Machine Learning

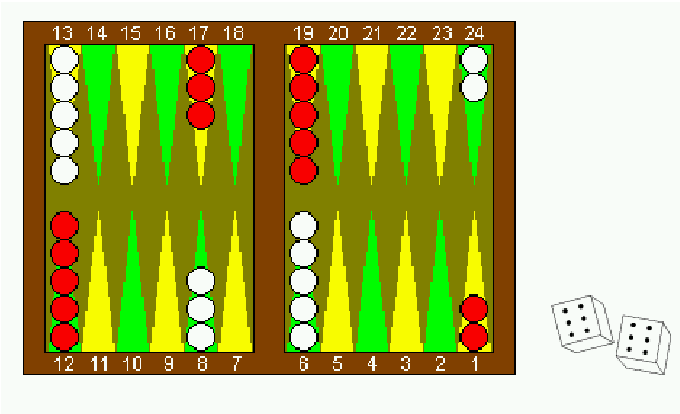
Reinforcement Learning

Prof. Dr. Martin Riedmiller
AG Maschinelles Lernen und Natürlichsprachliche Systeme
Institut für Informatik
Technische Fakultät
Albert-Ludwigs-Universität Freiburg

riedmiller@informatik.uni-freiburg.de

Motivation

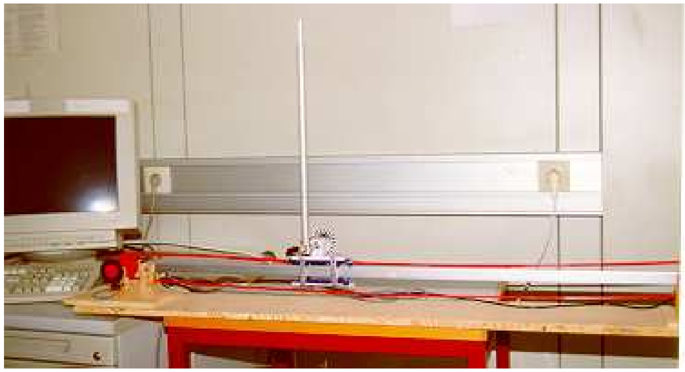
Can a software agent learn to play Backgammon by itself?



Learning from success or failure

Neuro-Backgammon:
playing at worldchampion level
(Tesauro, 1992)

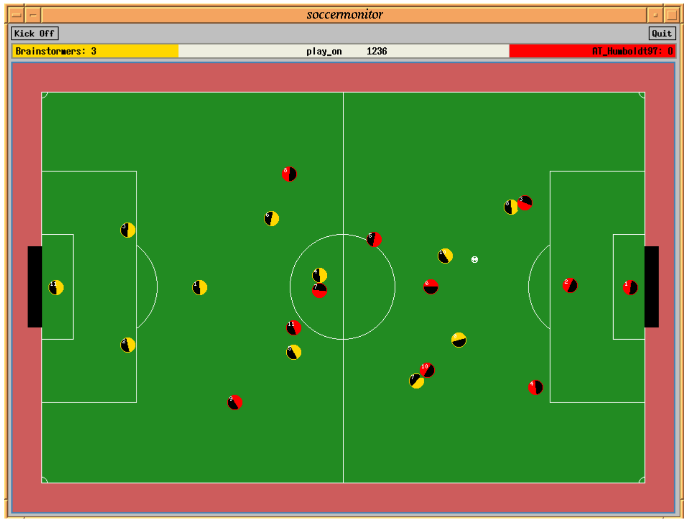
Can a software agent learn to balance a pole by itself?



Learning from success or failure

Neural RL controllers:
noisy, unknown, nonlinear (Riedmiller et.al.)

Can a software agent learn to cooperate with others by itself?



Learning from success or failure

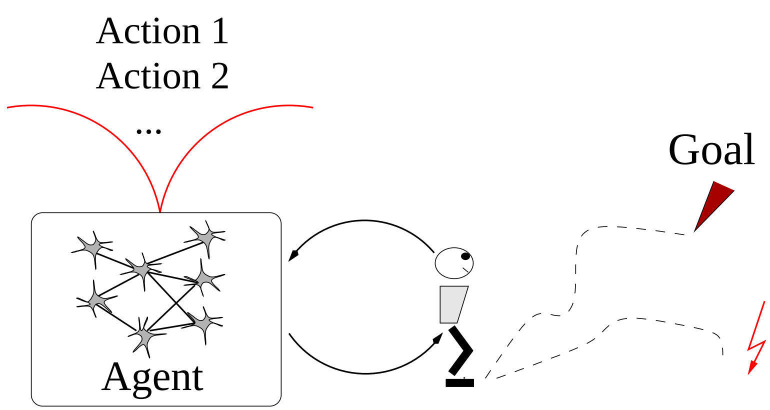
Cooperative RL agents:
complex, multi-agent, cooperative
(Riedmiller et.al.)

