



# MDPs: policy evaluation



# Evaluating a policy



## Definition: utility

Following a policy yields a **random path**.

The **utility** of a policy is the (discounted) sum of the rewards on the path (this is a random variable).

### Path

[in; stay, 4, end]

[in; stay, 4, in; stay, 4, in; stay, 4, end]

[in; stay, 4, in; stay, 4, end]

[in; stay, 4, in; stay, 4, in; stay, 4, in; stay, 4, end]

...

### Utility

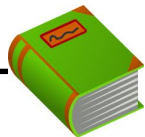
4

12

8

16

...



## Definition: value (expected utility)

The **value** of a policy at a state is the **expected** utility.

Value: 12

# Evaluating a policy: volcano crossing

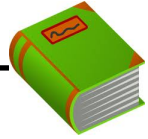
**Run** (or press ctrl-enter)

2.4 ↓	-0.5 ↓	-50	40	<i>a</i>	<i>r</i>	<i>s</i>
3.7 →	5 ↓	-50	31 ↑	E	-0.1	(2,1)
				S	-0.1	(2,2)
				E	-0.1	(3,2)
				E	-0.1	(3,3)
				E	-0.1	(3,4)
				N	-0.1	(2,4)
				N	-50.1	(2,3)
2	12.6 →	16.3 →	26.2 ↑			

Value: 3.73

Utility: -29.99

# Discounting



## Definition: utility

Path:  $s_0, a_1 r_1 s_1, a_2 r_2 s_2, \dots$  (action, reward, new state).

The **utility** with discount  $\gamma$  is

$$u_1 = r_1 + \gamma r_2 + \gamma^2 r_3 + \gamma^3 r_4 + \dots$$

Discount  $\gamma = 1$  (save for the future):

$$[\text{stay}, \text{stay}, \text{stay}, \text{stay}]: 4 + 4 + 4 + 4 = 16$$

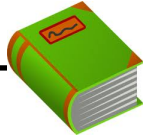
Discount  $\gamma = 0$  (live in the moment):

$$[\text{stay}, \text{stay}, \text{stay}, \text{stay}]: 4 + 0 \cdot (4 + \dots) = 4$$

Discount  $\gamma = 0.5$  (balanced life):

$$[\text{stay}, \text{stay}, \text{stay}, \text{stay}]: 4 + \frac{1}{2} \cdot 4 + \frac{1}{4} \cdot 4 + \frac{1}{8} \cdot 4 = 7.5$$

# Policy evaluation



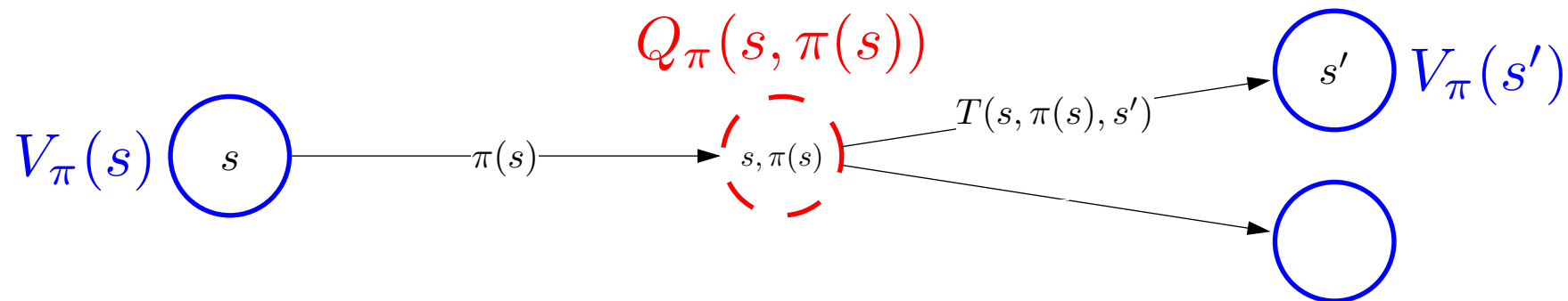
## Definition: value of a policy

Let  $V_\pi(s)$  be the expected utility received by following policy  $\pi$  from state  $s$ .



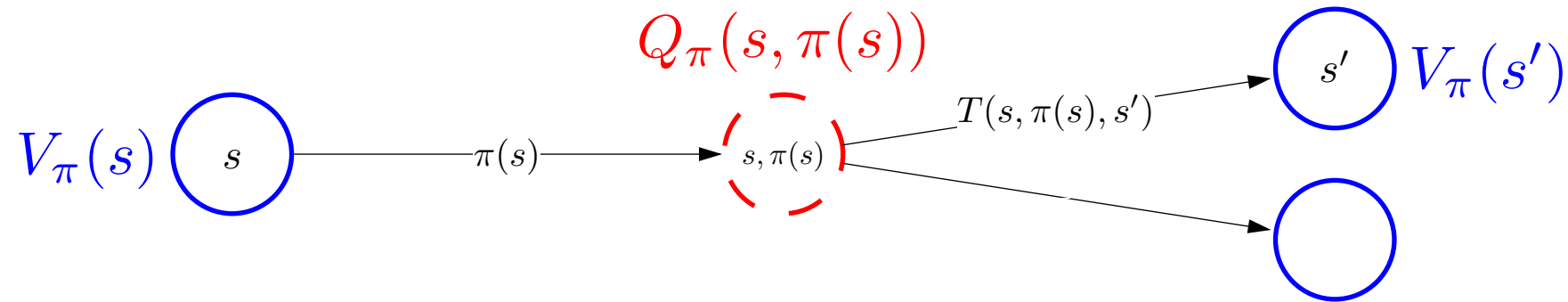
## Definition: Q-value of a policy

Let  $Q_\pi(s, a)$  be the expected utility of taking action  $a$  from state  $s$ , and then following policy  $\pi$ .



