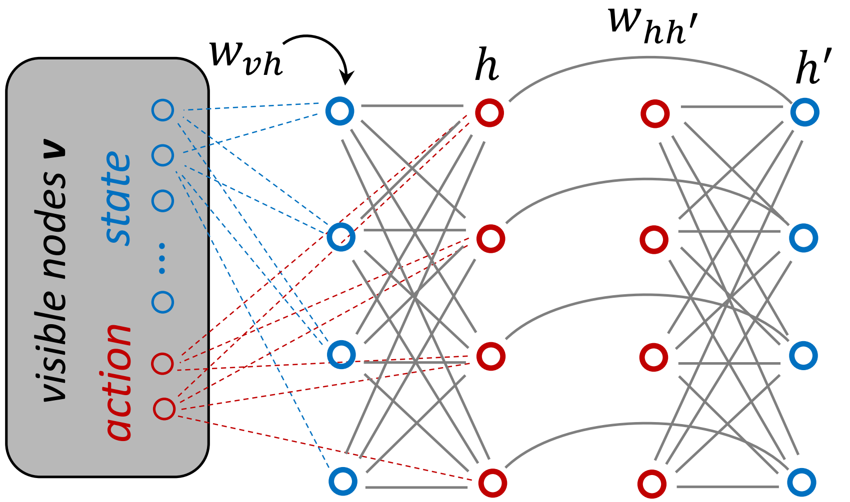
- **Network of coupled, stochastic, binary units** (spin up / down)
- $\hat{\boldsymbol{Q}}(\boldsymbol{s}, \boldsymbol{a})$ ≈ **negative free energy** of classical spin configurations c
- **Sampling** c using **(simulated) quantum annealing**
- **Clamped:** visible nodes not part of QBM; accounted for as biases
- Here **visible nodes are discrete, binary** *(restriction can be lifted)*
- **Using 16 qubits of D-Wave Chimera graph**

DQN: Q-net

- **Feed-forward, dense** neural network
- 2 hidden layers, 8 nodes each (≈ Chimera graph)

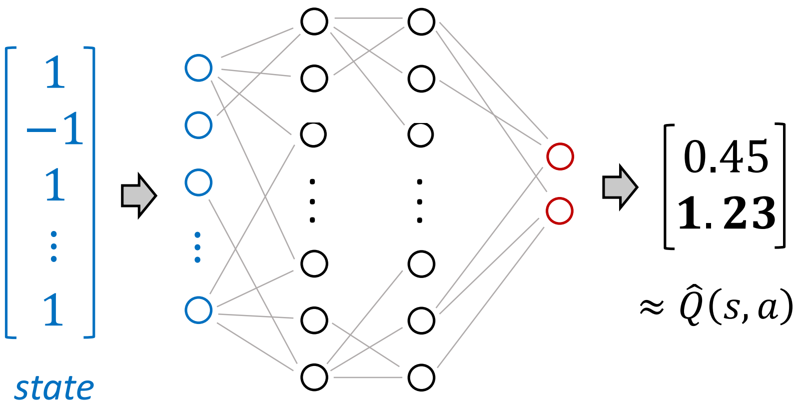
Learning: update Q by applying **temporal difference rule** to QBM and Q-net weights

Clamped QBM

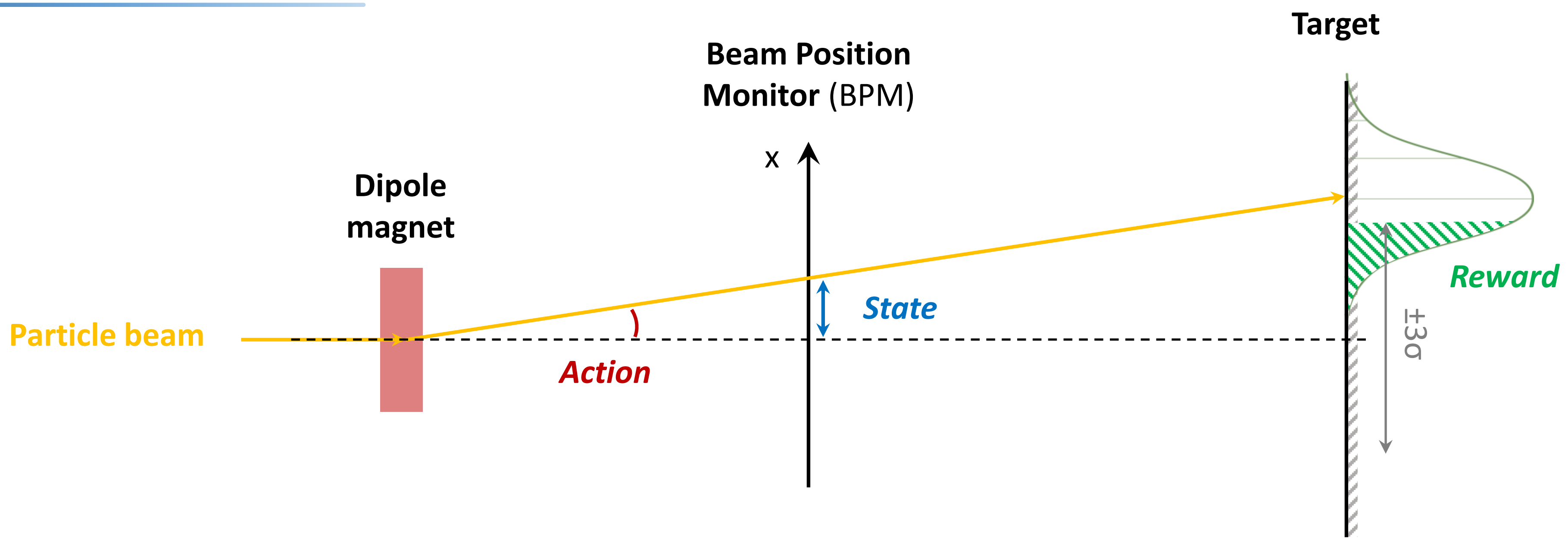


$$\hat{Q}(s,a) \approx -F(\boldsymbol{v}) = -\langle H_{\boldsymbol{v}}^{\mathrm{eff}} \rangle - \frac{1}{\beta} \sum_c \mathbb{P}(c|\boldsymbol{v}) \log \mathbb{P}(c|\boldsymbol{v})$$

