Reinforcement Learning
Winter 24/25
University of Tübingen

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Muhteshember

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SAC

$$\mathcal{H}(\pi(\cdot \mid s_t)) = \mathbb{E}_{a\sim\pi(\cdot|s_t)}[-\log(P(\pi(a \mid s_t))]$$

Optimal policy: Reward + entropy terms

$$\pi^* = \arg\max_{\pi} \mathbb{E}_{\tau\sim\pi}\left[\sum_{t=0}^{\infty} \gamma^t \left(R(s_t, a_t, s_{t+1}) + \alpha\mathcal{H}(\pi(\cdot|s_t))\right)\right]$$

2) Prioritized Experience Replay

Instead of uniform sampling, sample based on priority, calculated using TD error:

$$\delta = r + (1 - \text{done}) \cdot \gamma \cdot (\min(Q_{\theta_1}(s', a'), Q_{\theta_2}(s', a')) - \alpha \log \pi(a'|s')) - Q_{\theta_i}(s, a)$$

1) Automatic Temperature Tuning

$$\alpha_t^* = \arg\min_{\alpha_t} \mathbb{E}_{\mathbf{a}_t\sim\pi_t^*}\left[-\alpha_t \log \pi_t^*(\mathbf{a}_t|\mathbf{s}_t; \alpha_t) - \alpha_t\mathcal{H}_0\right]$$

Log trick to ensure non-negativity

$$\log \alpha_t^* = \arg\min_{\log \alpha_t} \mathbb{E}_{\mathbf{a}_t\sim\pi_t^*}\left[-e^{\log \alpha_t}(\log \pi_t^*(\mathbf{a}_t|\mathbf{s}_t) + \mathcal{H}_0)\right]$$

4) Pink Noise

Temporally correlated noise (colored noise) with $\beta = 1.0$

Soft Actor-Critic - Hyperparameter Selection

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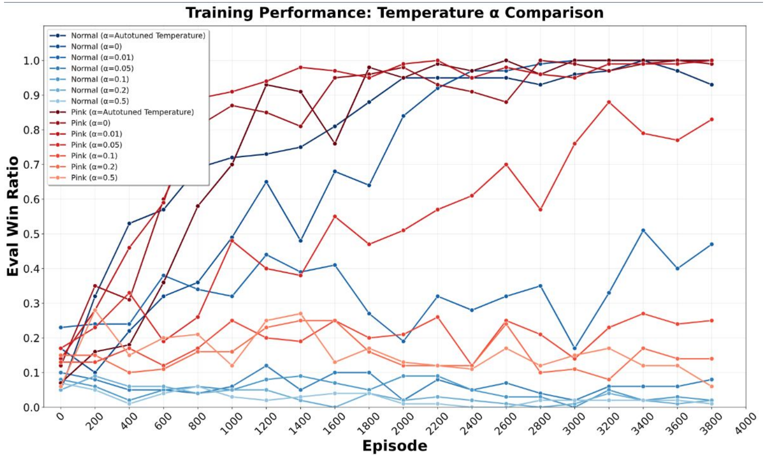

