

A hand holding a bone over a dog. The background is a gradient from dark grey to light grey. A hand is holding a bone over a dog. The dog is a small, white and brown dog, possibly a Jack Russell Terrier, sitting and looking up at the bone. The dog is wearing a blue collar with a red stripe.

CS 5/7320

Artificial Intelligence

Reinforcement Learning

AIMA Chapter 17+22

Slides by Michael Hahsler
with figures from the AIMA textbook.

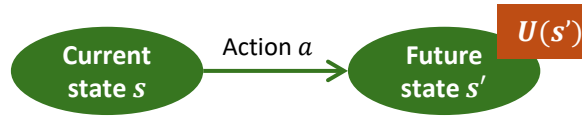


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Online Material

Remember Chapter 16: Making Simple Decisions



For a decision that we make frequently and making it once does not affect the future decisions (**episodic environment**), we can use the **Principle of Maximum Expected Utility (MEU)**.

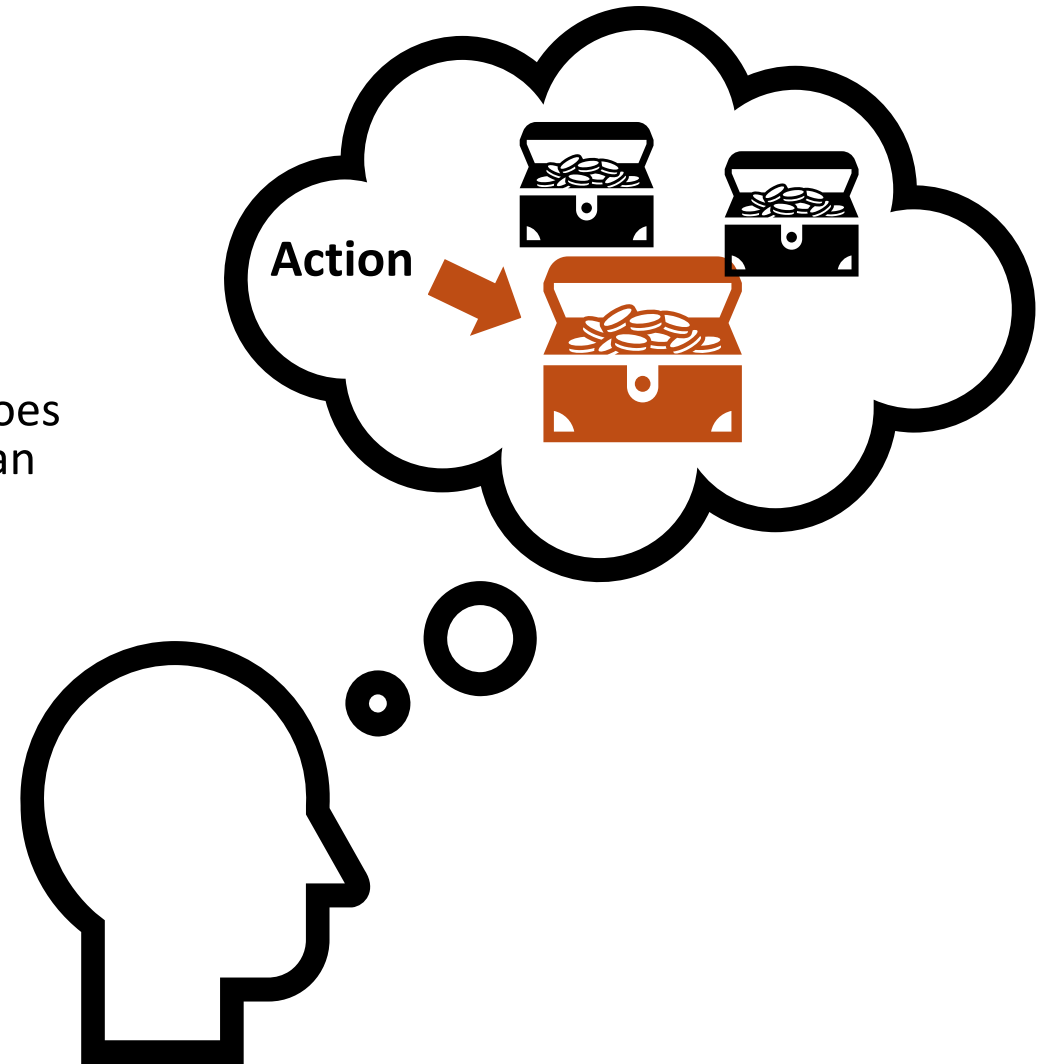
Given the expected utility of an action

$$EU(a) = \sum_{s'} \sum_s P(s) P(s'|s, a) U(s')$$

choose action that maximizes the expected utility:

$$a^* = \operatorname{argmax}_a EU(a)$$

Now we will talk about **sequential decision making**.