Reinforcement Learning

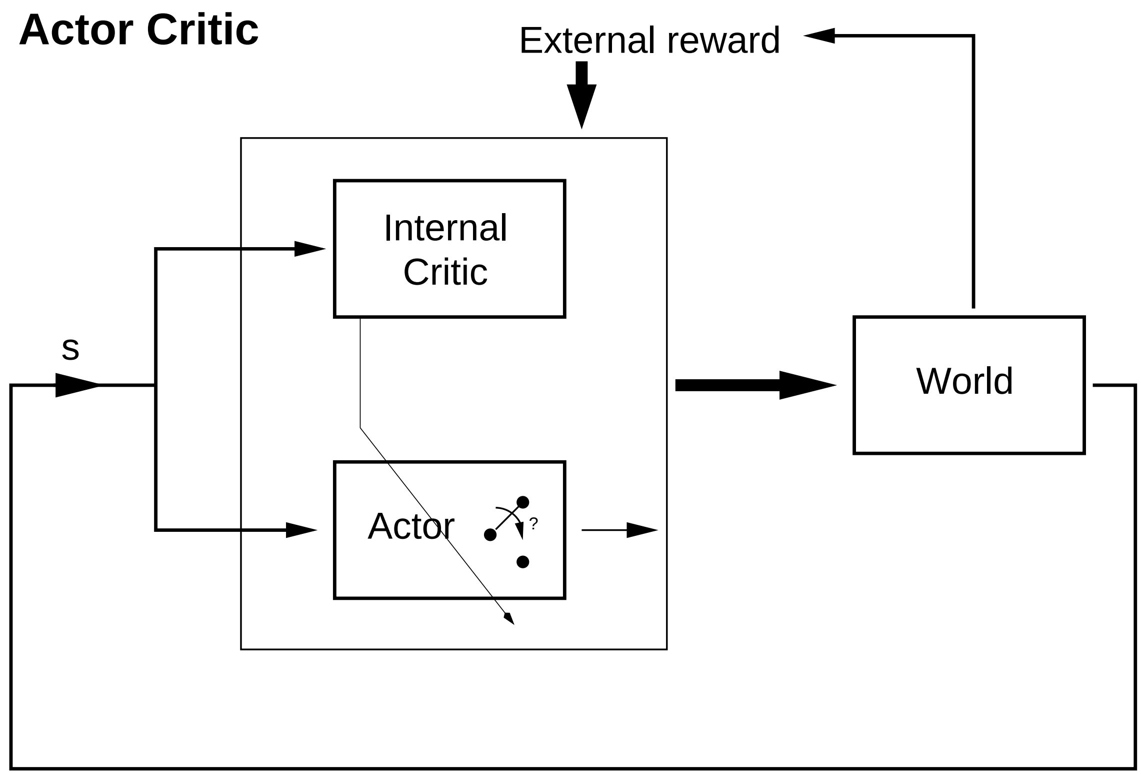
has biological roots: reward and punishment 'Happy Programming'

no teacher, but:

actions + goal $\overset{learn}{\longrightarrow}$ algorithm/ policy



Actor-Critic Scheme (Barto, Sutton, 1983)



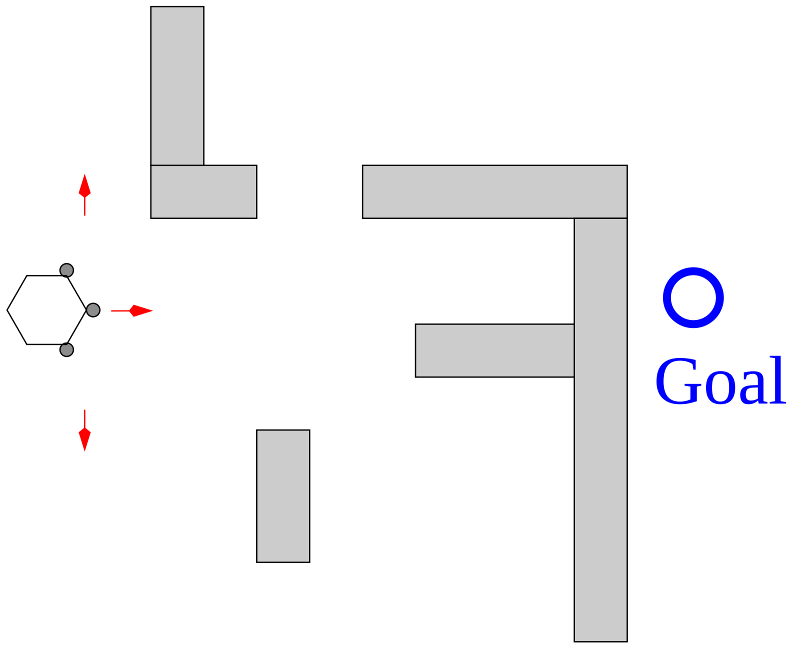
ACTOR-CRITIC SCHEME:

