Reinforcement learning

Applied Machine Learning (EDAN95)
Lectures 13 and 14
2018-12-17 and 2018-12-19
Elin A. Topp

Material based on “Hands-on Machine Learning with SciKit-learn and TensorFlow” (course book, chapter 16),
and on lecture “Belöningsbaserad inlärning / Reinforcement learning”
by Örjan Ekeberg, CSC/Nada, KTH, autumn term 2006 (in Swedish)

Outline

- Reinforcement learning
  - Problem definition
    - Learning situation
    - Role of the reward
    - Simplified assumptions
    - Central concepts and terms
  - Known environment
    - Bellman's equation
    - Approaches to solutions
  - Unknown environment
    - Temporal-Difference learning
    - Q-Learning
    - Sarsa-Learning
  - Improvements
    - The usefulness of making mistakes
    - Eligibility Trace

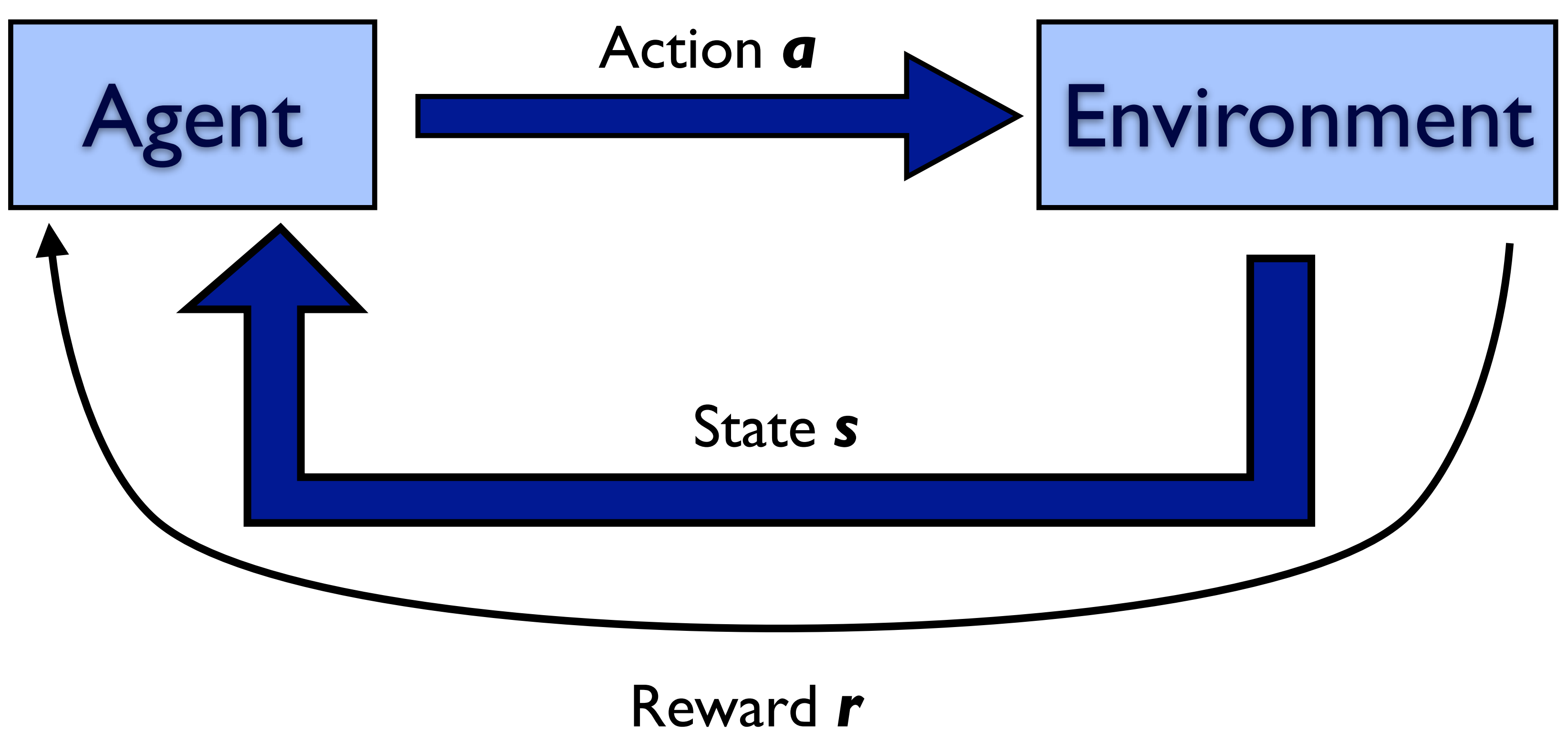
Learning situation: A model

An *agent* interacts with its *environment*

The agent performs *actions*

Actions have *influence* on the environment's *state*

The agent *observes* the environment's *state* and *receives* a *reward* from the environment



Outline

- Reinforcement learning
  - Problem definition
    - Learning situation
    - Roll of the reward
    - Simplified assumptions
    - Central concepts and terms
  - Known (observable) environment
    - Bellman's equation
    - Approaches to solutions