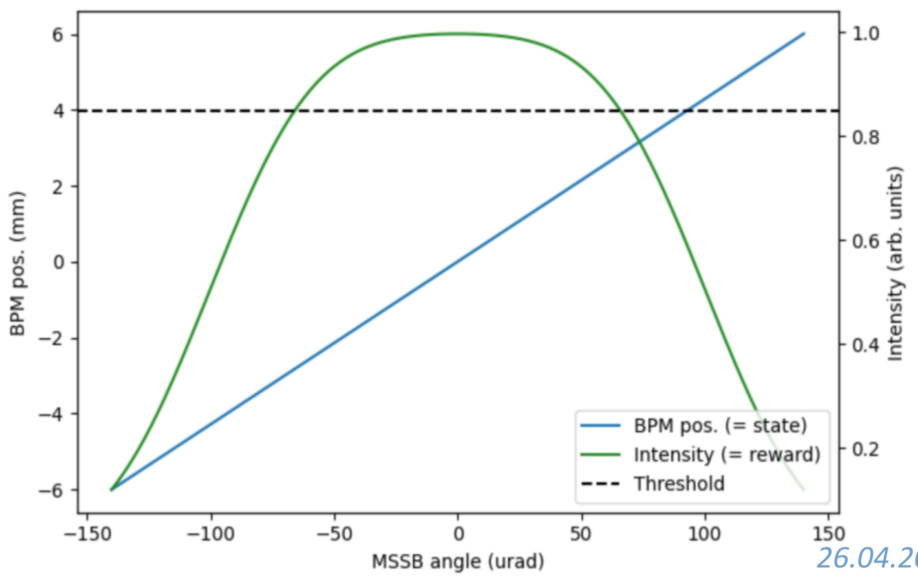
Q-net



Toy model: beam steering

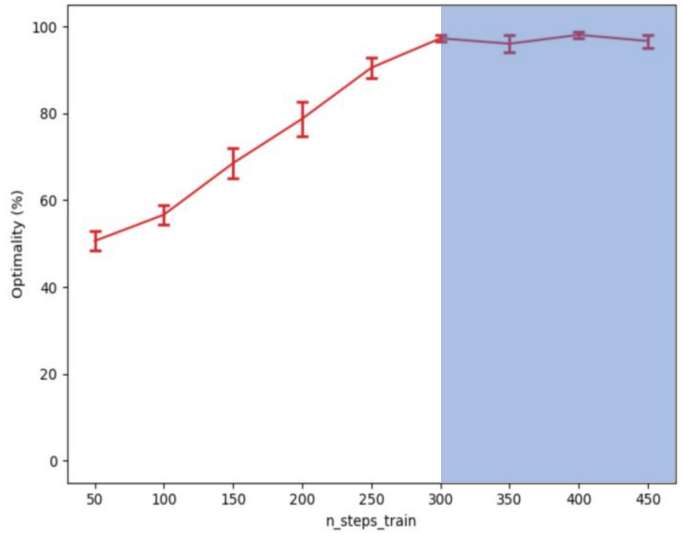


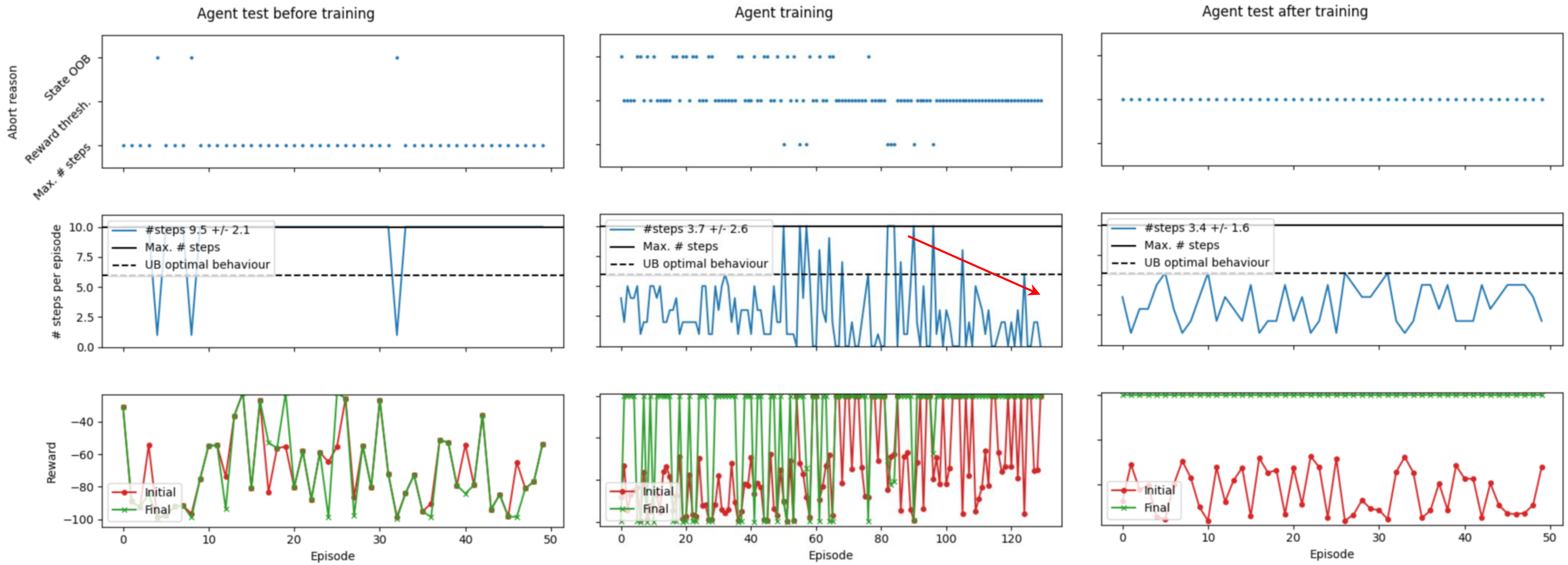
- **Toy model based on actual steering problem**, e.g. for fixed target experiments at CERN Super Proton Synchrotron
- [*OpenAI gym template*]
- **Action:** deflection angle
  - 2 possibilities: up or down by fixed amount
- **State:** beam position at BPM
- **Reward:** integrated beam intensity on target



DQN: discrete state space

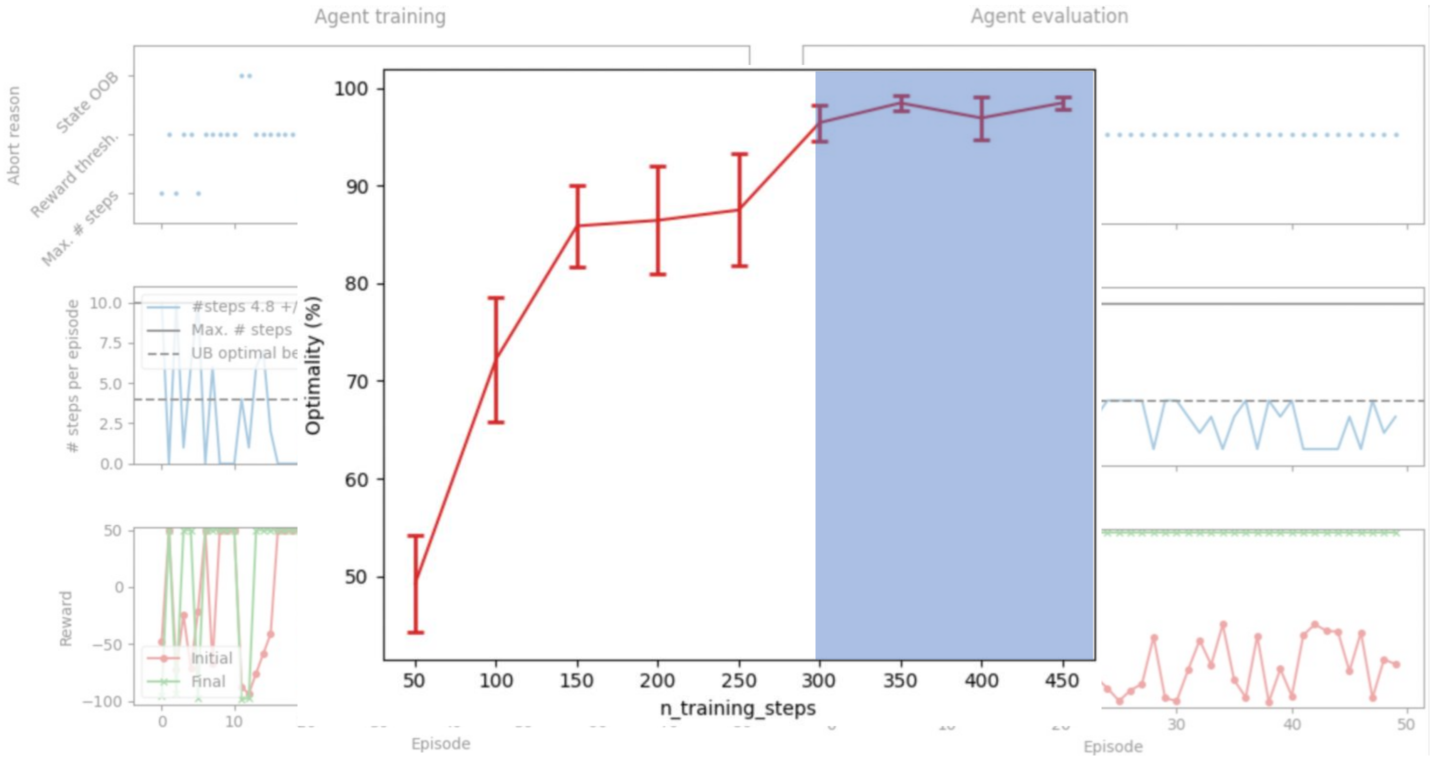
- *Stable-baselines3* implementation of DQN
- **Efficiency:** required **# training_steps** *after hyperparameter tuning*
- **300+** training steps: get optimal policy with nearly **100% success rate**

