Class Outline

1. search: heuristics, CSPs, games
2. knowledge representation: FOL, resolution
3. planning: STRIPS, MDPs
4. learning: supervised, unsupervised
5. uncertainty: particle filters, HMMs

Markov Decision Processes

Examples

1. robot navigation
2. driving
3. business
4. war
5. diagnosis
6. life

Probability

propositional

domain: discrete or continuous

0–1, sum to 1

distribution of continuous = density

$E(X) = \int x \, pdf(x) \, dx$

$P(X = x_1)$ written as $P(x_1)$ or if X is true/false, $P(x)$

conditional (=posterior): $P(x|y) = P(x \wedge y)/P(y)$

Markov Decision Process (MDP)

initial state: s_0

transition model: $T(s, a, s') =$ probability of going from s to s' after doing a.

reward function: $R(s)$ for landing in state s.

terminal states: sinks $=$ absorbing states (end the trial).

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total reward: reward over (finite) trajectory:
$R(s_0) + R(s_1) + R(s_2)$
discounted reward: penalize future by γ:
$R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) \ldots$

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find:

policy: $\pi(s) = a$
optimal policy: π^*
proper policy: reaches terminal state

What to do?

$$\pi^*(s) =$$

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The key:

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

(Richard Bellman, 1957)

Break

- asst 9 due Mon Apr 7
- projects: reading is fine, but probably best to talk with me before starting serious work

Solving MDPs

Value Iteration

Repeated Bellman updates:

Repeat until happy
  for each state s
    $U'(s) \leftarrow R(s) + \gamma \max_a \sum_{s'} T(s,a,s')U(s')$
  $U \leftarrow U'$

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For infinite updates everywhere, guaranteed to reach equilibrium.

Equilibrium is unique solution to Bellman equations!

asychronous works: converges if every state updated infinitely often (no state permanently ignored)

EOLQs

- What question didn't you get to ask today?
- What's still confusing?
- What would you like to hear more about?

Please write down your most pressing question about AI and put it in the box on your way out.
Thanks!