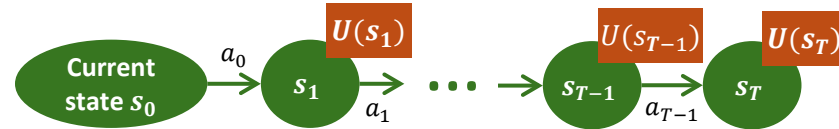




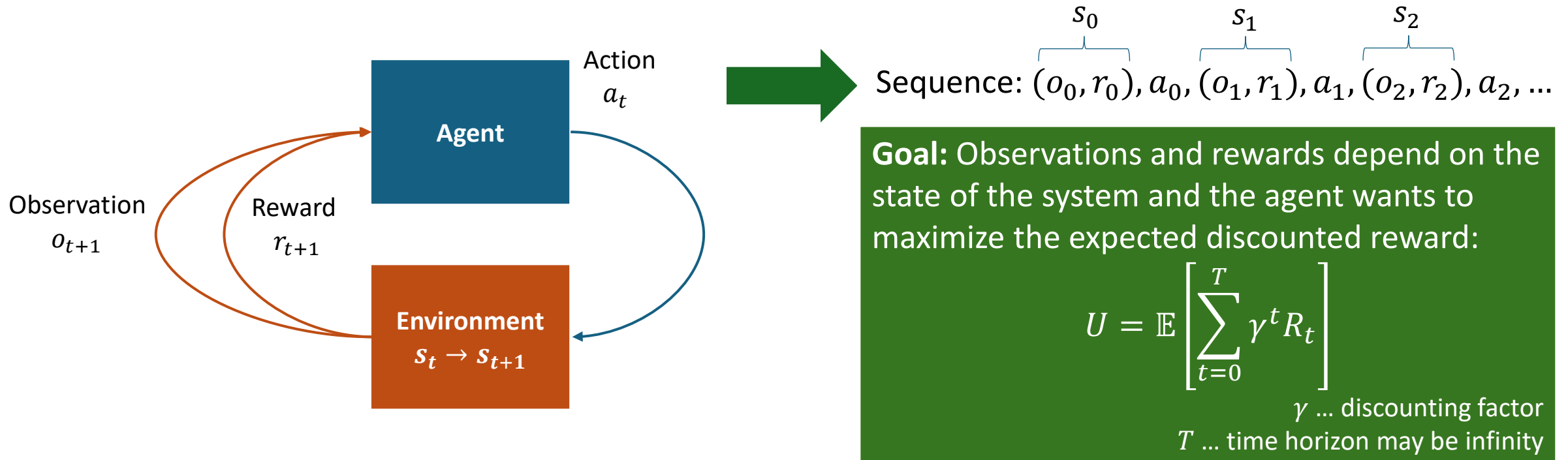
Making Complex Decisions: Sequential Decision Making

AIMA Chapter 17

Sequential Decision Problems



- **Utility-based agent:** The agent's utility depends on a sequence of decisions that depend on each other.
- Sequential decision problems incorporate utilities (called reward), uncertainty, and sensing.



Definition: Markov Decision Process (MDP)

MDPs are sequential decision problems with

- a fully observable, stochastic, and known environment;
- a Markovian transition model (i.e., future states do not depend on past states given the current state);
- additive rewards.

