Markov Decision Processes and Exact Solution Methods:

Value Iteration
Policy Iteration
Linear Programming

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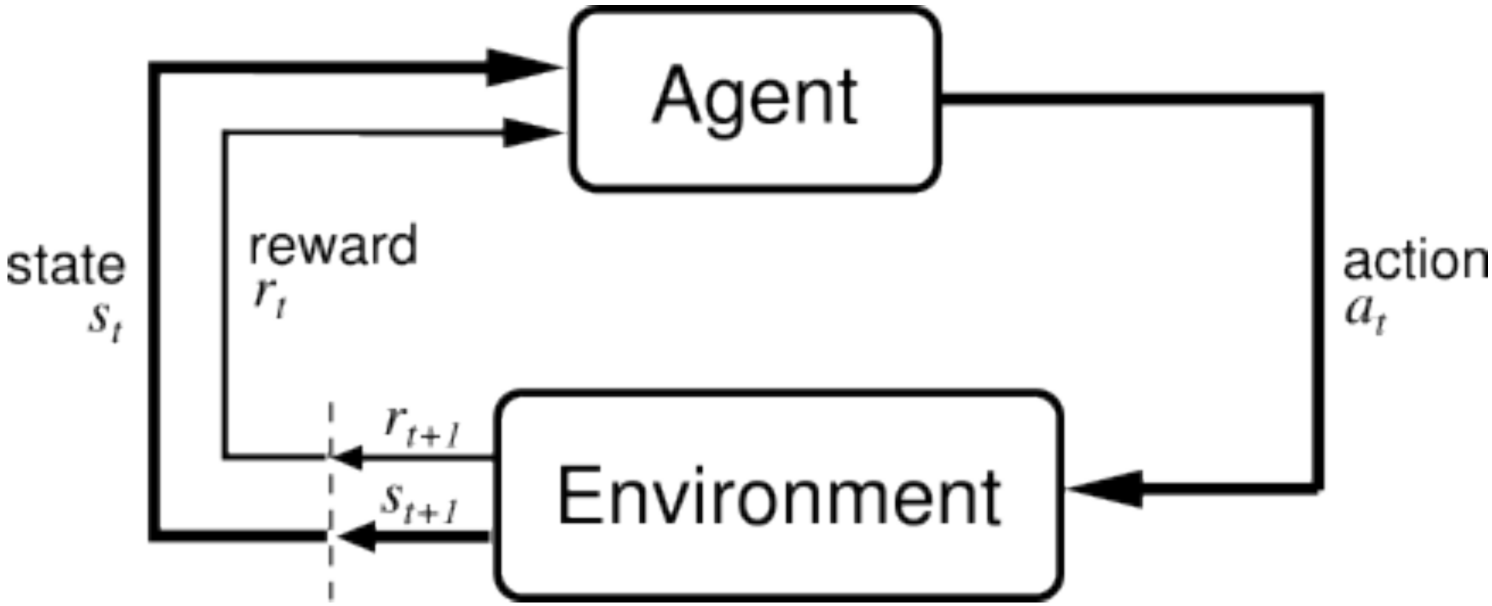
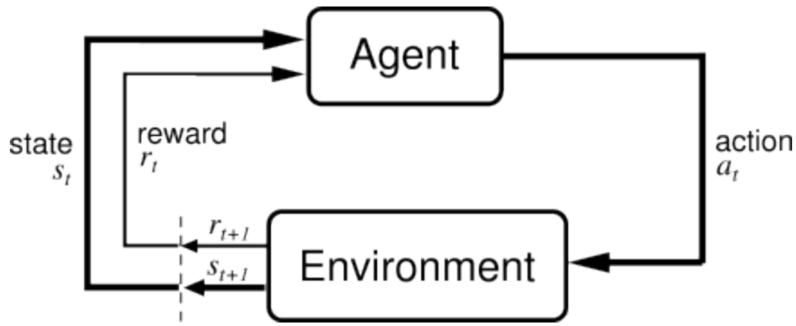
Markov Decision Process



Assumption: agent gets to observe the state

[Drawing from Sutton and Barto, Reinforcement Learning: An Introduction, 1998]

Markov Decision Process (S, A, T, R, H)



Given

- S: set of states
- A: set of actions
- T: S x A x S x {0,1,…,H} → [0,1], $T_t(s,a,s') = P(s_{t+1} = s' \mid s_t = s, a_t = a)$
- R: S x A x S x {0, 1, …, H} → $\Re$ $R_t(s,a,s')$ = reward for ($s_{t+1} = s'$, $s_t = s$, $a_t = a$)
- H: horizon over which the agent will act

Goal:

- Find π : S x {0, 1, …, H} → A that maximizes expected sum of rewards, i.e.,

$$\pi^* = \arg\max_{\pi} \mathrm{E}[\sum_{t=0}^{H} R_t(S_t, A_t, S_{t+1}) | \pi]$$

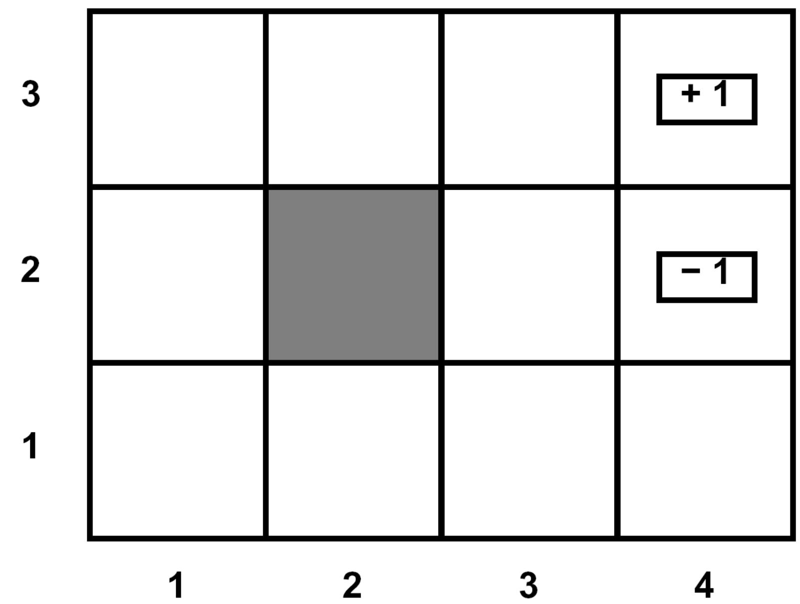
Examples

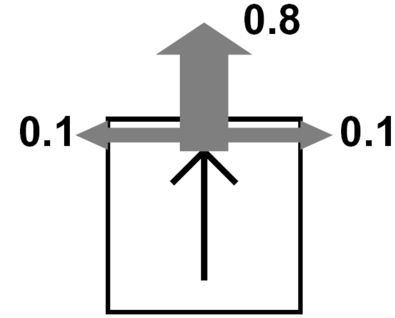
MDP (S, A, T, R, H), goal: $max_\pi \mathrm{E}[\sum_{t=0}^{H} R(S_t, A_t, S_{t+1})|\pi]$

- Cleaning robot
- Walking robot
- Pole balancing
- Games: tetris, backgammon
- Server management
- Shortest path problems
- Model for animals, people

