AI and Games

Model-Based Learning

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Model-based learning

Main Idea:

- Random trajectories (a lot)
- Until each transition is visited several times.
- Compute an optimal policy.

Potentially:

- Require drived exploration to go in every 'niche'
- But generally: only incomplete exploration can be performed

But first the Model

Markov Decision Process

A framework for modeling stochastic evolution of the system to control.

Bellman equation

Recursive evaluation of states to compute expected gains.

Solving algorithms

- Value iteration
- Policy iteration

MDP: $\langle S, A, T, R \rangle$:

S : set of system's states

A : set of possible actions

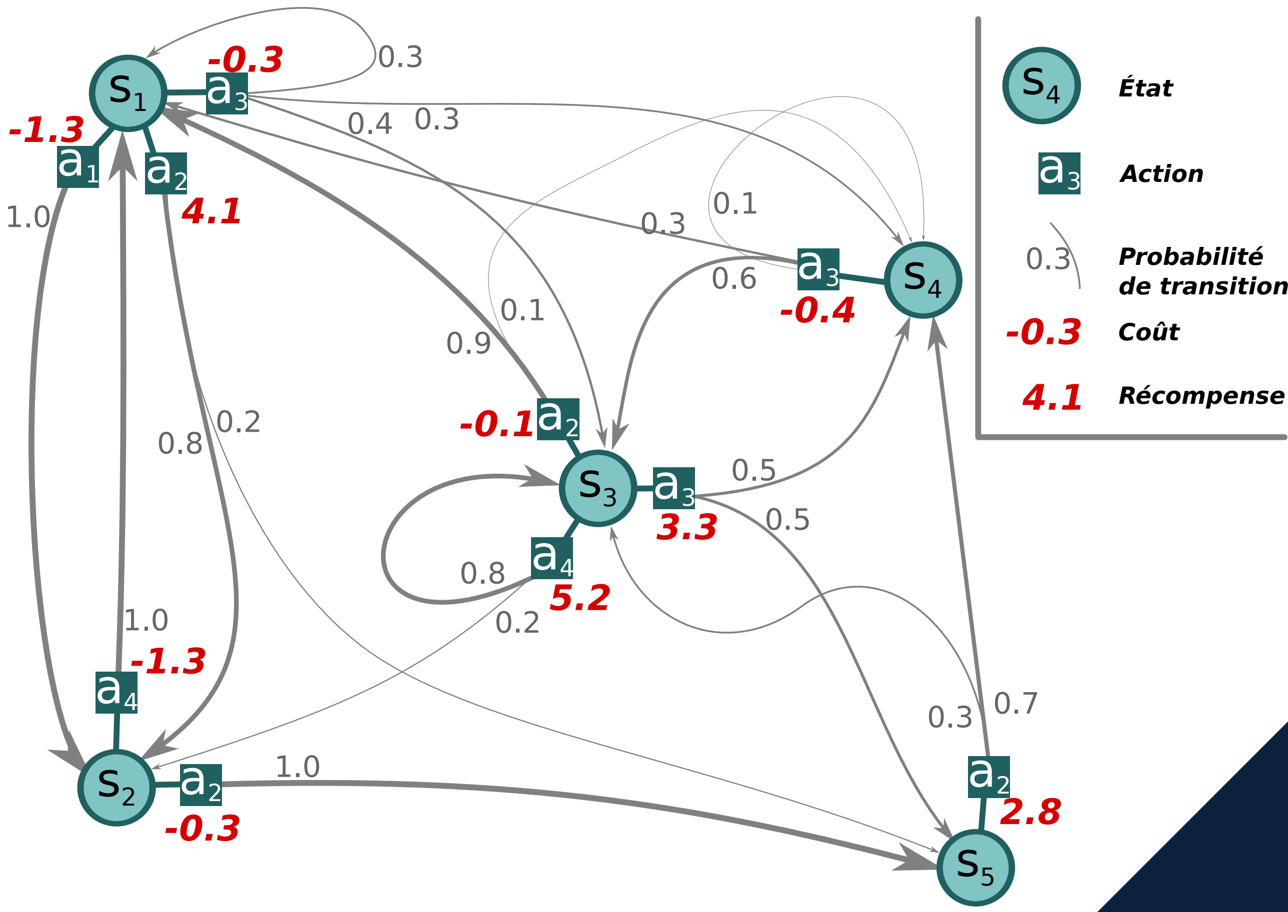
T : S × A × S → [0, 1] : transitions

R : S × A → R : average cost/rewards

Optimal policy:

π: a function returning the action to perform in each crossed states.

