Hybrid Quantum-Classical Reinforcement Learning in Latent Observation Spaces

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GPU DAY 2024

Outline

- Motivation
- RL, PPO, QRL with PPO
- Latent-space QRL
- Numerical results
- Summary & Outlook

Motivation

- **NISQ: Noisy Intermediate-Scale Quantum Devices**
  - Today already 50-100 noisy qubits (NISQ)
  - Early versions of error correction
  - Approaching regime of potential practical quantum advantage

Motivation

- **NISQ: Noisy Intermediate-Scale Quantum Devices**
  - Today already 50-100 noisy qubits (NISQ)
  - Early versions of error correction
  - Approaching regime of potential practical quantum advantage
- **Quantum computational supremacy demonstrated on:**
  - Superconducting device by Google (2019) https://www.nature.com/articles/s41586-019-1666-5
  - Photonic
    - Xanadu, 2022: https://www.nature.com/articles/s41586-022-04725-x
    - Jiuzhang 3.0, 2023: https://journals.aps.org/prl/abstract/10.1103/PhysRevLett.131.150601

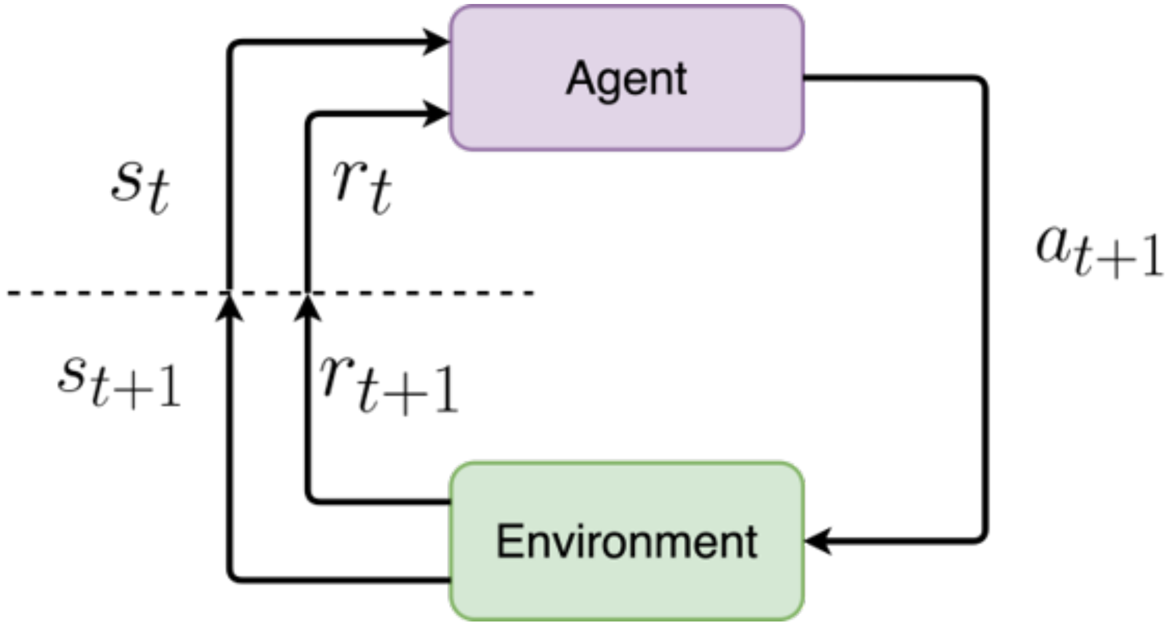
Motivation

- **NISQ-era candidates for practical quantum advantage:**
  - Simulation of quantum chemistry and many-body systems
  - Variational quantum optimization methods like QAOA
  - **Quantum Machine Learning (Includes Quantum Reinforcement Learning)**
  - **Hybrid Quantum-Classical methods enabled by classical HPC**

Motivation

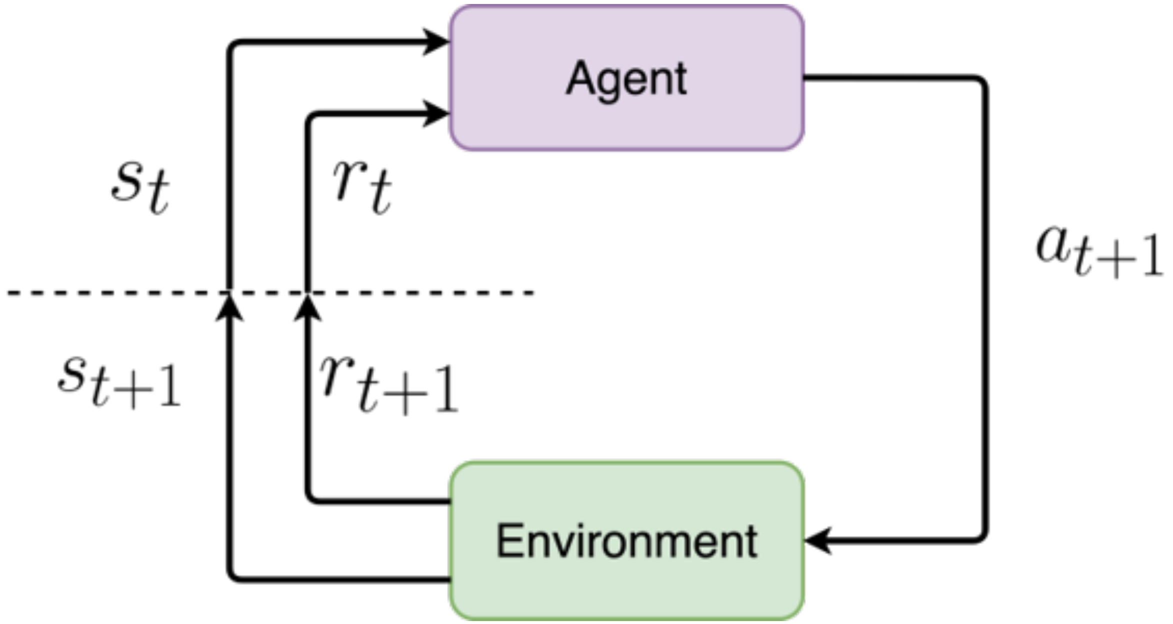
- **QRL is limited by the available QPU sizes**
  - Many RL environments have high dimensional state spaces (e.g. visual data)
  - We would need large scale QPUs to encode raw features into quantum states
  - <u>Solution: use latent features extracted by classical algorithms</u>

Reinforcement Learning



- **Reinforcement Learning (RL)** is a method designed to optimally solve a control problem in a simulated or real-world environment.
- In RL, an **Agent** is **observing the state** of the **environment** and choses **actions** accordingly.
- After the agent performs the action, the e**nvironment** returns a **reward** and the **next state.**

Reinforcement Learning



- The goal is to train an agent which maximizes the discounted cumulative reward,