    - Outlook: unknown environments, Monte Carlo method and policy gradients
  - Unknown environment
    - Temporal-Difference learning
    - Q-Learning
    - Sarsa-Learning
  - Improvements
    - The usefulness of making mistakes
    - Eligibility Trace

Solving the equation

There are two ways of solving (this "optimal" version of) *Bellman's equation*

$$U^{\pi}(s) = r(\, s, \pi(s)) + \ \gamma \cdot U^{\pi}(\, \delta(\, s, \pi(s)))$$

- Directly: $U^{\pi}(s) = r(\, s, \pi(s)) + \ \gamma \cdot \sum_{s'} P(\, s' \mid s, \pi(s))\ U^{\pi}(s')$

- Iteratively (*Value / utility iteration*), stop when equilibrium is reached, i.e., "nothing happens"

$$U^{\pi}_{k+1}(s) \longleftarrow r(\, s, \pi(s)) + \ \gamma \cdot U^{\pi}_{k}\ (\, \delta(\, s, \pi(s)))$$

Finding optimal policy and value function

How can we find an *optimal policy* π^*?

That would be easy if we had the *optimal value / utility function* U^*:

$$\pi^*(s) = \underset{a}{\operatorname{argmax}}(r(s, a) + \gamma \cdot U^*(\delta(s, a)))$$

Apply to the "optimal version" of Bellman's equation

$$U^*(s) = \max_{a}(r(s, a) + \gamma \cdot U^*(\delta(s, a)))$$

Tricky to solve ... but possible:

Combine policy and value iteration by switching in each iteration step

Policy iteration

Policy iteration provides exactly this switch.

