Self-Driving Cars

Lecture 4 – Reinforcement Learning

Prof. Dr.-Ing. Andreas Geiger

Autonomous Vision Group

University of Tübingen / MPI-IS

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

MAX-PLANCK-GESELLSCHAFT

ellis

European Laboratory for Learning and Intelligent Systems

Agenda

4.1 Markov Decision Processes

4.2 Bellman Optimality and Q-Learning

4.3 Deep Q-Learning

4.1
Markov Decision Processes

Reinforcement Learning

So far:

- Supervised learning, lots of expert demonstrations required
- Use of auxiliary, short-term loss functions
  - Imitation learning: per-frame loss on action
  - Direct perception: per-frame loss on affordance indicators

Now:

- Learning of models based on the loss that we actually care about, e.g.:
  - Minimize time to target location
  - Minimize number of collisions
  - Minimize risk
  - Maximize comfort
  - etc.

Sutton and Barto: Reinforcement Learning: An Introduction. MIT Press, 2017.

Types of Learning

Supervised Learning:

- Dataset: $\{(x_i, y_i)\}$ (x_i = data, y_i = label) Goal: Learn mapping $x \mapsto y$
- Examples: Classification, regression, imitation learning, affordance learning, etc.

Unsupervised Learning:

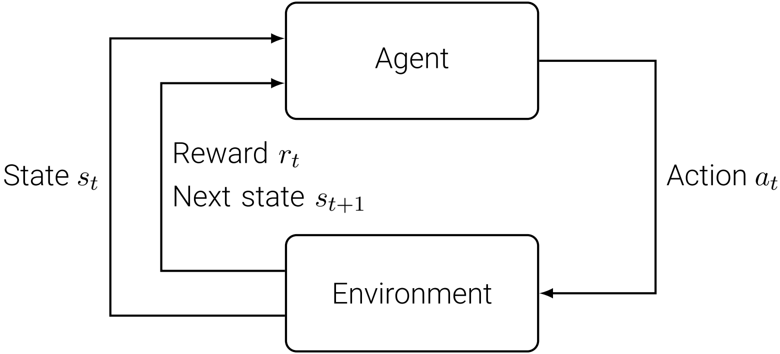
- Dataset: $\{(x_i)\}$ (x_i = data) Goal: Discover structure underlying data
- Examples: Clustering, dimensionality reduction, feature learning, etc.

Reinforcement Learning:

- Agent interacting with environment which provides numeric reward signals
- Goal: Learn how to take actions in order to maximize reward
- Examples: Learning of manipulation or control tasks (everything that interacts)

Sutton and Barto: Reinforcement Learning: An Introduction. MIT Press, 2017.

Introduction to Reinforcement Learning



- Agent oberserves environment state s_t at time t
- Agent sends action a_t at time t to the environment
- Environment returns the reward r_t and its new state s_{t+1} to the agent

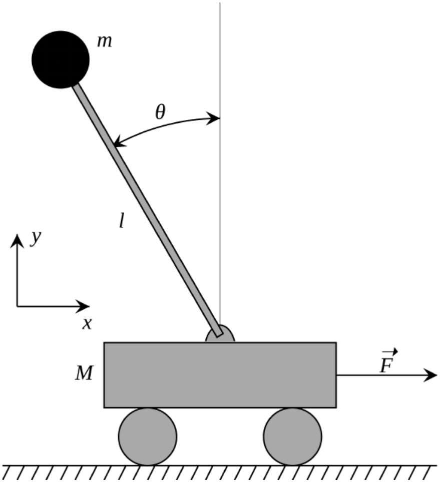
Sutton and Barto: Reinforcement Learning: An Introduction. MIT Press, 2017.

Introduction to Reinforcement Learning

- Goal: Select actions to maximize total future reward
- Actions may have long term consequences
- Reward may be delayed, not instantaneous
- It may be better to sacrifice immediate reward to gain more long-term reward
- Examples:
  - Financial investment (may take months to mature)
  - Refuelling a helicopter (might prevent crash in several hours)
  - Sacrificing a chess piece (might help winning chances in the future)

Sutton and Barto: Reinforcement Learning: An Introduction. MIT Press, 2017.

