Reinforcement Learning

Goal definition and examples

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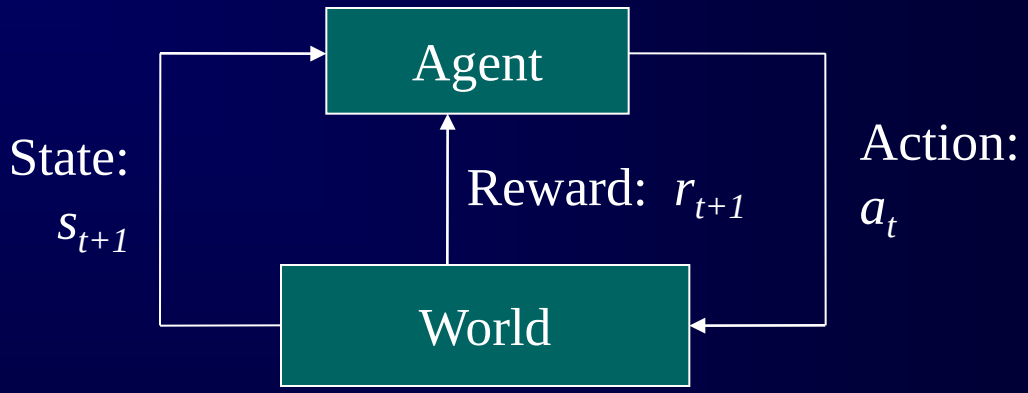
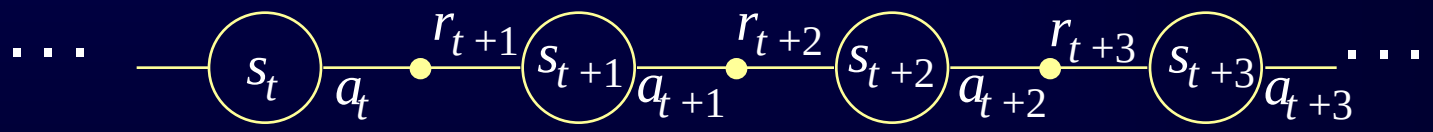
The Agent-Environment Interaction





$$r_{t+1} \in \Re$$

Goals and Rewards

- Is a scalar reward signal an adequate notion of a goal?—maybe not, but it is surprisingly flexible.
- A goal should specify **what** we want to achieve, not **how** we want to achieve it.
- A goal must be outside the agent's direct control—thus outside the agent.
- The agent must be able to measure success:
  - explicitly;
  - frequently during its lifespan.

Long Term Reward

- Learning a mapping from situations to actions to maximize long-term reward without using a model of the world
- Long term reward must be defined in terms of the goal of the agent
- Definition of long-term reward must be derived from local rewards

Finite horizon long-term reward

- First intuitive idea: sum of all rewards obtained.

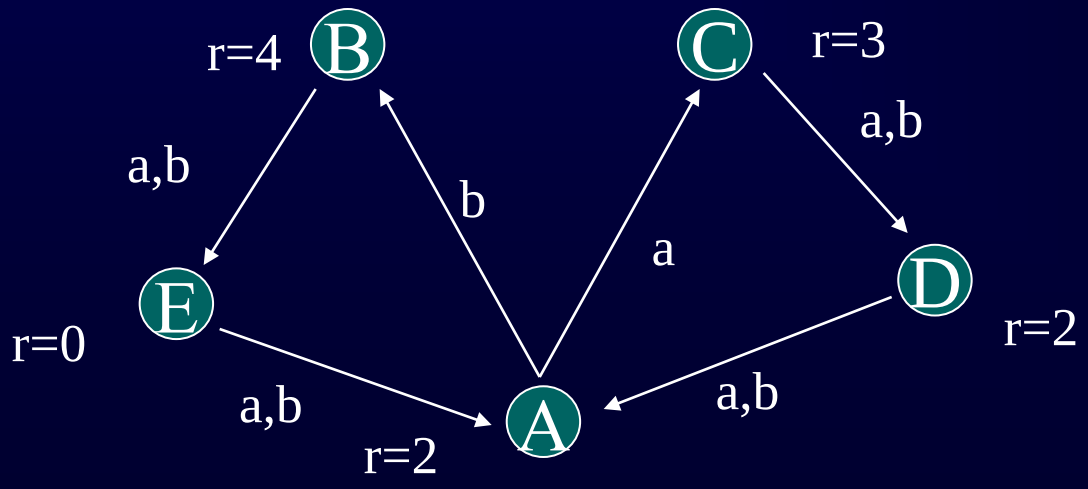
$$\sum_{k=t+1}^{\infty} r_k$$

- Problem: sum must be limited because it can take too large values (infinite values in non-ending tasks)

$$\sum_{k=t+1}^{T} r_k$$

Finite Horizon Rewards: Problems

- Limit must be chosen depending on the current task
- Problems: non stationary policies when the limit is not large enough