# Policy evaluation

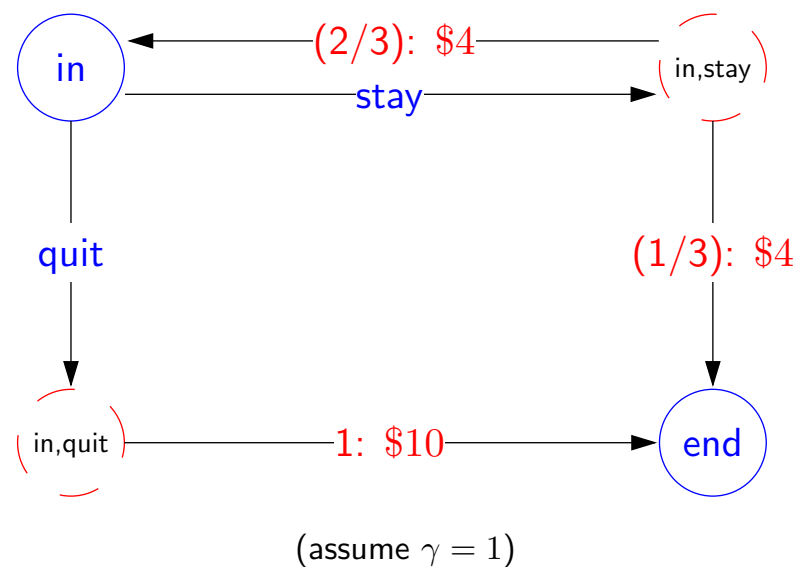
**Plan:** define recurrences relating value and Q-value



$$V_\pi(s) = \begin{cases} 0 & \text{if IsEnd}(s) \\ Q_\pi(s, \pi(s)) & \text{otherwise.} \end{cases}$$

$$Q_\pi(s, a) = \sum_{s'} T(s'|s, a) [\text{Reward}(s, a, s') + \gamma V_\pi(s')]$$

# Dice game



Let  $\pi$  be the "stay" policy:  $\pi(\text{in}) = \text{stay}$ .

$$V_{\pi}(\text{end}) = 0$$

$$V_{\pi}(\text{in}) = \frac{1}{3}(4 + V_{\pi}(\text{end})) + \frac{2}{3}(4 + V_{\pi}(\text{in}))$$

In this case, can solve in closed form:

$$V_{\pi}(\text{in}) = 12$$

# Policy evaluation



## Key idea: iterative algorithm

Start with arbitrary policy values and repeatedly apply recurrences to converge to true values.



## Algorithm: policy evaluation

Initialize  $V_{\pi}^{(0)}(s) \leftarrow 0$  for all states  $s$ .

For iteration  $t = 1, \dots, t_{\text{PE}}$ :

For each state  $s$ :

$$V_{\pi}^{(t)}(s) \leftarrow \underbrace{\sum_{s'} T(s'|s, \pi(s)) [\text{Reward}(s, \pi(s), s') + \gamma V_{\pi}^{(t-1)}(s')]}_{Q^{(t-1)}(s, \pi(s))}$$



# Policy evaluation implementation

How many iterations ( $t_{PE}$ )? Repeat until values don't change much:

$$\max_{s \in \text{States}} |V_{\pi}^{(t)}(s) - V_{\pi}^{(t-1)}(s)| \leq \epsilon$$

Don't store  $V_{\pi}^{(t)}$  for each iteration  $t$ , need only last two:

$$V_{\pi}^{(t)} \text{ and } V_{\pi}^{(t-1)}$$

# Complexity



## Algorithm: policy evaluation

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For iteration  $t = 1, \dots, t_{\text{PE}}$ :

For each state  $s$ :

$$V_{\pi}^{(t)}(s) \leftarrow \underbrace{\sum_{s'} T(s'|s, \pi(s)) [\text{Reward}(s, \pi(s), s') + \gamma V_{\pi}^{(t-1)}(s')]}_{Q^{(t-1)}(s, \pi(s))}$$

## MDP complexity

$S$  states

$A$  actions per state

$S'$  successors (number of  $s'$  with  $T(s'|s, a) > 0$ )

Time:  $O(t_{\text{PE}} S S')$

# Policy evaluation on dice game

Let  $\pi$  be the "stay" policy:  $\pi(\text{in}) = \text{stay}$ .

$$V_{\pi}^{(t)}(\text{end}) = 0$$

$$V_{\pi}^{(t)}(\text{in}) = \frac{1}{3}(4 + V_{\pi}^{(t-1)}(\text{end})) + \frac{2}{3}(4 + V_{\pi}^{(t-1)}(\text{in}))$$

$s$	end	in	$(t = 100 \text{ iterations})$
$V_{\pi}^{(t)}$	0.00	12.00	

Converges to  $V_{\pi}(\text{in}) = 12$ .



# Summary so far

- **MDP**: graph with states, chance nodes, transition probabilities, rewards
- **Policy**: mapping from state to action (solution to MDP)
- **Value of policy**: expected utility over random paths
- **Policy evaluation**: iterative algorithm to compute value of policy