Learning and Optimizing Probabilistic Models for Planning under Uncertainty

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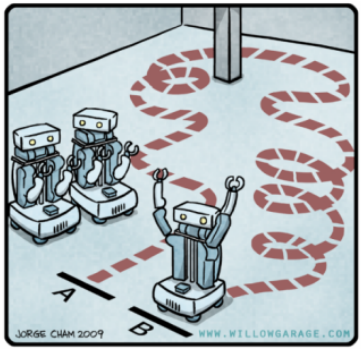
Planning under Uncertainty

Domain Characteristics



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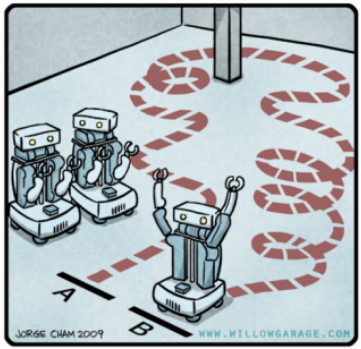

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- *Uncertain domain dynamics*, i.e. uncertainty may be present in:
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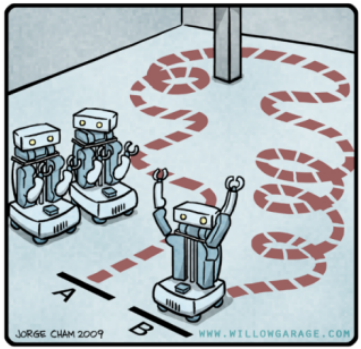
  - Exogenous factors (e.g., doors open/closed)
  - Percepts (e.g., sensor noise)



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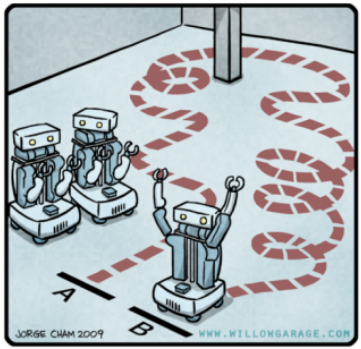
  - Percepts (e.g., sensor noise)
- *Sequential decision making*
  - Non-myopic agents
  - Selection of actions with high future pay-off



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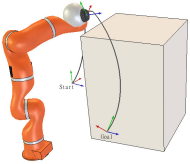
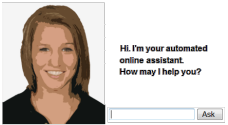
Example Domains

Path planning [7, 8]



Motion planning



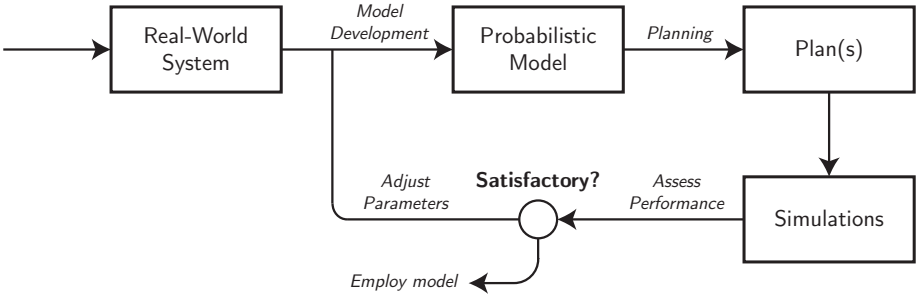
Dialog Management [2]

Operations planning [1, 13]

Image credits: Hawes et al. [7], Iocchi et al. [8], V-REP Manual, Bemidji State University

Planning under Uncertainty

Typical Development Routine



Planning under Uncertainty

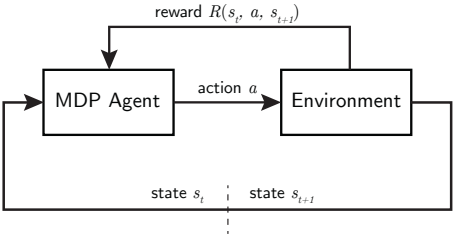
Markov Decision Processes (MDPs)

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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Planning with MDPs

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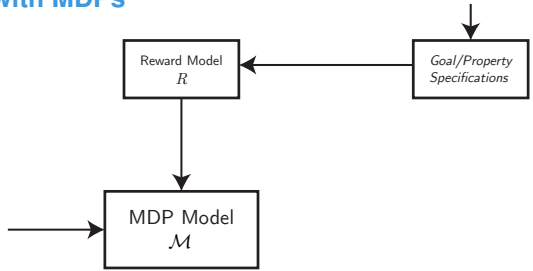

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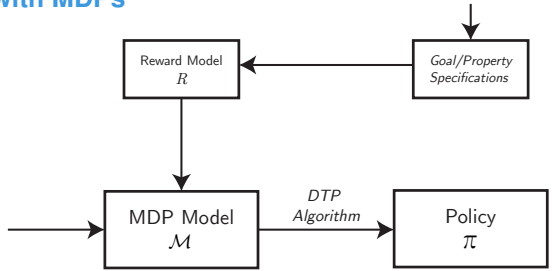

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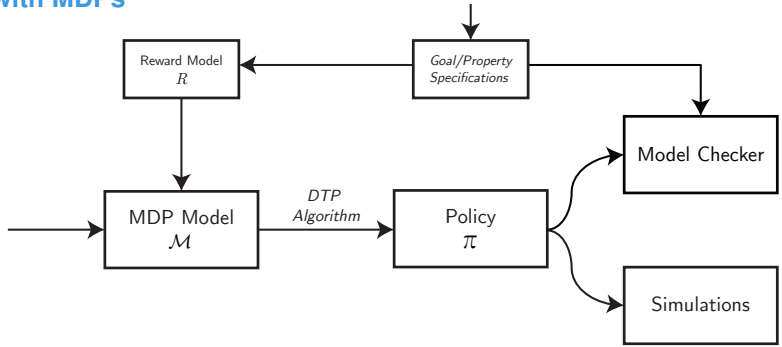

