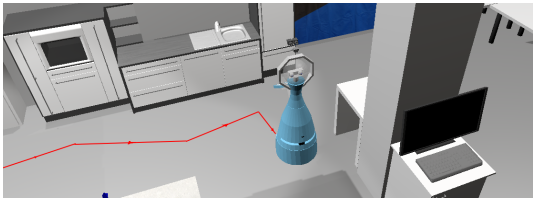
Learning and Optimizing Probabilistic Models for Planning under Uncertainty in Mobile Robot Navigation



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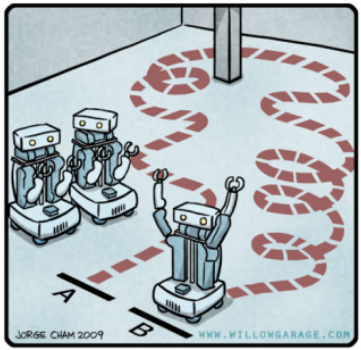
April 5, 2017

Decision-Theoretic Planning

DTP Problem Scope

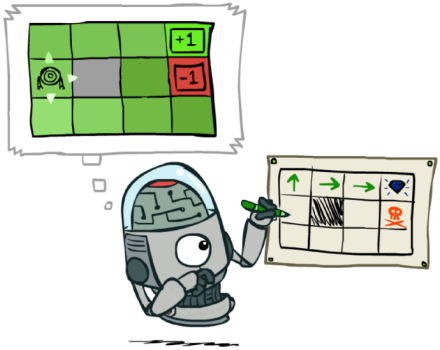
Systems:

- Dynamics are stochastic, i.e., involve uncertainty
  - Execution of actions (e.g., robot may slip)
  - Exogenous events (e.g., doors open/closed)
  - Observations (e.g., sensor noise)
- Controlled by one or more agents
- Sequential decisions of actions to execute

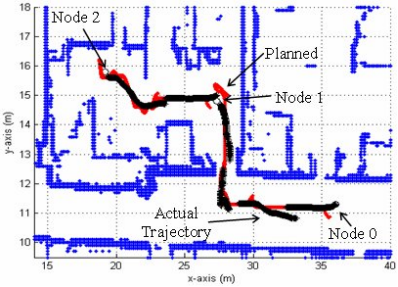


Decision-Theoretic Planning

Example Domain: Path Planning



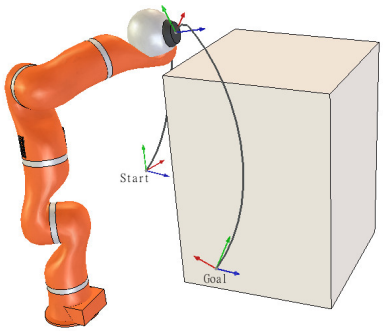
Source: Berkeley CS188 sheets



Source: `http://www.cs.cmu.edu/~gunhee/r_psr.html`

Decision-Theoretic Planning

Example Domain: Motion Planning



Source: http://www.coppeliarobotics.com/helpFiles/en/motionPlanningModule.htm

Decision-Theoretic Planning

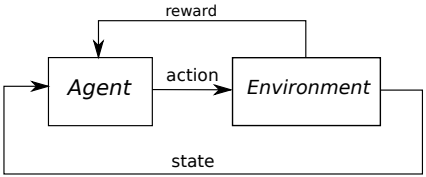
Markov Decision Processes (MDPs)

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

Definition

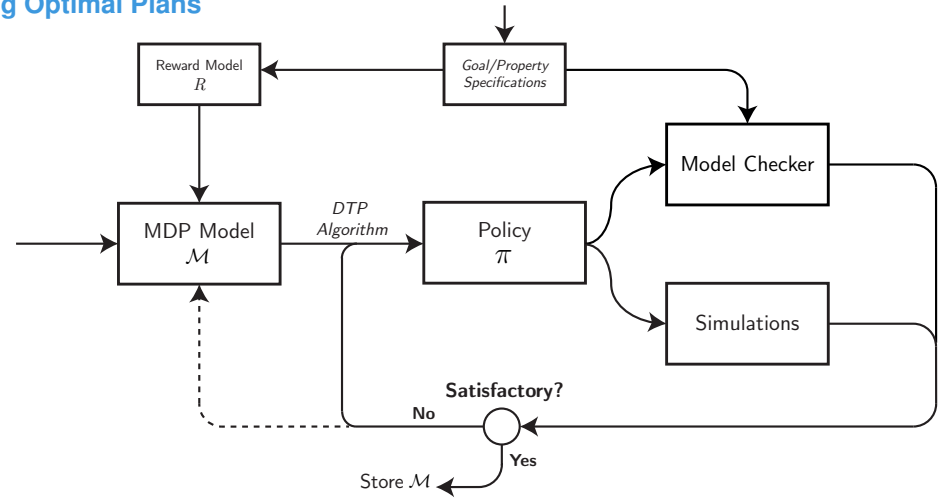
An MDP is a 5-tuple $\mathcal{M} = (\mathcal{S}, s_0, A, \delta, R)$:

