Partially Observable Markov Decision Processes for Planning in Uncertain Environments

Project Thesis
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Introduction

Types of Uncertainty

- state uncertainty
- outcome uncertainty

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Dealing with Uncertainty

- worst case disturbance sequences
- probabilistic reasoning

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POMDPs

- general framework
- computationally demanding

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POMDPs

- general framework
- computationally demanding
- recent research: faster solvers

Introduction

This Work

- problem specific approximations

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- problem specific approximations vs. full POMDP approaches

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- application domains:
  1. localization and planning
  2. motion planning with latent human intentions

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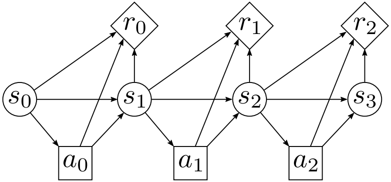
Outline

1. The Partially Observable Markov Decision Process
2. Approximate Online POMDP Solvers
    - DESPOT
    - POMCPOW
3. Application Domain: Localization and Planning
    - Baselines
    - POMDP Solvers
4. Conclusion and Future Work

The Partially Observable Markov Decision Process

Dynamic Decision Network



MDP

- state s
- action a
- reward r

Objective: Finding a policy π^* that maximizes

$$J(\pi) = E\left[\sum_{t=0}^{\infty} \gamma^t r_t\right].$$

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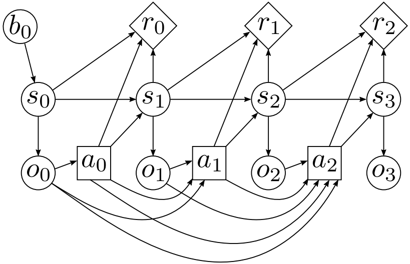

POMDP

- state s
- action a
- reward r
- observation o
- initial belief b_0

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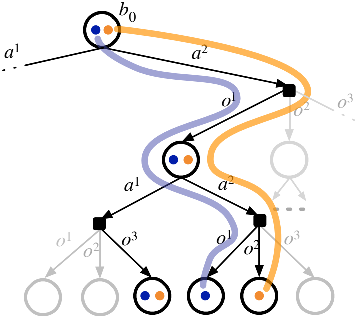
Determinized Sparse Partially Observable Tree (DESPOT)



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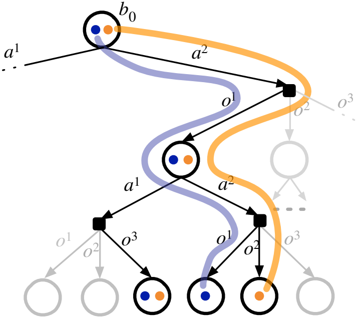

High Level Idea

- incrementally construct sparse tree
- maintain bounds on *value* at nodes
- choose action with best lower bound

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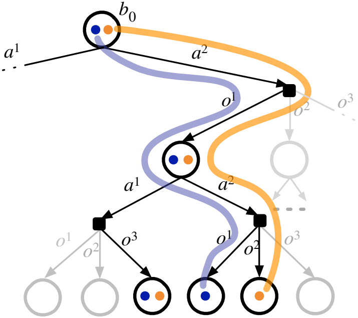

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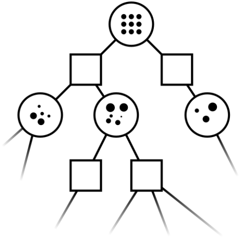
Domain Knowledge

- user-defined initial bound estimates

Partially Observable Monte-Carlo Planning with Observation Widening (POMCPOW)



High Level Idea

- Monte-Carlo tree search
- locally approximate the *value function* through Monte-Carlo simulations
- choose action with highest value

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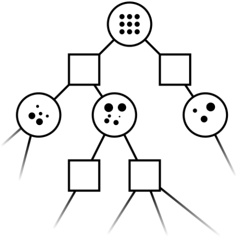

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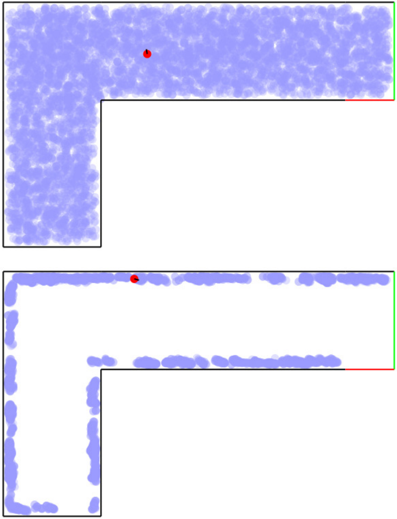
Localization and Planning