π^*: the optimal policy maximizing the gains (expected cumulated rewards).



Bellman Equation

State evaluation for a given policy π :

$$V^{\pi}(s) = R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \times V^{\pi}(s')$$

with : $a = \pi(s)$ and $\gamma \in [0,1]$ the discount factor (typically 0.99)

As a sum of gains:

- The immediate reward: $R(s,a)$.
- The future gains $V^{\pi}(s')$, for all possible next states $s' \in S$,
- proportionally to the probability to reach them $T(s,a,s')$

Solving MDP: Value Iteration

Input: an **MDP:** $\langle S, A, T, R \rangle$; precision error: ϵ ; discount factor: γ ; initial **V(s)**

1. Repeat until: **maximal delta <** ϵ

   For each state $s \in S$

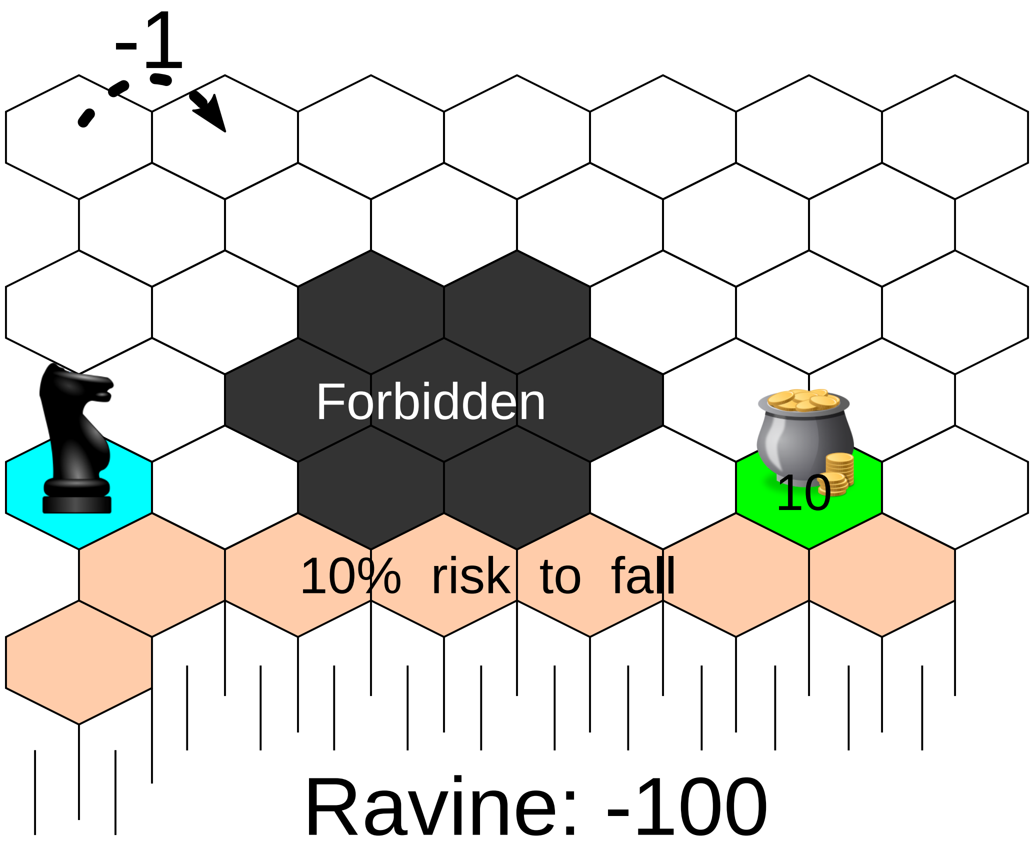
   - Search the action a^* maximizing the Bellman Equation on s
   - Update $\pi(s)$ and $V(s)$ by considering action a^*
   - Compute the delta value between the previous and the new $V(s)$

Output: an optimal π^* and associated V-values

Bellman Equation:

