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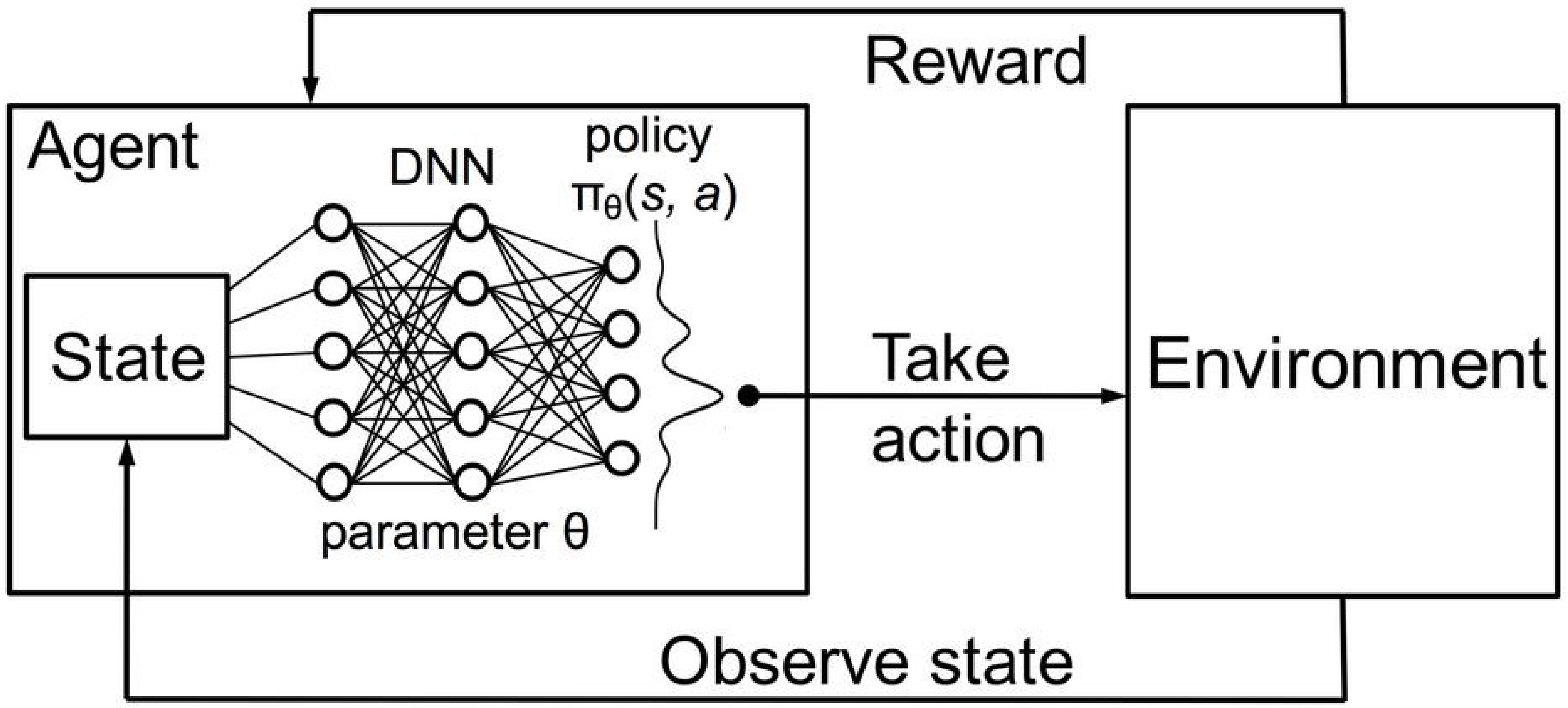
Deep Reinforcement Learning

Deep Q-Learning

Julien Vitay
Professur für Künstliche Intelligenz - Fakultät für Informatik

Value-based deep RL



- The basic idea in **value-based deep RL** is to approximate the Q-values in each possible state, using a **deep neural network** with free parameters θ:

$$Q_\theta(s, a) \approx Q^\pi(s, a) = \mathbb{E}_\pi (R_t | s_t = s, a_t = a)$$

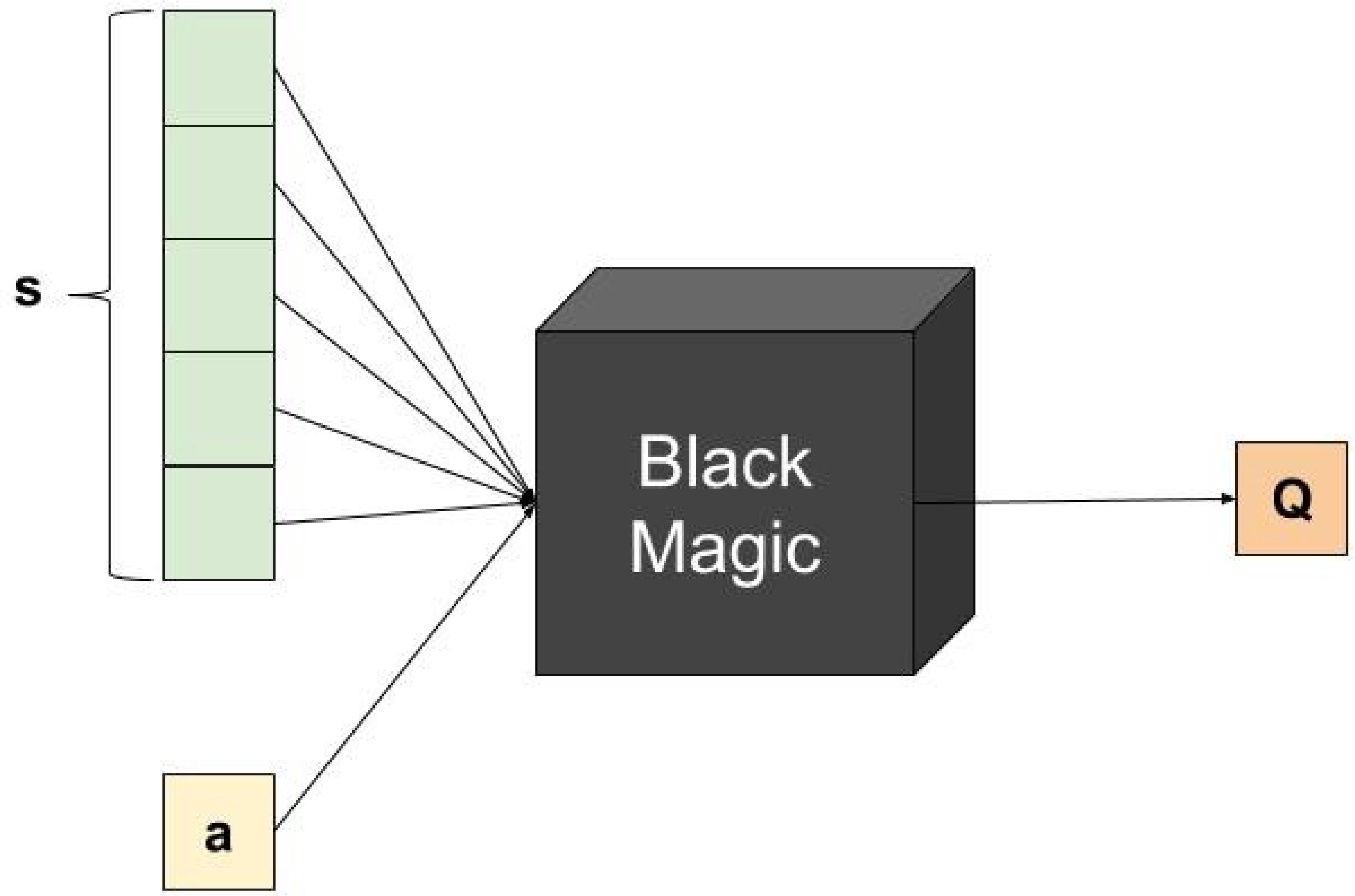
- The Q-values now depend on the parameters θ of the DNN.
- The derived policy π_θ uses for example an ϵ-greedy or softmax action selection scheme over the estimated Q-values:

$$\pi_\theta(s, a) \leftarrow \text{Softmax}(Q_\theta(s, a))$$

Function approximators to learn the Q-values

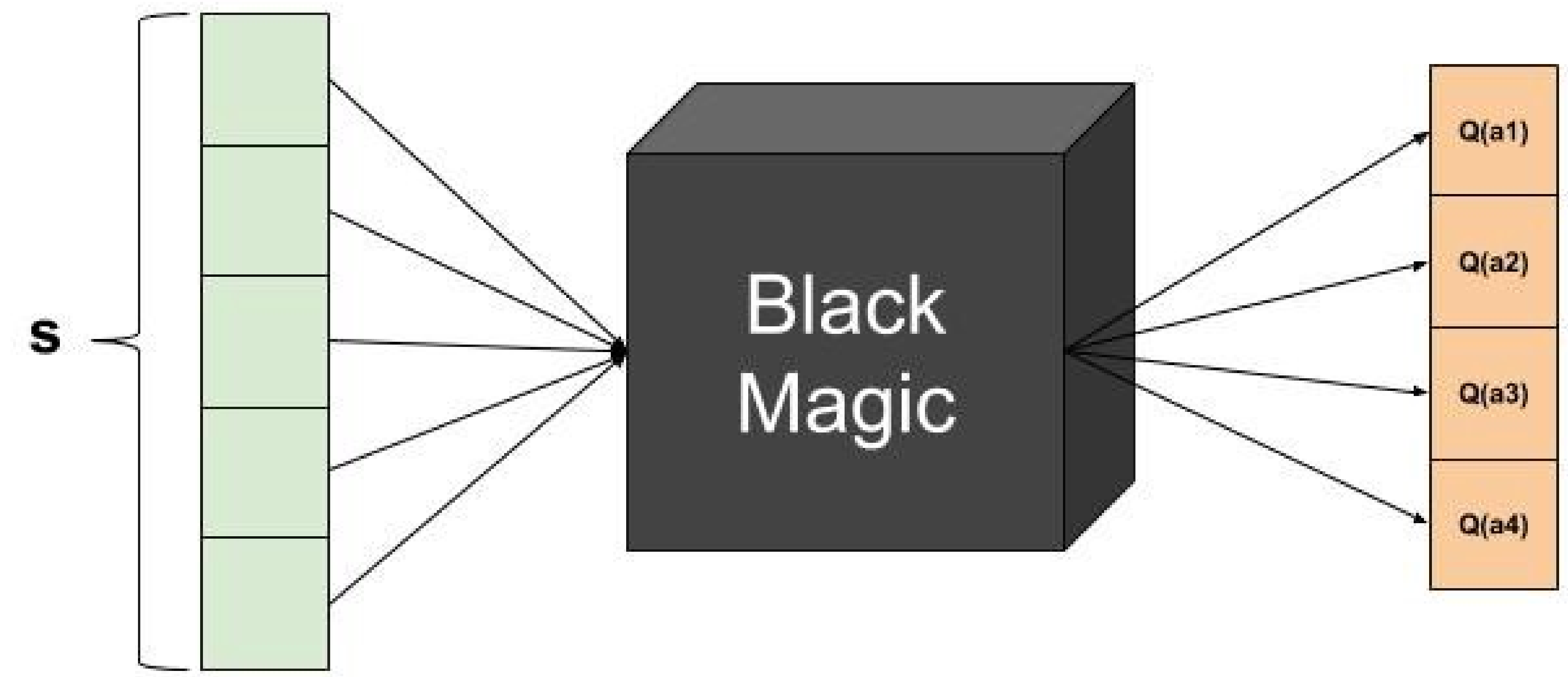
There are two possibilities to approximate Q-values $Q_\theta(s, a)$:

- The DNN approximates the Q-value of a single (s, a) pair.



- The action space can be continuous.

- The DNN approximates the Q-value of all actions a in a state s.



- The action space must be discrete (one neuron per action).

Source: https://towardsdatascience.com/qrash-course-deep-q-networks-from-the-ground-up-1bbda41d3677

First naive approach: Q-learning with function approximation

We could simply adapt Q-learning with FA to the DNN:

- Initialize the deep neural network with parameters θ.
- Start from an initial state s_0.
- for $t \in [0, T_\text{total}]$:
  - Select a_t using a softmax over the Q-values $Q_\theta(s_t, a)$.
  - Take a_t, observe r_{t+1} and s_{t+1}.
  - Update the parameters θ by minimizing the loss function:

  $$\mathcal{L}(\theta) = (r_{t+1} + \gamma \, \max_{a'} Q_\theta(s_{t+1}, a') - Q_\theta(s_t, a_t))^2$$

  - **if** s_t is terminal: sample another initial state s_0.

Remark: We will now omit the break for terminal states, it is always implicitly here.

DNN need stochastic gradient descent

- This naive approach will not work: DNNs cannot learn from single examples (online learning = instability).
- DNNs require **stochastic gradient descent** (SGD):

$$\mathcal{L}(\theta) = E_\mathcal{D}(||\mathbf{t} - \mathbf{y}||^2) \approx \frac{1}{K} \sum_{i=1}^K ||\mathbf{t}_i - \mathbf{y}_i||^2$$

- The loss function is estimated by **sampling** a minibatch of K **i.i.d** samples from the training set to compute the loss function and update the parameters θ.
- This is necessary to avoid local minima of the loss function.
- Although Q-learning can learn from single transitions, it is not possible using DNN.
- Why not using the last K transitions to train the network? We could store them in a **transition buffer** and train the network on it.

Second naive approach: Q-learning with a transition buffer

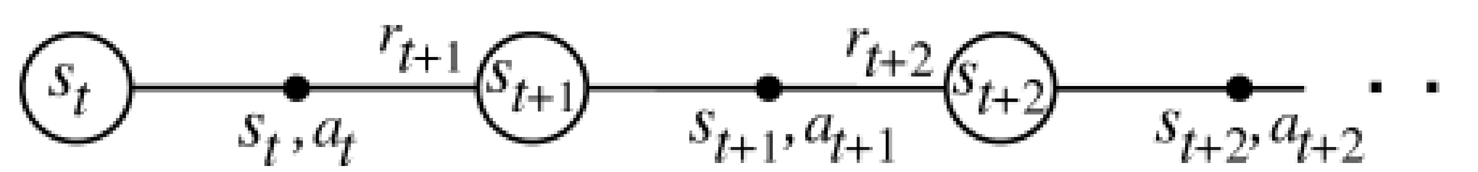
- Initialize the deep neural network with parameters θ.
- Initialize an empty **transition buffer** $\mathcal{D}$ of size K: $\{(s_k, a_k, r_k, s'_k)\}_{k=1}^K$.
- for $t \in [0, T_\text{total}]$:
  - Select a_t using a softmax over the Q-values $Q_\theta(s_t, a)$.
  - Take a_t, observe r_{t+1} and s_{t+1}.
  - Store $(s_t, a_t, r_{t+1}, s_{t+1})$ in the transition buffer.
  - Every K steps:
    - Update the parameters θ using the transition buffer:

$$\mathcal{L}(\theta) = \frac{1}{K} \sum_{k=1}^K (r_k + \gamma \, \max_{a'} Q_\theta(s'_k, a') - Q_\theta(s_k, a_k))^2$$

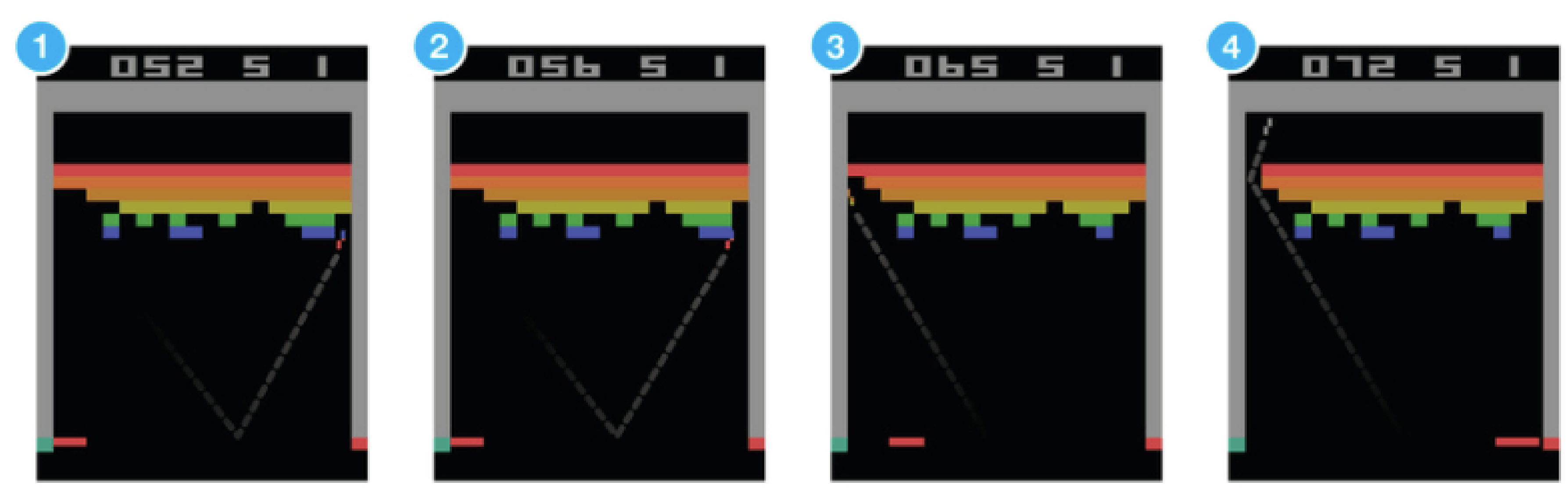
    - Empty the transition buffer.

Correlated inputs

- Unfortunately, this does not work either.
- The last K transitions (s, a, r, s') are not **i.i.d** (independent and identically distributed).



- The transition $(s_{t+1}, a_{t+1}, r_{t+2}, s_{t+2})$ **depends** on $(s_t, a_t, r_{t+1}, s_{t+1})$ by definition, i.e. the transitions are **correlated**.
- Even worse, when playing video games, successive frames will be very similar or even identical.



- The actions are also correlated: you move the paddle to the left for several successive steps.

Correlated inputs

- Feeding transitions sequentially to a DNN is the same as giving all MNIST 0's to a DNN, then all 1's, etc… It does not work.