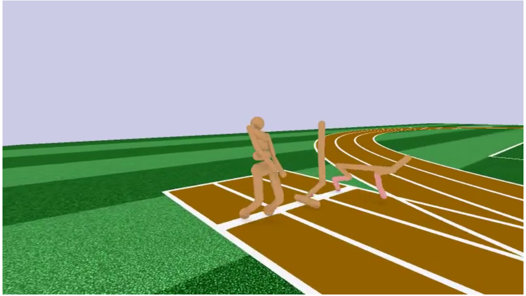
Example: Cart Pole Balancing



- **Objective:** Balance pole on moving cart
- **State:** Angle, angular vel., position, vel.
- **Action:** Horizontal force applied to cart
- **Reward:** 1 if pole is upright at time t

https://gym.openai.com/envs/#classic_control

Example: Robot Locomotion



http://blog.openai.com/roboschool/

- **Objective:** Make robot move forward
- **State:** Position and angle of joints
- **Action:** Torques applied on joints
- **Reward:** 1 if upright & forward moving

https://gym.openai.com/envs/#mujoco

Example: Atari Games

`http://blog.openai.com/gym-retro/`

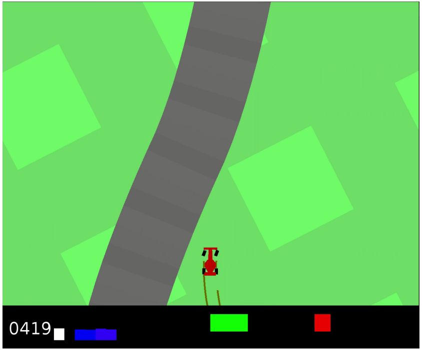
- **Objective:** Maximize game score
- **State:** Raw pixels of screen (210x160)
- **Action:** Left, right, up, down
- **Reward:** Score increase/decrease at t

Example: Go

www.deepmind.com/research/alphago/

- **Objective:** Winning the game
- **State:** Position of all pieces
- **Action:** Location of next piece
- **Reward:** 1 if game won, 0 otherwise

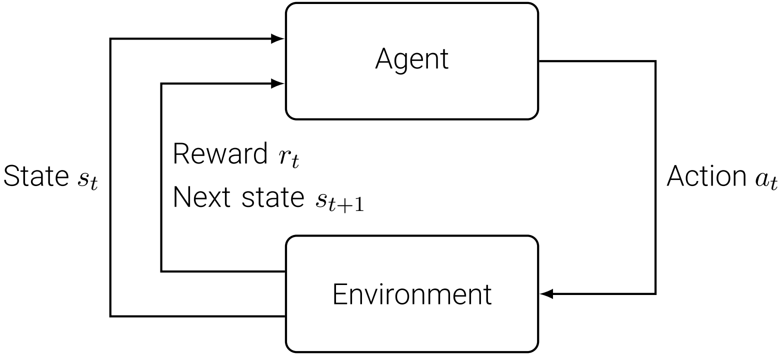
Example: Self-Driving



- **Objective:** Lane Following
- **State:** Image (96x96)
- **Action:** Acceleration, Steering
- **Reward:** - per frame, + per tile

https://gym.openai.com/envs/CarRacing-v0/

Reinforcement Learning: Overview



- How can we mathematically formalize the RL problem?

Markov Decision Process

Markov Decision Process (MDP) models the environment and is defined by the tuple

$$(\mathcal{S}, \mathcal{A}, \mathcal{R}, P, \gamma)$$

with

- $\mathcal{S}$: set of possible states
- $\mathcal{A}$: set of possible actions
- $\mathcal{R}(r_t|s_t, a_t)$: distribution of current reward given (state,action) pair
- $P(s_{t+1}|s_t, a_t)$: distribution over next state given (state,action) pair
- γ: discount factor (determines value of future rewards)

Almost all reinforcement learning problems can be formalized as MDPs

Markov Decision Process

Markov property: Current state completely characterizes state of the world

- A state s_t is *Markov* if and only if

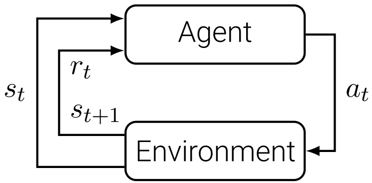
$$P(s_{t+1}|s_t) = P(s_{t+1}|s_1, ..., s_t)$$

- ”The future is independent of the past given the present”
- The state captures all relevant information from the history
- Once the state is known, the history may be thrown away
- The state is a sufficient statistics of the future

Markov Decision Process

Reinforcement learning loop:

- At time $t = 0$:
  - Environment samples initial state $s_0 \sim P(s_0)$
- Then, for $t = 0$ until done:
  - Agent selects action a_t
  - Environment samples reward $r_t \sim \mathcal{R}(r_t | s_t, a_t)$
  - Environment samples next state $s_{t+1} \sim P(s_{t+1} | s_t, a_t)$
  - Agent receives reward r_t and next state s_{t+1}



How do we select an action?

