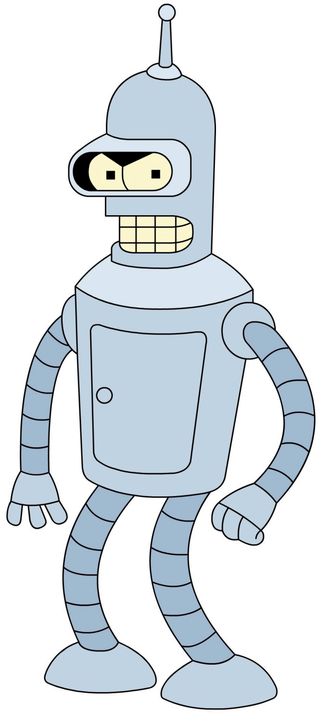
Reinforcement Learning

HSE, winter - spring 2024

Lecture 3: Intro to Deep RL, DQN



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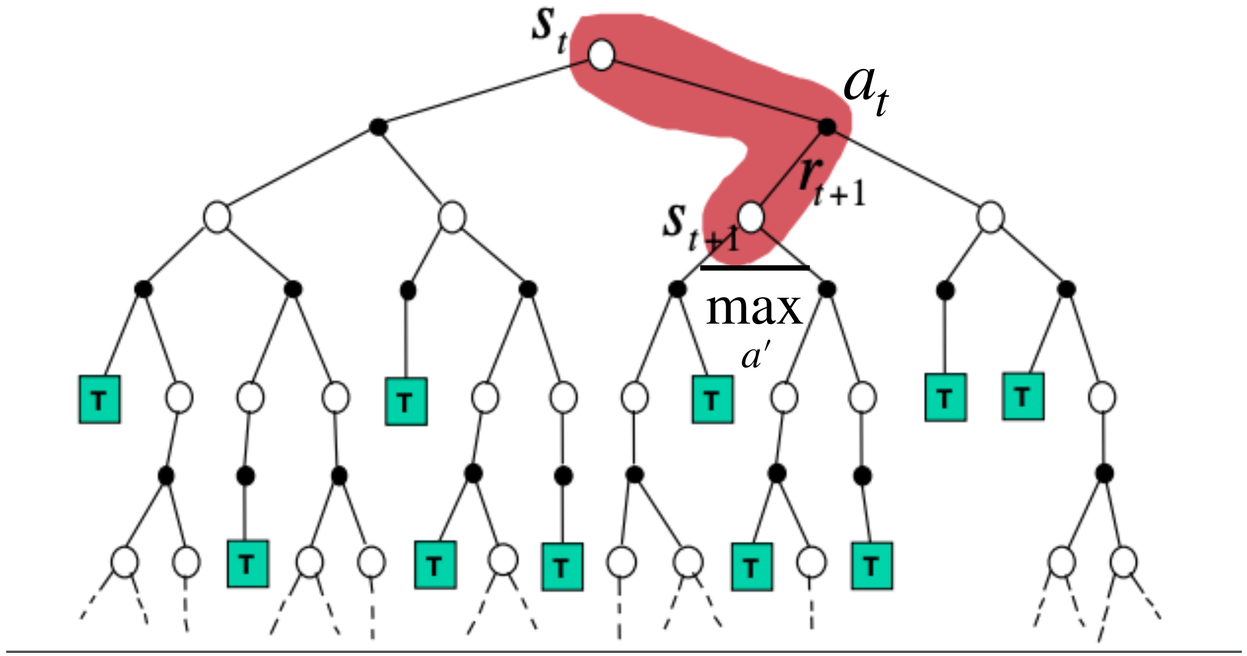
Recap: Q-Learning

Setup: $|\mathcal{A}| < +\infty, |\mathcal{S}| < +\infty$

$$Q_{k+1}(s,a) \leftarrow Q_k(s,a) + \alpha(r + \gamma \max_{a'} Q_k(s',a') - Q_k(s,a))$$

$$s' \sim p(.|s,a)$$

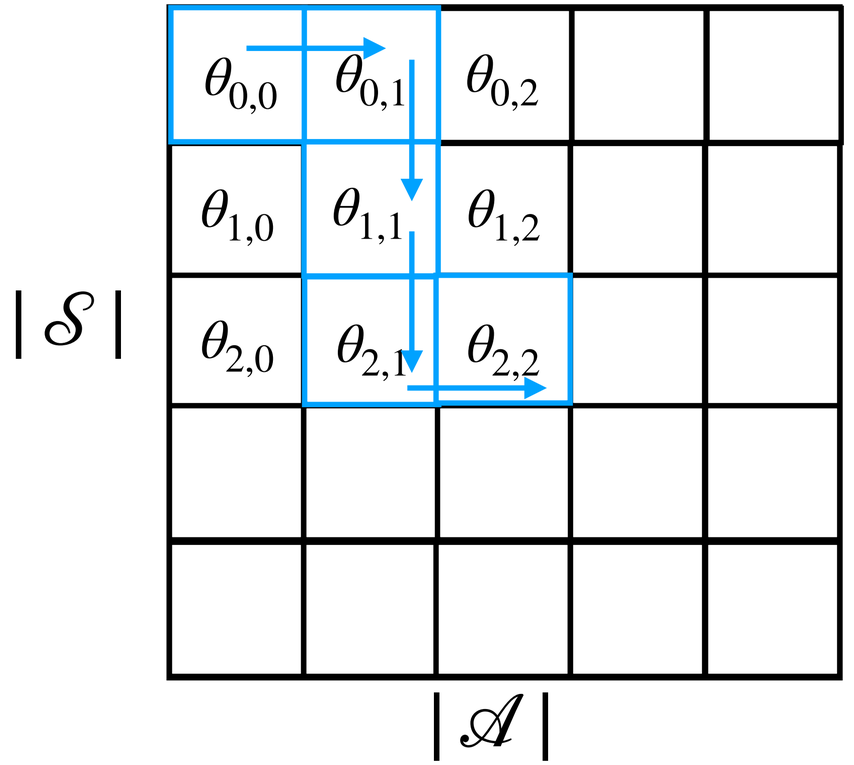


Q-Learning

Recall the Bellman optimality equation for Q^*

$$Q^*(s,a) = r(s,a) + \gamma \mathbb{E}_{s'} \max_{a'} Q^*(s',a')$$

$$Q(s,a) \approx \theta_{s,a}$$



$$Q_{k+1}(s,a) \leftarrow Q_k(s,a) + \alpha(r + \gamma \max_{a'} Q_k(s',a') - Q_k(s,a))$$

Q-Learning

For target $y_Q = r(s,a) + \gamma \max_{a'} Q(s',a')$ let's optimise MSE:

$$L(\theta) = \frac{1}{2}\mathbb{E}_{s'}[y_Q - \theta]^2 \to \min_{\theta}$$

$$\nabla_\theta L(\theta) = \mathbb{E}_{s'}[y_Q] - \theta = 0, \text{ so } \theta = Q(s,a) = \mathbb{E}_{s'} y_Q$$

In general infeasible

Q-Learning

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In general infeasible

For each s', y_Q is an unbiased estimate of $\mathbb{E}_{s'} y_Q$, so

$\theta - y_Q$ is an unbiased estimated of $\nabla_\theta L(\theta)$

Q-Learning

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In general infeasible

For each s', y_Q is an unbiased estimate of $\mathbb{E}_{s'} y_Q$, so

$\theta - y_Q$ is an unbiased estimated of $\nabla_\theta L(\theta)$

SGD: $\theta_{k+1} = \theta_k + \alpha(y_Q - \theta_k)$

Q-Learning Generalisation

$$Q(s,a) \approx Q_{\theta_k}(s,a)$$

For target $y_Q = r(s,a) + \gamma \max_{a'} Q_{\theta_k}(s',a')$ let's optimise MSE:

$$L(\theta) = \frac{1}{2}\mathbb{E}_{s'}[y_Q - Q_\theta(s,a)]^2 \to \min_\theta$$

$$\nabla_\theta L(\theta) \approx (Q_\theta(s,a) - y_Q)\nabla_\theta Q_\theta(s,a)$$

Q-Learning Generalisation

In general, for $y_Q = r(s,a) + \gamma \max\limits_{a'} Q_{\theta_k}(s',a')$

$$L(\theta) = \frac{1}{2}\mathbb{E}_{s,a\sim\rho(.),s'\sim p(.|s,a)}[y_Q - Q_\theta(s,a)]^2 \to \min\limits_{\theta}$$

where ρ is the behaviour distribution.

$$\nabla_\theta L(\theta) \approx \mathbb{E}_{s,a\sim\rho(.)}(Q_\theta(s,a) - y_Q)\nabla_\theta Q_\theta(s,a)$$