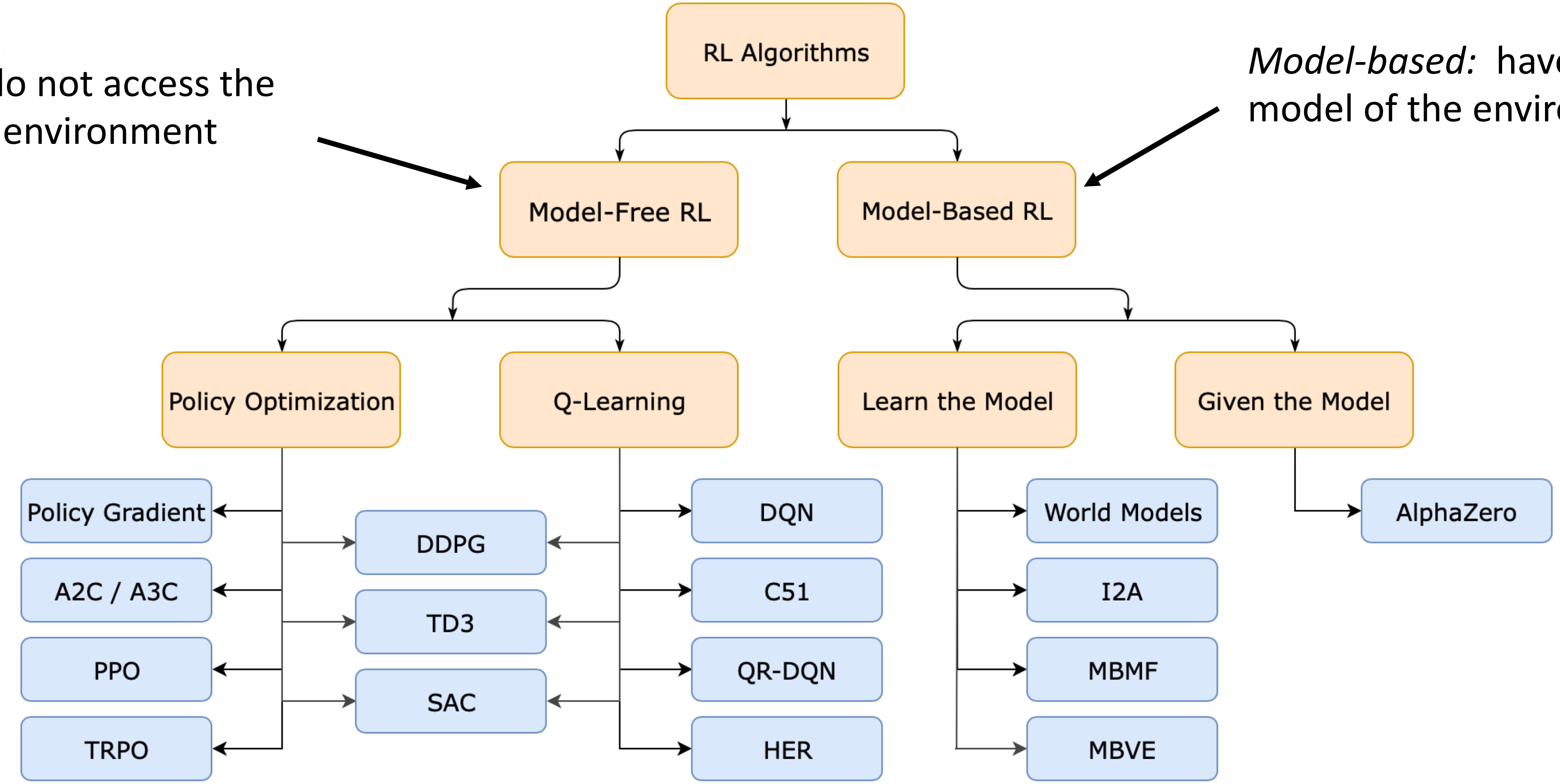
$$R = \sum_t \gamma^t r_t$$

- Such Agents are usually implemented as NNs.