Policy

A **policy** π is a function from $\mathcal{S}$ to $\mathcal{A}$ that specifies what action to take in each state:

- A policy fully defines the behavior of an agent
- Deterministic policy: $a = \pi(s)$
- Stochastic policy: $\pi(a|s) = P(a_t = a|s_t = s)$

Remark:

- MDP policies depend only on the **current state** and not the entire history
- However, the current state may include past observations

Policy

How do we learn a policy?

Imitation Learning: Learn a policy from **expert demonstrations**

- Expert demonstrations are provided
- Supervised learning problem

Reinforcement Learning: Learn a policy through **trial-and-error**

- No expert demonstrations given
- Agent discovers itself which actions **maximize the expected future reward**
  - The agent interacts with the environment and obtains reward
  - The agent discovers good actions and improves its policy π

Exploration vs. Exploitation

How do we discover good actions?

Answer: We need to explore the state/action space. Thus RL combines two tasks:

- **Exploration:** Try a novel action a in state s , observe reward r_t
  - Discovers more information about the environment, but sacrifices total reward
  - Game-playing example: Play a novel experimental move
- **Exploitation:** Use a previously discovered good action a
  - Exploits known information to maximize reward, but sacrifice unexplored areas
  - Game-playing example: Play the move you believe is best

Trade-off: It is important to explore and exploit simultaneously

Exploration vs. Exploitation

How to balance exploration and exploitation?

ϵ**-greedy** exploration algorithm:

- Try all possible actions with non-zero probability
- With probability ϵ choose an action at random (**exploration**)
- With probability $1 - \epsilon$ choose the best action (**exploitation**)
- Greedy action is defined as best action which was discovered so far
- ϵ is large initially and gradually annealed (=reduced) over time

4.2
Bellman Optimality and Q-Learning

Value Functions

How good is a state?

The **state-value function** V^π at state s_t is the expected cumulative discounted reward ($r_t \sim \mathcal{R}(r_t|s_t, a_t)$) when following policy π from state s_t:

$$V^\pi(s_t) = \mathbb{E}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots | s_t, \pi] = \mathbb{E}\left[\sum_{k \geq 0} \gamma^k r_{t+k} \middle| s_t, \pi\right]$$

- The discount factor $\gamma < 1$ is the value of future rewards at current time t
  - Weights immediate reward higher than future reward (e.g., $\gamma = \frac{1}{2} \Rightarrow \gamma^k = \frac{1}{1}, \frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}, \ldots$)
  - Determines agent's far/short-sightedness
  - Avoids infinite returns in cyclic Markov processes

Value Functions

How good is a state-action pair?

The **action-value function** Q^π at state s_t and action a_t is the expected cumulative discounted reward when taking action a_t in state s_t and then following the policy π:

$$Q^\pi(s_t, a_t) = \mathbb{E}\left[\sum_{k\geq 0} \gamma^k r_{t+k} \middle| s_t, a_t, \pi\right]$$

- The discount factor $\gamma \in [0, 1]$ is the value of future rewards at current time t
  - Weights immediate reward higher than future reward (e.g., $\gamma = \frac{1}{2} \Rightarrow \gamma^k = \frac{1}{1}, \frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}, \dots$)
  - Determines agent's far/short-sightedness
  - Avoids infinite returns in cyclic Markov processes

Optimal Value Functions

The **optimal state-value function** $V^*(s_t)$ is the best $V^\pi(s_t)$ over all policies π:

$$V^*(s_t) = \max_\pi V^\pi(s_t) \qquad\qquad V^\pi(s_t) = \mathbb{E}\left[\sum_{k\geq 0} \gamma^k r_{t+k} \middle| s_t, \pi\right]$$