Q-Learning Generalisation

In general, for $y_Q = r(s,a) + \gamma \max_{a'} Q_{\theta_k}(s',a')$

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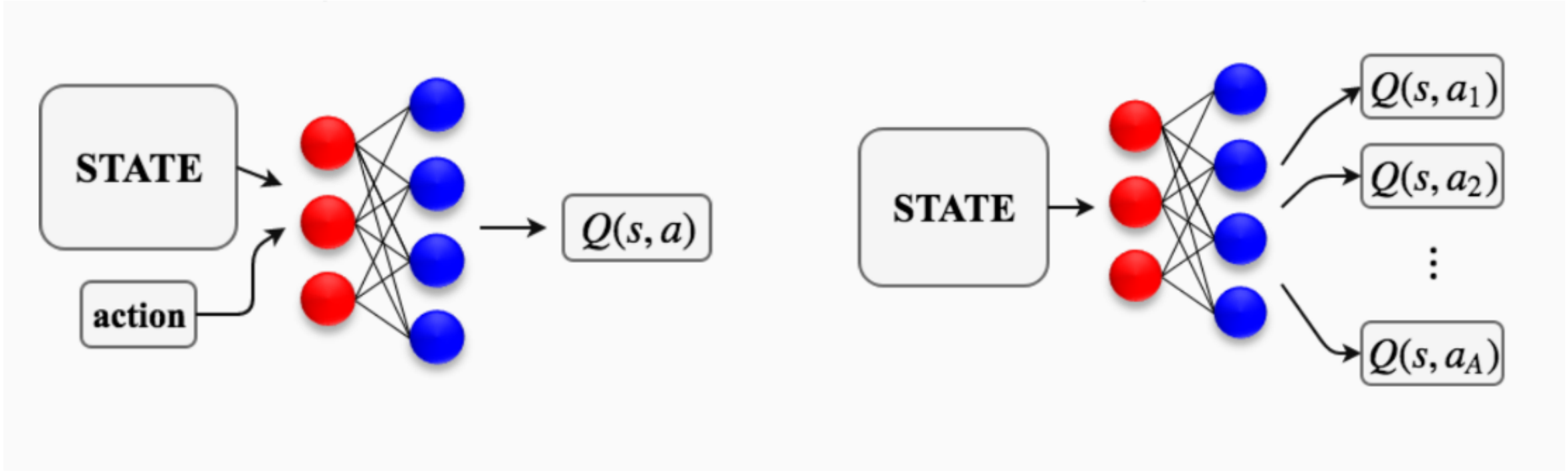
where ρ is the behaviour distribution.

$$\nabla_\theta L(\theta) \approx \mathbb{E}_{s,a\sim\rho(.)}(Q_\theta(s,a) - y_Q)\nabla_\theta Q_\theta(s,a)$$

Choose your fighter



Source

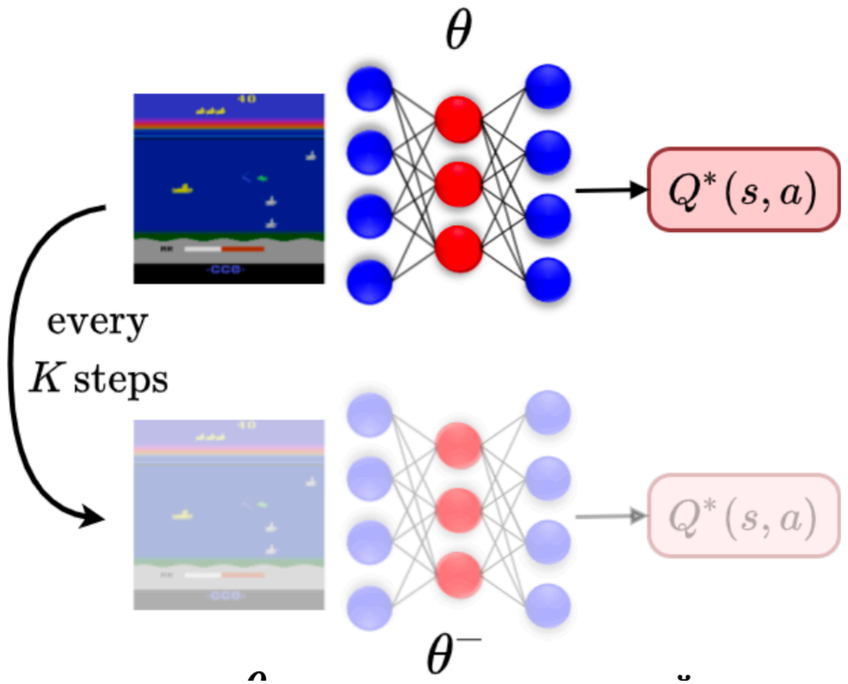
Target Network

If we use weights from the previous step to calculate y_Q they will be highly non-stationary.

Let's update the weights $\theta^-$of the target network every K steps or apply soft updates (Polyak update) with the parameter β:

A. $\theta^- \leftarrow \theta$ every K SGD iterations

B. $\theta^- \leftarrow (1-\beta)\theta^- + \beta\theta$ on each iteration



Behaviour Policy

Behaviour policy is ε-greedy policy:

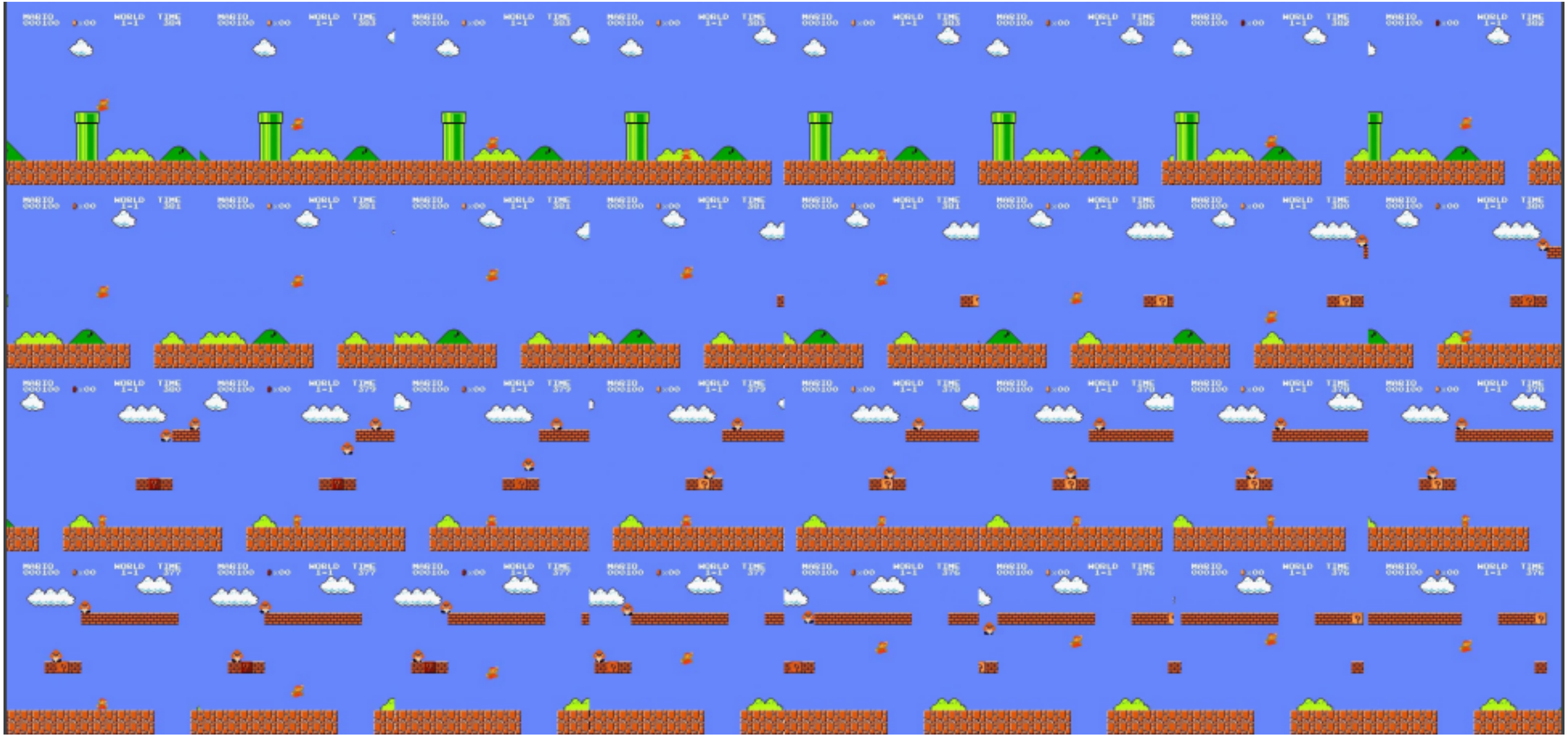
$$\mu = \begin{cases} \text{select random action with probabily } \varepsilon \\ \text{select greedy action with probabily } 1 - \varepsilon \end{cases}$$

We use ε-greedy strategies to avoid being stuck in local optima.

$$\nabla_\theta L(\theta) \approx (Q_\theta(s,a) - y_Q) \nabla_\theta Q_\theta(s,a), a \sim \mu(\,.\,|\,s)$$

$$\nabla_\theta L(\theta) \approx \frac{1}{B} \sum_{j=1}^{B} [(Q_\theta(s_j, a_j) - y_j) \nabla_\theta Q_\theta(s_j, a_j)], a_j \sim \mu(\,.\,|\,s_j)$$

Consecutive samples are extremely correlated so batch's elements are not i.i.d.