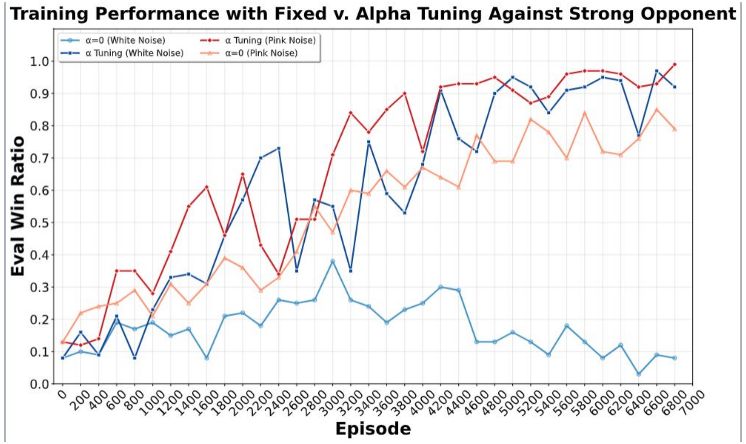

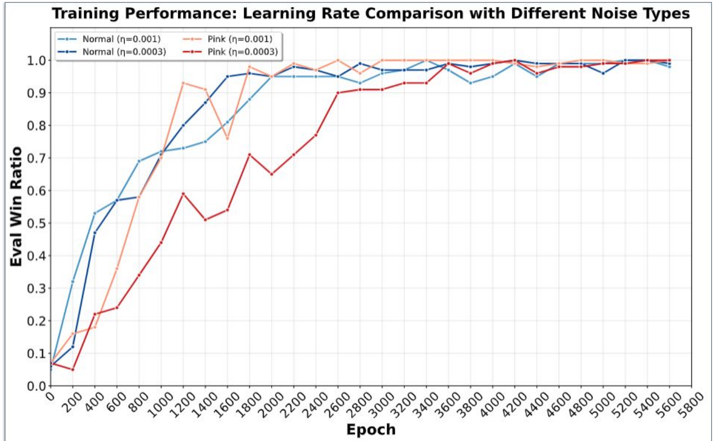

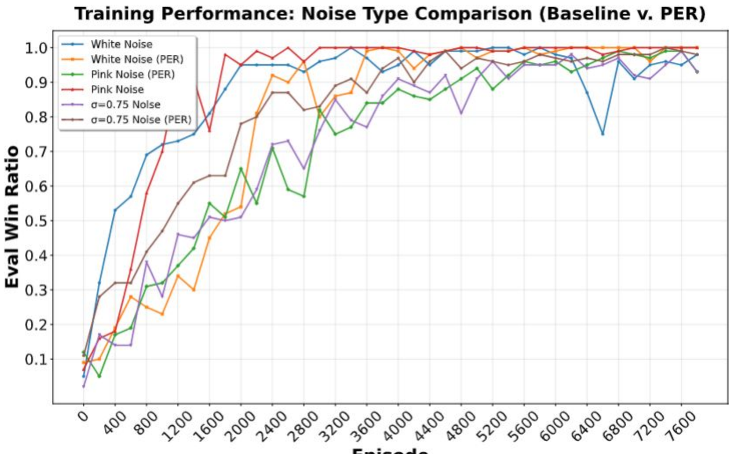

Soft Actor-Critic - Hyperparameter Selection

Parameter	Value
Number of hidden layers	2
Width of each hidden layer	256
Non-linearity	ReLU
Discount factor (γ)	0.99
Target update rate (τ)	0.005
Target update interval	1
Optimizer	Adam
Number of updates	Same as episode length K
Learning rate (η)	10^{-3}
Entropy coefficient (α)	Auto-tuned
Policy noise	0.2
Noise clip	0.5
Policy frequency	2
Batch size	256
Exploration noise exponent (β)	1.0 (Pink Noise)
Exploration noise deviation (σ)	0.1
Replay buffer size	10^6

Automatic entropy tuning is preferred.
PER is not used.
Pink noise is used as the exploration noise.
Discount factor is set to 0.99
Learning rate is set to 1e-3.

Soft Actor-Critic - Training

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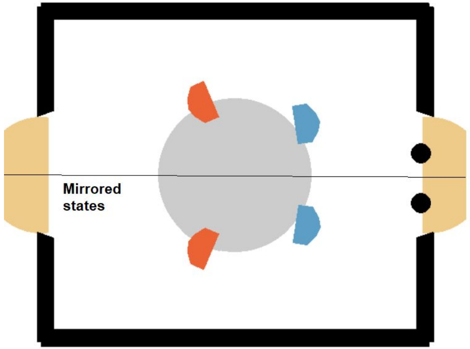
1) Mirrored states and actions



2) Augmented reward

$$
\begin{aligned}
r_{\mathrm{aug}} = {} & 0.5 \cdot \texttt{reward\_closeness\_to\_puck} \\
& + 2.0 \cdot \texttt{reward\_touch\_puck} \\
& + 1.0 \cdot \texttt{reward\_puck\_direction} \\
& + r_{\mathrm{w/l}}.
\end{aligned}
$$

