

Motion Planning Lecture 8

Introduction to Open Motion Planning Library

Wolfgang Hönig (TU Berlin) and Andreas Orthey (Realtime Robotics)

June 12, 2024

Last Week

- Optimal kinodynamic planning
- Planning without Steering (SST)
- Space-cost approach (AO-RRT)

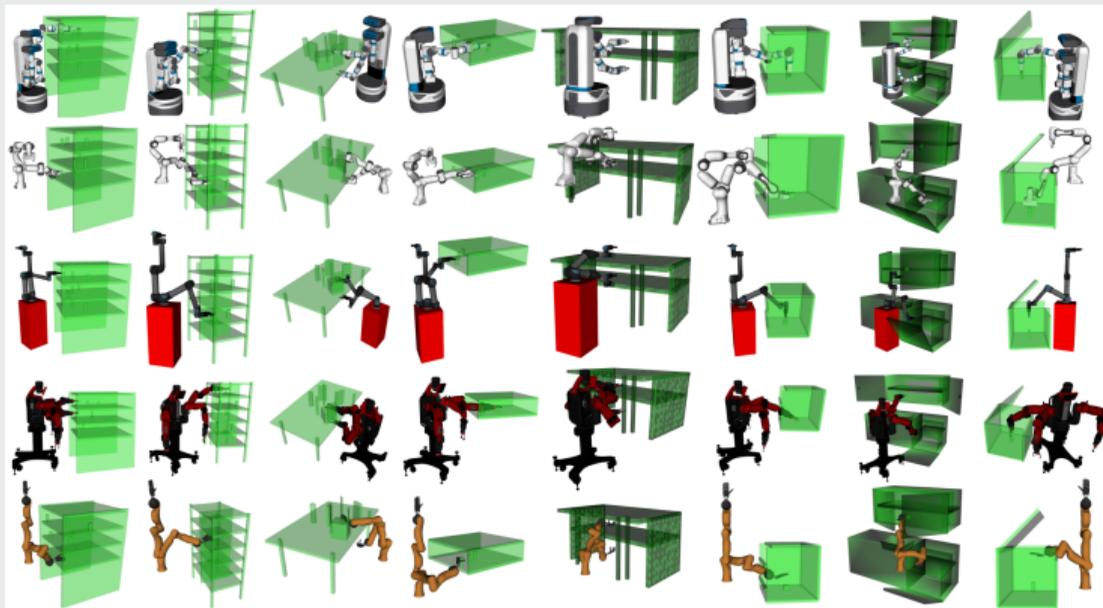
Today

- Introduction to open motion planning library (OMPL)
- General structure of OMPL
- How to setup problems in OMPL

OMPL

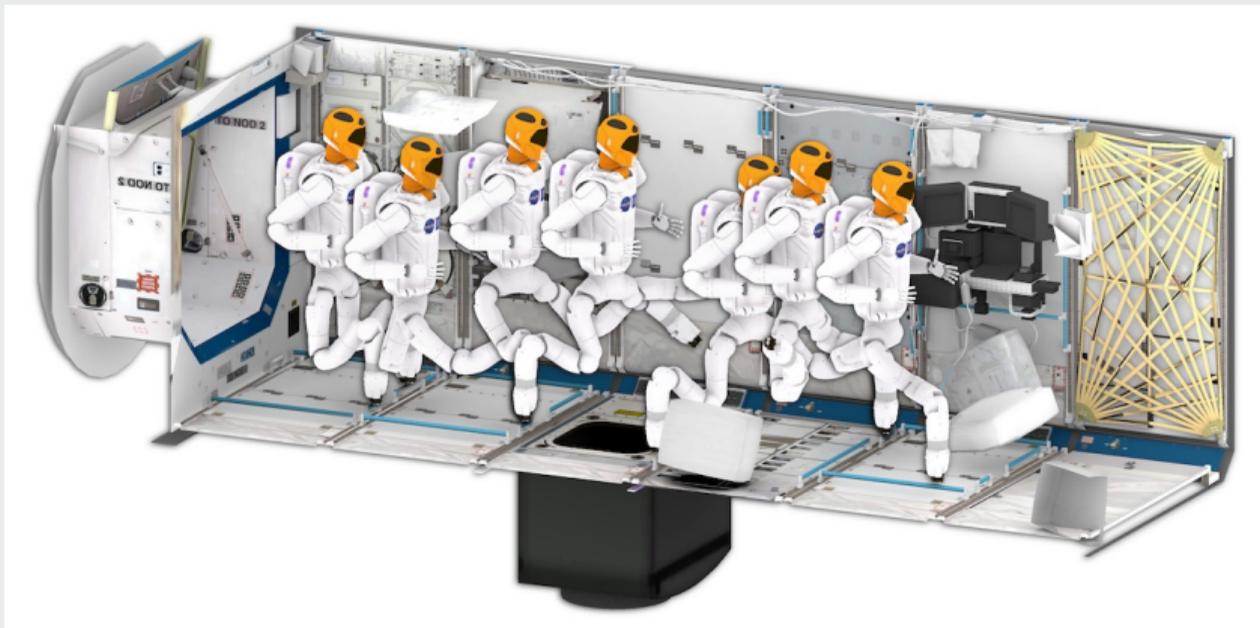
- Open-source software
- Collection of sampling-based planners
- Written and maintained by researchers in motion planning
- Modular, easily extendable
- Used by several robotics companies

OMPL



Chamzas et al., "MotionBenchMaker: A Tool to Generate and Benchmark Motion Planning Datasets", (2022)

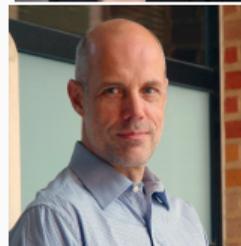
OMPL



Kingston et al., "Exploring Implicit Spaces for Constrained Sampling-Based Planning", (2019)

History

- Created by Lydia Kavraki, Professor at Rice University, Houston, TX
- Maintained by Mark Moll, Previous Director of Research at PickNik Robotics
- Contributions by many researchers worldwide



People



Sucan et al., "The Open Motion Planning Library", (2012)

Version History

- Version 1.6 (Jan 7, 2023)
- Version 1.4 (Jun 25, 2018)
- Version 1.2 (Jun 19, 2016)
- Version 1.0 (Oct 25, 2014)

Capabilities

- Solving geometrical problems
- Solving optimal with arbitrary objectives
- Solving kinodynamic problems
- Benchmarking planners