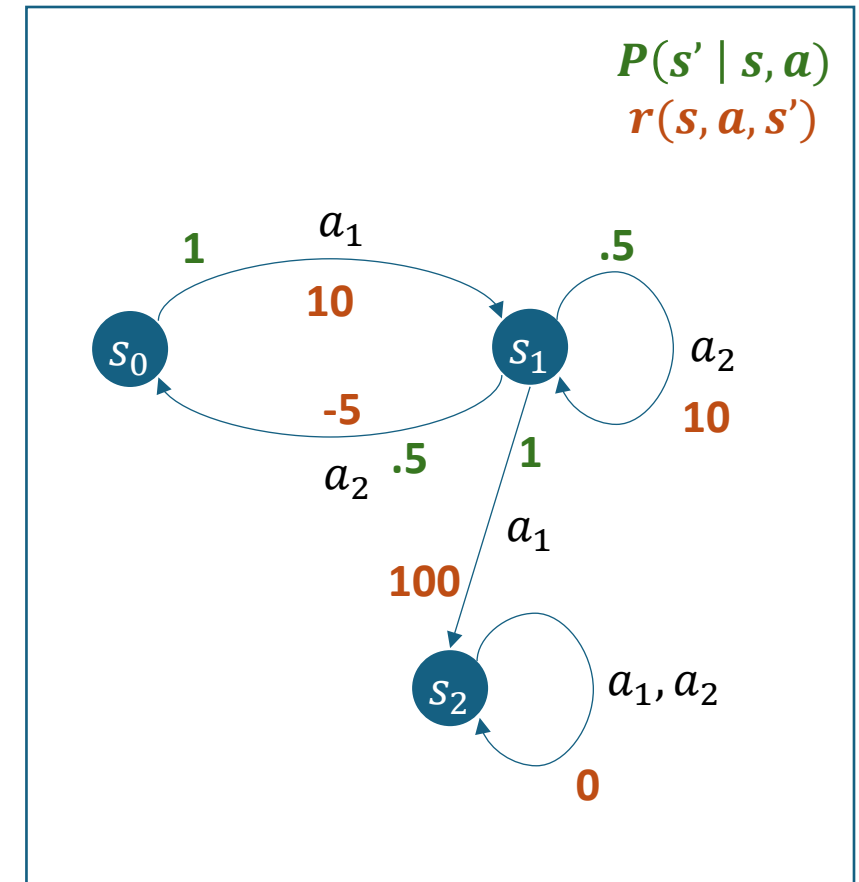
MDPs are discrete-time stochastic control processes defined by:

- a finite set of **states** $S = \{s_0, s_1, s_2, \dots\}$ (initial state s_0)
- a set of available **actions** $ACTIONS(s)$ in each state s
- a **transition model** $P(s' | s, a)$ where $a \in ACTIONS(s)$
- a **reward function** $r(s)$ where the reward depends on the current state (often $r(s, a, s')$ is used to make modelling easier)

Time horizon

- **Infinite horizon:** non-episodic (continuous) tasks with no terminal state.
- **Finite horizon:** episodic tasks. Episode ends after a number of periods or when a terminal state is reached. Episodes contain a sequence of several actions that affect each other.

This is different from the previous definition of an **episodic** environment!