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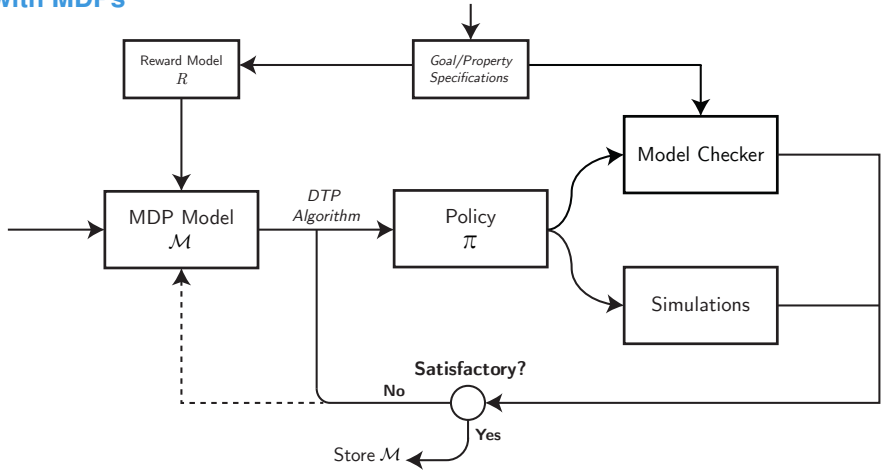

Planning under Uncertainty

Model Development

Problem: How to obtain a suitable MDP for offline planning?

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

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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

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- Making use of a dataset describing the system's dynamics
- Learn the components of MDPs:
  - State space (e.g., clustering, time-state merging)
  - Transition probabilities (e.g., maximum likelihood, Bayesian inference)
  - Emission probabilities in POMDPs (e.g., Baum-Welch, gradient ascent)

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Next Question: How to set the hyperparameters for these algorithms?

Problem Description

Research Questions [1/2]

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Main Research Question

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

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RQ1 Which learning algorithms exist that can be employed for learning MDPs from data for systems involving uncertainty that require plans for automated control?

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RQ2 How should a performance measure be defined which can be used to fairly compare the value of different MDPs?

Problem Description

Research Questions [2/2]

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RQ3 How can the parameter space of model learning algorithms cost-effectively be explored towards a global maximizer with only limited knowledge about the system under consideration?

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RQ4 How can the hierarchy of different abstraction levels be exploited to find a performance-maximizing MDP in a more cost-effective way?

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Given a set E of execution traces describing the dynamics of a system that involves uncertainty, an MDP $\mathcal{M}$ needs to be developed, utilizing learning algorithms parameterized by a set of hyperparameters θ configured in such way to maximize the performance yielded by following the policies computed from this model in a real-world setting.

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Related Work

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- Model Learning Algorithms
  - Baum-Welch for HMMs/POMDPs [15], e.g., Shatkay et al. [12]
  - Best-First Model Merging
  - State-Merging by Trajectory Clustering [10]

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  - Active RL [4] - Uses provided MDP as blueprint for exploration
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- MDPs with Transition Probability Uncertainty
  - MDP-IPs [3]
  - BMDPs [5]

Proposed Solution

General Idea

- Explore the hyperparameter space of model learning algorithms

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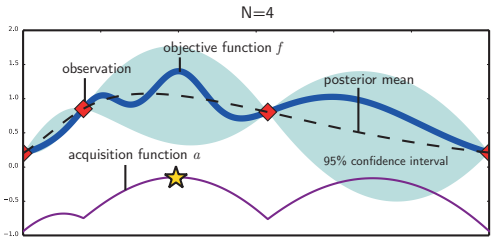
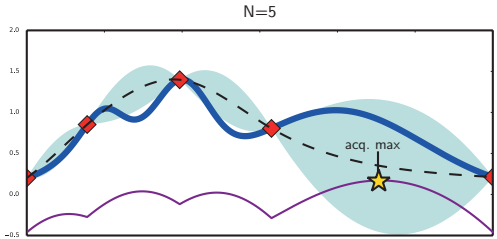
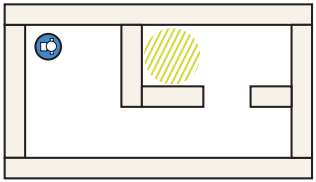




Proposed Solution

Running Example: Path Planning for Mobile Robot Navigation



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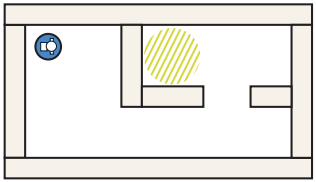

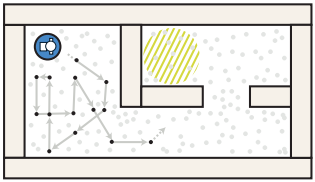

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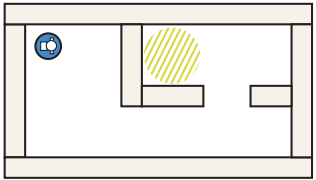