3) Train against strong opponent

4) Self-play using POB with D-UCB

Opponents with worse performance or limited exposure receive more training attention

Twin Delayed DDPG (TD3)

- **Clipped Double Q-Learning** (Twin critics): uses **two critics** to reduce overestimation bias.

$$y = r_t + \gamma \min_{i=1,2} Q_{\phi_{\text{targ},i}}(s_{t+1}, \tilde{a}_{t+1})$$

- **Delayed Policy Updates**: Actor updates happen less frequently to stabilize critic learning.

$$\tilde{a}_{t+1} = \pi_{\theta_{\text{targ}}}(s_{t+1}) + \epsilon, \quad \epsilon \sim \text{clip}(\mathcal{N}(0, \sigma), -c, c)$$

- **Policy Smoothing**: Adds noise to target actions to avoid exploiting Q-value spikes.

TD3 - Extensions

- **Pink Noise**: Replaces standard Gaussian noise for smoother, more correlated exploration.
- **Random Network Distillation (RND)**: Adds an intrinsic reward for visiting novel states.
- **Layer Normalization**: Normalizes activations to stabilize training and improve convergence.

TD3 - Experiments

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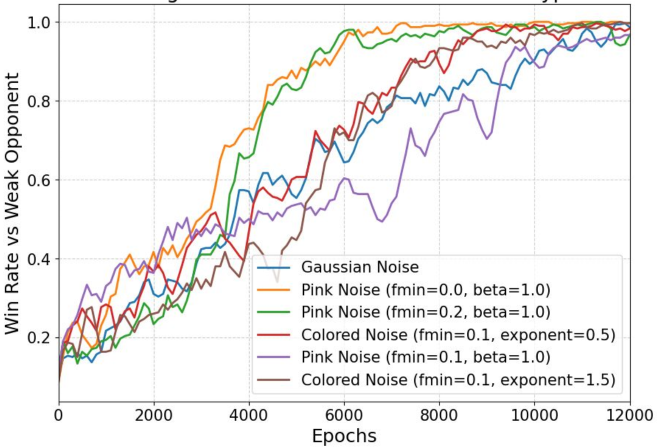
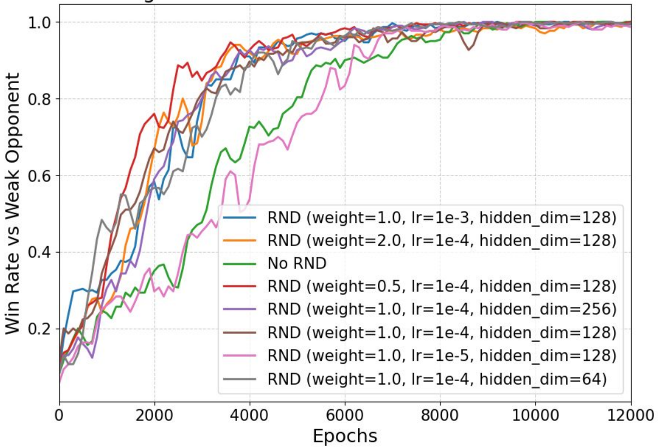
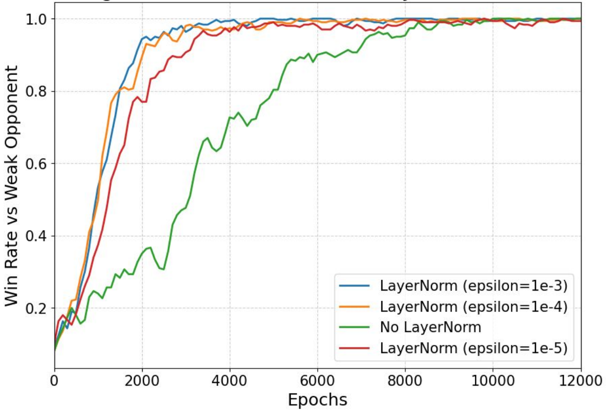
Training Performance with Different Noise Types