Reinforcement Learning

Model-free: do not access the model of the environment

Model-based: have access to a model of the environment



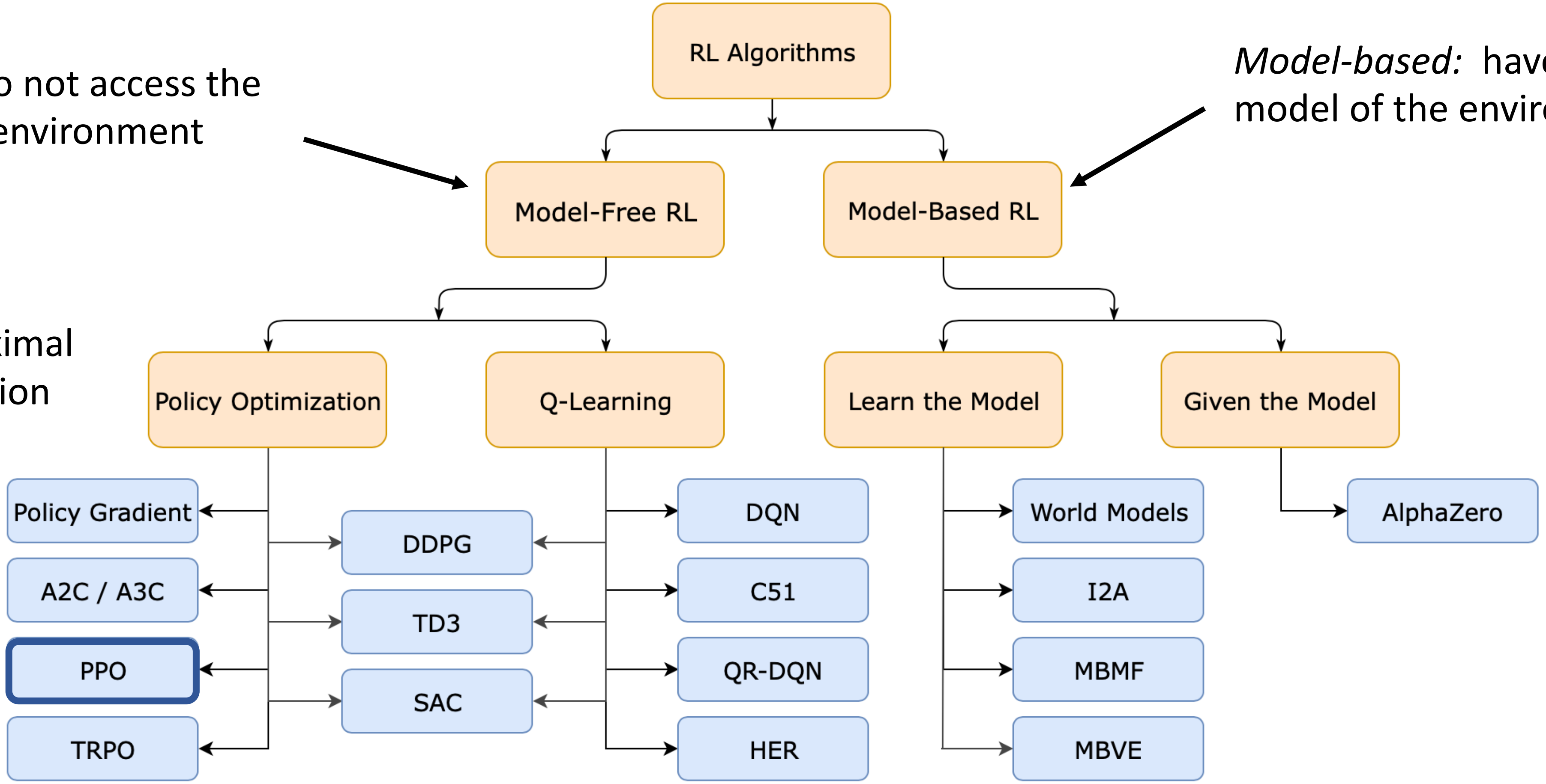
Source: https://spinningup.openai.com/

Reinforcement Learning

Model-free: do not access the model of the environment

Model-based: have access to a model of the environment

We will use Proximal Policy Optimization



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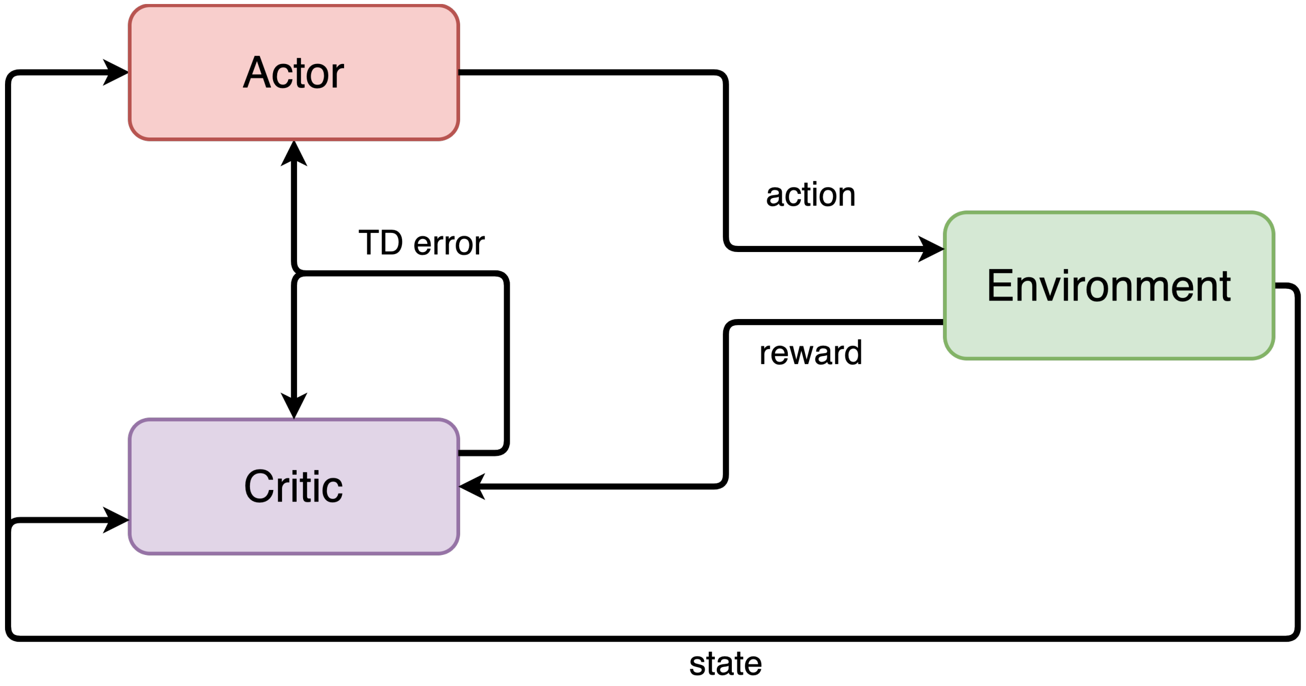
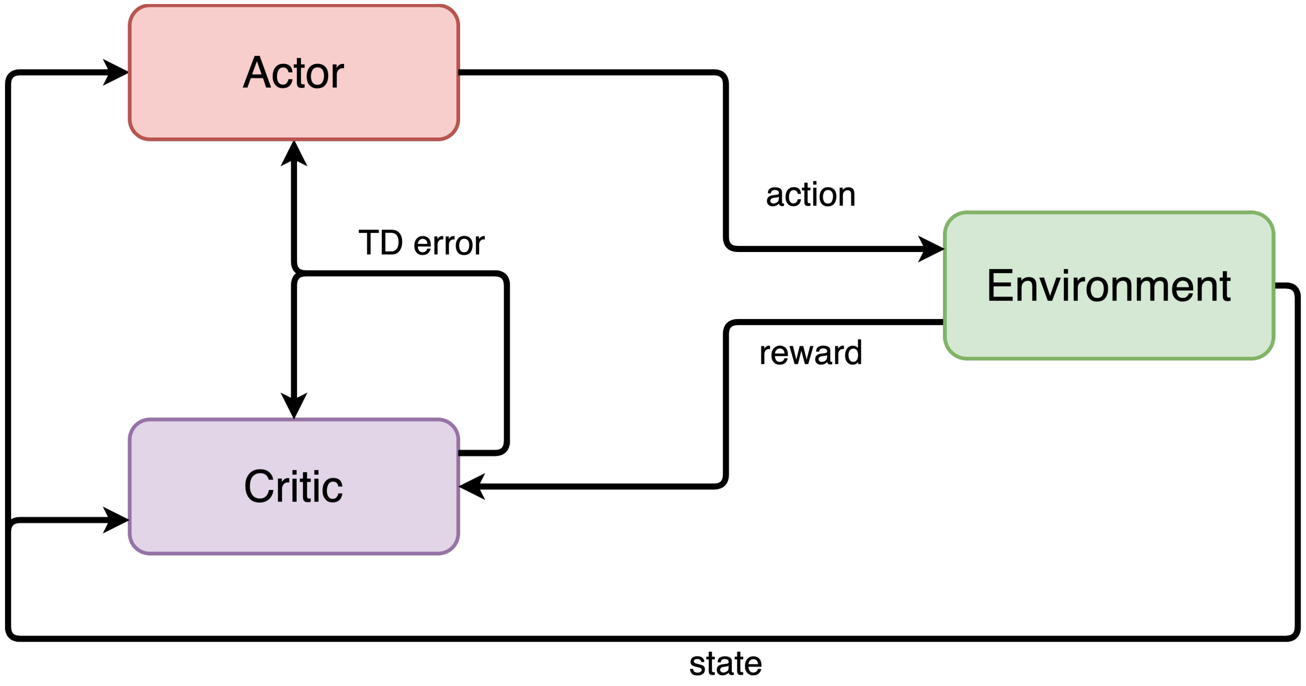
Proximal Policy Optimization (PPO)



- PPO is a model-free method using two function approximators:
  an **Actor** and a **Critic**.
- The Actor choses an action according to a policy π.
- The Critic calculates the estimated value of the state.