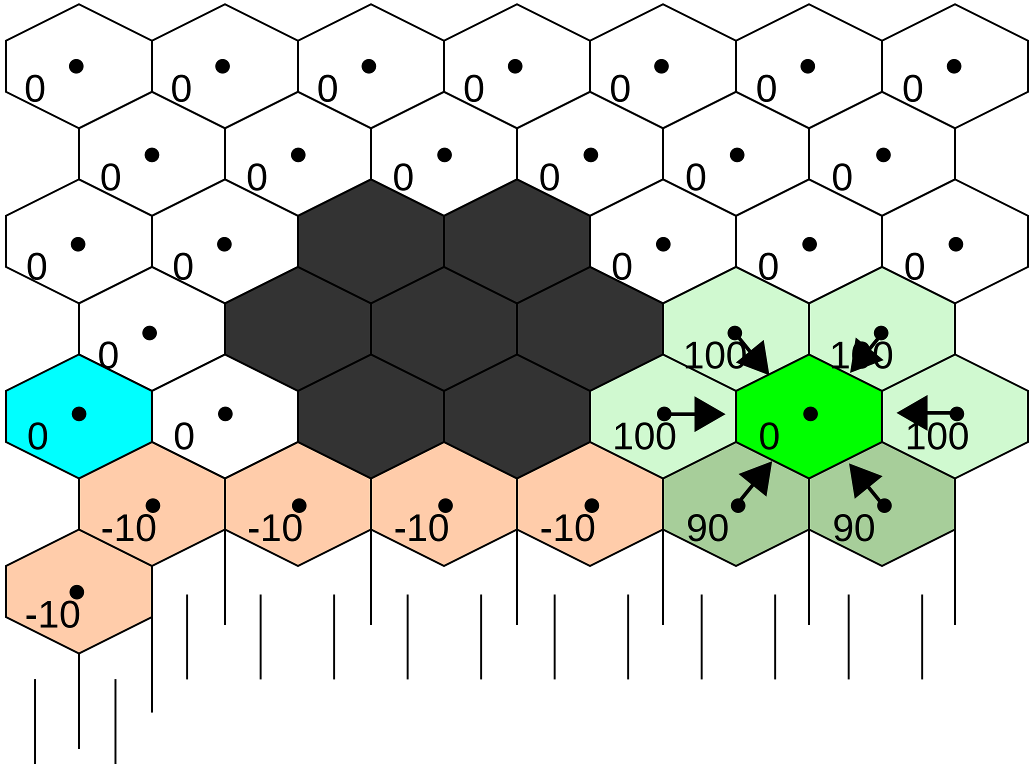
$$a^* = \arg\max_{a \in A} \left(R(s,a) + \gamma \sum_{s' \in S} T(s,a,s') \times V(s') \right)$$

Example: Dangerous move.



