Reinforcement learning

Applied artificial intelligence (EDA132)
Lecture 13
2012-04-26
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Material based on course book, chapter 21 (17),
and on lecture "Belöningsbaserad inlärning / Reinforcement learning"
by Örjan Ekeberg, CSC/Nada, KTH, autumn term 2006 (in Swedish)

Outline

- Reinforcement learning (chapter 21, with some references to 17)
  - Problem definition
    - Learning situation
    - Roll of the reward
    - Simplified assumptions
    - Central concepts and terms
  - Known environment
    - Bellman's equation
    - Approaches to solutions
  - Unknown environment
    - Monte-Carlo method
    - Temporal-Difference learning
    - Q-Learning
    - Sarsa-Learning
  - Improvements
    - The usefulness of making mistakes
    - Eligibility Trace

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Note: The reward is not given in direct connection with a good choice of action *(temporal credit assignment)*

Note: The reward does not tell what exactly it was, that made the "good" action *(structural credit assignment)*

Real life examples

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Riding a bicycle

Powder skiing

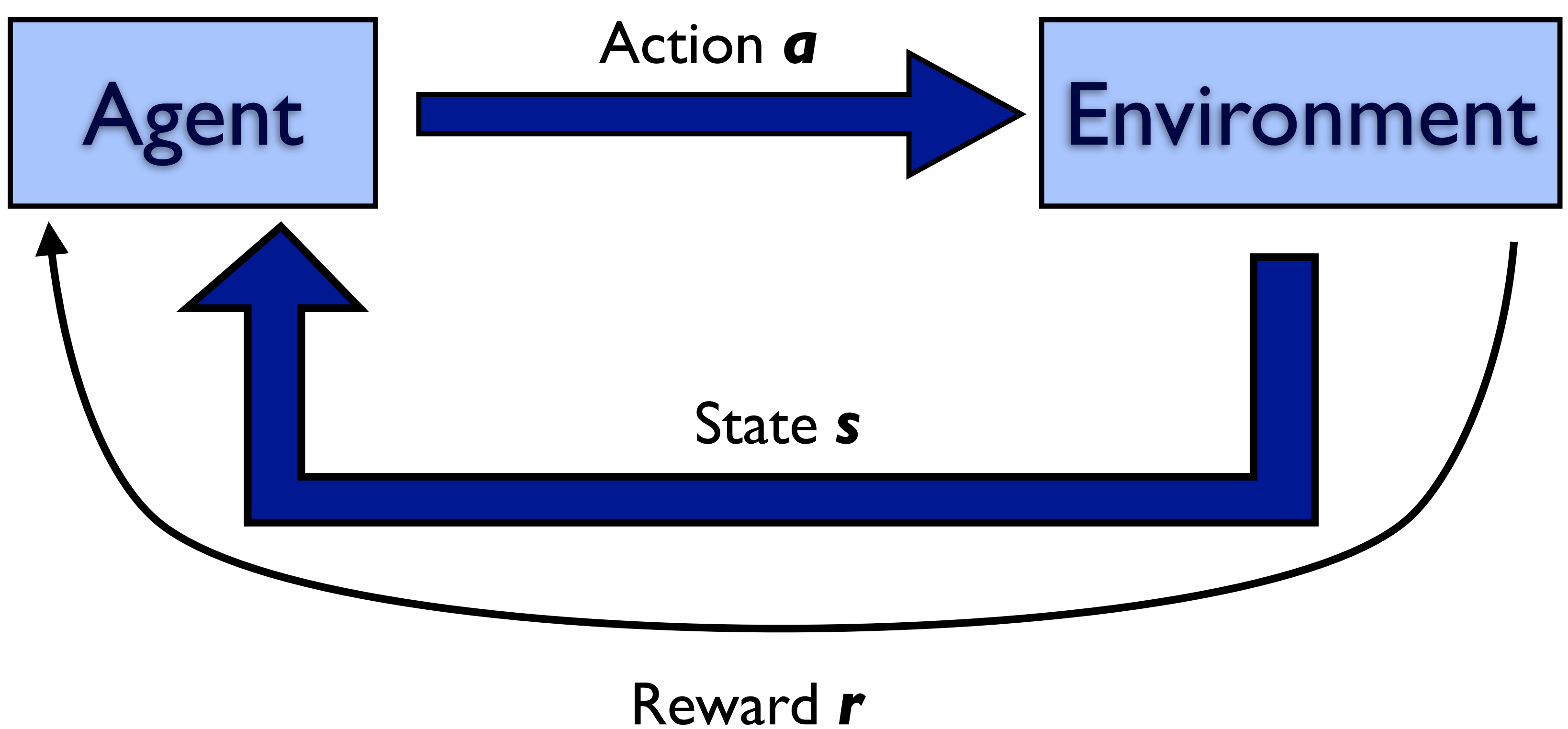
Learning situation: A model

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



Learning situation: The agent's task

The task:

Find a behaviour (action sequence) that maximises the overall reward

How long into the future should we spy?

Finite time horizon:

$$max\ E\left[\ \sum_{t=0}^{h}\ r_t\right]$$

Infinite time horizon:

$$max\ E\left[\ \sum_{t=0}^{\infty}\ \gamma^t\, r_t\right]$$

with γ being a discount factor for future rewards ($0 < \gamma < 1$)

The reward function's roll

The reward function depends on the type of task

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- Avoid mistakes (Riding a bike, Learning to fly according to hitchhiker's guide): Reward -1 when failing (falling)
- Find the shortest / cheapest / fastest path to a goal: Reward -1 for each step

A classic example: Grid World

Simplified "Wumpus world" with just two gold pieces

G			
			G

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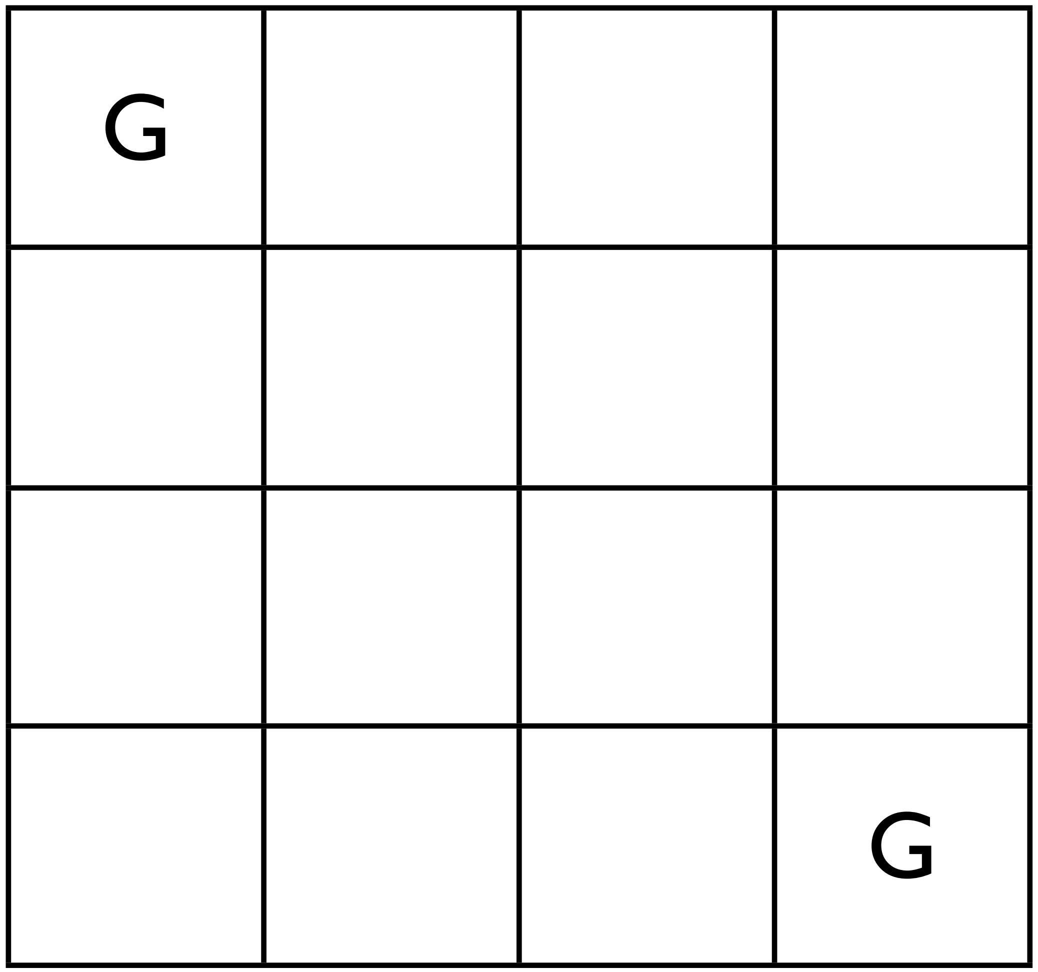
- Every state s_j is represented by a field in the grid



