

POMDPs: Myths, Legends, and Reality

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Outline

- ▶ Part 1: *What are POMDPs?*
- ▶ Part 2: *POMDP Variants and Applications*
- ▶ Part 3: *Implementation Recommendations*

What are POMDPs?

POMDPs are MDPs with sensors instead of direct observation of the current state.

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- ▶ The sensors are some probability distribution of some observation given a certain state.
 - ▶ Unlike traditional MDPs that map from states to actions, these map from belief states(observations) to actions.
 - ▶ Exact optimal solutions yield the optimal action for each possible belief state that minimizes our cost.
- woodcockFormalMethodsPractice2009

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- ▶ γ is the discount factor.

POMDPs rely on a belief update step, which itself can be an MDP.

► a

Value and policy function parameterizations

► a

The need for approximations

► a

Theory and undecidability

► a

POMDP Variants and Applications

► a

Implementation Recommendations

My favorite package: POMDPs.jl

```
using Pkg; Pkg.add("POMDPs"); Pkg.add("QMDP");
using POMDPs, QuickPOMDPs, POMDPTools, QMDP

m = QuickPOMDP(
    states = ["left", "right"],
    actions = ["left", "right", "listen"],
    observations = ["left", "right"],
    initialstate = Uniform(["left", "right"]),
    discount = 0.95,
    transition = function (s, a)
        if a == "listen"
            return Deterministic(s) # tiger stays behind the same
        else # a door is opened
            return Uniform(["left", "right"]) # reset
        end
    end,
    observation = function (s, a, sp)
        if a == "listen"
```

Alternative Packages

- ▶ Finite-state Controllers using Branch and Bound
- ▶ pomdp
- ▶ pyPOMDP
- ▶ zmdp

Temp 1






Temp 2

Temp 3

Temp 4

Temp 5

References

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