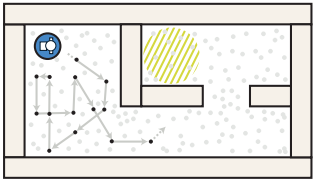

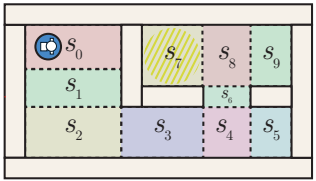

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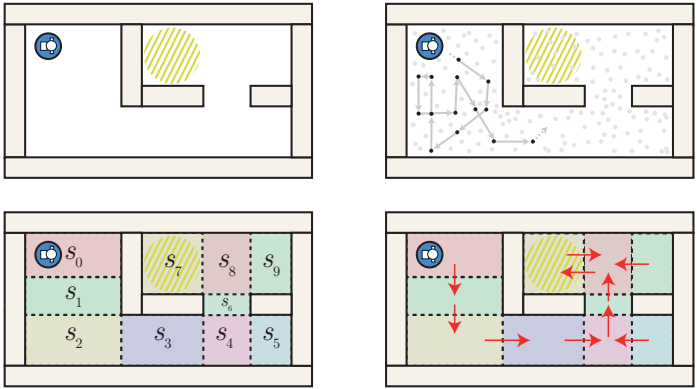

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- Combined:

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

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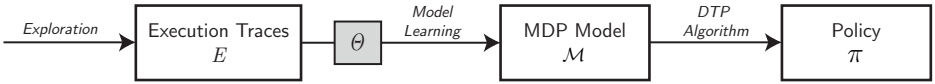
Base Framework



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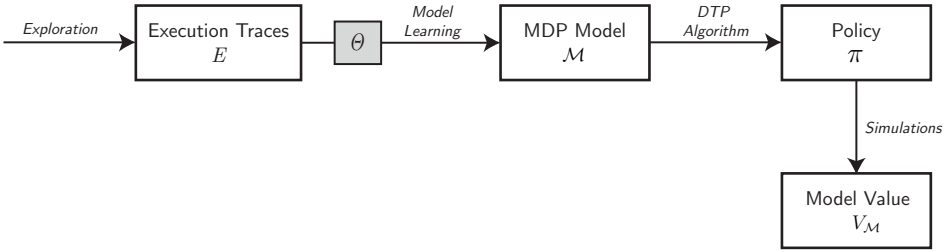

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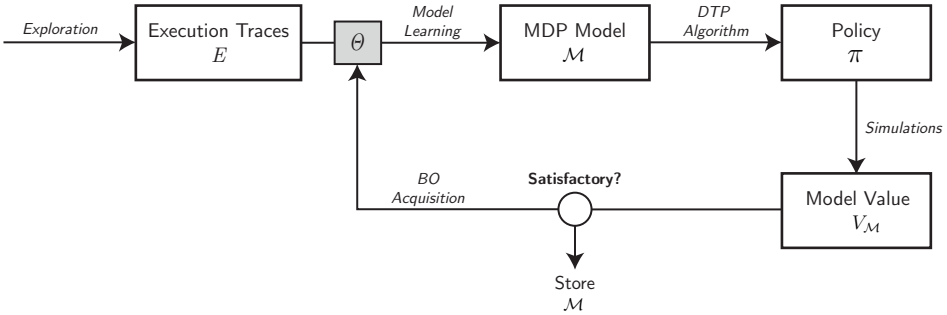

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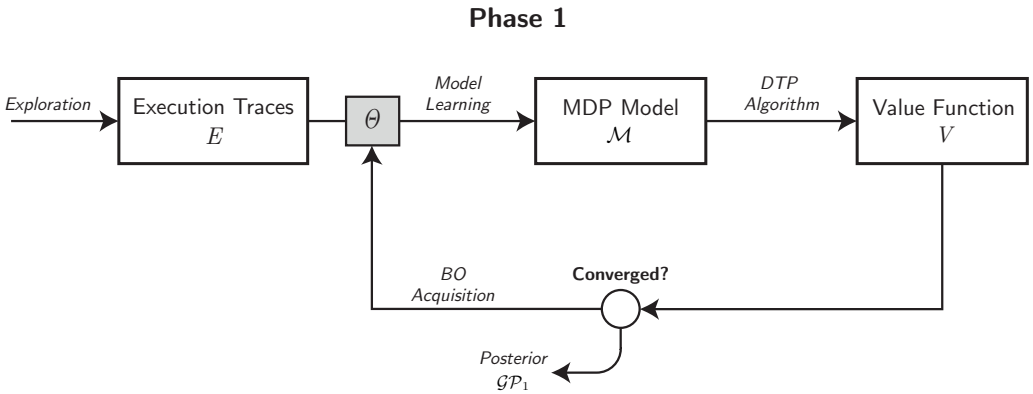
Multi-Phase Framework: Phase 1



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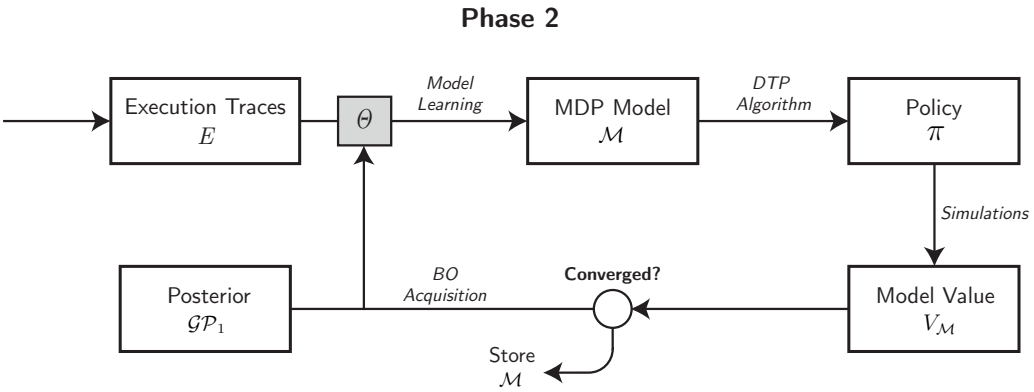
Multi-Phase Framework: Phase 2