Proximal Policy Optimization (PPO)



- The Critic receives the reward and calculates the temporal difference error, which is used to update both Actor and Critic networks.

Proximal Policy Optimization (PPO)

$s_t\,,\ a_t\,, r_t$ are the state, action & reward at timestep t.

$\boxed{\pi_\theta(\cdot|s)}$ is the policy, where theta are the tunable parameters.

$r_t(\theta) = \pi_\theta / \pi_{\theta_{\text{old}}}$ is the ratio of the new and old policies.

$V^\pi(s)$ is the value function used by the Critic.

$\hat{A}_t = \sum_{l=0}^{T-t-1} (\gamma\lambda)^l \delta_{t+l}$ is the estimated advantage with $\delta_t = r_t + \gamma V^\pi(s_{t+1}) - V^\pi(s_t)$

The advantage function estimates the extra reward that could be obtained by the agent by taking that particular action.

Proximal Policy Optimization (PPO)

Critic Loss:

$$\mathcal{L}^{VF} = \mathop{\mathbb{E}}_{t}\left[\left(V^{\pi}(\mathbf{s}_t) - V^{\pi}_{\mathrm{targ}}(\mathbf{s}_t)\right)^2\right]$$

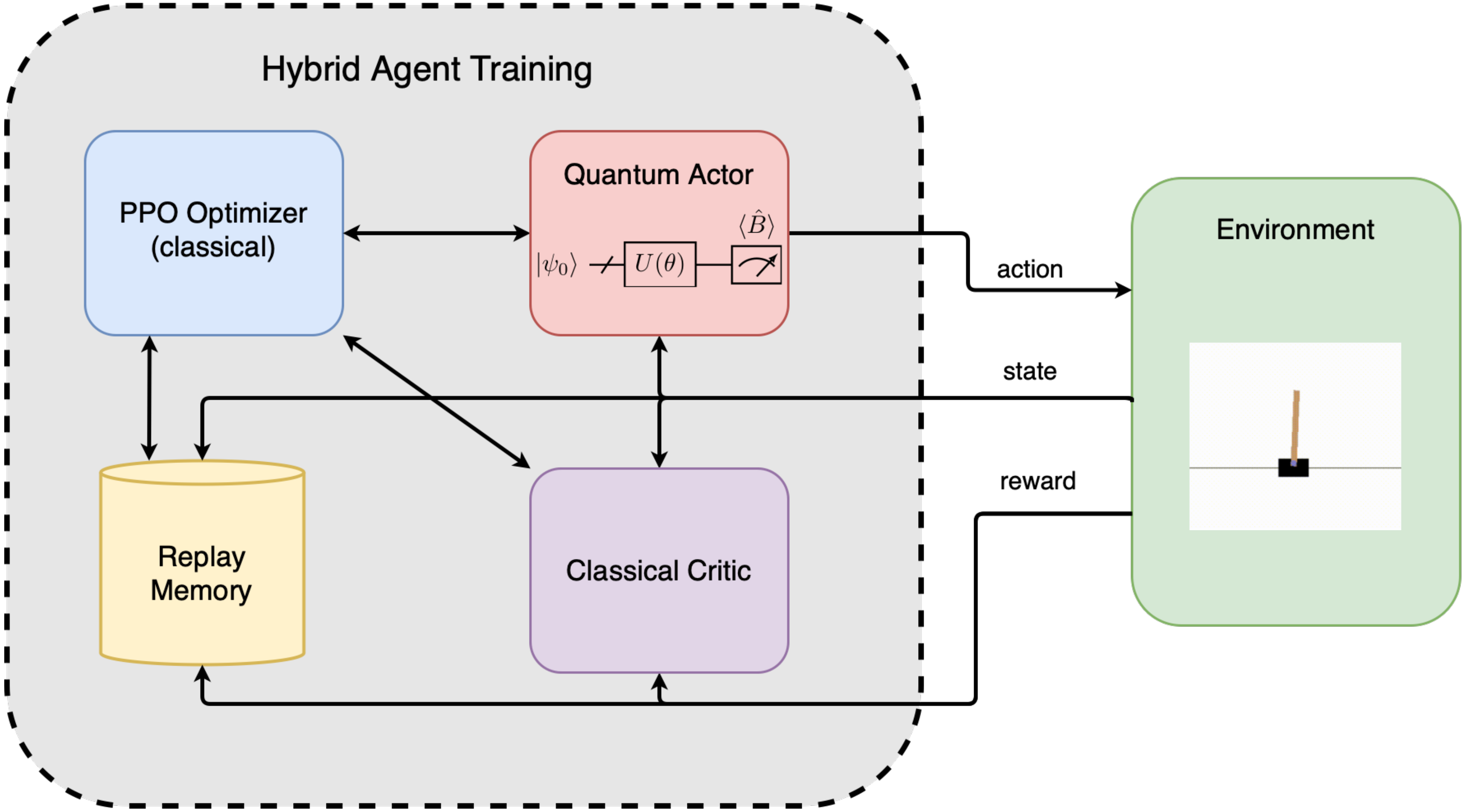
Clipped Surrogate Objective:

$$\mathcal{L}^{\mathrm{CLIP}}(\theta) = \mathbb{E}_t\left[\min\left(r_t(\theta)\hat{A}_t, \mathrm{clip}\left(r_t(\theta), \epsilon\right)\hat{A}_t\right)\right]$$

PPO Objective:

$$\boxed{\mathcal{L}^{\mathrm{PPO}} = \mathcal{L}^{\mathrm{CLIP}}(\theta) + c_1 S\left[\pi_\theta\right] + c_2 \mathrm{Reg}(\theta)}$$