Screenshot of the Simulator



Problem Details

- *known room* but *unknown location*

Localization and Planning

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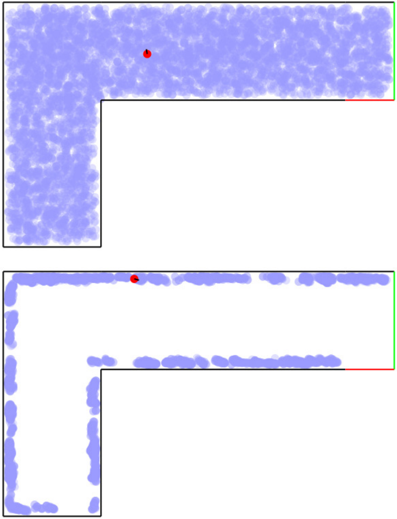

Problem Details

- *known room* but *unknown location*
- objective:
  - success: leave room at exit (green)
  - failure: falling down stairs (red)
  - penalties: time and collisions
- observations: collision sensor
- dynamics: noisy differential drive
  - actions: left, right, straight

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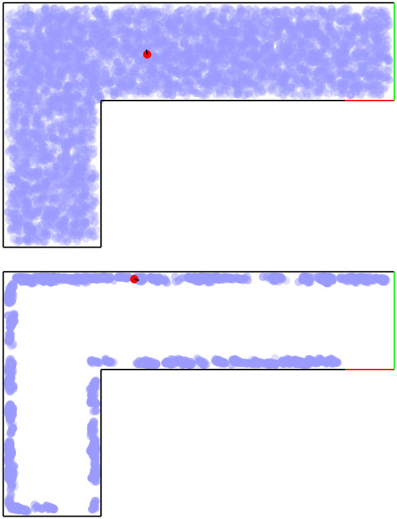

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POMDP

- continuous state space
- discrete action and observation space

Baselines

Mode Control

- use mode of belief to approximate the state
- treat POMDP as fully observable problem

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Most Likely Reflex Agent (MLRA)

- handcrafted feedback policy
- P-controller tracking preset path

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Most Likely Reflex Agent (MLRA)

- handcrafted feedback policy
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Most Likely Model Predictive Control (MLMPC)

- use MPC to plan a path
- cost function: negative reward

$\Rightarrow$ MLMPC is an optimal policy for the fully observed problem (MDP)

Integrating Domain Knowledge for POMDP Solvers

Value Estimates

1. Rollout Value Estimate
    - simulate default policy: “always straight”
2. Analytic Value Estimate
    - estimate remaining steps from distance to goal
    - approximate value by cumulative living penalty

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Value Estimates

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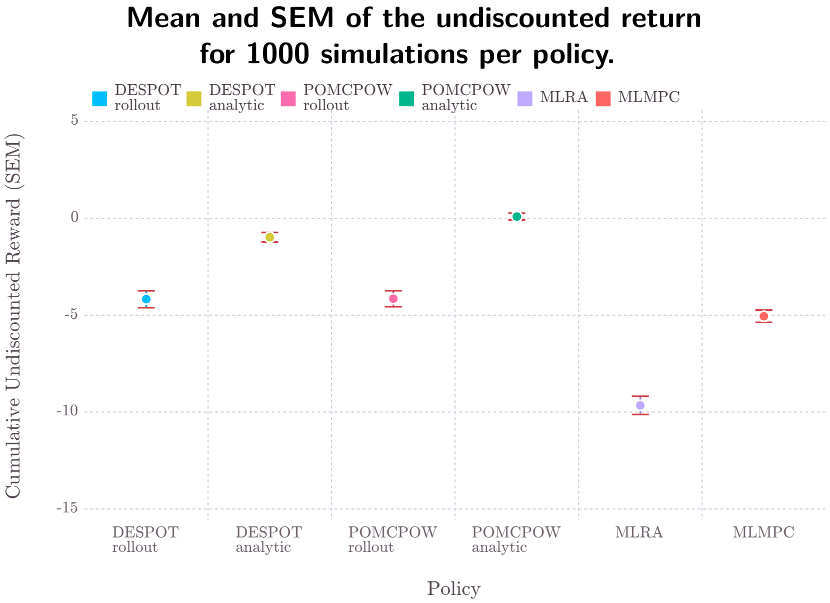
POMDP Solver Setups