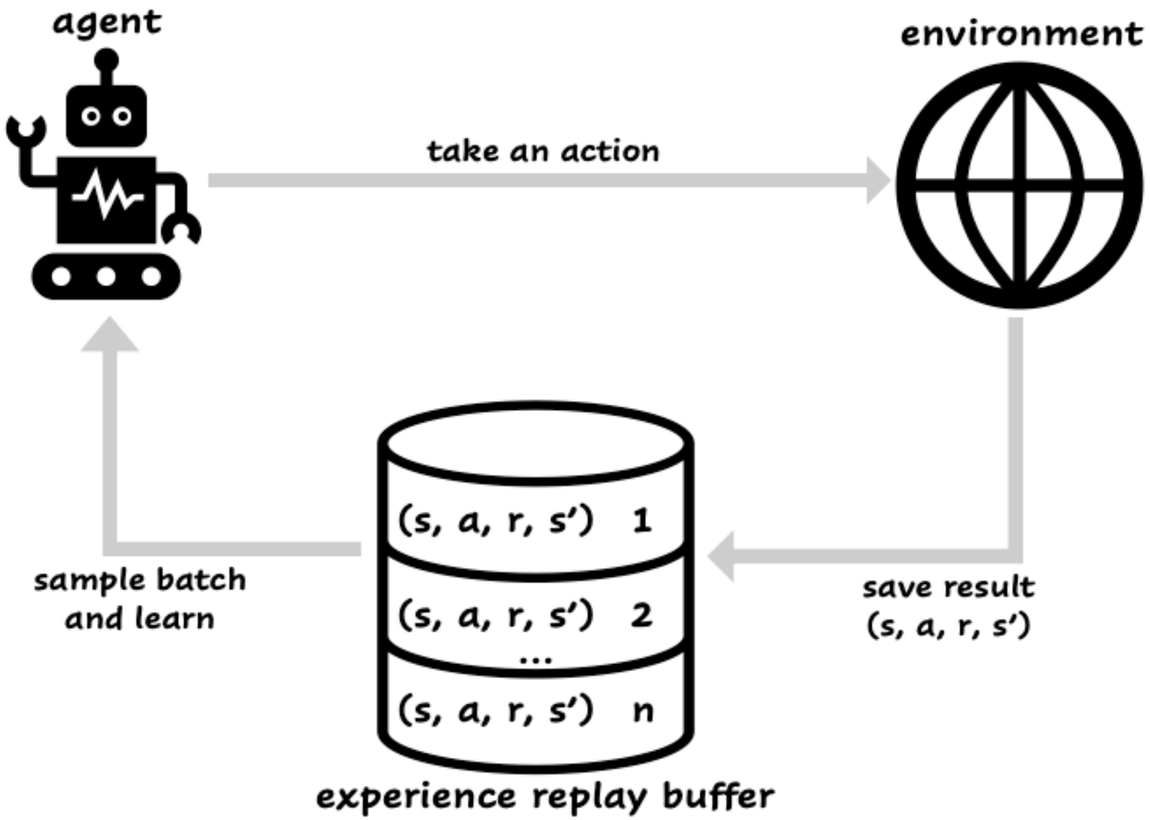
Recap: Experience Replay Buffer

Advantages:

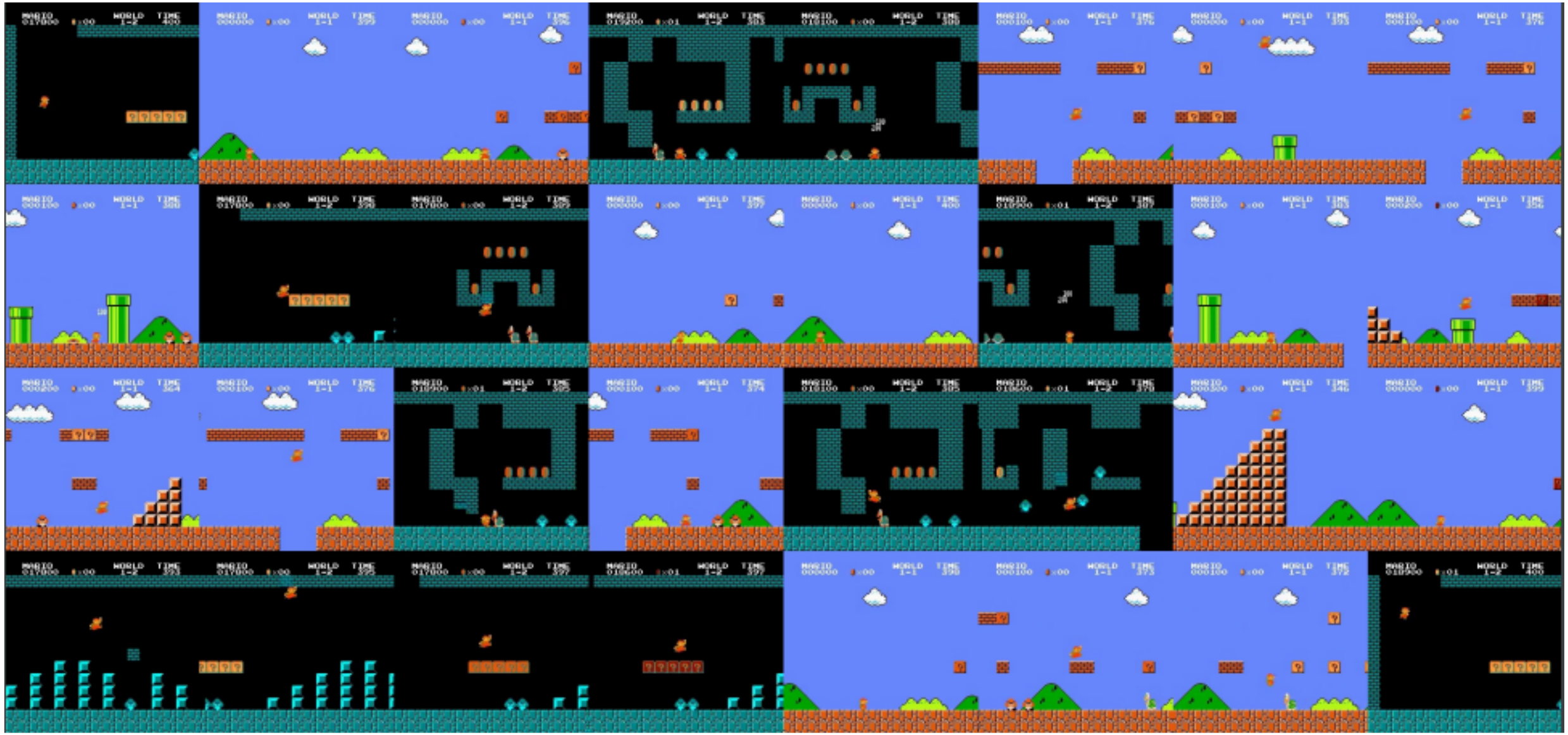
- No need to revisit same states many times
- Make the estimators consistent with the current policy, update estimators
- Decorrelate update samples to maintain i.i.d. assumption

Disadvantages:

- Not applicable for the on-policy learning



Let’s sample randomly from the Experience Replay Buffer which stores played transitions



DQN Algorithm

Initialise θ; $\theta^- = \theta$; replay buffer D is empty;

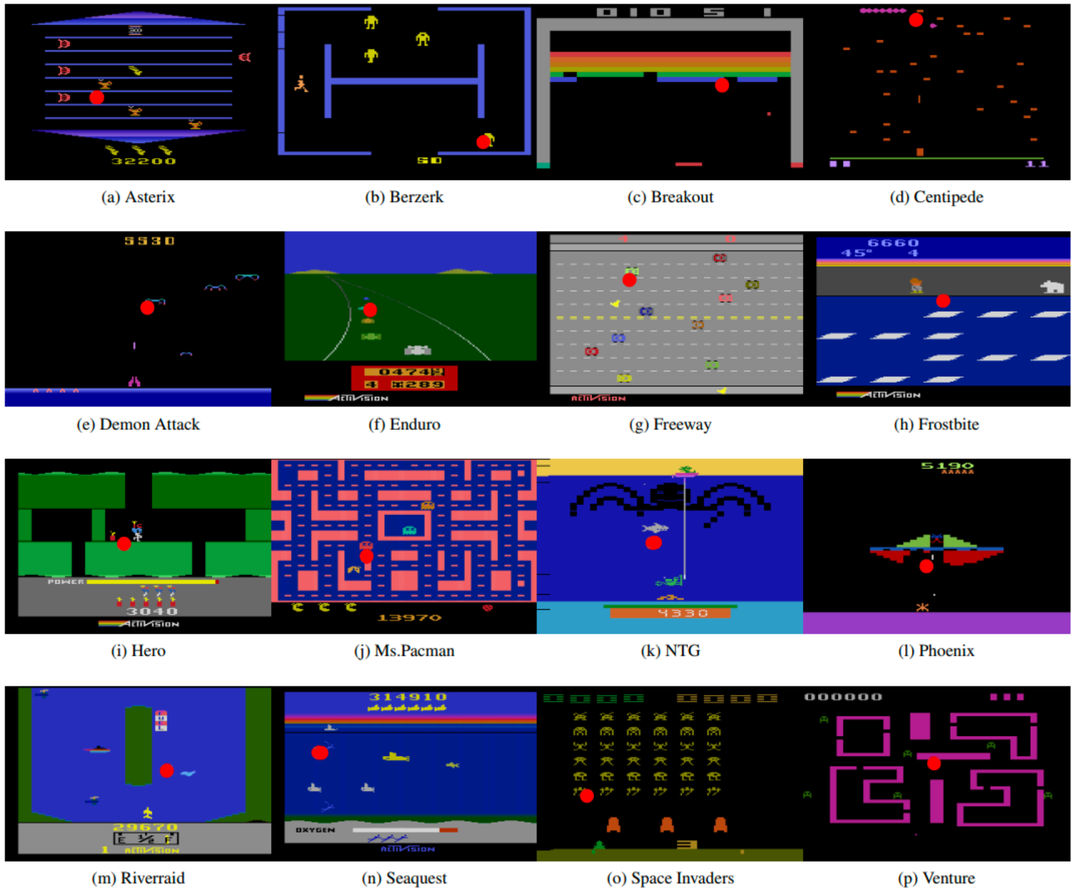
For $k = 0,1,\ldots$

- Observe s, take action a sampled from the ε-greedy policy w.r.t. $Q_{\theta_k}(s, a)$;
- Observe new $(r, s'$, done$)$, store $(s, a, r, s'$, done$)$ in D;
- If $B > |D|$, sample batch of transitions $(s_j, a_j, r_j, s'_j, \text{done}_{j+1})_{j=1}^{B}$ from D
- $y_j = r_j + \gamma(1 - \text{done}_{j+1}) \max_{a'} Q(s'_j, a'; \theta^-)$;
- Perform a gradient descent step: $\theta_{k+1} = \theta_k - \frac{\alpha}{B} \sum_{j=1}^{B} \nabla_\theta (y_j - Q_\theta(a_j, s_j))^2$
- If $k + 1$ mod $K = 0$ update target network: $\theta^- \leftarrow \theta_{k+1}$

