COMMONWEALTH OF AUSTRALIA

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Acknowledgements

This material includes content adapted from instructional resources made available by David Silver as part of his Reinforcement Learning course at UCL under CC-BY-NC 4.0.

Refer to https://www.davidsilver.uk/teaching/ for full details.

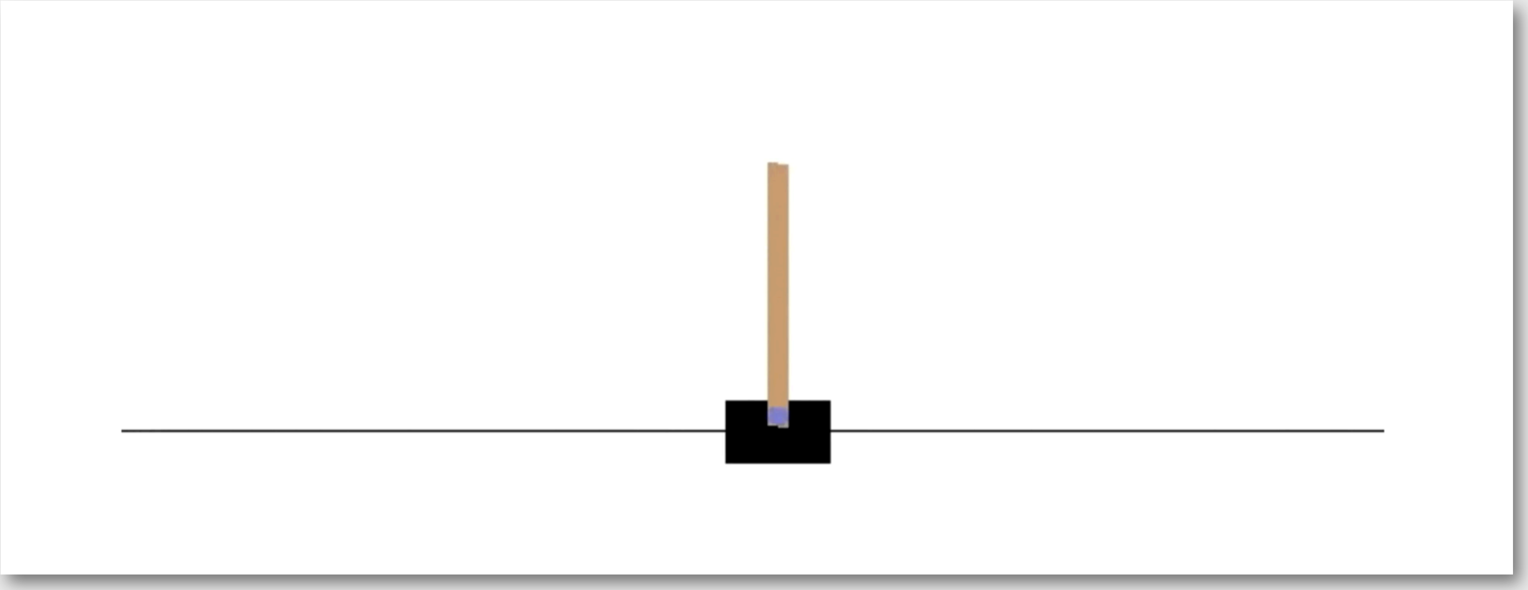
MONASH University
Information Technology

