

Robot grocery shopping in partially observable settings

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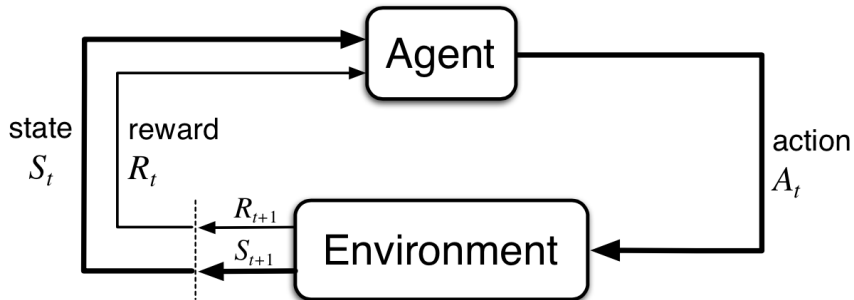
May 13, 2015

MIT, 6.834j Cognitive Robotics

1. Background on POMDPs
2. Grocery shopping as planning in a POMDP
3. Demo!
4. What worked
5. What failed

A *partially observable Markov decision process* (POMDP) is a tuple (S, A, Ω, R, T, O)

- S : state space
- A : action space
- Ω : observation space
- $R : S \times A \rightarrow \mathbb{R}$ reward function
- T : transition operator. $T(s' \mid s, a)$ is probability of next state s' given state s and action a
- O : observable operator. $O(o \mid s)$ is probability of observing o given at state s



A POMDP induces an equivalent representation as a *belief MDP* with tuple (B, A, τ, R)

- B : set of belief states over the POMDP states
- A : action space of original POMDP
- τ : belief state transition operator

$$\tau(b, a, b') = \sum_{o \in \Omega} P(b' \mid b, a, o) P(o \mid a, b)$$

- $r : B \times A \rightarrow \mathbb{R}$ belief state reward function

$$r(b, a) = \sum_{s \in S} b(s) R(s, a)$$

Implemented MDP solvers:

- ☐ Q-learning
- ☐ SARSA
- ☐ R-MAX
- ☐ Thompson sampling

There are a lot!

- ☐ Function approximations with adaptive basis functions
- ☐ BOSS
- ☐ Spectral methods
- ☐ Skill chaining
- ☐ ...

Implemented MDP solvers:

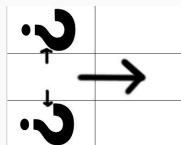
- Q-learning (Watkins, 1989)
- SARSA (Rummery and Niranjan, 1994)
- R-MAX (Brafman and Tennenholtz, 2002)
- Thompson sampling (Strens, 2000)

There are a lot more!

- Function approximations with adaptive basis functions (Mnih et al., 2013)
- BOSS (Asmuth et al., 2009)
- Spectral methods (Boots et al., 2009)
- Skill chaining (Konidaris and Barto, 2009)
- ...

Grid World POMDP

Uncertain movement



Can only see around current cell (partially observable)



World is not fully known beforehand

- ☐ Model of how items in the same aisle correlate.
- ☐ Unknown arrangement of aisles
- ☐ Unknown arrangement of items within aisles

pygame running the visuals

Every second:

- ☐ Agent provides next action based on current belief state
- ☐ Simulator executes action (errors may happen)
- ☐ Belief state is updated based on transition probabilities
- ☐ Belief state is updated based on observation
- ☐ Belief about the world is updated based on belief state, and observation

Challenges:

- ☐ Markov assumption is not completely accurate
- ☐ Bias towards increasing probability of most likely states

demo

We encode a **Max Probability** MDP

- Choose the most likely state from belief state to run value iteration

Value iteration:

$$\begin{aligned}v_{k+1}(s) &= \max_a \mathbb{E}[R_{t+1} + \gamma v_k(S_{t+1}) \mid S_t = s, A_t = a] \\&= \max_a \sum_{s'} p(s' \mid s, a) [r(s, a, s') + \gamma v_k(s')]\end{aligned}$$

- Continuous state space in belief MDP: Value iteration
- Thompson sampling
- TD(λ) methods

Play with it!



github.com/dustinvtran/bayesrl