- Critic maps external, delayed reward in internal training signal
- Actor represents policy

Overview

I Reinforcement Learning - Basics

A First Example

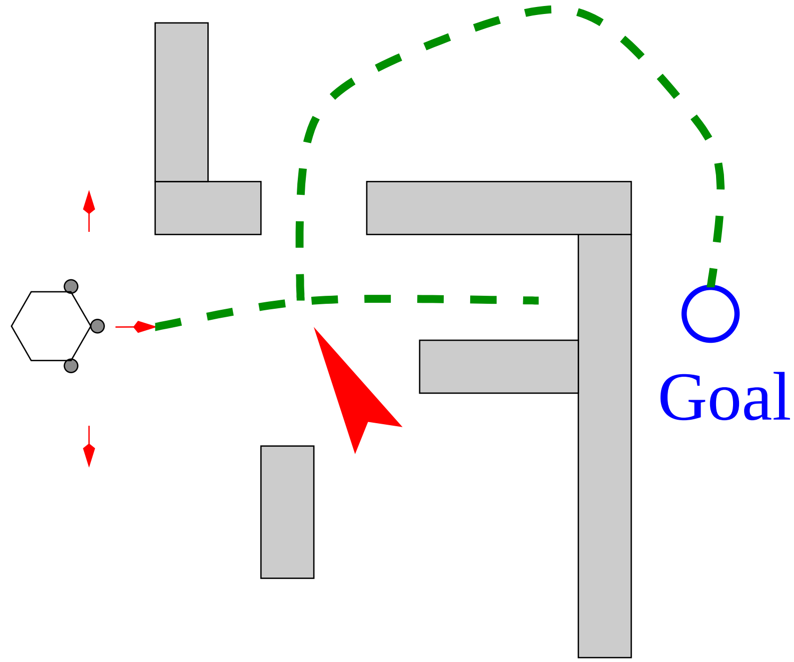


REPEAT

Choose: Action $a \in \{\rightarrow, \leftarrow, \uparrow\}$

UNTIL Goal is reached

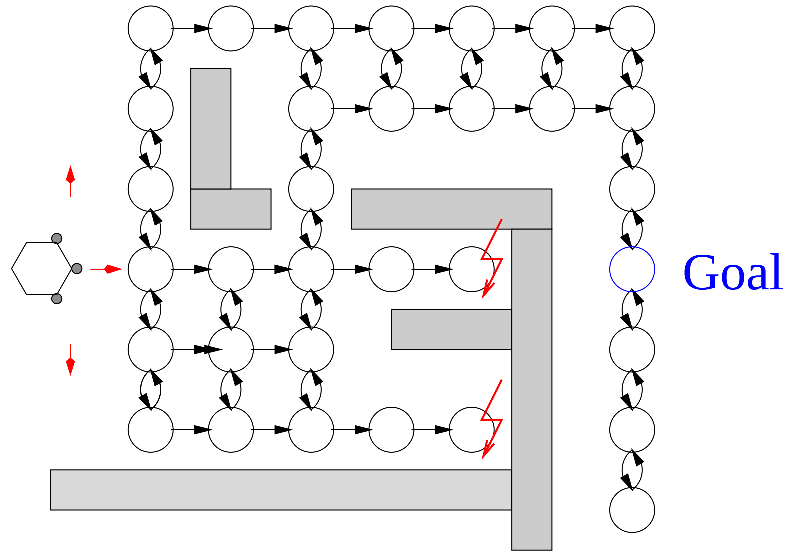
The 'Temporal Credit Assignment' Problem



Which action(s) in the sequence has to be changed?

$\Rightarrow$ Temporal Credit Assignment Problem

Sequential Decision Making



Examples:
Chess, Checkers (Samuel, 1959), Backgammon (Tesauro, 92)
Cart-Pole-Balancing (AHC/ ACE (Barto, Sutton, Anderson, 1983)), Robotics and control, . . .

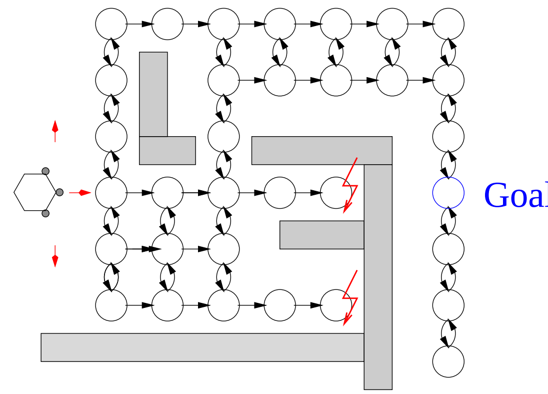
Three Steps

$\Rightarrow$ Describe environment as a Markov Decision Process (MDP)