FIT5226
Multi-agent System & Collective Behaviour

Wk 5: Deep Reinforcement and Deep-Q

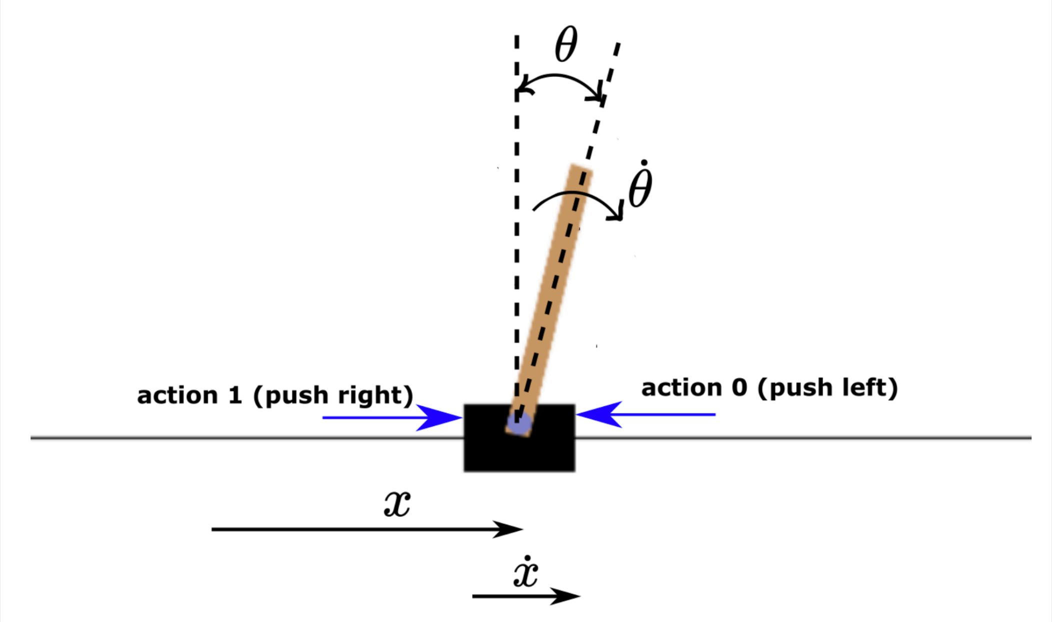
Bernd Meyer, August 2024

The Cart Pole Problem



cart pole *or* inverted pendulum

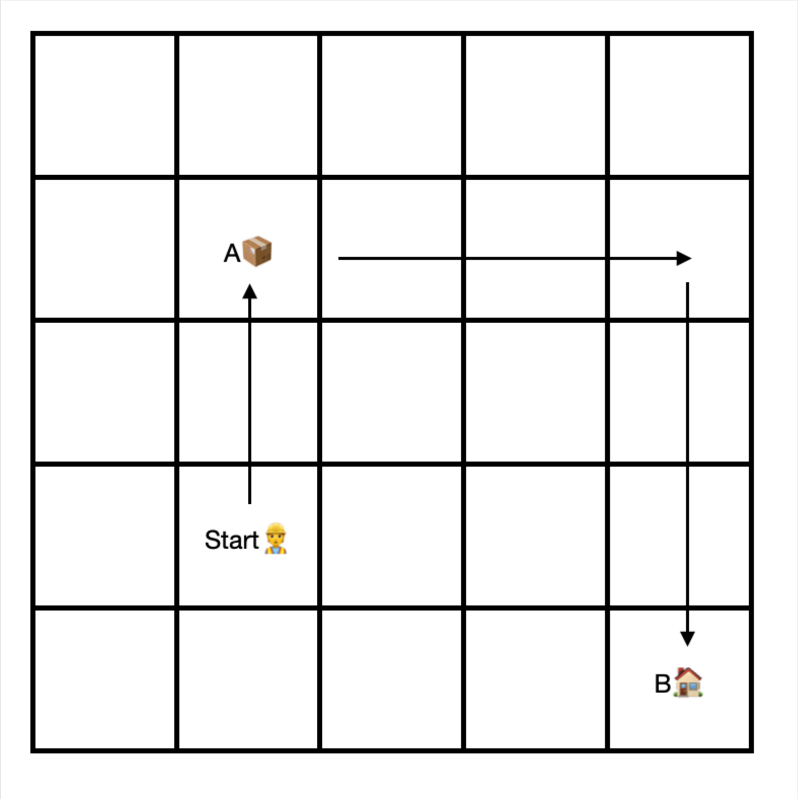
Continuous State Spaces

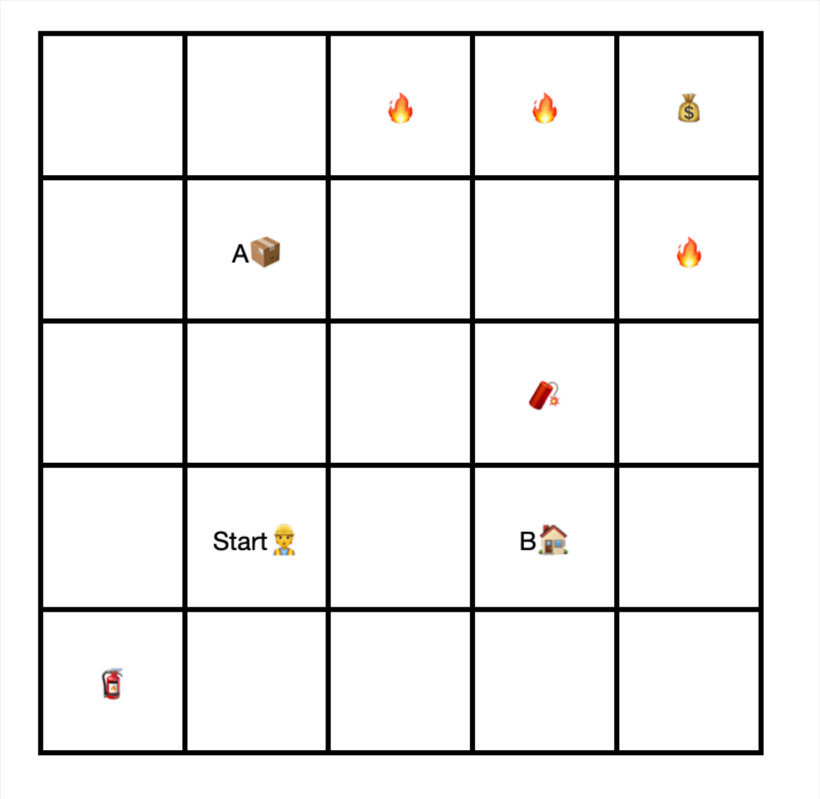


Observation (state) space

- Cart Position (x): The horizontal position of the cart on the track.
- Cart Velocity (dx/dt): The velocity of the cart.
- Pole Angle (θ): The angle of the pole from the vertical upright position.
- Pole Angular Velocity (dθ/dt): The angular velocity of the pole.

State Space Size





$\approx 25^2 = 625$

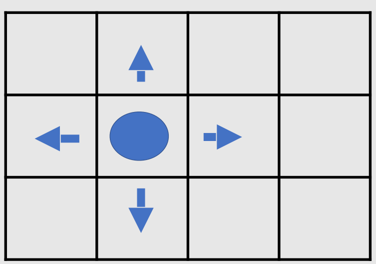
$\approx 25^9 = 3{,}814{,}697{,}265{,}625$

Backgammon: 10^{20}; Go: 10^{170}

Generalisation in more complex state spaces

- Mars rover must learn high-level control to traverse terrain
- Driving over hazardous terrain 10x slower

4 actions



Distance sensor

4	3	2	1
3	2	1	G
S	3	2	1

Terrain sensor

-1	-1	-10	-10
-1	-1	-1	-1
-1	-10	-1	-10

State Space for Mars Rover

- State space is a vector of features

$$s = \left(D_N, D_E, D_S, D_W,\ H_N, H_E, H_s, H_W\right)$$
$$s = (3, 2, 3, 4, 0, 1, 0, 0)$$

- Suppose:
  - Max distance 5, Boolean hazard sensor,
  - Then, $\left|S\right| = 5^4 + 2^4 = 10{,}000$ states, $\left|A\right| = 4$ actions,
  - 40,000 Q-table entries (about 157 kB of memory)

Generalisation

- After some exploration, our rover learned to navigate safely

- Now we change the map:

-1	-1	-10	-10
-1	-1	-1	G
S	-10	-1	-10

→

-1	-1	-1	-10
-1	-10	-1	G
S	-10	-1	-10

- What will happen?

