Fraunhofer IIS

Fraunhofer-Institut für Integrierte Schaltungen IIS

Reinforcement Learning

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Exercise 6: Value Function Approximation

Nico Meyer

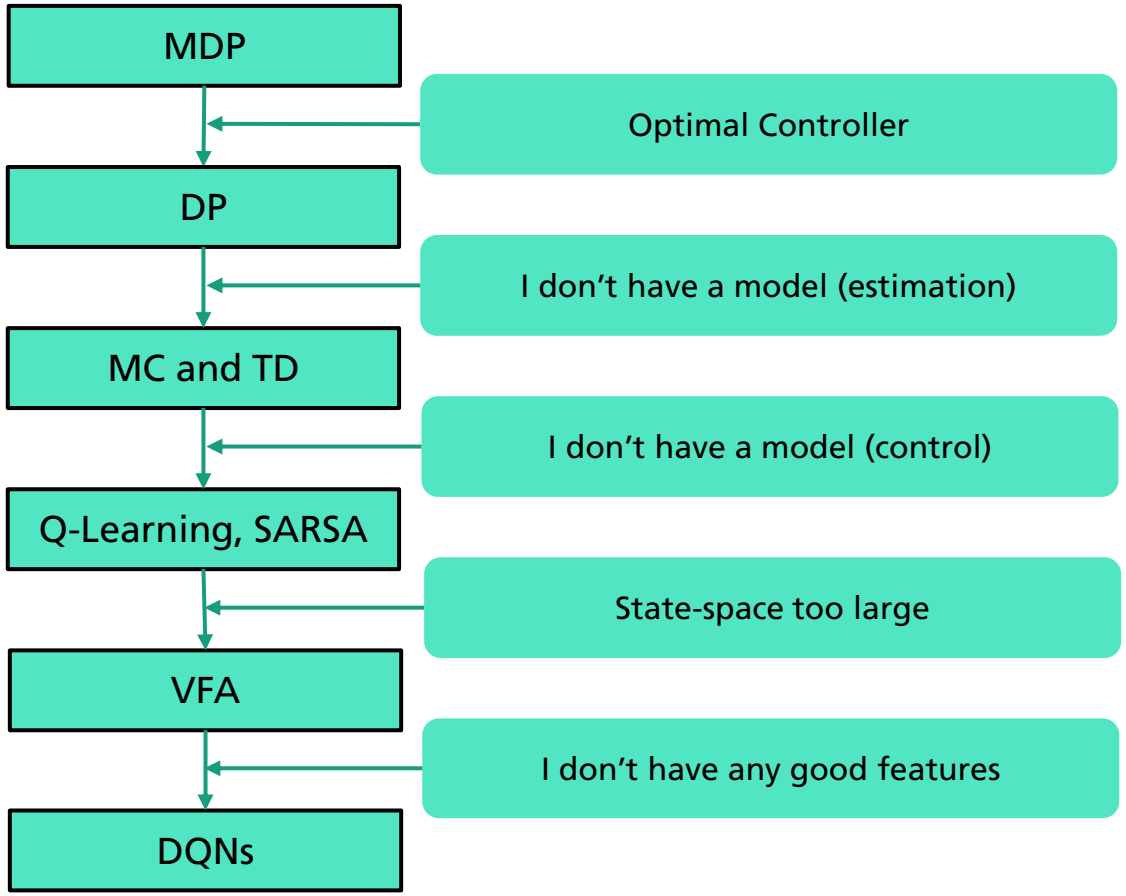
Overview

Exercise Content

Week	*Date*	*Topic*	*Material*	*Who?*
1	22.04.		*no exercises*	
2	29.04.	MDPs (slides)	ex1.pdf	Nico
3	06.05.	T.B.D.		
4	13.05.	Dynamic Programming (slides)	ex2.pdf, ex2_skeleton.zip	Alex
5	20.05.	OpenAI Gym, PyTorch-Intro (slides) TD-Learning (slides)		Nico
6	27.05.	TD-Control (slides)		Nico
7	03.06.	**Intermediate exam**		
8	*10.06.*		*no exercises*	
9	17.06.	DQN (slides)		Nico
10	24.06.	VPG (slides)		Alex
11	01.07.	A2C (slides)		Nico
12	08.07.	Multi-armed Bandits (slides)		Alex
13	15.07.	RND/ICM (slides)		Alex
14	22.07.	MCTS (slides)		Alex