Example: 4x3 Grid World

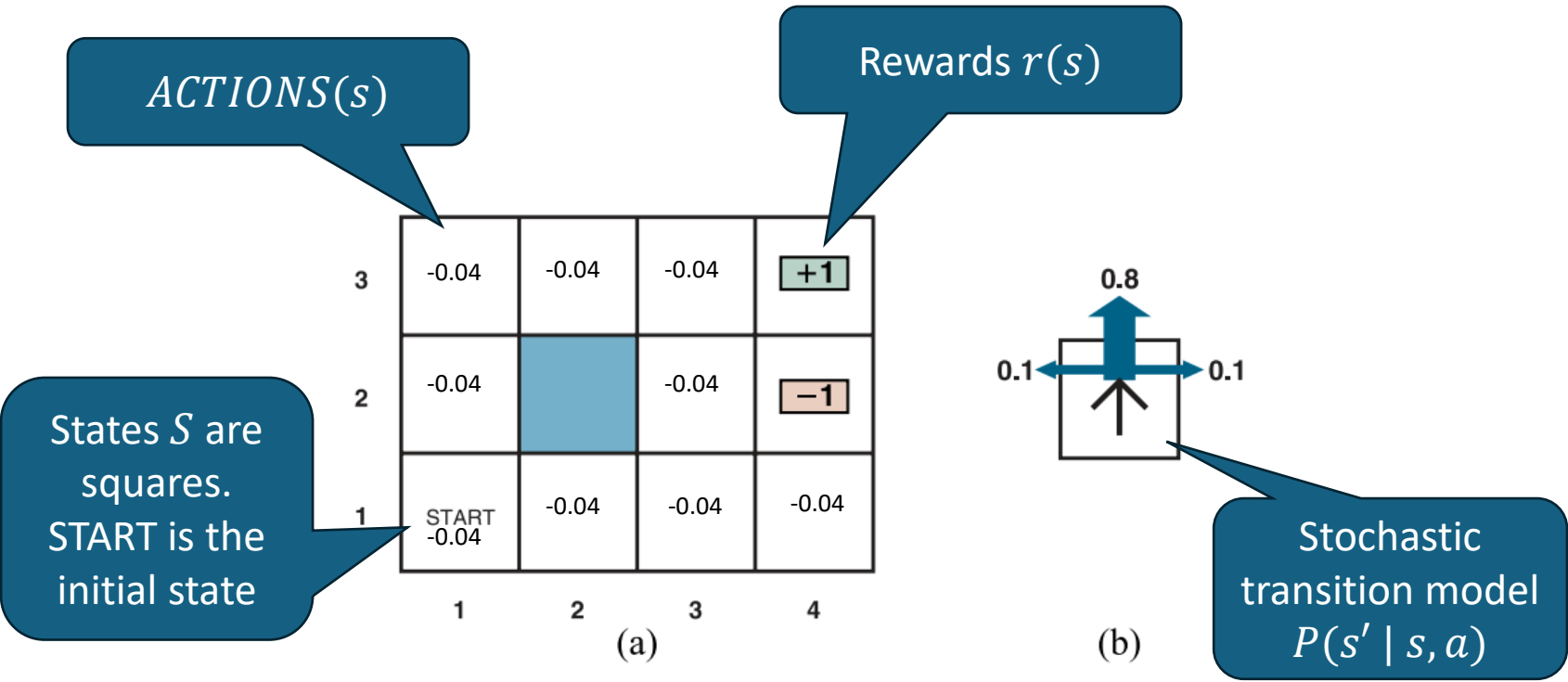


Figure 17.1 (a) A simple, stochastic 4×3 environment that presents the agent with a sequential decision problem. (b) Illustration of the transition model of the environment: the “intended” outcome occurs with probability 0.8, but with probability 0.2 the agent moves at right angles to the intended direction. A collision with a wall results in no movement. Transitions into the two terminal states have reward +1 and -1, respectively, and all other transitions have a reward of -0.04.

Since we know the complete MDP model, we can solve this as a **planning problem**.

For each square: specify what direction should we try to go to maximize the expected total utility.

This is called a **policy** written as the function

$$\pi: S \rightarrow ACTIONS(S)$$

Policy	
s	Action $\pi(s)$
(1,1)	Up
...	...
...	...

Value Function

- A policy $\pi = \{\pi(s_0), \pi(s_1), \dots\}$ defines for each state which action to take.
- The expected utility of being in state s under policy π (i.e., following the policy starting from s) can be calculated as the sum:

$$U^\pi(s) = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t r(s_t) \mid s_0 = s \right]$$

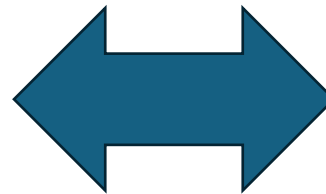
- $U^\pi(s)$ (often also written as $V(s)$) is called **the value function**. It is often stored as a table.

γ is a discounting factor to give more weight to immediate rewards.

E_π is the expectation over sequences that can be created by following π .

Value Function

3	0.8516	0.9078	0.9578	+1
2	0.8016		0.7003	-1
1	0.7453	0.6953	0.6514	0.4279
	1	2	3	4



Value Function

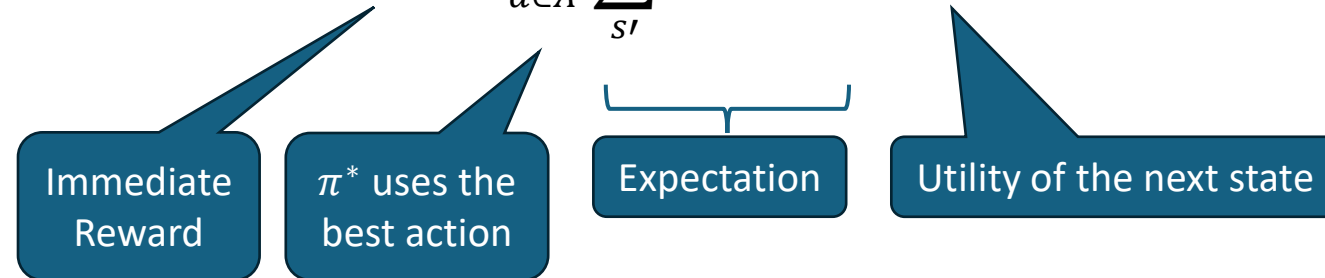
s	Value $U(s)$
(1,1)	0.7453
(1,2)	0.8016
...	...

