Robot grocery shopping in partially observable settings

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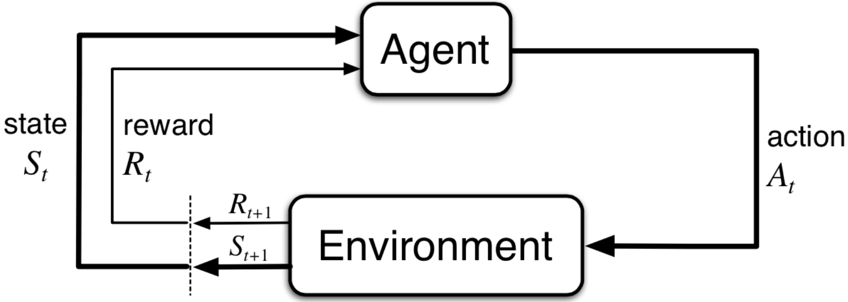
Outline

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
- $R : S \times A \to \mathbb{R}$ 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

Background



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[1]

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

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

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

[1] Given $b(s)$, after taking action a and observing o (and reaching state s'), update belief states

$$b'(s') = \frac{P(o \mid b, a, s')}{P(o \mid b, a)} = \frac{O(o \mid s', a) \sum_{s \in S} T(s' \mid s, a) b(s)}{\sum_{s' \in S} O(o \mid s', a) \sum_{s \in S} T(s' \mid s, a) b(s)} \tag{1}$$

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[2]

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

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

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

[2] Given $b(s)$, after taking action a and observing o (and reaching state s'), update belief states

$$b'(s') = \frac{P(o \mid b, a, s')}{P(o \mid b, a)} = \frac{O(o \mid s', a) \sum_{s \in S} T(s' \mid s, a) b(s)}{\sum_{s' \in S} O(o \mid s', a) \sum_{s \in S} T(s' \mid s, a) b(s)} \tag{2}$$

Background

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)

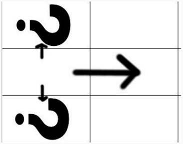
There are a lot more!

- 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)
- ...

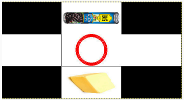
Grocery shopping

Setup: 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

Grocery shopping

GUI interface: *pygame*

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

- Motivated from greedy policies
- Choose the most likely state from belief states as one's position in an MDP
- Solve the MDP!

Our working solver

Value iteration:

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

Failed tasks

- Continuous state space in belief MDP: Value iteration
- Thompson sampling
- TD(λ) methods: Q-Learning, SARSA, Monte Carlo Tree Search

Most simplified task (GridWorld)

Play with it!

github.com/dustinvtran/bayesrl