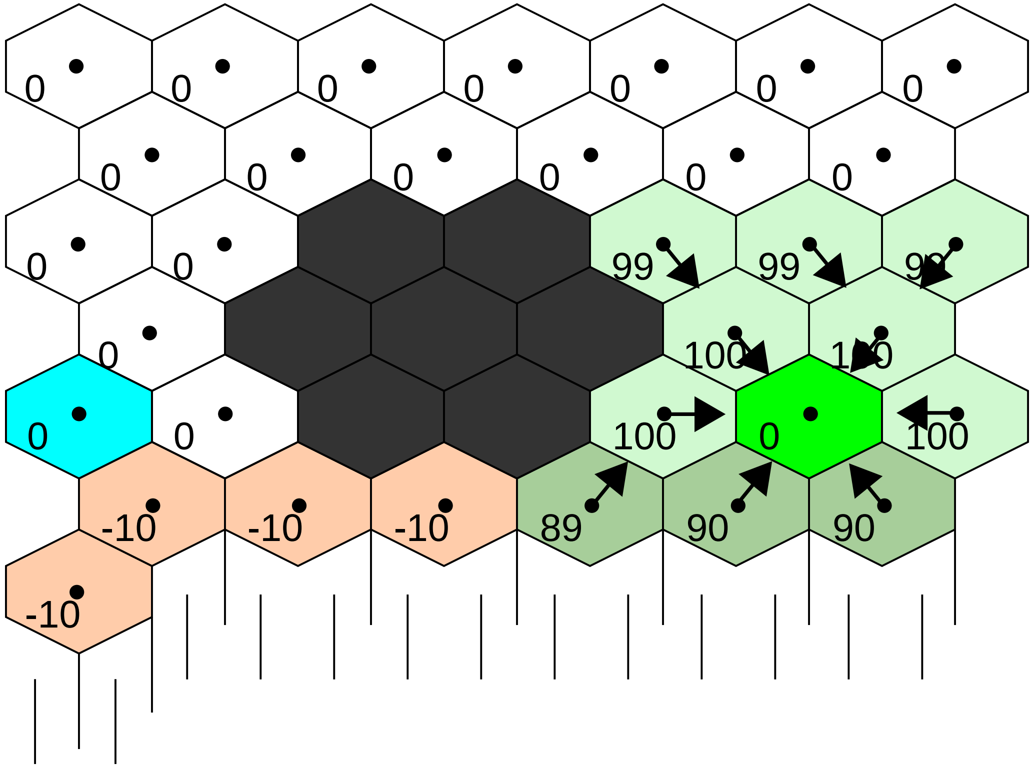
Probleme definition

Example: Dangerous move.



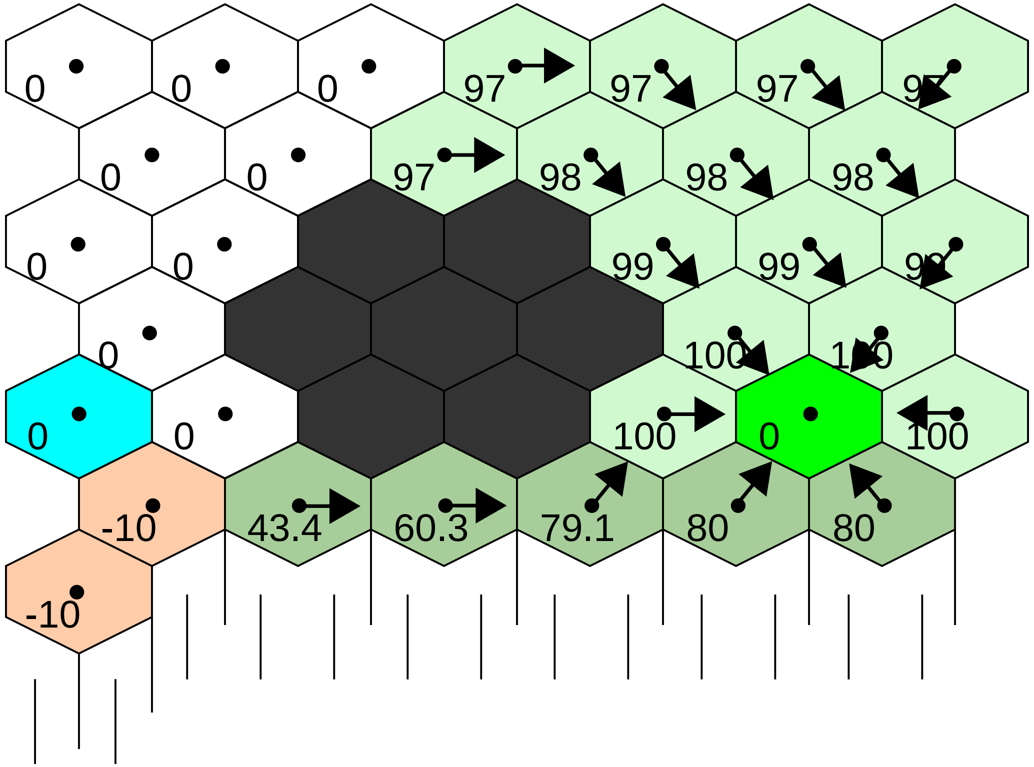
Value-Iteration: first iteration

Example: Dangerous move.