Planning: Finding the Optimal Policy

- The goal of solving an MDP is to find an optimal policy π that maximizes the expected future utility for each state

$$\pi^*(s) = \operatorname{argmax}_{\pi} U^{\pi}(s) \quad \text{for all } s \in S$$

- Issue:** π^* depends on U^{π} and vice versa!
- The problem can be formulated recursively using the **Bellman equation** which holds for the optimal value function U (“Bellman optimality condition”):

$$U^{\pi^*}(s) = r(s) + \gamma \max_{a \in A} \underbrace{\sum_{s'} P(s'|s, a)}_{\text{Expectation}} U^{\pi^*}(s')$$


Immediate Reward

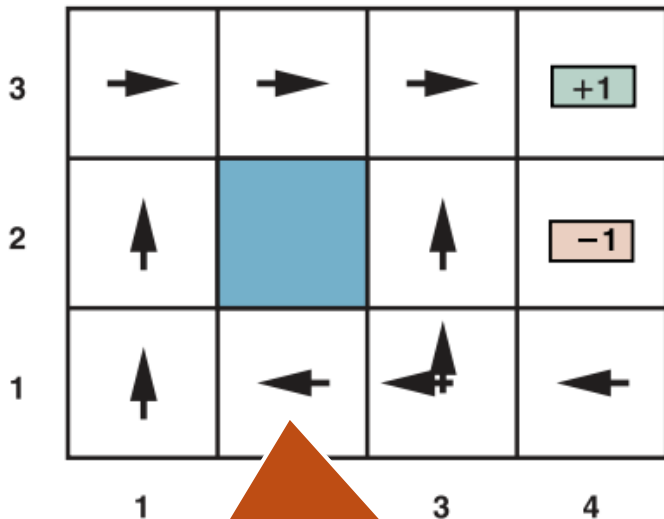
π^* uses the best action

Expectation

Utility of the next state

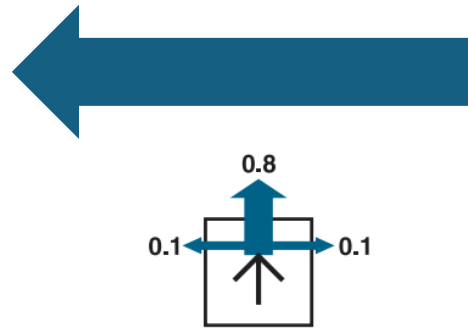
Solution: 4x3 Grid World

Optimal action in each state
(policy π^*)

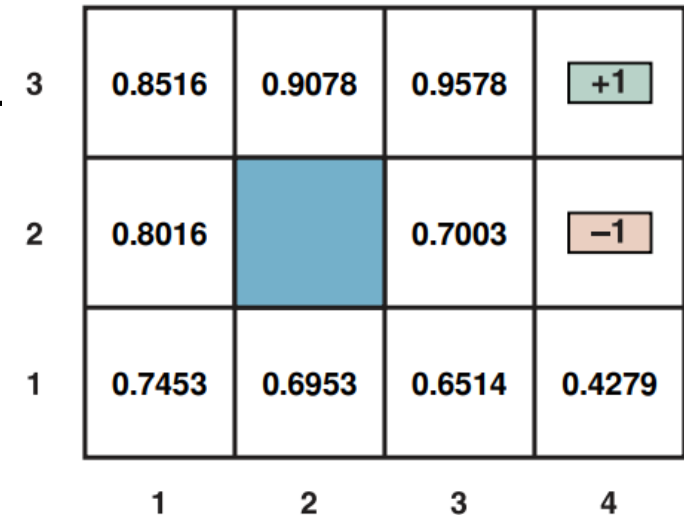


It is optimal to walk away from the +1 square!

Greedy policy:
Always pick the action
leading to the state with
the highest expected utility.



Value of being in a state $U^{\pi^*}(s)$
(given that we will follow π^*)



$\gamma = 1$

How to we find the optimal value function/optimal policy?

Policy Iteration

Value Iteration

Q-Function

- $Q(s, a)$ is called the state-action value function. It gives the expected utility of taking action a in state s and then following the policy.

$$Q(s, a) = r(s) + \gamma \sum_{s'} P(s'|s, a) [U(s')]$$

Immediate
Reward

Expected utility of the
next state

- The Relationship with the state value function: $U(s) = \max_a Q(s, a)$
- The Q-function lets us compare the value of taking an action in a given state and is often used for convenience in algorithms.