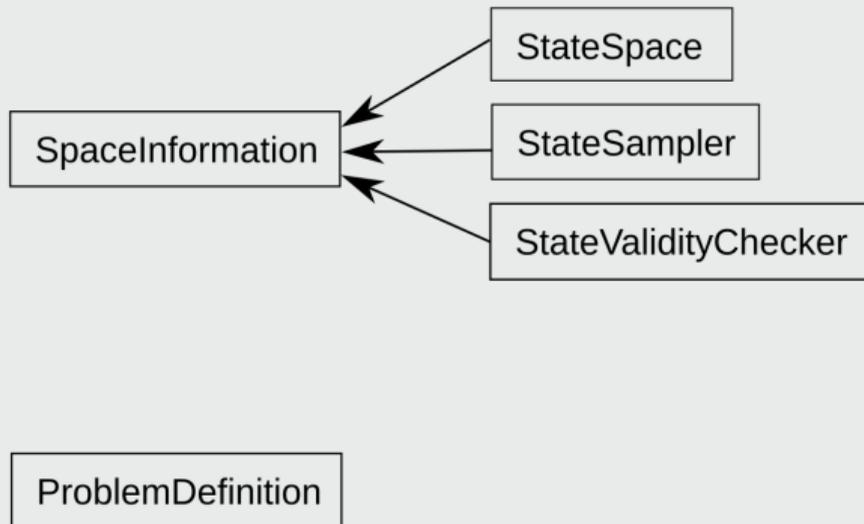
Overview OMPL

OMPL Structure

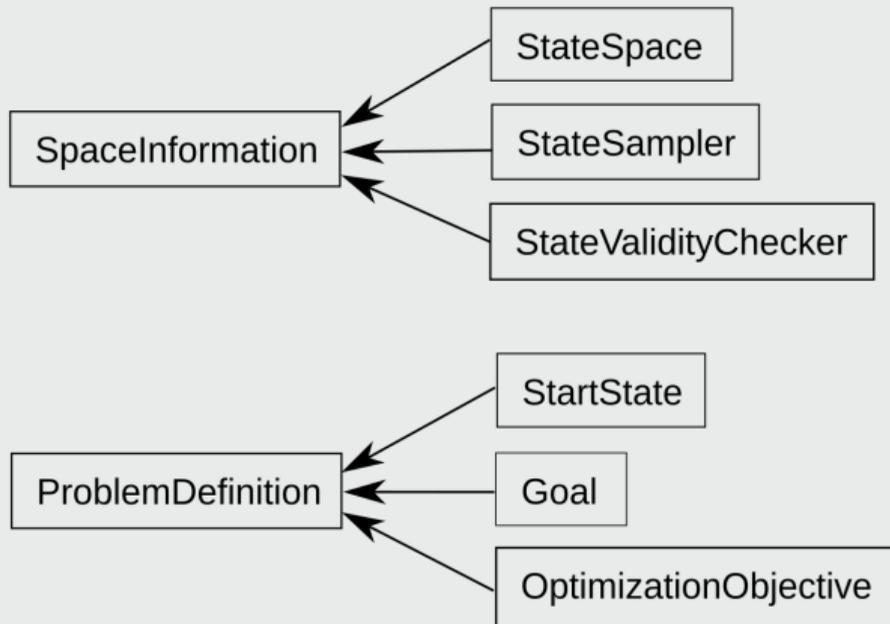
SpaceInformation

ProblemDefinition

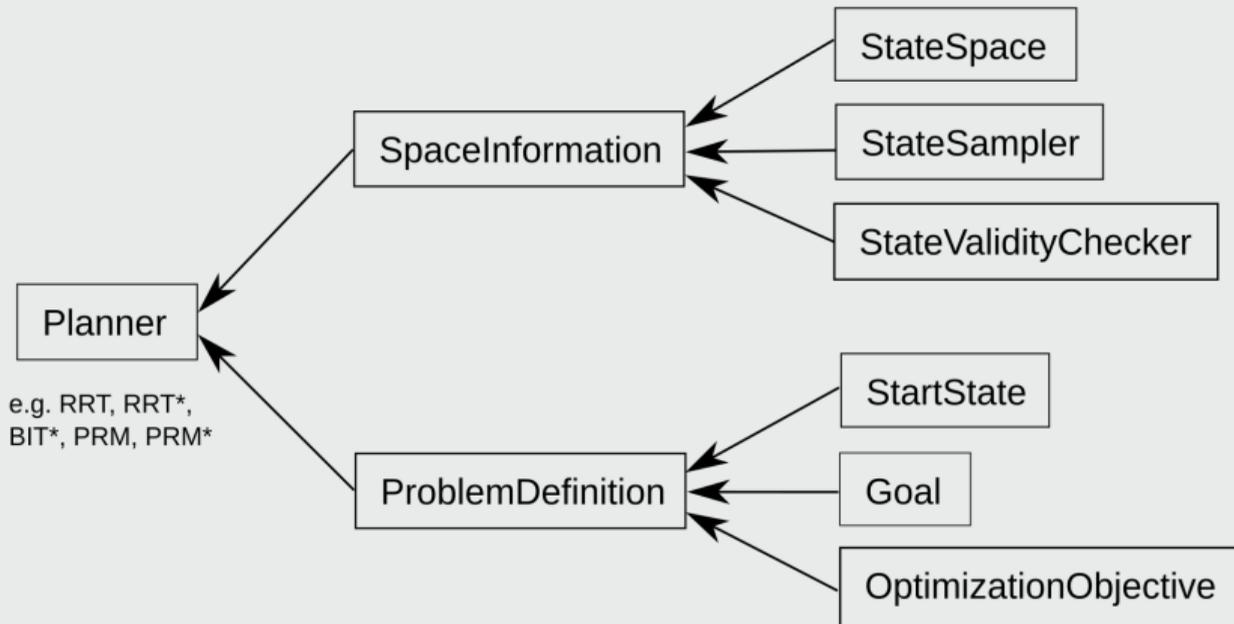
OMPL Structure



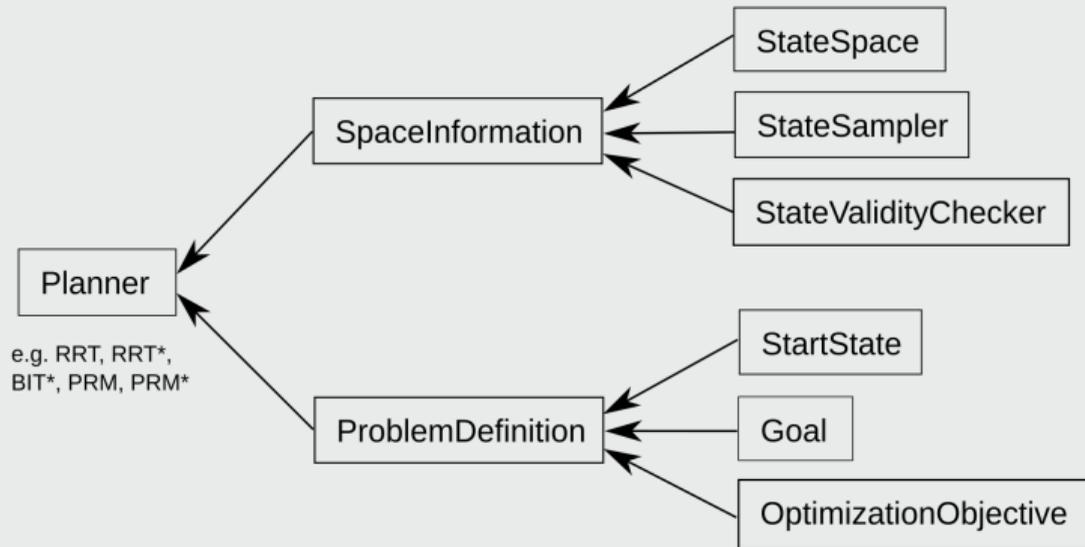
OMPL Structure



OMPL Structure

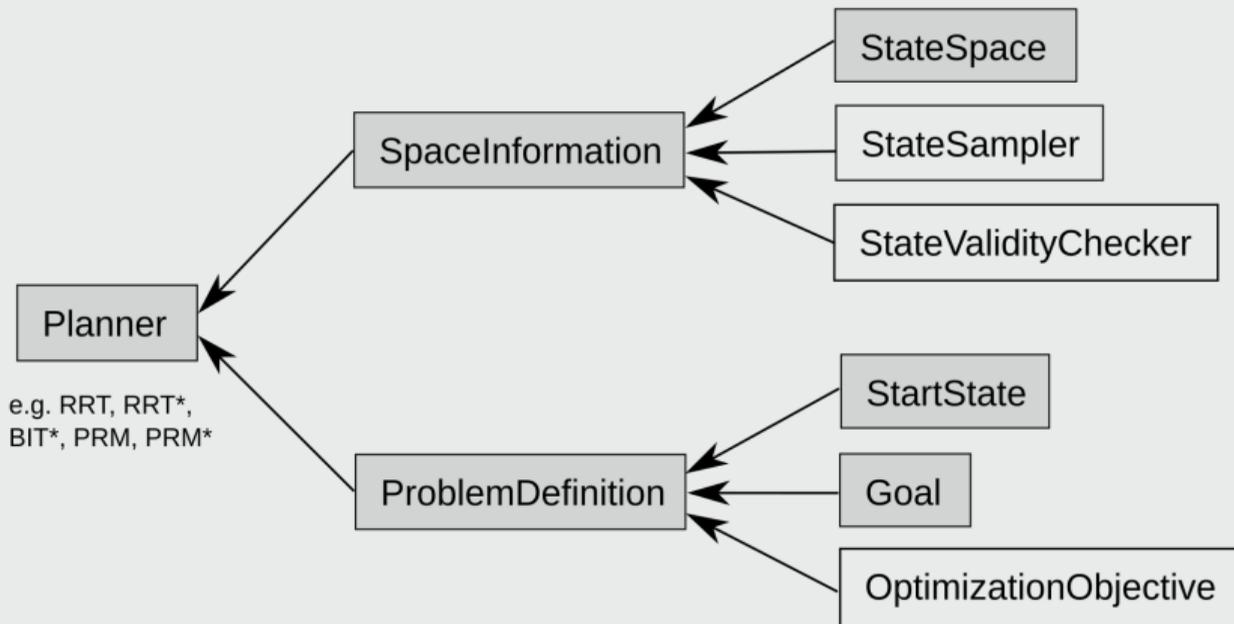


OMPL Structure



What are the necessary structures?

OMPL Structure



Overview OMPL

State Space

State Space

- RealVectorStateSpace R^n (Manipulator arm)
- SE2StateSpace $SE(2)$ (Mobile base, roomba)
- SE3StateSpace $SE(3)$ (Drone, rigid body)
- DubinsStateSpace (Car with constant forward velocity)
- TimeStateSpace (Only go forward in time)

Primitives

- Distance metric
- Uniform sampling
- Interpolation

Requirements

- Bounds
- Dimensionality

Overview OMPL

StateValidityChecker

StateValidityChecker

- Interface with collision checking libraries
- Custom code
- Flexible Collision Library (FCL)
`https://github.com/flexible-collision-library/fcl`
- Proximity Queries Package (PQP) `https://github.com/GammaUNC/PQP`

Primitives

- `bool IsValid(x)`: Check that all constraints are fulfilled
- `float clearance(x)`: Return distance to nearest invalid state [Optional]

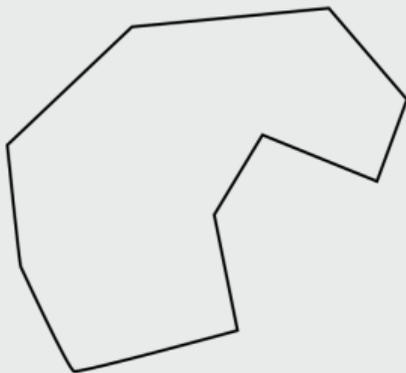
Overview OMPL

StateSampler

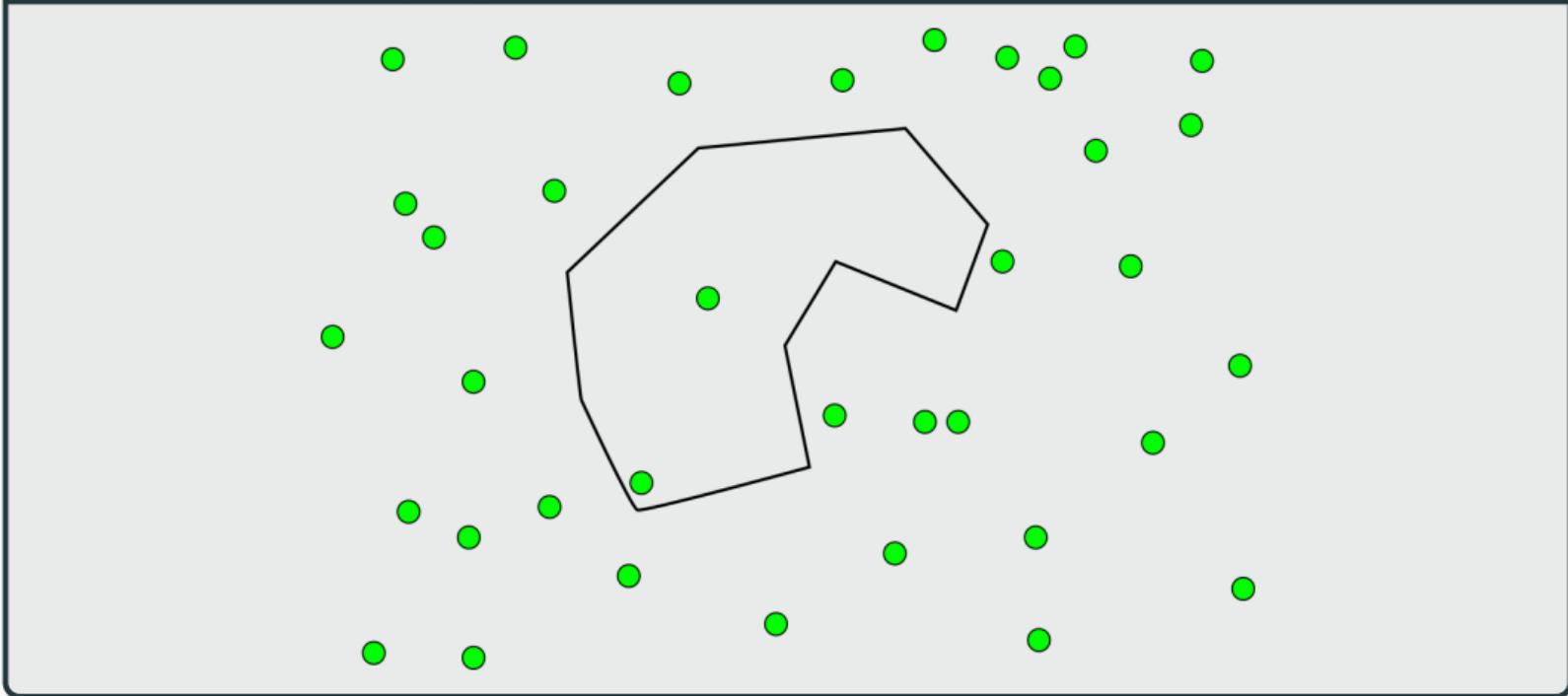
StateSampler

- Sample states from the state space
- Unbiased vs Biased
- Default: Unbiased in StateSpace
- Biased: Obstacle, Clearance, Deterministic

Obstacle-based sampling



Obstacle-based sampling



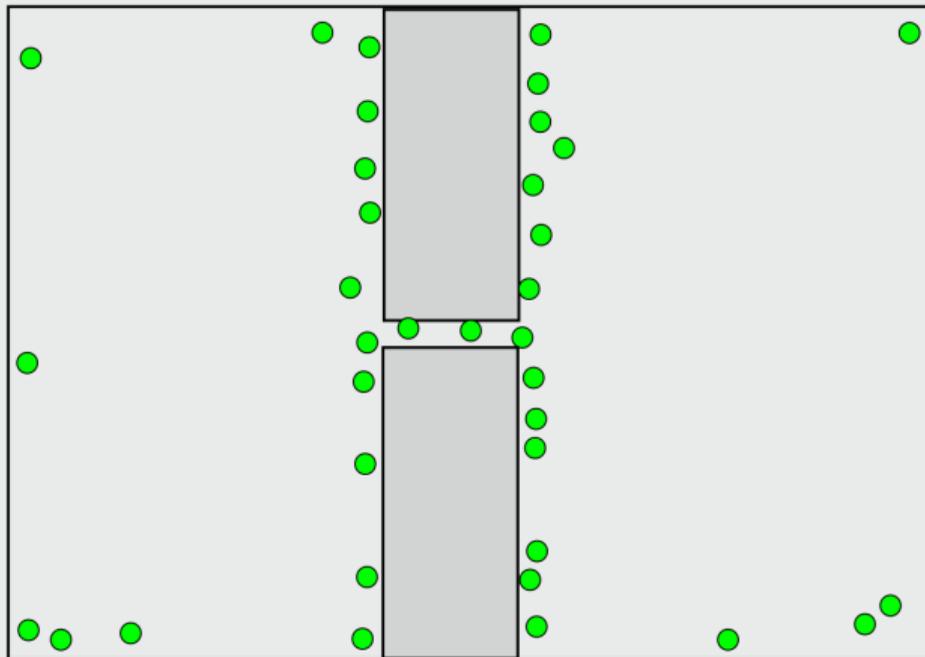
Question

What are the advantages of using obstacle-based sampling?

Obstacle-based sampling

- Narrow passages
- Path length bias

Obstacle-based sampling



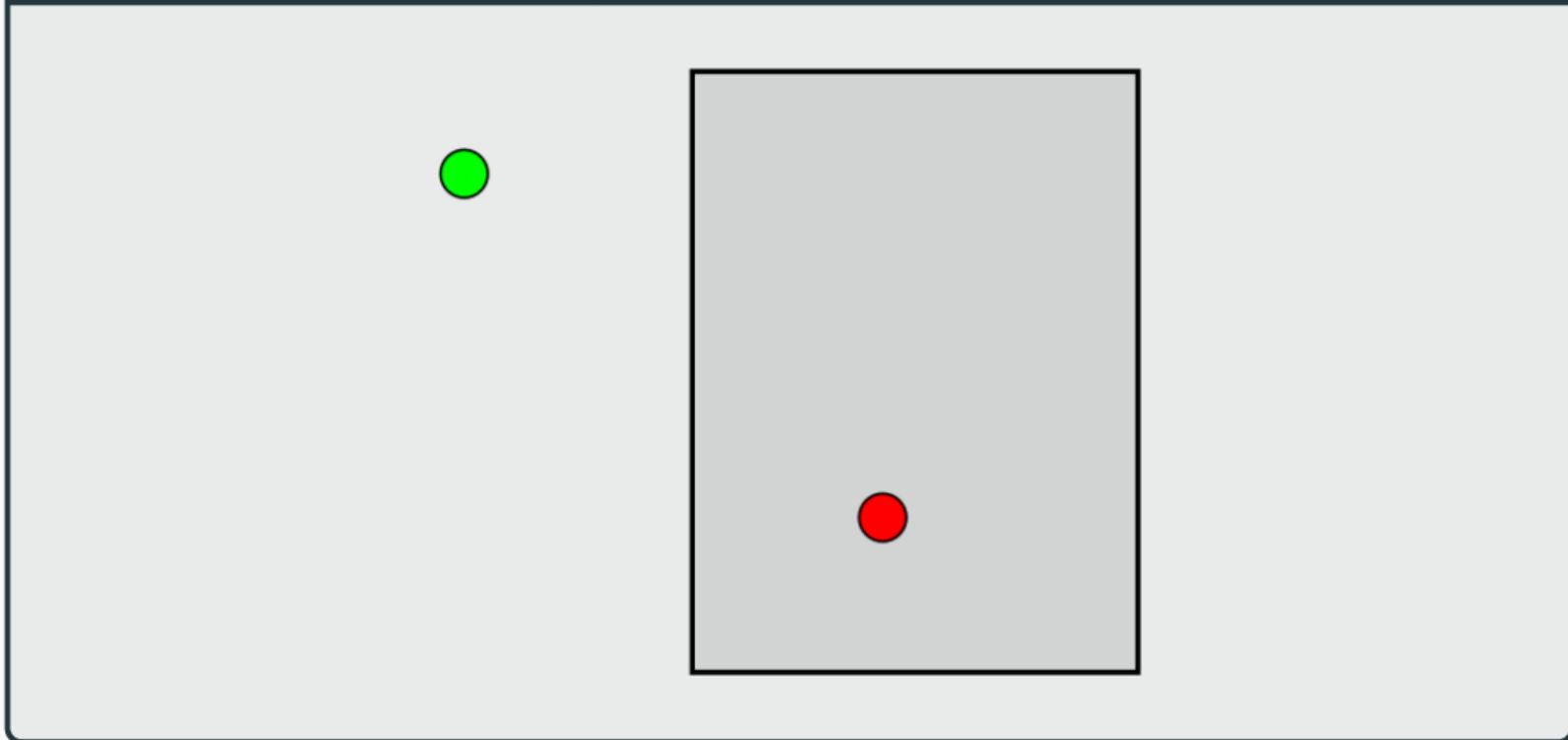
Obstacle-based sampling

- ObstacleBasedValidStateSampler
- GaussianValidStateSampler
- BridgeTestValidStateSampler

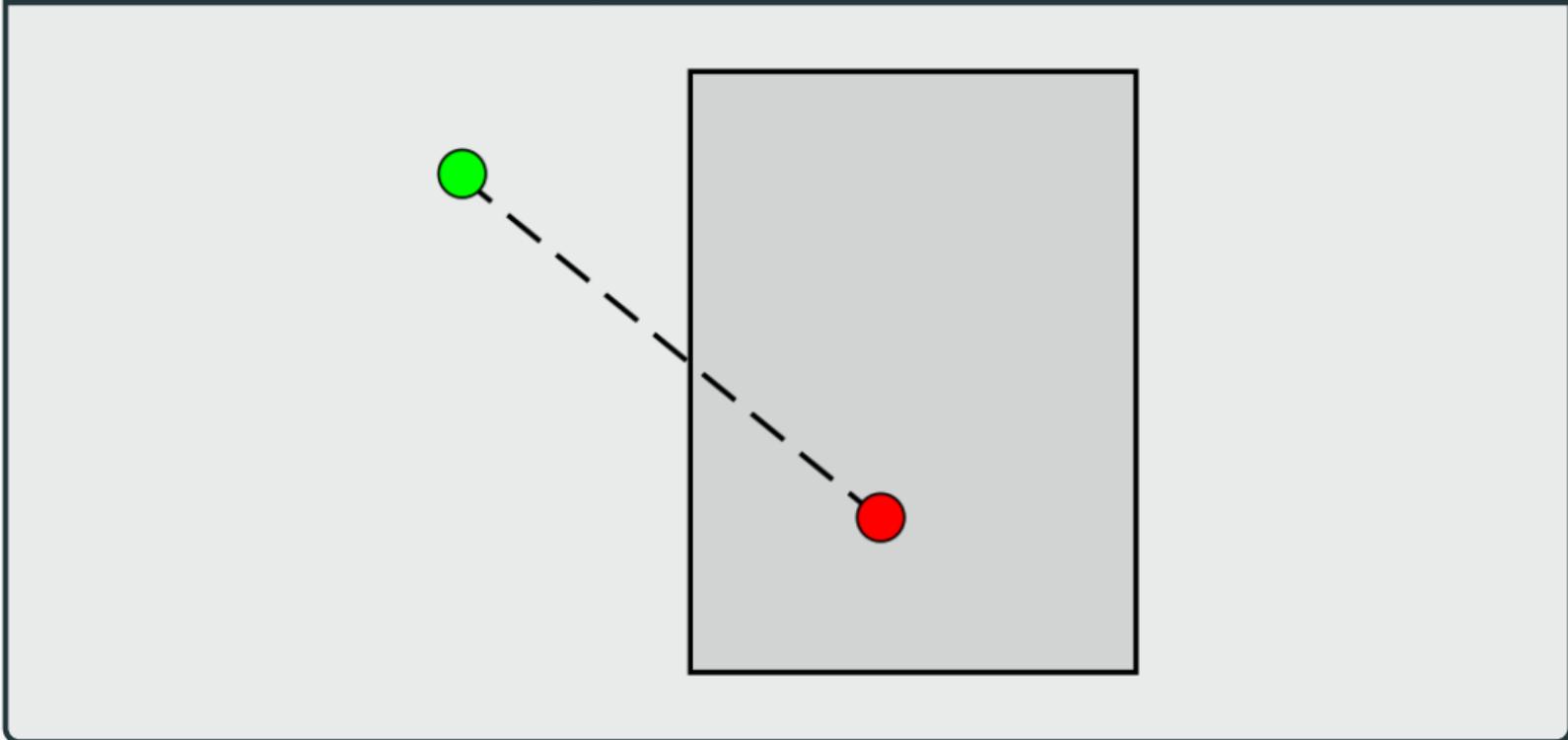
ObstacleBasedValidStateSampler



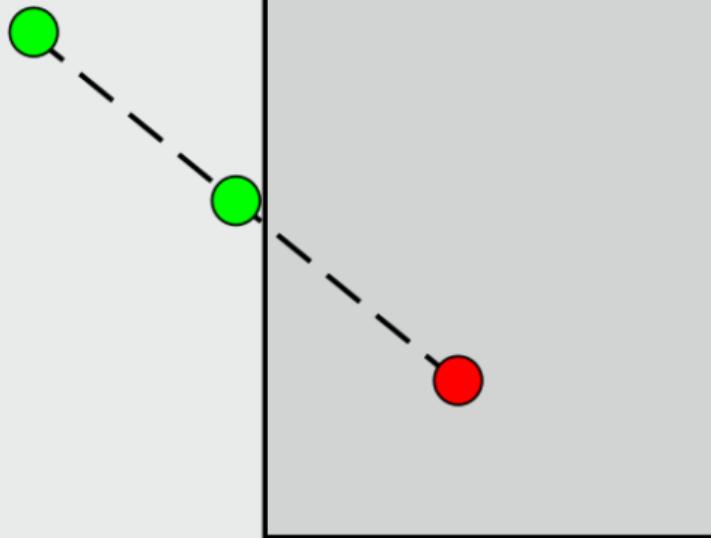
ObstacleBasedValidStateSampler



ObstacleBasedValidStateSampler



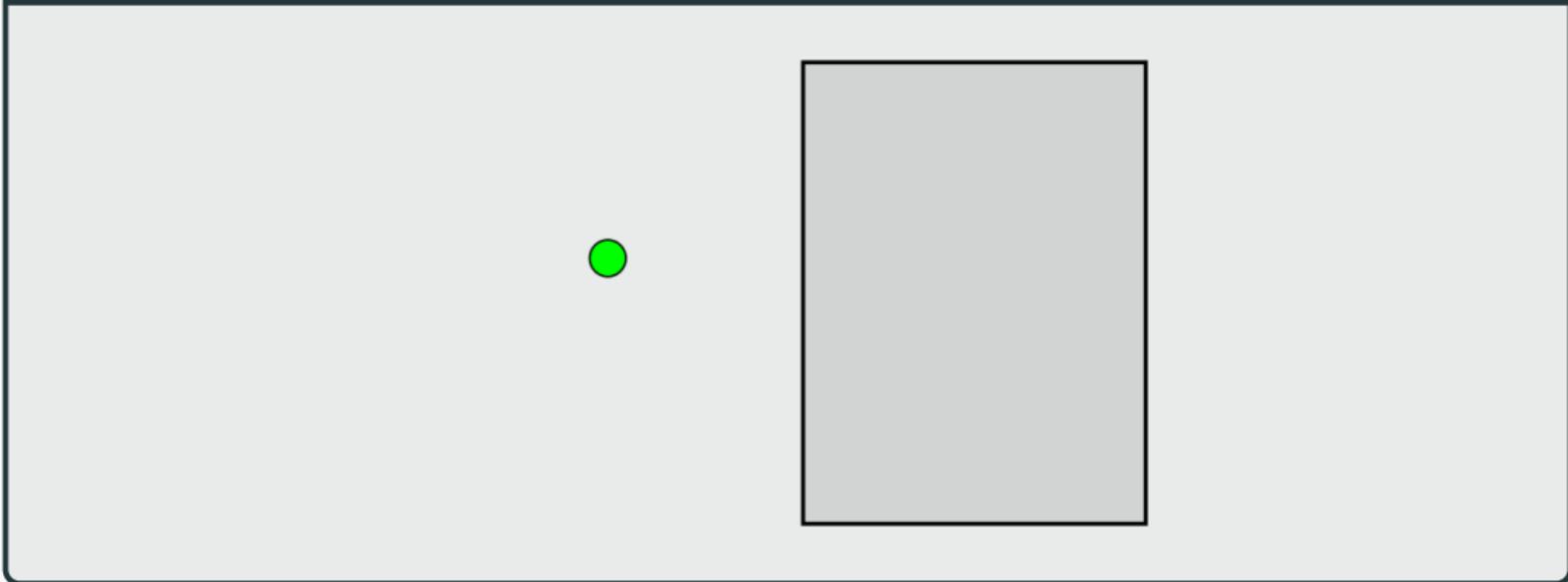
ObstacleBasedValidStateSampler



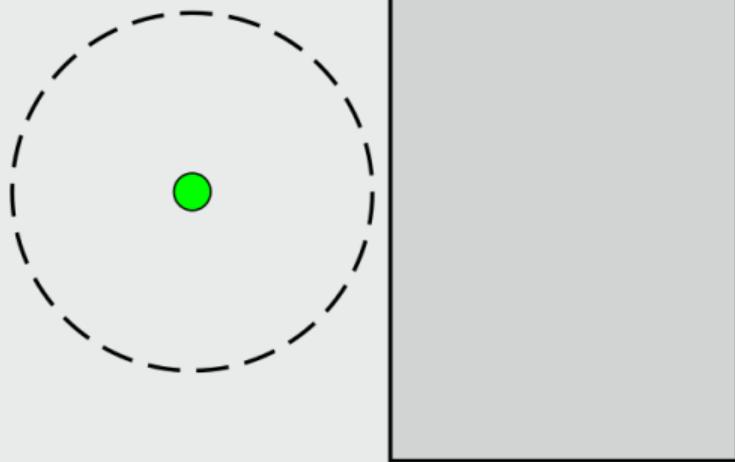
ObstacleBasedValidStateSampler



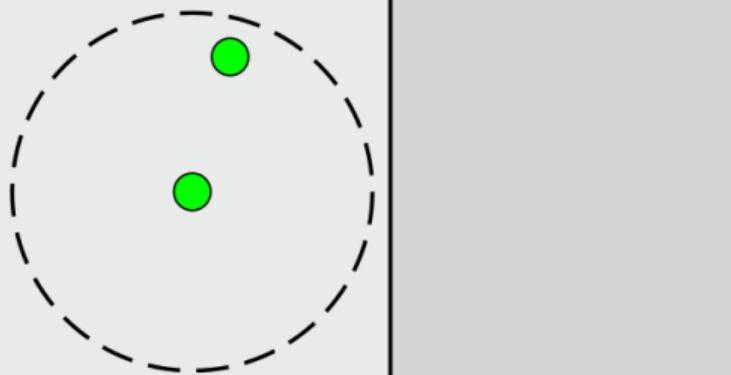
GaussianValidStateSampler



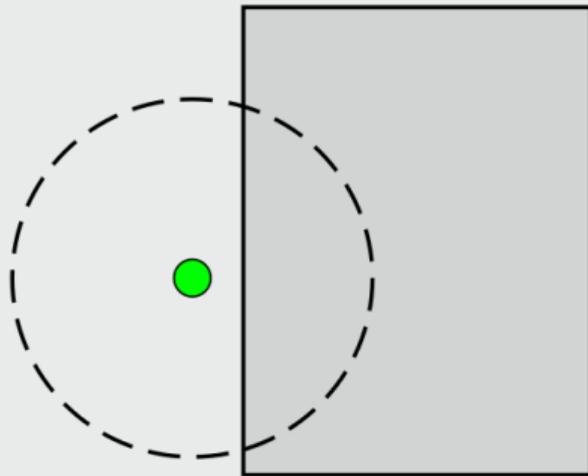
GaussianValidStateSampler



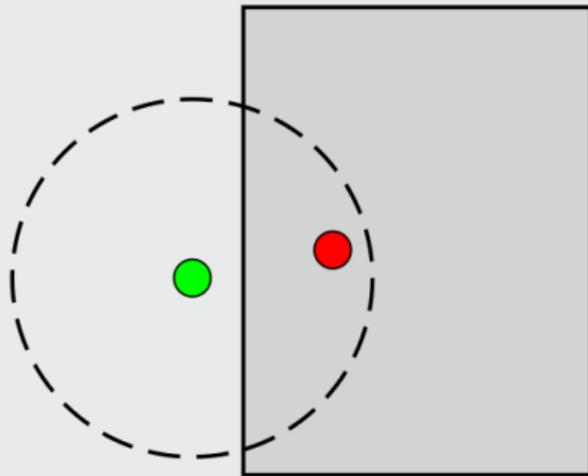
GaussianValidStateSampler



GaussianValidStateSampler



GaussianValidStateSampler



GaussianValidStateSampler



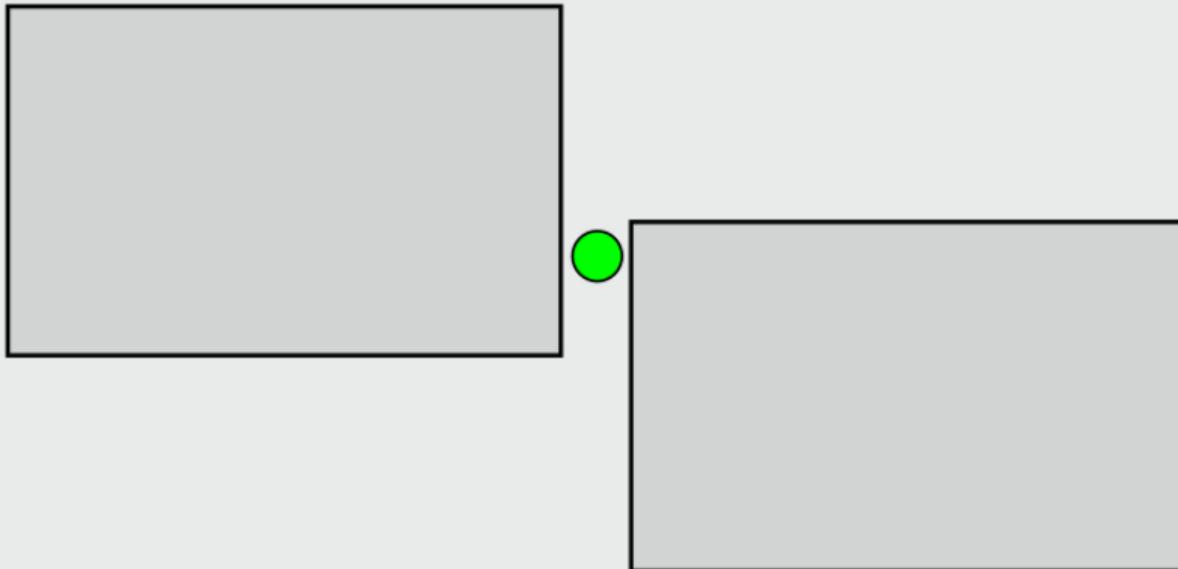
BridgeTestValidStateSampler



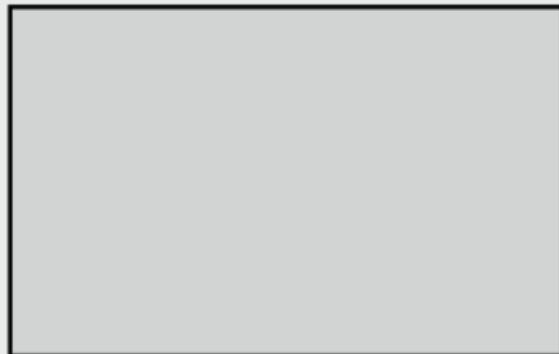
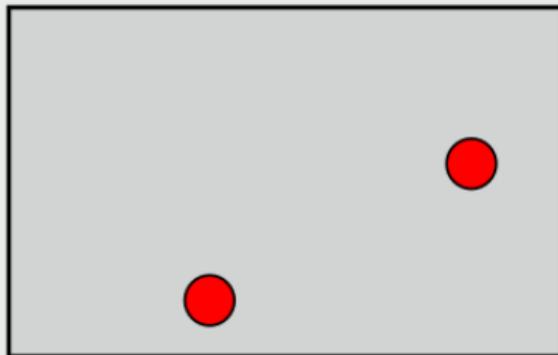
BridgeTestValidStateSampler



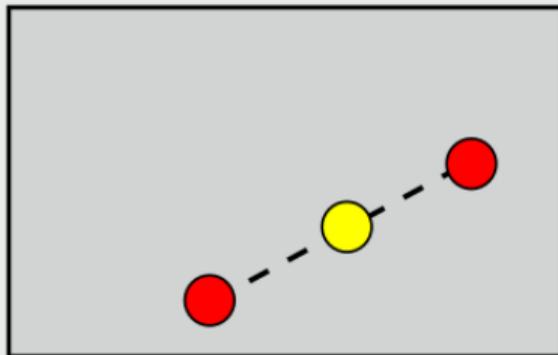
BridgeTestValidStateSampler



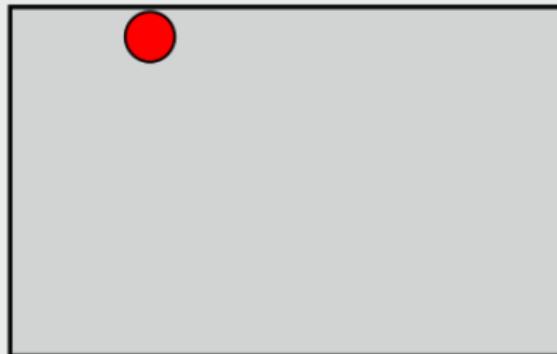
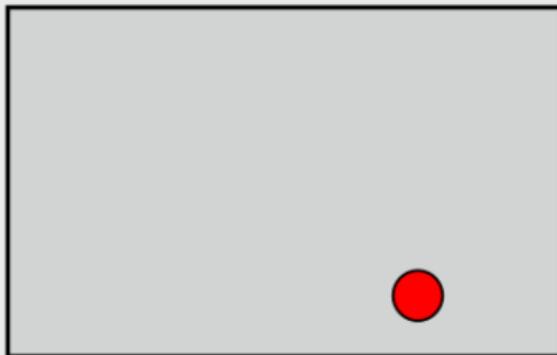
BridgeTestValidStateSampler



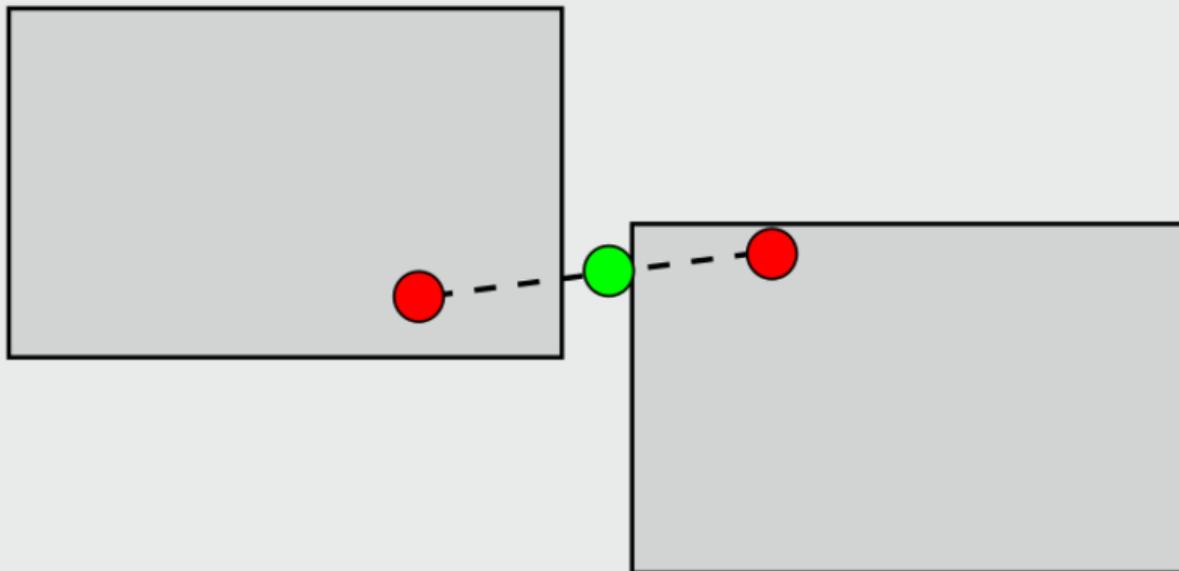
BridgeTestValidStateSampler



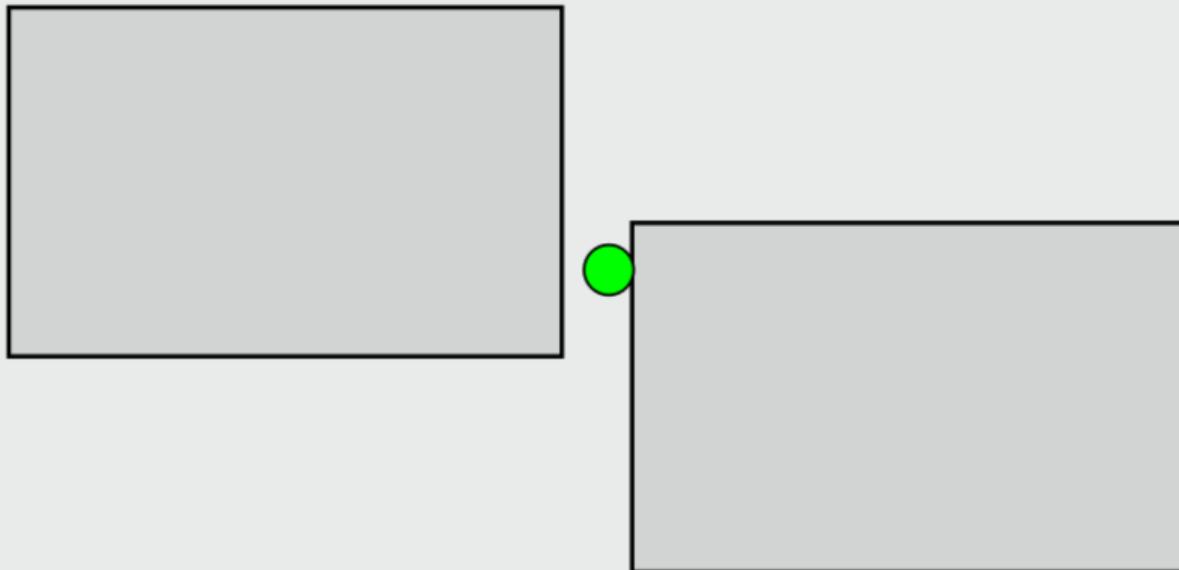
BridgeTestValidStateSampler



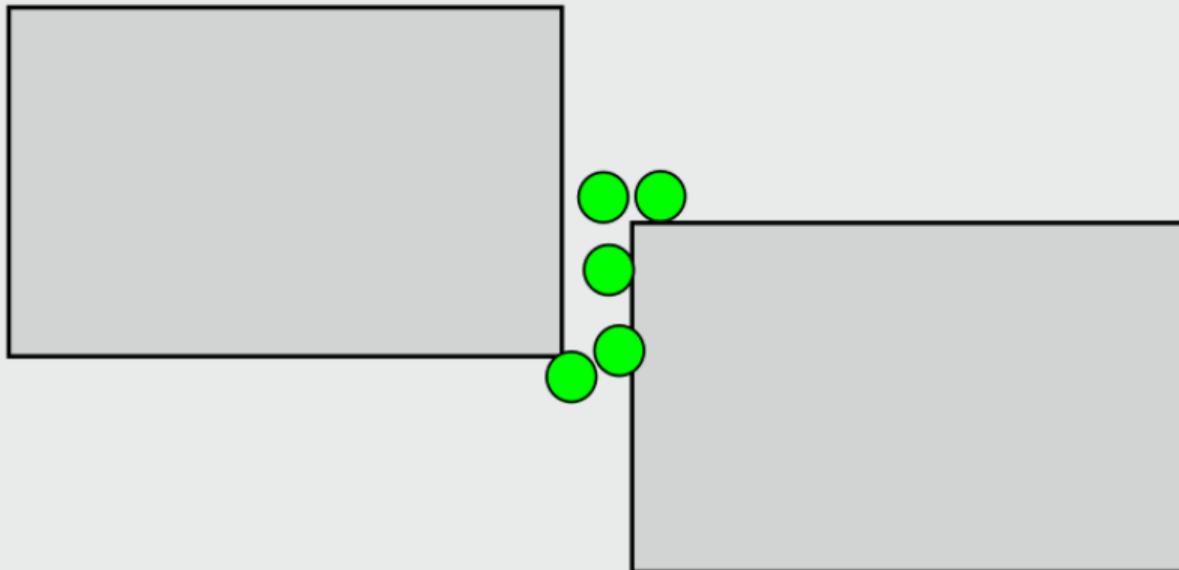
BridgeTestValidStateSampler



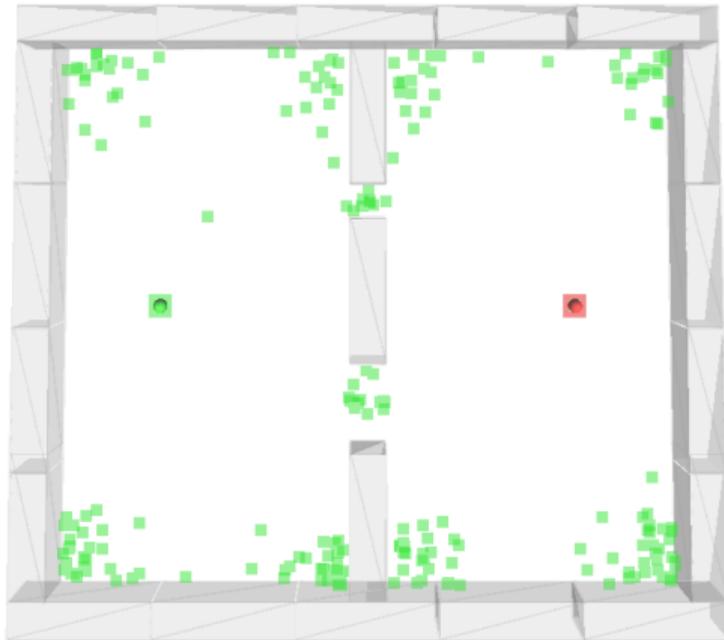
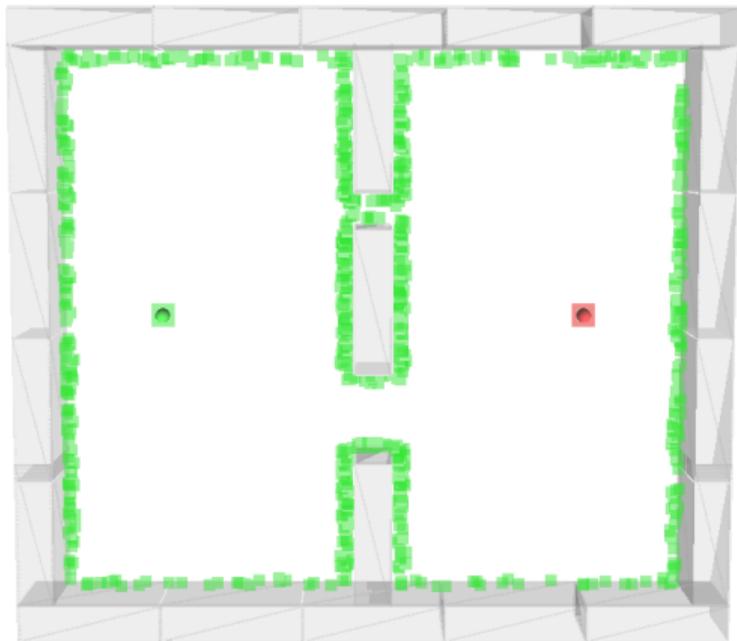
BridgeTestValidStateSampler