$\Rightarrow$ Formulate learning task as a dynamic optimization problem

$\Rightarrow$ Solve dynamic optimization problem by dynamic programming methods

1. Description of the environment



S: (finite) set of states
A: (finite) set of actions

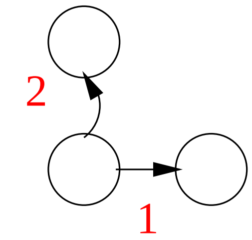
Behaviour of the environment 'model'
$p : S \times S \times A \rightarrow [0, 1]$
$p(s', s, a)$ Probability distribution of transition

For simplicity, we will first assume a deterministic environment. There, the model can be described by a transition function
$f : S \times A \rightarrow S$, $s' = f(s, a)$

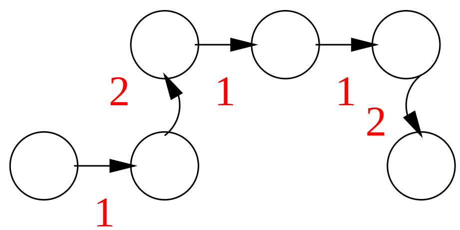
'Markov' property: Transition only depends on current state and action
$$Pr(s_{t+1}|s_t, a_t) = Pr(s_{t+1}|s_t, a_t, s_{t-1}, a_{t-1}, s_{t-2}, a_{t-2}, \ldots)$$

2. Formulation of the learning task

every transition emits transition costs, 'immediate costs', $c : S \times A \to \Re$ (sometimes also called 'immediate reward', r)



Now, an agent policy $\pi : S \to A$ can be evaluated (and judged):
Consider pathcosts:
$J^\pi(s) = \sum_t c(s_t, \pi(s_t)), s_0 = s$



Wanted: optimal policy $\pi^* : \mathcal{S} \to \mathcal{A}$
where $J^{\pi^*}(s) = \min_\pi\{\sum_t c(s_t, \pi(s_t))|s_0 = s\}$

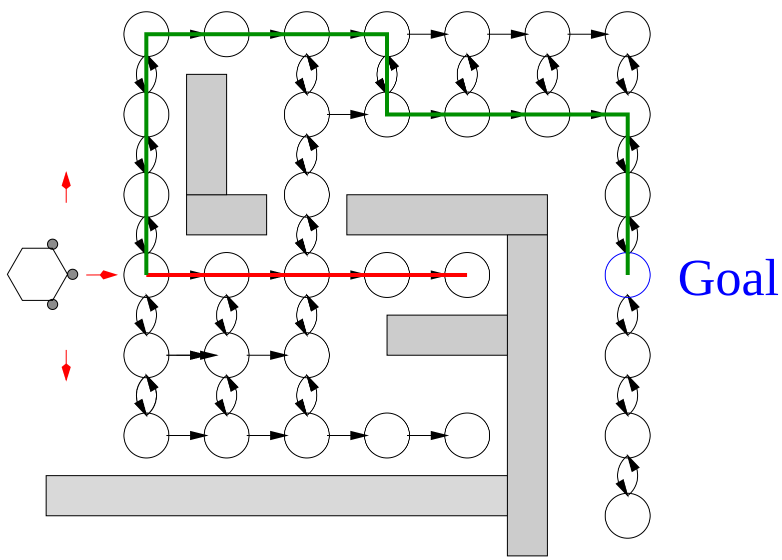
⇒ Additive (path-)costs allow to consider *all* events

⇒ Does this solve the temporal credit assignment problem? YES!

Choice of immediate cost function $c(\cdot)$ specifies policy to be learned

Example:

$$c(s) = \begin{cases} 0 & , \quad \text{if } s \text{ success } (s \in Goal) \\ 1000 & , \quad \text{if } s \text{ failure } (s \in Failure) \\ 1 & , \quad else \end{cases}$$



$$J^{\pi}(s_{start}) = 12$$
$$J^{\pi}(s_{start}) = 1004$$

$\Rightarrow$ specification of requested policy by $c(\cdot)$ is simple!

3. Solving the optimization problem

For the optimal path costs it is known that

$$J^*(s) = \min_a \{c(s,a) + J^*(f(s,a))\}$$

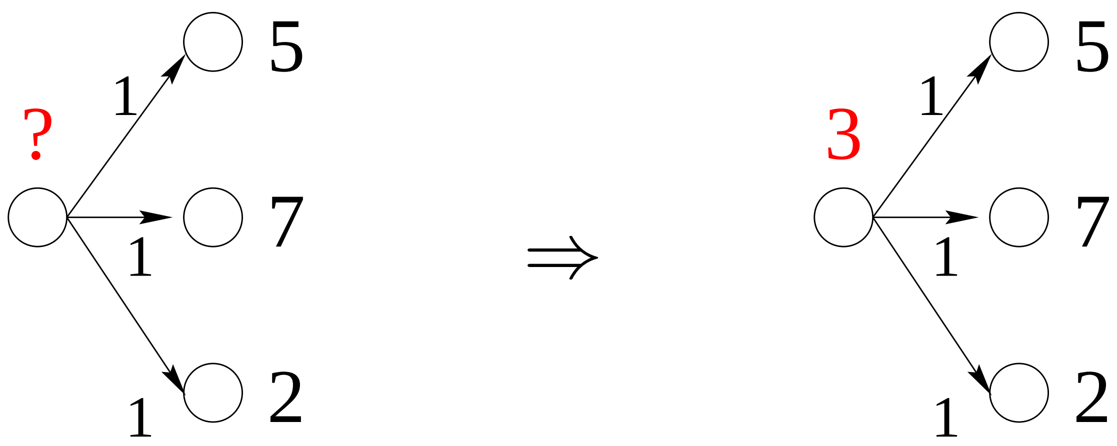
(Principle of Optimality (Bellman, 1959))