Sequential-Correlated

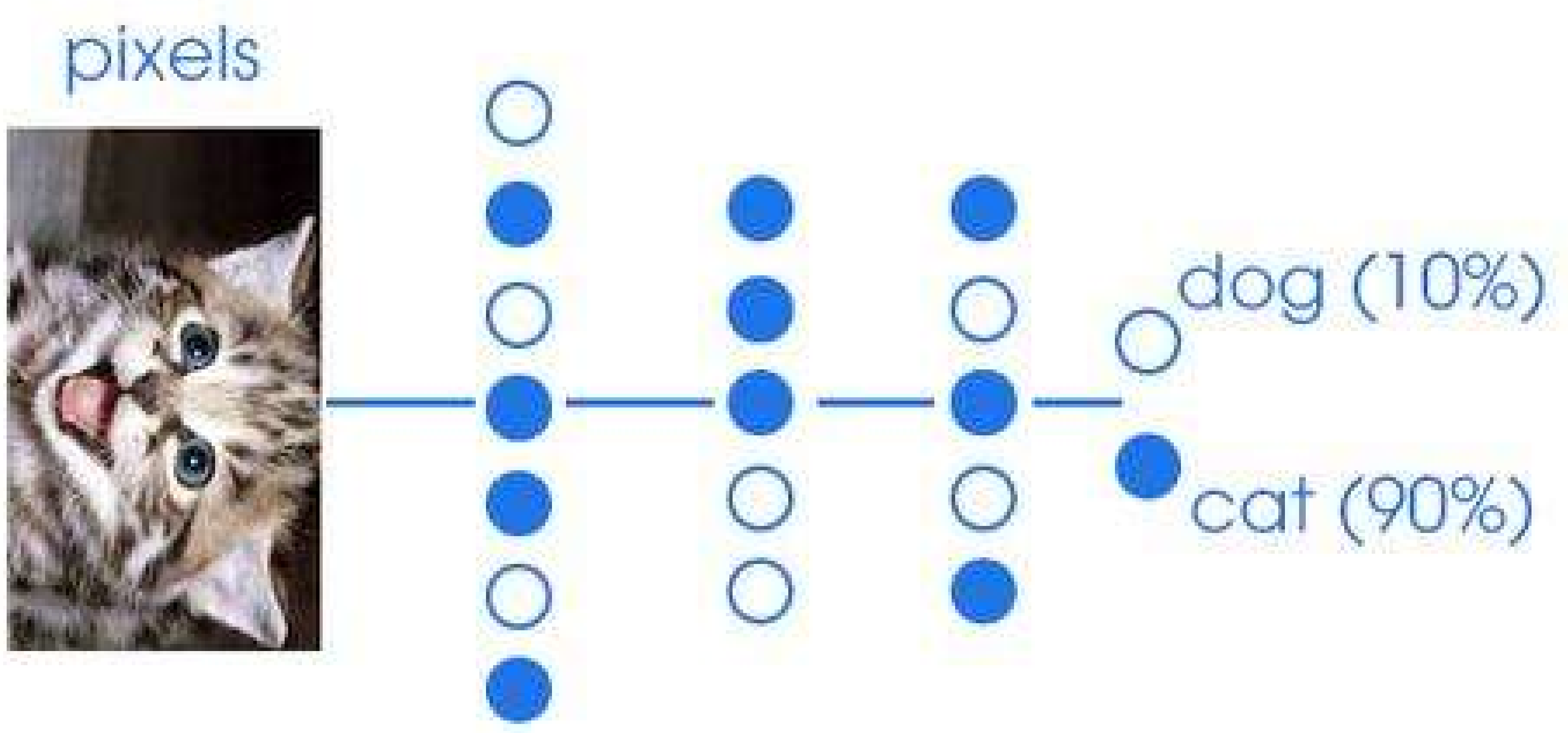
Varied Data Dist.

- In SL, we have all the training data **before** training: it is possible to get i.i.d samples by shuffling the training set between two epochs.
- In RL, we create the "training set" (transitions) **during** training: the samples are not i.i.d as we act sequentially over time.

Non-stationarity

- In SL, the **targets $\mathbf{t}$** do not change over time: an image of a cat stays an image of a cat throughout learning.

$$\mathcal{L}(\theta) = \mathbb{E}_{\mathbf{x}, \mathbf{t} \sim \mathcal{D}}[||\mathbf{t} - F_\theta(\mathbf{x})||^2]$$



- The problem is said **stationary**, as the distribution of the data does not change over time.

Non-stationarity

- In RL, the **targets** $t = r + \gamma \, \max_{a'} Q_\theta(s', a')$ do change over time:
  - $Q_\theta(s', a')$ depends on θ, so after one optimization step, all targets have changed!
  - As we improve the policy over training, we collect higher returns.

$$\mathcal{L}(\theta) = \mathbb{E}_{s,a \sim \pi_\theta} [(r + \gamma \, \max_{a'} Q_\theta(s', a') - Q_\theta(s, a))^2]$$

- NN do not like this. After a while, they give up and settle on a **suboptimal** policy.

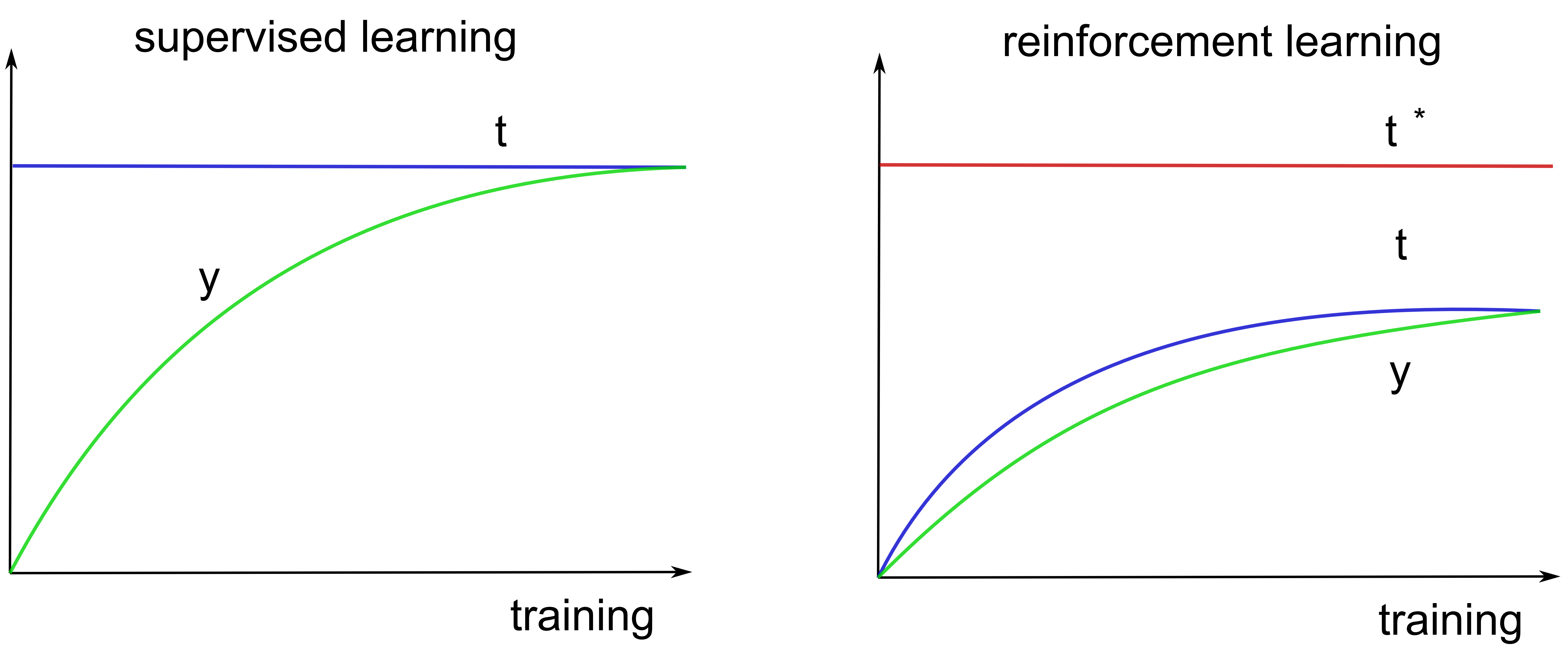


Illustration of non-stationary targets

- We want our value estimates to “catch” the true values.

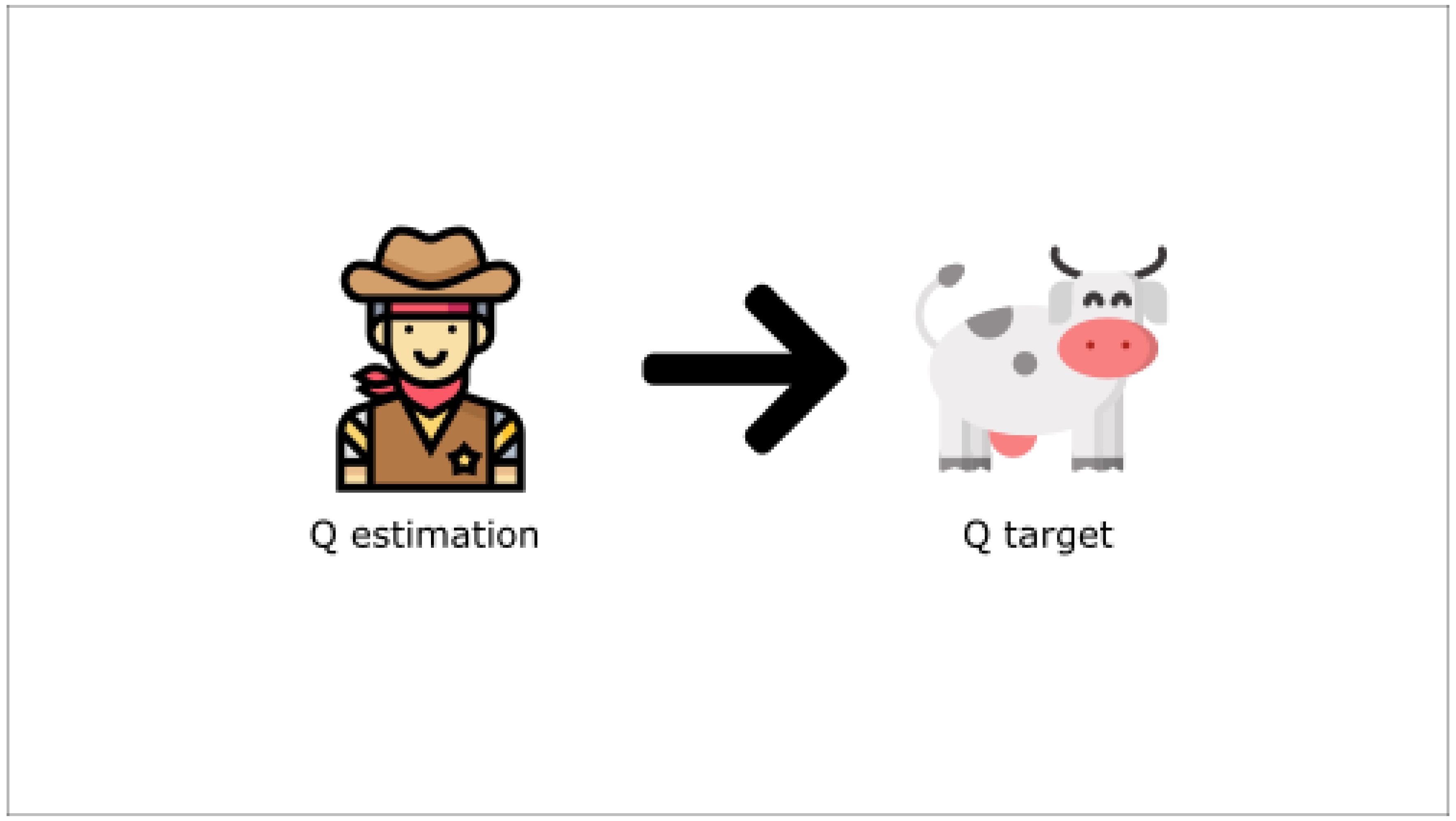


Illustration of non-stationary targets

- We update our estimate to come closer to the target.

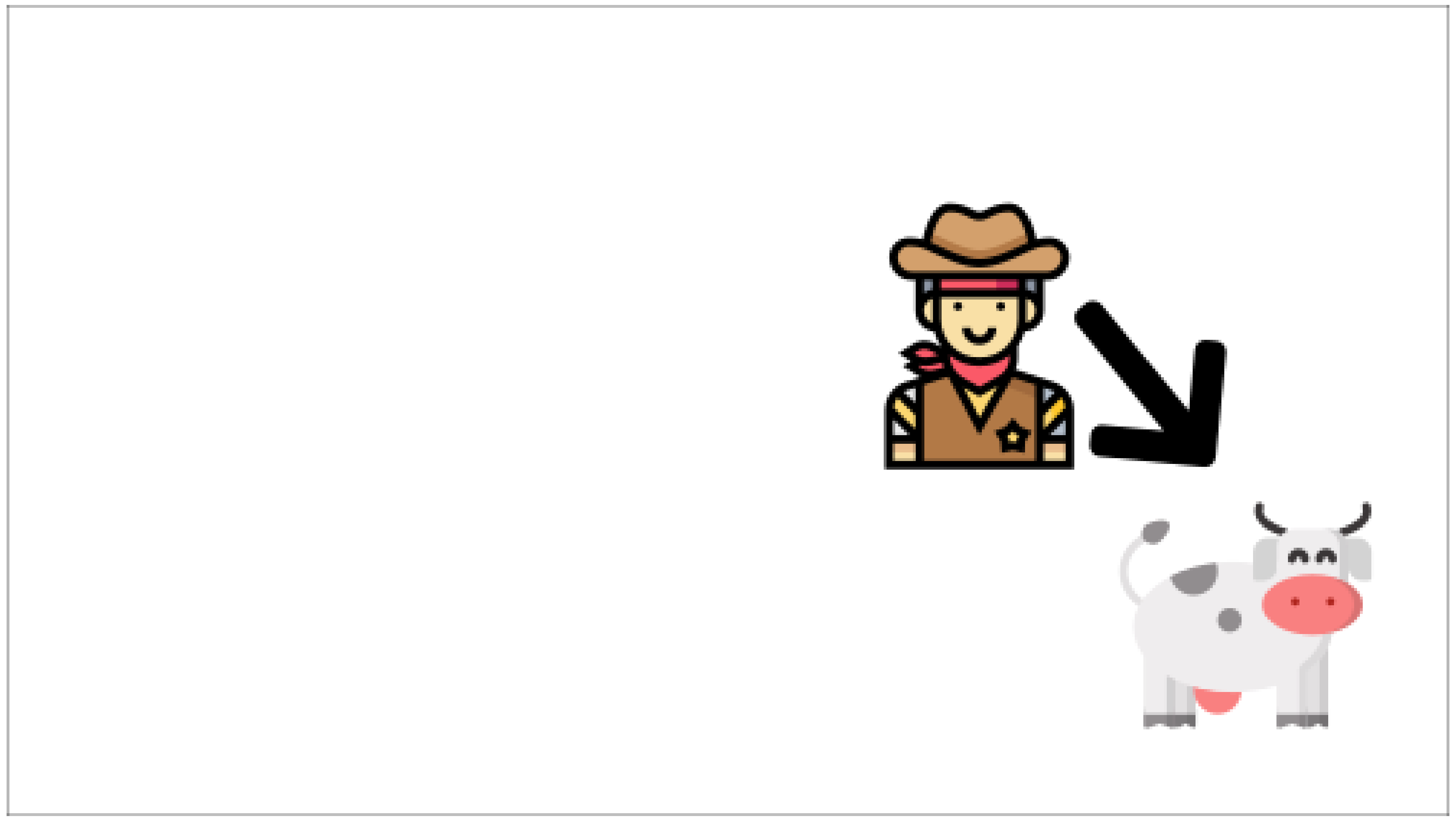
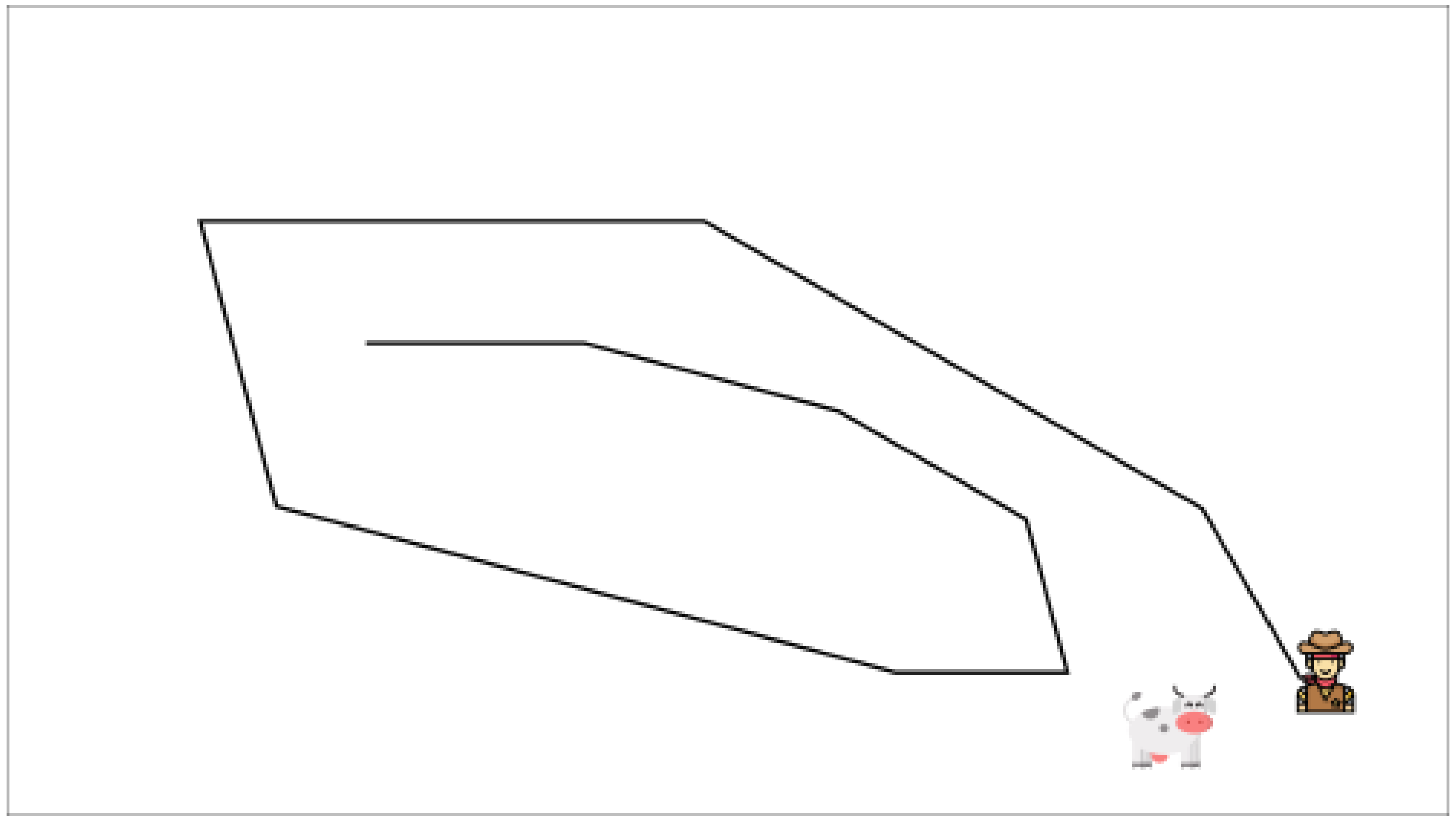


Illustration of non-stationary targets

- But the target moves! We need to update again.

