Learning and Optimizing Probabilistic Models for Planning under Uncertainty

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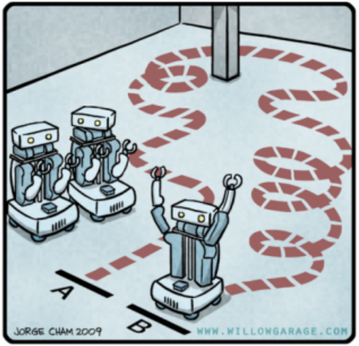
September 27, 2017

Planning under Uncertainty

Domain Characteristics

- A system is controlled by one or more *agents*
- *Uncertain domain dynamics*, i.e. uncertainty may be present in:
  - Execution of actions (e.g., robot may slip)
  - Exogenous factors (e.g., doors open/closed)
  - Percepts (e.g., sensor noise)
- *Sequential decision making*
  - Non-myopic agents
  - Selection of actions with high future pay-off



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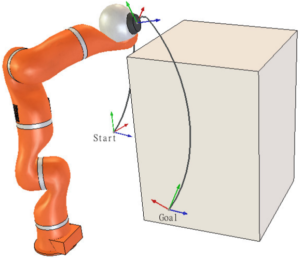
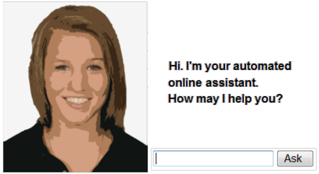
Example Domains

Path planning



Motion planning



Dialog management systems

Image credits: Hawes et al. [1], Iocchi et al. [2], V-REP Manual, Bemidji State University

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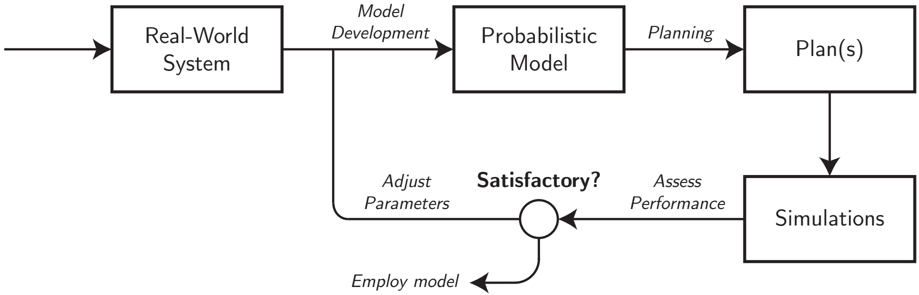
Typical Development Routine



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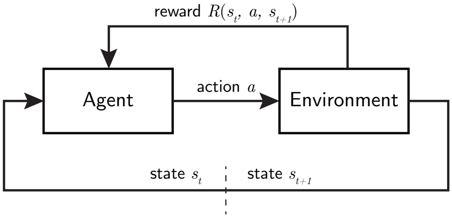
Markov Decision Processes (MDPs)

In DTP systems are modeled by probabilistic models, e.g. MDPs:

Definition

An MDP is a 5-tuple $\mathcal{M} = (\mathcal{S}, s_0, A, \delta, R)$:

- $\mathcal{S}$ is the state-space, $s_0 \in \mathcal{S}$ the initial state
- A is the action-space
- $\delta : \mathcal{S} \times A \times \mathcal{S} \mapsto [0, 1]$ is the transition function
- $R : \mathcal{S} \times A \times \mathcal{S} \mapsto \mathbb{R}$ is the reward function



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Model Development

Problem: How to find a suitable MDP?

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Classical approach: Model development by a *human designer*, however:

- Requires significant effort (e.g., trial-and-error)
- Typically demands knowledge/experience, accompanied by high costs

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Model Development

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Alternative: Use Reinforcement Learning instead of Planning, however:

- Requires direct interaction with environment
- One might require *reusable* models, applicable for multiple tasks

Problem Description

Problem Statement

Problem Description

Related Work

Problem Description

Research Questions

Main Research Question

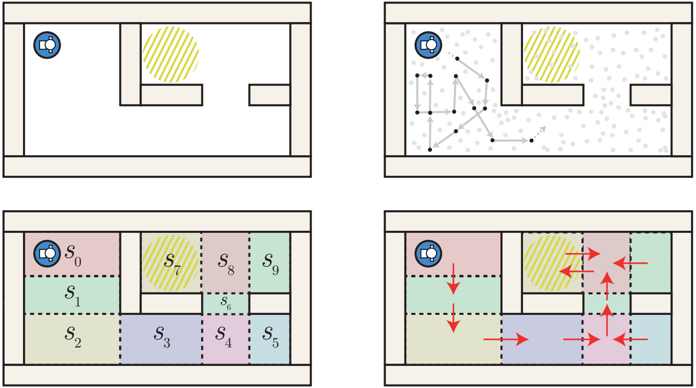
How can the task of obtaining an MDP that maximizes the yielded performance of executing plans that are derived from it, given a dataset about the system under consideration, be automated?

Proposed Solution

General Idea

Proposed Solution

Running Example: Path Planning for Mobile Robot Navigation



Proposed Solution

Performance Measure

- Value Function
- Simulations
- Lorem ipsum dolor sit amet

$$V_{\mathcal{M}} = \frac{\sum_{t \in T_{\mathcal{M}}} \beta \cdot V_{DTP,t} + (1 - \beta) \cdot V_{SIM,t}}{|T_{\mathcal{M}}|}$$

Proposed Solution

Base Framework

Proposed Solution

Multi-Phase Framework

Experimental Results

Conclusions and Recommendations

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