$\Rightarrow$Can we compute J^* (we will see why, soon)?

Computing J^*: the value iteration (VI) algorithm

Start with arbitrary $J_0(s)$

for all states s : $J_{k+1}(s) := \min_{a \in \mathcal{A}} \{c(s,a) + J_k(f(s,a))\}$



Convergence of value iteration

Value iteration converges under certain assumptions, i.e. we have $lim_{k\to\infty} J_k = J^*$

$\Rightarrow$ Discounted problems: $J^{\pi^*}(s) = \min_\pi \{\sum_t \gamma^t c(s_t, \pi(s_t)) | s_0 = s\}$ where $0 \leq \gamma < 1$ (contraction mapping)

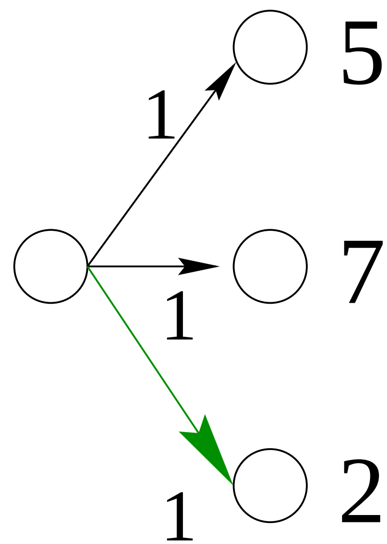
$\Rightarrow$ Stochastic shortest path problems:

- there exists an absorbing terminal state with zero costs
- there exists a 'proper' policy (a policy that has a non-zero chance to finally reach the terminal state)
- every non-proper policy has infinite path costs for at least one state