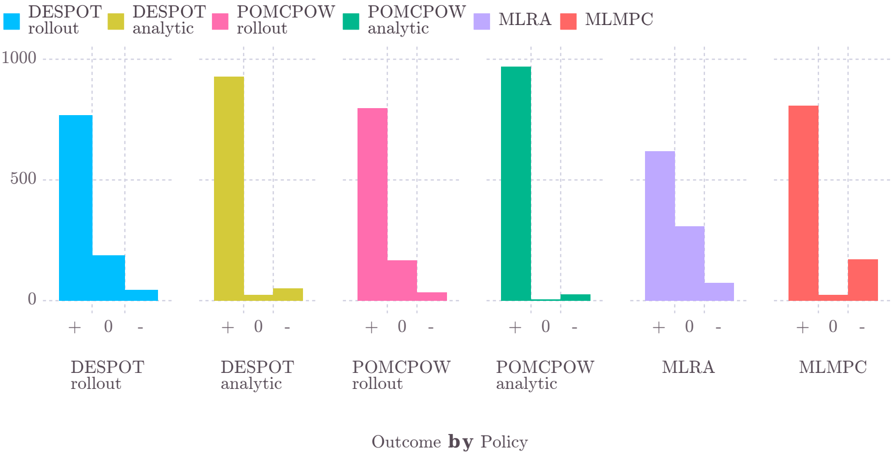
1. DESPOT-rollout
2. DESPOT-analytic
3. POMCPOW-rollout
4. POMCPOW-analytic

Evaluation – Undiscounted Return



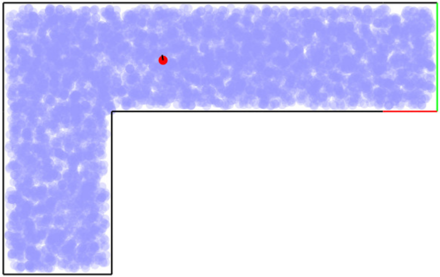
Evaluation – Outcome Distribution

Histogram of outcome frequencies grouped by policy.



Evaluation – Outcome Distribution

Initial Conditions



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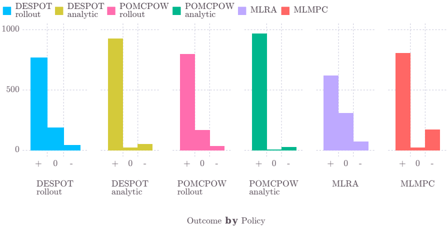

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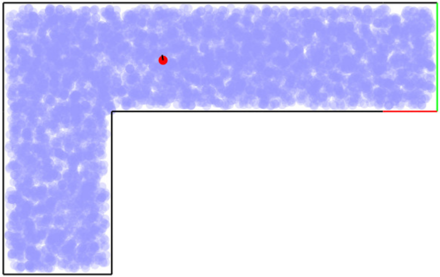

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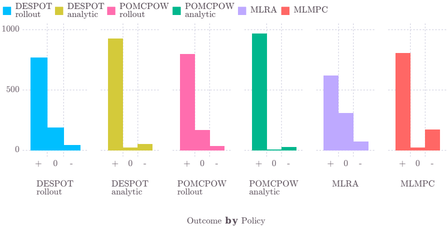

⇒ POMCPOW-analytic near optimal with respect to safety

Evaluation – Qualitative Analysis

MLMPC

POMCPOW-Analytic

Evaluation – Qualitative Analysis

MLMPC

- mode approximation compromises safety
- passive information gathering
- fails for highly symmetric beliefs

POMCPOW-Analytic

Evaluation – Qualitative Analysis

MLMPC

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POMCPOW-Analytic

- active information gathering
- reliably reduces uncertainty
- safe and efficient behaviors

Conclusion and Future Work

Conclusions

1. safe and efficient behaviors
   ⇒ suitable approach for safety vs. efficiency tradoff
2. near real-time planning capabilities
   ⇒ already a useful high-level planner for moderately sized problems
3. designing suitable heuristic guidance hard but cruitial for performance

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Future Work

1. theory for a-priory safety assurances
2. improving scalability by using GPU
3. learning for designing of heuristic guidance