Illustration of non-stationary targets

- This leads to very strange and inefficient optimization paths.



1 - Deep Q-networks (DQN)

Playing Atari with Deep Reinforcement Learning

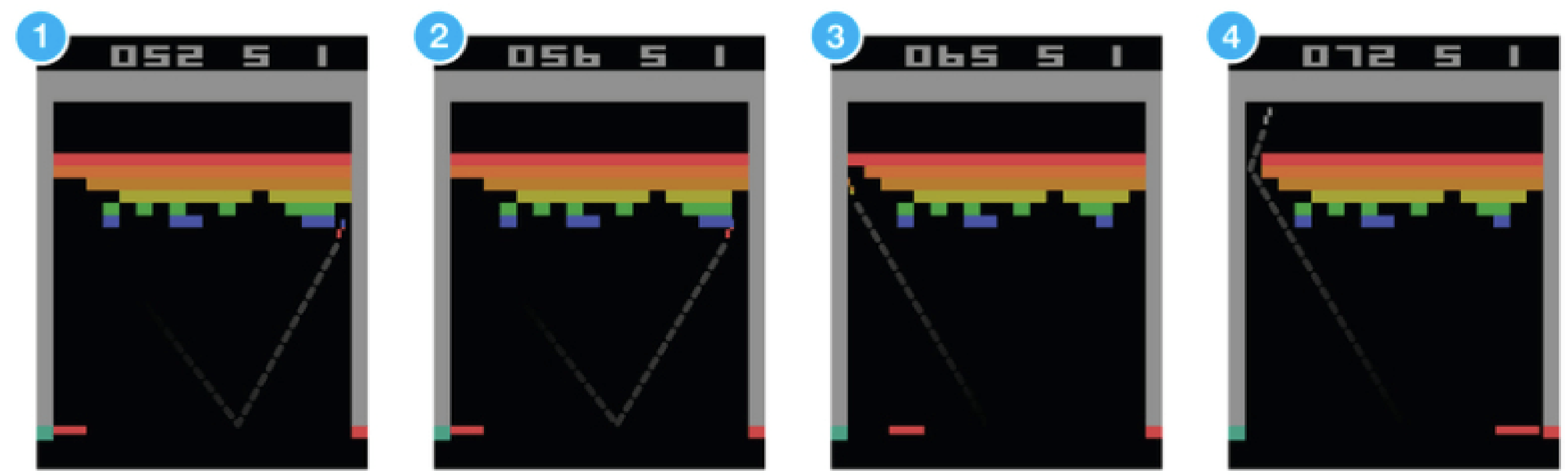
Volodymyr Mnih **Koray Kavukcuoglu** **David Silver** **Alex Graves** **Ioannis Antonoglou**

Daan Wierstra **Martin Riedmiller**

DeepMind Technologies

Mnih et al. (2013) Playing Atari with Deep Reinforcement Learning. http://arxiv.org/abs/1312.5602

Problem with non-linear approximators and RL

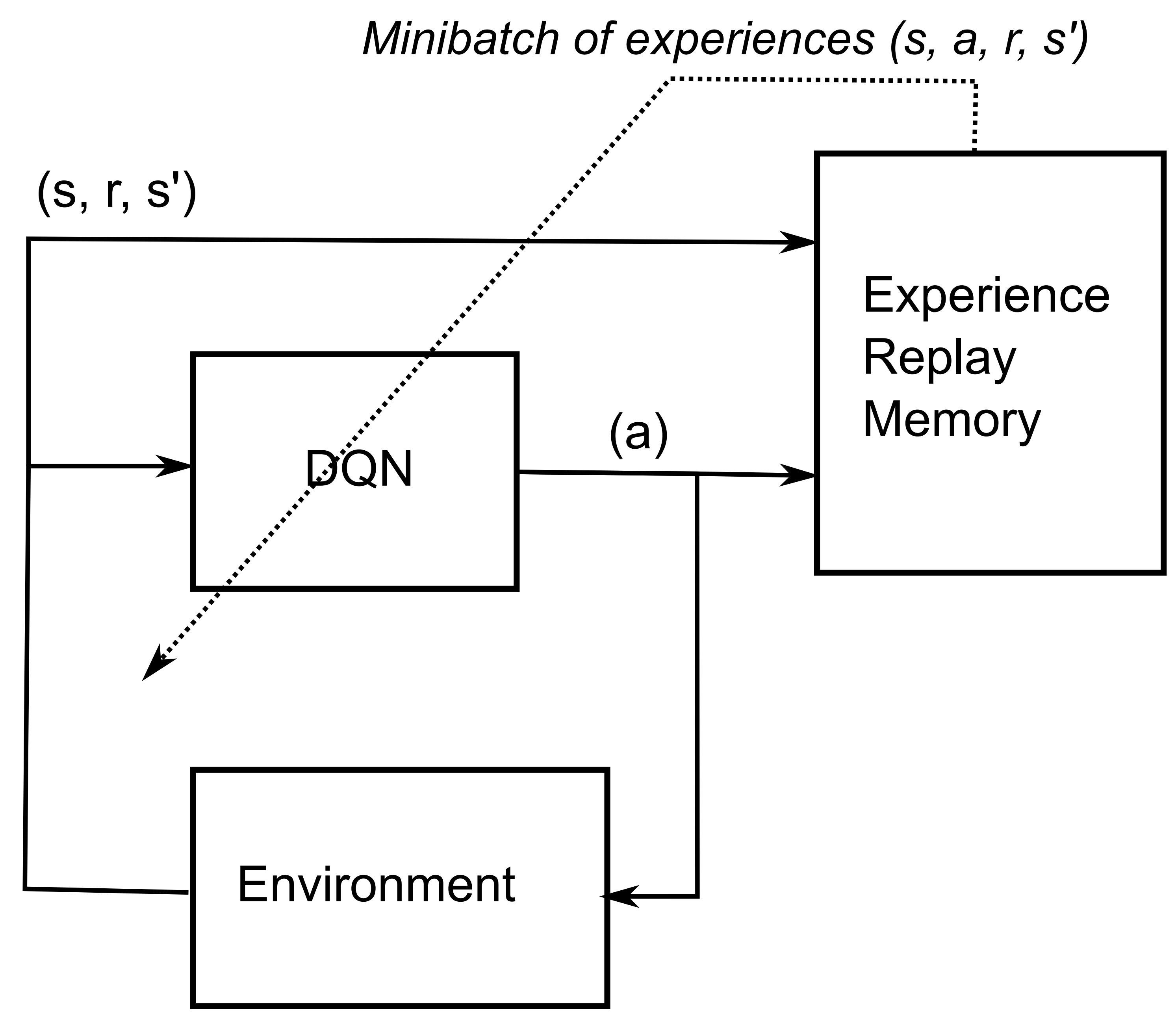


- Non-linear approximators never really worked with RL before 2013 because of:
    1. The correlation between successive inputs or outputs.
    2. The non-stationarity of the problem.
- These two problems are very bad for deep networks, which end up overfitting the learned episodes or not learning anything at all.
- Deepmind researchers proposed to use two classical ML tricks to overcome these problems:
    1. experience replay memory.
    2. target networks.

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., et al. (2013). Playing Atari with Deep Reinforcement Learning. http://arxiv.org/abs/1312.5602

Experience replay memory

- To avoid correlation between samples, Mnih et al. (2015) proposed to store the (s, a, r, s') transitions in a huge **experience replay memory** or **replay buffer** $\mathcal{D}$ (e.g. 1 million transitions).



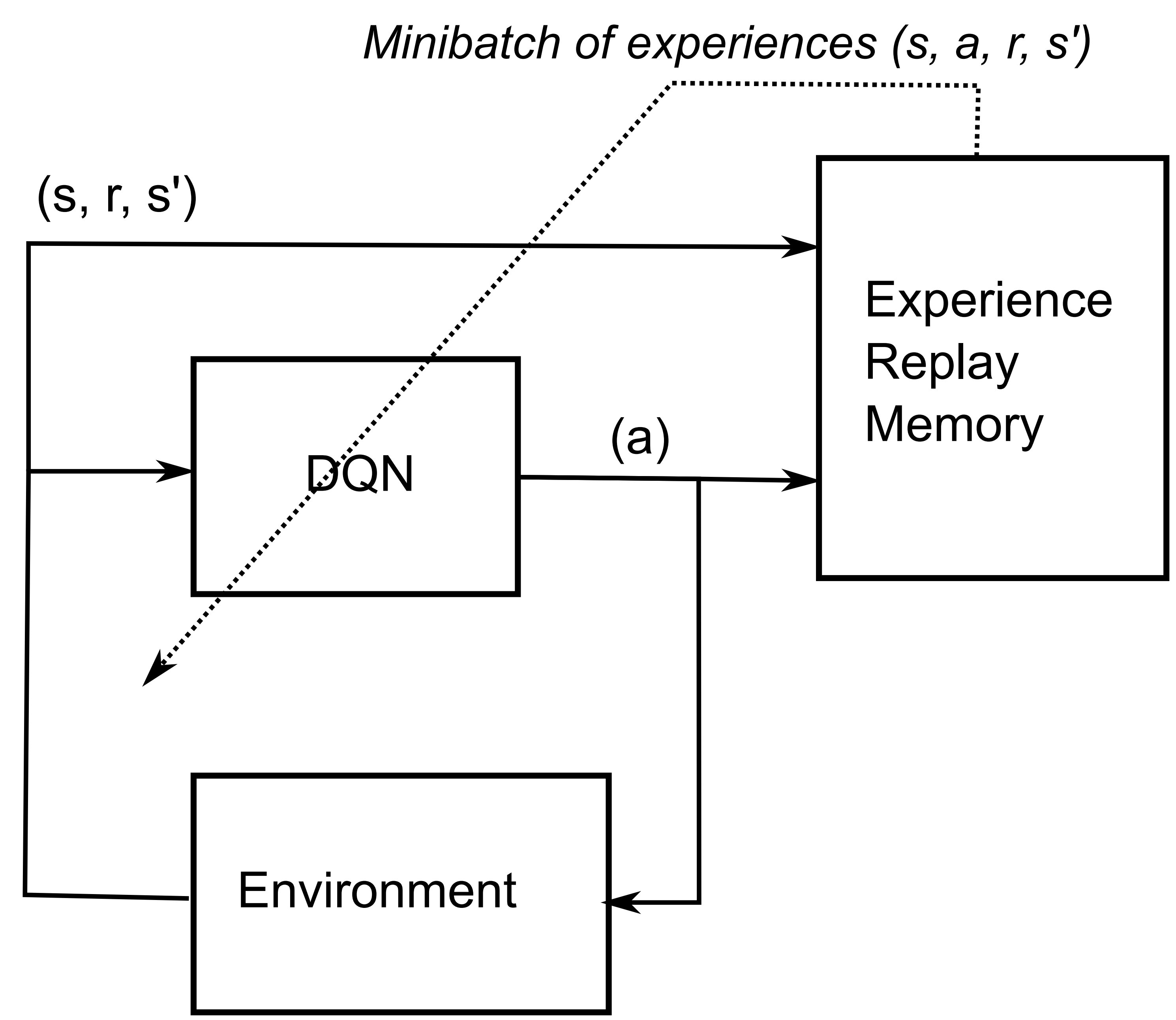
- When the buffer is full, we simply overwrite old transitions.
- The Q-learning update is only applied on a **random minibatch** of those past experiences, not the last transitions.
- This ensure the independence of the samples (non-correlated samples).

Experience replay memory

- Initialize value network Q_θ.
- Initialize experience replay memory $\mathcal{D}$ of maximal size N.
- for $t \in [0, T_\text{total}]$:
    - Select an action a_t based on $Q_\theta(s_t, a)$, observe s_{t+1} and r_{t+1}.
    - Store $(s_t, a_t, r_{t+1}, s_{t+1})$ in the experience replay memory.
    - Every T_train steps:
        - Sample a minibatch $\mathcal{D}_s$ randomly from $\mathcal{D}$.
        - For each transition (s_k, a_k, r_k, s'_k) in the minibatch:
            - Compute the target value $t_k = r_k + \gamma \, \max_{a'} Q_\theta(s'_k, a')$
        - Update the value network Q_θ on $\mathcal{D}_s$ to minimize:

$$\mathcal{L}(\theta) = \mathbb{E}_{\mathcal{D}_s}[(t_k - Q_\theta(s_k, a_k))^2]$$

Experience replay memory



- But wait! The samples of the minibatch are still not i.i.d, as they are not **identically distributed**:
  - Some samples were generated with a very old policy π_{θ_0}.
  - Some samples have been generated recently by the current policy π_θ.
- The samples of the minibatch do not come from the same distribution, so this should not work.

Experience replay memory

- This should not work, except if you use an **off-policy** algorithm, such as Q-learning!

$$Q^\pi(s, a) = \mathbb{E}_{s_t \sim \rho_b, a_t \sim b}[r_{t+1} + \gamma \, \max_a Q^\pi(s_{t+1}, a) | s_t = s, a_t = a]$$

- In Q-learning, you can take samples from **any** behavior policy b, as long as the coverage assumption stands:

$$\pi(s,a) > 0 \Rightarrow b(s,a) > 0$$

- Here, the behavior policy b is a kind of “superset” of all past policies π used to fill the ERM, so it “covers” the current policy.

$$b = \{\pi_{\theta_0}, \pi_{\theta_1}, \dots, \pi_{\theta_t}\}$$

- Samples from b are i.i.d, so Q-learning is going to work.

Experience replay memory

- Note: **it is not possible to use an experience replay memory with on-policy algorithms.**

$$Q^\pi(s, a) = \mathbb{E}_{s_t \sim \rho_\pi, a_t \sim \pi}[r_{t+1} + \gamma \, Q^\pi(s_{t+1}, a_{t+1}) | s_t = s, a_t = a]$$

- $a_{t+1} \sim \pi_\theta$ would not be the same between π_{θ_0} (which generated the sample) and π_{θ_t} (the current policy).
- The estimated return $r_{t+1} + \gamma \, Q^\pi(s_{t+1}, a_{t+1})$ would be biased, impairing convergence.

Target network

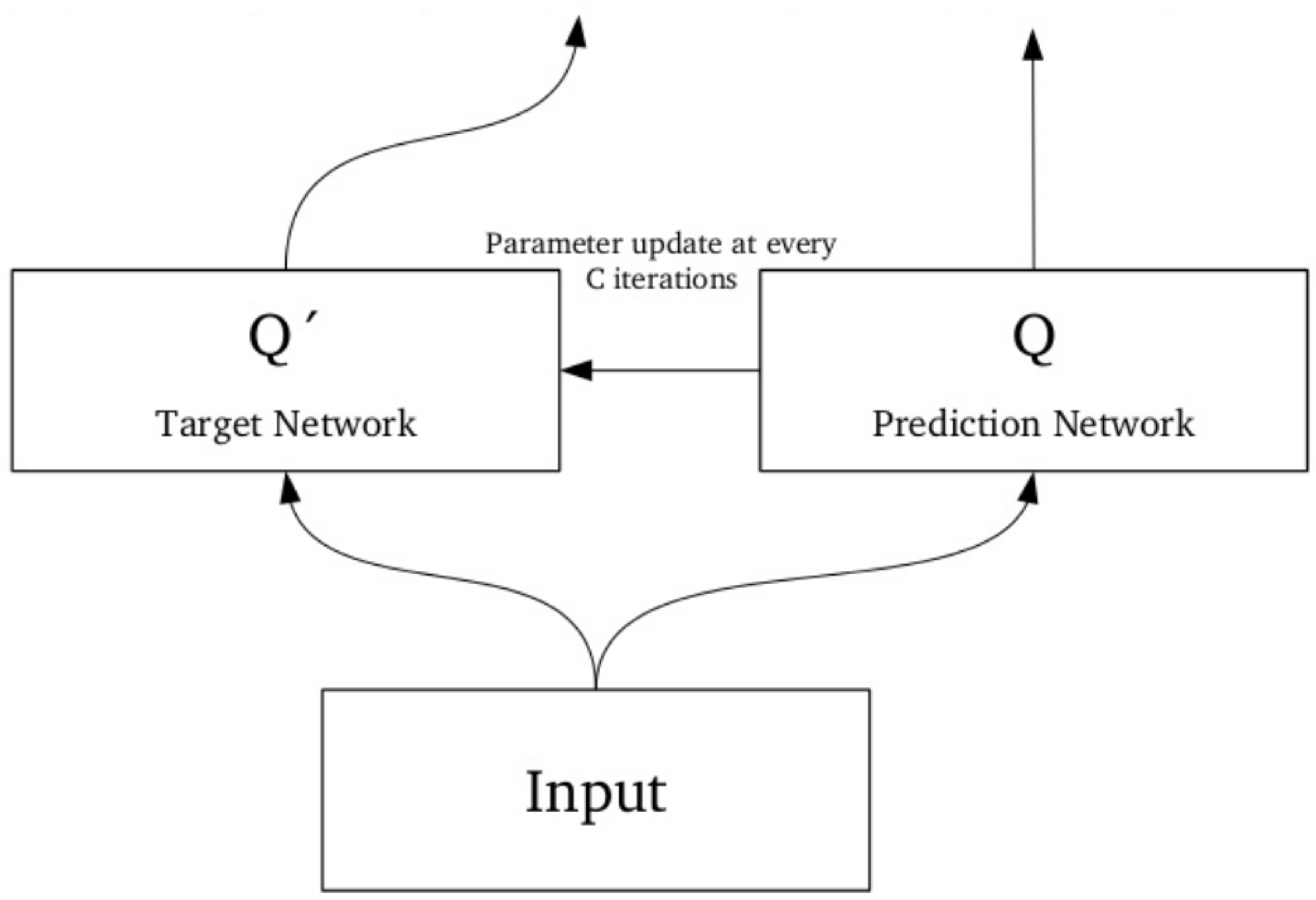
- The second problem when using DNN for RL is that the target is **non-stationary**, i.e. it changes over time: as the network becomes better, the Q-values have to increase.