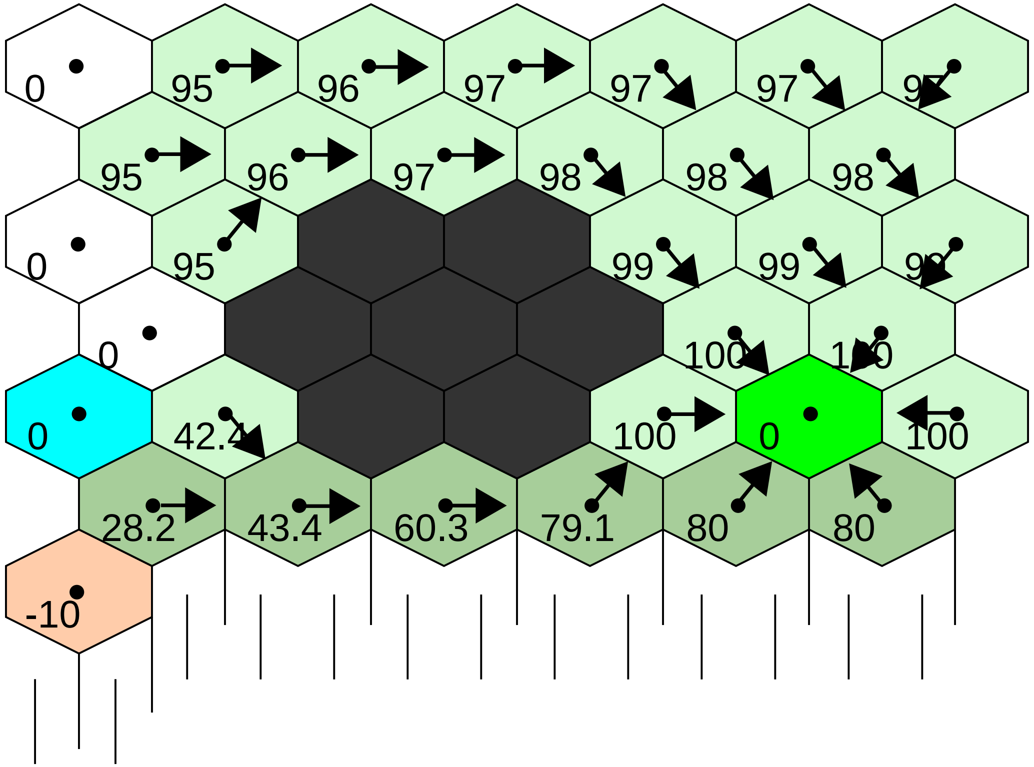
Value-Iteration: second iteration

Example: Dangerous move.



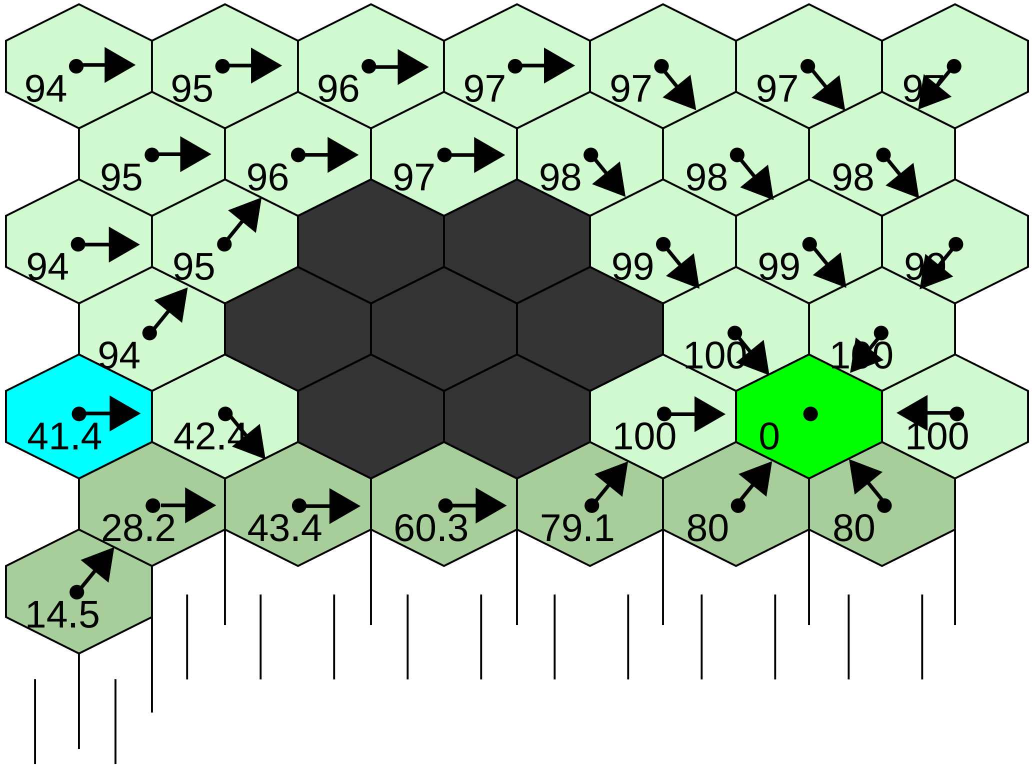
Value-Iteration: 4^{th} iteration

Example: Dangerous move.