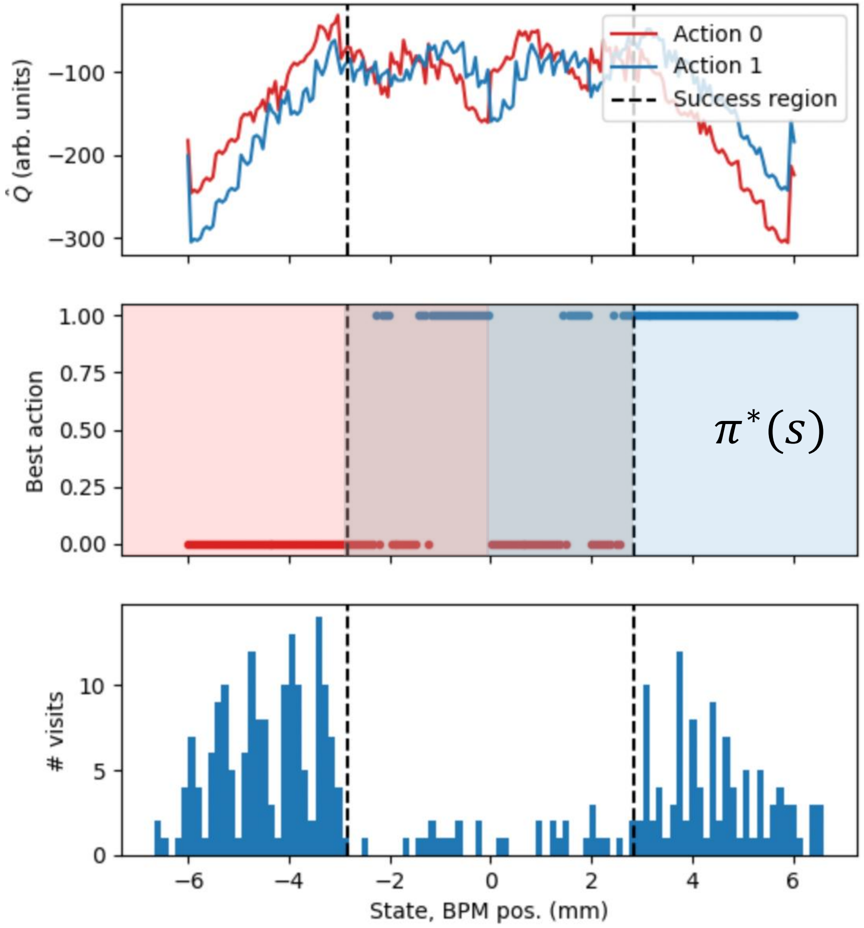




QBM: discrete state space, simulated quantum annealing

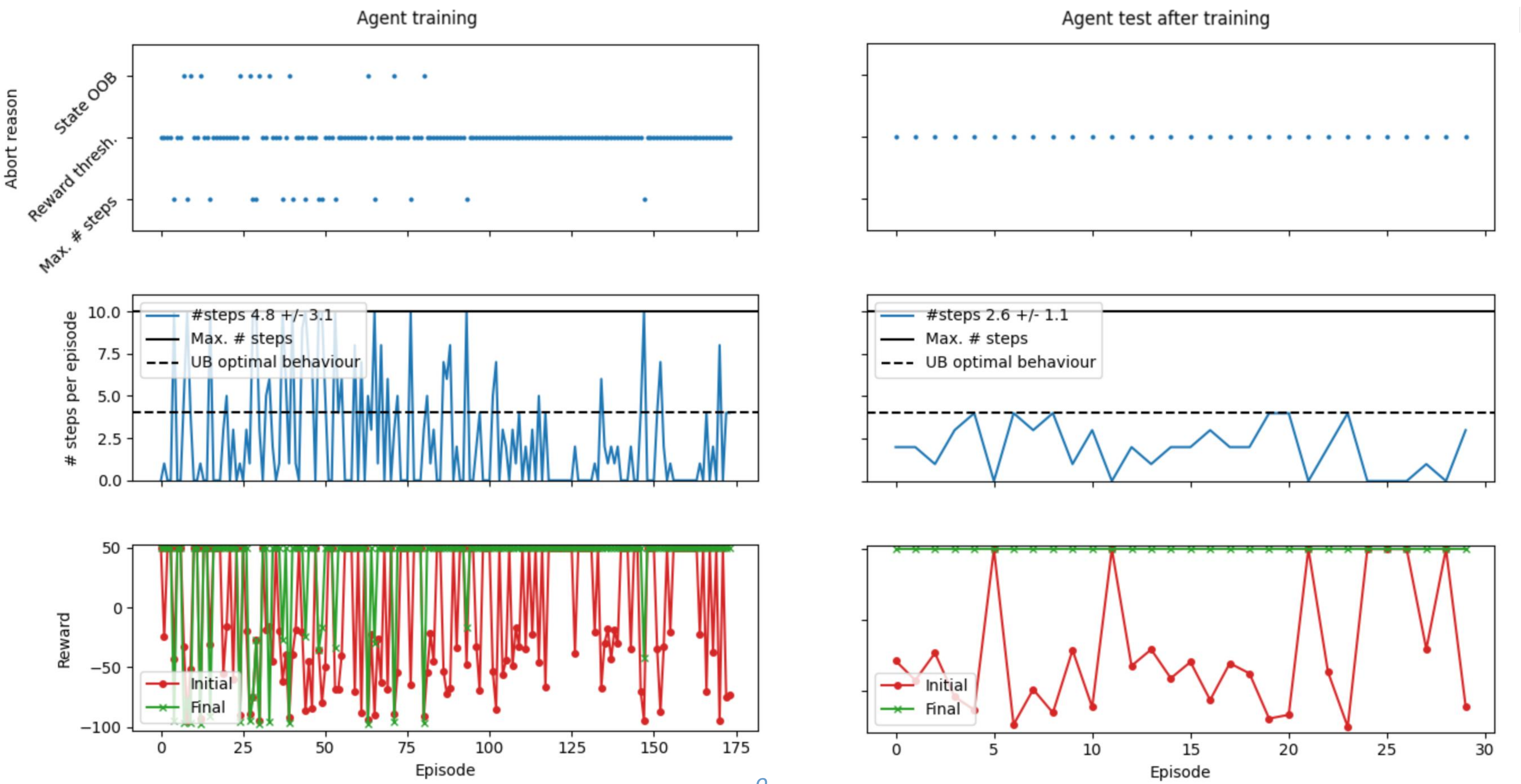
- **Tune QBM-RL with simulated quantum annealing** (SQA, *library: sqaod*) before moving on D-Wave QPU
- With some tuning: **successful training** *(300 iterations)*
- $\hat{Q}(s, a)$ leads to optimal policy
- **Similar efficiency to DQN**