Canonical Example: Grid World

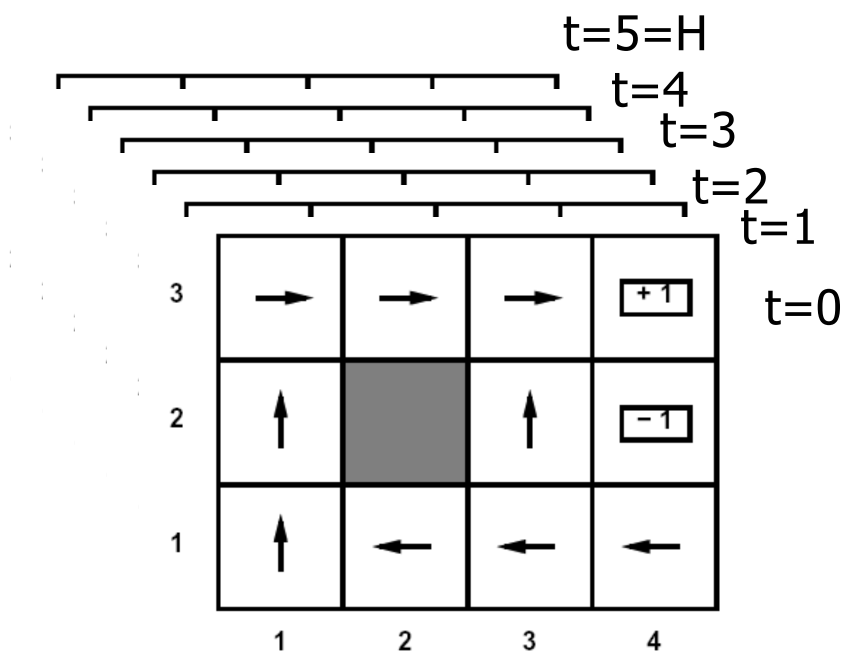
- The agent lives in a grid
- Walls block the agent's path
- The agent's actions do not always go as planned:
  - 80% of the time, the action North takes the agent North (if there is no wall there)
  - 10% of the time, North takes the agent West; 10% East
  - If there is a wall in the direction the agent would have been taken, the agent stays put
- Big rewards come at the end





Solving MDPs

- In an MDP, we want an optimal policy $\pi^*: S \times 0{:}H \rightarrow A$
  - A policy π gives an action for each state for each time



  - An optimal policy maximizes expected sum of rewards
- Contrast: In deterministic, want an optimal plan, or sequence of actions, from start to a goal

Outline

- Optimal Control

  =

  given an MDP (S, A, T, R, γ, H)

  find the optimal policy π^*

- Exact Methods:
  - ***Value Iteration***
  - Policy Iteration
  - Linear Programming

For now: discrete state-action spaces as they are simpler to get the main concepts across. Will consider continuous spaces later!

Value Iteration

- Algorithm:
  - Start with $V_0^*(s) = 0$ for all s.
  - For i=1, … , H

    Given V_i^*, calculate for all states $s \in S$:

$$V_{i+1}^*(s) \leftarrow \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + V_i^*(s')\right]$$

  - This is called a value update or Bellman update/back-up

- $V_i^*(s)$ = the expected sum of rewards accumulated when starting from state s and acting optimally for a horizon of i steps

Value Iteration in Gridworld

noise = 0.2, γ =0.9, two terminal states with R = +1 and -1

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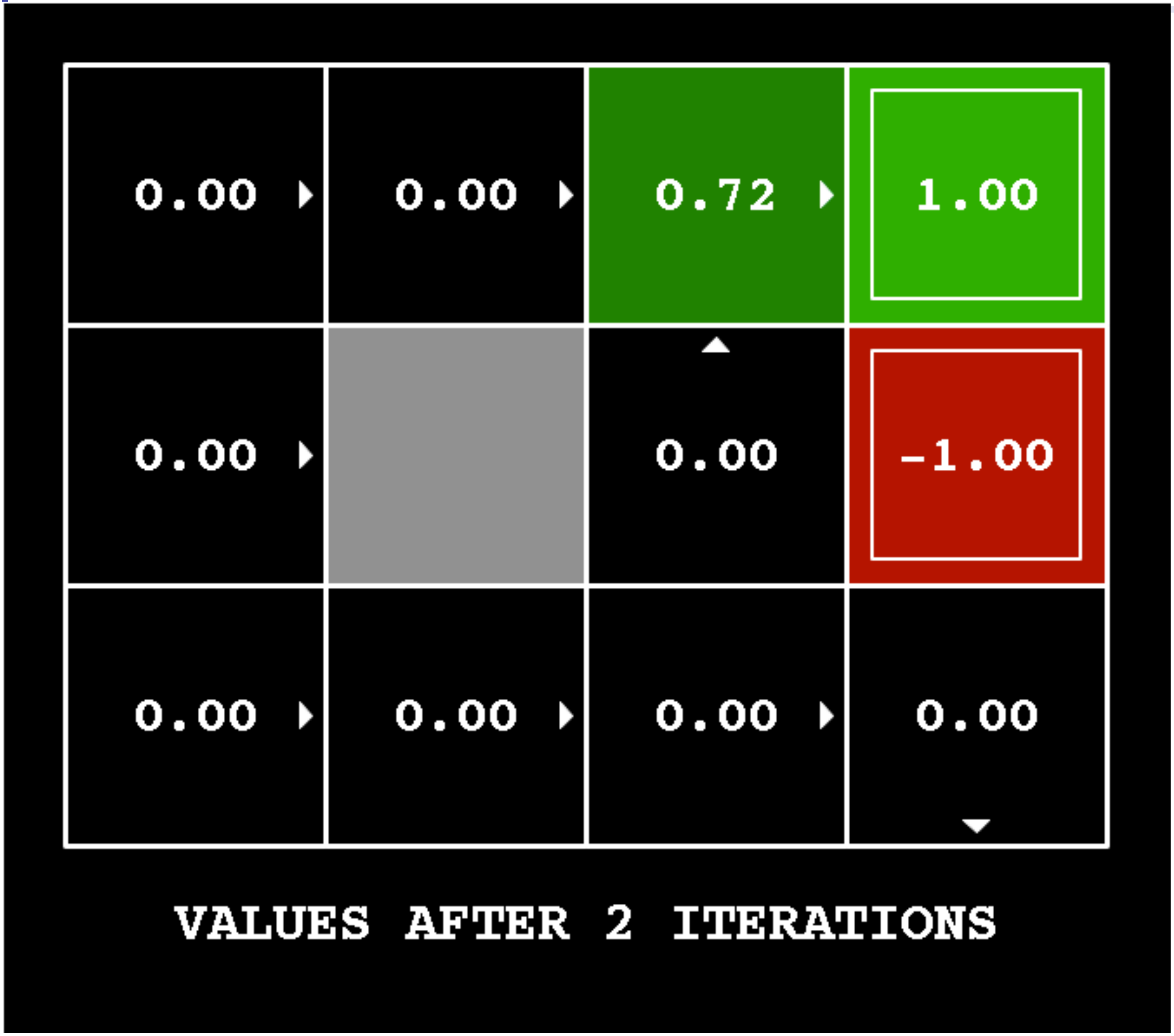