Atari

Setup: $|\mathcal{A}| < +\infty, |\mathcal{S}| < +\infty$

1. More than 57 different games
2. Only frames are available
3. State space is actually finite but too large to apply tabular methods
4. From 4 to 18 actions are available



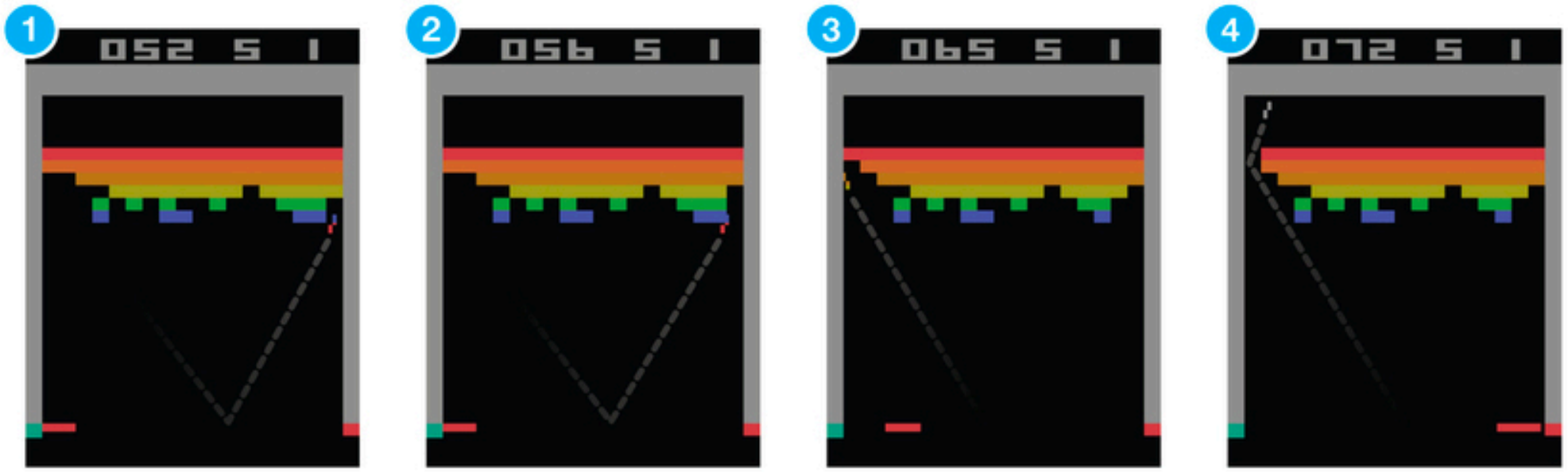
Source

The ultimate goal is to build a universal algorithm which can be applied to all of these environments without modifications and specific hyperparameters.

Is Atari Environment MDP?

Source

MDP from Frames



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Preprocessing

States:

- Crop image
- Grayscale
- Downsampling
- Stack 4 consecutive frames

Actions' frequency:

- MaxAndSkip
- Sticky actions (we won't use)

Environment:

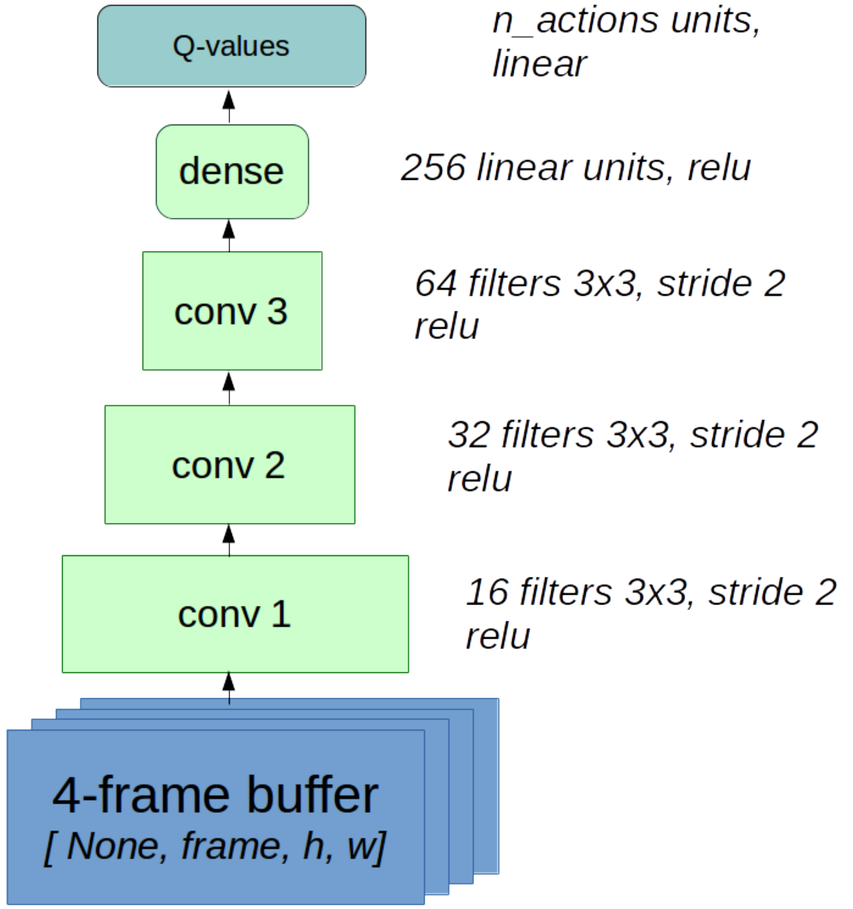
- EpisodicLife
- FireReset

Reward:

- ClipReward ($\{-1,0,1\}$)

Architecture

- No MaxPool
- No Dropout
- No BatchNorm



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Overestimation Bias

1. Maximum over estimated values is used implicitly as an estimate of the maximum value, which can lead to a significant positive bias due to approximation error.

2. Due to using the same samples (plays) both to determine the maximising action and to estimate its value.

Action selection

$$\max_{a'} Q(s', a') = Q(s', argmax_{a'} Q(s', a'))$$

Action evaluation

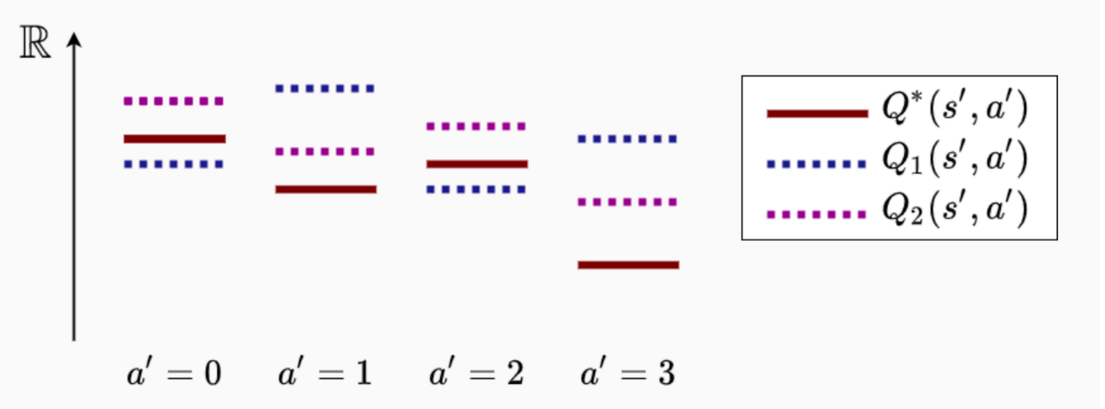
Double DQN

We can use two weakly correlated networks with independent buffers D_1 and D_2,:

$$y_1 = r + \gamma Q_{\theta_2}(s', argmax_{a'} Q_{\theta_1}(s', a'))$$

$$y_2 = r + \gamma Q_{\theta_1}(s', argmax_{a'} Q_{\theta_2}(s', a'))$$

but it can be too expensive…



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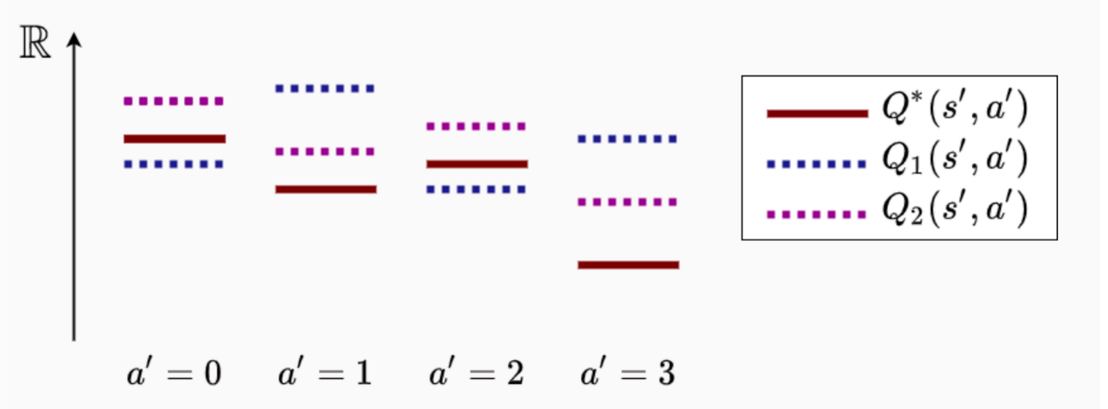