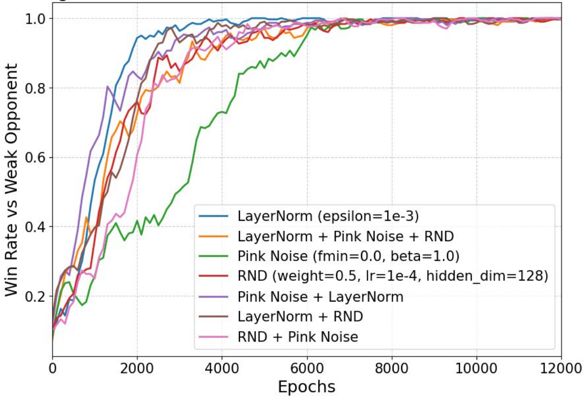
Training Performance with Different RND Parameters



Training Performance with Different Layernorm Parameters



Training Performance with Combined vs. Individual Best Parameters



DQN

- Introduced Q Function estimation with a deep neural network

$$L_i(\theta_i) = \mathbb{E}_{s,a,r,s'}\left[\left(y_i^{DQN} - Q(s, a; \theta_i)\right)\right]$$

$$y_i^{\text{DQN}} = r + \gamma \cdot \max_{\alpha'} Q(s', a'; \theta^-)$$

- θ^- are the target network parameters

Double DQN

- $\max$ uses the same value for action selection and evaluation
- Leads to overestimation
- Double DQN decouples selection and evaluation in training objective

$$y_i^{\text{DQN}} = r + \gamma \cdot \max_{\alpha'} Q(s', a'; \theta^-)$$

$$y_i^{\text{DDQN}} = r + \gamma \cdot Q(s', \arg\max_{a'} Q(s', a'; \theta_i); \theta^-)$$

- Splits Q estimator into Advantage and State-Value function estimators

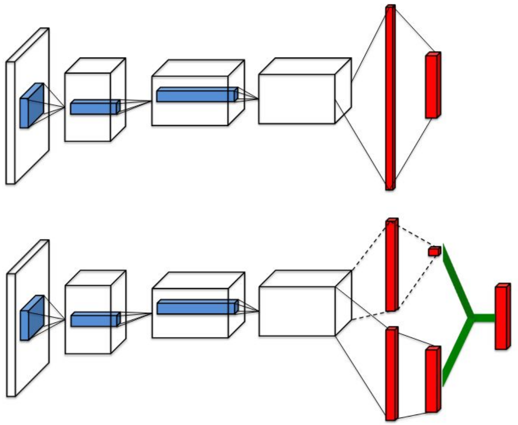


Figure 1. A popular single stream Q-network (**top**) and the dueling Q-network (**bottom**). The dueling network has two streams to separately estimate (scalar) state-value and the advantages for each action; the green output module implements equation (9) to combine them. Both networks output Q-values for each action.

$$Q(s,a;\theta,\alpha,\beta) = V(s;\theta,\beta) + \left(A(s,a;\theta,\alpha) - \frac{1}{|\mathcal{A}|}\sum_{a'} A(s,a';\theta,\alpha)\right)$$

(Wang et al., 2016)