Overview

Overall Picture



Value Function Approximation

Deep Q-Networks

Value Function Approximation

Why it is necessary and how it can be done

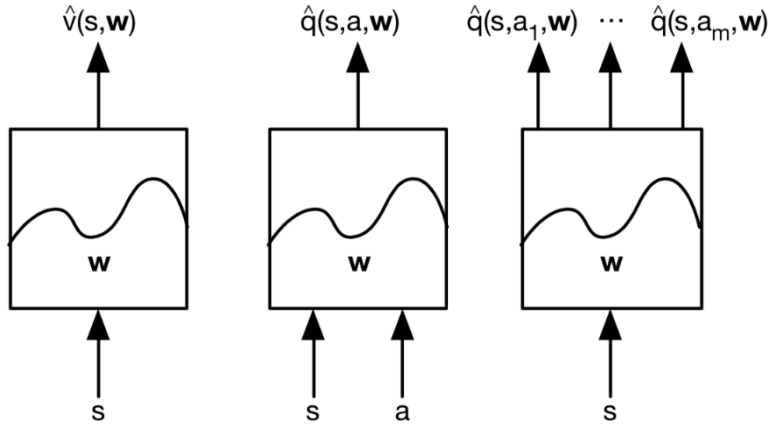
- Challenge: In real world problems, the state space can be large
  - Backgammon: 10^{20} states
  - Computer Go: 10^{170} states
  - Robot arm: **infinite** number of states! (continuous)

- Exact:
  - A table with a distinct value for each case
- Approximate:
  - Approximate V or Q with a function approximator
    (e.g., NN, polynomials, RBF, …)

$$\hat{v}(s, \boldsymbol{w}) \approx v_\pi(s)$$
$$\hat{q}(s, a, \boldsymbol{w}) \approx q_\pi(s, a)$$