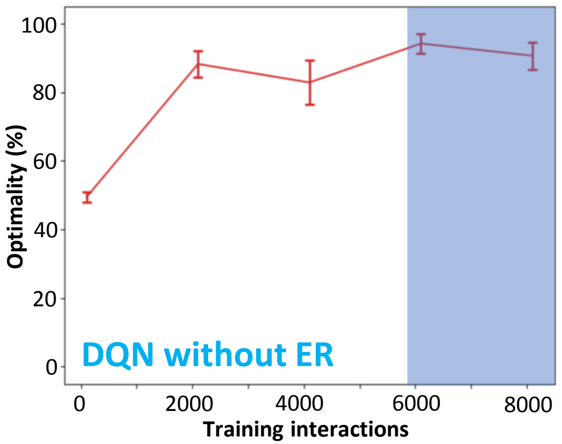
QBM: discrete state space, D-Wave 2000Q

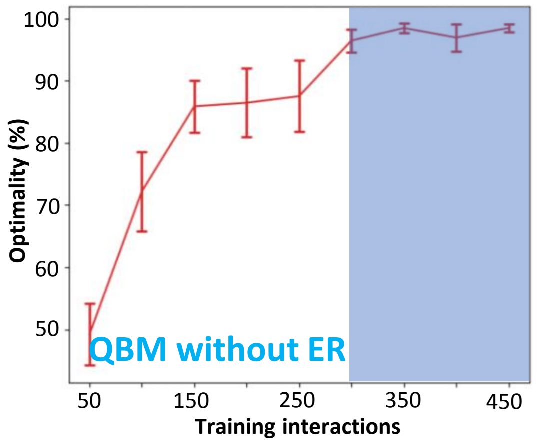
- **D-Wave training from scratch** *(600 iterations)* after hyperparameter tuning with SQA
- **Our first successful RL training on an actual QPU ☺ !**

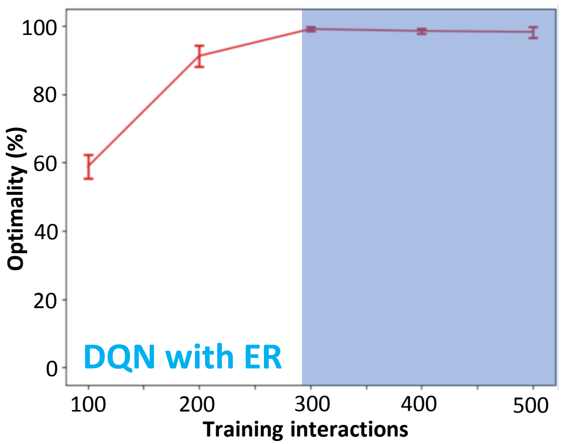


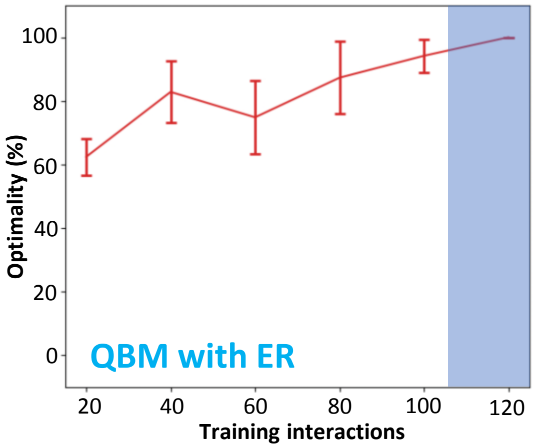
DQN vs QBM: effect of experience replay

- DQN vs QBM: **roughly same number of training interactions** required
- **Not consistent** with [original paper](#) *(40’000 vs. 500 interactions)*
- **Reason:** experience replay (ER)
  - **DQN:** 6000+ interactions (w/o ER) vs ~300 interactions (w/ ER)
  - **QBM:** ~300 interactions (w/o ER) vs ~120 interactions (w/ ER)



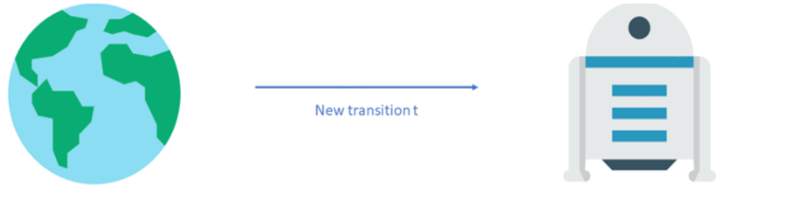






Online Learning

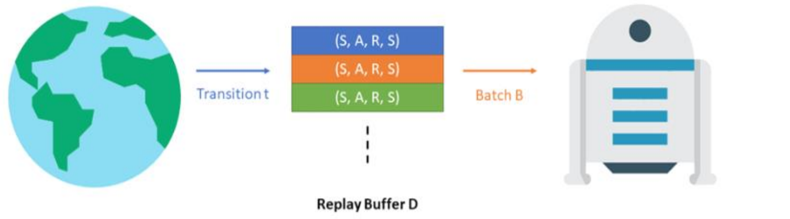
- Learn directly from latest experience
- Highly correlated data
- Agent learns from each interaction once and discards it immediately after



endtoend.ai

Experience Replay

- Save transitions into memory buffer
- Sample batch B from buffer to train agent at every step