- $\mathcal{S}$ is the state-space, $s_0 \in \mathcal{S}$ the initial state
- A is the action-space
- δ is the transition function (N.B.: accounts for uncertainty)
- R is the reward function (N.B.: defines the goals)



Decision-Theoretic Planning

Learning Optimal Plans



Decision-Theoretic Planning

Model Development

Problem: How to find a suitable MDP model?

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

Alternative: Use Reinforcement Learning instead of Planning, however:

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

Decision-Theoretic Planning

Model Development

Problem: How to find a suitable MDP model?

Idea: Automate the model building process by learning algorithms

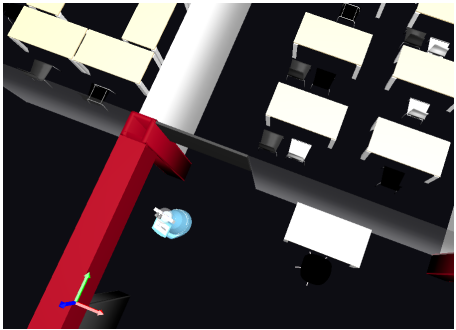
- Learn from (exploration) data about the environment
- Optimization for the best MDP model

Mobile Robot Navigation

Goal: Move robot to area while minimizing traveled distance

MDP Model $\mathcal{M}$ should define:

- States $\mapsto$ locations
- Actions $\mapsto$ robot translations
- Rewards $\mapsto$ goal areas
- Transition-function



Model-Learning for Mobile Robot Navigation

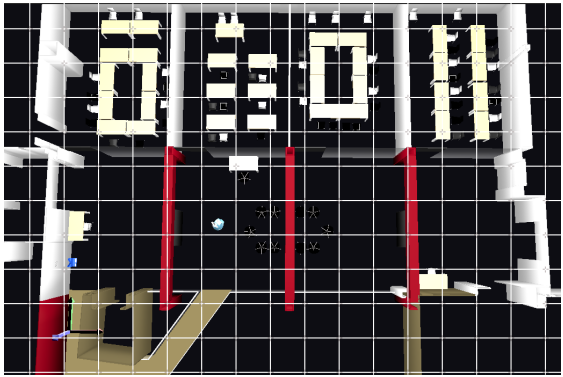
Learning State-Spaces

Given: Execution trace(s) from exploration-stage

Existing Approaches:

- Grid-discretization
- Best-First Model Merging
- State Merging by Trajectory Clustering

Issues: Dimensionality, grid resolution



Model-Learning for Mobile Robot Navigation

Learning State-Spaces

Given: Execution trace(s) from exploration-stage

Existing Approaches:

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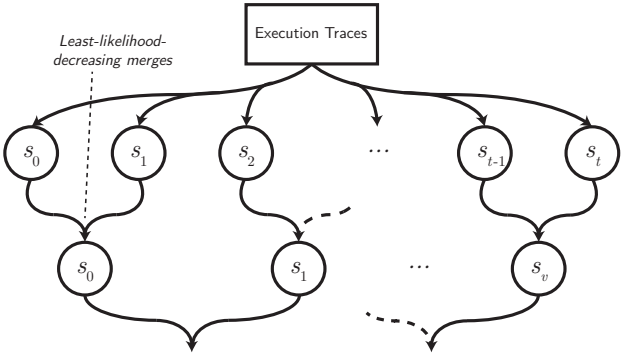
- State Merging by Trajectory Clustering