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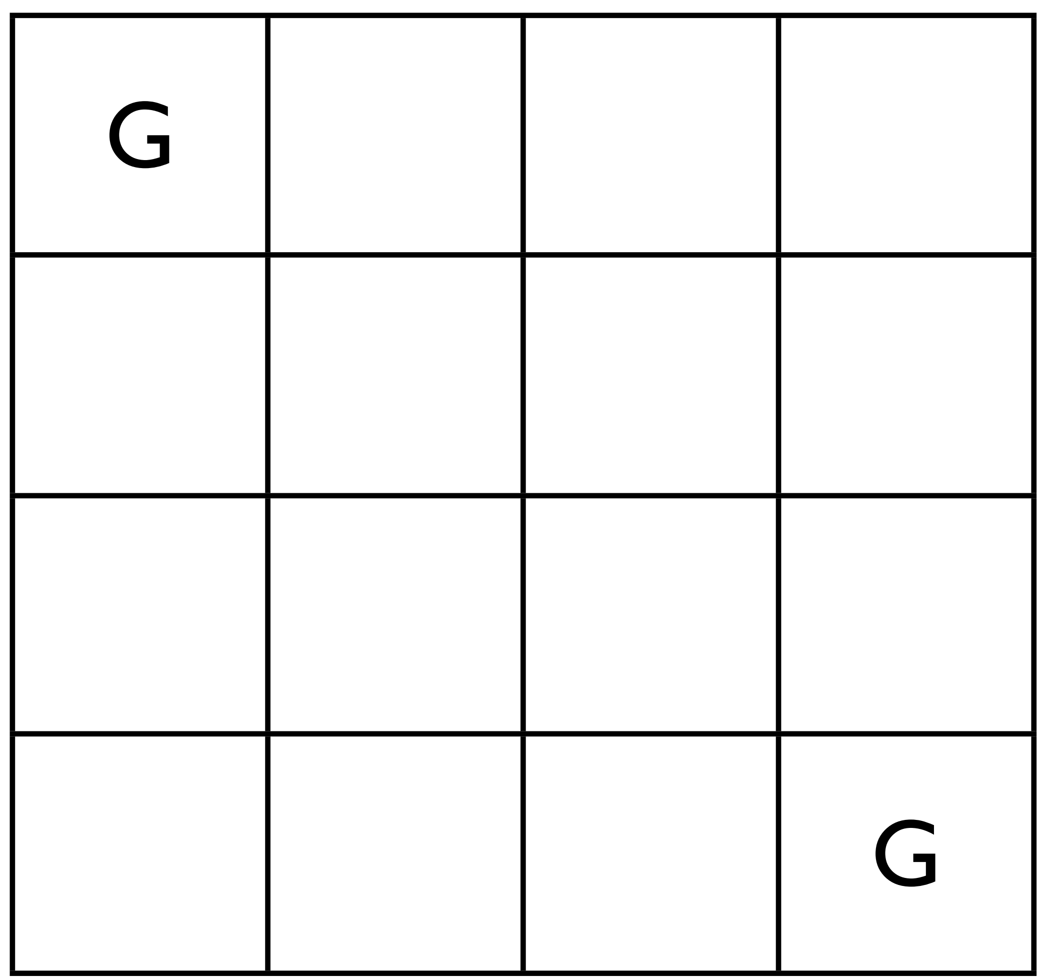