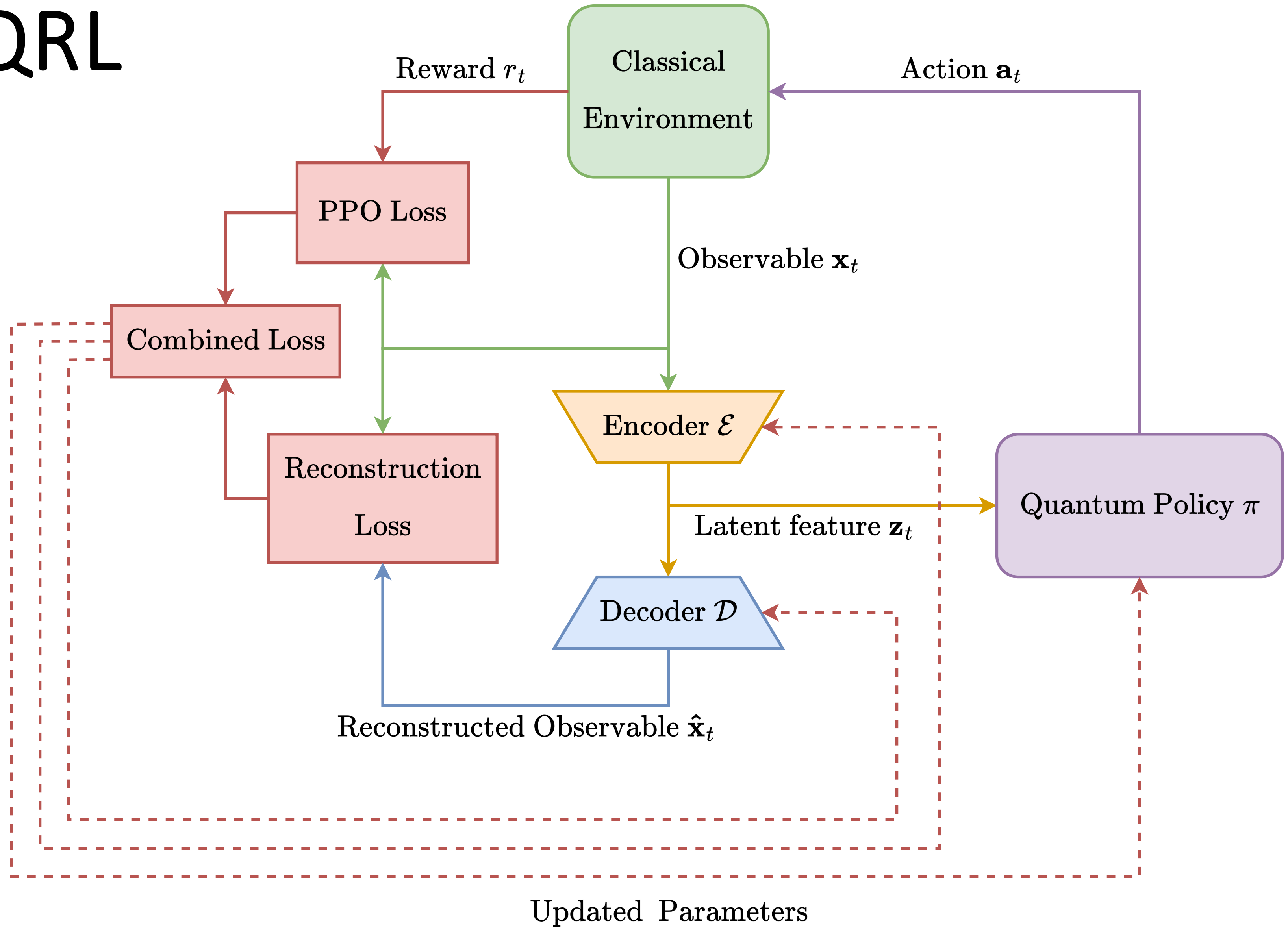
Quantum Reinforcement Learning with PPO



- Substitute the classical policy with a QNN
- Encode states into q-states, compute actions from measurements
- The rest of the system is classical
- Optimize the QNN policy parameters via gradient descent

Latent-space QRL

- As mentioned: environments often have high dimensional observables
- We can not encode the full observable into the initial state of a QNN
- We use a classical AE for feature extraction, and encode latent features
- The classical AE is trained together with the quantum agent

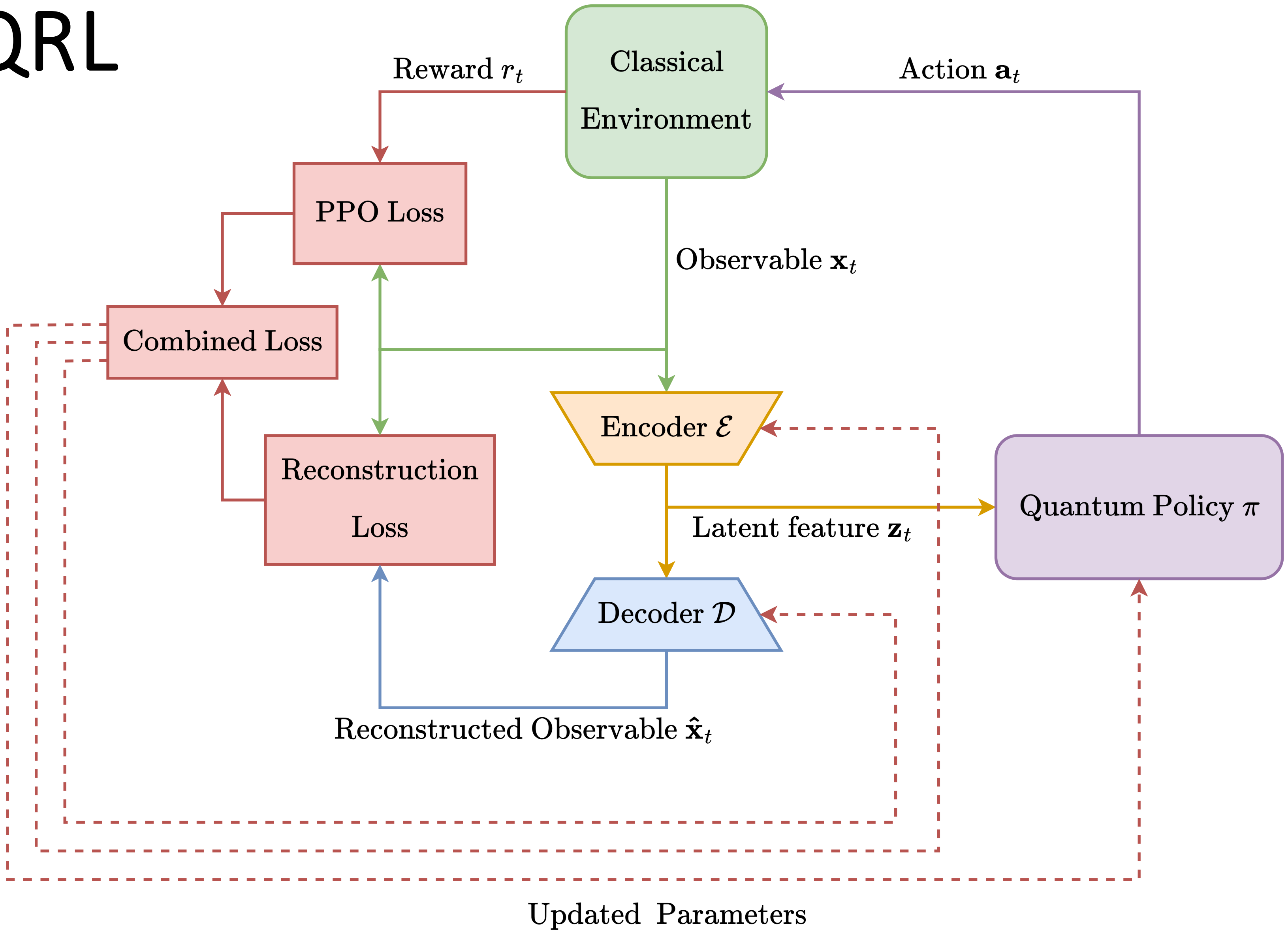


Latent-space QRL

- We optimize the hybrid system via a combined loss function:

$$\mathcal{L}^{(PPO+AE)} = \mathcal{L}^{(PPO)} + c_{\text{ae}}\mathcal{L}^{(AE)}$$