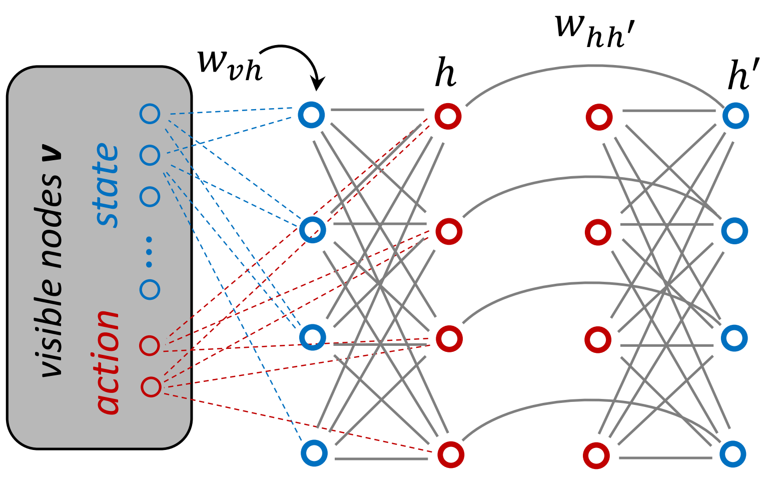
endtoend.ai

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

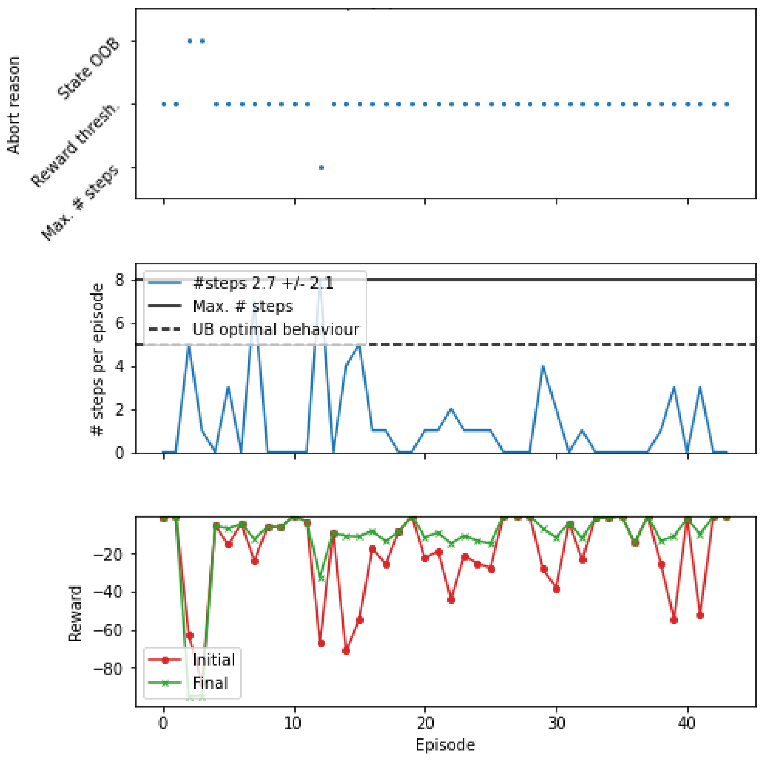
QBM: continuous state space

- **Visible nodes not** represented by **qubits => no need to be discrete, binary**
- **Training on D-Wave with continuous state space and ER**: ~120 interactions
- **Q functions more robust** thanks to smaller number of training weights
- **Opens doors for more complex and more practical applications**

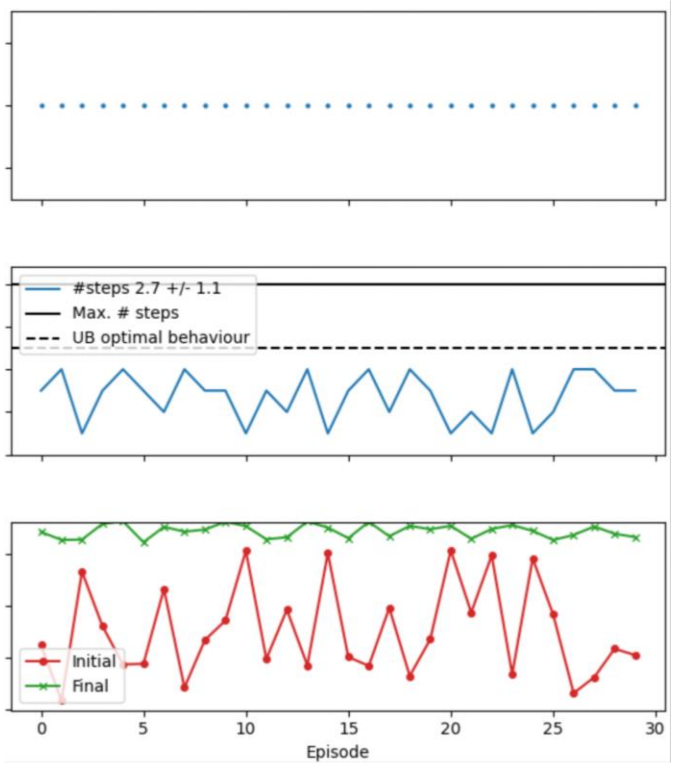
Clamped QBM



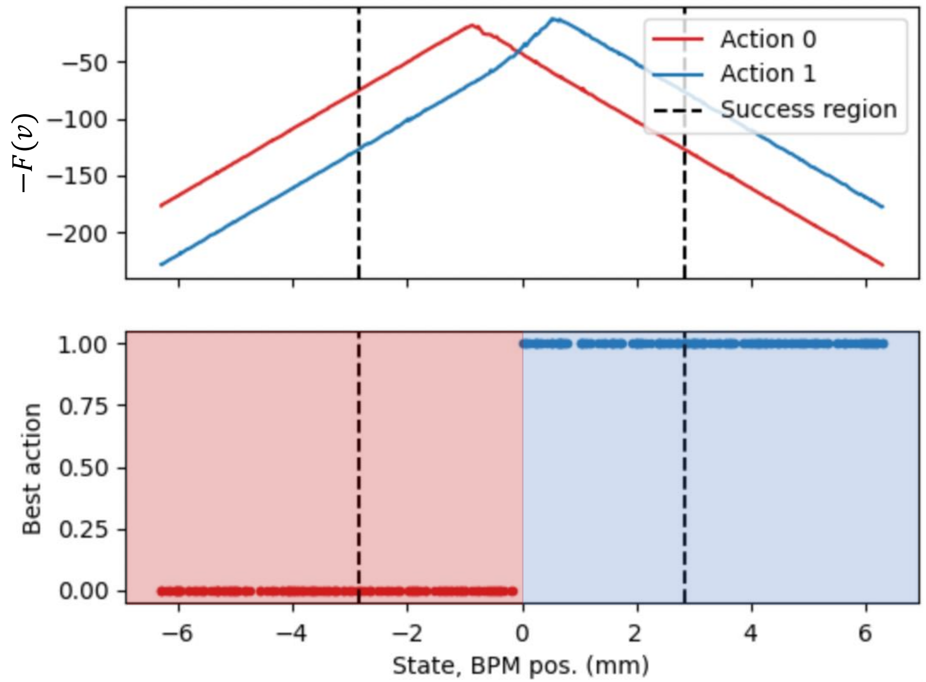
Training (D-Wave)



Evaluation (SQA)

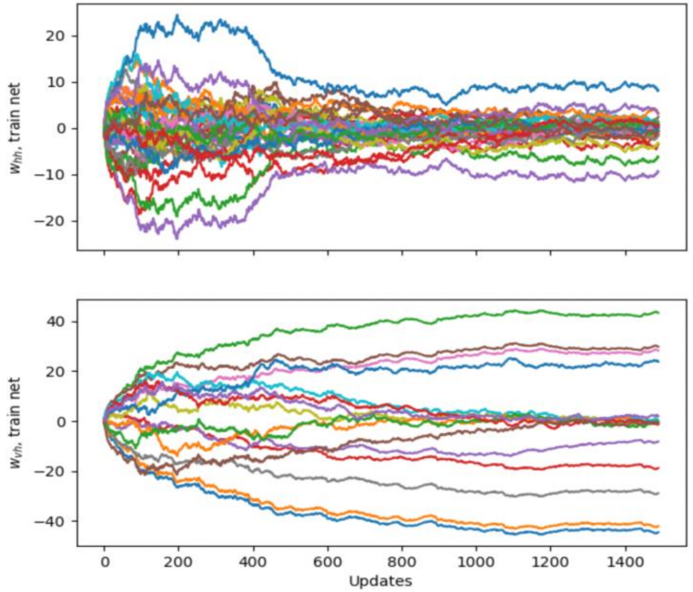


Q-functions (SQA)