Finite Horizon Rewards: Conclusions

- Drawbacks
  - Not useful for non-ending tasks
  - Choose for each task the limit
  - Non stationary when limit is not well chosen
- Nevertheless, finite horizon rewards can be used when:
  - Behavior can be learned in trials
  - Each trial is limited by a max. number of actions to execute and it can be estimated beforehand

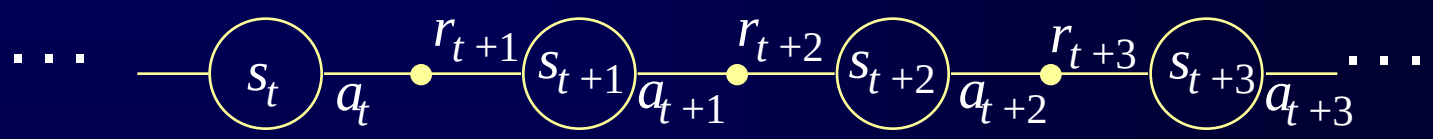
Discounted Infinite Horizon long-term Reward

- Weighted addition of local rewards

$$\sum_{k=t+1}^{\infty} \gamma^{k-t-1} r_k$$

- The γ parameter ($0 < \gamma < 1$) is called *discounting factor*

Discounted Infinite Horizon long-term Reward



$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

Discounted Infinite Horizon Reward

- Advantages
  - Finite values for non-ending (or infinite) tasks

    In the best case, (always maximum reinforcement “r”)

$$\sum_{i=1}^{\infty} \gamma^{i-1} r = r \sum_{i=0}^{\infty} \gamma^{i} = r \frac{1}{1-\gamma}$$

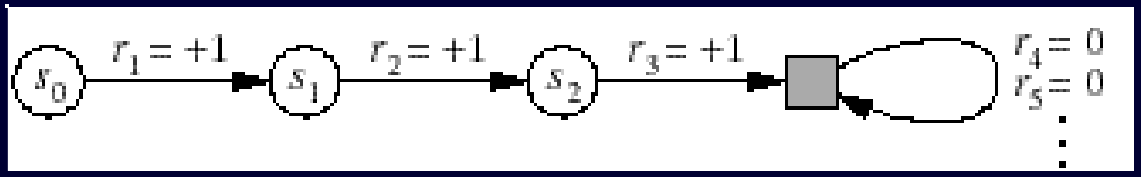
  - Greedy policies are always stationary
  - Elegant

Infinite Horizon Rewards

- Problem:
  - Close reinforcements are preferred over delayed reinforcements due to the discounting factor
- This is not always bad. Bias for immediate rewards
- In order to limit this problem, the γ value is chosen very close to 1 (from 0.9 up)

Infinite Horizon Rewards

- Discounted reward is the usual formalism in reinforcement learning, (also in tasks that can be expressed in trials because them can be reformulated in a continuous infinite trial)
- Discounted reward can cover episodic learning (Think of each episode as ending in an absorbing state that always produces reward of zero)



Differences With Supervised Learning

- No right answer, only evaluation
- No yes/no possibilities (learning values)

  Assume two actions

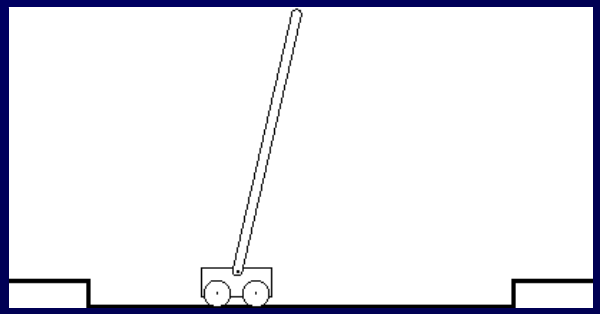
  $s,a_1 \rightarrow$ *punish* does not imply $s,a_2 \rightarrow$ *reward*

- No local evaluation, but global evaluation

Examples

- Robotics, pole-balancing
- Chess, backgammon, etc
- Industrial applications: (optimization tasks) elevator dispatching, job-shop scheduling, ATM facturing

An Example: Pole-balancing

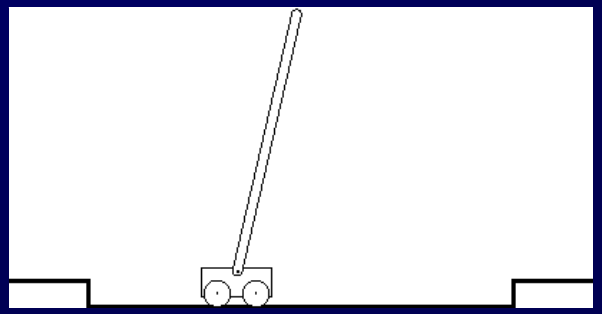


Avoid **failure:** the pole falling beyond a critical angle or the cart hitting end of track.