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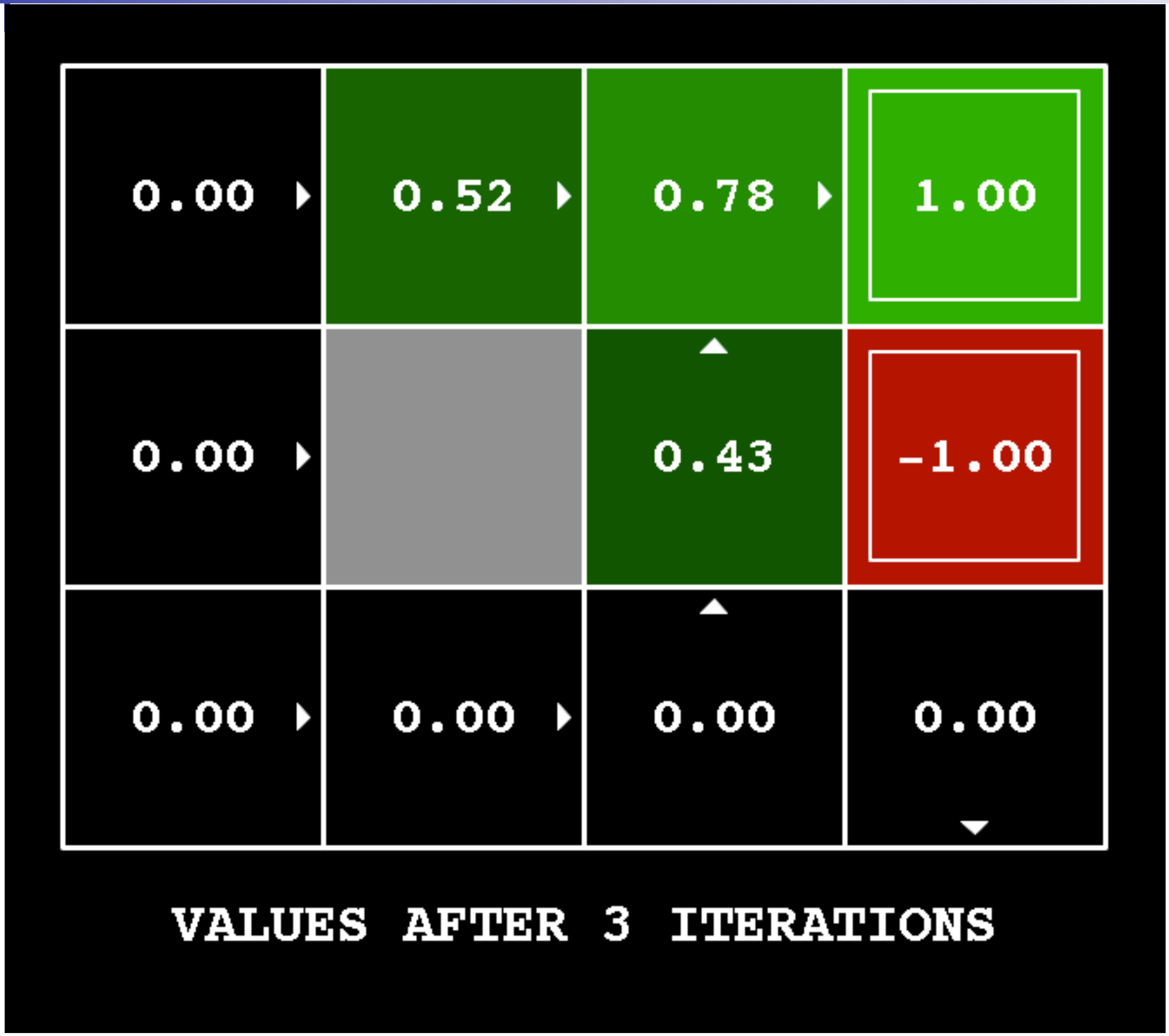

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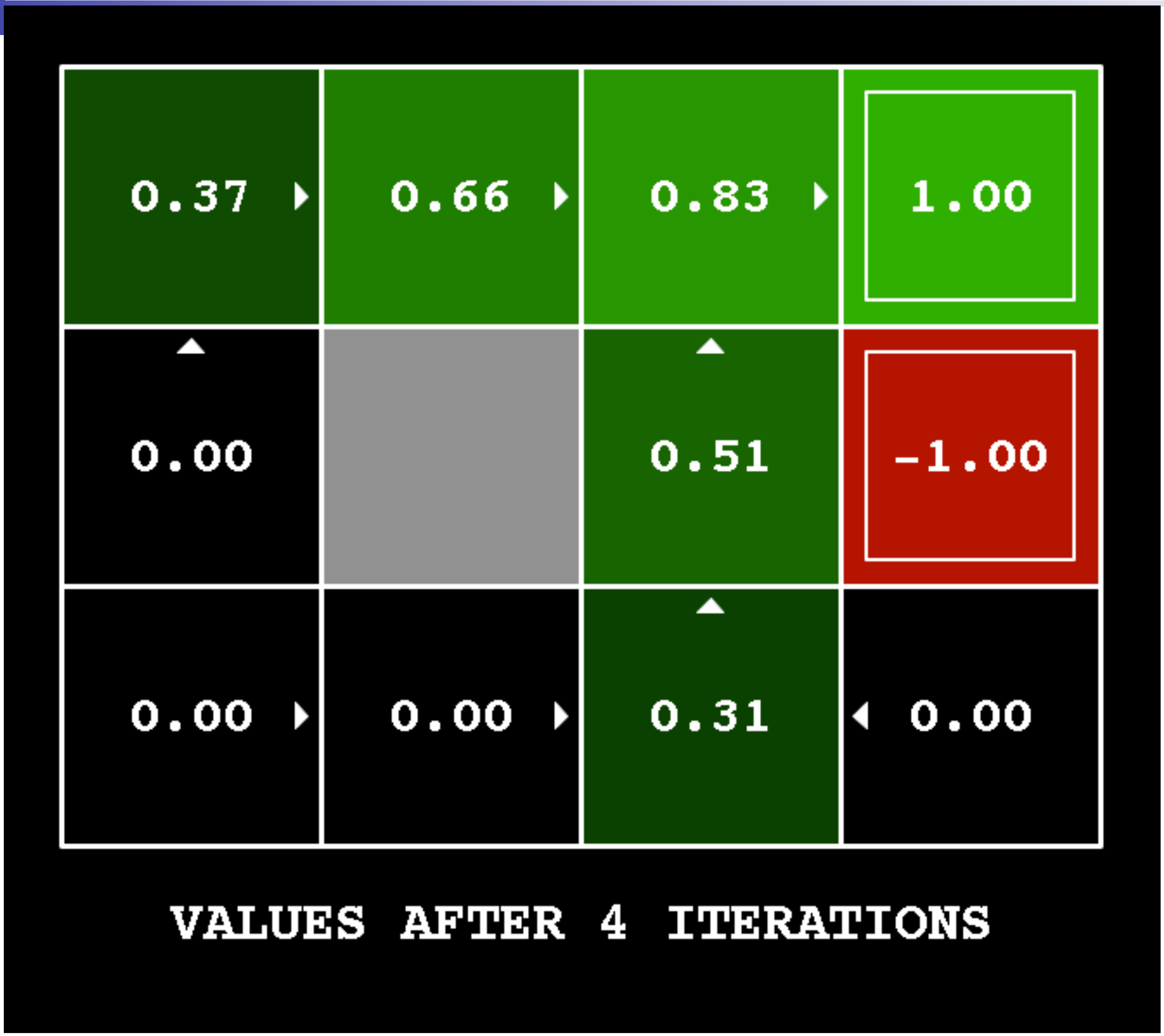