Issues: Greedy merging, $O(t^3)$ algorithm



Model-Learning for Mobile Robot Navigation

Learning State-Spaces

Given: Execution trace(s) from exploration-stage

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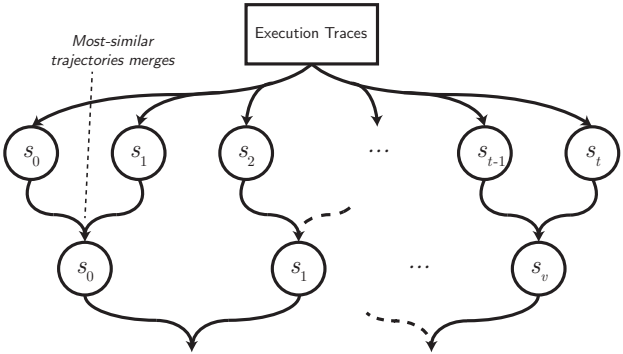
Note: For learning POMDPs facing *perceptual aliasing*



Model-Learning for Mobile Robot Navigation

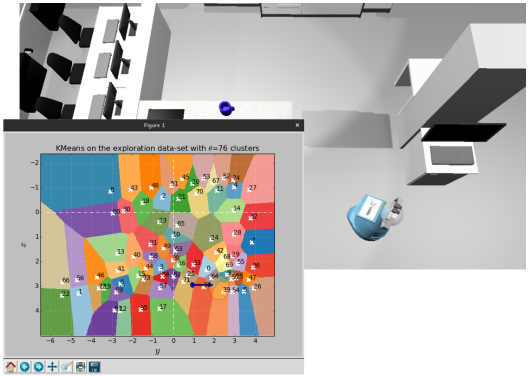
Learning State-Spaces

Given: Execution trace(s) from exploration-stage

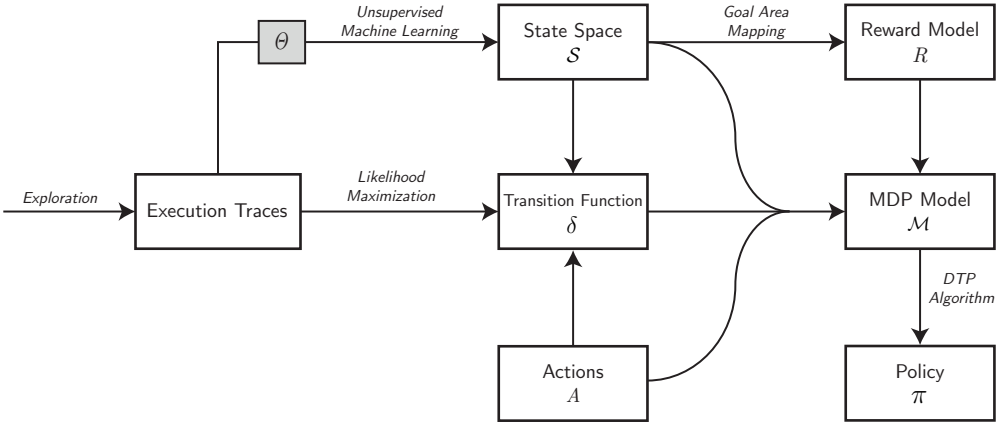
Approach: Unsupervised ML for state-spaces, i.e.:

- K-Means Clustering
- Gaussian Mixture Models
- . . .