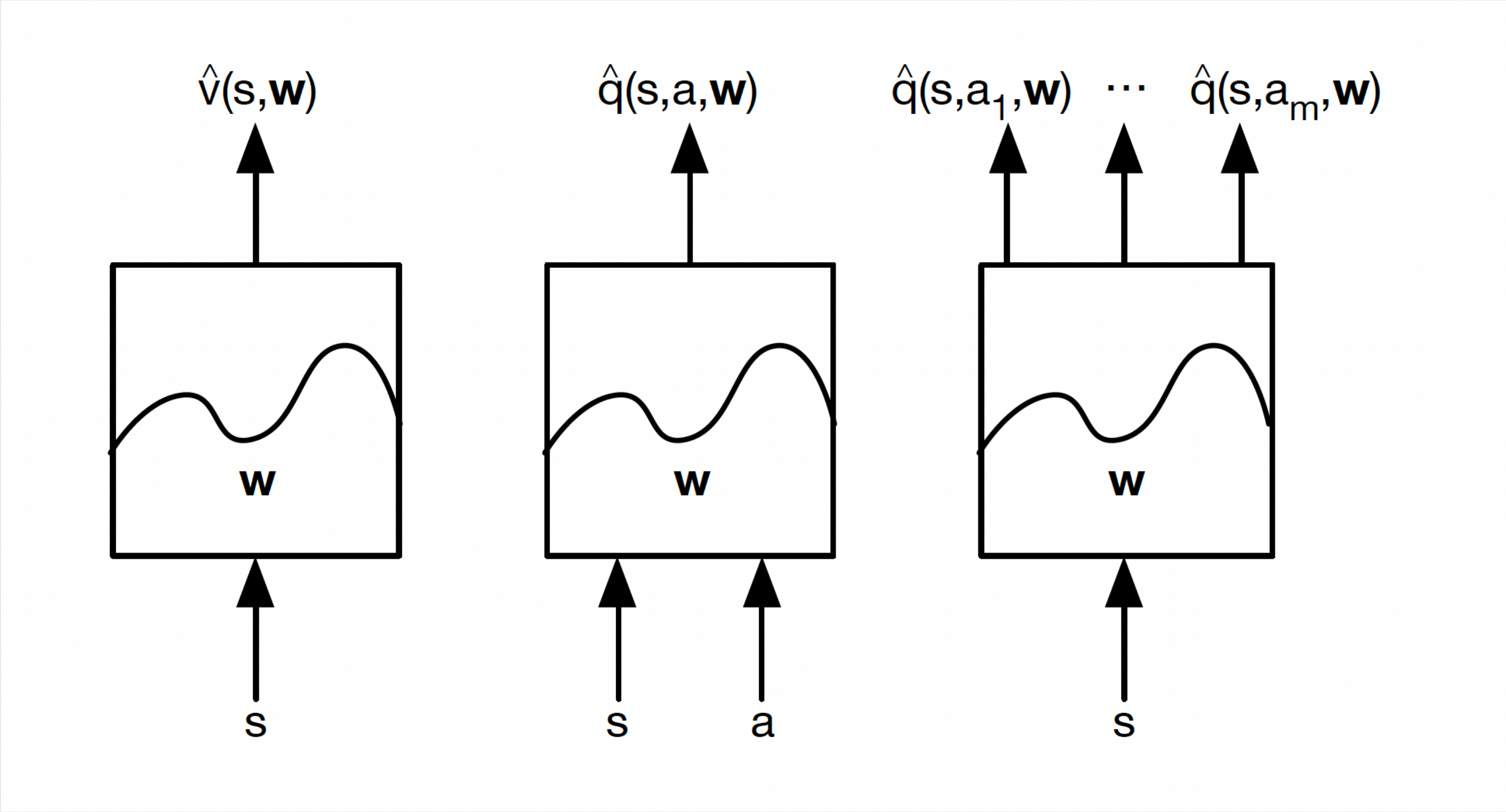
Value Function Approximation

- Very large state spaces
- Continuous state spaces
- Need for generalisation

➡ use a value function instead of a value table

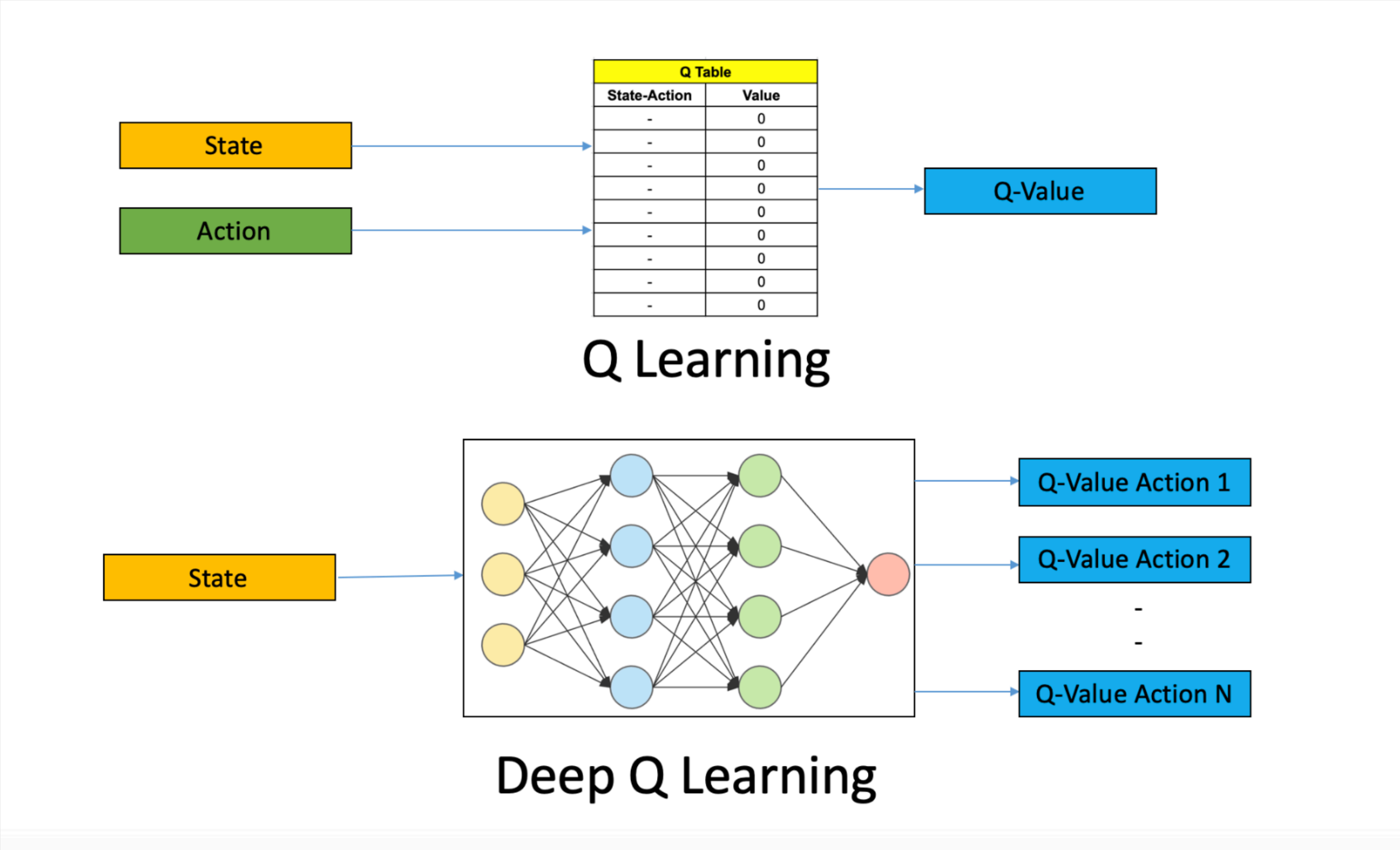
of course, this can only be approximate

Value Function Approximation Types