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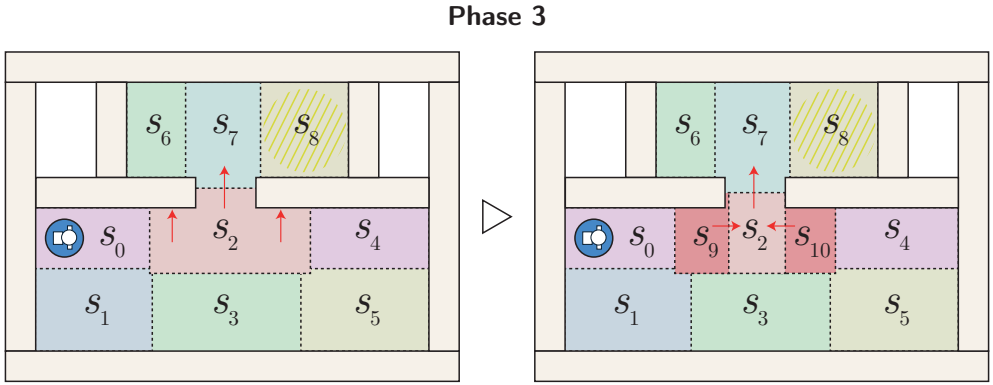
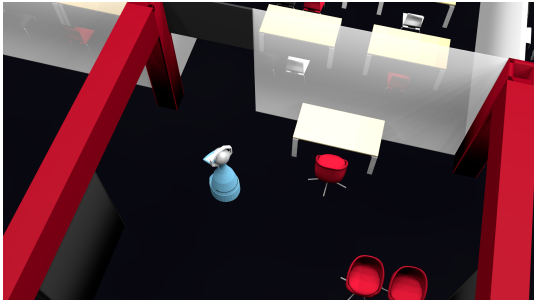
Multi-Phase Framework: Phase 3



Experimental Results

Implementation

- **Domain**: Mobile Robot Navigation



SCITOS-A5 mobile robot in a Morse simulation of the `uol_bl` *environment*

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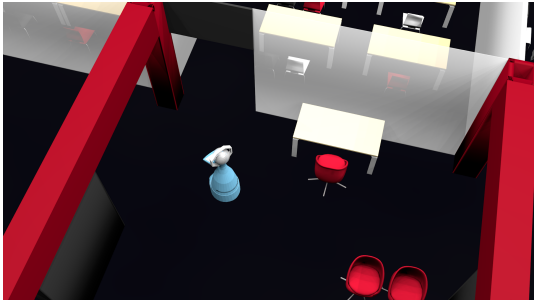

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- Execution traces with odometric readings
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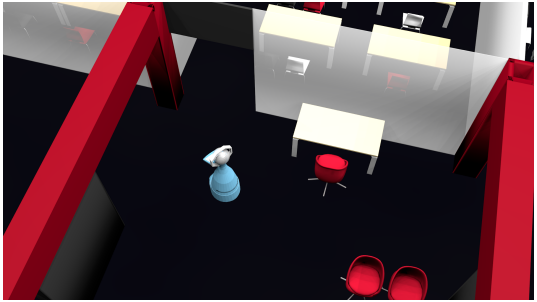
- Transition probabilities of MDPs computed by maximum likelihood
- Performance assessed through simulations
- Tested on small and large environment
- **Software**: Python, ROS, *Morse* simulator



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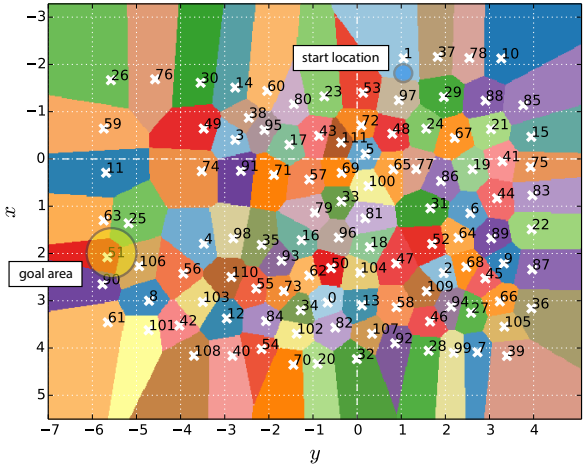