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We can use the target network as the second network:

$$y = r + \gamma Q_{\theta^-}(s', argmax_{a'} Q_{\theta}(s', a'))$$

Twin DQN

$$y_1 = r + \gamma \min_i Q_{\theta_i}(s', argmax_{a'} Q_{\theta_1}(s', a'))$$

$$y_2 = r + \gamma \min_i Q_{\theta_i}(s', argmax_{a'} Q_{\theta_2}(s', a'))$$

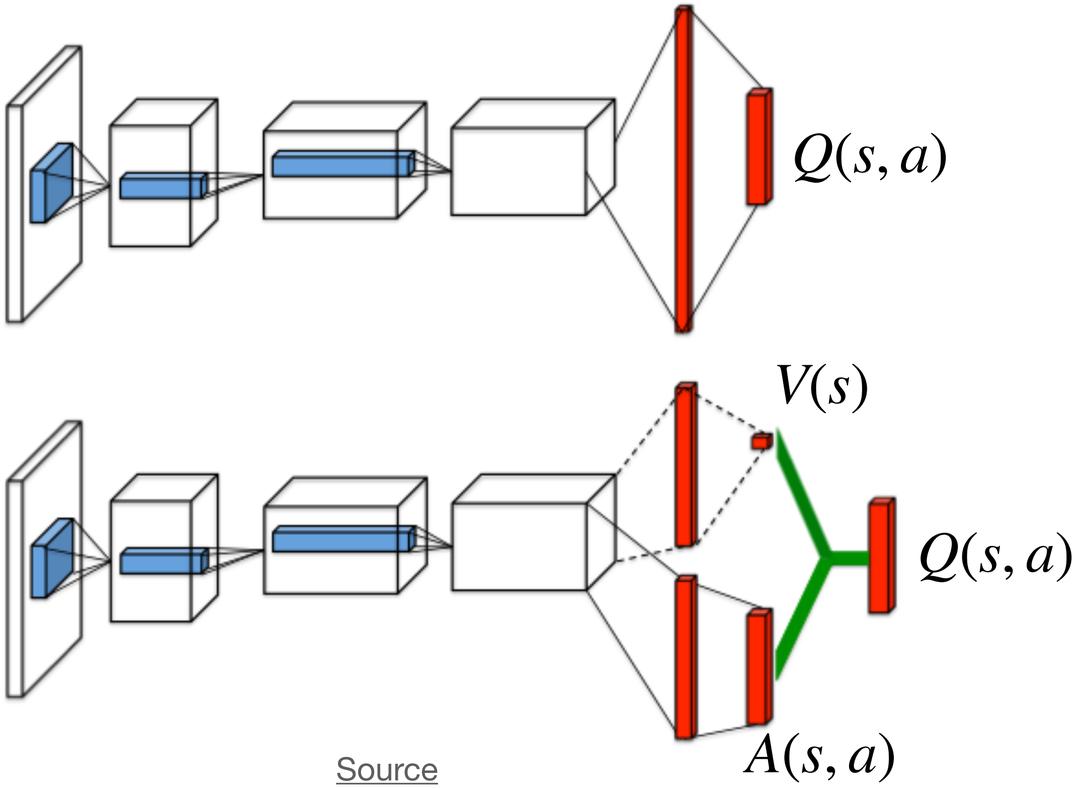
Dueling DQN

The advantage $A(s,a) = Q(s,a) - V(s)$ is a relative measure of the importance of each action.

Note that:

$$\mathbb{E}_{a\sim\pi(.|s)} A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s) = 0$$

$$\max_{a} A^{*}(s,a) = Q^{*}(s,a) - V^{*}(s) = 0$$



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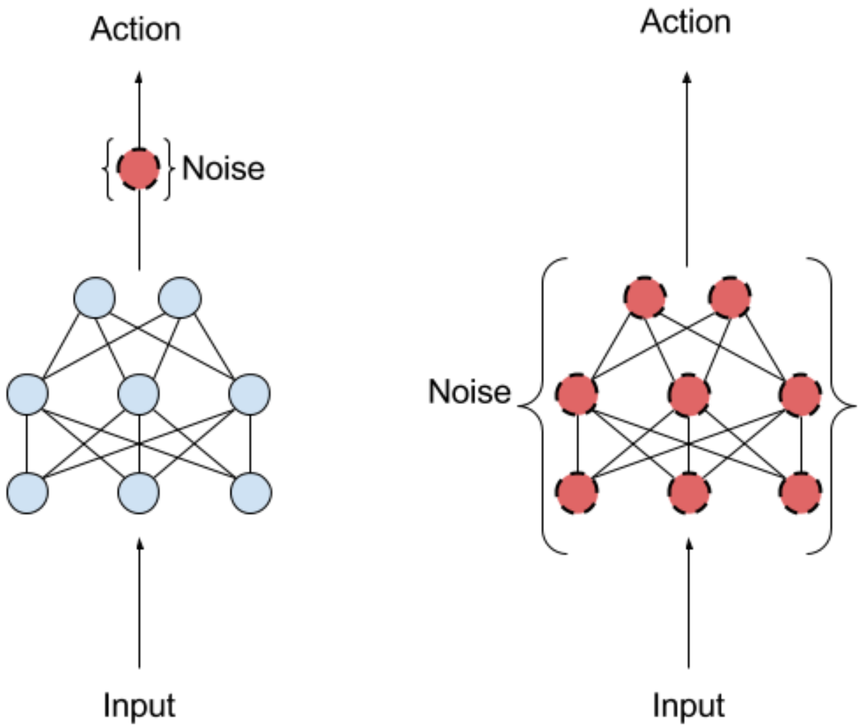
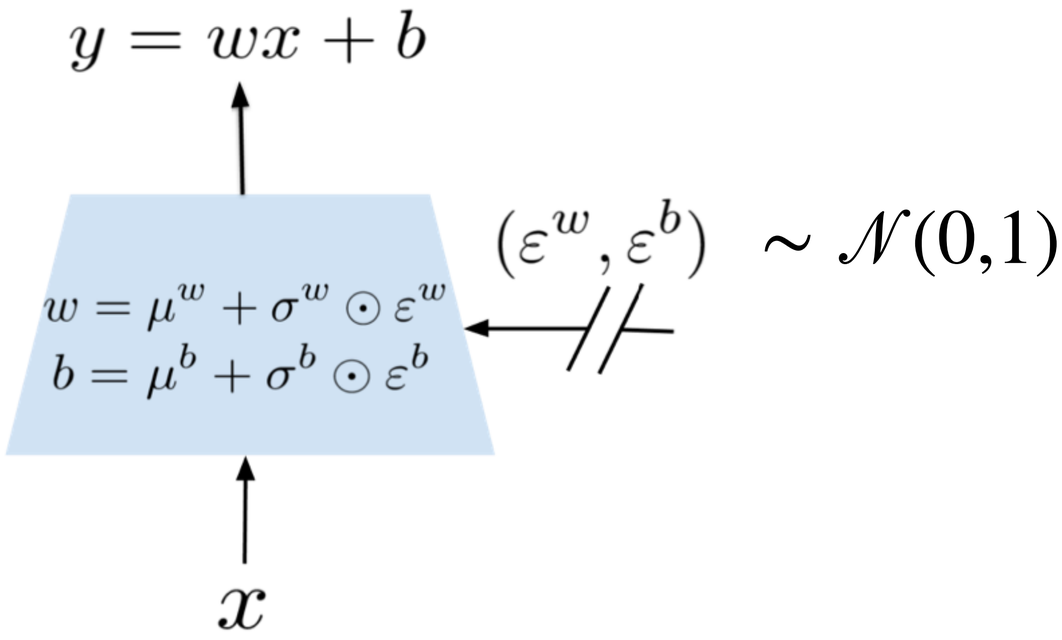
Noisy Networks

Issues with ε-greedy exploration:

- It's naive and must be adopted during training
- State-independent exploration





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Multi-step DQN

N-step Bellman equation: $Q^*(s,a) = \mathbb{E}_{s',a',s'',a'',\ldots}[\sum_{t=0}^{N} \gamma^t r_t + \gamma^N \mathbb{E}_{s^N} \max_{a^N} Q^*(s^N, a^N)]$

$$y_Q = r + \gamma r' + \gamma r'' + \ldots + \gamma^n \max_{a^{(N)}} Q(s^{(N)}, a^{(N)})$$

Multi-step DQN

$$y_Q = r + \gamma r' + \gamma r'' + \ldots + \gamma^n \max_{a^{(N)}} Q(s^{(N)}, a^{(N)})$$

Behave non-optimal N steps

Behave optimal w.r.t. to current Q

No theoretical guaranties in case of off-policy algorithm!