Value Function

3	0.8516	0.9078	0.9578	+1
2	0.8016		0.7003	-1
1	0.7453	0.6953	0.6514	0.4279
	1	2	3	4

Q-Table

s	a	$Q(s, a)$
(1,1)	Up	0.7453
(1,1)	Right	0.6709
(1,1)	Down	0.7003
(1,1)	Left	0.7109
...

Value Iteration: Estimate the Optimal Value Function U^{π^*}

Algorithm: Start with a U vector of 0 for all states and then update (Bellman update) the vector iteratively until it converges to the unique optimal solution U^{π^*} .

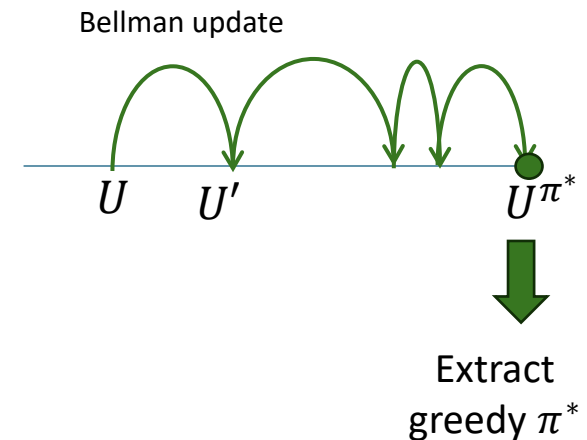
```
function VALUE-ITERATION( $mdp, \epsilon$ ) returns a utility function
  inputs:  $mdp$ , an MDP with states  $S$ , actions  $A(s)$ , transition model  $P(s' | s, a)$ ,
           rewards  $R(s, a, s')$ , discount  $\gamma$ 
            $\epsilon$ , the maximum error allowed in the utility of any state
  local variables:  $U, U'$ , vectors of utilities for states in  $S$ , initially zero
                      $\delta$ , the maximum relative change in the utility of any state

  repeat
     $U \leftarrow U'; \delta \leftarrow 0$ 
    for each state  $s$  in  $S$  do
       $U'[s] \leftarrow \max_{a \in A(s)} \text{Q-VALUE}(mdp, s, a, U)$ 
      if  $|U'[s] - U[s]| > \delta$  then  $\delta \leftarrow |U'[s] - U[s]|$ 
  until  $\delta \leq \epsilon(1 - \gamma)/\gamma$ 
  return  $U$ 
```

Update with the value of
the best action in state s .

Uses a proxy for policy loss
 $\|U^{\pi} - U\|_{\infty}$ as the stopping criterion

U converges to U^{π^*}
and we can extract π^*



Policy Iteration: Find the Optimal Policy π^*

Policy iteration tries to directly find the optimal policy by iterating policy evaluation and improvement.

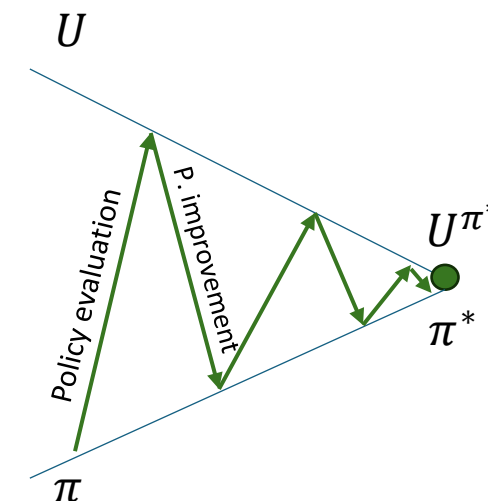
```
function POLICY-ITERATION(mdp) returns a policy
inputs: mdp, an MDP with states  $S$ , actions  $A(s)$ , transition model  $P(s' | s, a)$ 
local variables:  $U$ , a vector of utilities for states in  $S$ , initially zero
                   $\pi$ , a policy vector indexed by state, initially random

repeat
   $U \leftarrow \text{POLICY-EVALUATION}(\pi, U, \text{mdp})$ 
  unchanged?  $\leftarrow$  true
  for each state  $s$  in  $S$  do
     $a^* \leftarrow \operatorname{argmax}_{a \in A(s)} \text{Q-VALUE}(\text{mdp}, s, a, U)$ 
    if  $\text{Q-VALUE}(\text{mdp}, s, a^*, U) > \text{Q-VALUE}(\text{mdp}, s, \pi[s], U)$  then
       $\pi[s] \leftarrow a^*$ ; unchanged?  $\leftarrow$  false
  until unchanged?
return  $\pi$ 
```