+ We only need to store the approximator parameters

- Convergence properties do not hold anymore

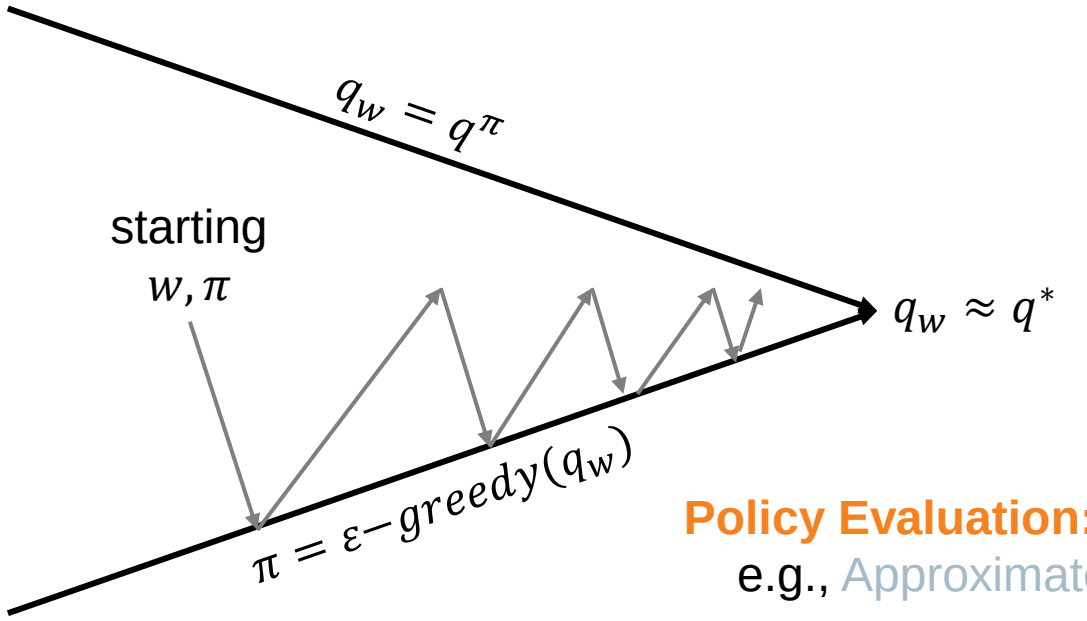


David Silver. 2016.

Value Function Approximation

Policy Evaluation and Improvement

- Our goal is to learn good parameters w that approximate the true value function well:



Policy Evaluation: Estimate $\hat{q}(\cdot, \cdot, w) \approx q_\pi$
e.g., Approximate Policy Evaluation

Policy Improvement: Generate $\pi' \geq \pi$
e.g., ϵ-greedy Policy Improvement

Value Function Approximation

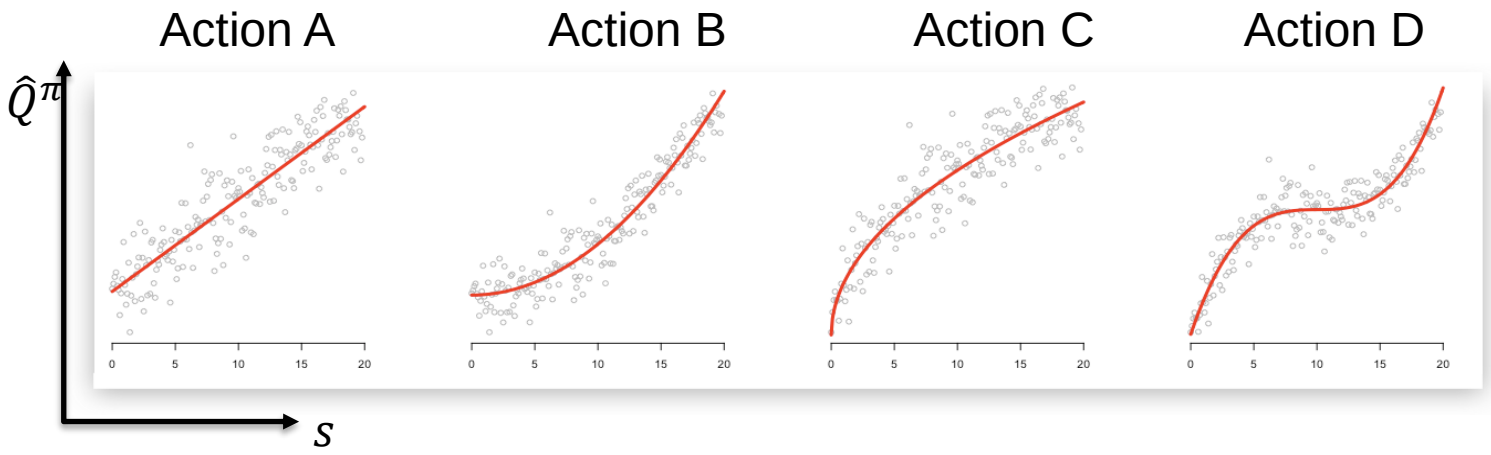
Linear Approximation

- Linear Value Function Approximation (careful: non-linear features)

$$\hat{Q}^{\pi}(s,a;w) = \phi(s,a)^T w$$

- Example features: Polynomial Basis, for instance:

$$(s_1, s_2)^T \rightarrow (1, s_1, s_2, s_1 s_2)^T$$
$$(s_1, s_2)^T \rightarrow (1, s_1, s_2, s_1 s_2, s_1^2, s_2^2, s_1 s_2^2, s_1^2 s_2, s_1^2 s_2^2)$$