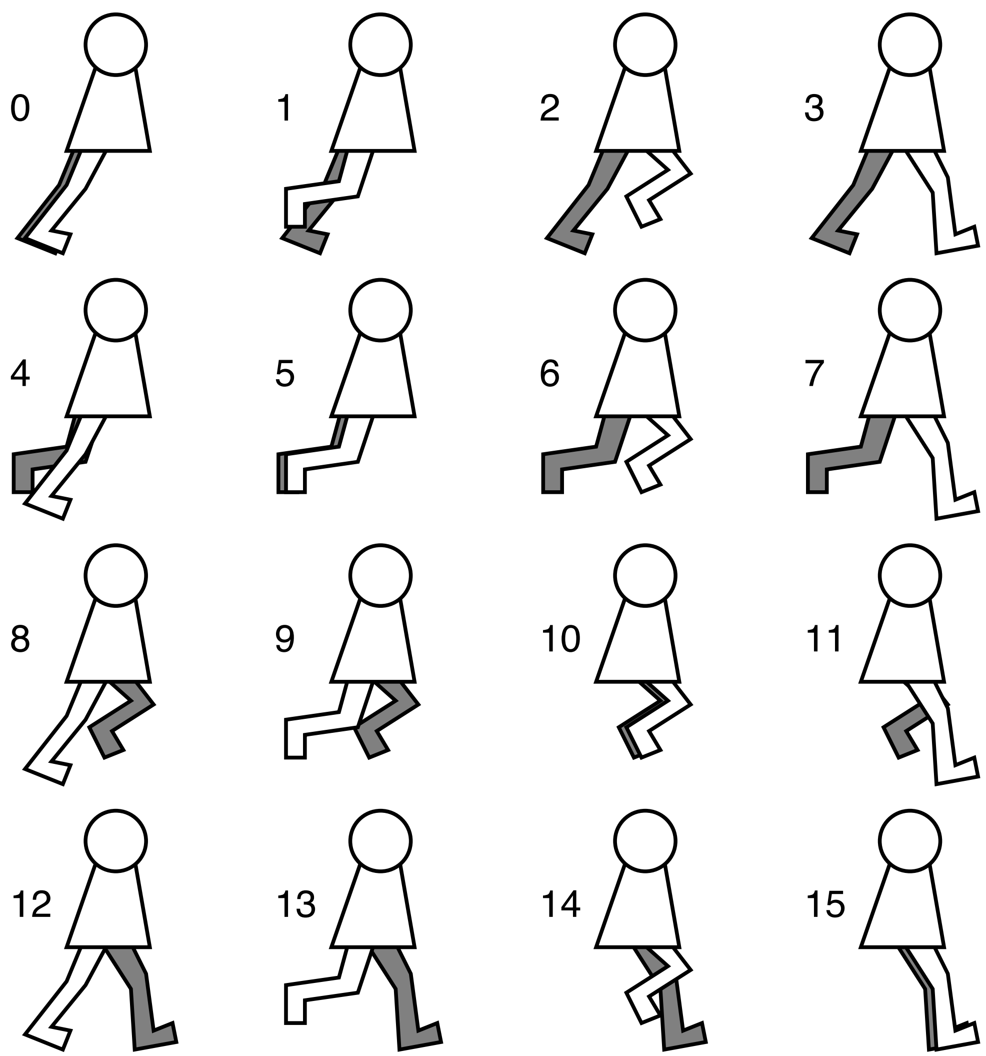
For each iteration step k:

$$\pi_k(s) = \underset{a}{\operatorname{argmax}}(r(s, a) + \gamma \cdot U_k(\delta(s, a)))$$

$$U_{k+1}(s) = r(s, \pi_k(s)) + \gamma \cdot U_k(\delta(s, \pi_k(s)))$$

Policy Iteration for Cartoon Walker

We cheat a bit, and use entirely known reward and transition functions…



Action	Effect
0	Move right (white) leg up / down
1	Move right (white) leg backward / forward
2	Move left (grey) leg up / down
3	Move left (grey) leg backward / forward

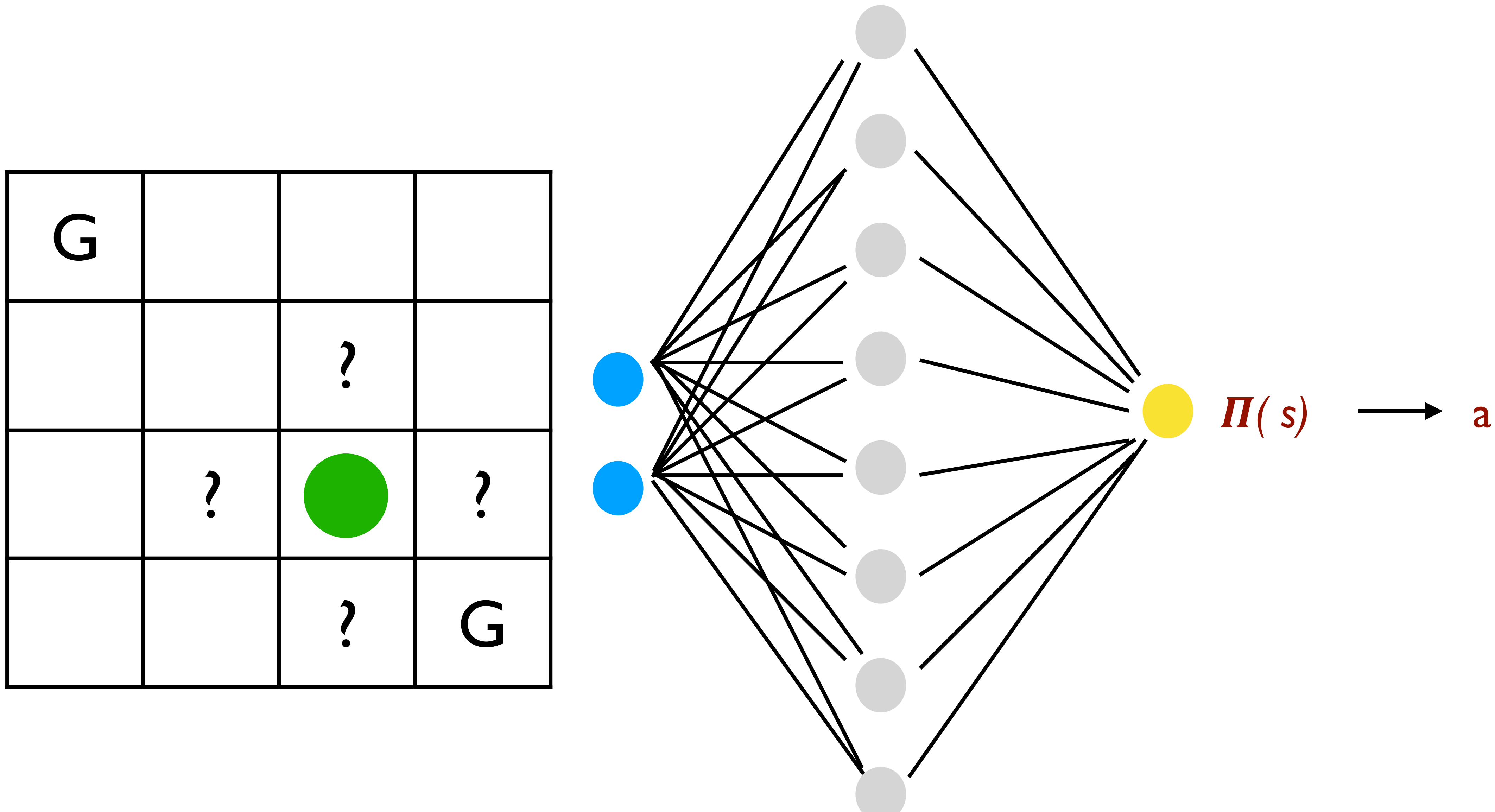
```
for s in range(len(policy)):
    policy[s] = argmax(
        lambda a: rew[s][a] + gamma * value[trans[s][a]],
        range(len(trans[s])))

for s in range(len(value)):
    a = policy[s]
    value[s] = rew[s][a] + gamma * value[trans[s][a]]
```

Policy gradients

What if…

… we take help of an ANN to learn a good policy?



Training the network

If we had a "label" saying after a forward run that DOWN is the optimal thing to do for this state…

… we would compute the loss as:

$$- \log P(y=DOWN \mid x)$$

… but we do not have this label, so we use the reward R we get from using our

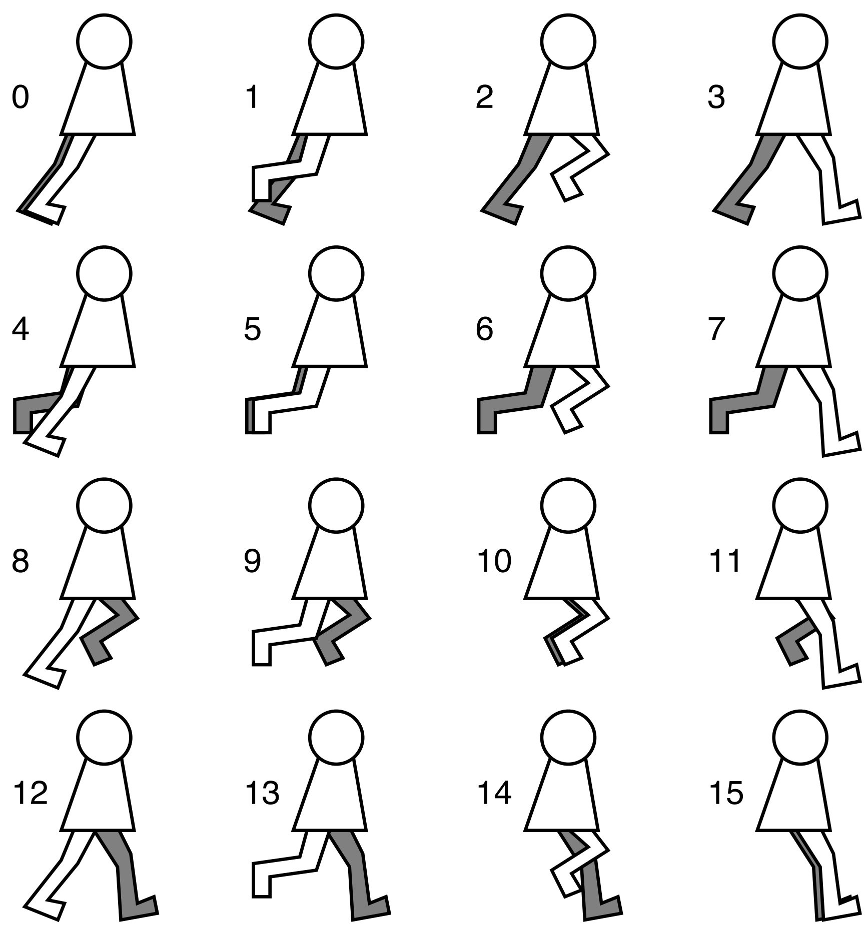
policy (the sampled action) to compute the loss:

$$Loss = - R \log P(a) \text{ with R being } r(s, a)$$

but that means that we have to save the gradients along our path through the state-action space (if we do not train immediately after each episode), and all the <s, a, r> tuples (or actually <s, a, r, s'>)

Policy Gradients for Cartoon Walker

Represent the walker's policy in a network with
- a single valued array (one input value) for the state
- one of four possible output "classes" (sampled from probability distribution)
- softmax activation
- and not too many hidden neurons ;-)



Action	Effect
0	Move right (white) leg up / down
1	Move right (white) leg backward / forward
2	Move left (grey) leg up / down
3	Move left (grey) leg backward / forward

Will need a lot more time and tweaking than the policy iteration!

Outline

- Reinforcement learning
  - Problem definition
    - Learning situation
    - Roll of the reward
    - Simplified assumptions
    - Central concepts and terms
  - Known environment
    - Bellman’s equation
    - Approaches to solutions
    - Outlook: unknown environments, Monte Carlo method and policy gradients
  - Unknown environment
    - Temporal-Difference learning
    - Q-Learning
    - Sarsa-Learning
  - Improvements
    - The usefulness of making mistakes
    - Eligibility Trace

Monte Carlo approach

Usually the reward $r(s, a)$ and the state transition function $\delta(s, a)$ are unknown to the learning agent.

(What does that mean for learning to ride a bike? $\boxed{}$)

Still, we can estimate U^* from *experience*, as a *Monte Carlo approach* will do:

- Start with a randomly chosen s
- Follow a policy π, store rewards and s_t for the step at time t
- When the goal is reached, update the $U^\pi(s)$ estimate for all visited states s_t with the future reward that was given when reaching the goal
- Start over with a randomly chosen s ...

Converges slowly...

Temporal Difference learning

Temporal Difference learning ...

... uses the fact that there are two estimates for the value of a state:

before and *after* visiting the state

Or: What the agent believes *before* acting

$U^{\pi}(s_t)$

and *after* acting

$r_{t+1} + \gamma \cdot U^{\pi}(s_{t+1})$

Applying the estimates

The second estimate in the *Temporal Difference* learning approach is obviously "better", ...