- In DQN, the target for the update is not computed from the current deep network θ:

$$r + \gamma \, \max_{a'} Q_\theta(s', a')$$

but from a **target network** $\theta´$ updated only every few thousands of iterations.

$$r + \gamma \, \max_{a'} Q_{\theta'}(s', a')$$



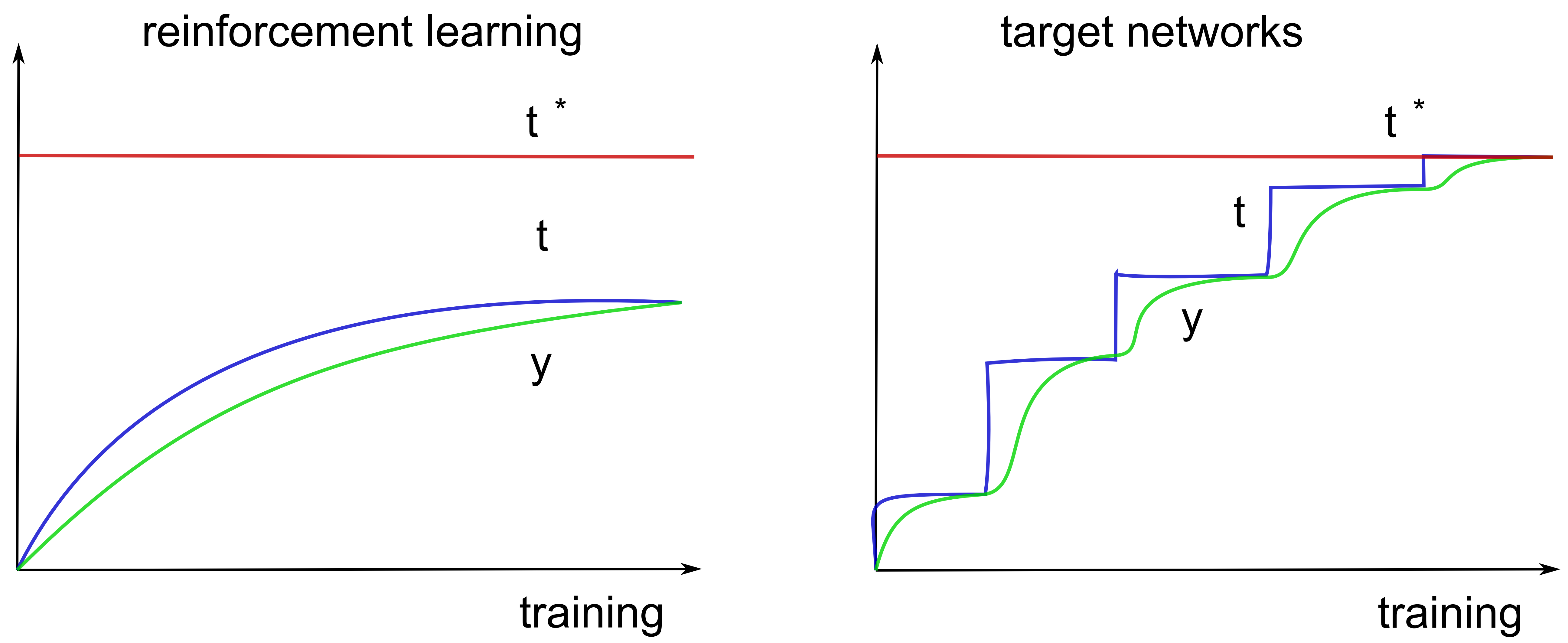
- θ' is simply a copy of θ from the past.

- DQN loss function:

$$\mathcal{L}(\theta) = \mathbb{E}_\mathcal{D}[(r + \gamma \, \max_{a'} Q_{\theta'}(s', a')) - Q_\theta(s, a))^2]$$

Target network

- This allows the target $r + \gamma \, \max_{a'} Q_{\theta'}(s', a')$ to be **stationary** between two updates.
- It leaves time for the trained network to catch up with the targets.



- The update is simply replacing the parameters θ' with the trained parameters θ:

$$\theta' \leftarrow \theta$$

- The value network θ basically learns using an older version of itself…

Mnih et al. (2013) Playing Atari with Deep Reinforcement Learning. http://arxiv.org/abs/1312.5602

DQN: Deep Q-network

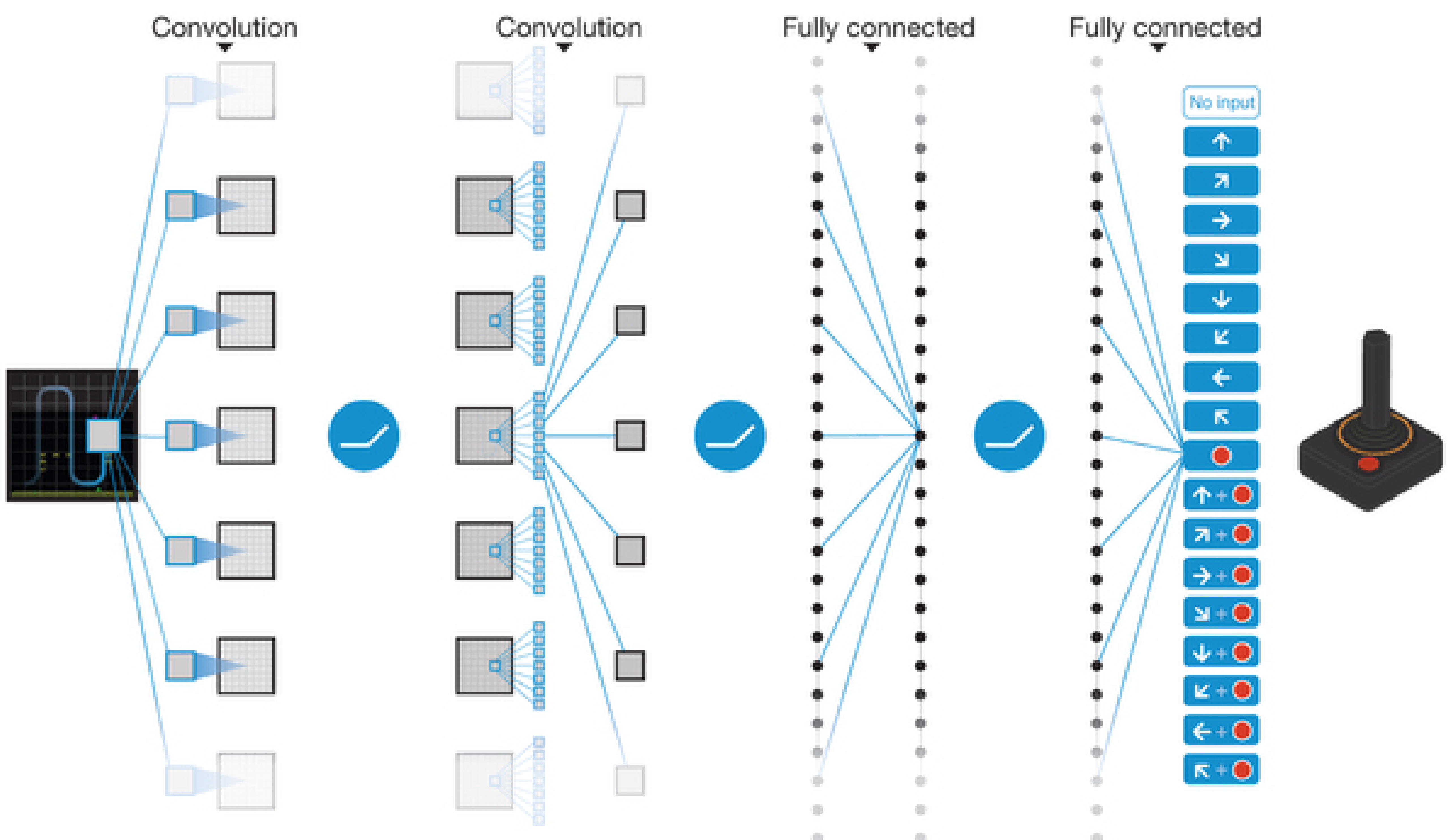
- Initialize value network Q_{θ} and target network $Q_{\theta'}$.
- Initialize experience replay memory $\mathcal{D}$ of maximal size N.
- for $t \in [0, T_\text{total}]$:
    - Select an action a_t based on $Q_\theta(s_t, a)$, observe s_{t+1} and r_{t+1}.
    - Store $(s_t, a_t, r_{t+1}, s_{t+1})$ in the experience replay memory.
    - Every T_train steps:
        - Sample a minibatch $\mathcal{D}_s$ randomly from $\mathcal{D}$.
        - For each transition (s_k, a_k, r_k, s'_k) in the minibatch:
            - Compute the target value $t_k = r_k + \gamma \, \max_{a'} Q_{\theta'}(s'_k, a')$ using the target network.
        - Update the value network Q_{θ} on $\mathcal{D}_s$ to minimize:

$$\mathcal{L}(\theta) = \mathbb{E}_{\mathcal{D}_s}[(t_k - Q_\theta(s_k, a_k))^2]$$

    - Every T_target steps:
        - Update target network: $\theta' \leftarrow \theta$.

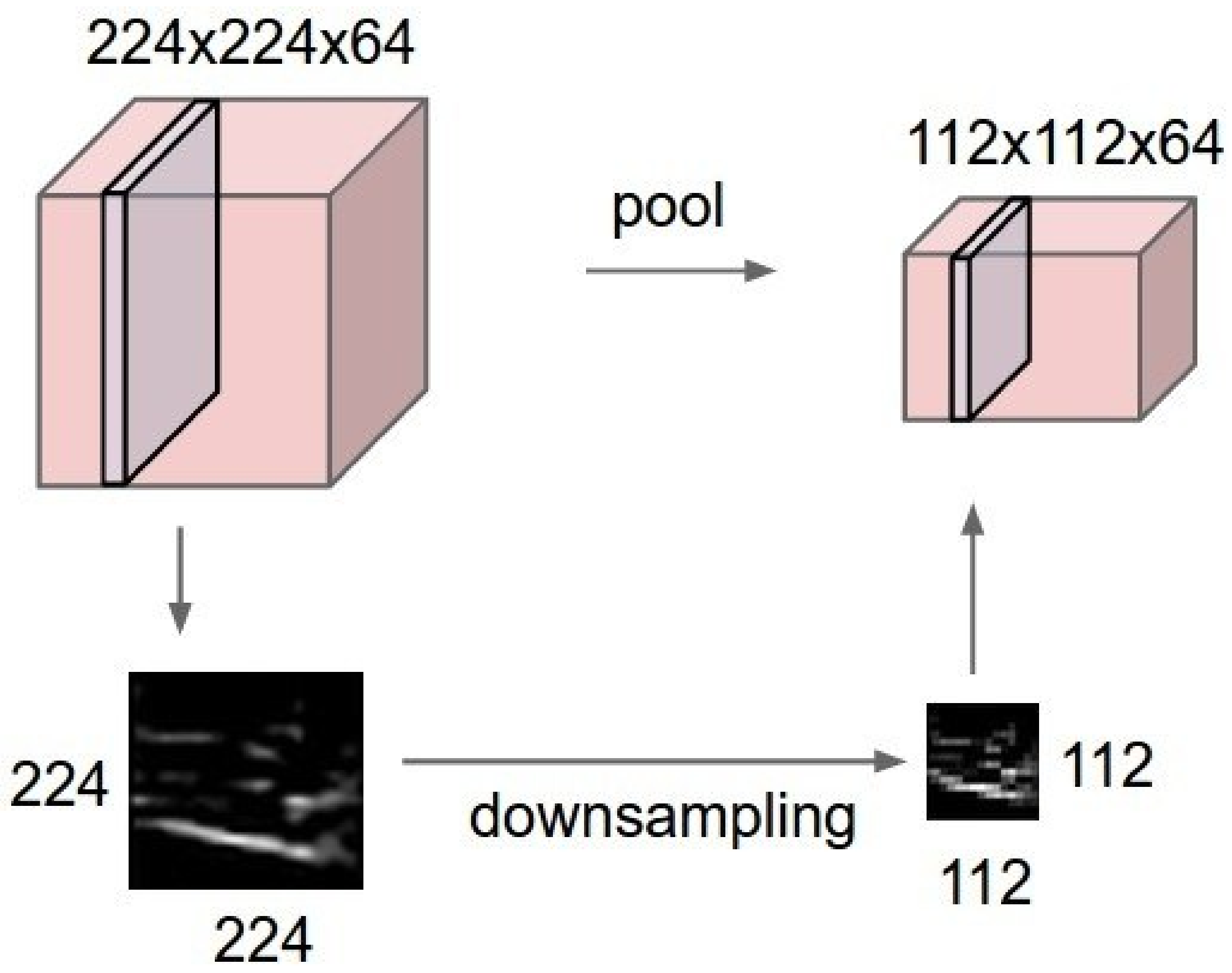
DQN: Deep Q-network

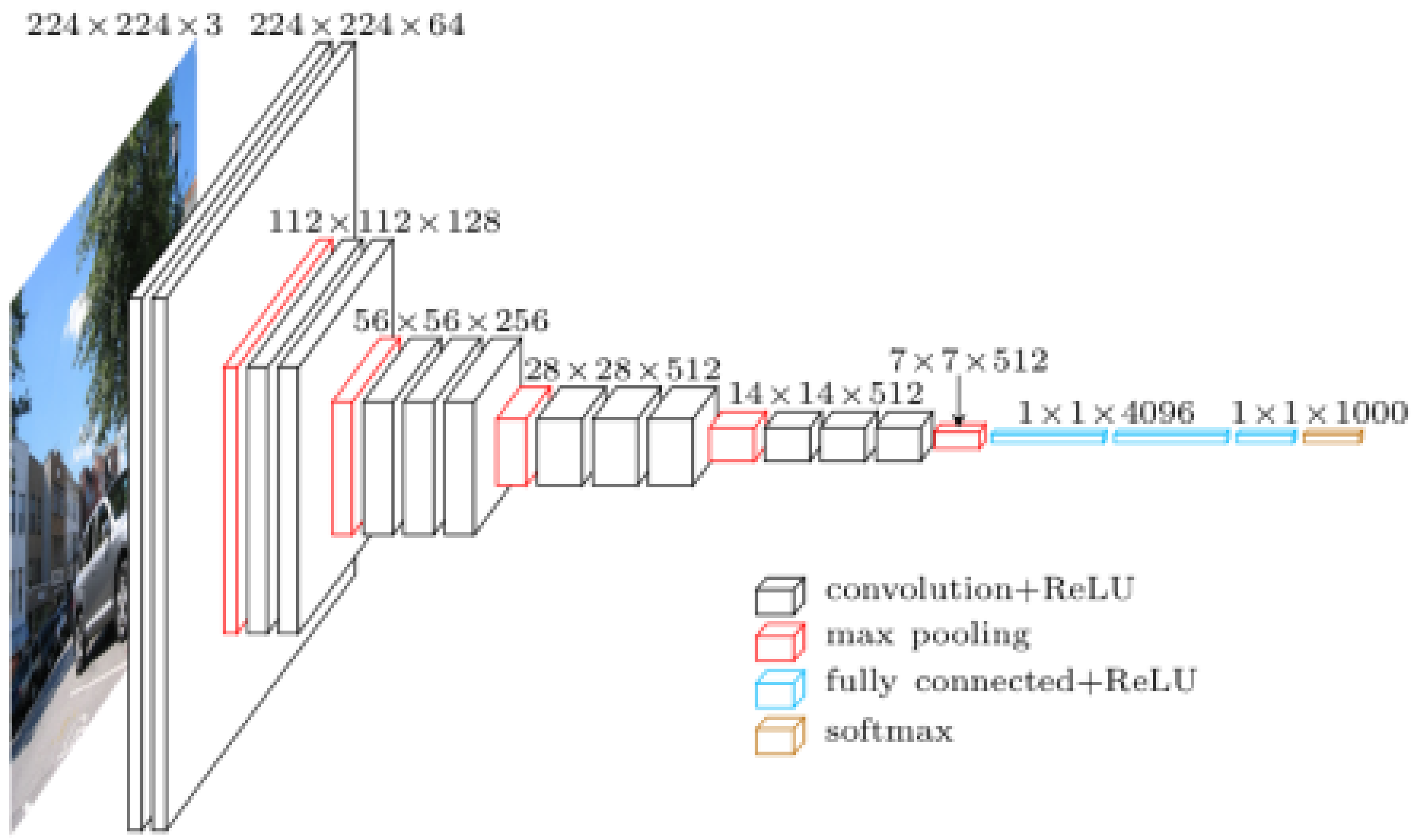
- The deep network can be anything. Deep RL is only about defining the loss function adequately.
- For pixel-based problems (e.g. video games), convolutional neural networks (without max-pooling) are the weapon of choice.



Mnih et al. (2013) Playing Atari with Deep Reinforcement Learning. http://arxiv.org/abs/1312.5602

Why no max-pooling?





- The goal of max-pooling is to get rid of the spatial information in the image.
- For object recognition, you do not care whether the object is in the center or on the side of the image.
- Max-pooling brings **spatial invariance**.
- In video games, you **want** to keep the spatial information: the optimal action depends on where the ball is relative to the paddle.