Value Function Approximation

Convergence Guarantees

- Idea: Why don't we replace linear approximation with NNs?
  - Because theory tells us that this doesn't work out

Algorithm	Table Lookup	Linear	Non-linear
Monte-Carlo Control	✓	(✓)	✗
SARSA	✓	(✓)	✗
Q-learning	✓	✗	✗

(✓) =chatters around near-optimal value function

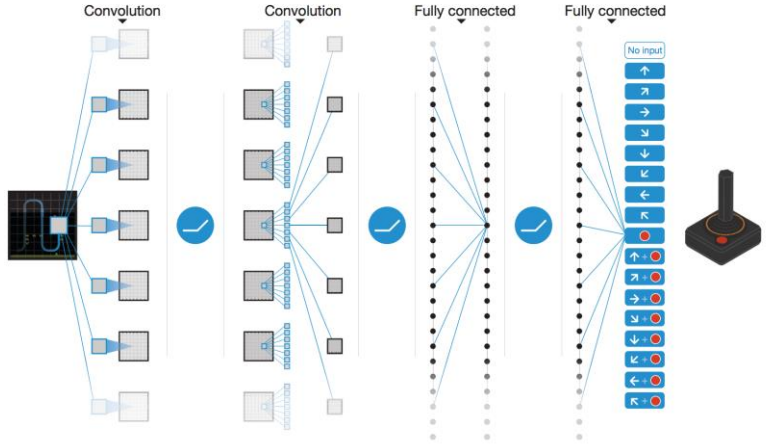
Besides some few hand-crafted and tuned successes NNs have not been managed to be applied "as is" to RL -> at least till 2014!!

Value Function Approximation

Deep Q-Networks (DQNs)

- Then a game-changing result was published in Nature:
  DQN from DeepMind (now Google DeepMind)

- How does it work?
  - A convolutional neural network reads the image from the game (i.e., a framestack that uses the last $N = 4$ frames).
  - The CNN is a value function approximator for the $Q(s, a)$ function.
  - The reward is the game score.
  - The network weights are tuned using backpropagation signals of the rewards.



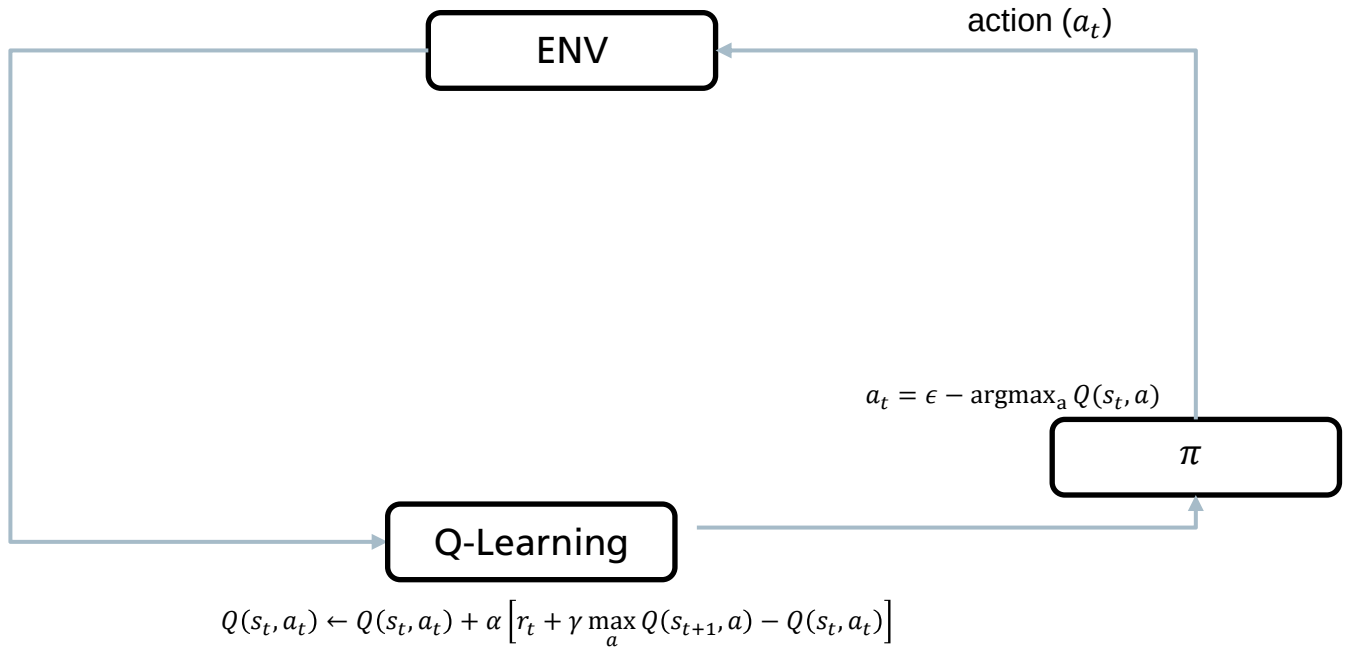
https://storage.googleapis.com/deepmind-media/dqn/DQNNaturePaper.pdf