End

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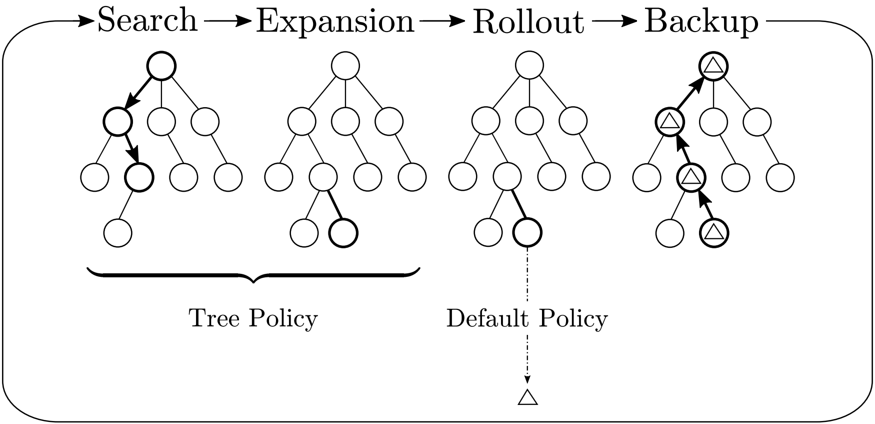
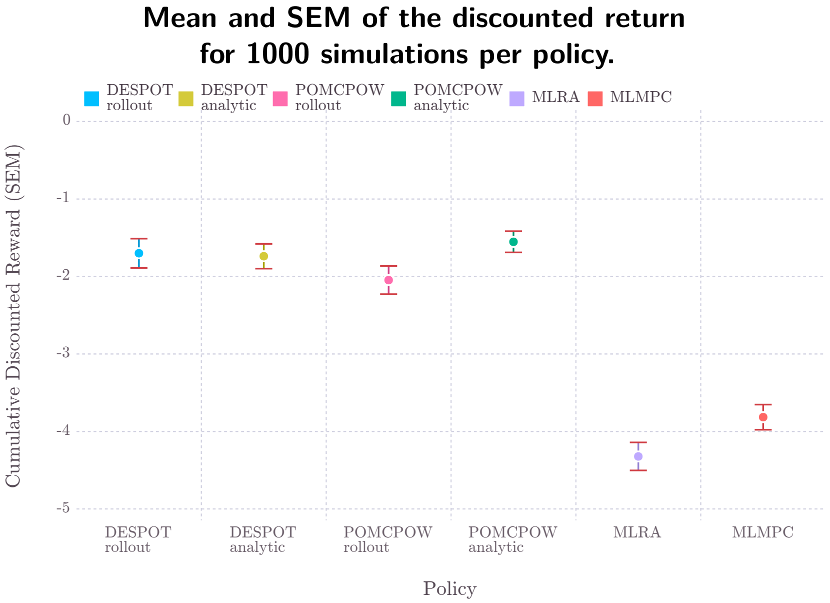
Monte-Carlo Tree Search

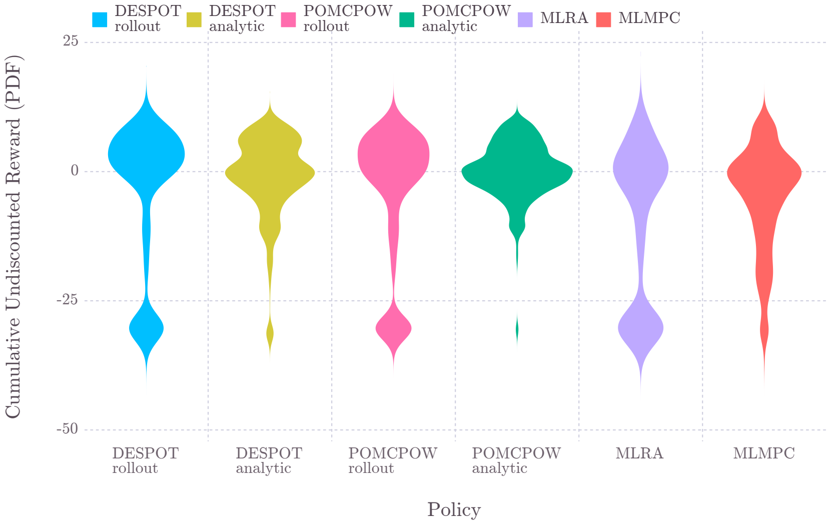


Evaluation: Localization and Planning – Objective Value



Evaluation – Undiscounted Return

Distribution of the undiscounted return for 1000 simulations per policy.