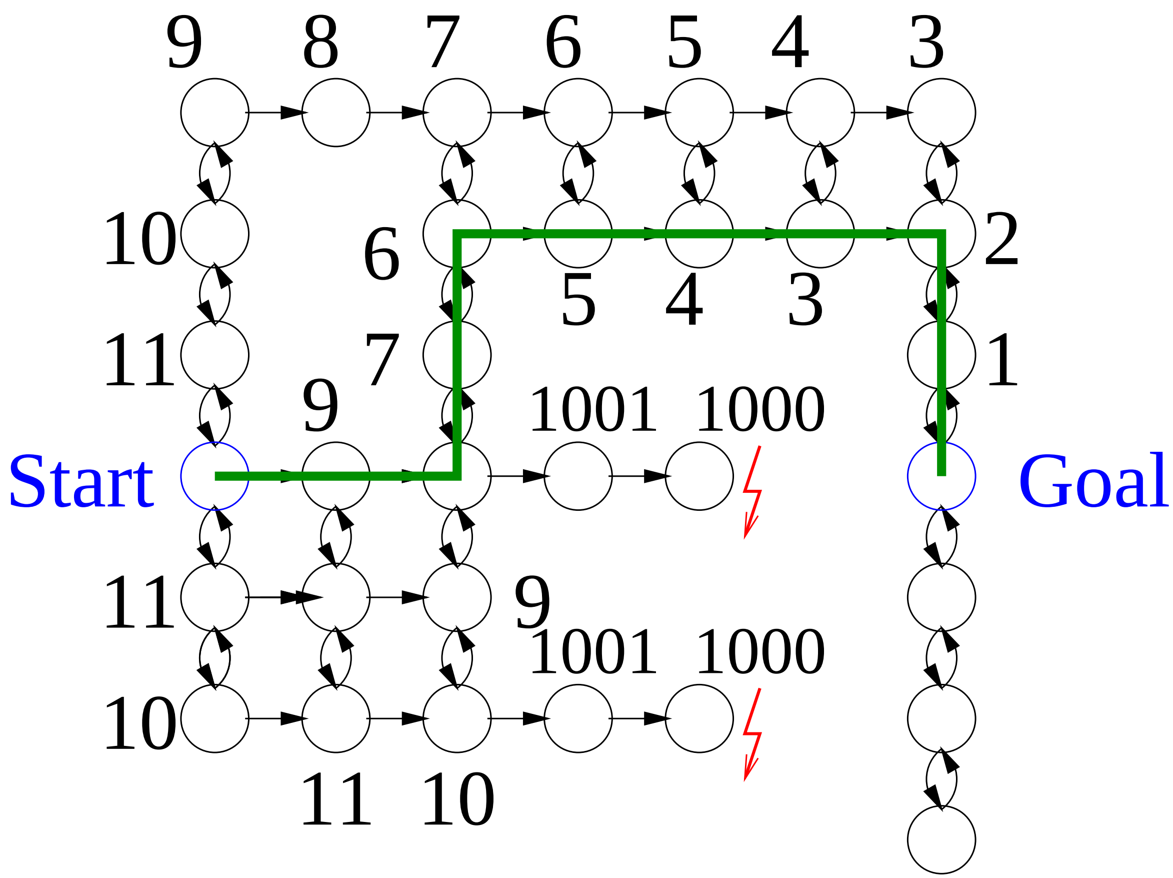
Ok, now we have J^*

$\Rightarrow$ when J^* is known, then we also know an optimal policy:

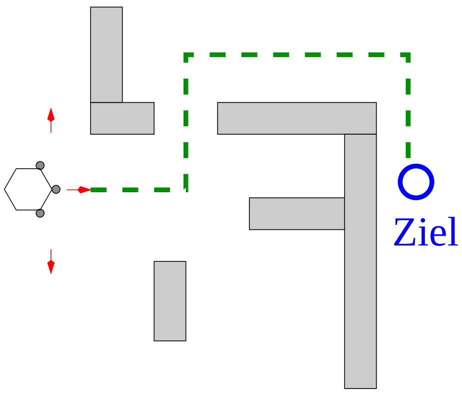
$$\pi^*(s) \in \arg\min_{a\in\mathcal{A}}\{c(s,a) + J^*(f(s,a))\}$$



Back to our maze

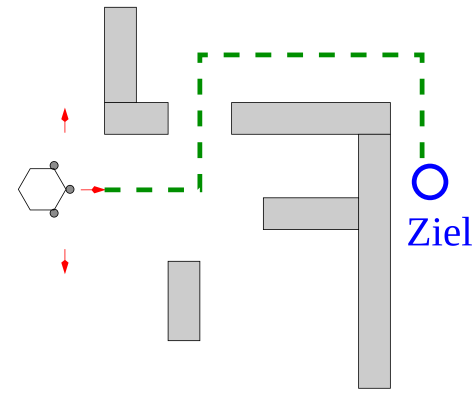


Overview of the approach so far



- Description of the learning task as an MDP
  S, A, T, f, c
  c specifies requested behaviour/ policy
- iterative computation of optimal pathcosts J^*:
  $\forall s \in \mathcal{S} : J_{k+1}(s) = \min_{a \in \mathcal{A}} \{c(s,a) + J_k(f(s,a))\}$
- Computation of an optimal policy from J^*
  $\pi^*(s) \in \arg\min_{a \in \mathcal{A}} \{c(s,a) + J^*(f(s,a))\}$
- value function ('costs-to-go') can be stored in a table

Overview of the approach: Stochastic Domains



- value iteration in stochastic environments:
  $\forall s \in \mathcal{S} : J_{k+1}(s) = \min_{a \in \mathcal{A}} \{ \sum_{s' \in S} p(s, s', a) \, (c(s, a) + J_k(s')) \}$
- Computation of an optimal policy from J^*
  $\pi^*(s) \in \arg\min_{a \in \mathcal{A}} \{ \sum_{s' \in S} p(s, s', a) \, (c(s, a) + J_k(s')) \}$
- value function J ('costs-to-go') can be stored in a table

Reinforcement Learning

Problems of Value Iteration:

for all $s \in \mathcal{S}$:$J_{k+1}(s) = \min_{a \in \mathcal{A}}\{c(s,a) + J_k(f(s,a))\}$

problems:

- Size of S (Chess, robotics, . . .) $\Rightarrow$ learning time, storage?
- 'model' (transition behaviour) $f(s,a)$ or $p(s', s, a)$ must be known!

Reinforcement Learning is dynamic programming for very large state spaces and/ or model-free tasks

Important contributions - Overview

- Real Time Dynamic Programming
  (Barto, Sutton, Watkins, 1989)

- Model-free learning (Q-Learning,(Watkins, 1989))