- DQNs are „Q-Learning on steroids“ (Deep NN as VFA)
- Training possible in Tensorflow (or Pytorch, Keras, …)
- Objective function for gradient descent:

$$L(w_i) = \mathbb{E}_{s,a,r,s' \sim D_i}[(y_i - Q(s, a, w))^2]$$

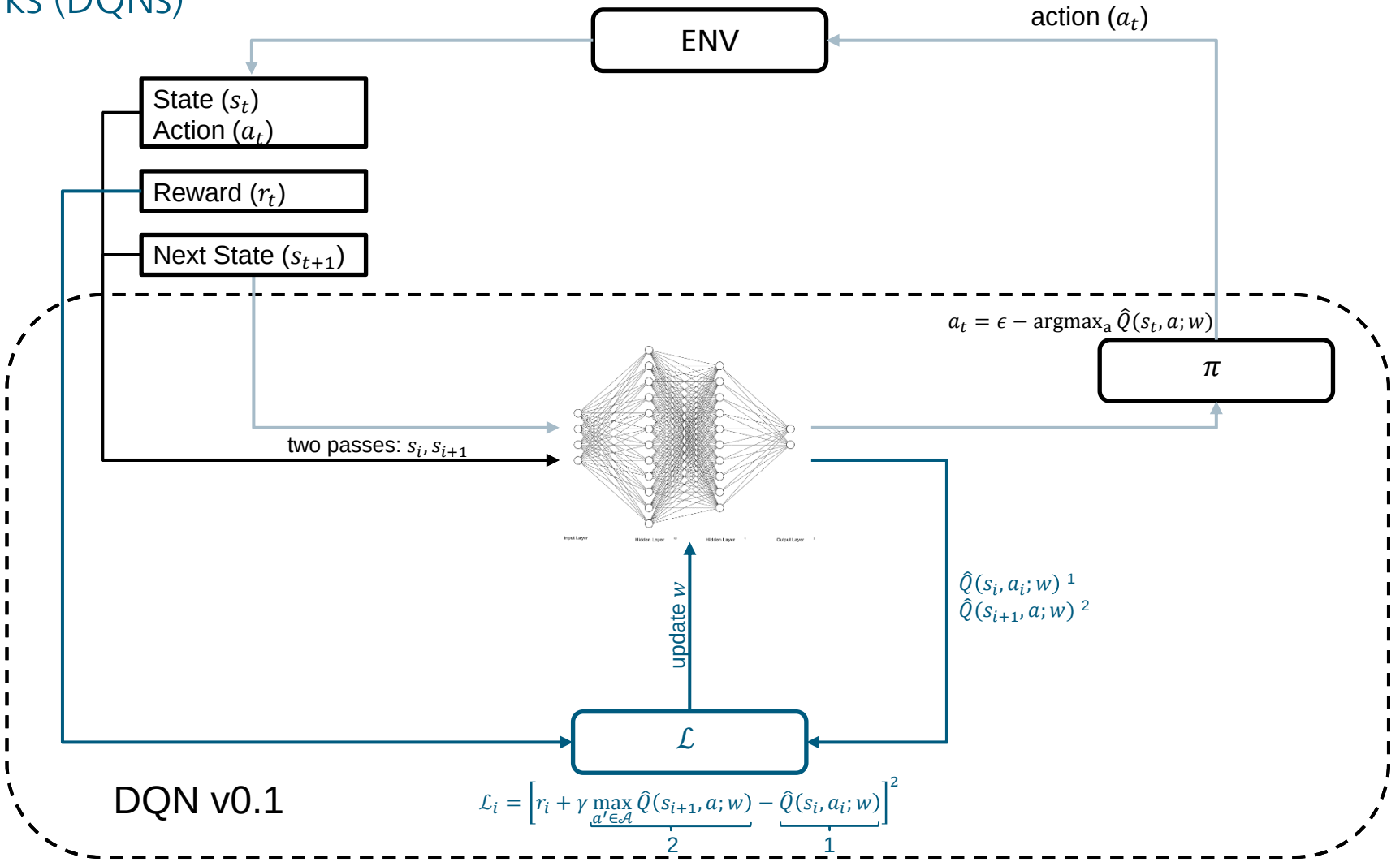
Value Function Approximation

Deep Q-Networks (DQNs)



Value Function Approximation

Deep Q-Networks (DQNs)