https://arxiv.org/abs/1901.07510

Prioritized Experience Replay

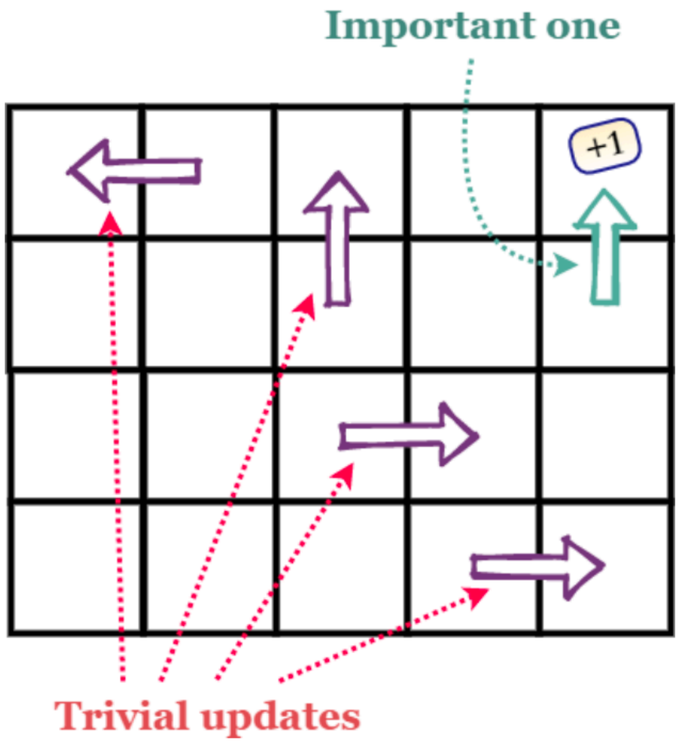
$\delta_i = y_i - Q(s_i, a_i; \theta)$ - TD-error

$p_i = |\delta_i| + \epsilon, \epsilon > 0$

$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$ is the probability of sampling transition i

However, we induce a bias in a Q-function approximation:

s' can be not from $p(\,.\,|\,s, a)$



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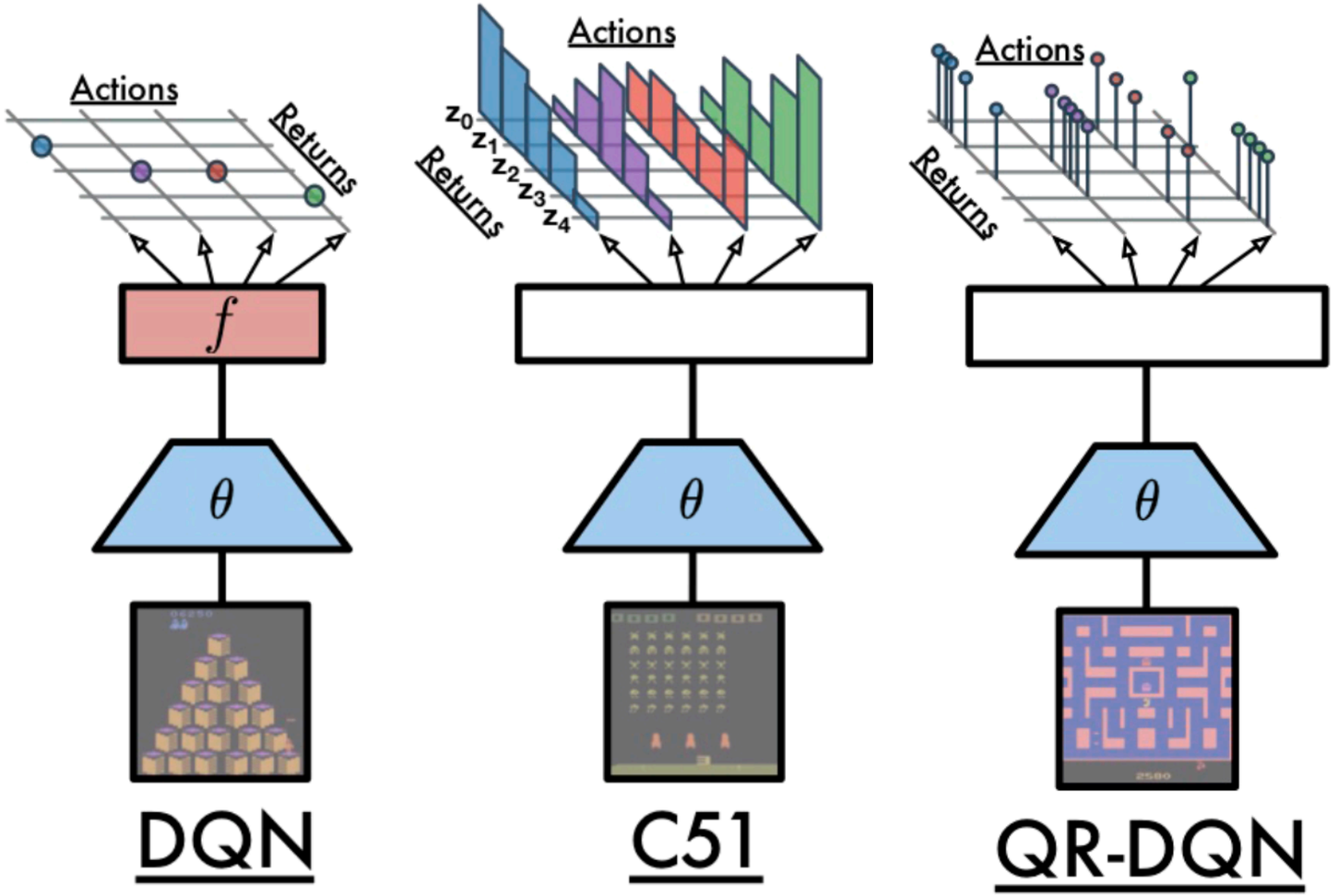
We can correct this bias by using Importance-Sampling (IS) weights

$w_i = \left(\frac{1}{N}\frac{1}{P(i)}\right)^\beta$ with beta annealing from 0 to 1 and $w_i\delta_i$ instead of δ_i.

Distributional RL



Ablation Study

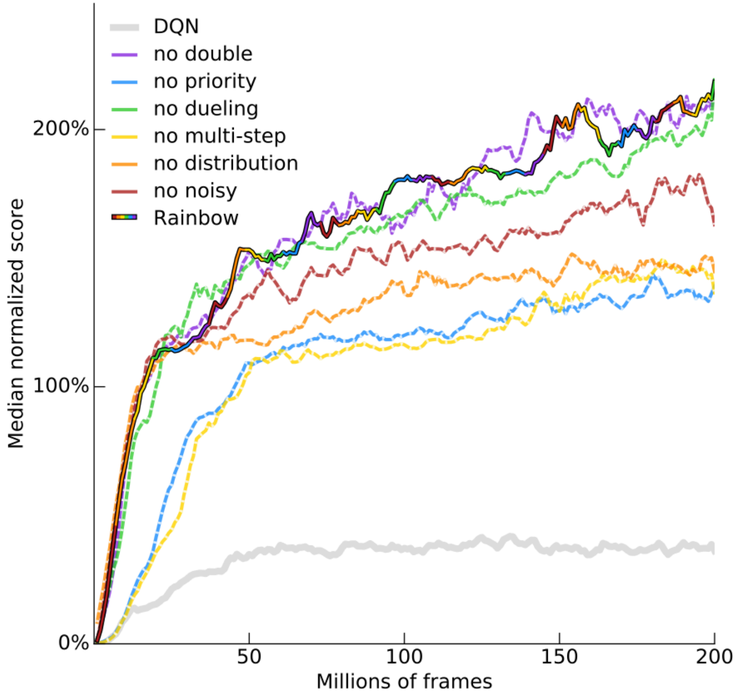


Figure 3: **Median human-normalized performance** across 57 Atari games, as a function of time. We compare our integrated agent (rainbow-colored) to DQN (gray) and to six different ablations (dashed lines). Curves are smoothed with a moving average over 5 points.

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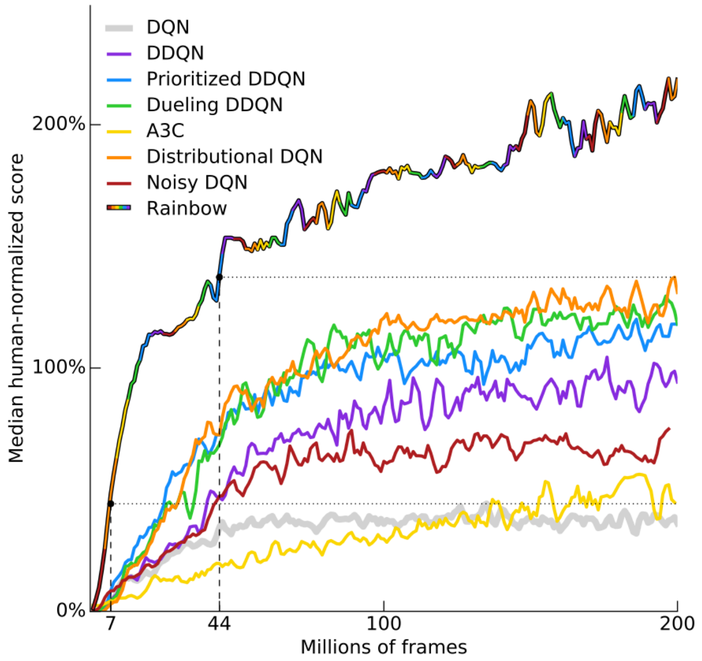