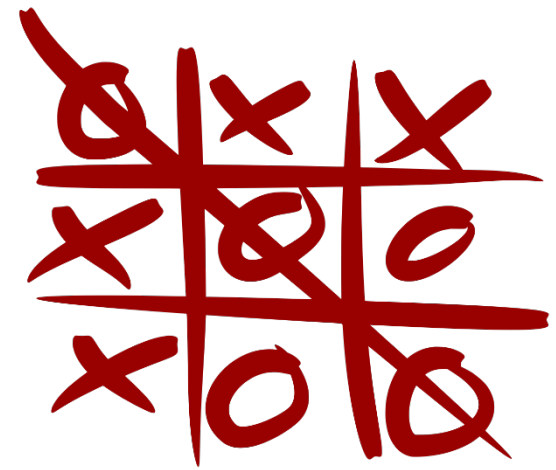
Calculate U given current policy
(either solve an LP or value
iteration with fixed policy)

Greedy policy
Improvement

π converges to π^*
(and U converges to U^{π^*})



Playing a Game as a Sequential Decision Problem: Tic-Tac-Toe



- Definitions from the Chapter 5 on Games for a goal-based agent:

s_0	Empty board.	
$Actions(s)$	Play empty squares.	
$Result(s, a)$	Symbol (x/o) is placed on empty square.	→ Stochastic transition model $P(s' s, a)$
$Terminal(s)$	Did a player win or is the game a draw?	
$Utility(s)$	+1 if x wins, -1 if o wins and 0 for a draw. Utility is only defined for terminal states.	⎵ Reward function $r(s)$

- We can set up an MDP to find the optimal policy $\pi^*(s)$, but it will be hard to solve since:
 - There are many states, so the table $U(s)$ has many entries.
 - The stochastic transition model $P(s'|s, a)$ needs to be known. The tables are very large.
 - All the reward is delayed. Immediate regards are always 0 until the end of the game.
- This makes planning hard! A solution is to use online learning like model-free reinforcement learning.



Reinforcement Learning

AIMA Chapter 22

Reinforcement Learning (RL)

- RL assumes that the problem can be modeled as an **MDP**.
- However, we do not know the transition or the reward model. This means we have an **unknown environment**.
- We cannot use offline planning in unknown environments. The agent needs to interact with the environment (try actions) and **use the reward signal to update its estimate of the utility of states and actions**. This is a learning process where the reward provides positive reinforcement.
- A popular algorithm is Q-Learning which tries to learn the state-action value function of important states.

Q-Learning

Q-Learning learns the state-action value function as a table from interactions with the environment.

Q-Table

s	a	$Q(s, a)$

function Q-LEARNING-AGENT(*percept*) **returns** an action

inputs: *percept*, a percept indicating the current state s' and reward signal r

persistent: Q , a table of action values indexed by state and action, initially zero

N_{sa} , a table of frequencies for state–action pairs, initially zero

s, a , the previous state and action, initially null

New episode
has no s .

if s is not null **then**

increment $N_{sa}[s, a]$

$Q[s, a] \leftarrow Q[s, a] + \alpha(N_{sa}[s, a])(r + \gamma \max_{a'} Q[s', a'] - Q[s, a])$

$s, a \leftarrow s', \operatorname{argmax}_{a'} f(Q[s', a'], N_{sa}[s', a'])$

return a

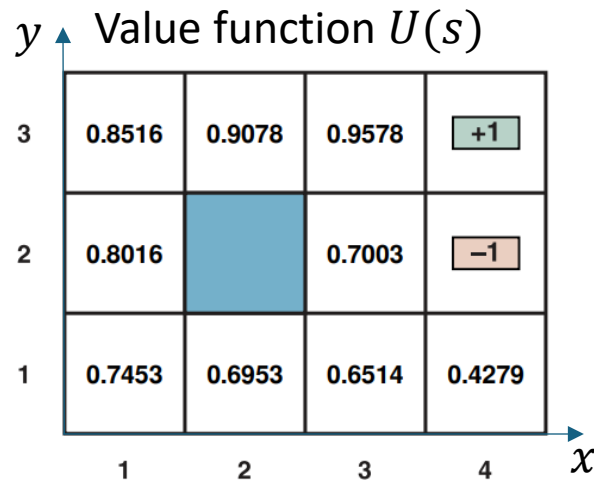
Learning rate

Make $Q[s, a]$ a little more similar to the received reward + the best Q-value of the successor state.

f is the exploration function and decides on the next action. As N increases it can exploit good actions more.