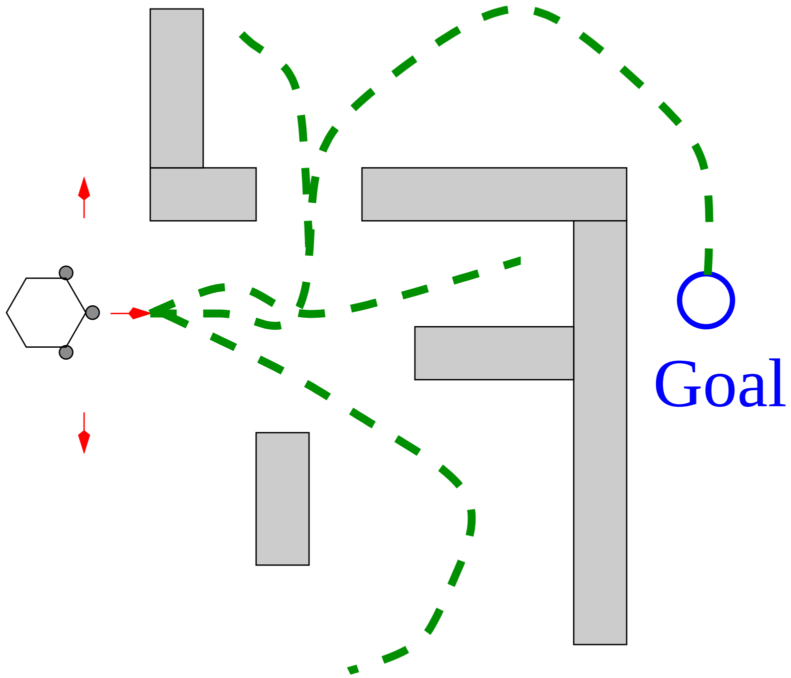
- neural representation of value function (or alternative function approximators)

Real Time Dynamic Programming (Barto, Sutton, Watkins, 1989)

Idea:

instead For all $s \in S$ now For some $s \in \mathcal{S}$ . . .

$\Rightarrow$ learning based on trajectories (experiences)



Q-Learning

Idea (Watkins, Diss, 1989):
In every state store for every action the expected costs-to-go.
$Q_\pi(s,a)$ denotes the expected future pathcosts for applying action a in state s (and continuing according to policy π):

$$Q_\pi(s,a) := \sum_{s' \in S} p(s',s,a)(c(s,a) + J_\pi(s'))$$

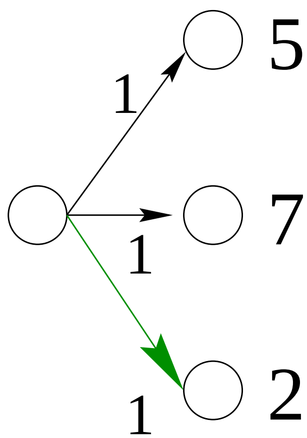
where $J_\pi(s')$ expected pathcosts when starting from s' and acting according to π

Q-learning: Action selection

is now possible without a model:

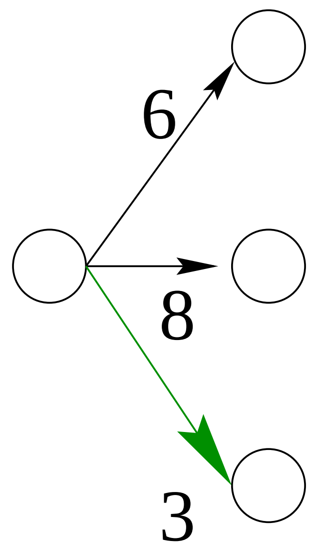
Original VI: state evaluation
Action selection:

$$\pi^*(s) \in \arg\min\{c(s,a)+J^*(f(s,a))\}$$



Q: state-action evaluation
Action selection:

$$\pi^*(s) = \arg\min Q^*(s,a)$$



Learning an optimal Q-Function

To find Q^*, a value iteration algorithm can be applied

$$Q_{k+1}(s,u) := \sum_{s' \in S} p(s',s,a)(c(s,a) + J_k(s'))$$

where $J_k(s) = \min_{a' \in \mathcal{A}(s)} Q_k(s,a')$

◇ Furthermore, learning a Q-function without a model, by experience of transition tuples $(s,a) \to s'$ only is possible:

Q-LEARNING (Q-Value Iteration + Robbins-Monro stochastic approximation)

$$Q_{k+1}(s,a) := (1-\alpha)\, Q_k(s,a) + \alpha\, (c(s,a) + \min_{a' \in \mathcal{A}(s')} Q_k(s',a'))$$

Summary Q-learning

Q-learning is a variant of value iteration when no model is available
it is based on two major ingredigents:

- uses a representation of costs-to-go for state/ action-pairs $Q(s, a)$
- uses a stochastic approximation scheme to incrementally compute expectation values on the basis of observed transititions $(s, a) \to s'$

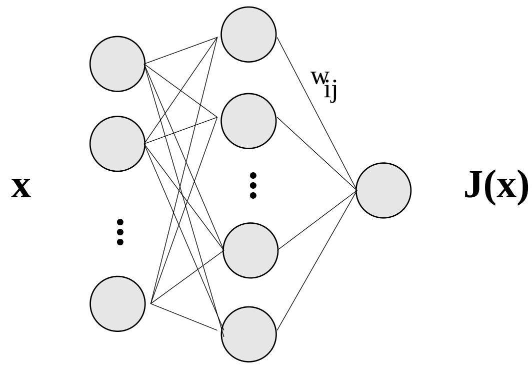
$\diamond$ converges under the same assumption as value iteration $+$ *'every state/ action pair has to be visited infinitely often'* $+$ conditions for stochastic approximation