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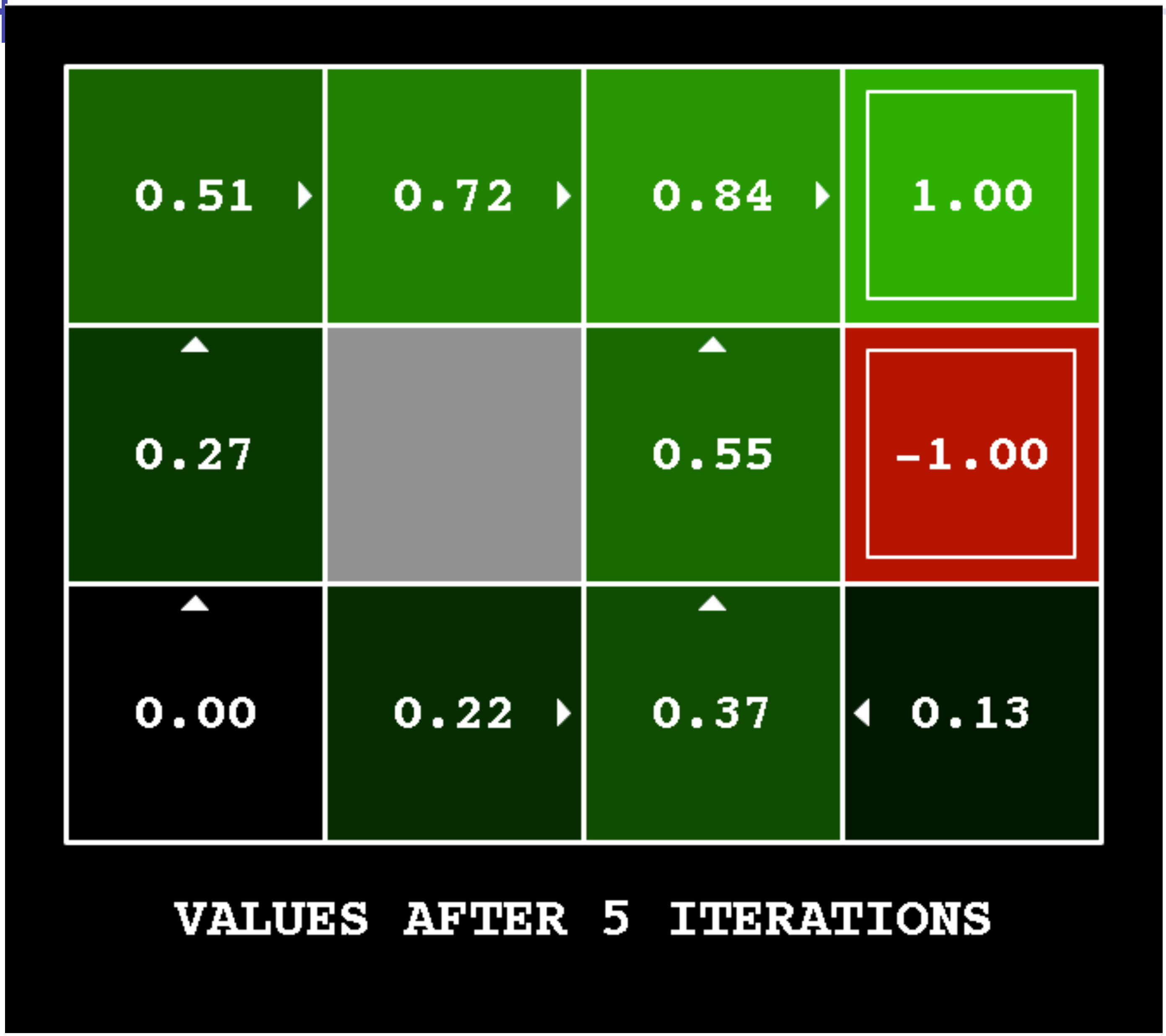

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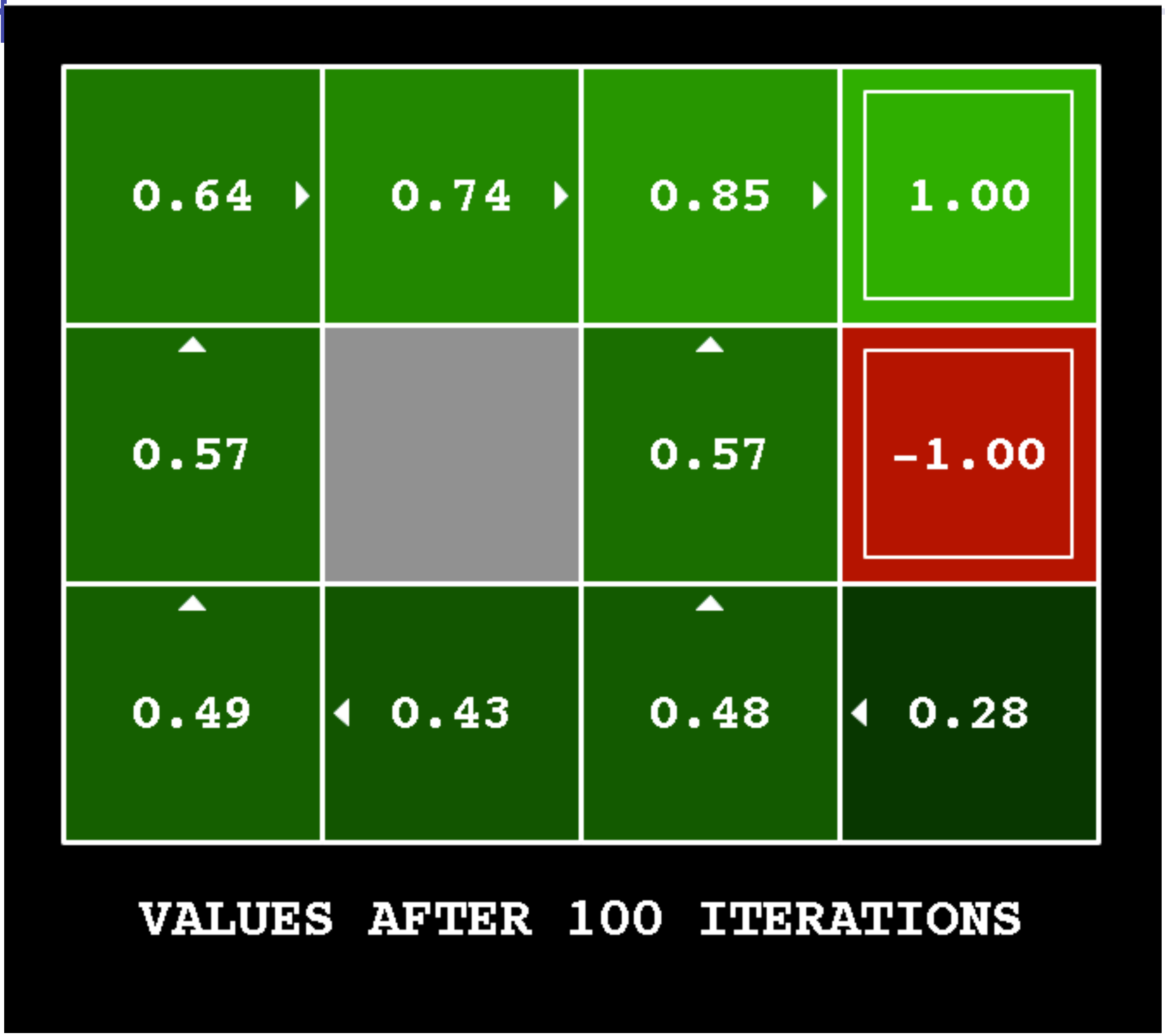