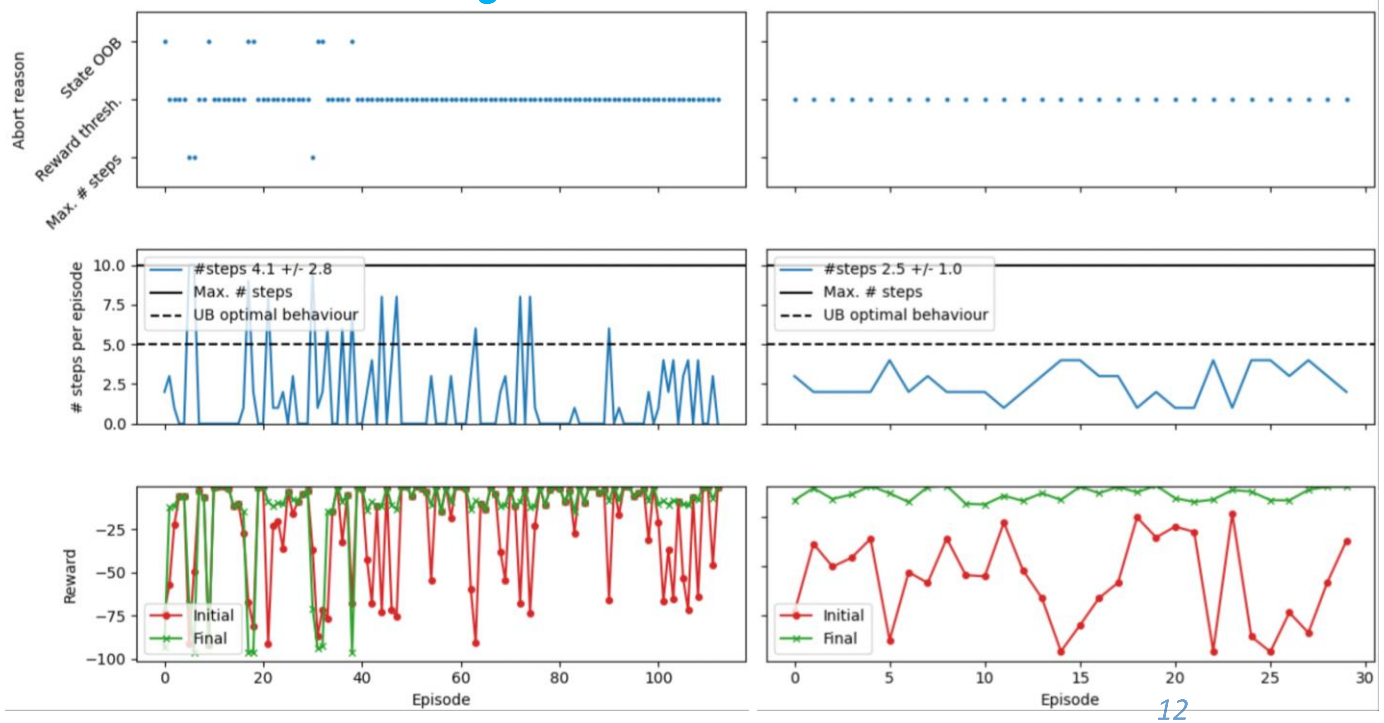


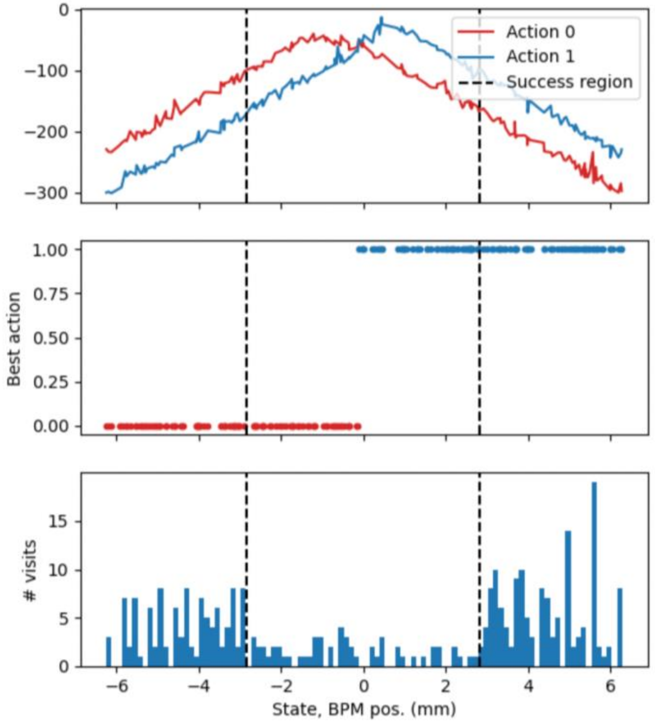
Ongoing work: QBM using QAOA

- [**QAOA:** Quantum Approximate Optimization Algorithm]
- **Solver** for combinatorial optimization problems: find spin configuration with minimum energy, **not based on annealing**
- **Works well,** but quite **compute-intensive** *(~5.5 h for 100 interactions)*
- On hardware (e.g. IBM): to be tested, could be affected by noise



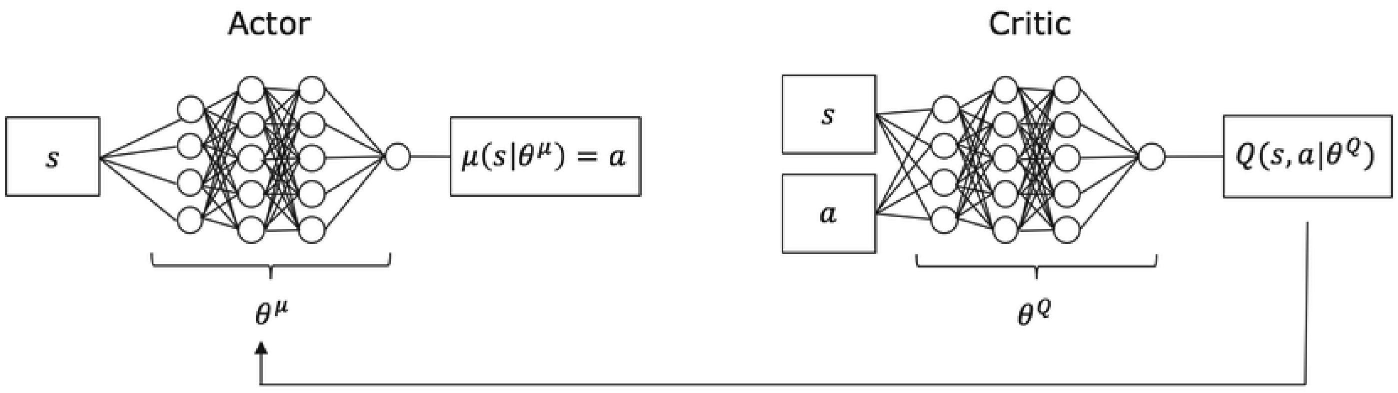
Training ***Evaluation***





Ongoing work: actor-critic

- **Goal: continuous state *and* action spaces** to tackle **real-world problems**
- **DQN not suitable:** only for discrete, low-dimensional action spaces
- **Actor-critic algorithm** *[Deep Deterministic Policy Gradient (DDPG)]*
  - **Actor** (= policy network): parameterized action function, mapping states to actions
  - **Critic** (= Q-net): similar to DQN, estimator for Q(s,a)



Policy Gradient: $\nabla_{\theta^\mu}\mu = \mathbb{E}_\mu[\nabla_{\theta^\mu}Q(s,\mu(s|\theta^\mu)|\theta^Q)] = \mathbb{E}_\mu[\nabla_a Q(s,a|\theta^Q)\cdot\nabla_{\theta^\mu}\mu(s|\theta^\mu)]$

- **Plan is to create hybrid:** replace Q-net by QBM; keep classical NN for actor

Summary and outlook

Summary

- **Comparison between Deep Q-learning** *(Q-net)* **and Free Energy Based RL** *(QBM)*
- **QBM** works for both **discrete and continuous state space**
- It can be trained successfully with **SQA, D-Wave hardware, and QAOA simulator**
- **Experience replay** has an **important impact** on the training efficiency *(here: factor ~3)*
- First steps made towards **continuous action space using DDPG**

Outlook

- Participate in *BQIT:21* workshop with poster presentation *(26.04. to 28.04.)*
- **Finish actor-critic implementation**
- **Continue studies with QAOA**
- Move to **more complex, higher dimensional environment**

Thank you !