Are individual frames good representations of states?

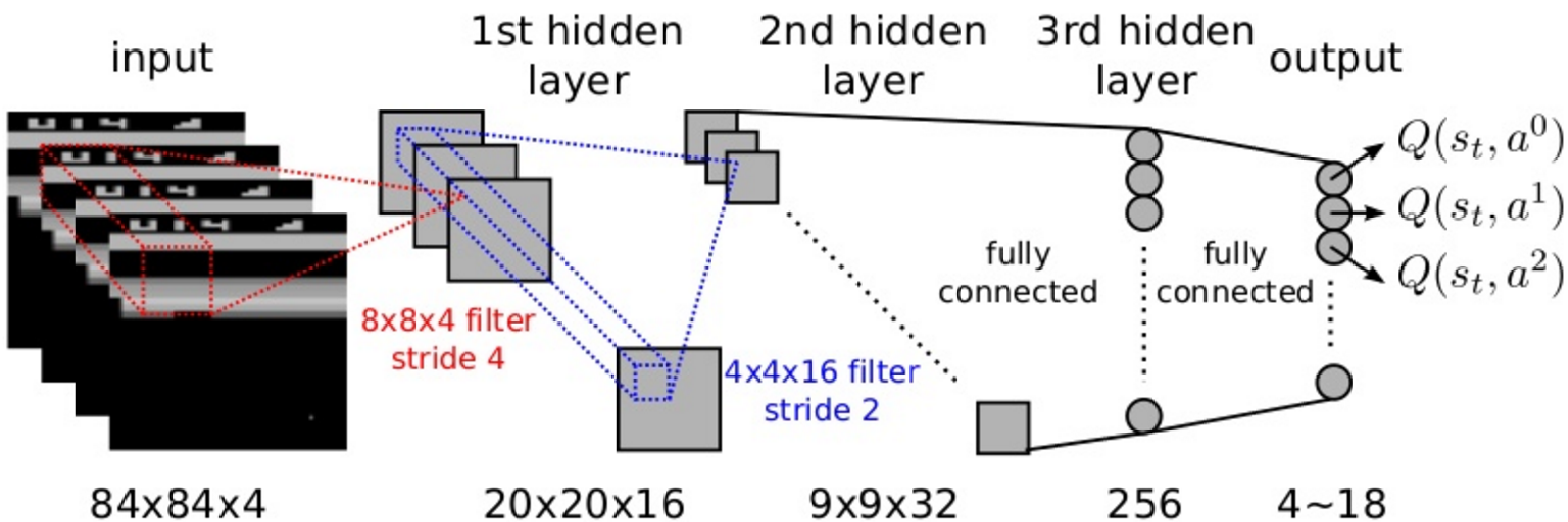
- Is the ball moving from the child to the baseball player, or the other way around?

- Using video frames as states breaks the Markov property: the speed and direction of the ball is a very relevant information for the task, but not contained in a single frame.
- This characterizes a **Partially-observable Markov Decision Process** (POMDP).

Source: https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-6-partial-observability-and-deep-recurrent-q-68463e9aeefc

Markov property in video games

- The simple solution retained in the original DQN paper is to **stack** the last four frames to form the state representation.
- Having the previous positions of the ball, the network can **learn** to infer its direction of movement.



DQN code in Keras

- Creating the CNN in keras / tensorflow / pytorch is straightforward:

```
model = Sequential()

model.add(Input((4, 84, 84)))

model.add(Conv2D(16, (8, 8), strides=(4, 4)), activation='relu'))

model.add(Conv2D(32, (4, 4), strides=(2, 2), activation='relu'))

model.add(Flatten())

model.add(Dense(256, activation='relu'))

model.add(Dense(nb_actions, activation='linear'))

optimizer = RMSprop(lr=0.00025, rho=0.95, epsilon=0.01)

model.compile(optimizer, loss='mse')
```

DQN code in Keras

- Each step of the algorithm follows the GPI approach:

```python
def q_iteration(env, model, state, memory):

    # Choose the action with epsilon-greedy
    if np.random.random() < epsilon:
        action = env.action_space.sample()
    else:
        # Predict the Q-values for the current state and take the greedy action
        values = model.predict([state])[0]
        action = values.argmax()

    # Play one game iteration
    new_state, reward, terminal, truncated, info = env.step(action)

    # Append the transition to the replay buffer
    memory.add(state, action, new_state, reward, terminal or truncated)

    # Sample a minibatch from the memory and fit the DQN
    s, a, r, s_, t = memory.sample_batch(32)
    fit_batch(model, s, a, r, s_, t)
```

DQN code in Keras

- The only slight difficulty is actually to compute the targets for learning:

```
def fit_batch(model, states, actions, rewards, next_states, terminals)

    # Predict the Q-values in the current state
    Q_values = model.predict(states)

    # Predict the Q-values in the next state using the target model
    next_Q_value = target_model.predict(next_states).max(axis=1)

    # Terminal states have a value of 0
    next_Q_value[terminals] = 0.0

    # Compute the target
    targets = Q_values.copy()
    for i in range(batch_size):
        targets[i, actions[i]] = rewards[i] + self.gamma * next_Q_value[i]

    # Train the model on the minibatch
    self.model.fit(states, targets, epochs=1, batch_size=batch_size, verbose=0)
```

DQN training

- 50M frames (38 days of game experience) per game. Replay buffer of 1M frames.
- Action selection: ϵ-greedy with $\epsilon = 0.1$ and annealing. Optimizer: RMSprop with a batch size of 32.

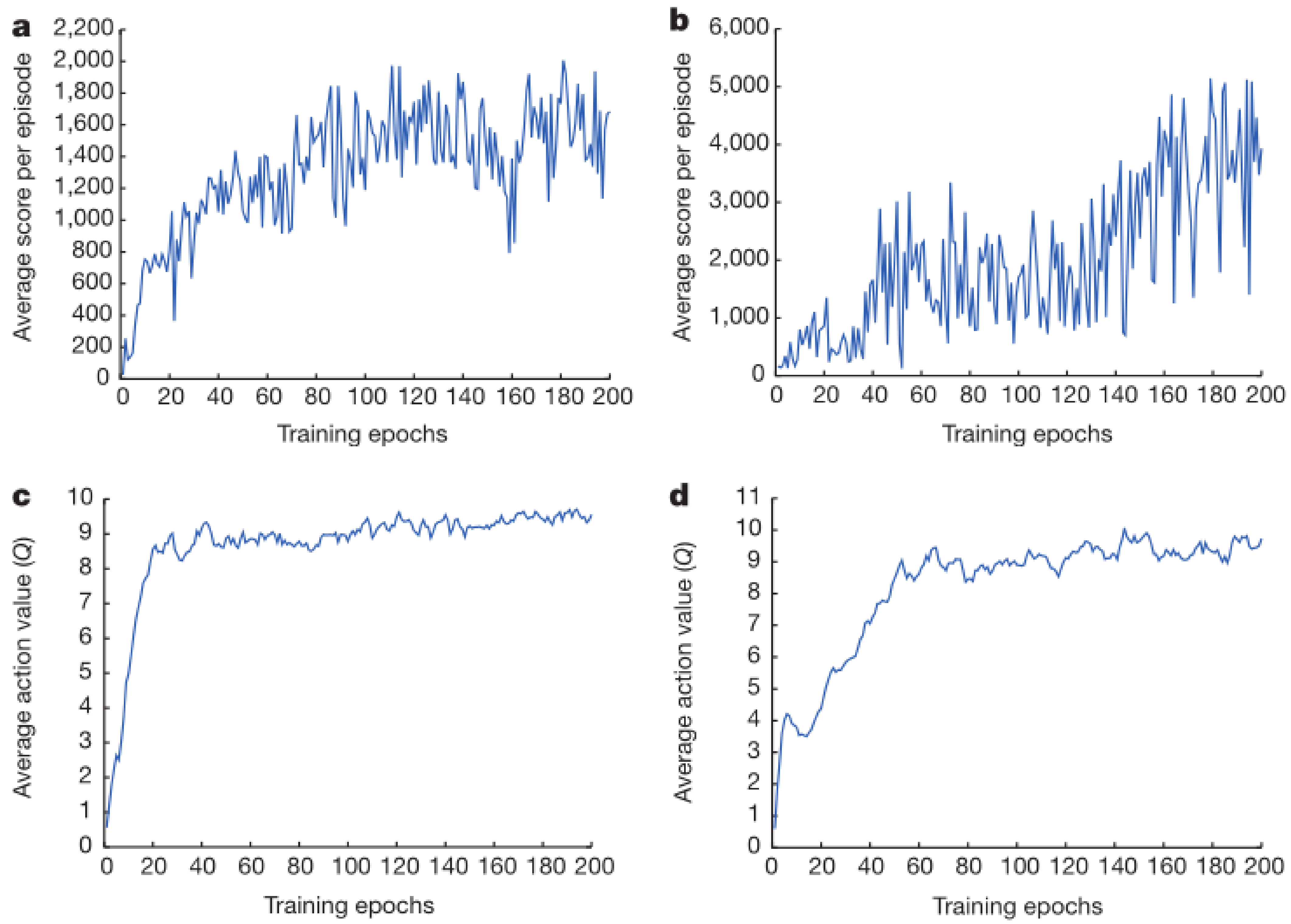


Figure 2 | Training curves tracking the agent's average score and average predicted action-value. **a**, Each point is the average score achieved per episode after the agent is run with ε-greedy policy ($\varepsilon = 0.05$) for 520 k frames on Space Invaders. **b**, Average score achieved per episode for Seaquest. **c**, Average predicted action-value on a held-out set of states on Space Invaders. Each point on the curve is the average of the action-value Q computed over the held-out set of states. Note that Q-values are scaled due to clipping of rewards (see Methods). **d**, Average predicted action-value on Seaquest. See Supplementary Discussion for details.

Mnih et al. (2015) Human-level control through deep reinforcement learning. Nature 518, 529–533. doi:10.1038/nature14236.

DQN to solve multiple Atari games

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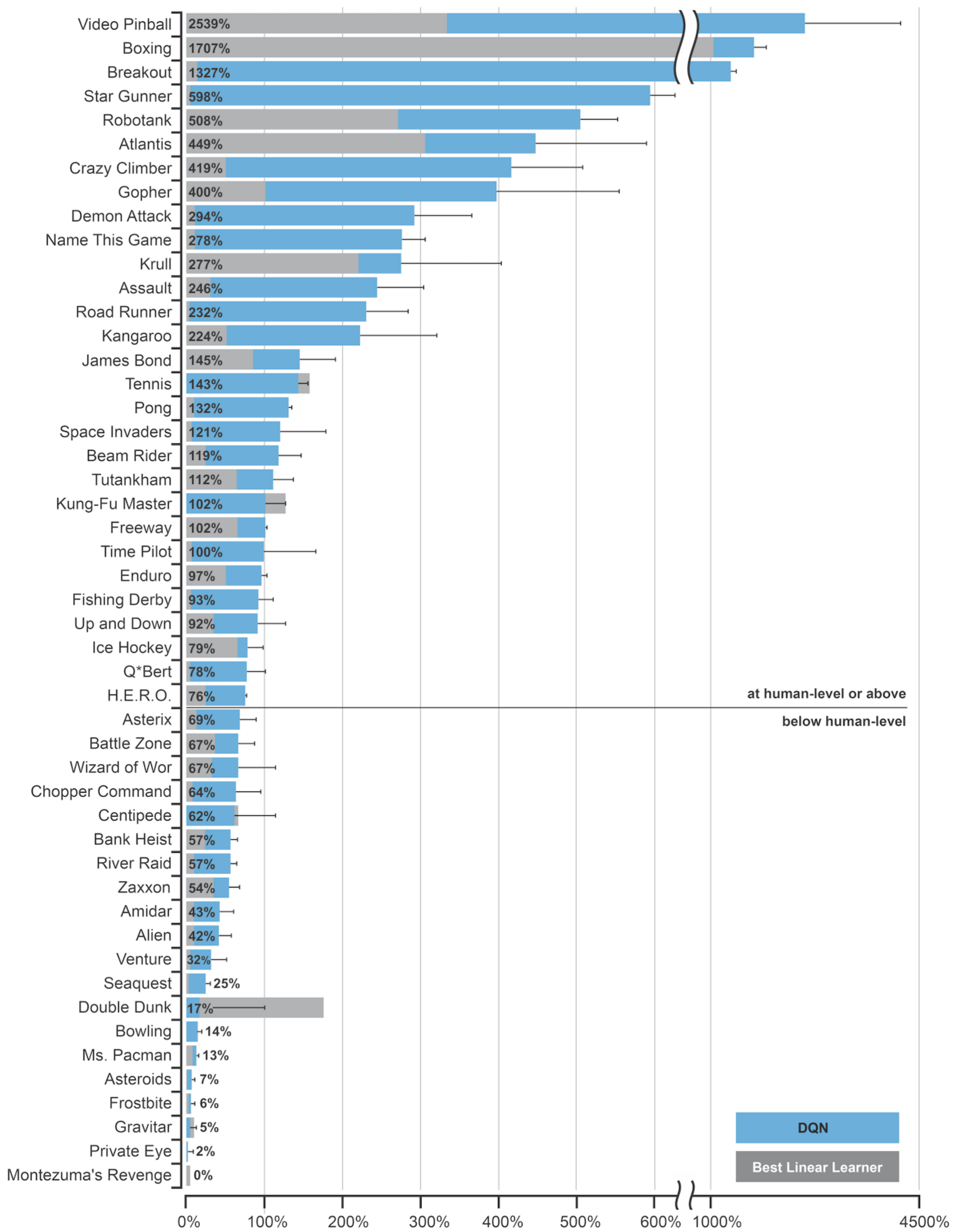
DQN to solve multiple Atari games



- The DQN network was trained to solve 49 different Atari 2600 games **with the same architecture and hyperparameters**.
- In most of the games, the network reaches **super-human** performance.
- Some games are still badly performed (e.g. Montezuma's revenge), as they require long-term planning.
- It was the first RL algorithm able to learn different tasks (no free lunch theorem).
- The 2015 paper in Nature started the hype for deep RL.

Mnih et al. (2015) Human-level control through deep reinforcement learning. Nature 518, 529–533. doi:10.1038/nature14236.

2 - Double DQN

Deep Reinforcement Learning with Double Q-learning

Hado van Hasselt and **Arthur Guez** and **David Silver**
Google DeepMind

Double DQN

- Q-learning methods, including DQN, tend to **overestimate** Q-values, especially for the non-greedy actions:

$$Q_\theta(s, a) > Q^\pi(s, a)$$

- This does not matter much in action selection, as we apply ϵ-greedy or softmax on the Q-values anyway, but it may make learning slower (sample complexity) and less optimal.

van Hasselt et al. (2015) Deep Reinforcement Learning with Double Q-learning, arXiv:1509.06461.

Double DQN

- To avoid optimistic estimations, the target is computed by both the value network θ and the target network θ':
  - **Action selection**: The next greedy action a^* is calculated by the **value network** θ (current policy):

$$a^* = \text{argmax}_{a'} Q_{\theta}(s', a')$$

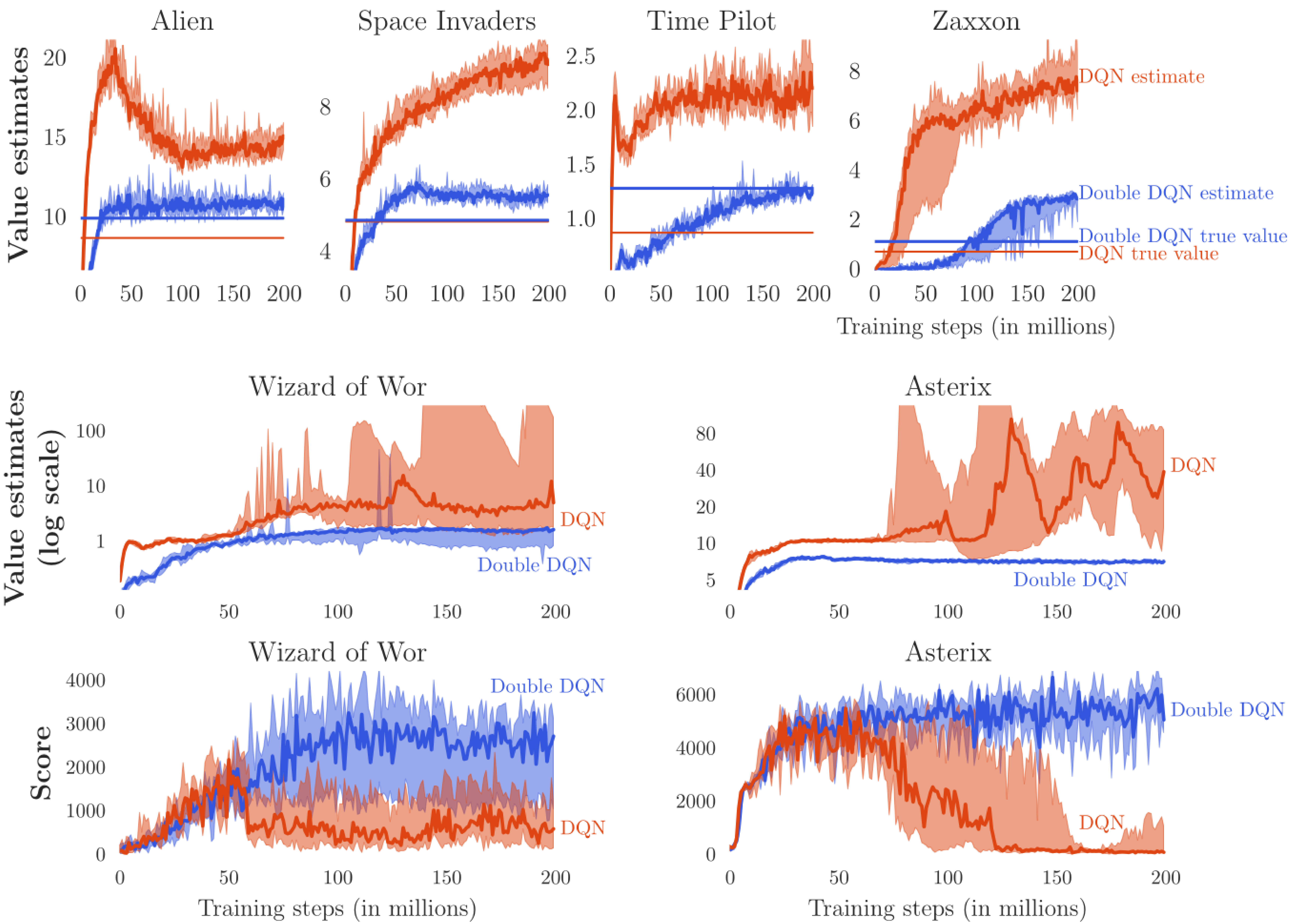
  - **Action evaluation**: Its Q-value for the target is calculated using the **target network** θ' (older values):

$$t = r + \gamma \, Q_{\theta'}(s´, a^*)$$

- This gives the following loss function for **double DQN** (DDQN):

$$\mathcal{L}(\theta) = \mathbb{E}_\mathcal{D} [(r + \gamma \, Q_{\theta'}(s´, \text{argmax}_{a'} Q_{\theta}(s', a')) - Q_\theta(s, a))^2]$$

van Hasselt et al. (2015) Deep Reinforcement Learning with Double Q-learning, arXiv:1509.06461.



van Hasselt et al. (2015) Deep Reinforcement Learning with Double Q-learning, arXiv:1509.06461.