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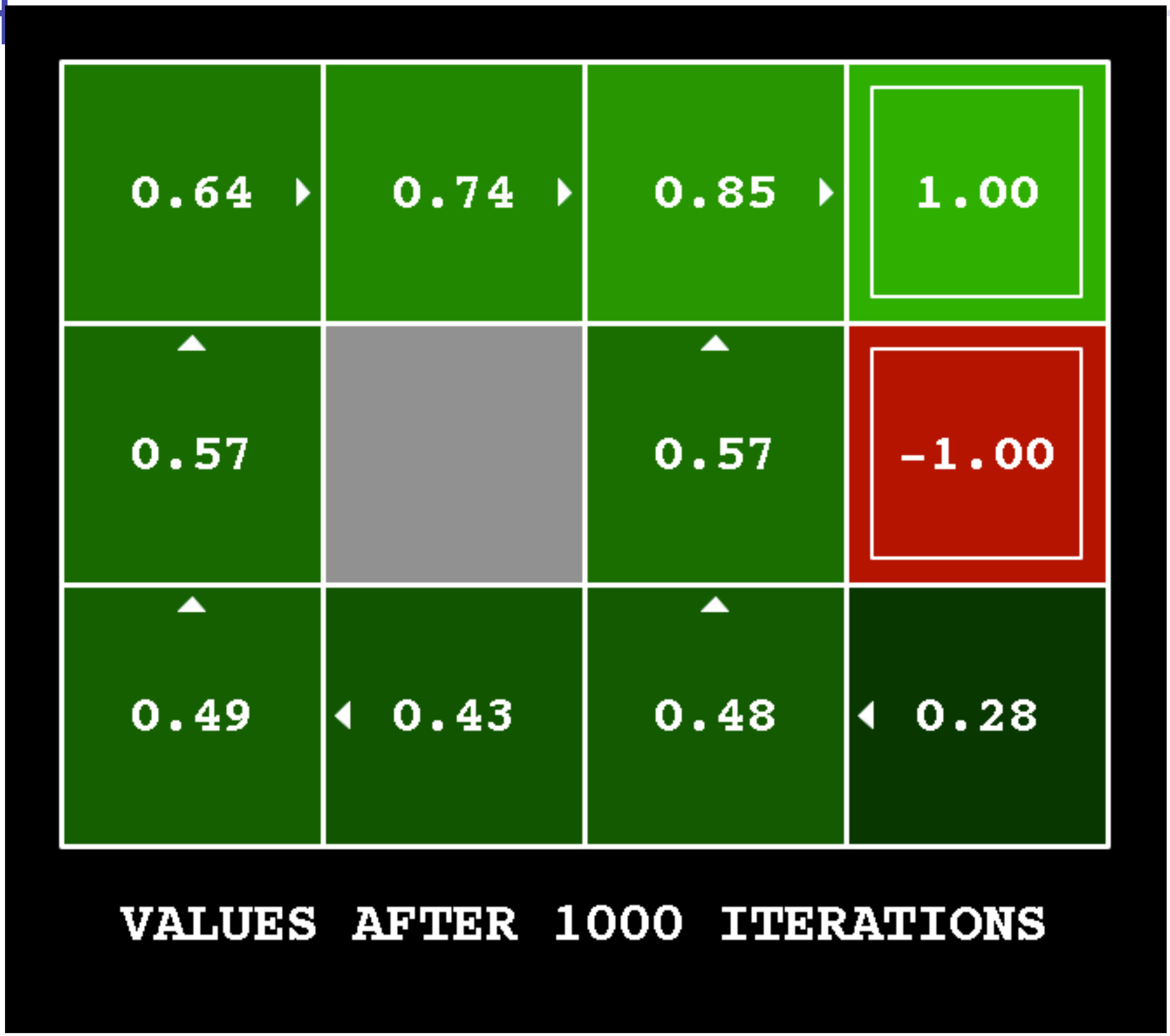
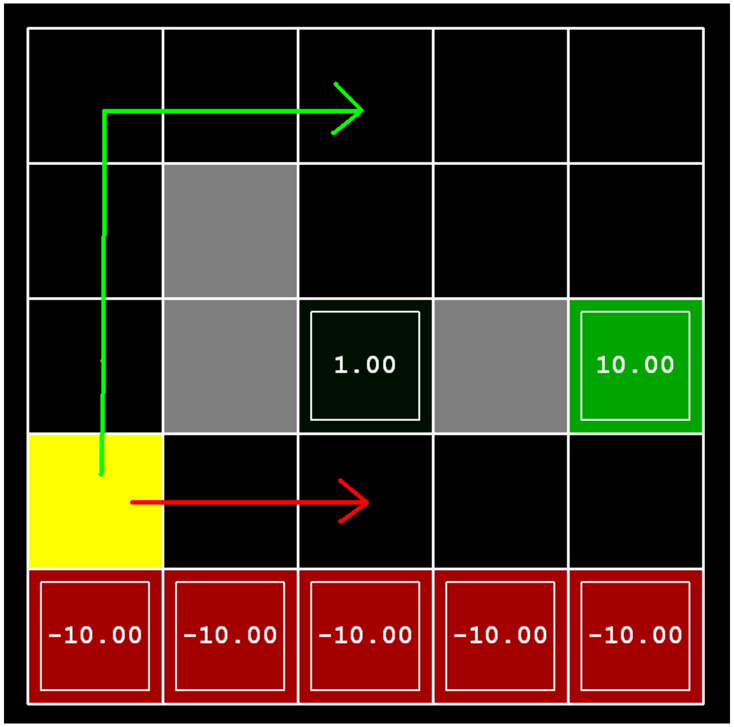


Exercise 1: Effect of discount, noise



(a) Prefer the close exit (+1), risking the cliff (-10)

(b) Prefer the close exit (+1), but avoiding the cliff (-10)

(c) Prefer the distant exit (+10), risking the cliff (-10)

(d) Prefer the distant exit (+10), avoiding the cliff (-10)