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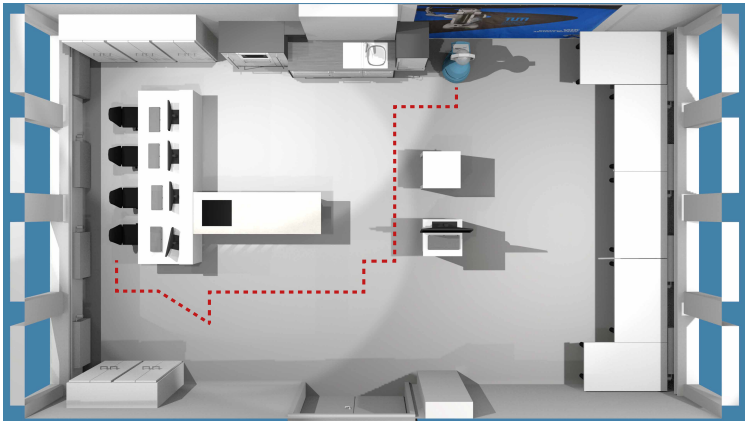
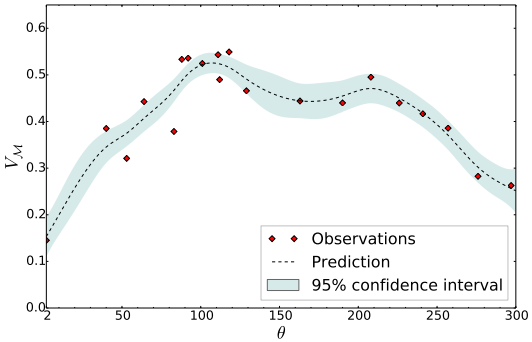
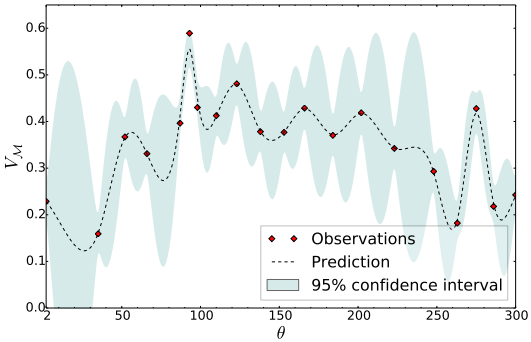


Experimental Results

Base Framework - Small Environment - Dataset Size

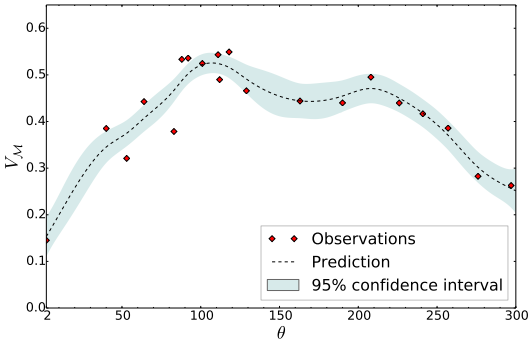


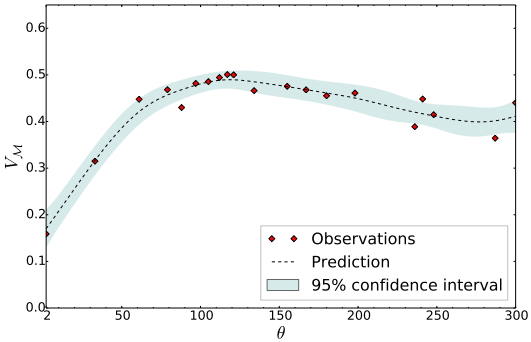


Resulting GP approximation with 100% and 50% of our dataset used
(k-Means, `tum_kitchen` environment, EI acquisition, 20 iterations)

Experimental Results

Base Framework - Small Environment - β factor



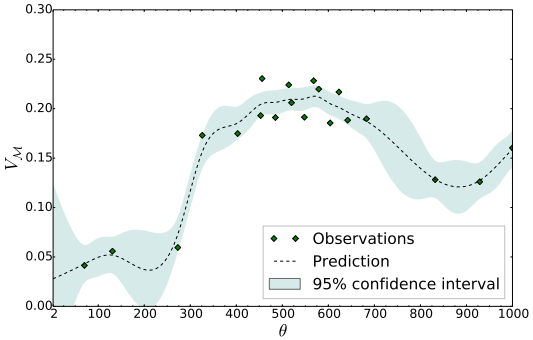


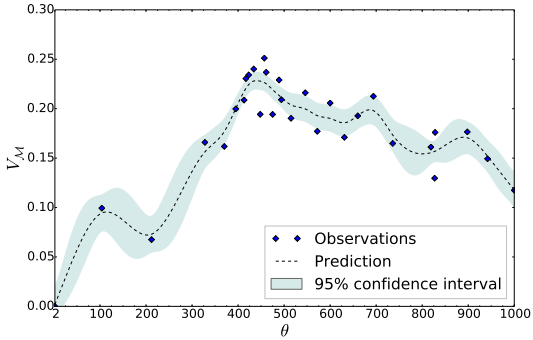
Resulting GP approximation with $\beta = 0.0$ and $\beta = 0.5$

(k-Means, `tum_kitchen` environment, EI acquisition, 20 iterations, 100% dataset used)

Experimental Results

Base Framework - Large Environment

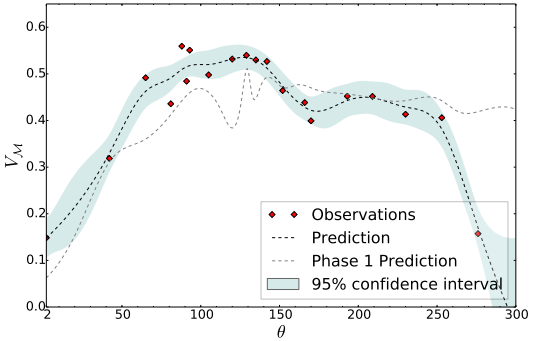


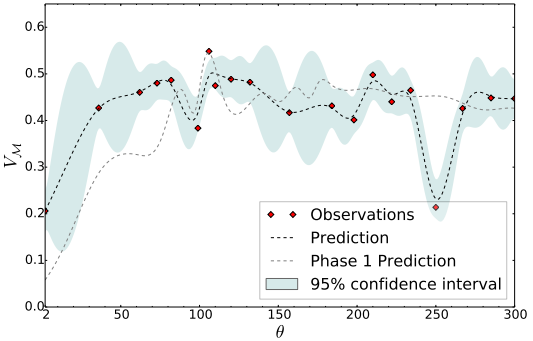


Resulting GP approximation with GP-UCB and EIPS acquisition functions used
(k-Means, `uol_bl` environment, 100% dataset used)