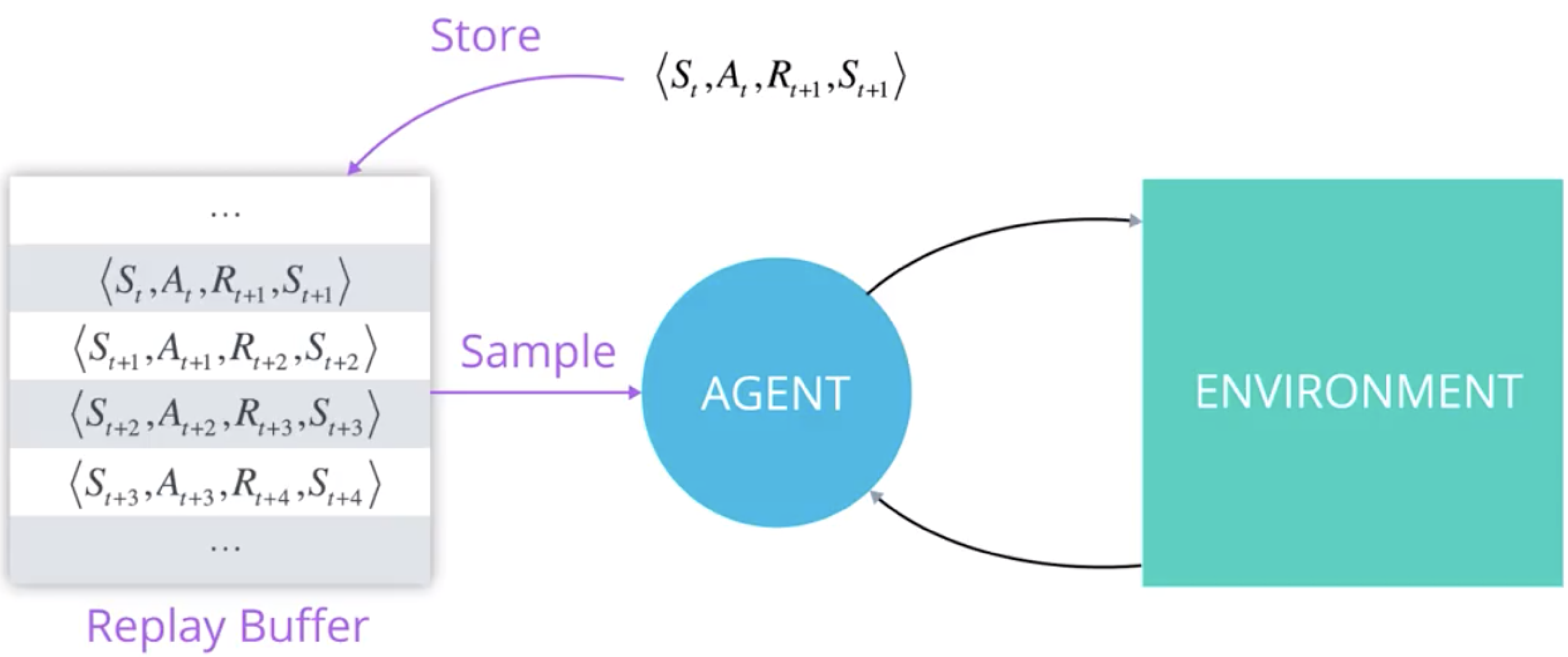
3 - Prioritized Experience Replay

Published as a conference paper at ICLR 2016

Prioritized Experience Replay

Tom Schaul, John Quan, Ioannis Antonoglou and David Silver
Google DeepMind
{schaul,johnquan,ioannisa,davidsilver}@google.com

Prioritized Experience Replay

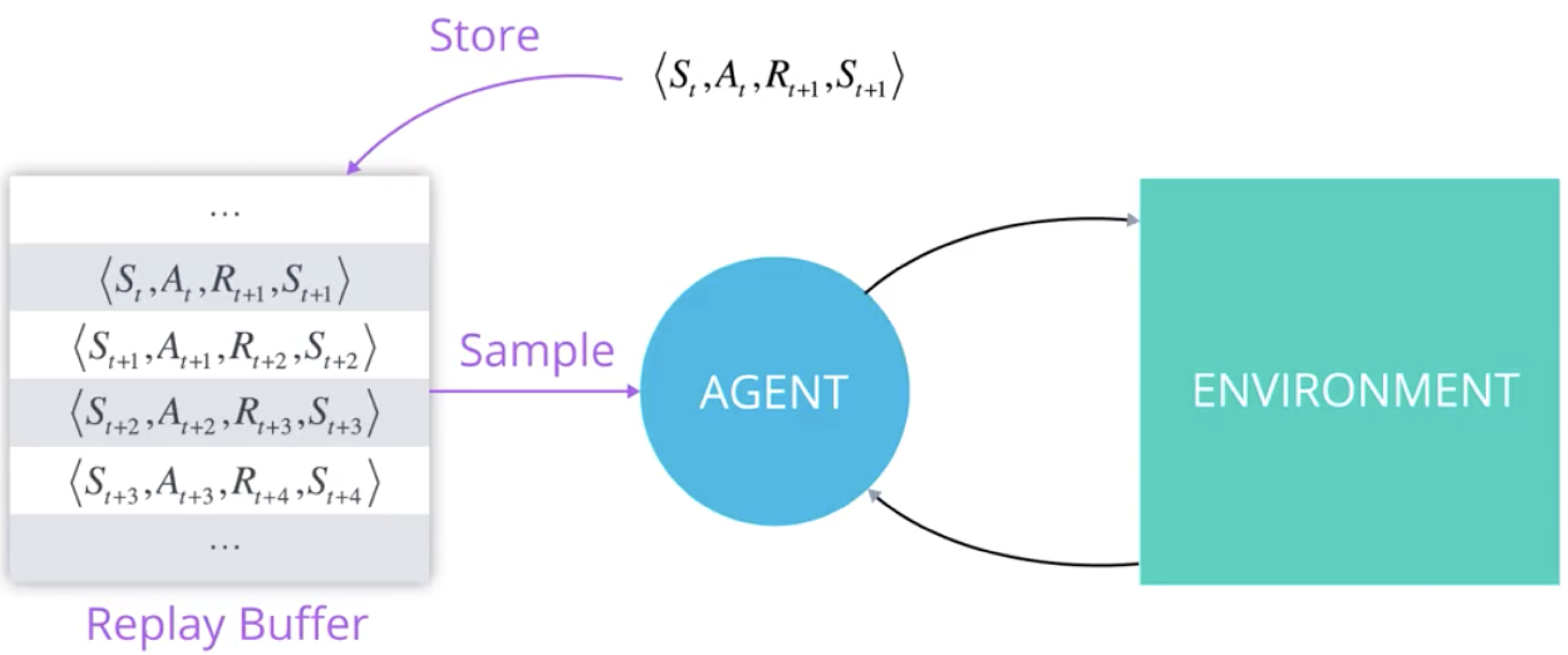


Source: https://parksurk.github.io/deep/reinfocement/learning/drlnd_2-4_value_based_methods-post/

- The **experience replay memory** or **replay buffer** is used to store the last 1M transitions (s, a, r, s').
- The learning algorithm **randomly samples** a minibatch of size K to update its parameters.
- Not all transitions are interesting:
  - Some transitions were generated by a very old policy, the current policy won't take them anymore.
  - Some transitions are already well predicted: the TD error is small, there is nothing to learn from.

$$\delta_t = r_{t+1} + \gamma \max_{a'} Q_\theta(s_{t+1}, a_{t+1}) - Q_\theta(s_t, a_t) \approx 0$$

Prioritized Experience Replay



Source: https://parksurk.github.io/deep/reinfocement/learning/drlnd_2-4_value_based_methods-post/

- The experience replay memory makes learning very **slow**: we need a lot of samples to learn something useful:
  - High **sample complexity**.
- We need a smart mechanism to preferentially pick the transitions that will boost learning the most, without introducing a bias.
  - **Prioritized sweeping** is actually a quite old idea:

> Moore and Atkeson (1993) Prioritized sweeping: Reinforcement learning with less data and less time. Machine Learning, 13(1):103–130.

Prioritized Experience Replay

- The idea of **prioritized experience replay** (PER) is to sample in priority those transitions whose TD error is the highest:

$$\delta_t = r_{t+1} + \gamma \, \max_{a'} Q_\theta(s_{t+1}, a_{t+1}) - Q_\theta(s_t, a_t)$$

- In practice, we insert the transition (s, a, r, s', δ) into the replay buffer.
- To create a minibatch, the sampling algorithm select a transition k based on the probability:

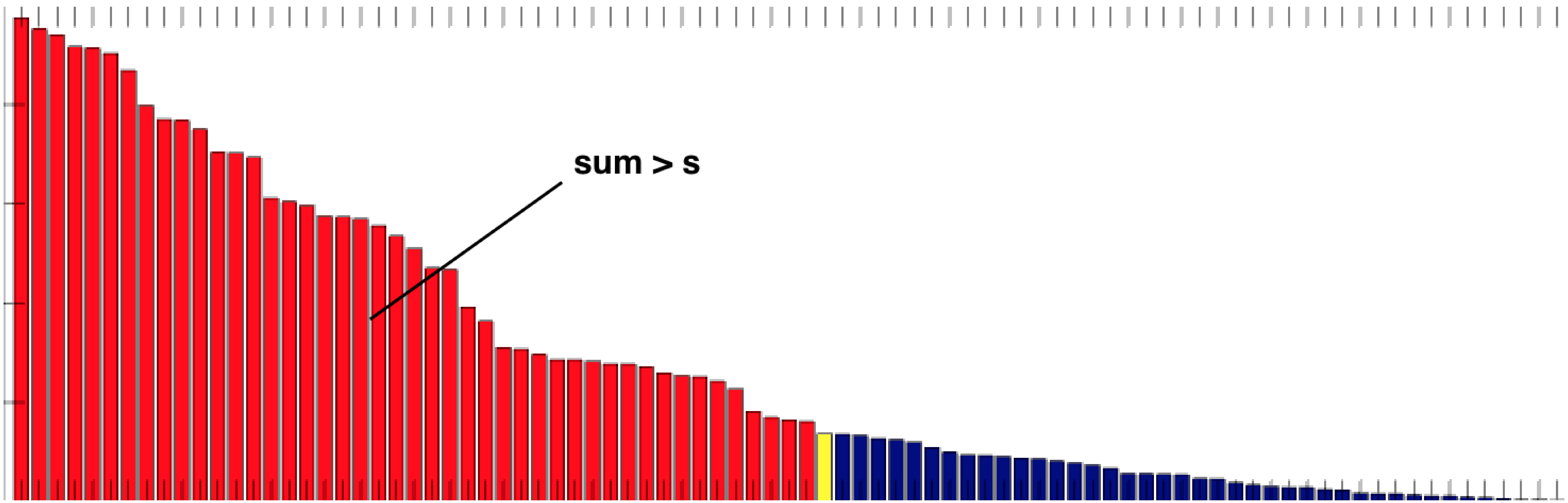
$$P(k) = \frac{(|\delta_k| + \epsilon)^\alpha}{\sum_k (|\delta_k| + \epsilon)^\alpha}$$

- ϵ is a small parameter ensuring that transition with no TD error still get sampled from time to time.
- α allows to change the behavior from uniform sampling ($\alpha=0$, as in DQN) to fully prioritized sampling ($\alpha=1$). α should be annealed from 0 to 1 during training.
- Think of it as a “kind of” **softmax** over the TD errors.
- After the samples have been used for learning, their TD error δ is updated in the PER.

Schaul et al. (2015). Prioritized Experience Replay. arXiv:1511.05952

Prioritized Experience Replay

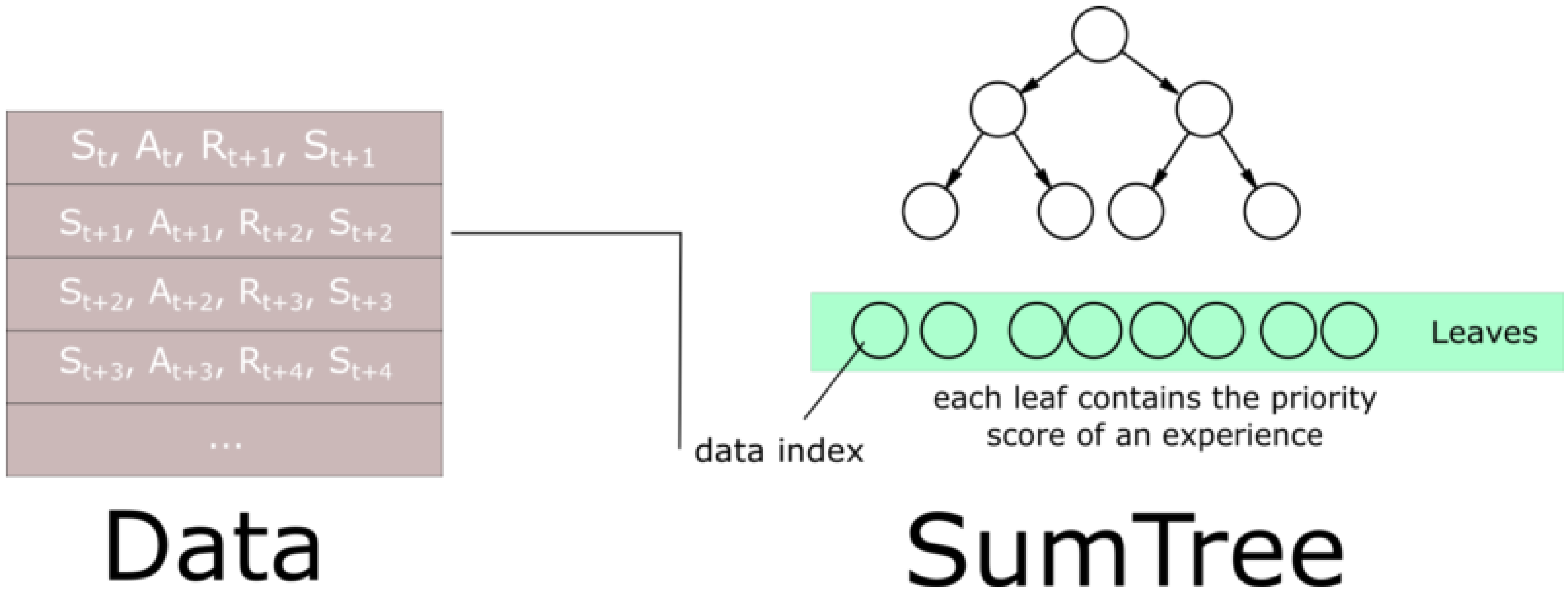
- The main drawback is that inserting and sampling can be computationally expensive if we simply sort the transitions based on $(|\delta_k| + \epsilon)^\alpha$:
  - Insertion: $\mathcal{O}(N \, \log N)$.
  - Sampling: $\mathcal{O}(N)$.