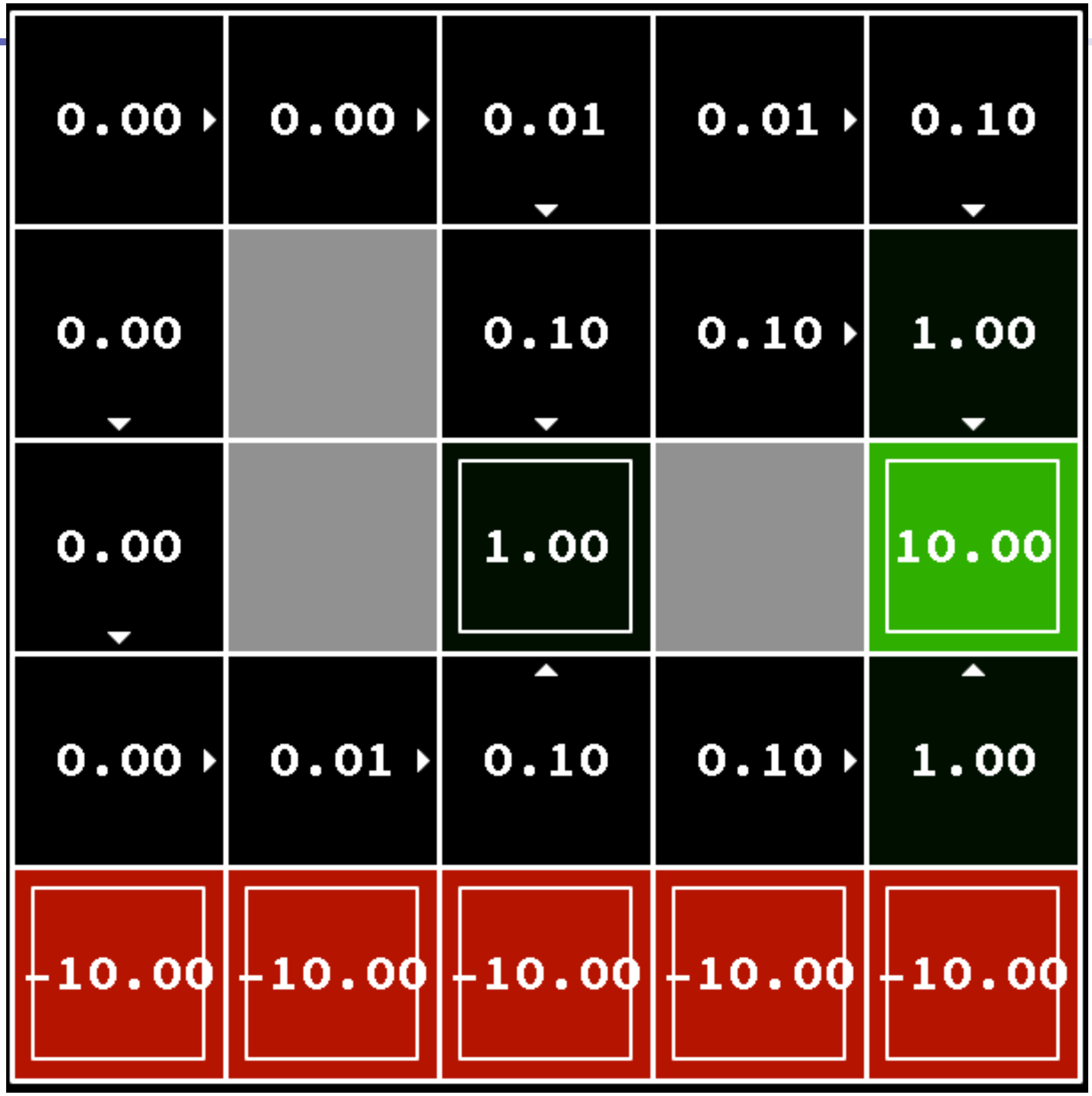
(1) γ = 0.1, noise = 0.5

(2) γ = 0.99, noise = 0

(3) γ = 0.99, noise = 0.5

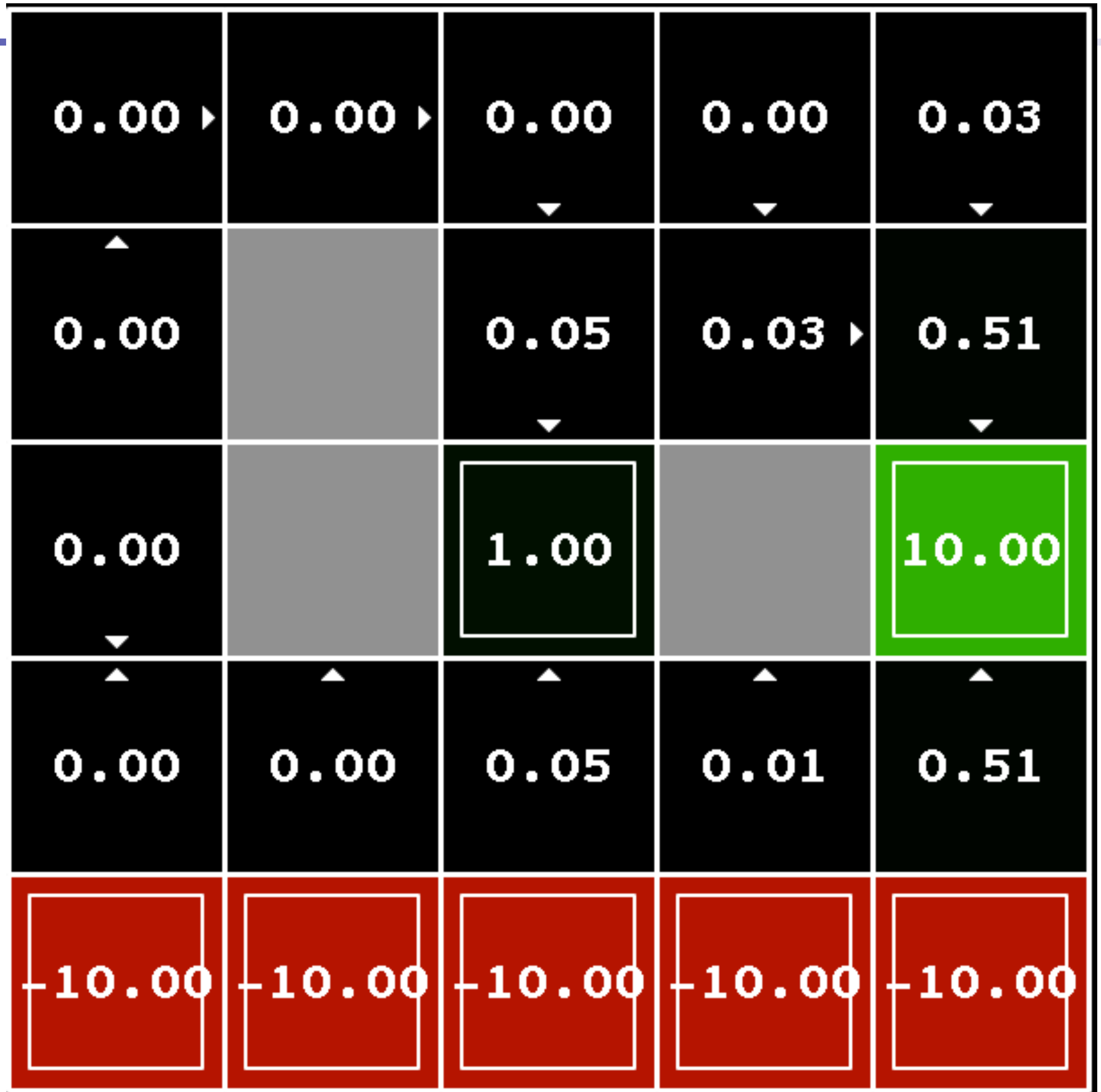
(4) γ = 0.1, noise = 0

Exercise 1 Solution



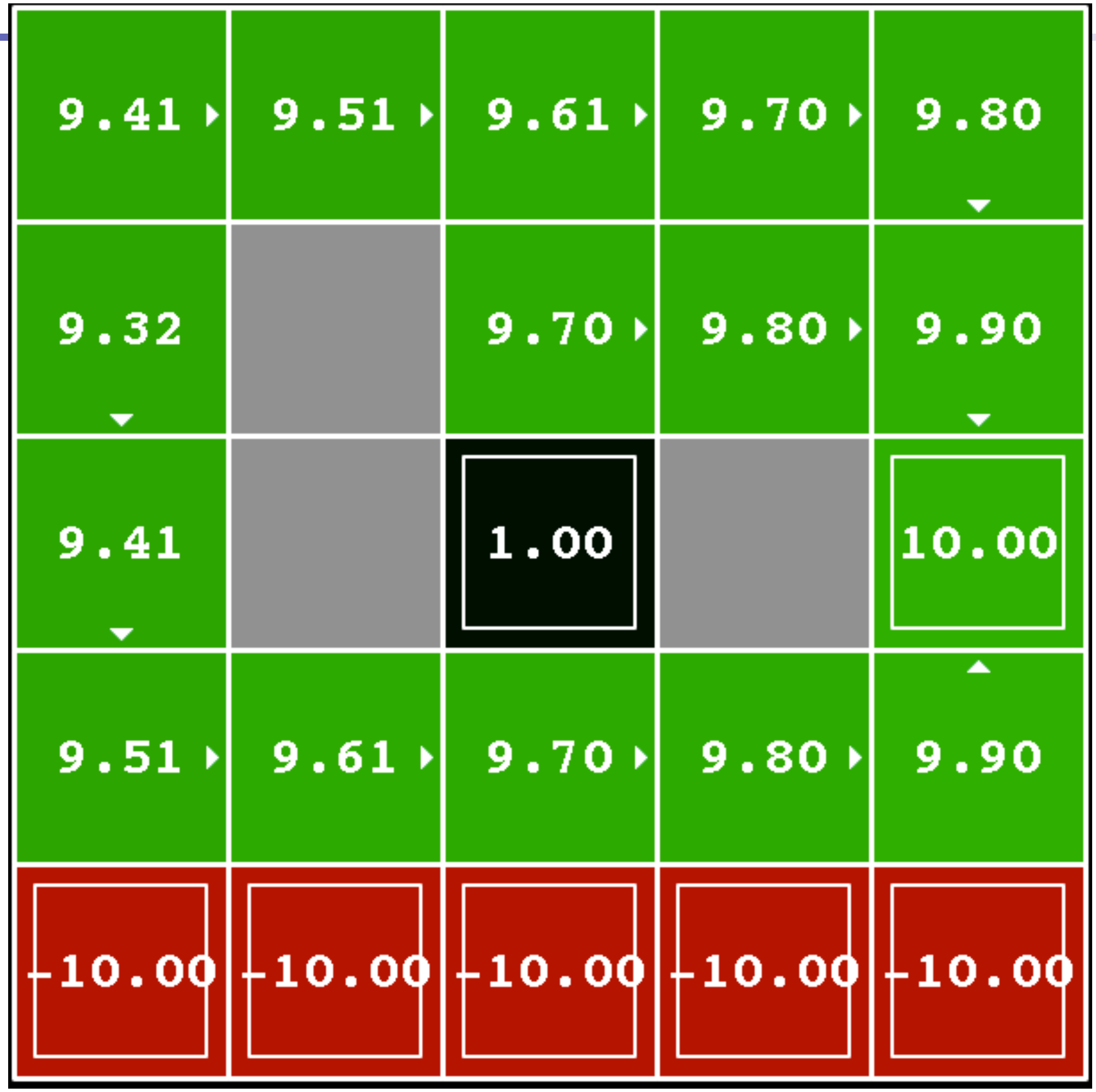
(a) Prefer close exit (+1), risking the cliff (-10) --- γ = 0.1, noise = 0

Exercise 1 Solution



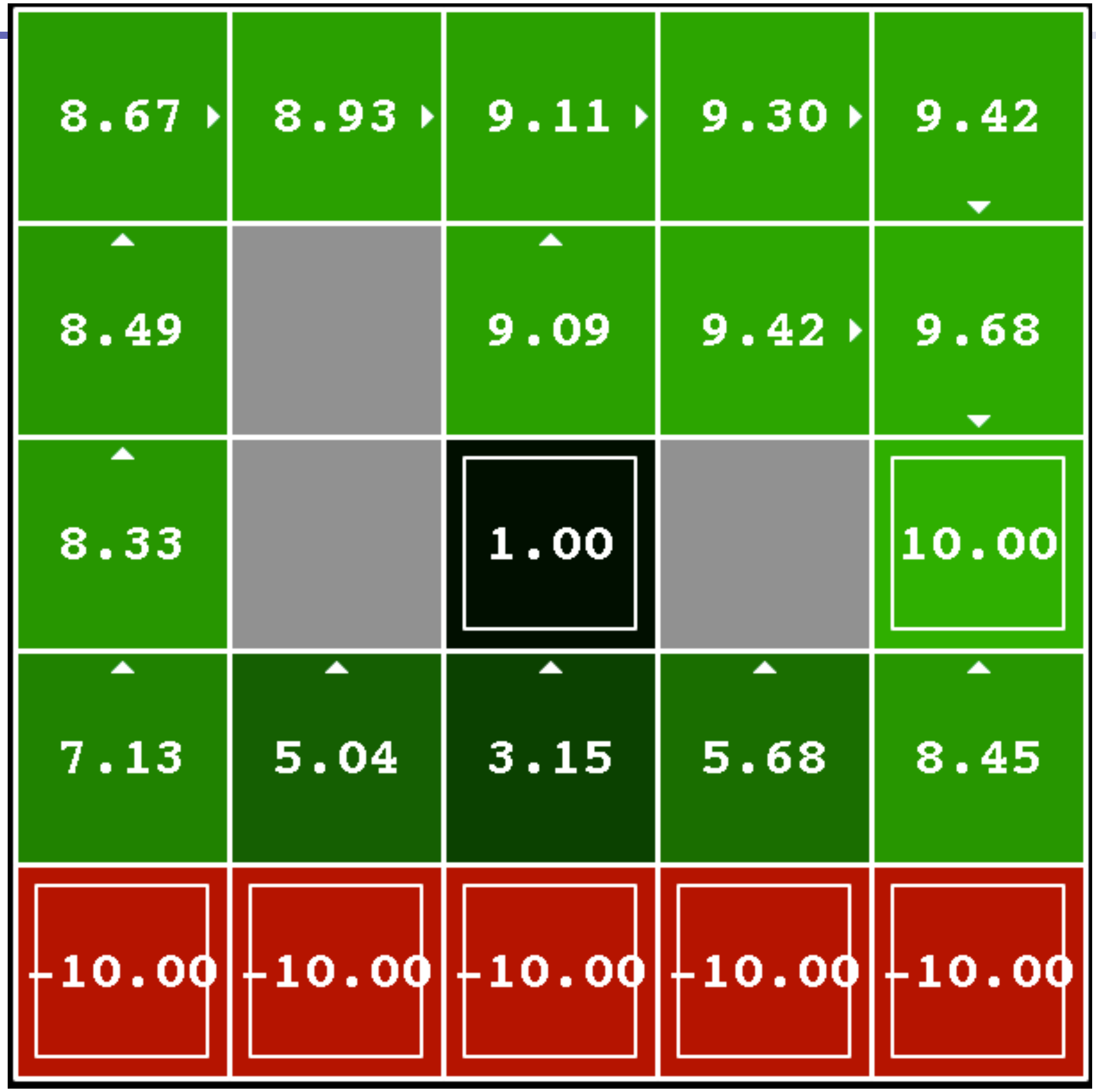
(b) Prefer close exit (+1), avoiding the cliff (-10) -- γ = 0.1, noise = 0.5

Exercise 1 Solution



(c) Prefer distant exit (+1), risking the cliff (-10) -- γ = 0.99, noise = 0

Exercise 1 Solution



(d) Prefer distant exit (+1), avoid the cliff (-10) -- γ = 0.99, noise = 0.5

Value Iteration Convergence

Theorem. Value iteration converges. At convergence, we have found the optimal value function V* for the discounted infinite horizon problem, which satisfies the Bellman equations

$$\forall S \in S: \quad V^*(s) = \max_A \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^*(s')\right]$$

- Now we know how to act for infinite horizon with discounted rewards!
  - Run value iteration till convergence.
  - This produces V*, which in turn tells us how to act, namely following:

$$\pi^*(s) = \arg\max_{a \in A} \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V^*(s')]$$

- Note: the infinite horizon optimal policy is stationary, i.e., the optimal action at a state s is the same action at all times. (Efficient to store!)