$F : S \rightarrow \mathbb{R}$ $F : S \times A \rightarrow \mathbb{R}$ $F : S \rightarrow A \times \mathbb{R}$

Value Function Approximation with Deep-Q Network

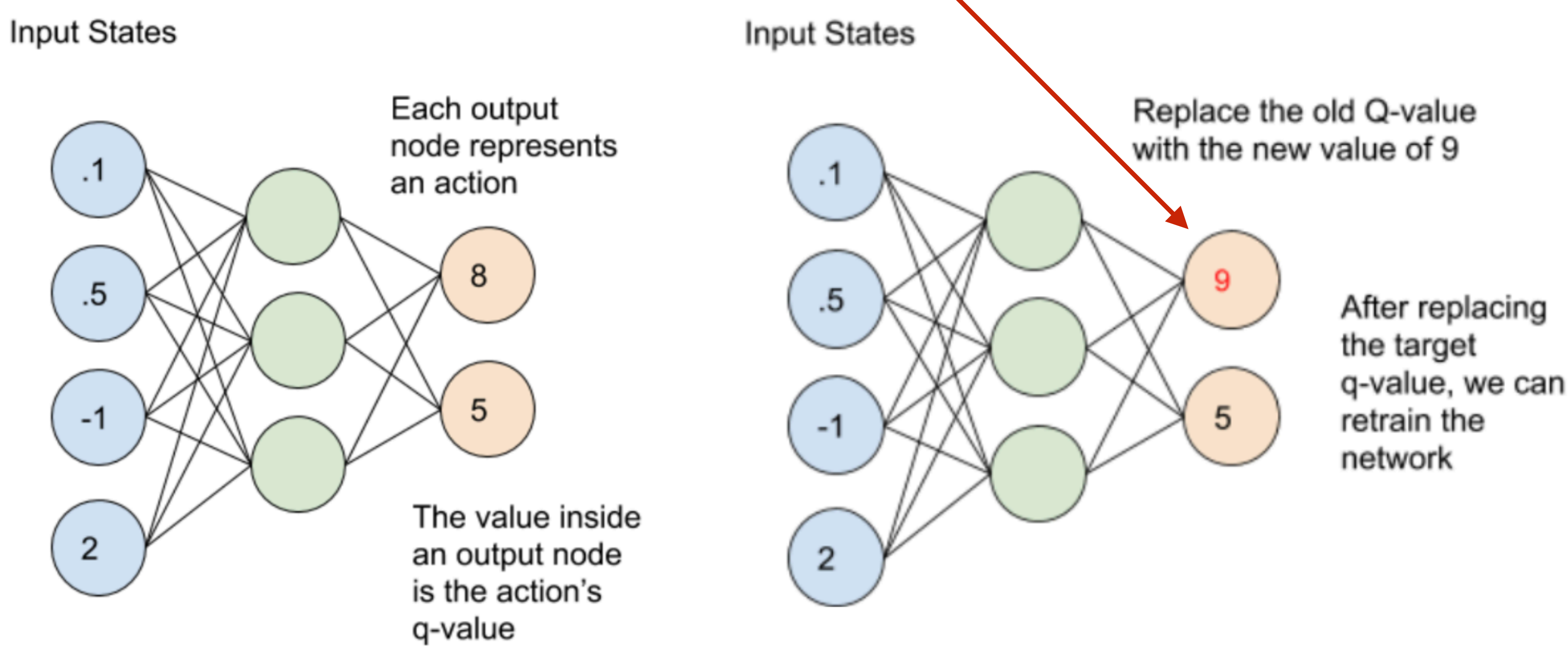


from: https://www.analyticsvidhya.com/blog/2019/04/introduction-deep-q-learning-python/