Situations: Dynamic states of the cart-pole system
[Discretized velocity, angle, position]

Actions: Push left, Push Rigth

An Example: Pole-balancing



Avoid **failure:** the pole falling beyond a critical angle or the cart hitting end of track.

As an **episodic task** where episode ends upon failure:

$$\text{reward} = +1 \text{ for each step before failure}$$

$$\Rightarrow \text{return} = \text{number of steps before failure}$$

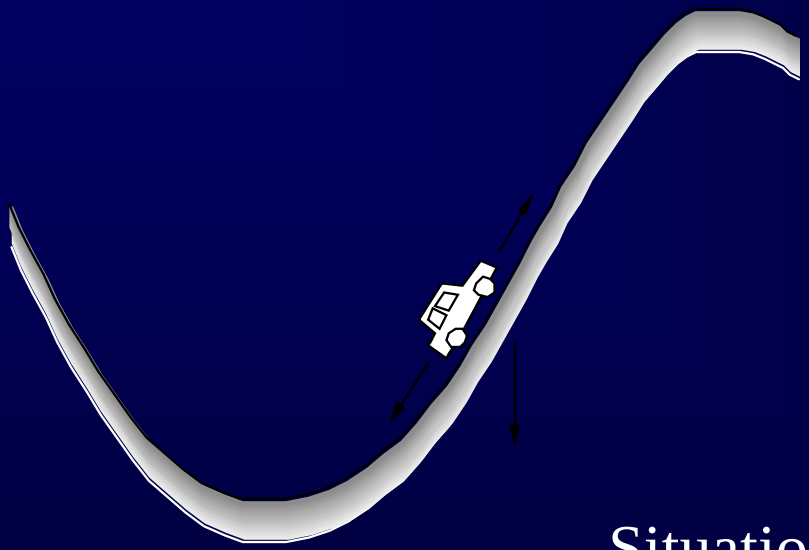
As a **continuing task** with discounted return:

$$\text{reward} = -1 \text{ upon failure; } 0 \text{ otherwise}$$

$$\Rightarrow \text{return} = -\gamma^k, \text{ for } k \text{ steps before failure}$$

In either case, return is maximized by avoiding failure for as long as possible.

Another example: Mountain Car Problem

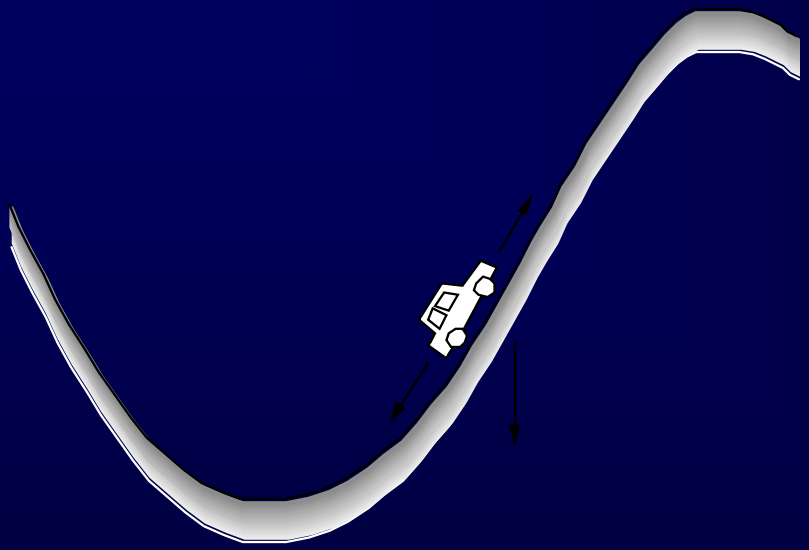


Get to the top of the hill
as quickly as possible.