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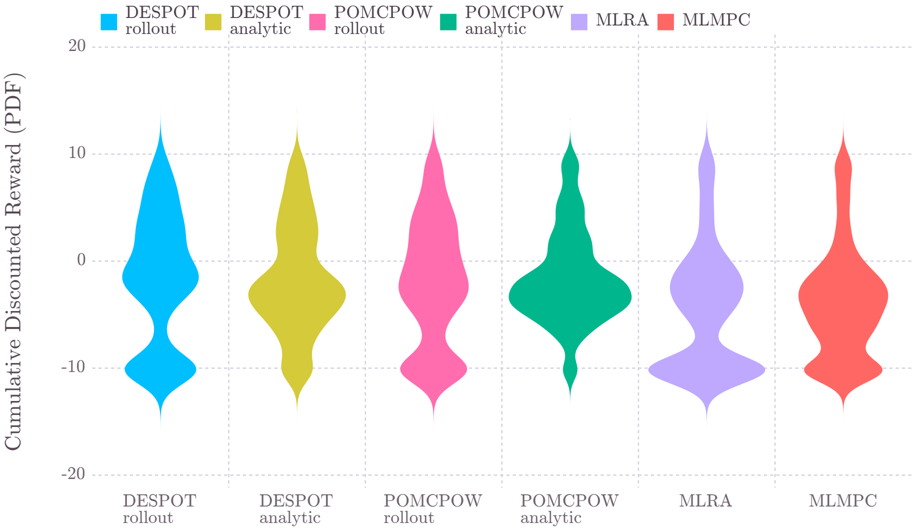
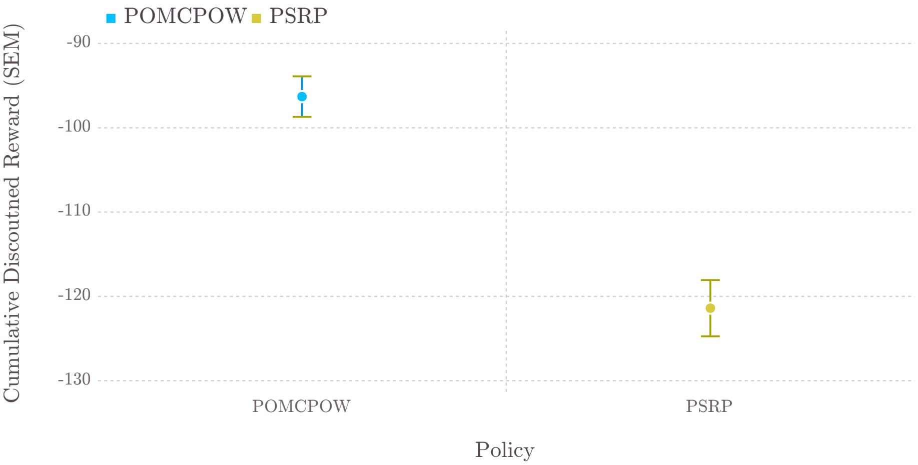


Evaluation: Motion Planning with Latent Human Intentions



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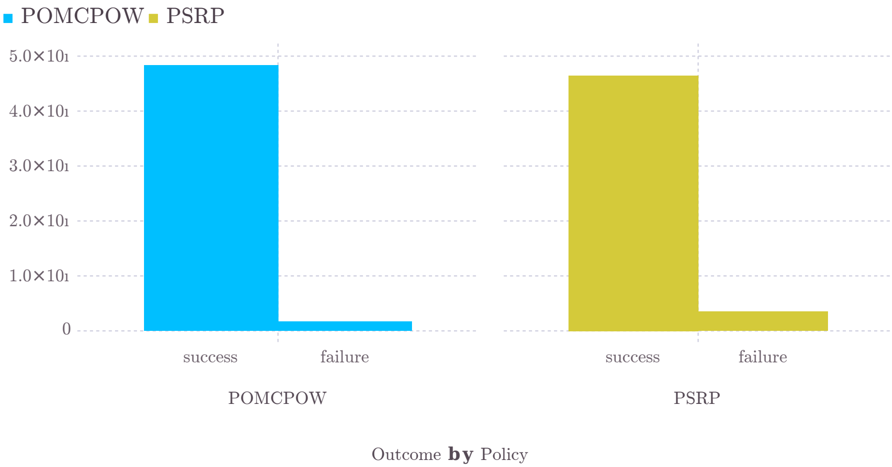
■ POMCPOW ■ PSRP
5.0×10^{1}
4.0×10^{1}
3.0×10^{1}
2.0×10^{1}
1.0×10^{1}
success
failure
POMCPOW
success
failure
PSRP
Outcome **by** Policy