Value Function Approximation

- U (or Q) tables needs to store and estimate one entry for each state (state/action combination).
- Issues and solutions
 - Too many entries to store → lossy compression
 - Many combinations are rarely seen → generalize to unseen entries
- **Idea:** Estimate the state value by learning an approximation function $\hat{U}(s) = g_{\theta}(s)$ based on features of s .
- **Example:** 4x3 Grid World with a linear combination of state features (x, y) and learn θ from observed data.

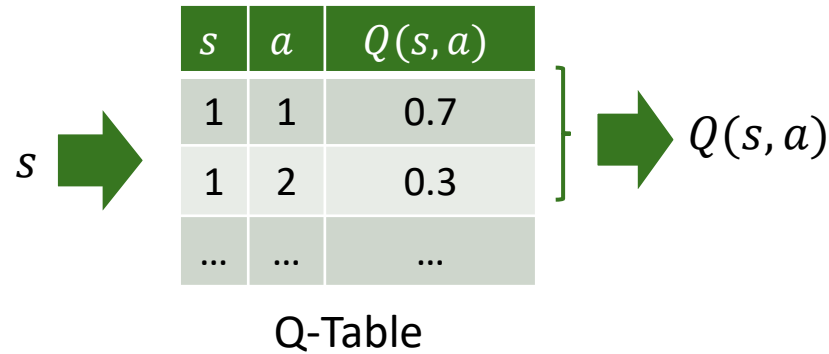


Learn θ from observed interactions with the environment to approximate $U(s)$

$$\hat{U}_{\theta}(x, y) = \theta_0 + \theta_1 x + \theta_2 y$$

θ can be updated iteratively after each new observed utility using gradient descent.

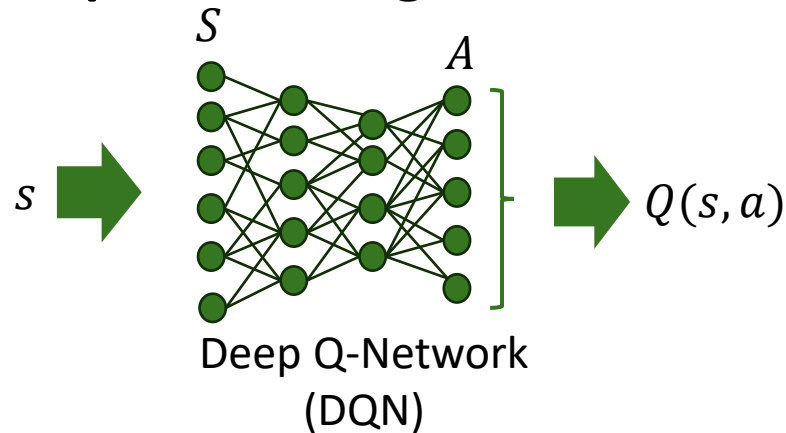
Traditional Q-Learning



function Q-LEARNING-AGENT(*percept*) **returns** an action
inputs: *percept*, a percept indicating the current state s' and reward signal r
persistent: Q , a table of action values indexed by state and action, initially zero
 N_{sa} , a table of frequencies for state–action pairs, initially zero
 s, a , the previous state and action, initially null

if s is not null **then**
 increment $N_{sa}[s, a]$
 $Q[s, a] \leftarrow Q[s, a] + \alpha(N_{sa}[s, a])(\underbrace{r + \gamma \max_{a'} Q[s', a']}_{\text{target}} - \underbrace{Q[s, a]}_{\text{prediction}})$
 $s, a \leftarrow s', \operatorname{argmax}_{a'} f(Q[s', a'], N_{sa}[s', a'])$
return a

Deep Q-Learning



Target networks: It turns out that the Q-Network is unstable if the same network is used to estimate $Q(s, a)$ and also $Q(s', a')$. Deep Q-Learning uses a second target network for $Q(s', a')$ that is updated with the prediction network every C steps.

Experience replay: To reduce instability more, generate actions using the current network and store the experience $\langle s, a, r, s' \rangle$ in a table. Update the model parameters by sampling from the table.

Loss function: squared difference between prediction and target.



Summary

- Agents can learn the value of being in a state from **reward signals**.
- Rewards can be delayed (e.g., at the end of a game).
- Not being able to fully **observe the state** makes the problem more difficult (POMDP).
- **Unknown transition models** lead to the need of exploration by trying actions (model free methods like Q-Learning).
- All these problems are computationally very expensive and often can only be solved by **approximation**. State of the art is to use deep artificial neural networks for function approximation.