... hence, we update the overall approximation of a state's value towards the more accurate estimate

$$U^{\pi}(s_t) \longleftarrow U^{\pi}(s_t) + \alpha[\, r_{t+1} + \gamma \cdot U^{\pi}(s_{t+1}) - U^{\pi}(s_t)]$$

Which gives us a measure of the "surprise" or "disappointment" for the outcome of an action.

Converges significantly faster than the pure Monte Carlo approach.

Q-learning

Problem:

even if U is appropriately estimated, it is not possible to compute π, as the agent has no knowledge about δ and r, i.e., it needs to learn also that.

Solution (trick): Estimate $Q(s, a)$ instead of $U(s)$:

$Q(s, a)$: Expected total reward when choosing a in s

$$\pi(s) = \underset{a}{argmax}\ Q(s, a)$$

$$U^*(s) = \max_{a} Q^*(s, a)$$

Learning Q

How can we learn *Q*?

Also the *Q*-function can be learned using the Temporal Difference approach:

$$Q(s, a) \longleftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

With *s’* being the next state that is reached when choosing action *a’*

Again, a problem: the *max* operator requires obviously a search through all possible actions that can be taken in the next step...

SARSA-learning

SARSA-learning works similar to *Q-learning*, but it is the *currently active policy* that controls the actually taken action *a'*:

$$Q(s, a) \longleftarrow Q(s, a) + \alpha[r + \gamma Q(s', a') - Q(s, a)]$$

Got its name from the "experience tuples" having the form

State-Action-Reward-State-Action

$$< s, a, r, s', a' >$$

Outline

- Reinforcement learning
  - Problem definition
    - Learning situation
    - Roll of the reward
    - Simplified assumptions
    - Central concepts and terms
  - Known environment
    - Bellman's equation
    - Approaches to solutions
    - Outlook: unknown environments, Monte Carlo method and policy gradients
  - Unknown environment
    - Temporal-Difference learning
    - Q-Learning
    - Sarsa-Learning
  - Improvements
    - The usefulness of making mistakes
    - Eligibility Trace

Improvements and adaptations

What can we do, when ...

- ... the environment is not fully observable?
- ... there are too many states?
- ... the states are not discrete?
- ... the agent is acting in continuous time?

Allowing to be wrong sometimes

Exploration - Exploitation dilemma: When following one policy based on the current estimate of Q, it is not guaranteed that Q actually converges to Q^* (the optimal Q).

A simple solution: Use a policy that has a certain probability of "being wrong" once in a while, to explore better.

- *ε-greedy*: Will sometimes (with probability ε) pick a random action instead of the one that looks best (*greedy*)
- *Softmax*: Weighs the probability for choosing different actions according to how "good" they appear to be.