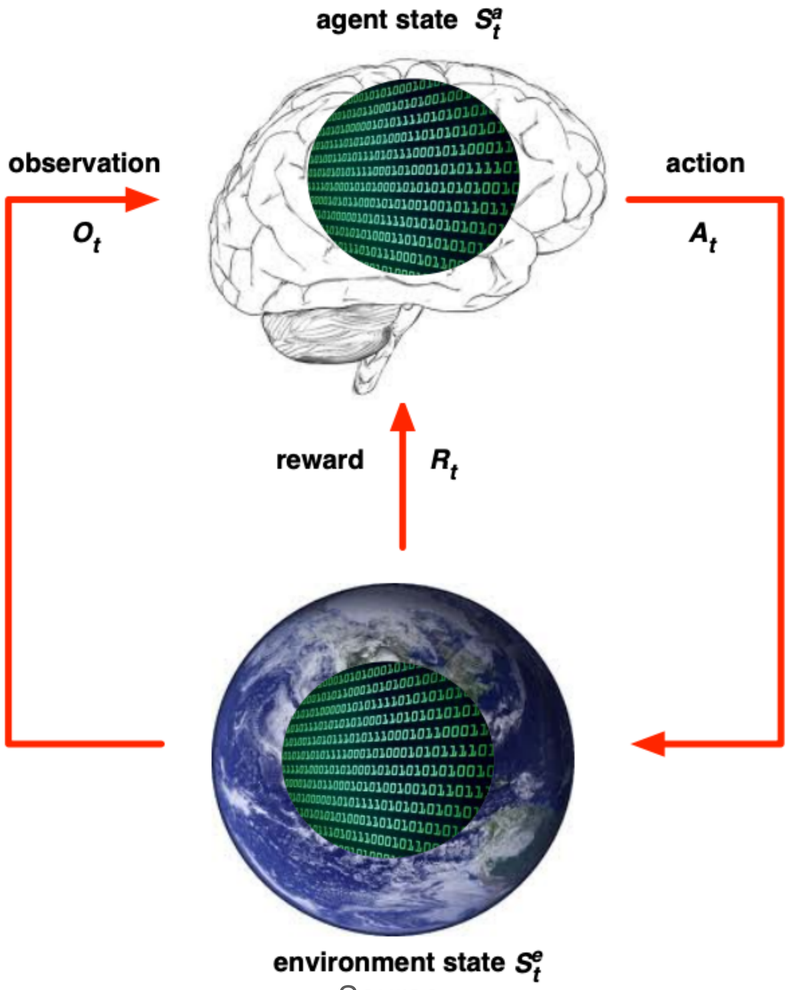
Figure 1: **Median human-normalized performance** across 57 Atari games. We compare our integrated agent (rainbow-colored) to DQN (grey) and six published baselines. Note that we match DQN's best performance after 7M frames, surpass any baseline within 44M frames, and reach substantially improved final performance. Curves are smoothed with a moving average over 5 points.

Source

POMDP

Partially observable: $S_t^e \neq S_t^a$

1. MDP +
2. $\mathcal{O}$ is a set of possible observations
3. $p(o \mid s) = \mathbb{P}(O_t = o \mid S_t = s)$ is a probability to get the observation given the state



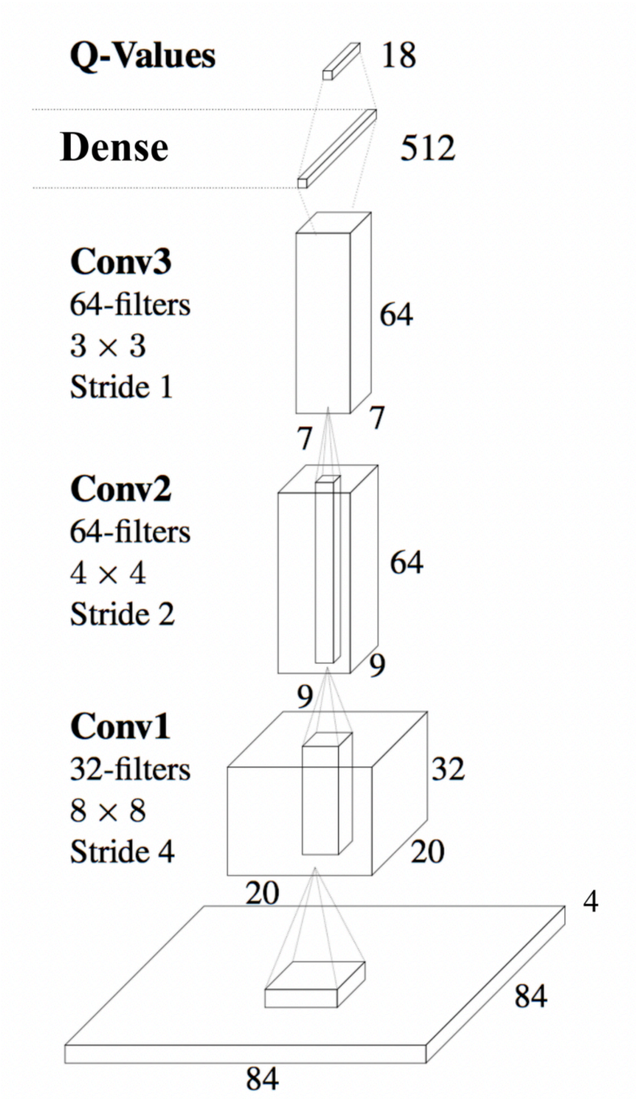
Source

DRQN

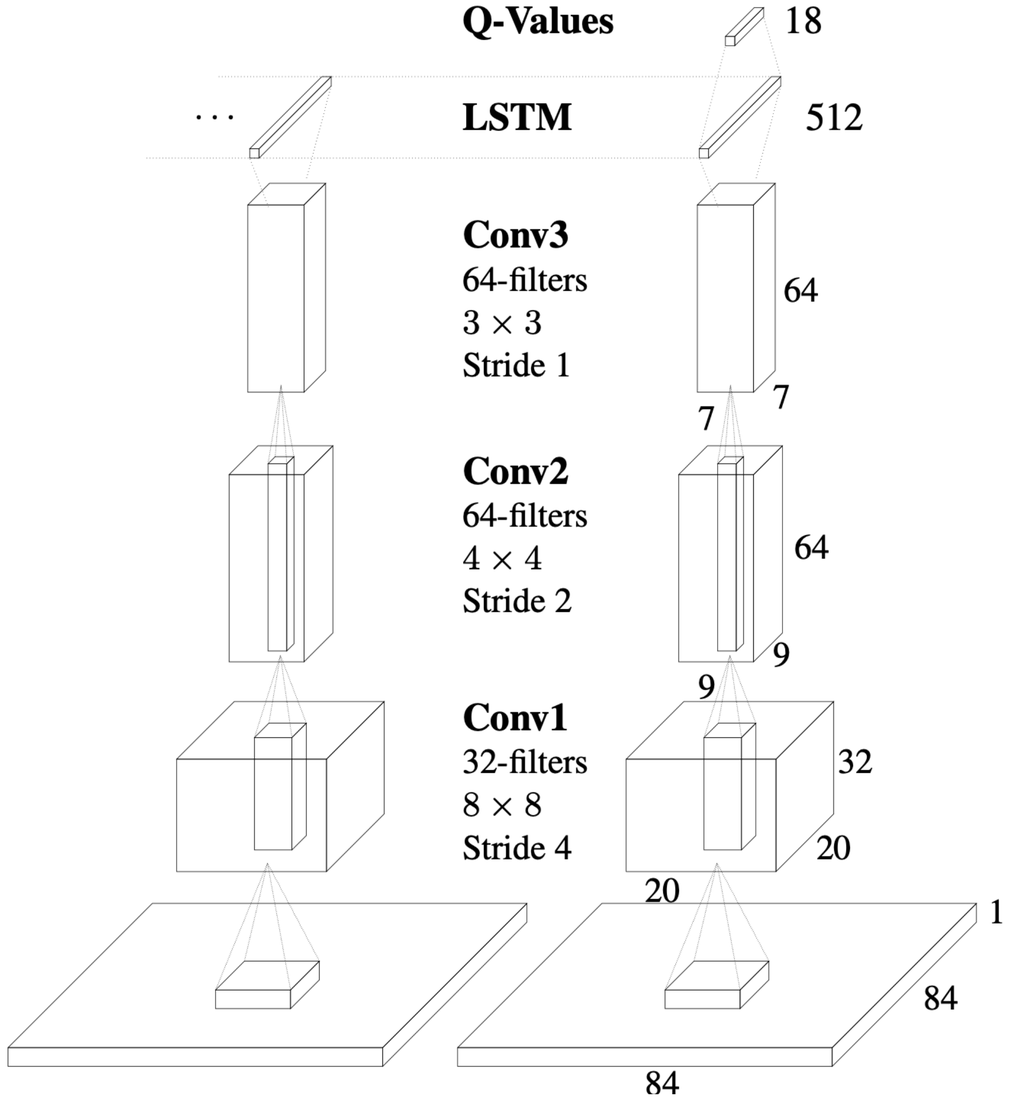
In the general case, estimating a Q-value from an observation can be arbitrarily bad since $Q_\theta(o, a) \neq Q_\theta(s, a)$.

- Let's equip agent with memory h_t
- $Q(s_t, a_t) \approx Q(o_t, h_{t-1}, a_t)$
- $h_t = LSTM(o_t, h_{t-1})$

DQN vs DRQN



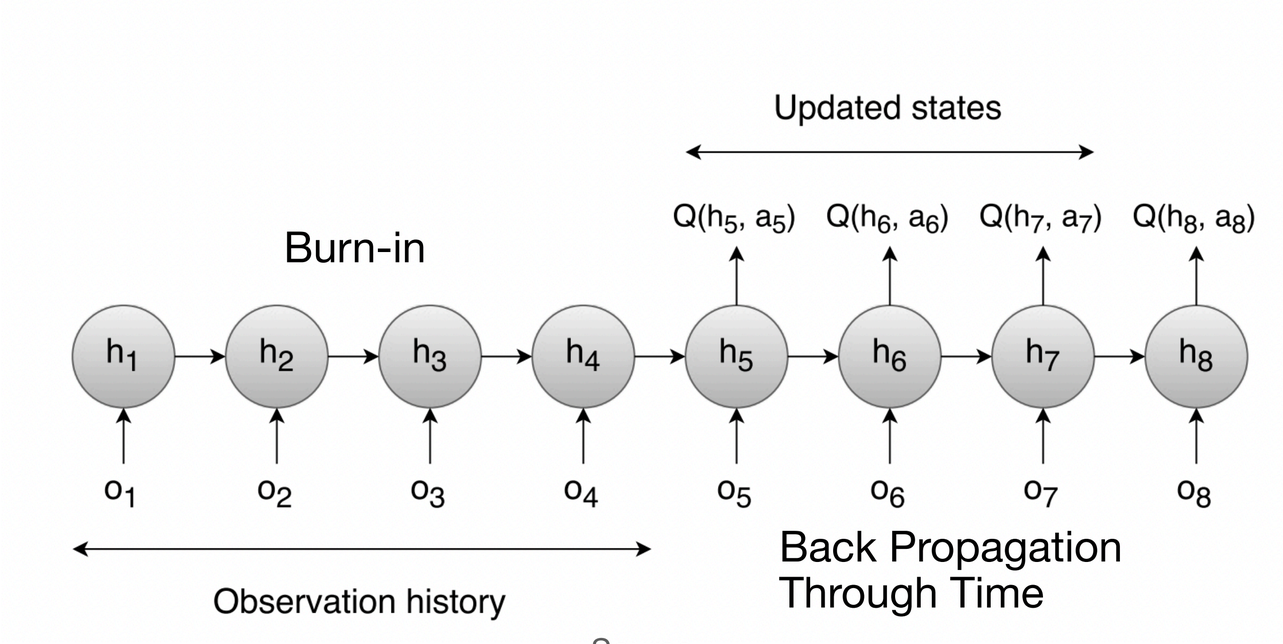
Original paper



Original paper

Recurrent Experience Replay

- Sample random time step
- Consider N consecutive transitions
- Update only last M



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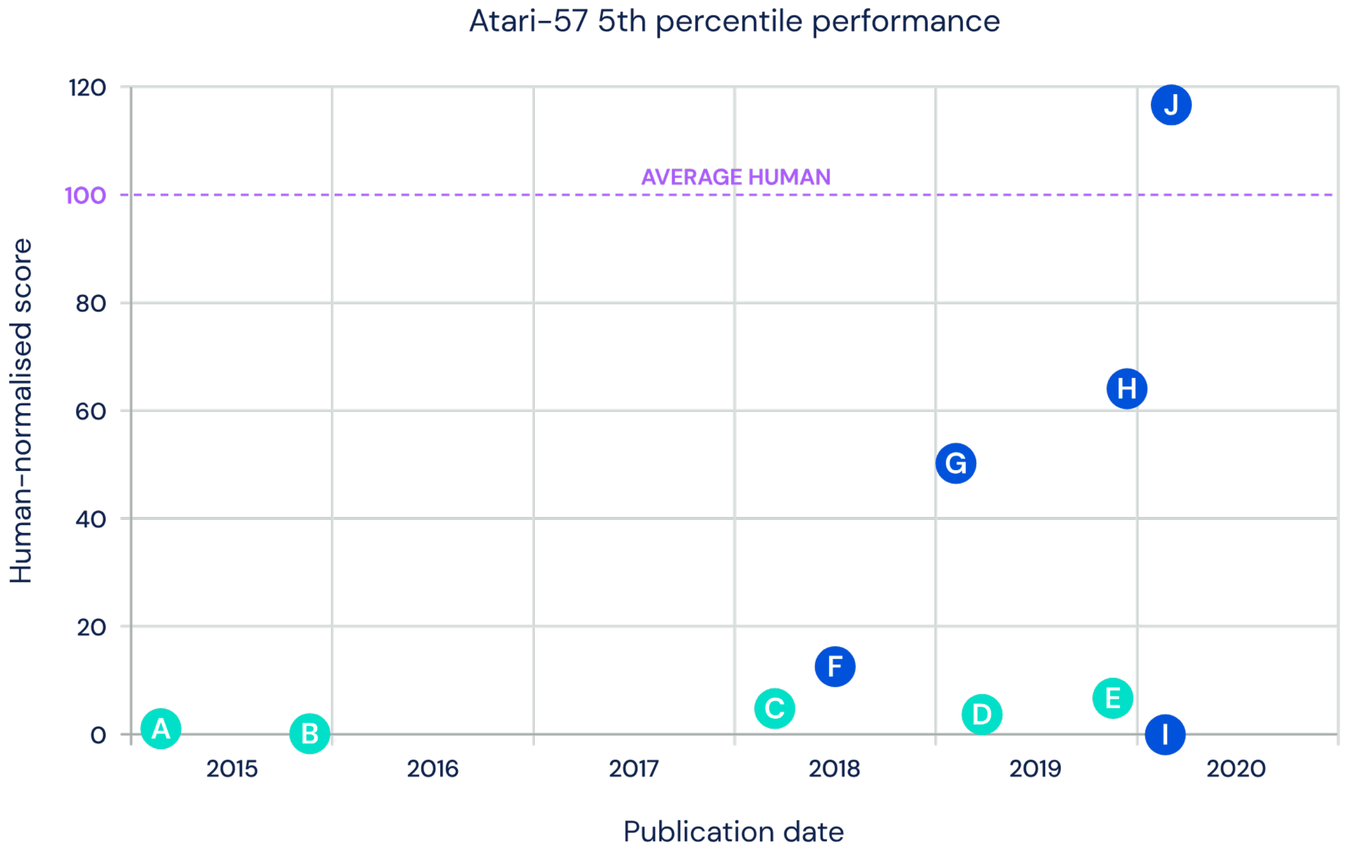


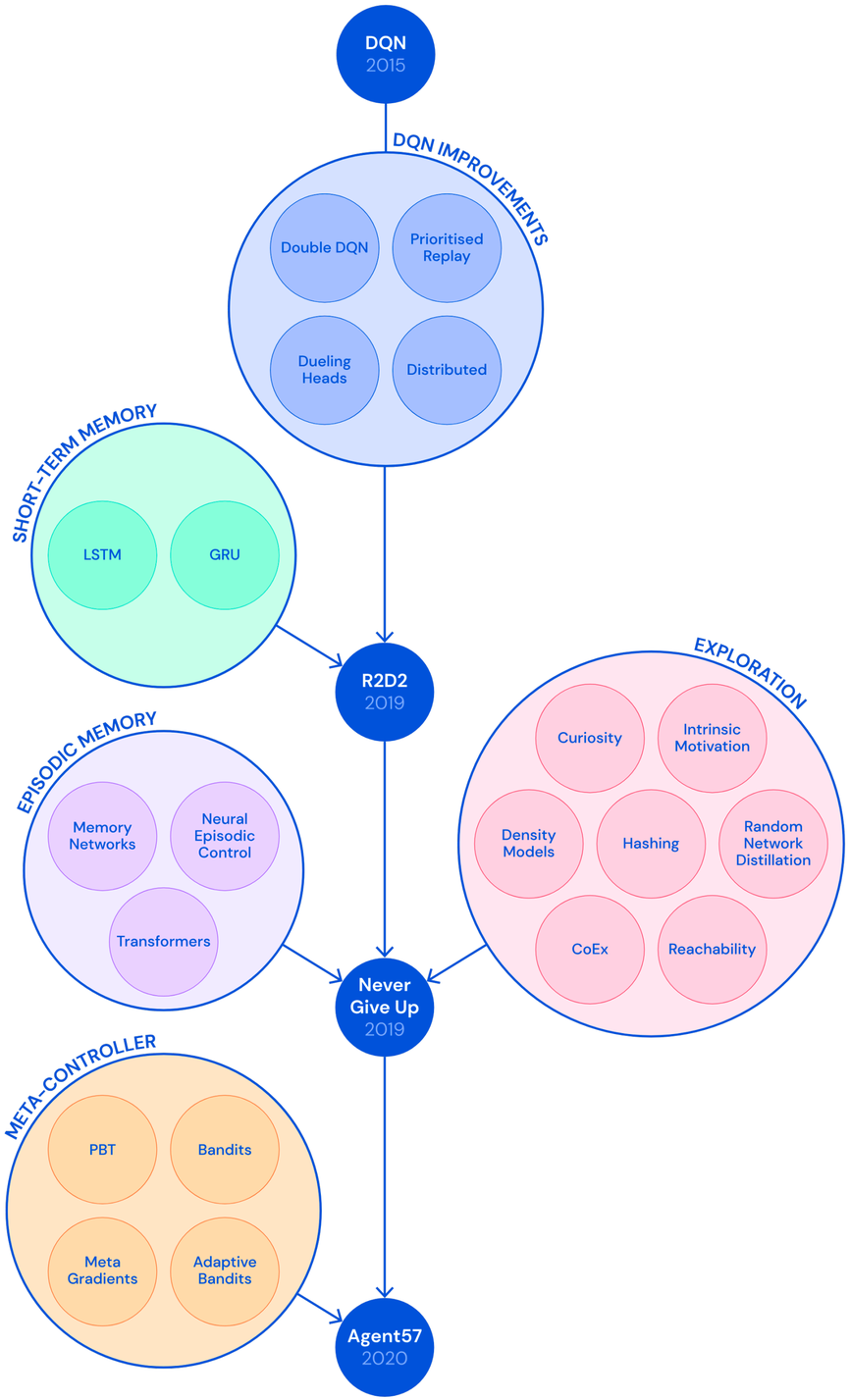
Single-actor agents

- A DQN
- B Prioritised Dueling
- C Rainbow
- D C51-IDS
- E FQF

Distributed agents

- F ApeX
- G R2D2
- H NGU
- I MuZero
- J Agent57

https://deepmind.google/discover/blog/agent57-outperforming-the-human-atari-benchmark/



Background

1. Practical RL course by YSDA, week 4
2. Reinforcement Learning Textbook (in Russian): 4

Thank you for your attention!