Experimental Results

Multi-Phase Framework - Small Environment

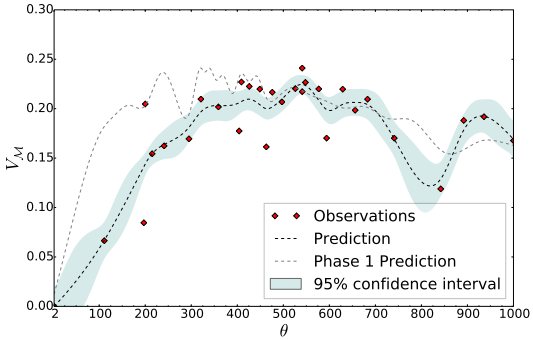


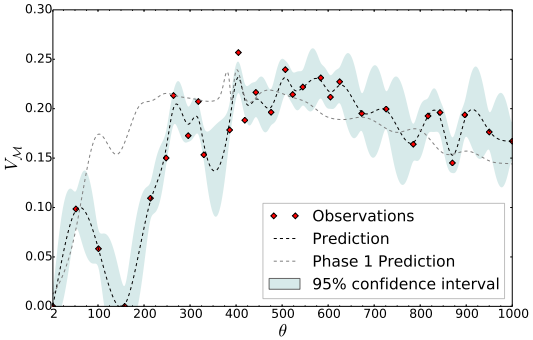


Resulting GP approximation with EI and GP-UCB acquisition functions used in Phase 1 (k-Means, `tum_kitchen` environment, 20 iterations, 100% dataset used)

Experimental Results

Multi-Phase Framework - Large Environment





Resulting GP approximation with GP-UCB and EIPS acquisition functions used
(k-Means, `uol_bl` environment, 30 iterations, 100% dataset used)

Discussion

Conclusions:

- Handcrafting MDPs for planning under uncertainty is a daunting task
  - Given a dataset, learning algorithms can ease the development

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- Evaluating all hyperparameter settings is a cost-expensive endeavor
  - Determining appropriate settings more effectively approached by BO

Discussion

Conclusions:

- Handcrafting MDPs for planning under uncertainty is a daunting task
  - Given a dataset, learning algorithms can ease the development
- Evaluating all hyperparameter settings is a cost-expensive endeavor
  - Determining appropriate settings more effectively approached by BO
- The multi-phase approach can help to find a global maximizer of the performance faster
  - With the first phase abstracting more, but being significantly cheaper

Discussion

Future work suggestions:

- Investigate other application domains, e.g., learning POMDPs for dialogue management [2]

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Future work suggestions:

- Investigate other application domains, e.g., learning POMDPs for dialogue management [2]
- Automated Model Checking [9]

- Combination with model-based RL techniques (using offline learned MDPs as blueprints for exploration)
- Coverage and size of datasets for model learning

Learning and Optimizing Probabilistic Models for Planning under Uncertainty

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Delft University of Technology

September 27, 2017

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Bayesian Optimization

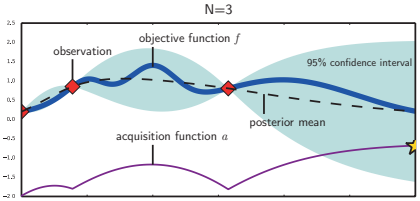
- Given an expensive, unknown objective function $f : \mathcal{X} \mapsto \mathbb{R}$ ($\mathcal{X} \subset \mathbb{R}^m$)
- Find global maximizer $x^* \in \mathcal{X}$ s.t.:

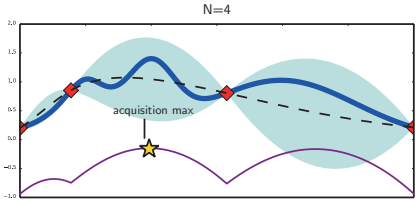
$$x^* = \arg\max_{x \in \mathcal{X}} f(x)$$

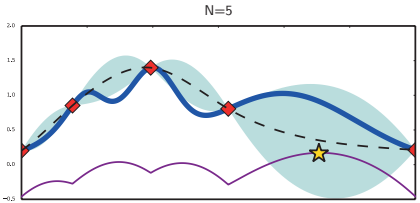
- Bayesian Optimization components:
  - *Prior over* f: Gaussian Process $f \sim GP(\mu(\cdot), K(\cdot, \cdot))$
  - *Evidence set*: $\mathcal{D}_{1:t} = \{(x_i, y_i) \mid i = 1 \dots t\}$
  - *Posterior* or *Surrogate function* ('estimate of f')
  - *Acquisition* or *Utility function*: $u : \mathcal{X} \mapsto \mathbb{R}$

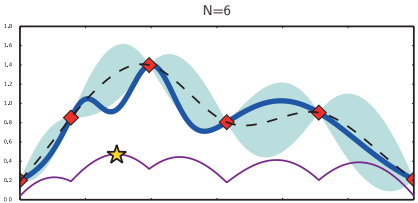
Bayesian Optimization

Toy Example









Bayesian Optimization

Acquisition Functions

Let $f(x^+)$ be the best observation, then the acquisition functions sample the maximizer x of the following quantities:

Probability of Improvement (PI)	$P(f(x) \geq f(x^+) + \xi)$
Expected Improvement (EI)	$\mathbb{E}[\max(0, \mu_f(x) - f(x^+) - \xi)]$
GP Upper Confidence Bound (GP-UCB)	$\mu_f(x) + \beta\sigma_f(x)$
Expected Improvement Per Second (EIPS)	$\mathrm{EI}(x)/\mu_s(x)$

where $\xi \geq 0$ is an exploration-exploitation trade-off parameter, $\beta \geq 0$ specifies number of standard deviations, μ_s is the mean of a timing GP.