ε-greedy Q-learning

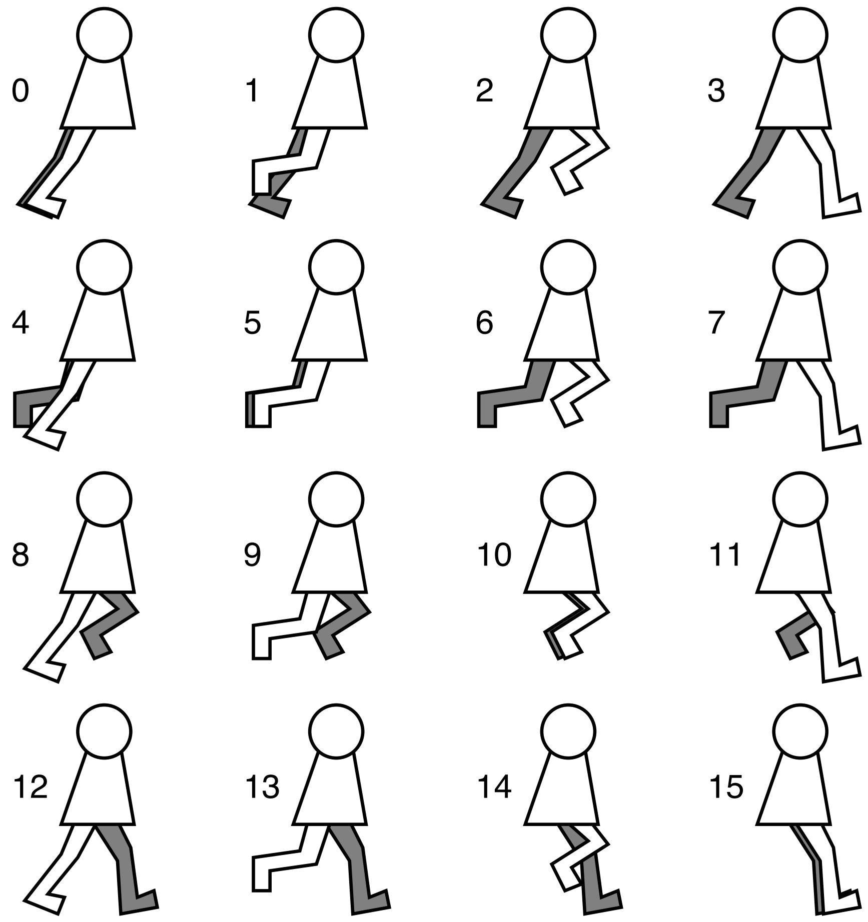
A suggested algorithm (ε-greedy implementation, given some "black box", that produces *r* and *s'*, given *s* and *a*)

- Initialise $Q(s, a)$ arbitrarily $\forall s, a$, choose learning rate α and discount factor γ
- Initialise *s*
- Repeat for each step:
    - Choose *a* from *s* using ε-greedy policy based on $Q(s, a)$
    - Take action *a*, observe reward *r*, and next state *s'*
    - Update $Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$
    - replace *s* with *s'*

  until T steps.

Q-Learning for Cartoon Walker

Use the reward-function estimated in the Policy Iteration experiment. Apply Q-Learning with ε-greedy policy to compute (s', a') from (s, a)



Action	Effect
0	Move right (white) leg up / down
1	Move right (white) leg backward / forward
2	Move left (grey) leg up / down
3	Move left (grey) leg backward / forward

```
for i in range(steps):
    a = eps_greedyPolicy(Q[s], eps)
    s_n, rew, _ = env.go(a) #obtain new state and reward from s, a
    sequence.append(s_n)
    Q[s][a] = Q[s][a] + eta*(rew + gamma * max( Q[s_n]) - Q[s][a])
    s = s_n
```

Speeding up the process

Idea: the Time Difference (TD) updates can be used to improve the estimation also of states where the agent has already been earlier.

$$\forall s, a \ : \ Q(s, a) \longleftarrow Q(s, a) + \alpha[\, r_{t+1} + \gamma\, Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)] \cdot e$$

With e the *eligibility trace*, telling how long ago the agent visited *s* and chose action *a*

Often called *TD(λ)*, with λ being the time constant that describes the "*annealing rate*" of the trace.

Application examples

- End-to-end learning systems
  - learning to interact with humans
    (Ali Ghadirzadeh et al, IROS 2016,
    https://ieeexplore.ieee.org/document/7759417)
    accessible from inside LU's network (or when running over VPN)

Application examples

- End-to-end learning systems
  - learning to throw a ball to hit the Pokèmon
    (Ali Ghadirzadeh et al, IROS 2017,
    https://ieeexplore.ieee.org/document/8206046)
    accessible from inside LU's network (or when running over VPN)

Application examples

- End-to-end learning systems
  - learning to play Go [https://www.nature.com/articles/nature24270]

Lab assignment 7

- The lab assignment is given as a package with instructions, code skeleton and some useful links also to hands-on material at https://github.com/ErikGartner/edan95-rlagent-handout

- Some hands-on experimenting material can be found at https://github.com/ageron/handson-ml