Q-Learning algorithm

REPEAT
  start in arbitrary initial state s_0; $t = 0$
  REPEAT
    choose action greedily $u_t := \arg\min_{a \in \mathcal{A}} Q_k(s_t, a)$
    or u_t according to an exploration scheme
    apply u_t in the environment: $s_{t+1} = f(s_t, u_t, w_t)$
    learn Q-value:
    $Q_{k+1}(s_t, u_t) := (1 - \alpha) Q_k(s_t, u_t) + \alpha(c(s_t, u_t) + J_k(s_{t+1}))$
    where $J_k(s_{t+1}) := \min_{a \in \mathcal{A}} Q_k(s_{t+1}, a)$
  UNTIL Terminal state reached
UNTIL policy is optimal ('enough')

Representation of the path-costs in a function approximator

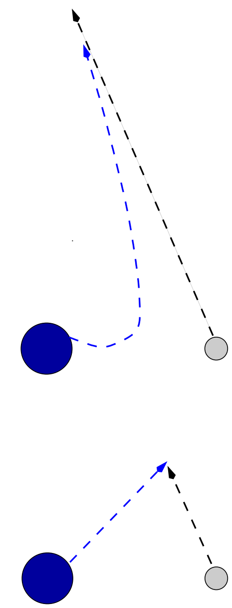
Idea: neural representation of value function (or alternative function approximators) (Neuro Dynamic Programming (Bertsekas, 1987))



$\Rightarrow$ few parameters (here: weights) specify value function for a large state space

$\Rightarrow$ learning by gradient descent: $\frac{\partial E}{\partial w_{ij}} = \frac{\partial (J(s') - c(s,a) - J(s))^2}{\partial w_{ij}}$

Example: learning to intercept in robotic soccer



- as fast as possible (anticipation of intercept position)
- random noise in ball and player movement $\rightarrow$ need for corrections
- sequence of TURN(θ)and DASH(v)-commands required

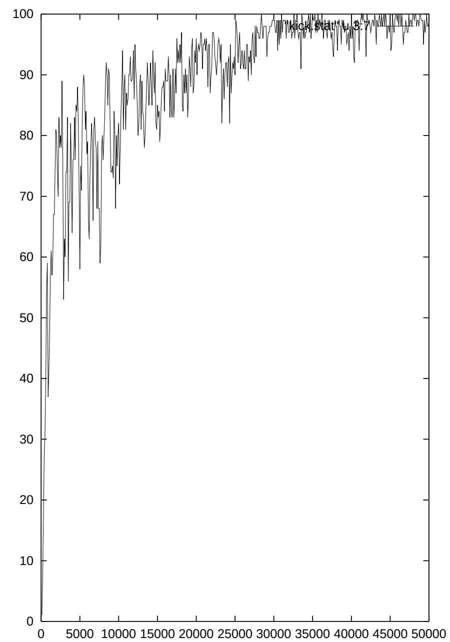
$\Rightarrow$handcoding a routine is a lot of work, many parameters to tune!

Reinforcement learning of intercept

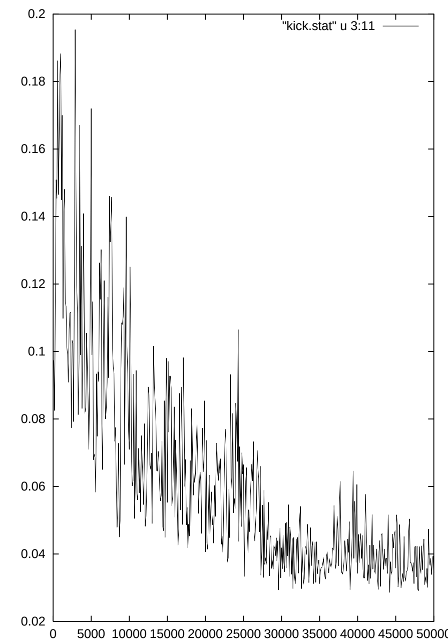
Goal: Ball is in kickrange of player

- state space: S^{work} = positions on pitch
- S^{+}: Ball in kickrange
- S^{-}: e.g. collision with opponent
- $c(s) = \begin{cases} 0 & , \quad s \in S^{+} \\ 1 & , \quad s \in S^{-} \\ 0.01 & , \quad else \end{cases}$
- Actions: $\textsc{turn}(10^o)$, $\textsc{turn}(20^o)$, ... $\textsc{turn}(360^o)$, ... $\textsc{dash}(10)$, $\textsc{dash}(20)$, ...
- neural value function (6-20-1-architecture)

Learning curves



Percentage of successes



Costs (time to intercept)