The **optimal action-value function** $Q^*(s_t, a_t)$ is the best $Q^\pi(s_t, a_t)$ over all policies π:

$$Q^*(s_t, a_t) = \max_\pi Q^\pi(s_t, a_t) \qquad\qquad Q^\pi(s_t, a_t) = \mathbb{E}\left[\sum_{k\geq 0} \gamma^k r_{t+k} \middle| s_t, a_t, \pi\right]$$

- The optimal value functions specify the best possible performance in the MDP
- However, searching over all possible policies π is computationally intractable

Optimal Policy

If $Q^*(s_t, a_t)$ would be known, what would be the **optimal policy**?

$$\pi^*(s_t) = \operatorname*{argmax}_{a' \in \mathcal{A}} \; Q^*(s_t, a')$$

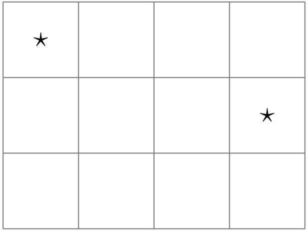
- Unfortunately, searching over all possible policies π is intractable in most cases
- Thus, determining $Q^*(s_t, a_t)$ is hard in general (for most interesting problems)
- Let's have a look at a simple example where the optimal policy is easy to compute

A Simple Grid World Example

actions = {
1. right $\rightarrow$
2. left $\leftarrow$
3. up $\uparrow$
4. down $\downarrow$

}

states

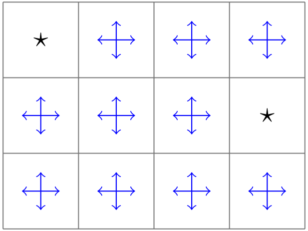


reward: $r = -1$ for each transition

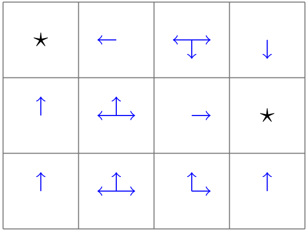
Objective: Reach one of terminal states (marked with '$\star$') in least number of actions

- Penalty (negative reward) given for every transition made

A Simple Grid World Example



Random Policy



Optimal Policy

- The arrows indicate equal probability of moving into each of the directions

Solving for the Optimal Policy

Bellman Optimality Equation

- The **Bellman Optimality Equation** is named after Richard Ernest Bellman who introduced **dynamic programming** in 1953
- Almost any problem which can be solved using **optimal control theory** can be solved via the appropriate Bellman equation

Richard Ernest Bellman

Sutton and Barto: Reinforcement Learning: An Introduction. MIT Press, 2017.

Bellman Optimality Equation

The **Bellman Optimality Equation (BOE)** decomposes Q^* as follows:

$$\begin{aligned} Q^*(s_t, a_t) &= \mathbb{E}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots \middle| s_t, a_t\right] \\ &\overset{BOE}{=} \mathbb{E}\left[r_t + \gamma \max_{a' \in \mathcal{A}} Q^*(s_{t+1}, a') \middle| s_t, a_t\right] \end{aligned}$$

This **recursive formulation** comprises two parts:

- Current reward: r_t
- Discounted optimal action-value of successor: $\gamma \max_{a' \in \mathcal{A}} Q^*(s_{t+1}, a')$

We want to **determine** $Q^*(s_t, a_t)$. How can we **solve** the BOE?

- The BOE is non-linear (because of max-operator) $\Rightarrow$ no closed form solution
- Several iterative methods have been proposed, most popular: Q-Learning

Sutton and Barto: Reinforcement Learning: An Introduction. MIT Press, 2017.

Proof of the Bellman Optimality Equation

Proof of the **Bellman Optimality Equation** for the **optimal action-value function** Q^*:

$$
\begin{aligned}
Q^*(s_t, a_t) &= \mathbb{E}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots | s_t, a_t\right] \\
&= \mathbb{E}\left[\sum_{k \geq 0} \gamma^k r_{t+k} | s_t, a_t\right] \\
&= \mathbb{E}\left[r_t + \gamma \sum_{k \geq 0} \gamma^k r_{t+k+1} | s_t, a_t\right] \\
&= \mathbb{E}\left[r_t + \gamma V^*(s_{t+1}) | s_t, a_t\right] \\
&= \mathbb{E}\left[r_t + \gamma \max_{a'} Q^*(s_{t+1}, a') | s_t, a_t\right]
\end{aligned}
$$

Sutton and Barto: Reinforcement Learning: An Introduction. MIT Press, 2017.

