



MDPs

MDPs

Calculating Policies

Solving MDPs

Markov Decision Processes

MDPs

- **discounted reward:** penalize future rewards by γ
 - $R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \dots + \gamma^n R(s_n)$
- **policy:** $\pi(s) = a$ gives an action for each state
- **optimal policy:** π^*

Calculating π^*

Optimal policy is based on optimal utility:

$$\pi^*(s) = \operatorname{argmax}_{a \in A(s)} \sum_{s'} T(s, a, s') U^{\pi^*}(s')$$

Utility of a policy is based on expected rewards:

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

Utility of a state is its reward plus the best utility of an action in that state:

$$U(s) = R(s) + \gamma \max_a \sum_{s'} T(s, a, s') U(s')$$

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MDPs

Solving MDPs

Value Iteration

Example

Solving MDPs

Value Iteration

Repeated Bellman updates:

- 1: **for all** States s **do**
 - 2: $U(s) \leftarrow R(s)$
 - 3: **while** unsatisfied **do**
 - 4: **for each** state s **do**
 - 5: $U'(s) \leftarrow R(s) + \gamma \max_a \sum_{s'} T(s, a, s') U(s')$
 - 6: $U \leftarrow U'$
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Utility values are guaranteed to converge with enough updates
This equilibrium gives an optimal policy

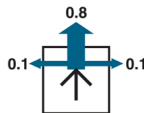
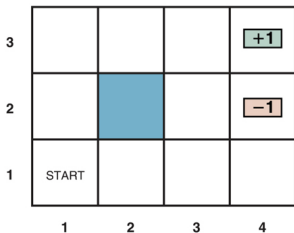
MDP Example

MDPs

Solving MDPs

Value Iteration

Example



Transitions to terminal states have rewards of -1 and 1 , all other transition rewards are $-.04$

Probability of $.8$ to move in intended direction, $.1$ to move at a right angle

$0 < \gamma \leq 1$ – let's pick $\gamma = .5$