Automated Model Checking

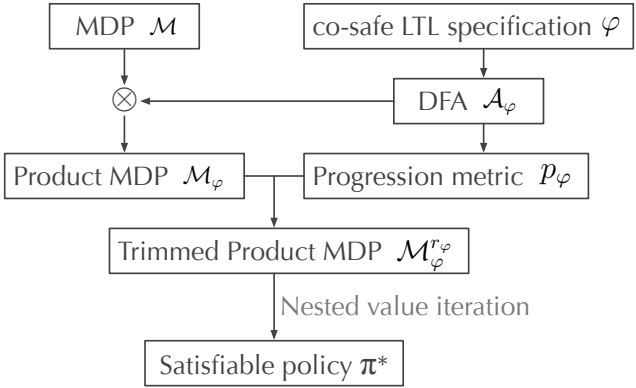
Objective

Goal: Compose algorithms that construct probabilistic models which (partially) satisfy temporal goals.

- Temporal goals expressed through LTL formulas
- Example: $\varphi = (a \,\mathcal{U}\, b) \wedge \mathcal{X} c$
  "a should hold until b is true after which c should become true"

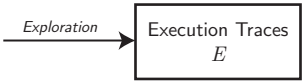
Automated Model Checking

Example Lacerda et al. [9]



Proposed Solution

Base Framework



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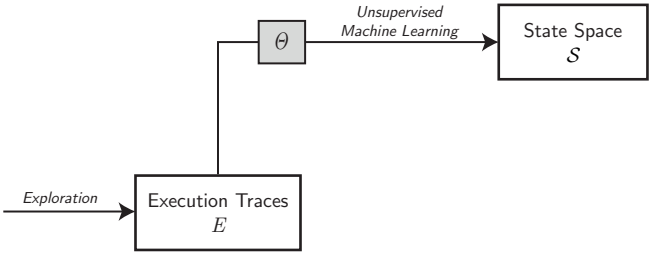

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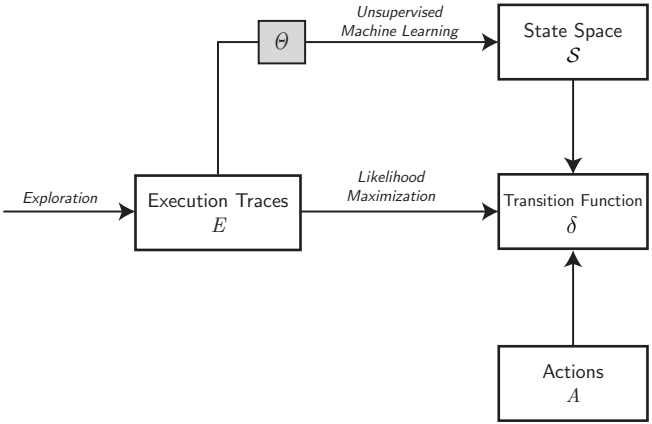

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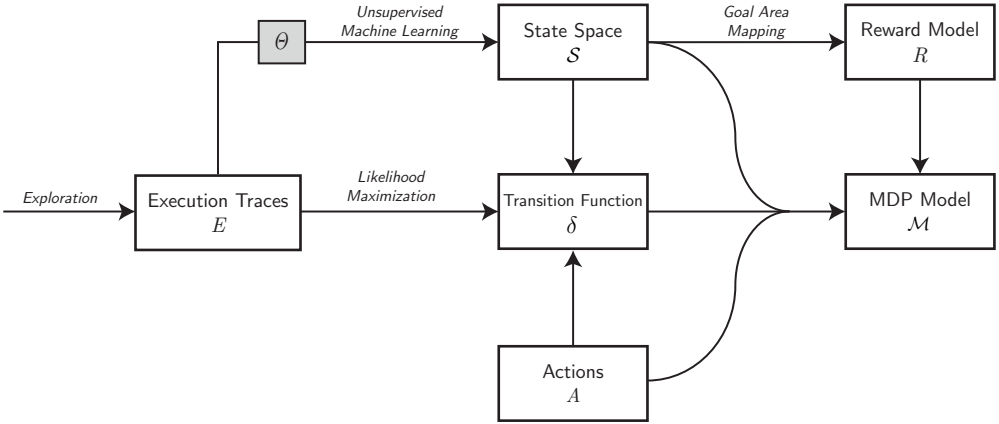
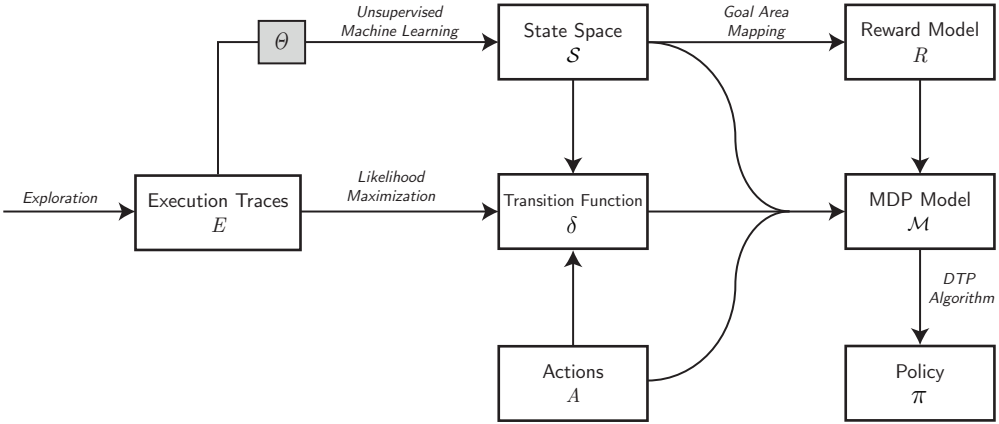