From Bellman Update to Loss Function

$$Q(S_t, A_t) = (1 - \alpha)\, Q(S_t, A_t) + \alpha * (R_t + \lambda * max_a\, Q(S_{t+1}, a))$$

TD-target



DQN Algorithm

```
Initialize the Agent to interact with the Environment
while not converged do
    /* Sample phase
    ϵ ← setting new epsilon with ϵ-decay
    Choose an action a from state s using policy ϵ-greedy(Q)
    Agent takes action a, observe reward r, and next state s'
    Store transition (s, a, r, s', done) in the experience replay memory D

    if enough experiences in D then
        /* Learn phase
        Sample a random minibatch of N transitions from D
        for every transition (s_i, a_i, r_i, s'_i, done_i) in minibatch do
            if done_i then
                y_i = r_i
            else
                y_i = r_i + γ max_{a'∈A} Q̂(s'_i, a')
            end
        end
        Calculate the loss L = 1/N Σ_{i=0}^{N-1} (Q(s_i, a_i) − y_i)^2
        Update Q using the SGD algorithm by minimizing the loss L
        Every C steps, copy weights from Q to Q̂
    end
end
```

Experience Replay

- Equivalent to standard Q-learning: adapt the network for every action as it is performed (usually using a single SDG step and MSE loss)

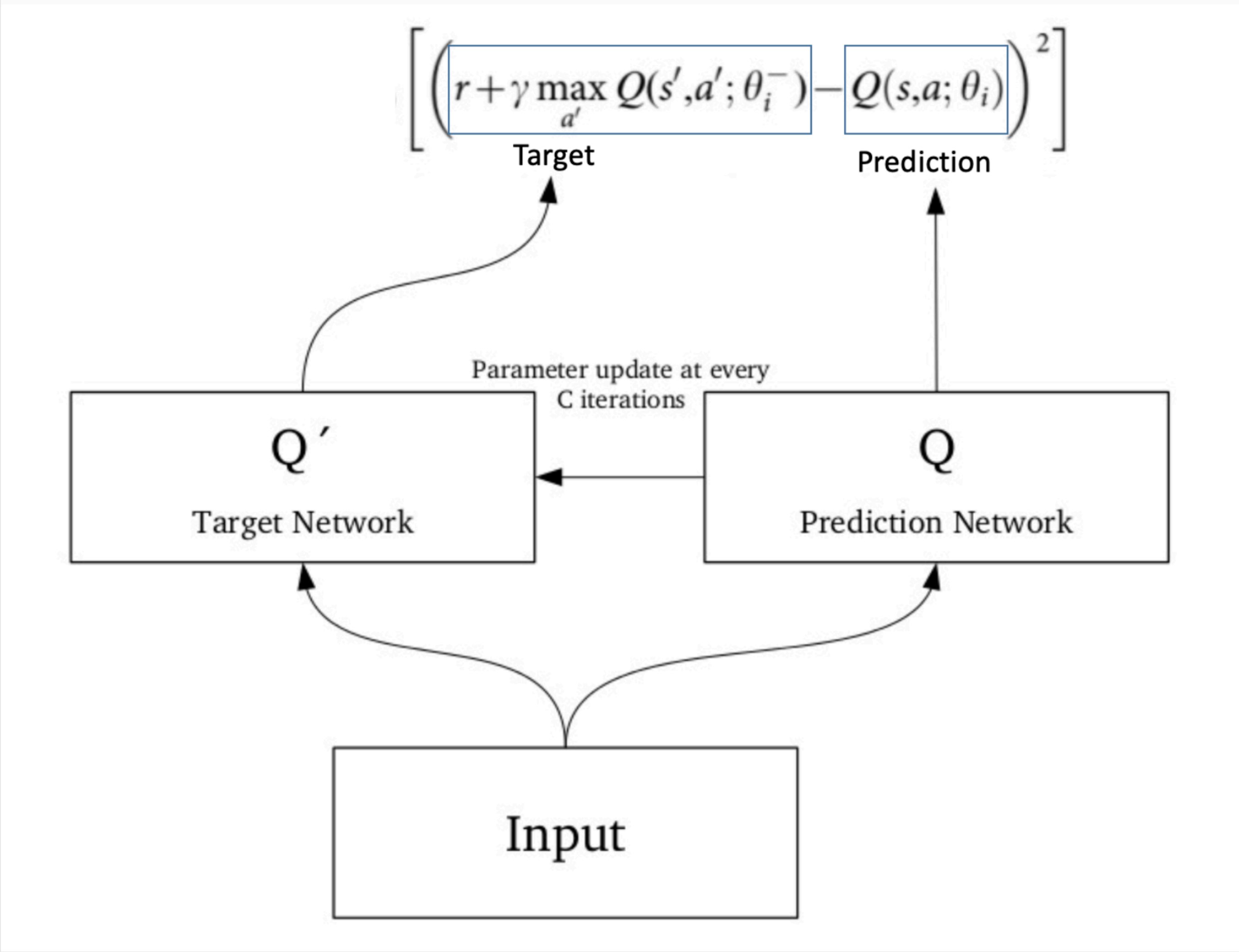
- **This can be unstable. To stabilise we perform *Experience Replay***

- All Transitions (state, action, reward, new state) are stored in a ring buffer of limited size