Bellman Optimality Equation

Why is it useful to solve the BOE?

- A greedy policy which chooses the action that maximizes the optimal action-value function Q^* or the optimal state-value function V^* takes into account the reward consequences of all possible future behavior
- Via Q^* and V^* the optimal expected long-term return is turned into a quantity that is locally and immediately available for each state / state-action pair
- For V^*, a one-step-ahead search yields the optimal actions
- Q^* effectively caches the results of all one-step-ahead searches

Sutton and Barto: Reinforcement Learning: An Introduction. MIT Press, 2017.

Q-Learning

Q-Learning: Iteratively solve for Q^*

$$Q^*(s_t, a_t) = \mathbb{E}\left[r_t + \gamma \max_{a' \in \mathcal{A}} Q^*(s_{t+1}, a') \middle| s_t, a_t \right]$$

by constructing an **update sequence** $Q_1, Q_2, \ldots$ using learning rate α:

$$\begin{aligned} Q_{i+1}(s_t, a_t) \quad &\leftarrow \quad (1-\alpha) Q_i(s_t, a_t) + \alpha(r_t + \gamma \max_{a' \in \mathcal{A}} Q_i(s_{t+1}, a')) \\ &= \quad Q_i(s_t, a_t) + \alpha \underbrace{(\underbrace{r_t + \gamma \max_{a' \in \mathcal{A}} Q_i(s_{t+1}, a')}_{\text{target}} - \underbrace{Q_i(s_t, a_t)}_{\text{prediction}})}_{\text{temporal difference (TD) error}} \end{aligned}$$

- Q_i will converge to Q^* as $i \to \infty$

Note: policy π learned implicitly via Q table!

Watkins and Dayan: Technical Note Q-Learning. Machine Learning, 1992.

Q-Learning

Implementation:

- Initialize Q table and initial state s_0 randomly
- Repeat:
  - Observe state s_t, choose action a_t according to ϵ-greedy strategy
    (Q-Learning is "off-policy" as the updated policy is different from the behavior policy)
  - Observe reward r_t and next state s_{t+1}
  - Compute TD error: $r_t + \gamma \max_{a' \in \mathcal{A}} Q_i(s_{t+1}, a') - Q_i(s_t, a_t)$
  - Update Q table

What's the problem with using Q tables?

- **Scalability:** Tables don't scale to high dimensional state/action spaces (e.g., GO)
- **Solution:** Use a function approximator (neural network) to represent $Q(s, a)$

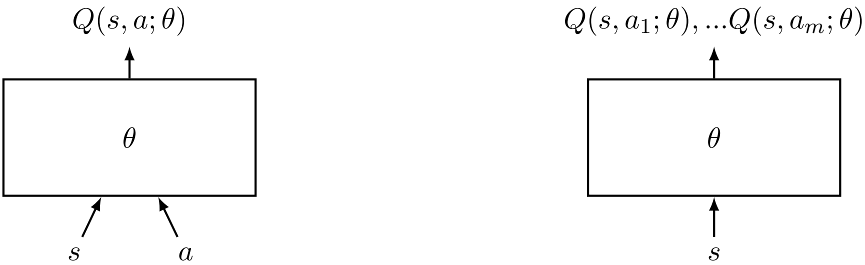
Watkins and Dayan: Technical Note Q-Learning. Machine Learning, 1992.

4.3
Deep Q-Learning

Deep Q-Learning

Use a **deep neural network** with weights θ as function approximator to estimate Q:

$$Q(s,a;\theta) \approx Q^*(s,a)$$



Mnih et al.: Human-level control through deep reinforcement learning. Nature, 2015.

Training the Q Network

Forward Pass:

Loss function is the mean-squared error in Q-values:

$$\mathcal{L}(\theta) = \mathbb{E}\left[\left(\underbrace{r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta)}_{\text{target}} - \underbrace{Q(s_t, a_t; \theta)}_{\text{prediction}}\right)^2\right]$$

Backward Pass:

Gradient update with respect to Q-function parameters θ:

$$\nabla_\theta \mathcal{L}(\theta) = \nabla_\theta \, \mathbb{E}\left[\left(r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta) - Q(s_t, a_t; \theta)\right)^2\right]$$

Optimize objective end-to-end with stochastic gradient descent (SGD) using $\nabla_\theta \mathcal{L}(\theta)$.