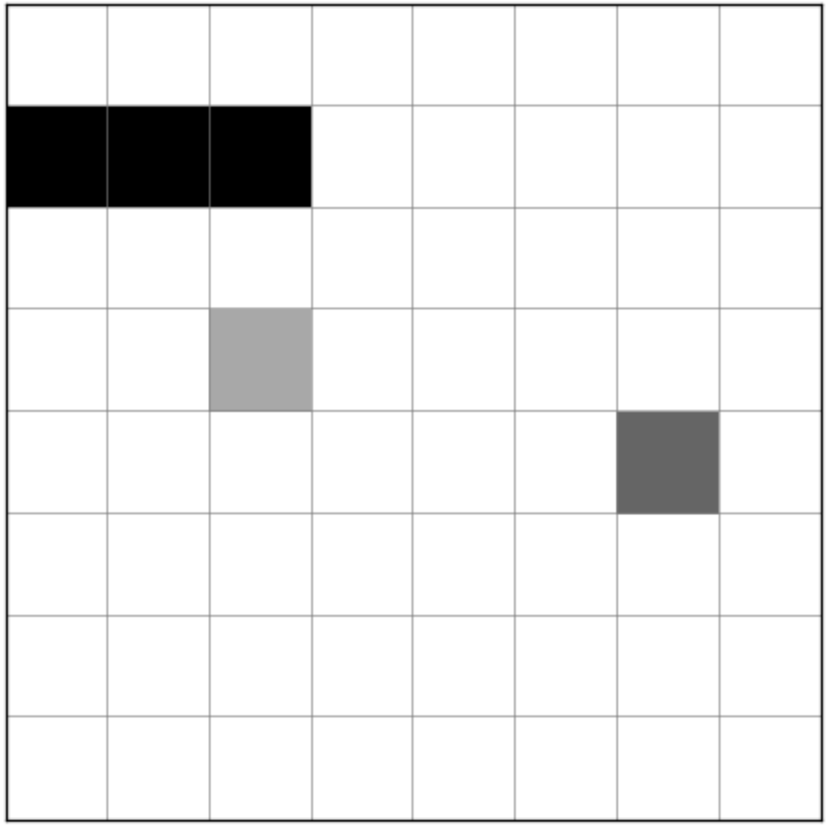
- Optionally, the AE can be pre-trained



Numerical experiments

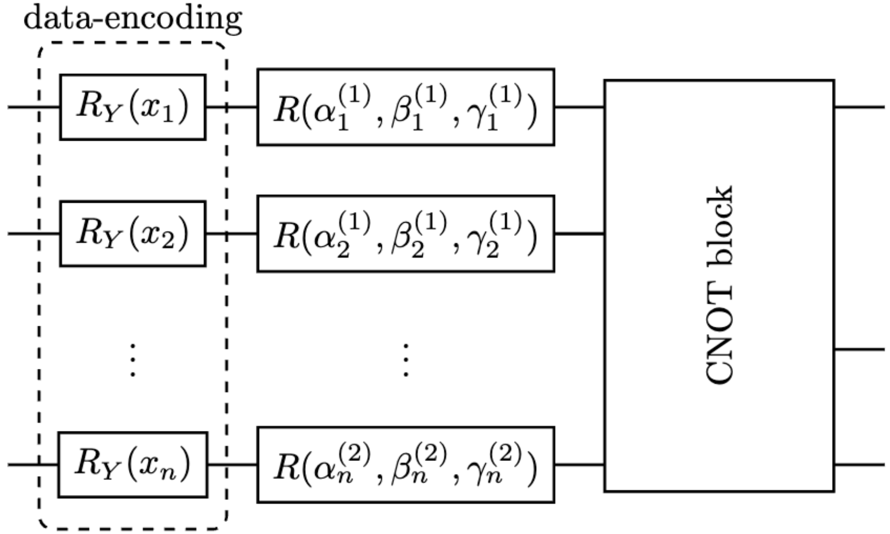
- We tested this approach with various configurations:
  - Three environments: Cartpole-v1, Acrobot-v1 and Maze-v0
  - Various AE sizes, and various number of QNN layers
  - Both qubit-based and photonic QNNs
  - “Cold started” AEs versus pre-trained Aes
  - Compared with fully classical baselines