- Instead of just using the least action for each training step we use a mini-batch to update
    - randomly sample a mini-batch from the buffer
    - compute loss and back-propagate for the whole mini-batch
    - we may do this only every *k* actions

- Note that this if <u>off-policy</u>
  (and thus requires an off-policy base algorithm like Q-learning)

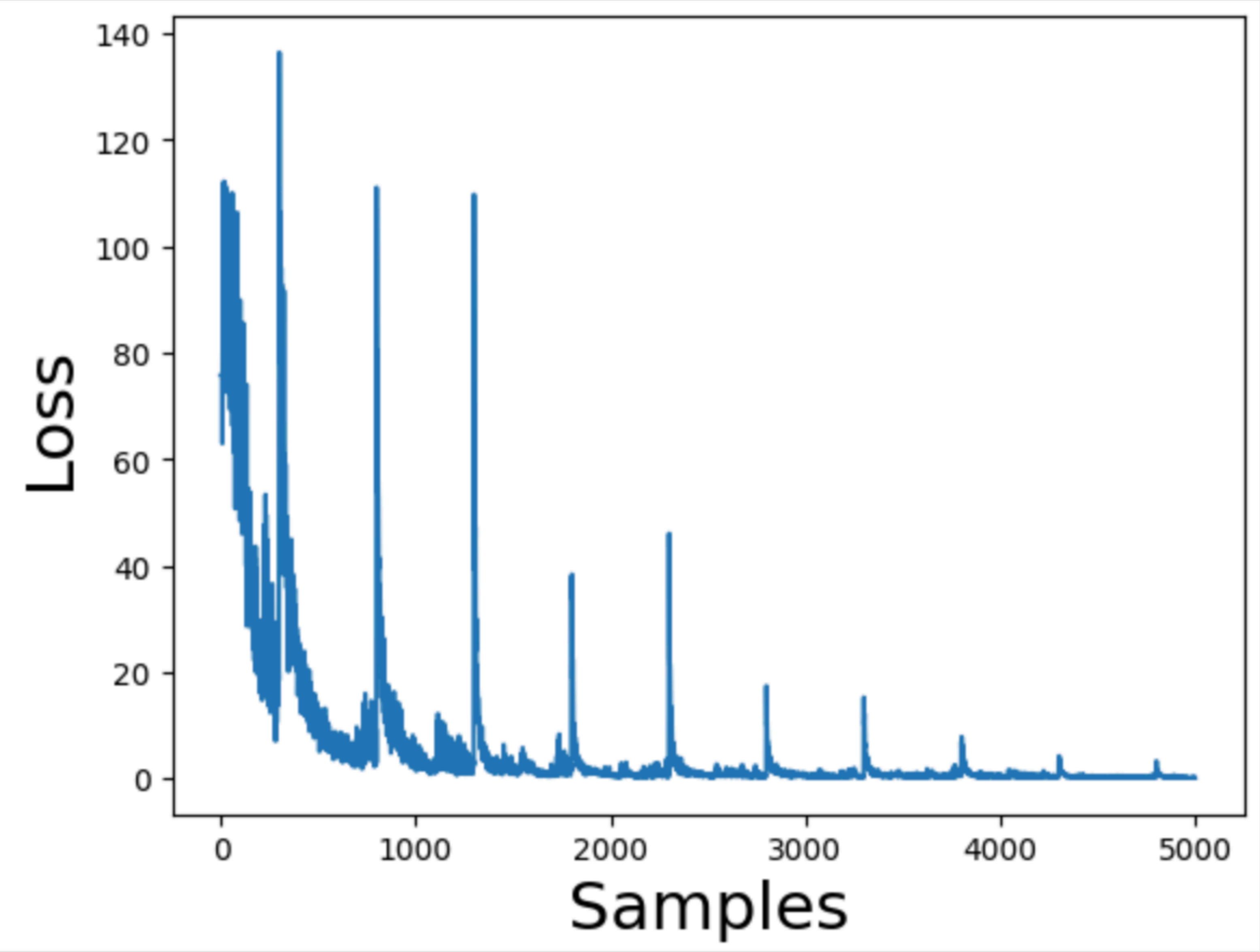
Target Network versus Prediction (main) network



$= \mathscr{L}$

from: https://www.analyticsvidhya.com/blog/2019/04/introduction-deep-q-learning-python/