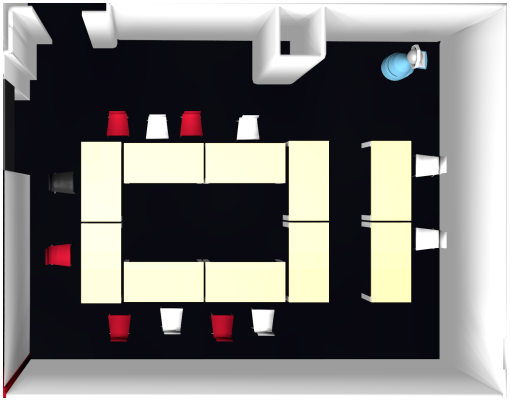
Proposed Solution

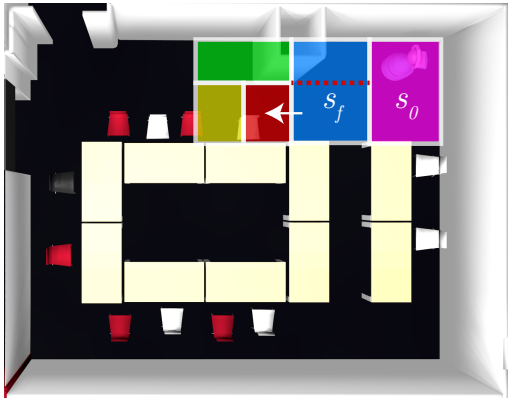
Base Framework



Model Optimization Framework

Multi-Phase Framework: Fine-Tuning Example





Model Learning Algorithms

Baum-Welch for HMMs/POMDPs

Goal: Maximize $P(\lambda|O)$ with λ the model parameters and O the observation sequences

High-level steps:

1. Provide initial probability estimates
2. Repeat the following until convergence:
   1. *E-step*: Compute expectations of how often transitions and emissions are used
   2. *M-step*: Update parameters based on these expectations

Model Learning Algorithms

Baum-Welch for HMMs/POMDPs

Goal: Maximize $P(\lambda|O)$ with λ the model parameters and O the observation sequences

Detailed Steps [15]:

- Compute the following quantities using the *forward* and *backward* procedures given observation sequences O of length T:

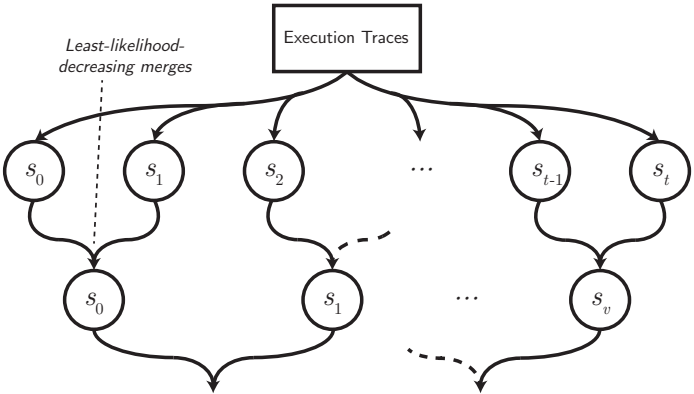
$$\xi_{ij}(t) = P(q_t = s_i, q_{t+1} = s_j) \qquad \gamma_i(t) = \sum_{j=1}^{|\mathcal{S}|} \xi_{ij}(t)$$

- Update model parameters as follows:

$$a_{ij}(t) = \frac{\sum_{t=1}^{T-1} \xi_{ij}(t)}{\sum_{t=1}^{T-1} \gamma_i(t)} \qquad b_{jk}(t) = \frac{\sum_{o_t = v_k} \gamma_j(t)}{\sum_{t=1}^{T} \gamma_j(t)} \qquad \pi_i = \gamma_i(1)$$

Model Learning Algorithms

Time-State Merging / Model Merging

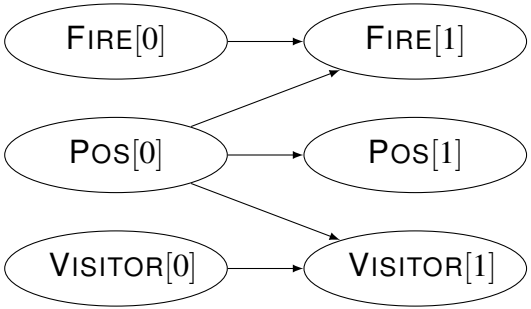


Factored MDPs

Definition

A Factored Markov Decision Process is a tuple $\mathcal{M} = (\mathcal{X}, s_0, A, T, R)$ in which:

- $\mathcal{X} = \{X_1, \ldots, X_n\}$ is a set of state variables (or *features*) with $s_0 \in \mathcal{X}$
- A is the action space
- $T : \mathcal{X} \times A \times \mathcal{X}$ is a transition function
- $R : \mathcal{X} \mapsto \mathbb{R}$ a reward function



Decision epoch t Decision epoch $t + 1$