Source: https://jaromiru.com/2016/11/07/lets-make-a-dqn-double-learning-and-prioritized-experience-replay/

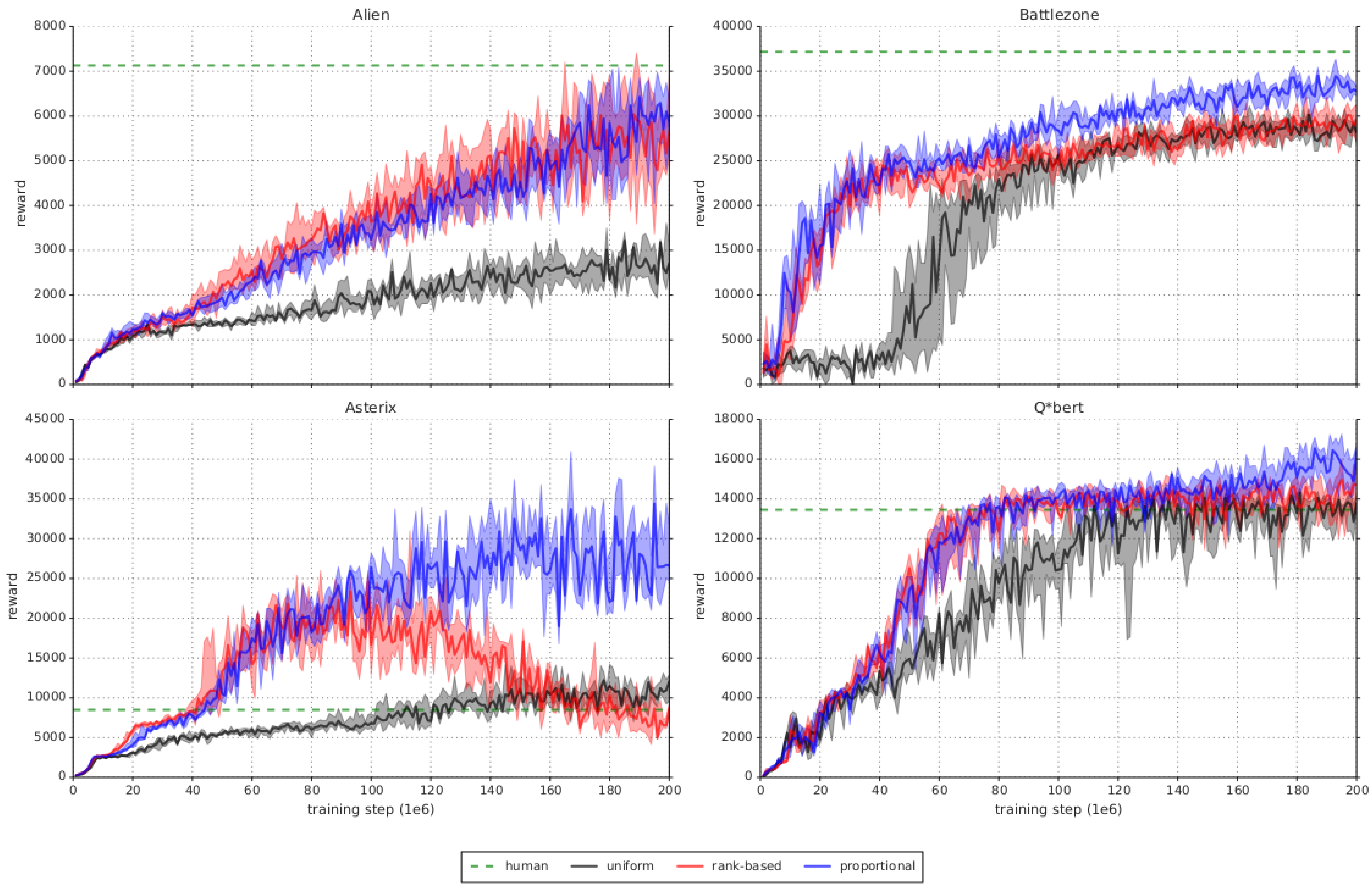
Prioritized Experience Replay

- Using binary **sumtrees**, prioritized experience replay can be made efficient in both insertion ($\mathcal{O}(\log N)$) and sampling ($\mathcal{O}(1)$).
- Instead of a linear queue, we use a binary tree to store the transitions.
- Details in a real computer science course…



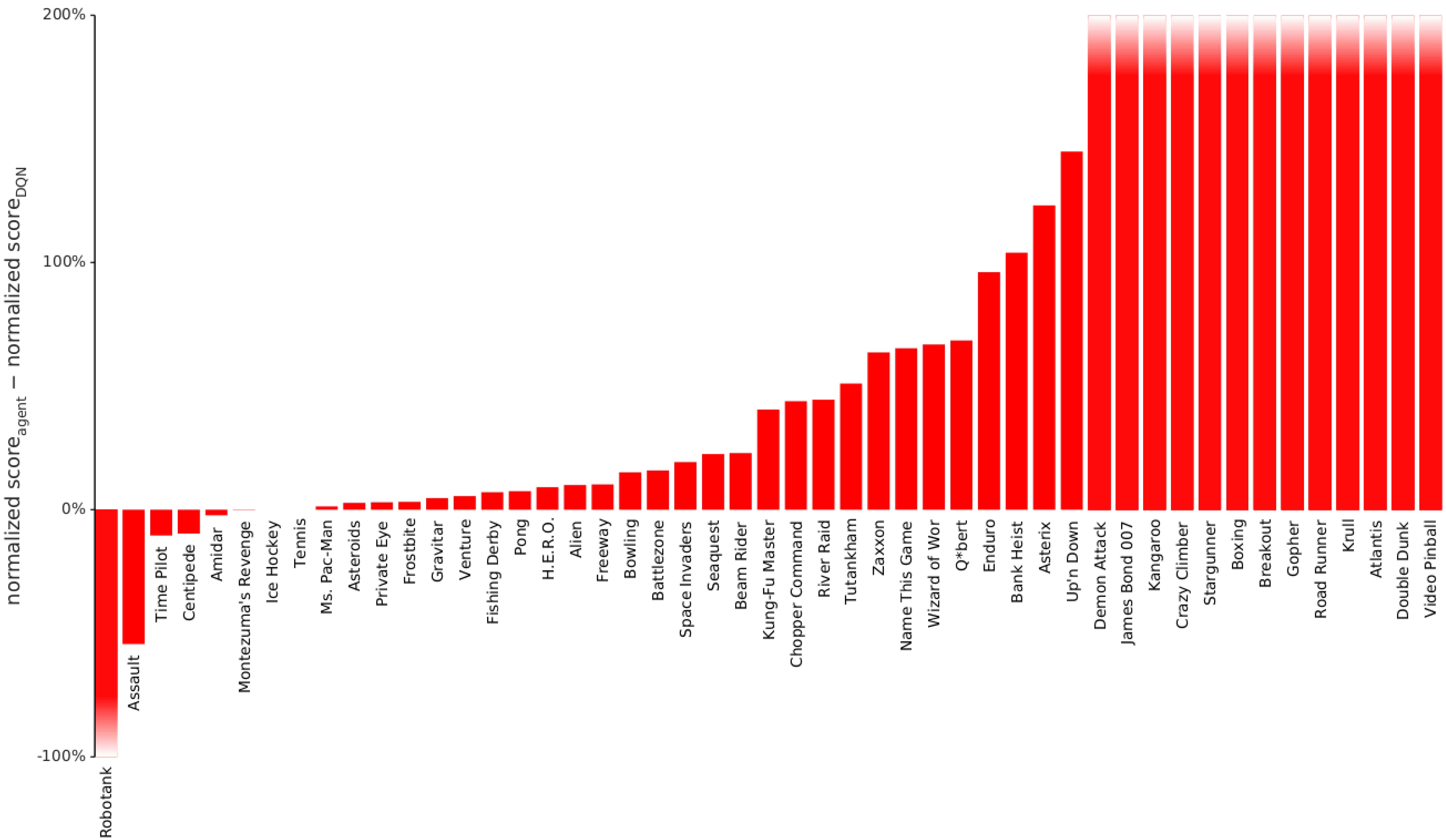
Source: https://www.freecodecamp.org/news/improvements-in-deep-q-learning-dueling-double-dqn-prioritized-experience-replay-and-fixed-58b130cc5682/

Prioritized Experience Replay



Schaul et al. (2015) Prioritized Experience Replay. arXiv:1511.05952

Prioritized Experience Replay



4 - Dueling networks

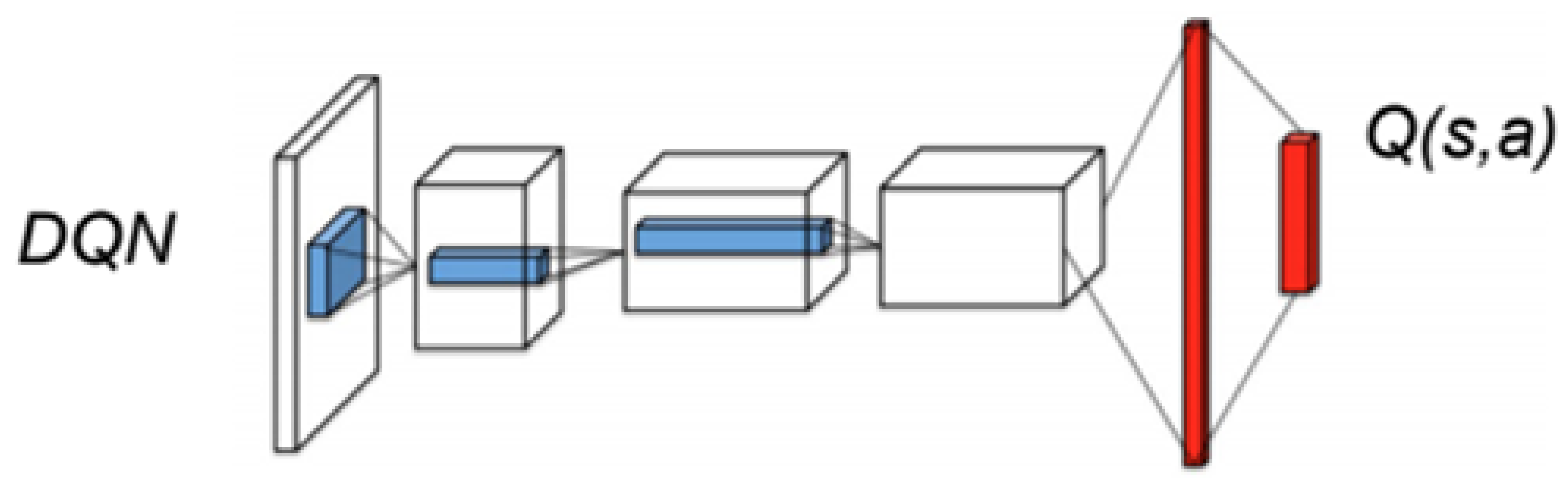
Dueling Network Architectures for Deep Reinforcement Learning

Ziyu Wang ZIYU@GOOGLE.COM
Tom Schaul SCHAUL@GOOGLE.COM
Matteo Hessel MTTHSS@GOOGLE.COM
Hado van Hasselt HADO@GOOGLE.COM
Marc Lanctot LANCTOT@GOOGLE.COM
Nando de Freitas NANDODEFREITAS@GMAIL.COM
Google DeepMind, London, UK

Wang et al. (2016) Dueling Network Architectures for Deep Reinforcement Learning. arXiv:1511.06581.

Dueling networks

- DQN and its variants learn to predict directly the Q-value of each available action.



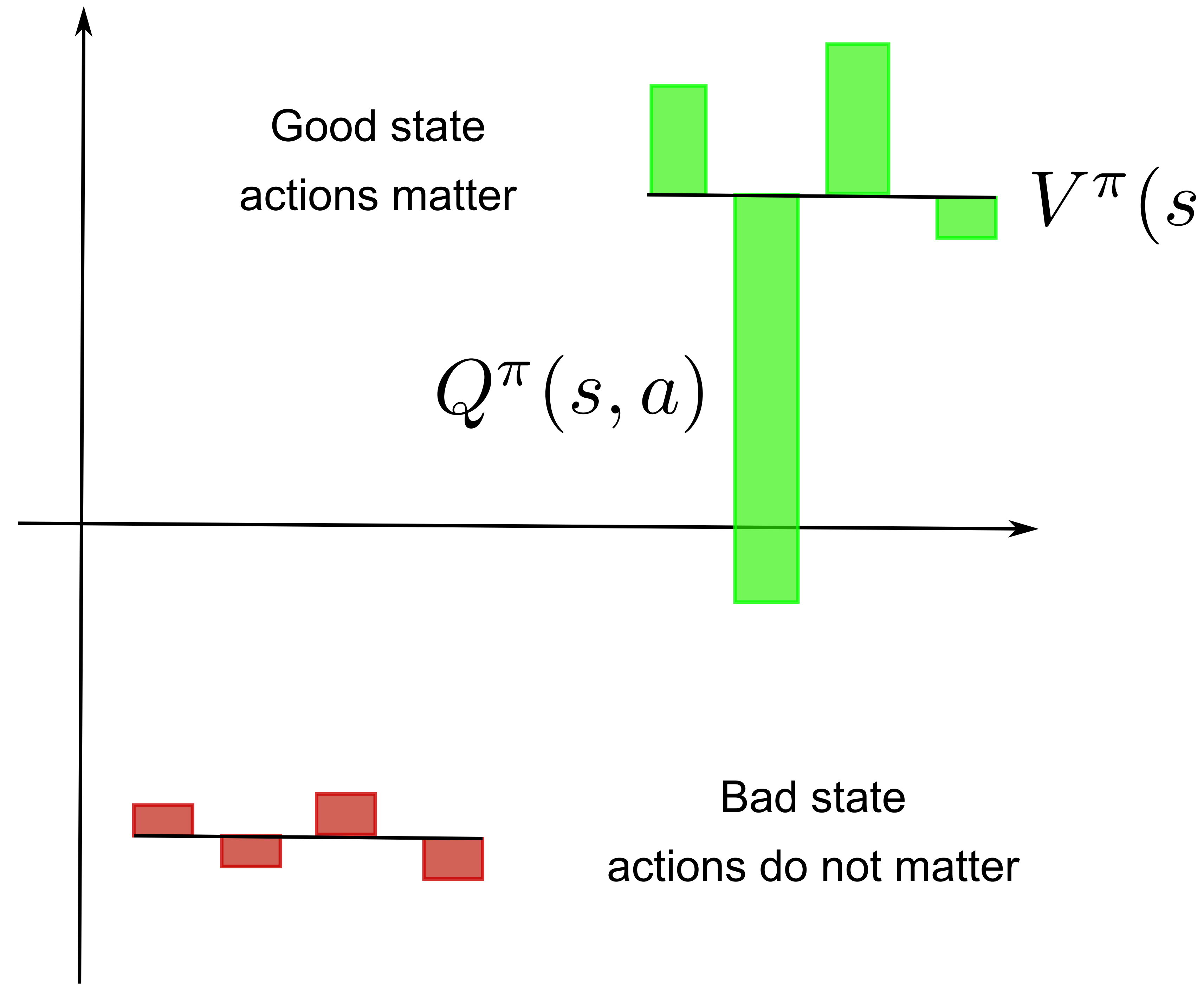
- Several problems with predicting Q-values with a DNN:
    - The Q-values can take high values, especially with different values of γ.
    - The Q-values have a high variance, between the minimum and maximum returns obtained during training.
    - For a transition (s_t, a_t, s_{t+1}), a single Q-value is updated, not all actions in s_t.

Wang et al. (2016) Dueling Network Architectures for Deep Reinforcement Learning. arXiv:1511.06581.

Dueling networks

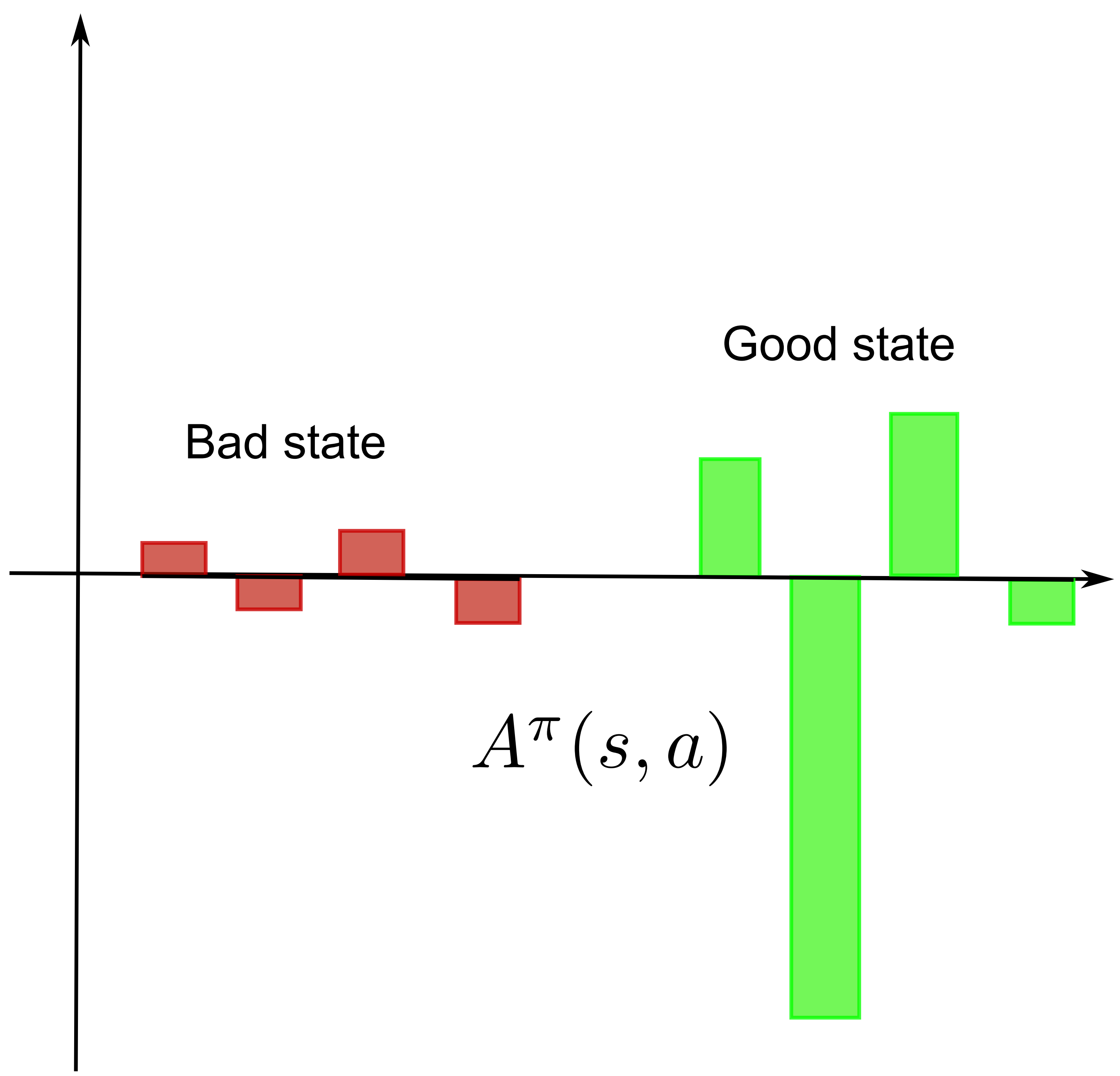
- Enduro game.

Source: https://gfycat.com/clumsypaleimpala



- The exact Q-values of all actions are not equally important.
  - In **bad** states (low $V^\pi(s)$), you can do whatever you want, you will lose.
  - In neutral states, you can do whatever you want, nothing happens.
  - In **good** states (high $V^\pi(s)$), you need to select the right action to get rewards, otherwise you lose.