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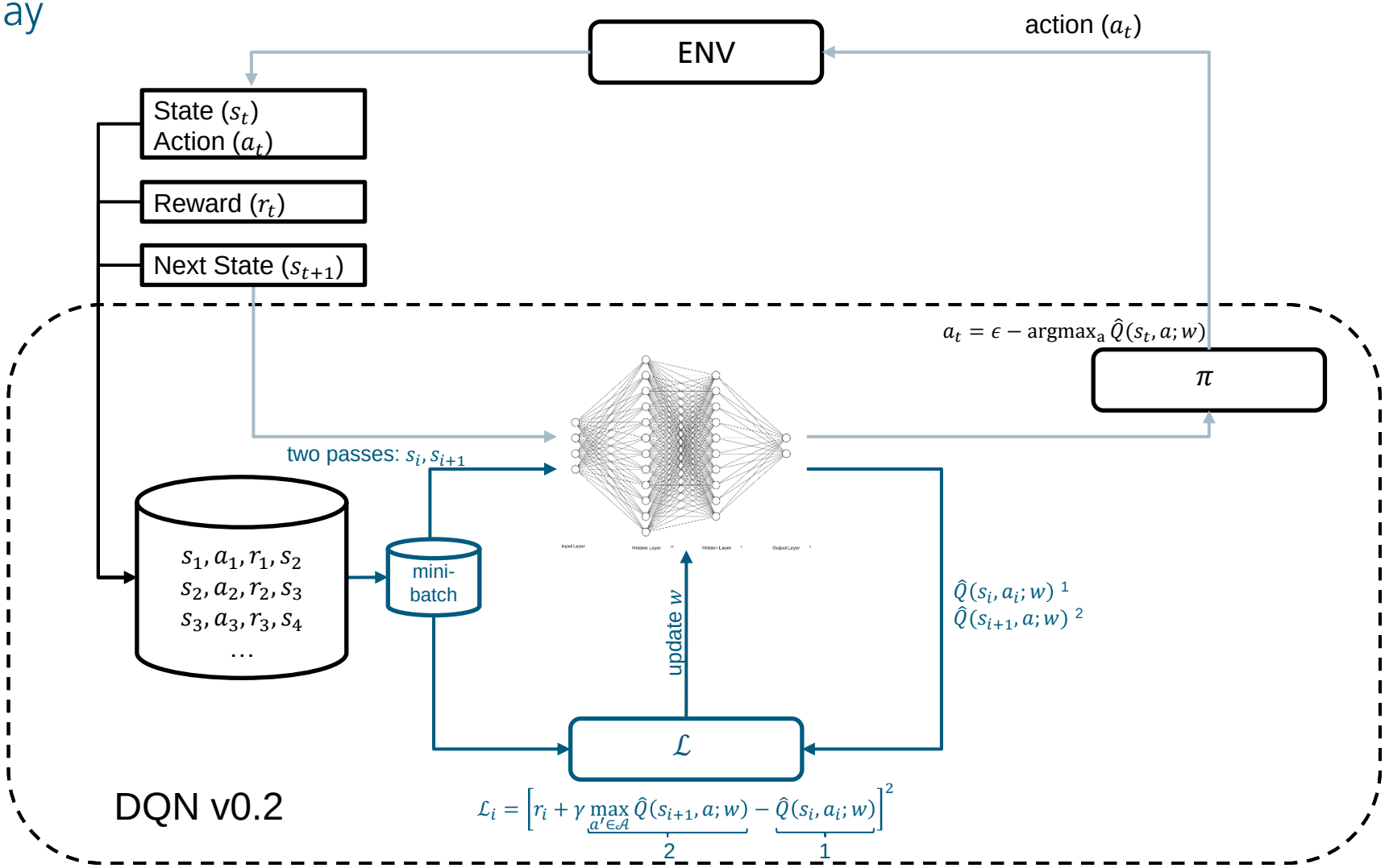