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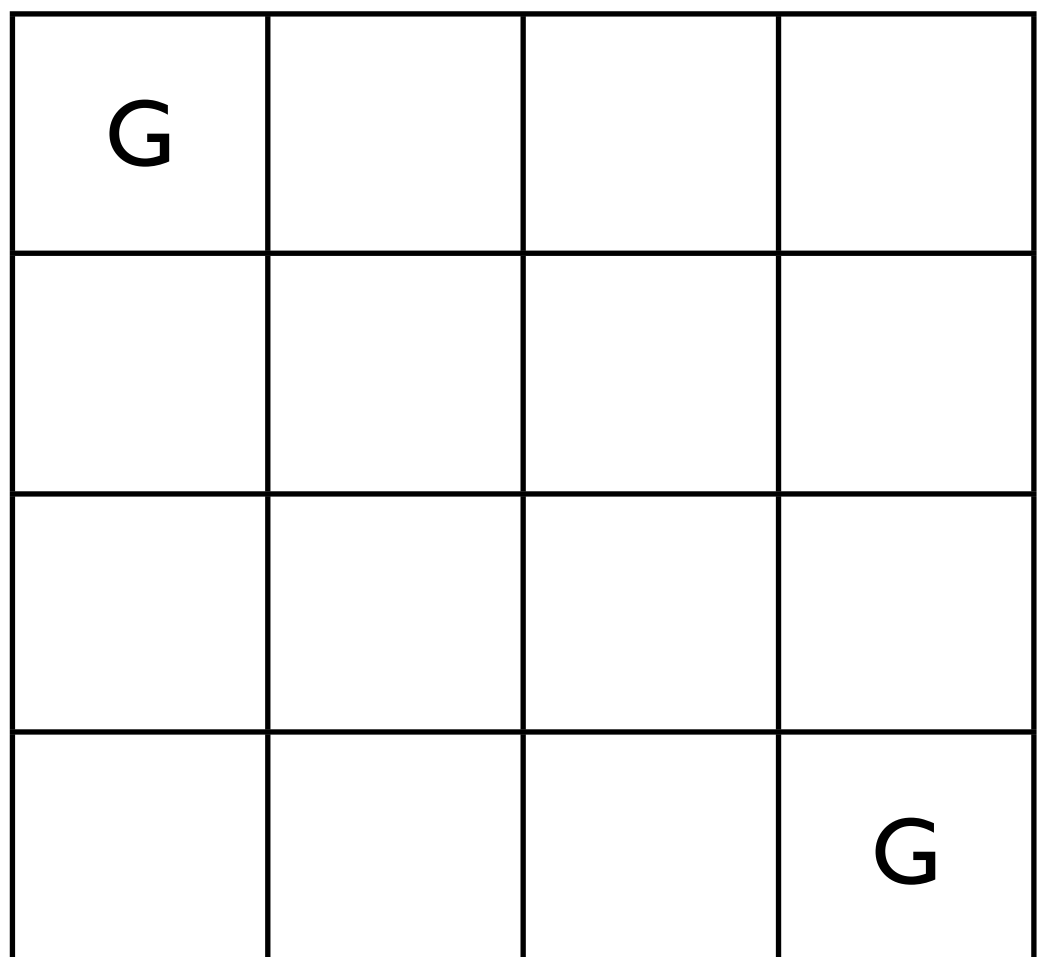
- Every state s_j is represented by a field in the grid
- Action *a* the agent can choose consists of moving one step to a neighbouring field
- *Reward*: -1 in every step until one of the goals (G) is reached.