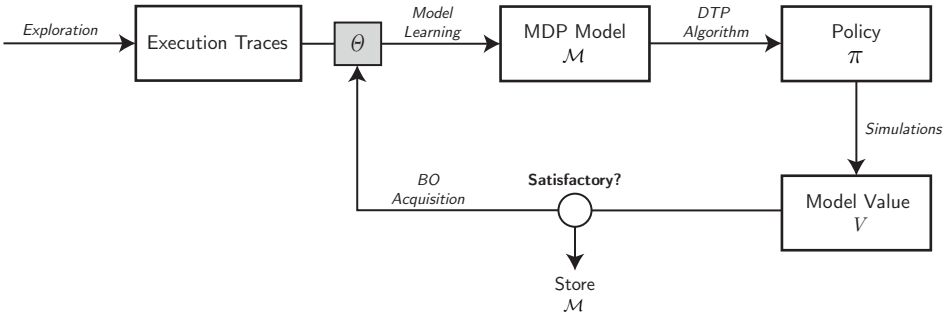
Variable: θ parameter of ML-algorithm



Model-Optimization Routine



Model-Optimization Routine



Bayesian Optimization

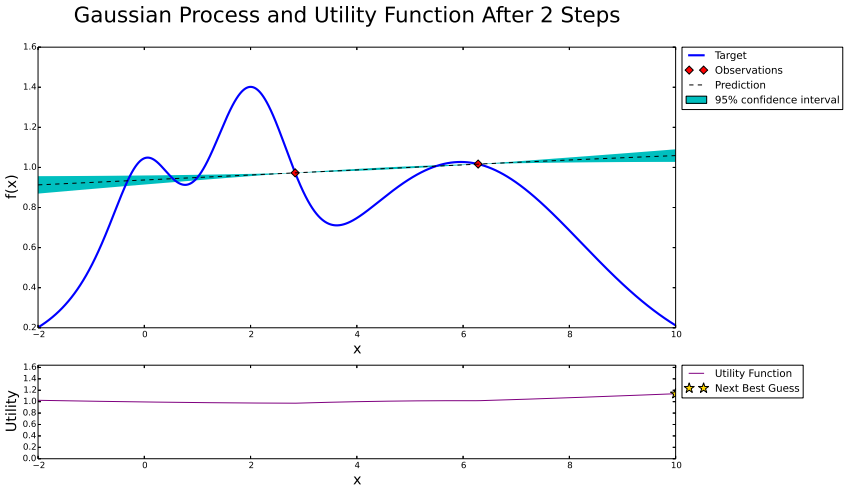
- Given an expensive, unknown objective function $f : \mathcal{X} \mapsto \mathbb{R}$ ($\mathcal{X} \subset \mathbb{R}^m$)
- Find global maximizer $x^* \in \mathcal{X}$ s.t.:

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

- 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*: $u : \mathcal{X} \mapsto \mathbb{R}$

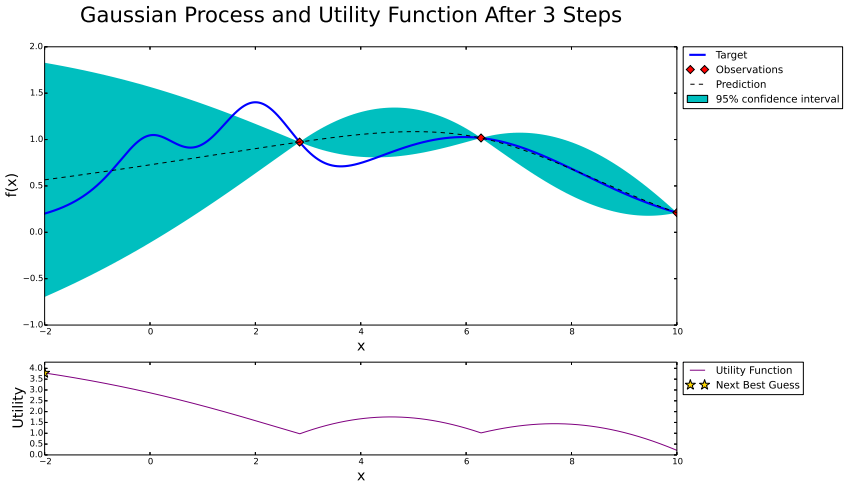
Bayesian Optimization

Example



Bayesian Optimization

Example



Bayesian Optimization

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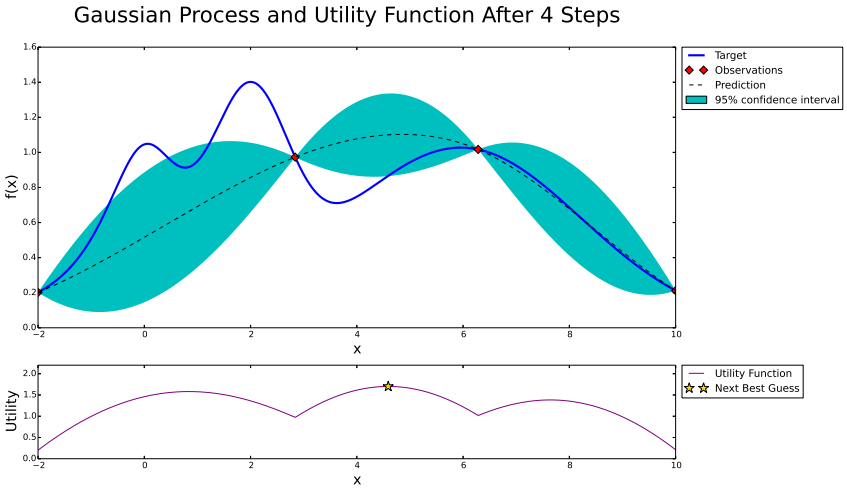

Bayesian Optimization

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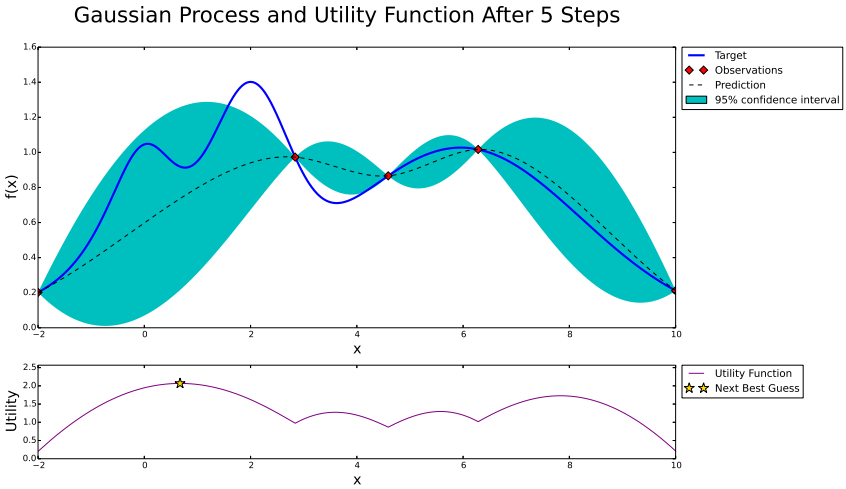
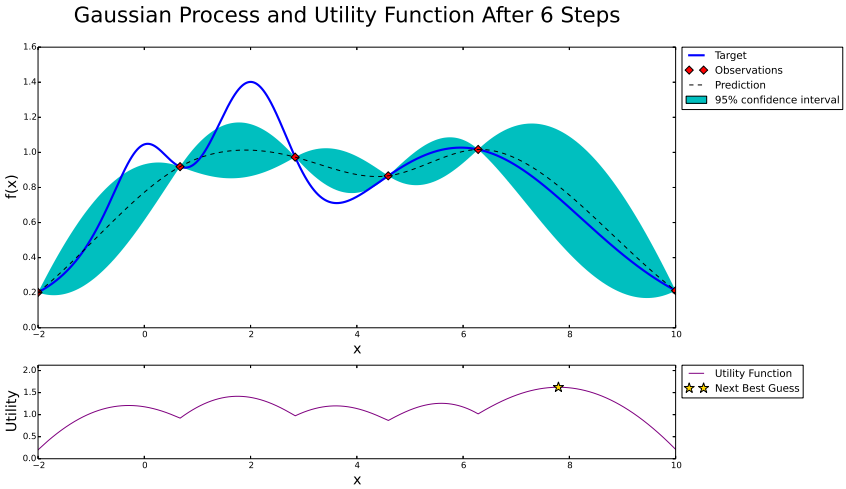


Bayesian Optimization

Example



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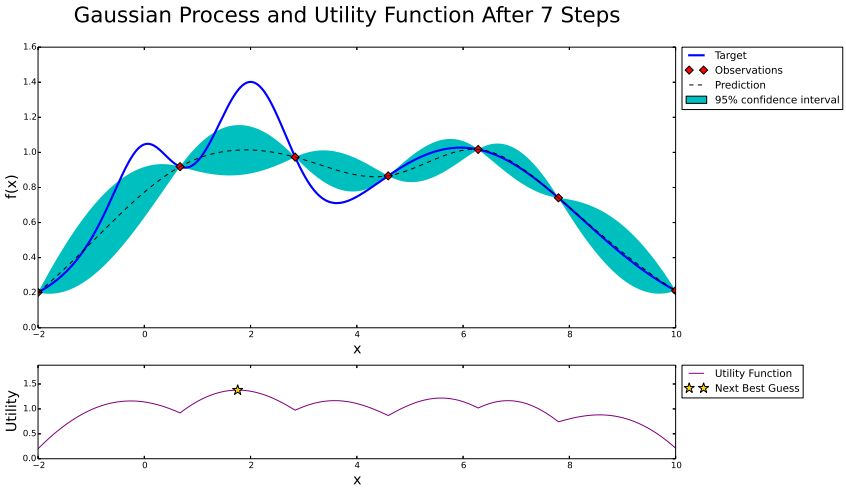

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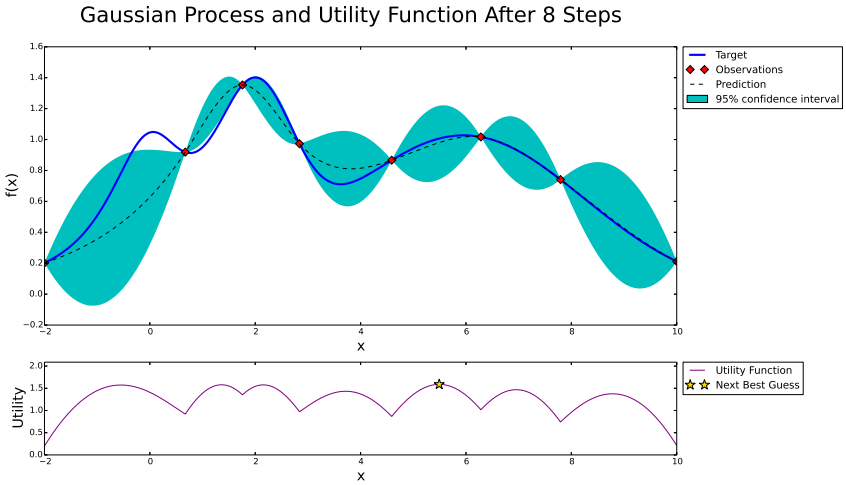

Bayesian Optimization

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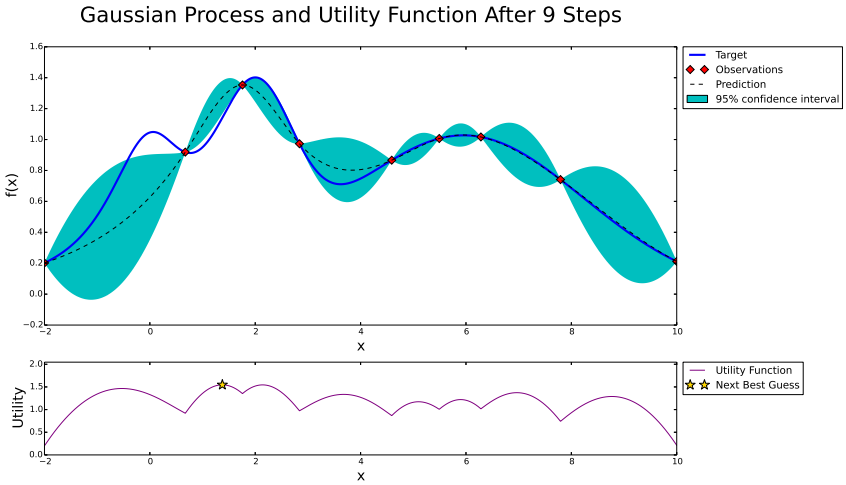

Implementation of Model-Optimization Routine

- **Exploration:** 'Randomly' navigating, writing execution trace to files
- **Optimization:** Objective function defined by performance in simulations:
  - Goal area(s) reached (before time-out)?
  - Time passed
  - Part of goal area covered by corresponding final states

- **Software:** Python, ROS, Morse simulator
- **Robot:** Scitos A5, mobile service robot

DEMO

Next Steps

- Cost-Sensitive Optimization
  - BO acquisition based on *Expected Improvement per second*
- Identification of incomplete exploration data
  - Feedback from simulation trajectories
  - Use feedback in BO to reduce noise/uncertainty in observations
- Variable Resolution in State-Space Acquisition
- Inspect influence of other variables in the optimization loop
  - Discount factor γ in MDP solver
  - ML-algorithm (K-Means, GMM, ...)
  - Gaussian-Process hyper-parameters?

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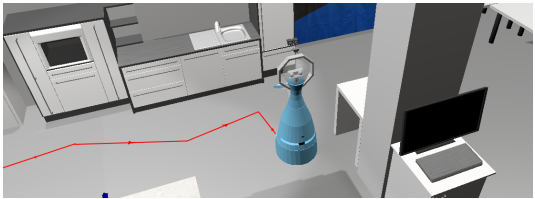

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