Mnih et al.: Human-level control through deep reinforcement learning. Nature, 2015.

Experience Replay

To speed-up training we like to train on **mini-batches:**

- Problem: Learning from consecutive samples is inefficient
- Reason: Strong correlations between consecutive samples

Experience replay stores agent's experiences at each time-step

- Continually update a **replay memory** D with new experiences $e_t = (s_t, a_t, r_t, s_{t+1})$
- Train on samples $(s_t, a_t, r_t, s_{t+1}) \sim U(D)$ drawn uniformly at random from D
- Breaks correlations between samples
- Improves data efficiency as each sample can be used multiple times

In practice, a **circular replay memory** of finite memory size is used.

Mnih et al.: Human-level control through deep reinforcement learning. Nature, 2015.

Fixed Q Targets

Problem: Non-stationary targets

- As the policy changes, so do our targets: $r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta)$
- This may lead to oscillation or divergence

Solution: Use fixed Q targets to stabilize training

- A target network Q with weights θ^- is used to generate the targets:

$$\mathcal{L}(\theta) = \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim U(D)} \left[\left(r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-) - Q(s_t, a_t; \theta) \right)^2 \right]$$

- Target network Q is only updated every C steps by cloning the Q-network
- Effect: Reduces oscillation of the policy by adding a delay

Mnih et al.: Human-level control through deep reinforcement learning. Nature, 2015.

Putting it together

Deep Q-Learning using experience replay and fixed Q targets:

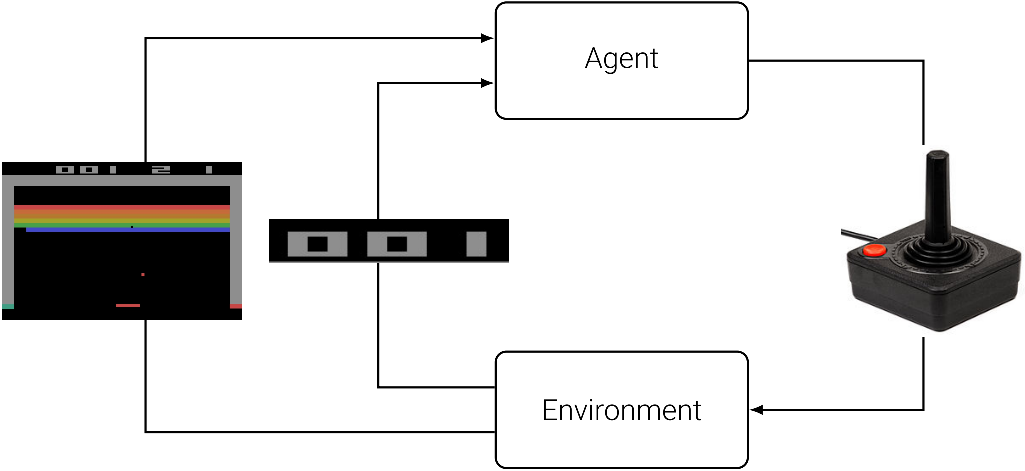
- Take action a_t according to ϵ-greedy policy
- Store transition (s_t, a_t, r_t, s_{t+1}) in replay memory D
- Sample random mini-batch of transitions (s_t, a_t, r_t, s_{t+1}) from D
- Compute Q targets using old parameters θ^-
- Optimize MSE between Q targets and Q network predictions

$$\mathcal{L}(\theta) = \mathbb{E}_{s_t, a_t, r_t, s_{t+1} \sim D} \left[\left(r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-) - Q(s_t, a_t; \theta) \right)^2 \right]$$

using stochastic gradient descent.

Mnih et al.: Human-level control through deep reinforcement learning. Nature, 2015.

Case Study: Playing Atari Games



Objective: Complete the game with the highest score

Mnih et al.: Human-level control through deep reinforcement learning. Nature, 2015.

Case Study: Playing Atari Games

$Q(s, a; \theta)$: Neural network with weights θ

FC-Out (Q values)

FC-256

32 4x4 conv, stride 2

16 8x8 conv, stride 2

Output: Q values for all (4 to 18) Atari actions
(efficient: single forward pass computes Q for all actions)

Input: $84 \times 84 \times 4$ stack of last 4 frames
(after grayscale conversion, downsampling, cropping)

Mnih et al.: Human-level control through deep reinforcement learning. Nature, 2015.