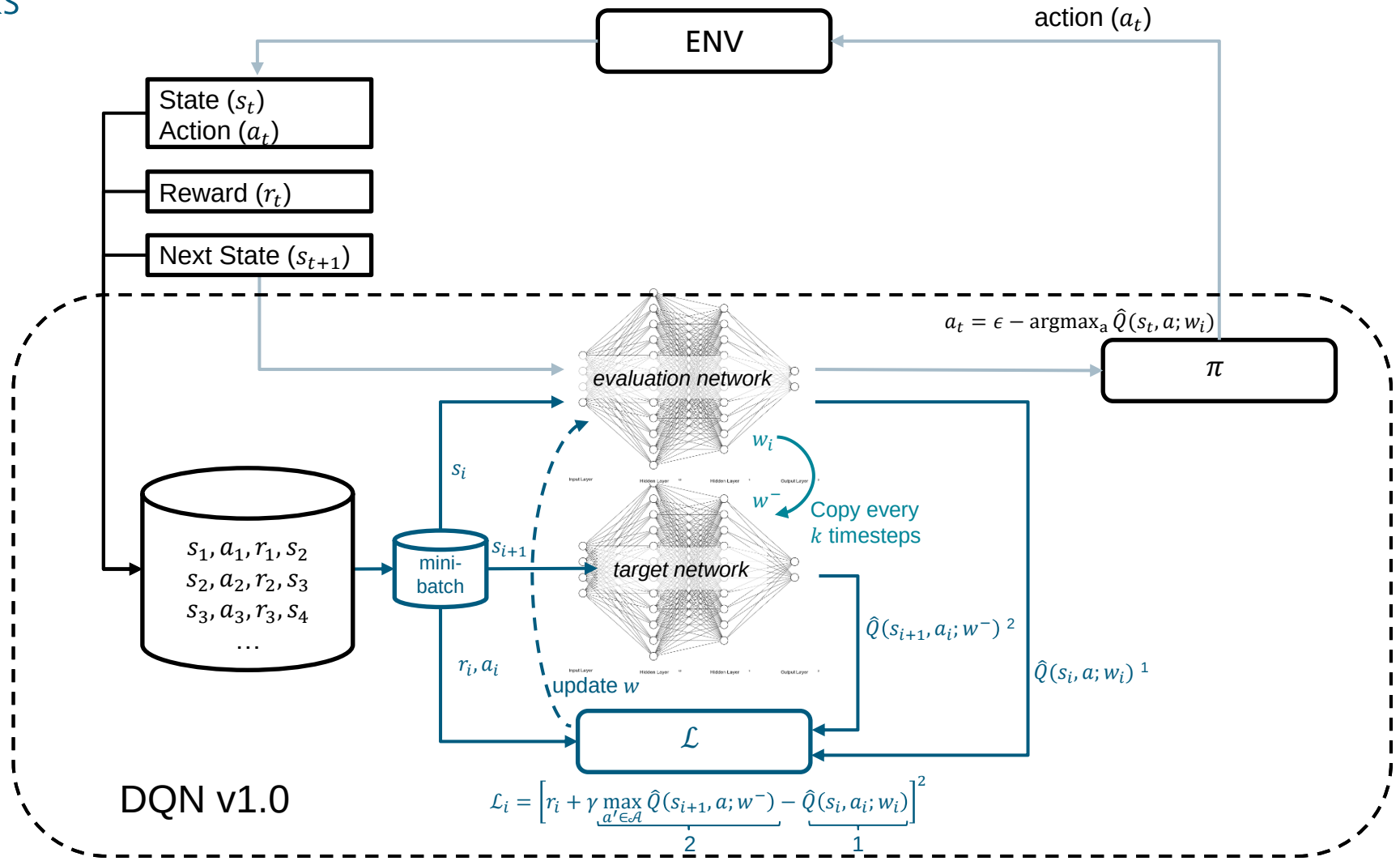
Value Function Approximation

Experience Replay



Value Function Approximation

Target Networks



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Value Function Approximation

DQN Algorithm

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N

Initialize action-value function Q with random weights θ

Initialize target action-value function $\hat{Q}$ with weights $\theta^{-} = \theta$

For episode = 1, M **do**

  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

  For t = 1,T **do**

    With probability ε select a random action a_t

    otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$

    Execute action a_t in emulator and observe reward r_t and image x_{t+1}

    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D

    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D

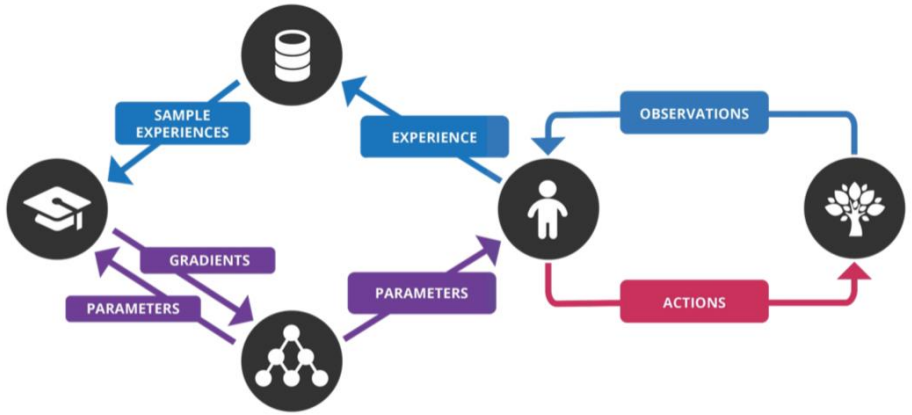
    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^{-}) & \text{otherwise} \end{cases}$

    Perform a gradient descent step on $\left(y_j - Q(\phi_j, a_j; \theta)\right)^2$ with respect to the network parameters θ

    Every C steps reset $\hat{Q} = Q$

  End For

End For



https://sites.google.com/view/deep-rl-bootcamp/lectures

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Thank you for your attention!