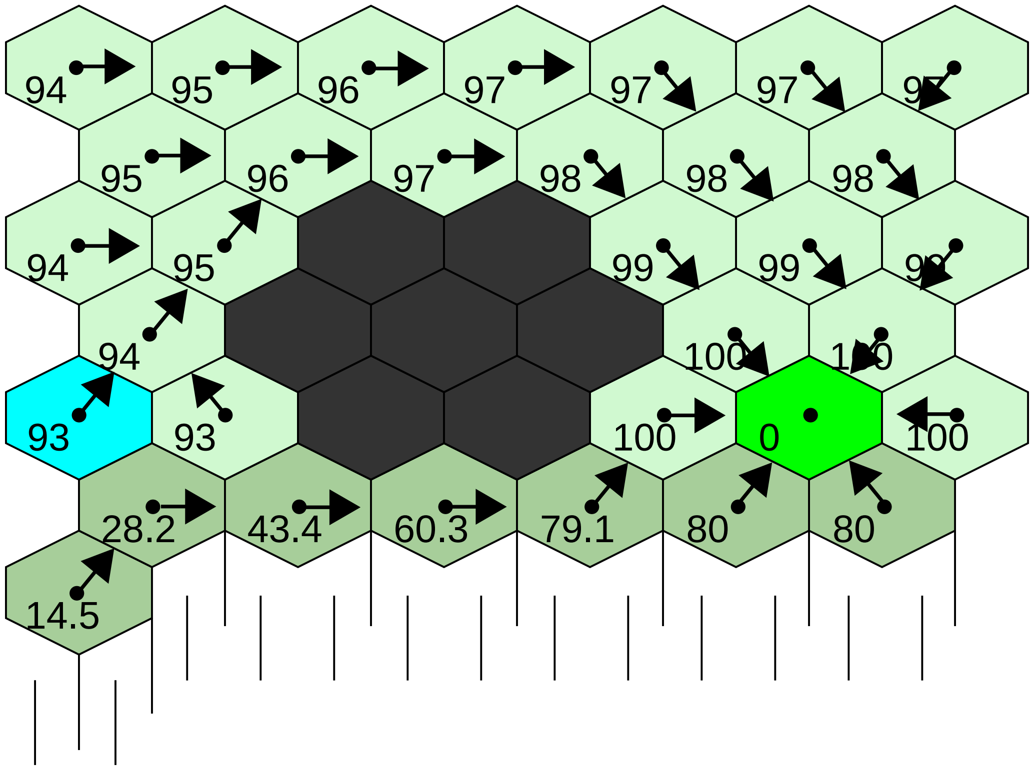
Value-Iteration: 6^{th} iteration

Example: Dangerous move.



Value-Iteration: 7^{th} iteration

Example: Dangerous move.



Value-Iteration: 8^{th} iteration

Solving MDP: Policy Iteration

Input: an **MDP:** $\langle S, A, T, R\rangle$; precision error: ϵ ; discount factor: γ ; initial **V(s)**

1. Compute $\pi(s)$ according to $V(s)$, for each state $s \in S$
2. Repeat until $\pi(s)$ is stable:
   - Update $V(s)$ with $\pi(s)$ at ϵ error, for each state $s \in S$
   - Update $\pi(s)$ according to $V(s)$, for each state $s \in S$

Output: an optimal π^* and associated V-values

Ok now learn the model...

- Define the state-space (small but covering).
- Define the action-space.
- Explore the system:
  - Compute the average rewards $R(s, a)$.
  - Compute all transition probability $T(s, a, s')$

Learn the transition

The transition function is the core object to learn.

It is a 3-dimension structure of floating point values (probabilities).

$$|S|^2 \times |A| \text{ values.}$$

A simple game as **421** with **168** states and **8** actions
would requires **225 792** values.

Luky for us, in application, most of the transitions are null (ie. imposible).