Convergence and Contractions

- Define the max-norm: $||U|| = \max_s |U(s)|$

- Theorem: For any two approximations U and V

$$||U_{i+1} - V_{i+1}|| \leq \gamma \, ||U_i - V_i||$$

  - I.e. any distinct approximations must get closer to each other, so, in particular, any approximation must get closer to the true U and value iteration converges to a unique, stable, optimal solution

- Theorem:

$$||V_{i+1} - V_i|| < \epsilon, \Rightarrow ||V_{i+1} - V^*|| < 2\epsilon\gamma/(1-\gamma)$$

  - I.e. once the change in our approximation is small, it must also be close to correct

Outline

- Optimal Control

  =

  given an MDP (S, A, T, R, γ, H)

  find the optimal policy π^*

- Exact Methods:
  - ✓ Value Iteration
  - ***Policy Iteration***
  - Linear Programming

For now: discrete state-action spaces as they are simpler to get the main concepts across. Will consider continuous spaces later!

Policy Evaluation

- Recall value iteration iterates:

$$V_{i+1}^*(s) \leftarrow \max_a \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V_i^*(s')]$$

- Policy evaluation:

$$V_{i+1}^\pi(s) \leftarrow \sum_{s'} T(s,\pi(s),s')[R(s,\pi(s),s') + \gamma V_i^\pi(s')]$$

  - At convergence:

$$\forall s \quad V^\pi(s) = \sum_{s'} T(s,\pi(s),s')[R(s,\pi(s),s') + \gamma V^\pi(s')]$$

Exercise 2

Consider a stochastic policy $\mu(a|s)$, where $\mu(a|s)$ is the probability of taking action a when in state s. Which of the following is the correct value iteration update to perform policy evaluation for this stochastic policy?

1. $V_{i+1}^{\mu}(s) \leftarrow \max_a \sum_{s'} T(s,a,s')(R(s,a,s') + \gamma V_i^{\mu}(s'))$
2. $V_{i+1}^{\mu}(s) \leftarrow \sum_{s'} \sum_a \mu(a|s) T(s,a,s')(R(s,a,s') + \gamma V_i^{\mu}(s'))$
3. $V_{i+1}^{\mu}(s) \leftarrow \sum_a \mu(a|s) \max_{s'} T(s,a,s')(R(s,a,s') + \gamma V_i^{\mu}(s'))$

Policy Iteration

- Alternative approach:
  - Step 1: Policy evaluation: calculate utilities for some fixed policy (not optimal utilities!) until convergence
  - Step 2: Policy improvement: update policy using one-step look-ahead with resulting converged (but not optimal!) utilities as future values
  - Repeat steps until policy converges

- This is policy iteration
  - It's still optimal!
  - Can converge faster under some conditions

Policy Evaluation Revisited

- *Idea 1:* modify Bellman updates

$$V_0^{\pi}(s) = 0$$

$$V_{i+1}^{\pi}(s) \leftarrow \sum_{s'} T(s, \pi(s), s')[R(s, \pi(s), s') + \gamma V_i^{\pi}(s')]$$

- Idea 2: it's just a linear system, solve with Matlab (or whatever),
  variables: $V^{\pi}(s)$,
  constants: T, R

$$\forall s \quad V^{\pi}(s) = \sum_{s'} T(s, \pi(s), s')[R(s, \pi(s), s') + \gamma V^{\pi}(s')]$$

Policy Iteration Guarantees

Policy Iteration iterates over:

- Policy evaluation: with fixed current policy π, find values with simplified Bellman updates:
  - Iterate until values converge

$$V^{\pi_k}_{i+1}(s) \leftarrow \sum_{s'} T(s,\pi_k(s),s') \left[R(s,\pi_k(s),s') + \gamma V^{\pi_k}_i(s')\right]$$

- Policy improvement: with fixed utilities, find the best action according to one-step look-ahead

$$\pi_{k+1}(s) = \arg\max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^{\pi_k}(s')\right]$$

Theorem. Policy iteration is guaranteed to converge and at convergence, the current policy and its value function are the optimal policy and the optimal value function!

Proof sketch:

(1) Guarantee to converge: In every step the policy improves. This means that a given policy can be encountered at most once. This means that after we have iterated as many times as there are different policies, i.e., (number actions)$^{\text{(number states)}}$, we must be done and hence have converged.

(2) Optimal at convergence: by definition of convergence, at convergence π_{k+1}(s) = π_k(s) for all states s. This means $\forall s \;\; V^{\pi_k}(s) = \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^{\pi_k}_i(s')\right]$

Hence V^{π_k} satisfies the Bellman equation, which means V^{π_k} is equal to the optimal value function V*.

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Infinite Horizon Linear Program

- Recall, at value iteration convergence we have

$$\forall s \in S: \quad V^*(s) = \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^*(s')\right]$$

- LP formulation to find V^*:

$$\begin{aligned} \min_V \quad & \sum_s \mu_0(s) V(s) \\ \text{s.t.} \quad & \forall s \in S, \forall a \in A: \\ & V(s) \geq \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^*(s')\right] \end{aligned}$$

μ_0 is a probability distribution over S, with $\mu_0(s) > 0$ for all $s \in S$.

Theorem. V^* is the solution to the above LP.

Theorem Proof

Let F be the Bellman operator, i.e., $V^*_{i+1} = F(V_i)$. Then the LP can be written as:

$$\begin{array}{ll} \min_V & \mu_0^\top V \\ \text{s.t.} & V \geq F(V) \end{array}$$

Property: Monotonicity. If $U \geq V$ then $F(U) \geq F(V)$.
Hence, if $V \geq F(V)$ then $F(V) \geq F(F(V))$, and by repeated application, $V \geq F(V) \geq F^2 V \geq F^3 V \geq \ldots \geq F^\infty V = V^*$.
Any feasible solution to the LP must satisfy $V \geq F(V)$, and hence must satisfy $V \geq V^*$. Hence, assuming all entries in μ_0 are positive, V^* is the optimal solution to the LP.

Dual Linear Program

$$\max_\lambda \quad \sum_{s\in S}\sum_{a\in A}\sum_{s'\in S}\lambda(s,a)T(s,a,s')R(s,a,s')$$

$$\text{s.t.} \quad \forall s' \in S : \sum_{a'\in A}\lambda(s',a') = \mu_0(s) + \gamma\sum_{s\in S}\sum_{a\in A}\lambda(s,a)T(s,a,s')$$

- Interpretation:
  - $\lambda(s,a) = \sum_{t=0}^{\infty}\gamma^t P(s_t = s, a_t = a)$
  - Equation 2: ensures λ has the above meaning
  - Equation 1: maximize expected discounted sum of rewards
- Optimal policy: $\pi^*(s) = \arg\max_a \lambda(s,a)$

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Today and forthcoming lectures

- Optimal control: provides general computational approach to tackle control problems.
  - Dynamic programming / Value iteration
    - ✓ Exact methods on discrete state spaces (DONE!)
    - Discretization of continuous state spaces
    - Function approximation
    - Linear systems
    - LQR
    - Extensions to nonlinear settings:
      - Local linearization
      - Differential dynamic programming
  - Optimal Control through Nonlinear Optimization
    - Open-loop
    - Model Predictive Control
  - Examples: