Markov Decision Processes (MDPs)

- •S: state
- A: action
- •T: state transition probability matrix
- •R: reward function
- gamma: discount factor

Optimal Policy

- •Provides optimal action for any state
- Maximize rewards

Optimal Policy =
$$\pi^*$$
, $\pi^*(S) = A^*$

Bellman Equation

- Used to update value
- •For both policy & value iteration

$$V^*(S) = \max_{a} E[R(s, a) + \gamma V^*(S')]$$

Cumulative Reward: $\sum_{t=0}^{\infty} \gamma^t R_{a_t}(s_t, s_{t+1})$

Robot Environment

7 Possible robot actions

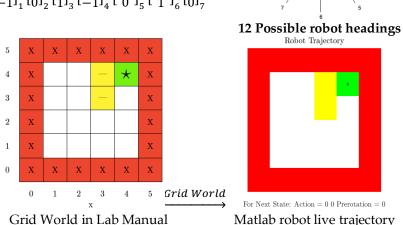
Movement (Forward 1, None 0, Backward -1)

Rotation (Left -1, None 0, Right 1)

[Movement]

 $\begin{bmatrix} Rotation \end{bmatrix}_{action\#} =$

 $\begin{bmatrix} 1 \\ -1 \end{bmatrix}_{1} \begin{bmatrix} 1 \\ 0 \end{bmatrix}_{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix}_{3} \begin{bmatrix} -1 \\ -1 \end{bmatrix}_{4} \begin{bmatrix} -1 \\ 0 \end{bmatrix}_{5} \begin{bmatrix} -1 \\ 1 \end{bmatrix}_{6} \begin{bmatrix} 0 \\ 0 \end{bmatrix}_{7}$



Policy Iteration

Psuedo Code

 $\pi_0(s) = a \ \forall \ s \in S$

Loop

$$\pi \xrightarrow{corresponds to} \pi$$

Compute values of π using Bellman Equation

$$V^{\pi}(S) = E[r|s,\pi(s)] + \gamma \sum_{s' \in S} P(s'|s,\pi(s)) V^{\pi}(s')$$

Improve policy at each state

$$\pi'(S) \leftarrow argmax_a[E[r|s,a] + \gamma \sum_{s' \in S} P(s'|s,a)V^{\pi}(s')]$$

Until $\pi = \pi'$

Value Iteration

Psuedo Code

$$V_0(s) = 0 \ \forall \ s \in S$$

Assign arbitrary values to V(s)

Loop

$$\forall s \in S$$

$$\forall a \in A$$

$$Q(s,a) \leftarrow Q(s,a) = E[r|s,a] + \gamma \sum_{s' \in S} P(s'|s,a)V(s')$$

$$V(s) \leftarrow \max Q(s,a)$$

Until V(s) converges

heading and next state shown