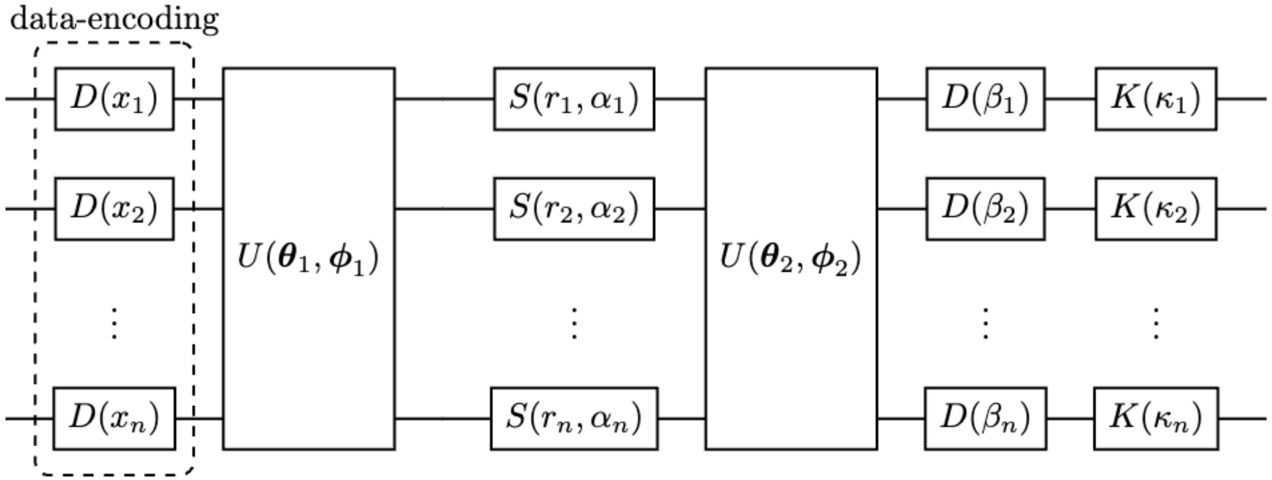
Numerical experiments



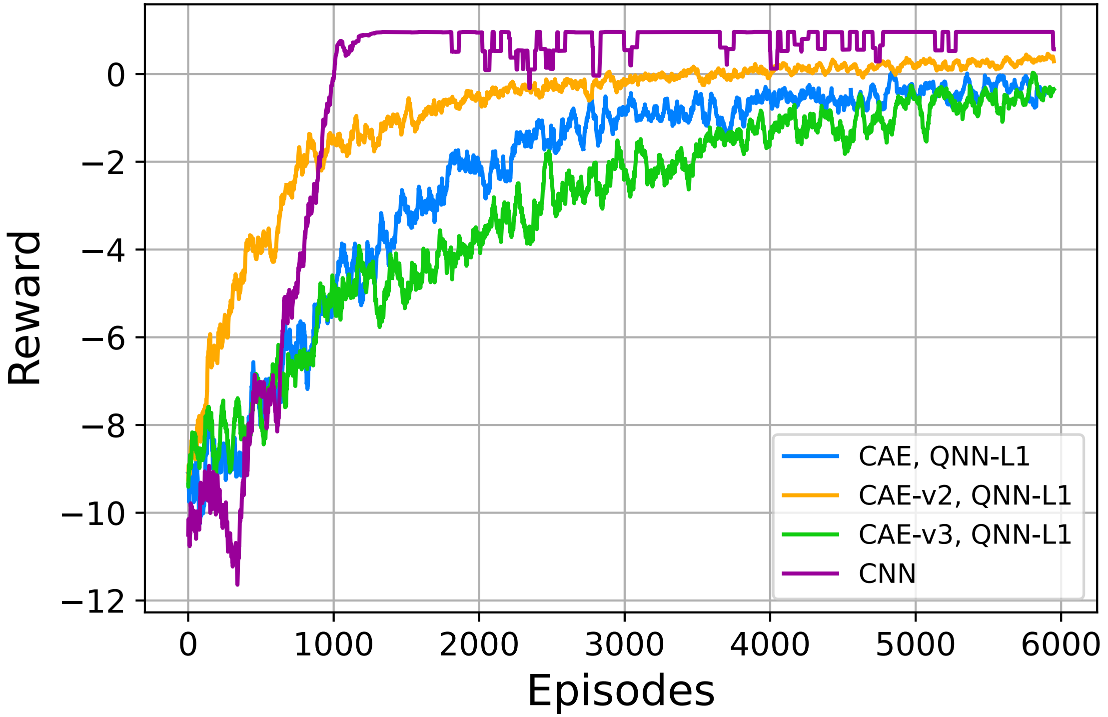
- Maze-v0 environment
- 48x48 grayscale image
- 4 possible actions: up, down, left, right
- The agent starts at a random cell