Backup

FERL

https://www.jmlr.org/papers/volume5/sallans04a/sallans04a.pdf

- In RL: need to **estimate action-value functions in high dimensional state-action space** where not all state-action pairs can be visited (e.g. 2^{40})
- Can no longer use table: **use function approximator $\widehat{Q}(s, a)$**
- Conditions: need to be able to **calculate derivative of $\widehat{Q}$ wrt. its weights** to train using TD rule
- One option: **Product of Experts (PoE) models**
    - Combine **simple probabilistic models by multiplying** their probability distributions with each other
    - e.g. stochastic binary units of BM
- **Free energy of such models** can be used as approximator of value function, but needs training for different visible nodes (state-action pairs)
- Once trained, **sampling according to PoE will give probability distribution over actions** given a fixed state (Boltzmann exploration policy)

$$P(\mathbf{a}|\mathbf{s}) = \frac{e^{-F(\mathbf{s},\mathbf{a})/T}}{Z} \approx \frac{e^{Q(\mathbf{s},\mathbf{a})/T}}{Z}$$

- Intuition: **good actions sampled more likely than bad ones**
- **Probabilistic nature** provides advantage in large state-action spaces compared to traditional NN

FERL: Clamping

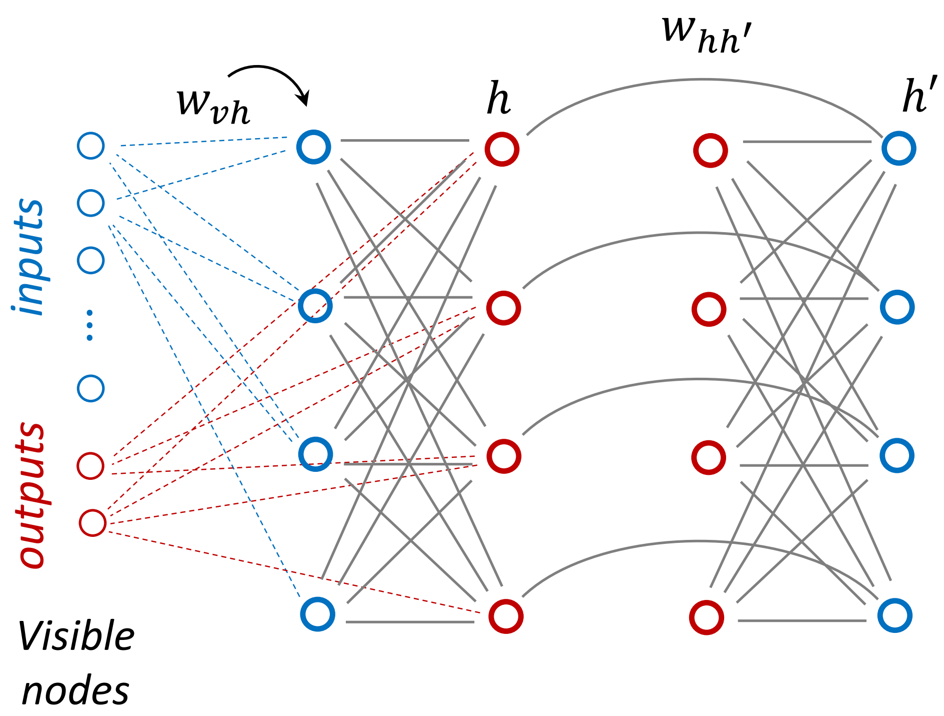
- **All nodes of QBM are hidden**
- **Clamping: add visible nodes as self-couplings** (biases) to hidden nodes they are connected to **and remove them from the graph**

- Every **spin configuration has specific energy** described by Hamiltonian of the transverse-field Ising model

$$\mathcal{H}_{\mathbf{v}} = -\sum_{v\in V,\, h\in H} w^{vh} v \sigma_h^z - \sum_{\{h,h'\}\subseteq H} w^{hh'} \sigma_h^z \sigma_{h'}^z - \Gamma \sum_{h\in H} \sigma_h^x$$

Γ: transverse field strength, $\sigma^{x,z}$: Pauli spin matrices

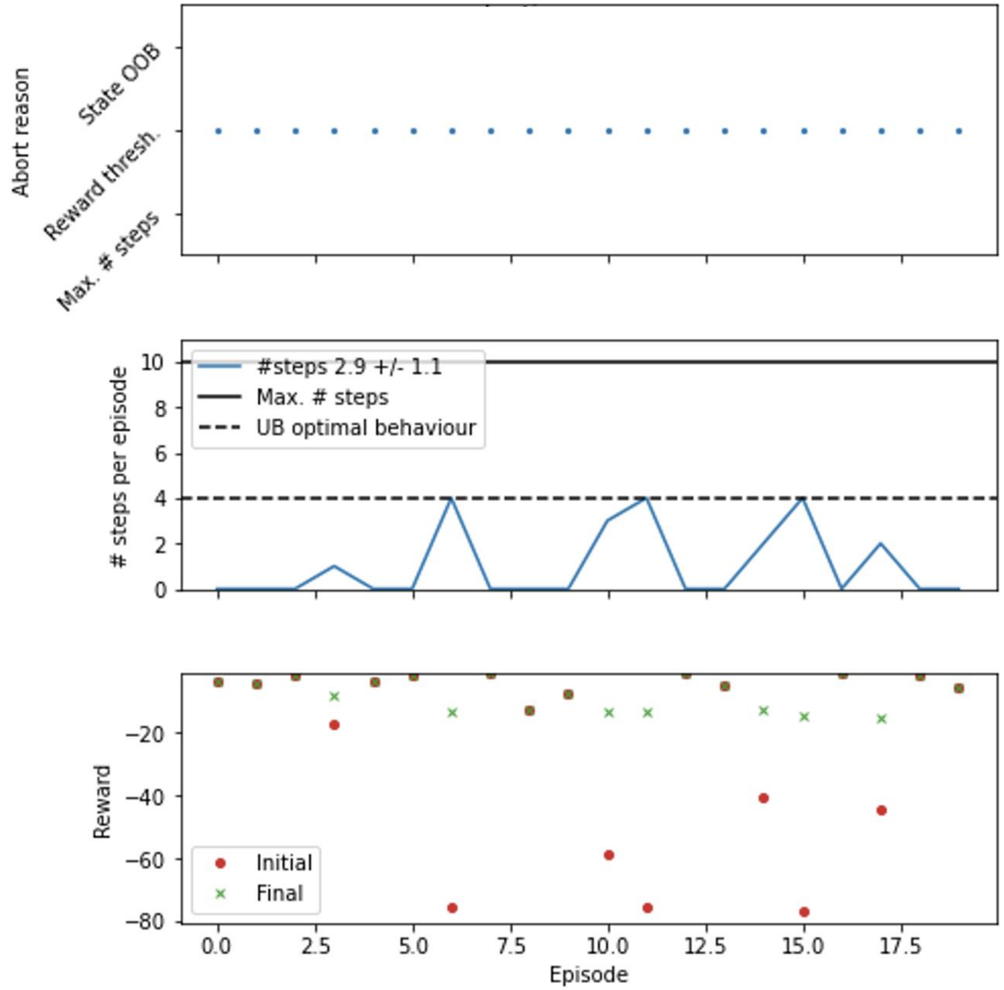
- Once **we measure spin in z direction**, we no longer have access to transverse component **=> cannot know system's energy**
- Can be fixed using replica stacking (Suzuki-Trotter expansion)
  see https://arxiv.org/pdf/1706.00074.pdf and refs. therein