Updating the Target Network

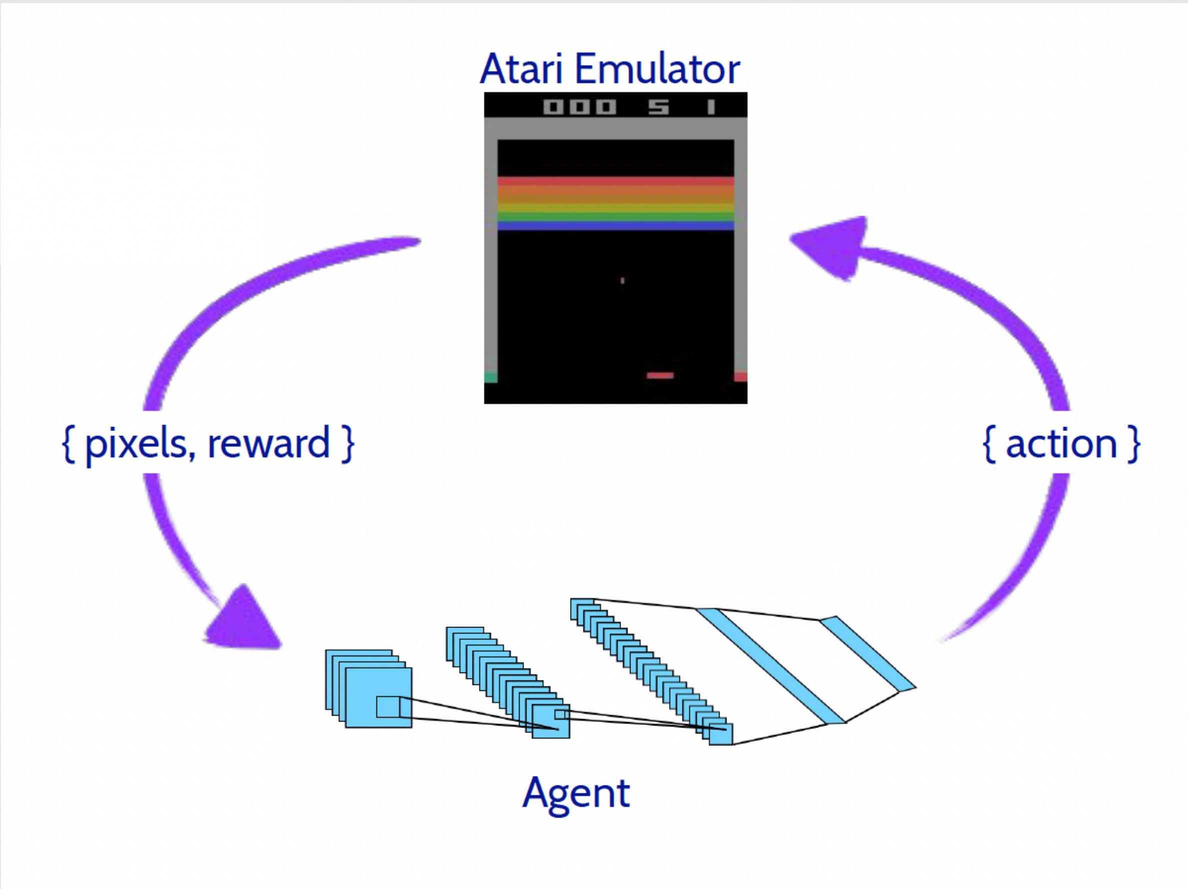


Noisy-fying the state

- Discrete states (e.g. in grid wolds), especially one-hot can lead to “Dead Neurons”
- A trick to avoid this is to add a small amount of noise to the states
- This problem occurs specifically with ReLU (rectified linear unit) activation functions since these are non-differentiable at zero when the state vector is sparse (i.e. most its elements are zero) as is the case, for example, in our grid worlds in the lab.

```
state = state.reshape(1,k) + np.random.rand(1,k)/c
```

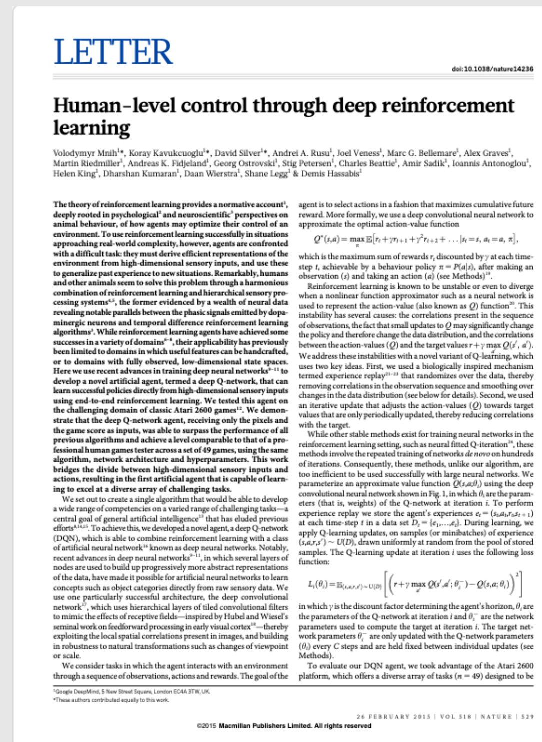
End-to-end State Spaces



Nature Journal
https://www.nature.com › letters

Human-level control through deep reinforcement learning

by V Mnih · 2015 · Cited by 25488 — The theory of **reinforcement** learning provides a normative account, **deeply** rooted in psychological and neuroscientific perspectives on animal ...



LETTER

doi:10.1038/nature14236

Human-level control through deep reinforcement learning

Volodymyr Mnih[1]*, Koray Kavukcuoglu[1]*, David Silver[1]*, Andrei A. Rusu[1], Joel Veness[1], Marc G. Bellemare[1], Alex Graves[1], Martin Riedmiller[1], Andreas K. Fidjeland[1], Georg Ostrovski[1], Stig Petersen[1], Charles Beattie[1], Amir Sadik[1], Ioannis Antonoglou[1], Helen King[1], Dharshan Kumaran[1], Daan Wierstra[1], Shane Legg[1] & Demis Hassabis[1]

Breakout (DeepMind)

Image Feature Vectors

RED	GREEN	BLUE
0	0	0
255	255	255
0	0	0
210	210	0
0	0	0
210	210	0
0	0	0

State space for Atari Games

- We could use the image pixel values directly,
  - Vector $(p^R_{1,1}, p^G_{1,1}, p^B_{1,1}, p^R_{1,2}, \ldots, p^R_{h,w}, p^G_{h,w}, p^B_{h,w})$
  - Atari frame, 3 x 210 x 160 = 100,800 inputs
- Two problems:
  - Huge input size;
  - Is a single frame enough for decisions?