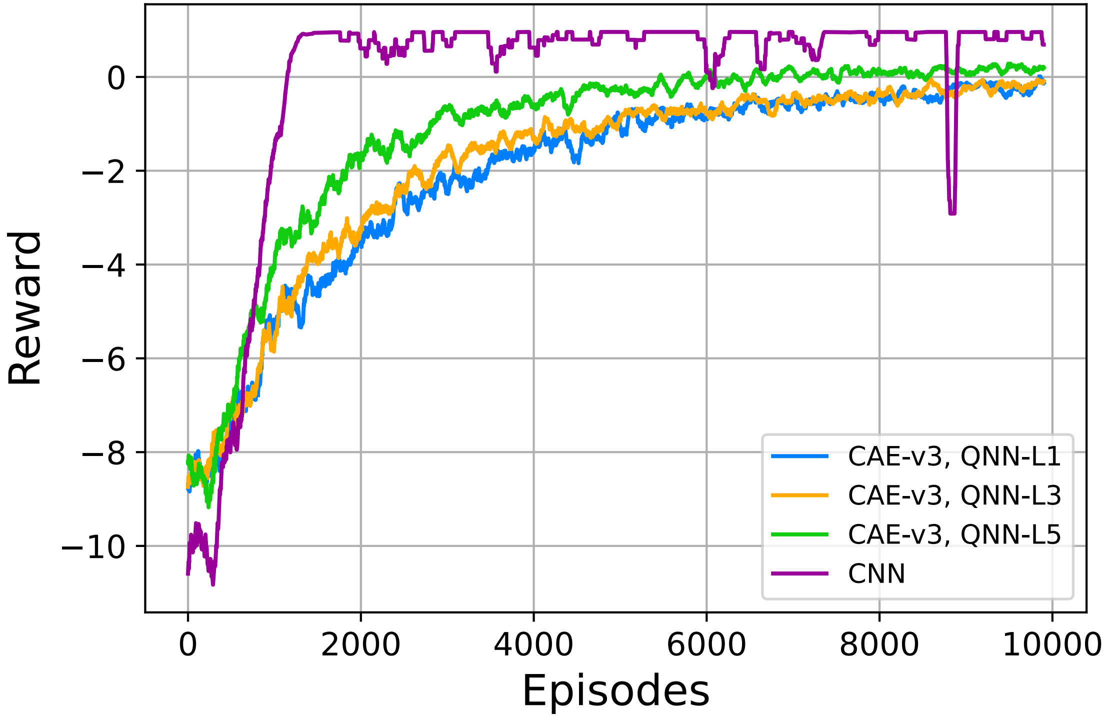
Numerical experiments





Numerical experiments

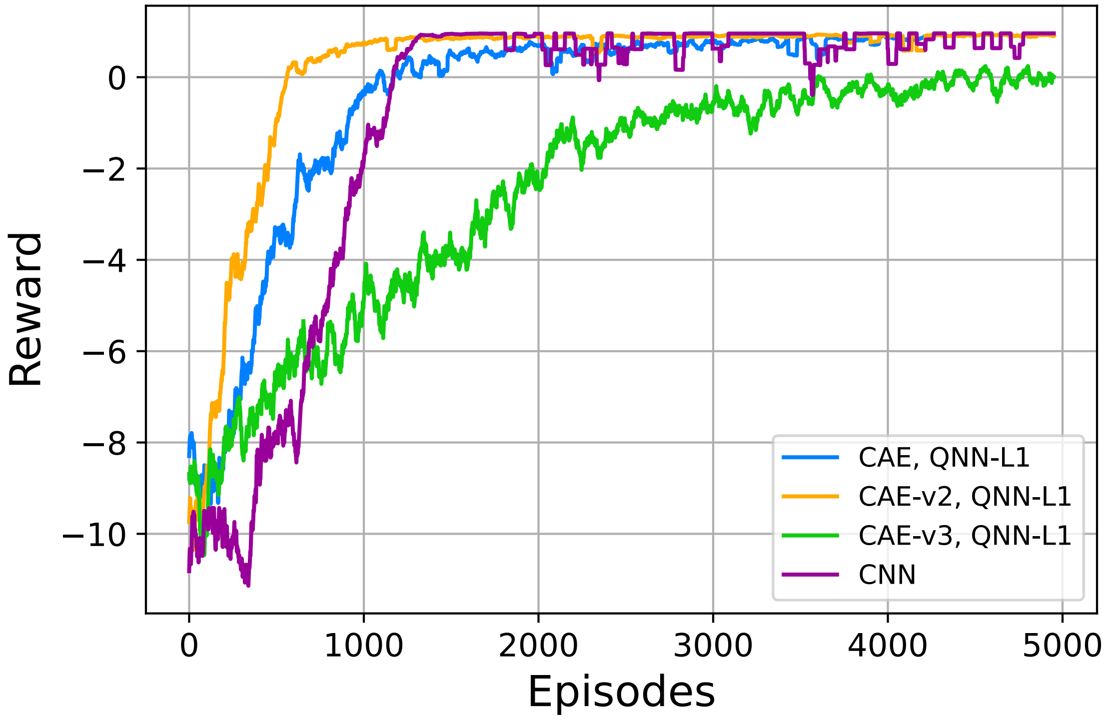


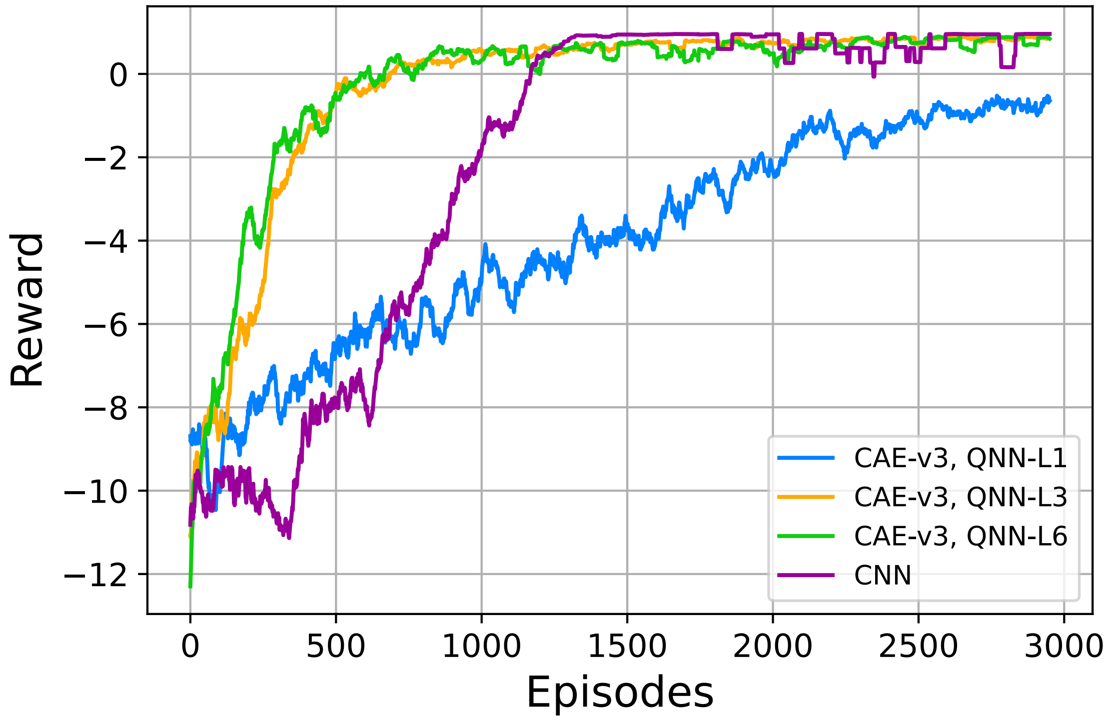


Qubit-based results simulated with Pennylane. Left: Comparing different AE sizes with 1-layer QNN; Right: Comparing different QNN layer count with the smallest AE.

Each curve is a smoothed average over five agents run in parallel

Numerical experiments





Photonic results simulated with Piquasso. Left: Comparing different AE sizes with 1-layer QNN;
Right: Comparing different QNN layer count with the smallest AE.

Each curve is a smoothed average over five agents run in parallel

Conclusions

- We demonstrated that the AE+QNN method enables the application of QRL for high dimensional environments.
- We showed that the joint training of a classical AE and a QRL agent is necessary for convergence.
- We see a tradeoff between AE size and QNN layer count
- We conclude that in some cases, the AE + QNN method can outperform the fully classical approach in terms of parameter count, however this needs further research

Outlook

- A manuscript is in progress with more details.
- Further tasks:
  - Introduce a quantum critic alongside the quantum policy
  - Try to find the best value for the c_ae coefficient

Thank You

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Suppplimentary information

Environment	Name	platform	QNN params
CartPole-v1	QNN-l1	qubit	6
CartPole-v1	QNN-l3	qubit	18
CartPole-v1	QNN-l6	qubit	32
CartPole-v1	QNN-l1	qumode	14
CartPole-v1	QNN-l3	qumode	42
CartPole-v1	QNN-l6	qumode	84
CartPole-v1	MPL	classic	114
Acrobot-v1	QNN-l1	qubit	9
Acrobot-v1	QNN-l3	qubit	27
Acrobot-v1	QNN-l6	qubit	54
Acrobot-v1	QNN-l1	qumode	28
Acrobot-v1	QNN-l3	qumode	84
Acrobot-v1	QNN-l6	qumode	168
Acrobot-v1	MPL	classic	163
Maze-v0	QNN-l1	qubit	24
Maze-v0	QNN-l3	qubit	72
Maze-v0	QNN-l5	qubit	120
Maze-v0	QNN-l1	qumode	94
Maze-v0	QNN-l3	qumode	282
Maze-v0	QNN-l6	qumode	564
Maze-v0	CNN	classic	81140

Environment	Name	Hidden Sizes	Encoder Params	Decoder Params
CartPole-v1	AE-h0	-	10	12
CartPole-v1	AE-h4	4	30	32
Acrobot-v1	AE-h0	-	21	24
Acrobot-v1	AE-h4	4	43	46

Name	Platform	Filter Sizes	Pooling size	Encoder Params	Decoder Params
CAE	qumode	2, 2, 4, 4	2	504	679
CAE-v2	qumode	2, 4, 8, 8	2	1414	2057
CAE-v3	qumode	2, 2	4	172	221
CAE	qubit	2, 2, 4, 4	2	578	751
CAE-v2	qubit	2, 4, 8, 8	2	1560	2075
CAE-v3	qubit	2, 2	4	210	257