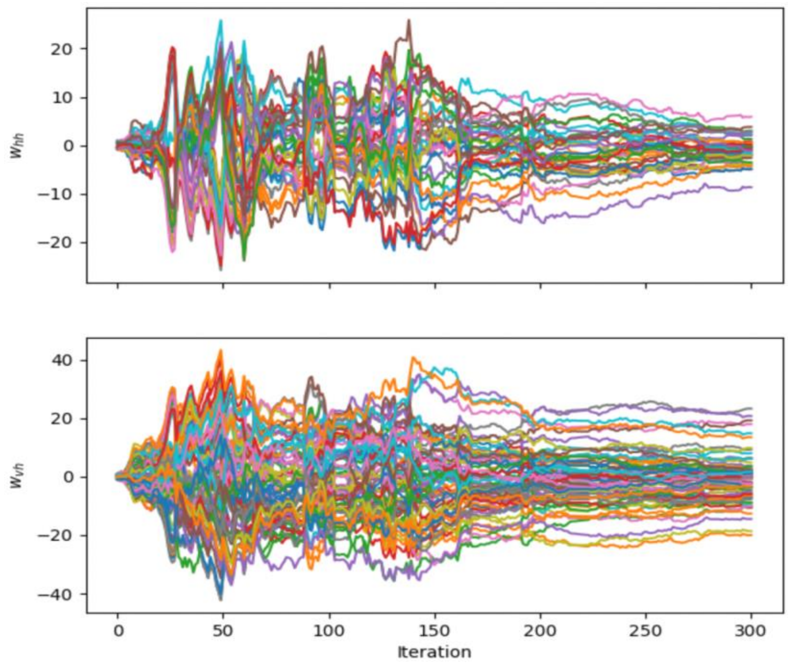


QBM: results on D-Wave 2000Q, part I

- AWS Braket platform: D-Wave 2000Q
- **First trainings not successful:** hyperparameter scans on hardware too expensive
- Train QBM with SQA and **reload trained weights on D-Wave**
- **Evaluation on D-Wave looks promising!**

SQA agent evaluation on D-Wave 2000Q



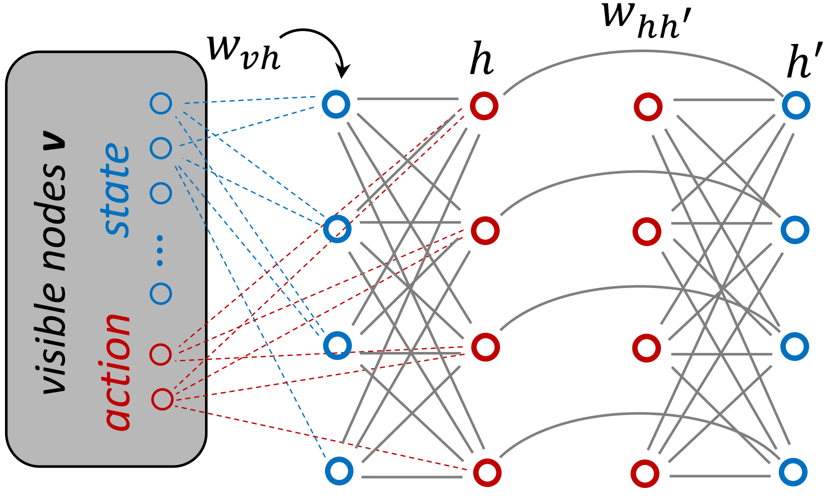


Evolution of QBM weights during training with SQA

QBM: continuous state space I

- **Major limitation: discrete, binary state space**
  - E.g. here we use 8 nodes => 256 bins
  - Limited resolution, limited state space dimension, large number of coupling weights, slow, training less robust
- **QBM is clamped**
  - Visible nodes are **not actually represented by qubits**, which are binary by definition (spin up / down)
  - They **enter system only as biases** => no need to be discrete, binary
- **Continuous state space possible**
  - Opens doors for more complex systems and more practical applications
  - Later today: actor-critic setup

Clamped QBM



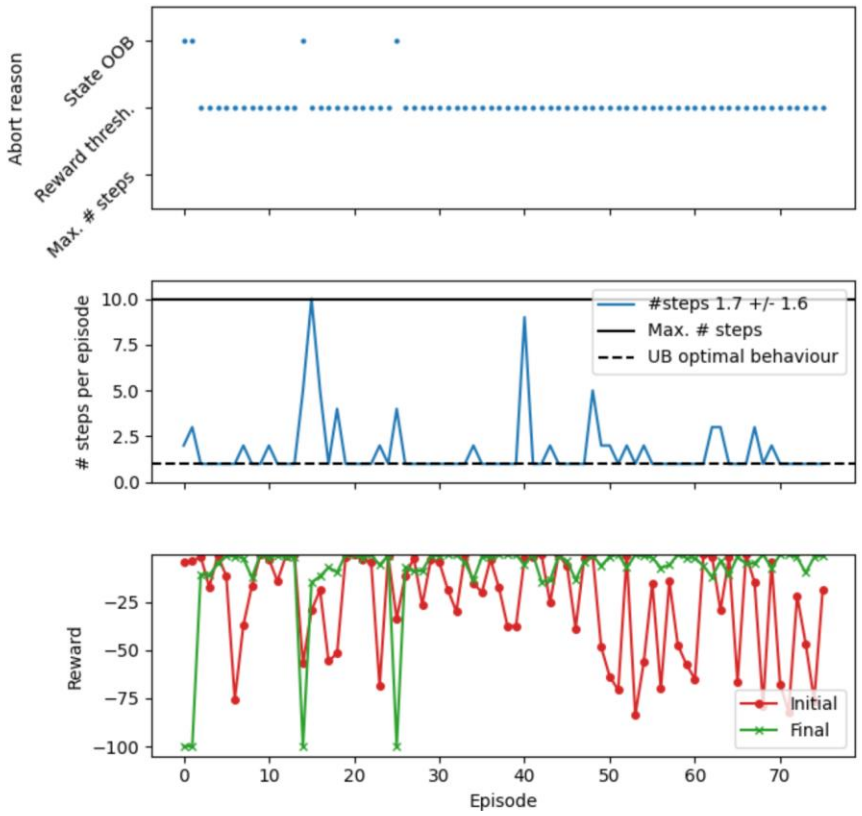
$$\hat{Q}(s,a) \approx -F(\boldsymbol{v}) = -\langle H_v^{\text{eff}} \rangle - \frac{1}{\beta} \sum_c \mathbb{P}(c|\boldsymbol{v}) \log \mathbb{P}(c|\boldsymbol{v})$$

$$H_v^{\text{eff}} = -\sum_{v \in V,\, h \in H} w_{vh}\, v\, \sigma_h^v - \sum_{h,h' \in H} w_{hh'}\, \sigma_h^z \sigma_{h'}^z$$

Ongoing work: actor-critic II

- **Step 1: test with our implementation of DDPG**
  - Already separates actor and critic for easier replacement of Q-net (step 2)
  - With continuous action space: **optimal behaviour means 1 step is enough** to solve the problem
  - **Works well**

Training



Evaluation