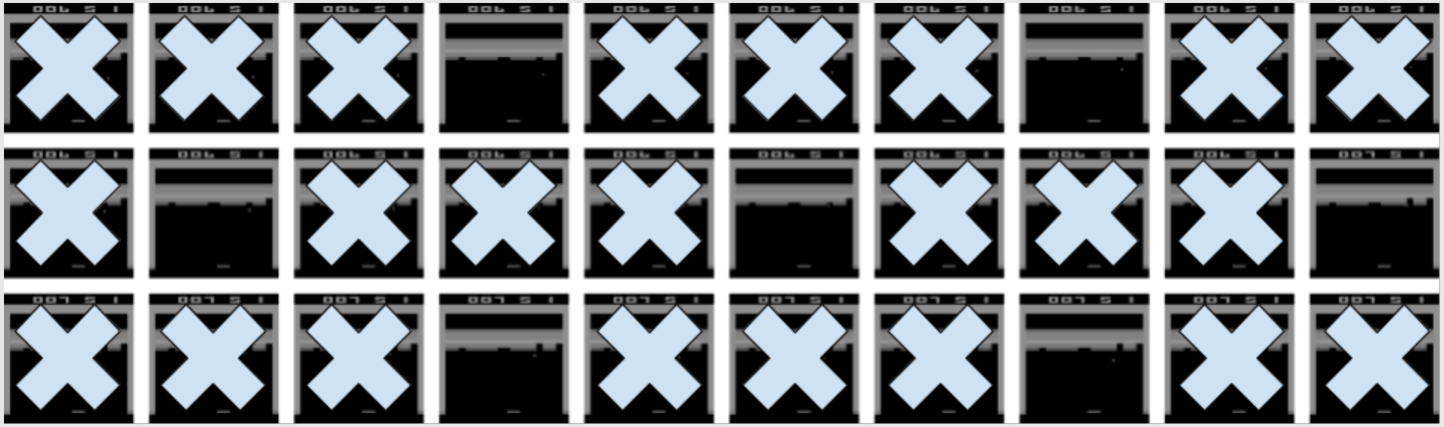
Movement

Which direction is the ball moving?

Encoding Motion

- Accurate control needs motion information,
  - Use multiple frames
- Reduce size of the input image by
  - Using greyscale,
  - Rescaling frame size to 84 x 84

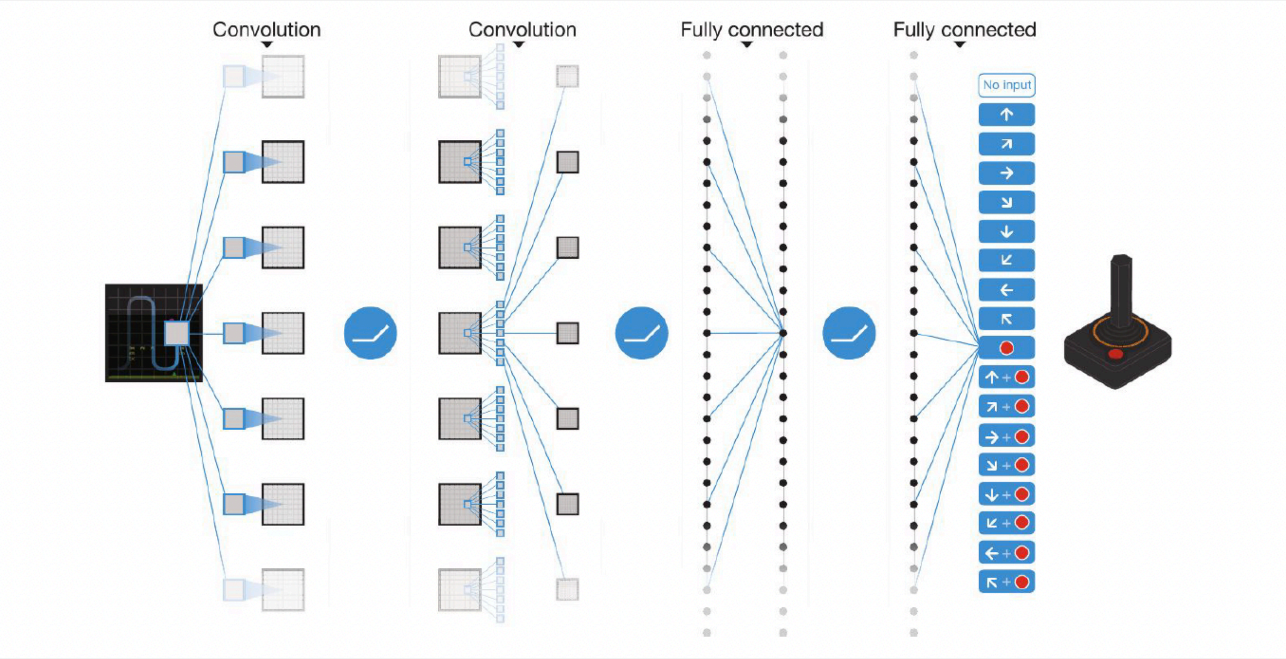
Subsampling



2-dimensional input (spatial context)

- By reducing input size we end up with 4 x 84 x 84 = 28,224 pixels
- Flattening these into an input layer is possible, **but loses spatial context**
- Solution: use Convolutional Neural Networks

Q-Network Structure



- s = 4 x 84 x 84 grayscale input,
- 32 filters of 8x8 with stride 4,
- 64 filters of 4x4 with stride 2,
- 64 filters of 3x3 with stride 1,
- Fully connected, 512 units
- Fully connected, |A|=18 output

Advanced Deep-RL Methods

DQN (2013)

Double DQN

Duelling DQN

Prioritized Replay

Multi-step returns

Distributional Returns (C51)

Rainbow (2018)

Implicit Quantile Nets (IQN)

Munchausen RL (M-IQN; 2020)

And many more algorithms from other base algorithms, like deep policy gradients, actor critics

Take home lessons

- Large state spaces, continuous state spaces and generalisation require function approximation
- We can use neural networks to approximate the state(action) value function
- Deep-Q = Q-Learning + (DNN substitutes Q-Table)
    - the loss is calculated as difference to the TD-target
- Experience replay is required to improve learning
- Dual networks are required to avoid catastrophic forgetting
- Adding Noise helps to avoid “Dead neurons”
- Deep-Q is only just the beginning …