Case Study: Playing Atari Games

Mnih et al.: Human-level control through deep reinforcement learning. Nature, 2015.

Deep Q-Learning Shortcomings

Deep Q-Learning suffers from several **shortcomings:**

- Long training times
- Uniform sampling from replay buffer $\Rightarrow$ all transitions equally important
- Simplistic exploration strategy
- Action space is limited to a discrete set of actions (otherwise, expensive test-time optimization required)

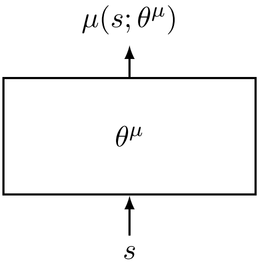
Various **improvements** over the original algorithm have been explored.

Deep Deterministic Policy Gradients

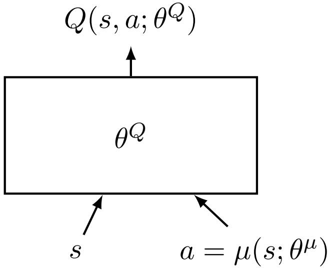
DDPG addresses the problem of continuous action spaces.

Problem: Finding a continuous action requires optimization at every timestep.

Solution: Use two networks, an **actor** (deterministic policy) and a **critic.**



Actor



Critic

Lillicrap et al.: Continuous Control with Deep Reinforcement Learning. ICLR, 2016.

Deep Deterministic Policy Gradients

- **Actor** network with weights θ^μ estimates agent's deterministic policy $\mu(s;\theta^\mu)$
  - Update deterministic policy $\mu(\cdot)$ in direction that most improves Q
  - Apply chain rule to the **expected return** (this is the policy gradient):

$$\nabla_{\theta^\mu} \mathbb{E}_{s_t,a_t,r_t,s_{t+1}\sim D}\left[Q(s_t,\mu(s_t;\theta^\mu);\theta^Q)\right] = \mathbb{E}\left[\nabla_{a_t} Q(s_t,a_t;\theta^Q)\,\nabla_{\theta^\mu}\mu(s_t;\theta^\mu)\right]$$

- **Critic** estimates value of current policy $Q(s,a;\theta^Q)$
  - Learned using the **Bellman Optimality Equation** as in Q Learning:

$$\nabla_{\theta^Q} \mathbb{E}_{s_t,a_t,r_t,s_{t+1}\sim D}\left[\left(r_t + \gamma Q(s_{t+1},\mu(s_{t+1};\theta^{\mu-});\theta^{Q-}) - Q(s_t,a_t;\theta^Q)\right)^2\right]$$

  - Remark: No maximization over actions required as this step is now learned via $\mu(\cdot)$

Deep Deterministic Policy Gradients

Experience replay and **target networks** are again used to stabilize training:

- Replay memory D stores transition tuples (s_t, a_t, r_t, s_{t+1})
- Target networks are updated using "soft" target updates
  - Weights are not directly copied but slowly adapted:

$$
\begin{aligned}
\theta^{Q-} &\leftarrow \tau\theta^{Q} + (1-\tau)\theta^{Q-} \\
\theta^{\mu-} &\leftarrow \tau\theta^{\mu} + (1-\tau)\theta^{\mu-}
\end{aligned}
$$

where $0 < \tau \ll 1$ controls the tradeoff between speed and stability of learning

Exploration is performed by adding noise ∇_{θ^μ} to the policy $\mu(s)$:

$$\mu(s;\theta^{\mu}) + \mathcal{N}$$

Lillicrap et al.: Continuous Control with Deep Reinforcement Learning. ICLR, 2016.

Prioritized Experience Replay

Prioritize experience to replay important transitions more frequently

- Priority δ is measured by magnitude of temporal difference (TD) error:

$$\delta = \left| r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^{Q-}) - Q(s_t, a_t; \theta^{Q}) \right|$$

- TD error measures how “surprising” or unexpected the transition is
- Stochastic prioritization avoids overfitting due to lack of diversity
- Enables learning speed-up by a factor of 2 on Atari benchmarks

Schaul et al.: Prioritized Experience Replay. ICLR, 2016.