Situations: Car's position and velocity

Actions: forward, reverse, none

Another example: Mountain Car Problem



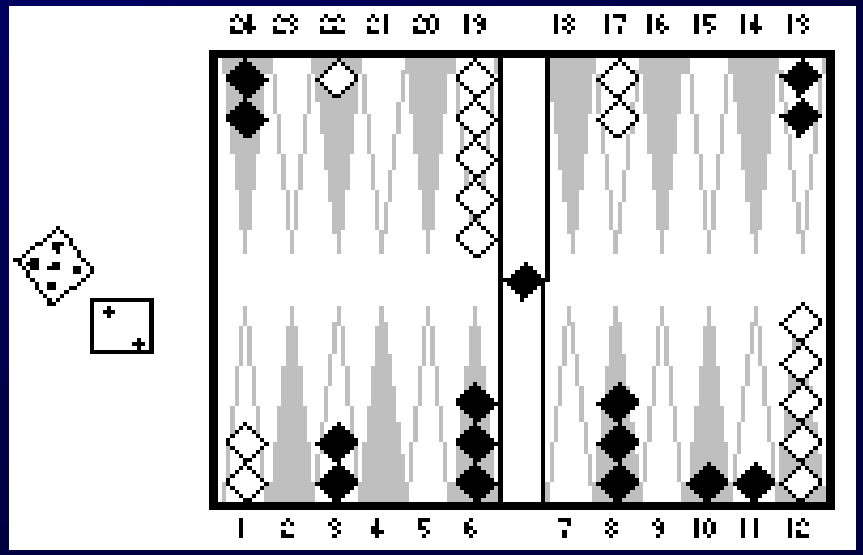
Get to the top of the hill
as quickly as possible.

reward $= -1$ for each step where **not** at top of hill

$\Rightarrow$ return $=$ – number of steps before reaching top of hill

Return is maximized by minimizing
number of steps reach the top of the hill.

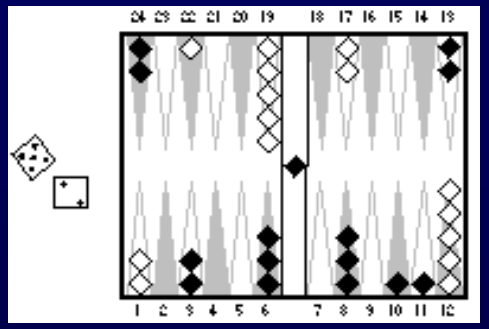
Backgammon

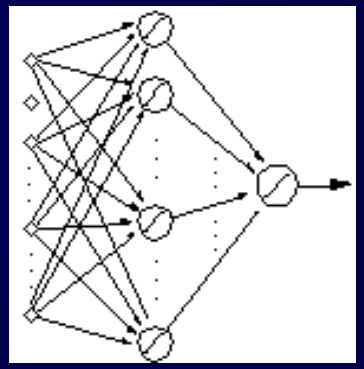


Situations: Configurations of the playing board (about 10^{20})
Actions: Legal moves at each turn
Rewards: Win +1, Lose -1, else 0

TD-Gammon

Tesauro, 1992–1995





Value

Action selection by 2–3 ply search

Start with a random network

Play very many games against self

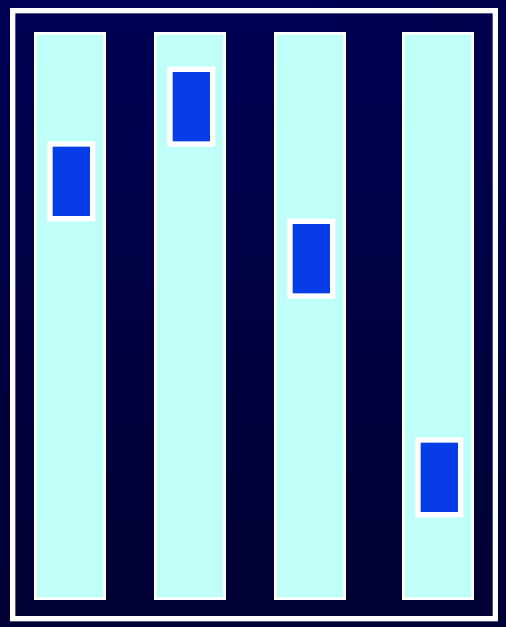
Learn a value function from this simulated experience

This produces arguably the best player in the world

Elevator Dispatching

Crites and Barto, 1996

10 floors, 4 elevator cars



STATES: button states; positions, directions, and motion states of cars; passengers in cars & in halls

ACTIONS: stop at, or go by, next floor

REWARDS: roughly, –1 per time step for each person waiting

Conservatively about 10^{22} states

Performance Comparison