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- The context is a constant MDP (*Markov Decision Process*), where reward and new state s' only depend on s, a, and (random) *noise*
- Environment is observable

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$$\pi(s) \longmapsto a$$

- An agent’s *utility function* U describes the expected future reward given s, when following policy π

$$U^{\pi}(s) \longmapsto \Re$$

Grid World: A state's value

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0	-1	-2	-3
-1	-2	-3	-2
-2	-3	-2	-1
-3	-2	-1	0

U with optimal policy

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U with optimal policy

0	-14	-20	-22
-14	-18	-22	-20
-20	-22	-18	-14
-22	-20	-14	0

U with random policy

A 4x3 world

- Fixed policy - passive learning.

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U		U	-1
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0.812	0.868	0.918	+1
0.762		0.660	-1
0.705	0.655	0.611	0.388

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Environment model

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- Where do we get in each step?

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The utility values of different states obey *Bellman's equation*, given a fixed policy π:

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

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

Recap: Random policy

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-20	-22	-18	-14
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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"

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

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This means to assume a prior probability for each hypothesis on how the model might look like and then applying Bayes' rule to obtain the posterior.

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We are not going into details here!

Finding optimal policy and value function

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Tricky to solve ... but possible:

Combine policy and value iteration by switching in each iteration step

Policy iteration

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For each iteration step k:

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

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

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- Start with a randomly chosen s
- Follow a policy π, store rewards and s_t for the step at time t
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Converges slowly...

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Or: What the agent believes *before* acting

$U^{\pi}(s_t)$

and *after* acting

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

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Converges significantly faster than the pure Monte Carlo approach.

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

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

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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

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- 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.

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

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- 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'

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until T steps.

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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.

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

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

- Game playing.
  - A. Samuel's checkers program (1959). Remarkable: did not use any rewards... but was managed to converge anyhow...
  - G. Tesauro's backgammon program from 1992, first introduced as Neurogammon, with a neural network representation of Q(s, a). Required an expert for tedious training ;-) The newer version TD-gammon learned from self-play and rewards at the end of the game according to generalised TD-learning. Played quite well after two weeks of computing time ...
- Robotics
  - Classic example: the inverse pendulum (cart-pole). Two actions: jerk right or jerk left (bang-bang control). First learning algorithm to this problem applied in 1968 (Michie and Chambers), using a real cart!
  - More recently: Pancake flipping ;-)

Flipping ... a piece of (pan)cake?

Video from programming-by-demonstration.org
(Dr. Sylvain Calinon & Dr. Petar Kormushev)

Homework for Machine Learning

- Homework 3 is related to machine learning, announced on the course page
- Choose between 3a, 3b, 3c (or do several), but only one (the best) will contribute in the end as homework 3
- 3c is in the area of today's lecture (slides will be provided after the lecture ;-)
- The task: get a little two-legged agent ("robot") to learn to "walk"
- Some programming effort is involved (instructions provided)
- Main idea is to explore different reinforcement learning approaches and compare their effect on the agent's success (or failure...) and report on the experience
- A series of images for "animation" of the agent is provided
- Support methods for the "animation" of the agent's walk are provided in Matlab and Python (transferring to Java should also be easily possible, the Matlab code is less than 30 lines long)

Homework for Machine Learning cont'd

- Seemingly "simple" task - just doing it gives a grade 3 at maximum.
- BUT: the important part of this task is the INTERPRETATION and DISCUSSION of results, which should be done in a thoroughly prepared and written REPORT. Please make sure you have read the instructions carefully before starting the work!

- Deadline for handing in: May 10, 2012.