Learning to Drive in a Day

Real-world RL demo by Wayve:

- Deep Deterministic Policy Gradients with Prioritized Experience Replay
- **Input:** Single monocular image
- **Action:** Steering and speed
- **Reward:** Distance traveled without the safety driver taking control (requires no maps / localization)
- 4 Conv layers, 2 FC layers
- Only 35 training episodes

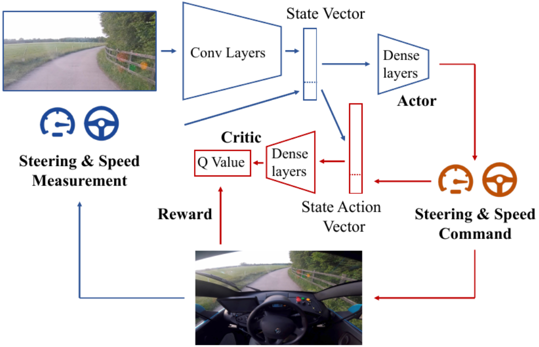


Fig. 1: We design a deep reinforcement learning algorithm for autonomous driving. This figure illustrates the actor-critic algorithm which we use to learn a policy and value function for driving. Our agent maximises the reward of distance travelled before intervention by a safety driver.

Learning to Drive in a Day

Kendall, Hawke, Janz, Mazur, Reda, Allen, Lam, Bewley and Shah: Learning to Drive in a Day. ICRA, 2019.

Other flavors of Deep RL

Asynchronous Deep Reinforcement Learning

Execute multiple agents in separate environment instances:

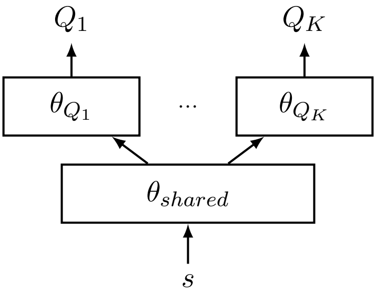
- Each agent interacts with its own environment copy and collects experience
- Agents may use different exploration policies to maximize experience diversity
- Experience is not stored but directly used to update a shared global model
- Stabilizes training in similar way to experience replay by decorrelating samples
- Leads to reduction in training time roughly linear in the number of parallel agents

Mnih et al.: Asynchronous Methods for Deep Reinforcement Learning. ICML, 2016.

Bootstrapped DQN

Bootstrapping for efficient exploration:

- Approximate a distribution over Q values via K bootstrapped "heads"
- At the start of each epoch, a single head Q_k is selected uniformly at random
- After training, all heads can be combined into a single ensemble policy



Double Q-Learning

Double Q-Learning

- Decouple Q function for selection and evaluation of actions to avoid Q overestimation and stabilize training. Target:

$$
\begin{aligned}
DQN \quad &: \quad r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-) \\
DoubleDQN \quad &: \quad r_t + \gamma Q(s_{t+1}, \operatorname*{argmax}_{a'} Q(s_{t+1}, a'; \theta); \theta^-)
\end{aligned}
$$

  - Online network with weights θ is used to determine greedy policy
  - Target network with weights θ^- is used to determine corresponding action value
- Improves performance on Atari benchmarks

van Hasselt et al.: Deep Reinforcement Learning with Double Q-learning. AAAI, 2016.

Deep Recurrent Q-Learning

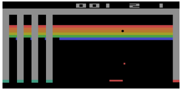
Add recurrency to a deep Q-network to handle *partial observability* of states:

FC-Out (Q-values)

LSTM

32 4x4 conv, stride 2

16 8x8 conv, stride 2



Replace fully-connected layer with **recurrent LSTM layer**

Hausknecht and Stone: Deep Recurrent Q-Learning for Partially Observable MDPs. AAAI, 2015

Faulty Reward Functions

https://blog.openai.com/faulty-reward-functions/

Summary

- Reinforcement learning learns through **interaction** with the environment
- The environment is typically modeled as a **Markov Decision Process**
- The goal of RL is to **maximize the expected future reward**
- Reinforcement learning requires trading off **exploration** and **exploitation**
- **Q-Learning** iteratively solves for the optimal action-value function
- The policy is learned implicitly via the **Q table**
- **Deep Q-Learning** scales to continuous/high-dimensional state spaces
- **Deep Deterministic Policy Gradients** scales to continuous action spaces
- Experience replay and target networks are necessary to stabilize training