Performance of DQN Additions

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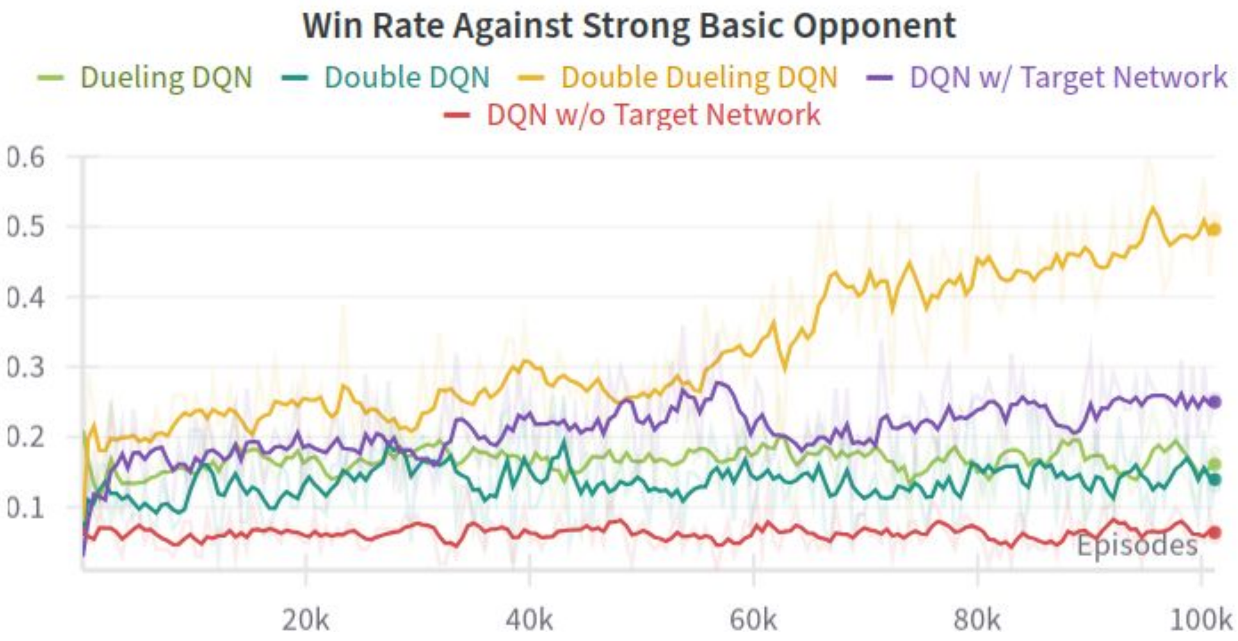

Performance of DQN Additions

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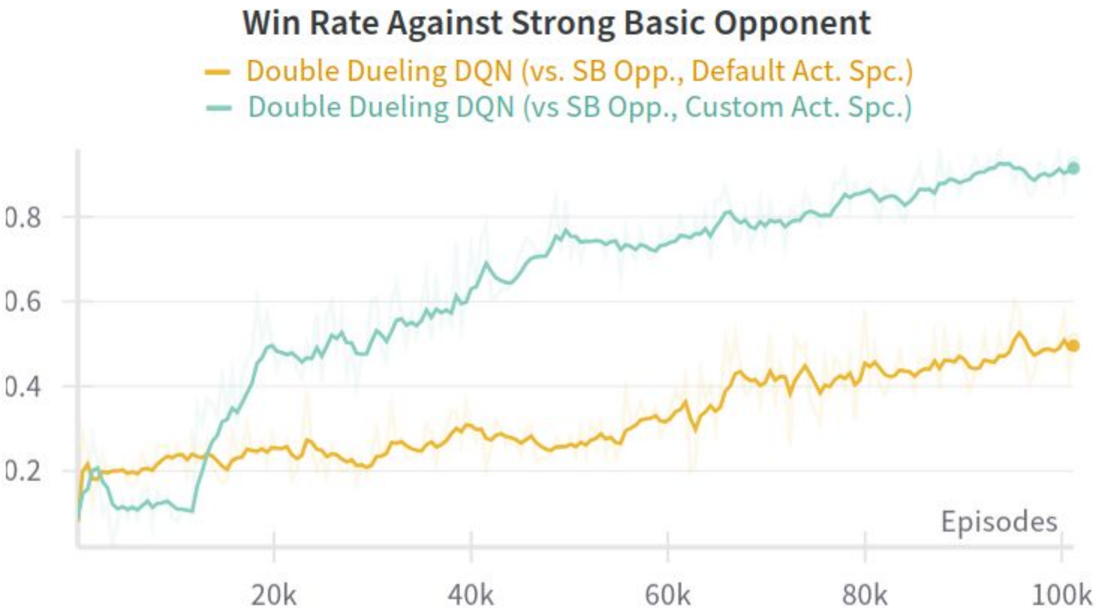

Final Comparison

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