Advantage functions



- An important notion is the **advantage** $A^\pi(s, a)$ of an action:

$$A^\pi(s, a) = Q^\pi(s, a) - V^\pi(s)$$

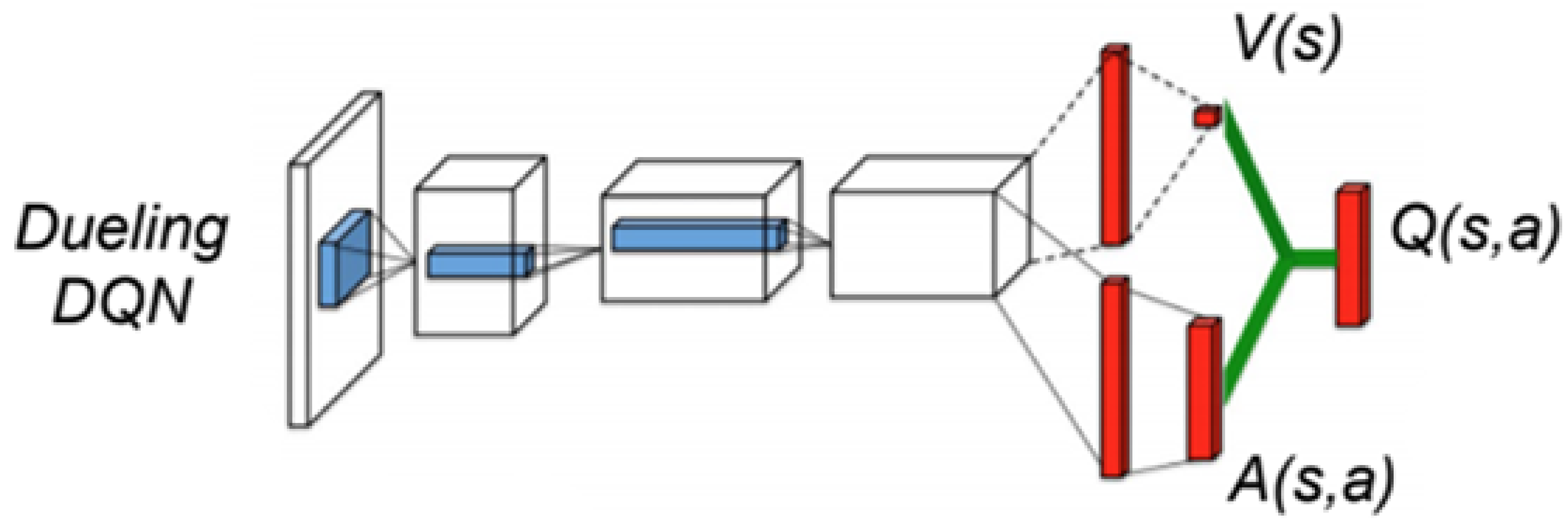
- It tells how much return can be expected by taking the action a in the state s, **compared** to what is usually obtained in s with the current policy.
- If a policy π is deterministic and always selects a^* in s, we have:

$$A^\pi(s, a^*) = 0$$

$$A^\pi(s, a \neq a^*) < 0$$

- This is particularly true for the optimal policy.
- But if we have separate estimates $V_\varphi(s)$ and $Q_\theta(s, a)$, some actions may have a positive advantage.
- Advantages have **less variance** than Q-values.

Dueling networks



- In **dueling networks**, the network is forced to decompose the estimated Q-value $Q_\theta(s, a)$ into a state value $V_\alpha(s)$ and an advantage function $A_\beta(s, a)$:

$$Q_\theta(s, a) = V_\alpha(s) + A_\beta(s, a)$$

- The parameters α and β are just two shared subparts of the NN θ.
- The loss function

$$\mathcal{L}(\theta) = \mathbb{E}_\mathcal{D}[(r + \gamma \, Q_{\theta'}(s´, \text{argmax}_{a'} Q_\theta(s', a')) - Q_\theta(s, a))^2]$$

is exactly the same as in (D)DQN: only the internal structure of the NN changes.

Wang et al. (2016) Dueling Network Architectures for Deep Reinforcement Learning. arXiv:1511.06581.

Unidentifiability

- The Q-values are the sum of two functions: $Q_\theta(s, a) = V_\alpha(s) + A_\beta(s, a)$
- However, the sum is **unidentifiable**:

$$\begin{aligned} Q_\theta(s, a) = 10 &= 1 + 9 \\ &= 2 + 8 \\ &= 3 + 7 \end{aligned}$$

- To constrain the sum, (Wang et al. 2016) propose that the greedy action w.r.t the advantages should have an advantage of 0:

$$Q_\theta(s, a) = V_\alpha(s) + (A_\beta(s, a) - \max_{a'} A_\beta(s, a'))$$

- This way, there is only one solution to the addition. The operation is differentiable, so backpropagation will work.
- (Wang et al. 2016) show that subtracting the mean advantage works better in practice:

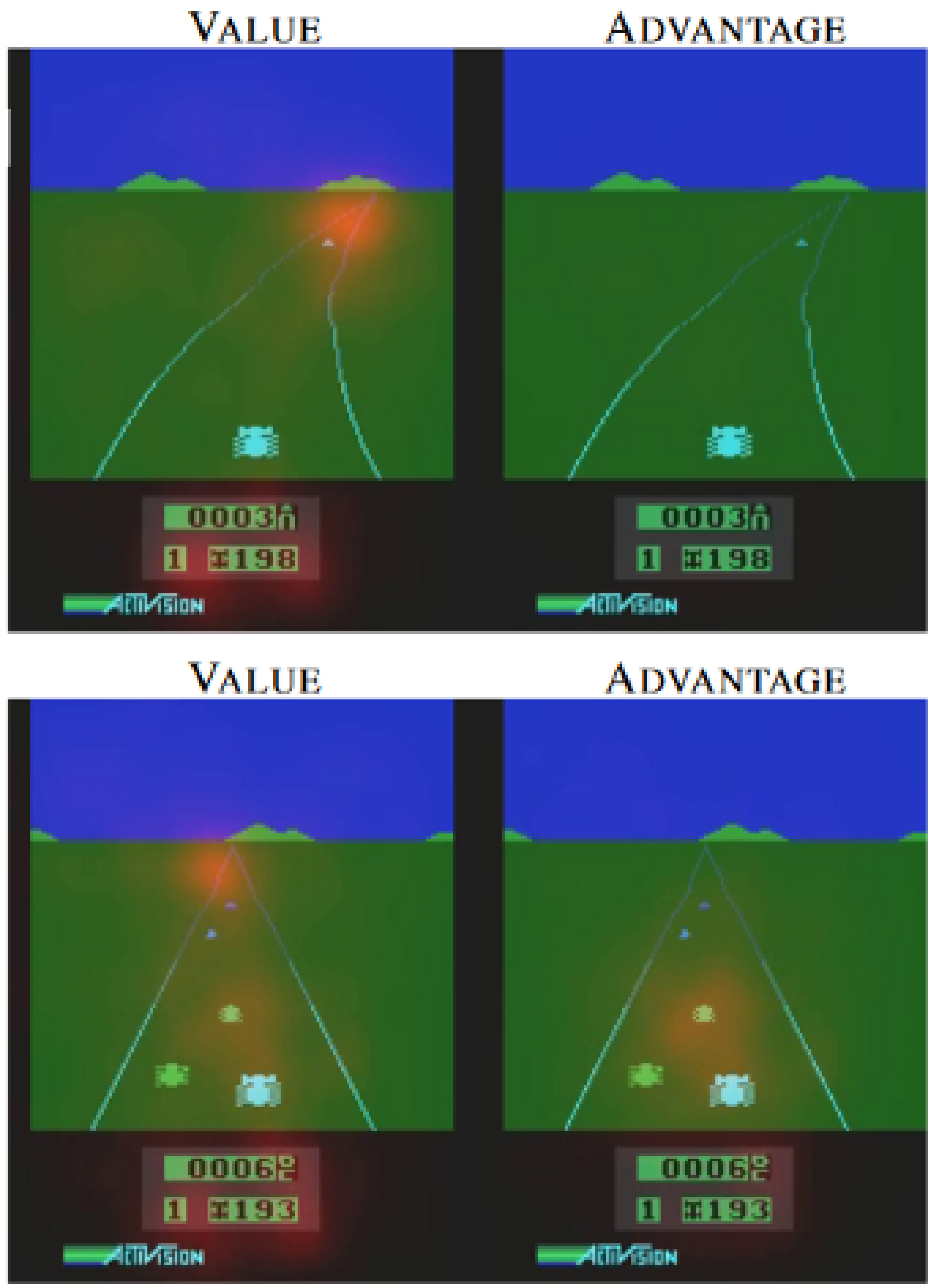
$$Q_\theta(s, a) = V_\alpha(s) + (A_\beta(s, a) - \frac{1}{|\mathcal{A}|} \sum_{a'} A_\beta(s, a'))$$

Wang et al. (2016) Dueling Network Architectures for Deep Reinforcement Learning. arXiv:1511.06581.

Visualization of the value and advantage functions

- Which pixels change the most the value and advantage functions?

<u>Focus on 2 things:</u>
- The horizon where new cars appear
- On the score

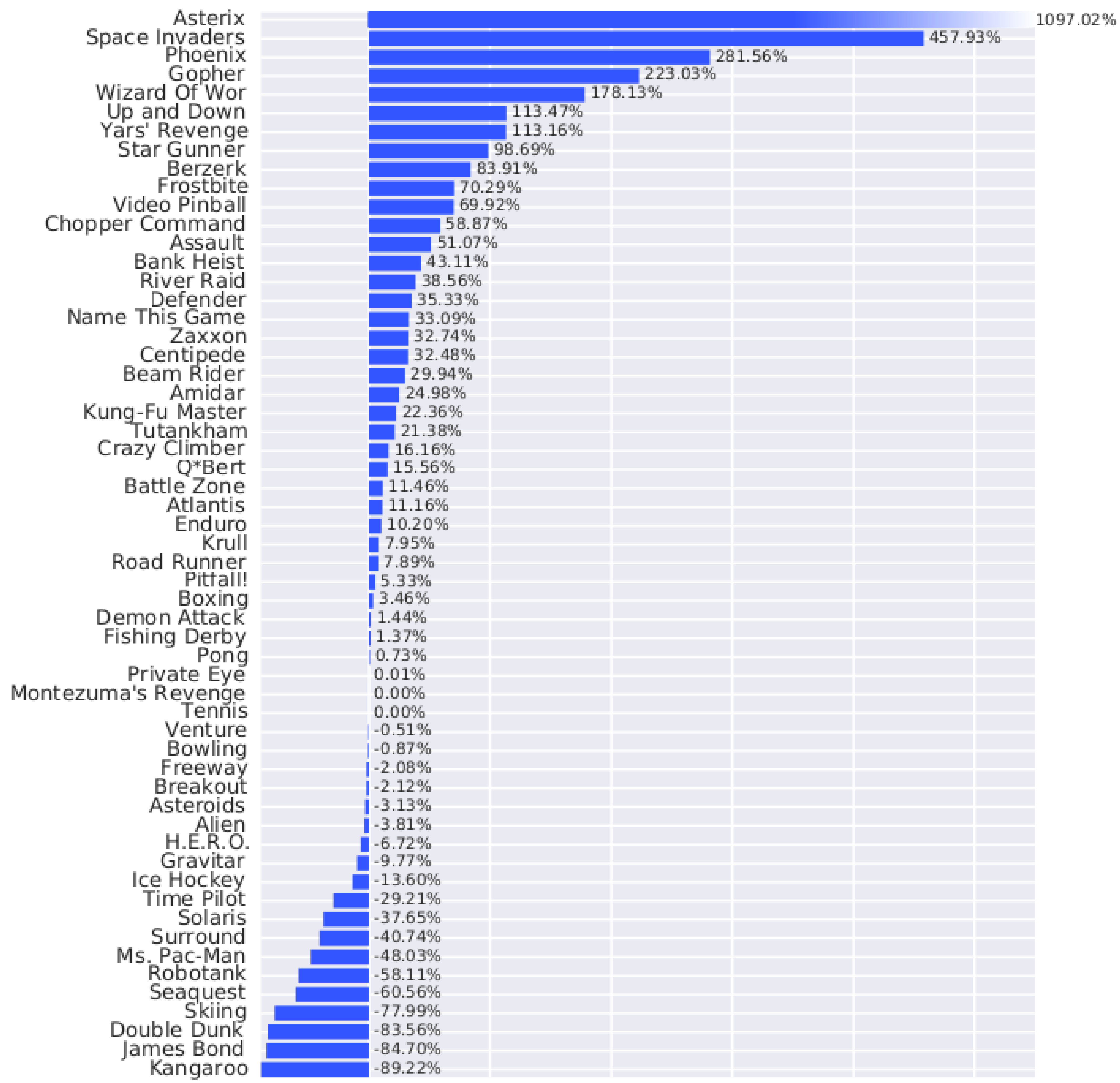


No car in front, **does not pay much attention because action choice making is not relevant**

Pays attention to the front car, in this case **choice making is crucial to survive**

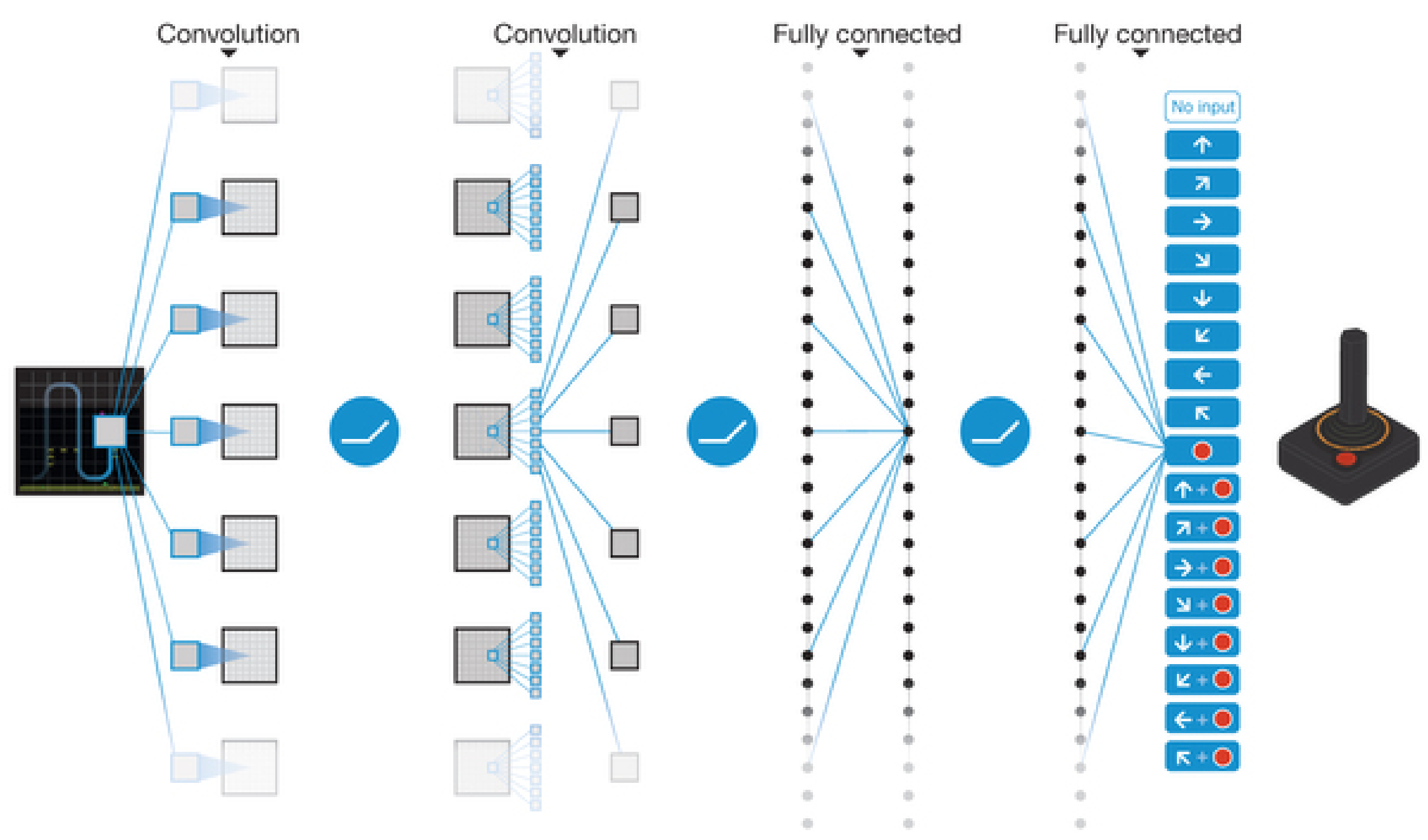
Wang et al. (2016) Dueling Network Architectures for Deep Reinforcement Learning. arXiv:1511.06581.

Improvement over prioritized DDQN



Wang et al. (2016) Dueling Network Architectures for Deep Reinforcement Learning. arXiv:1511.06581.

Summary of DQN



- DQN and its early variants (double duelling DQN with PER) are an example of **value-based deep RL**.
- The value $Q_\theta(s, a)$ of each possible action in a given state is approximated by a convolutional neural network.
- The NN has to minimize the mse between the predicted Q-values and the target value corresponding to the Bellman equation:

$$\mathcal{L}(\theta) = \mathbb{E}_\mathcal{D}[(r + \gamma \, Q_{\theta'}(s', \text{argmax}_{a'} Q_{\theta}(s', a')) - Q_\theta(s, a))^2]$$

- The use of an **experience replay memory** and of **target networks** allows to stabilize learning and avoid suboptimal policies.
- The main drawback of DQN is **sample complexity**: it needs huge amounts of experienced transitions to find a correct policy. The sample complexity come from the deep network itself (gradient descent is iterative and slow), but also from the ERM: it contains 1M transitions, most of which are outdated.
- Only works for **small and discrete action spaces** (one output neuron per action).

References

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., et al. (2013). Playing Atari with Deep Reinforcement Learning. http://arxiv.org/abs/1312.5602.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., et al. (2015). Human-level control through deep reinforcement learning. *Nature* 518, 529–533. doi:10.1038/nature14236.

Moore, A. W., and Atkeson, C. G. (1993). Prioritized sweeping: Reinforcement learning with less data and less time. *Mach Learn* 13, 103–130. doi:10.1007/BF00993104.

Schaul, T., Quan, J., Antonoglou, I., and Silver, D. (2015). Prioritized Experience Replay. http://arxiv.org/abs/1511.05952.

van Hasselt, H., Guez, A., and Silver, D. (2015). Deep Reinforcement Learning with Double Q-learning. http://arxiv.org/abs/1509.06461.

Wang, Z., Schaul, T., Hessel, M., van Hasselt, H., Lanctot, M., and de Freitas, N. (2016). Dueling Network Architectures for Deep Reinforcement Learning. http://arxiv.org/abs/1511.06581.