BridgeTestValidStateSampler



BridgeTestValidStateSampler



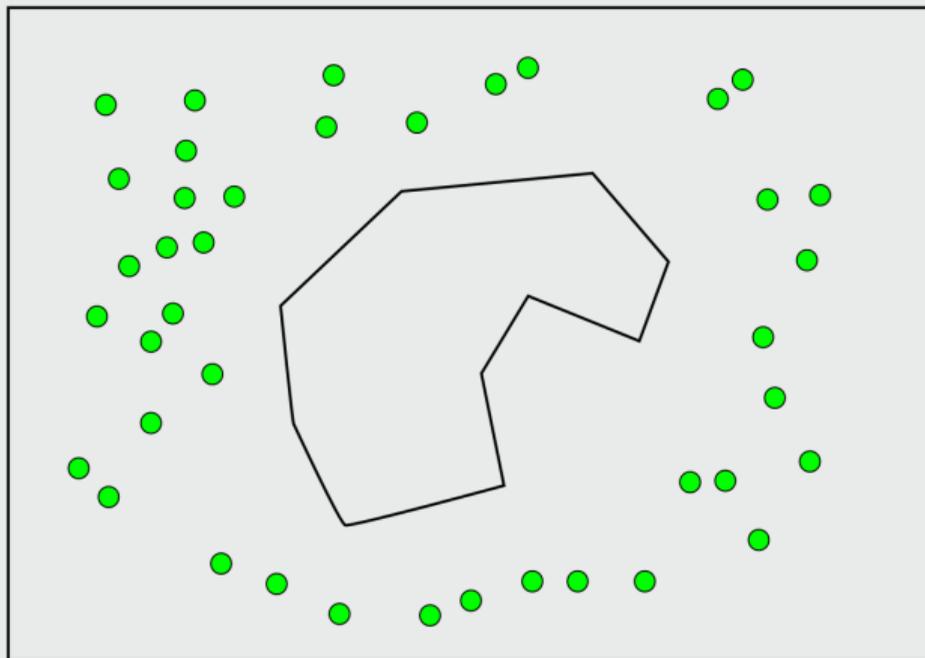
Question

What are the disadvantages of using obstacle-based sampling?

Obstacle-based sampling

- Trade-off quality vs. runtime
- Path length

Clearance-based sampling



Question

What are the advantages of using clearance-based sampling?

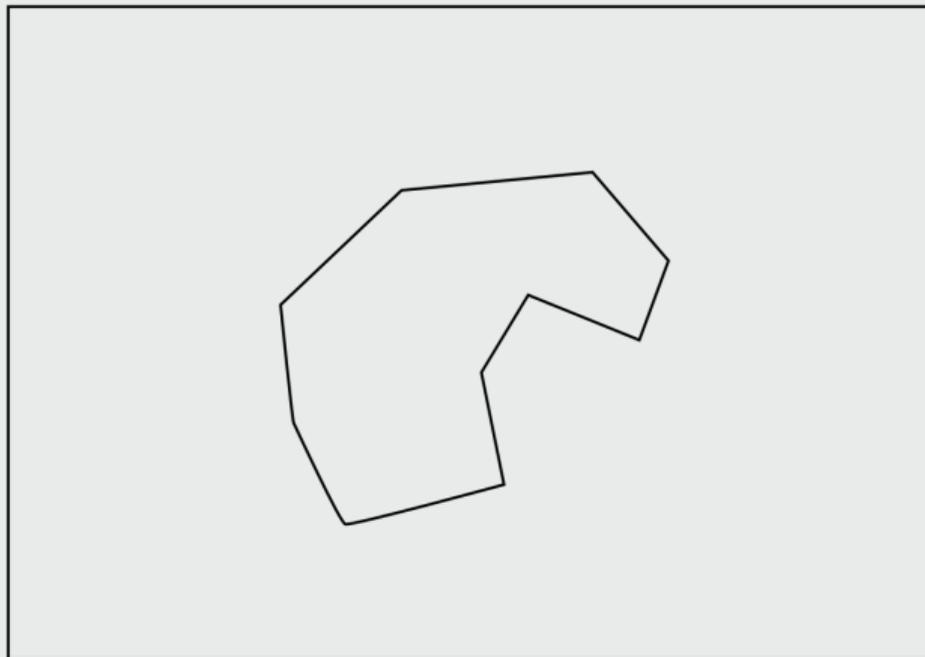
Clearance-based sampling

- Execution uncertainty
- Clearance as safety fence

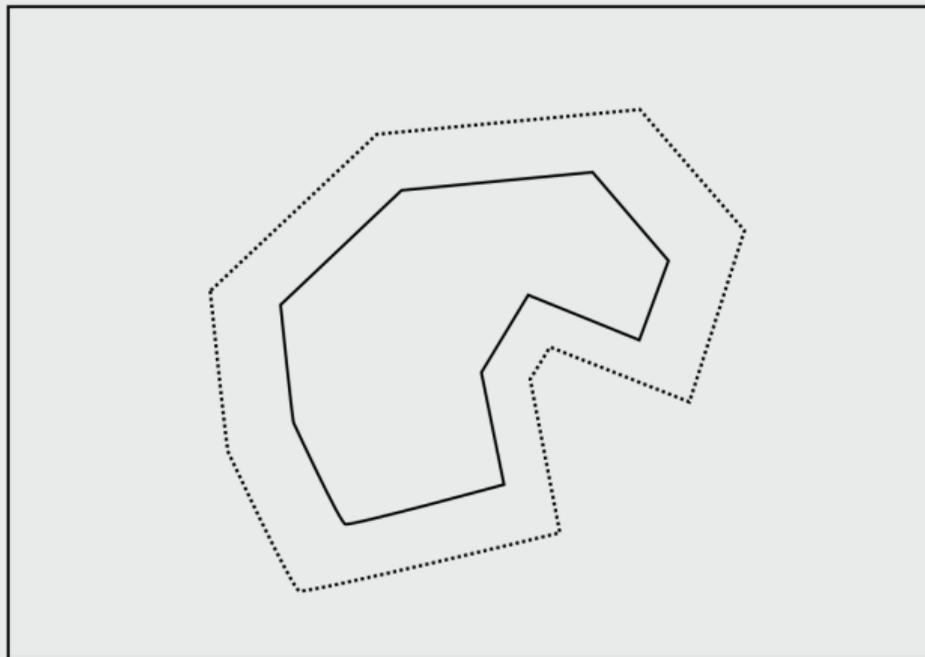
Types of clearance-based sampling

- Minimum clearance
- Maximize clearance

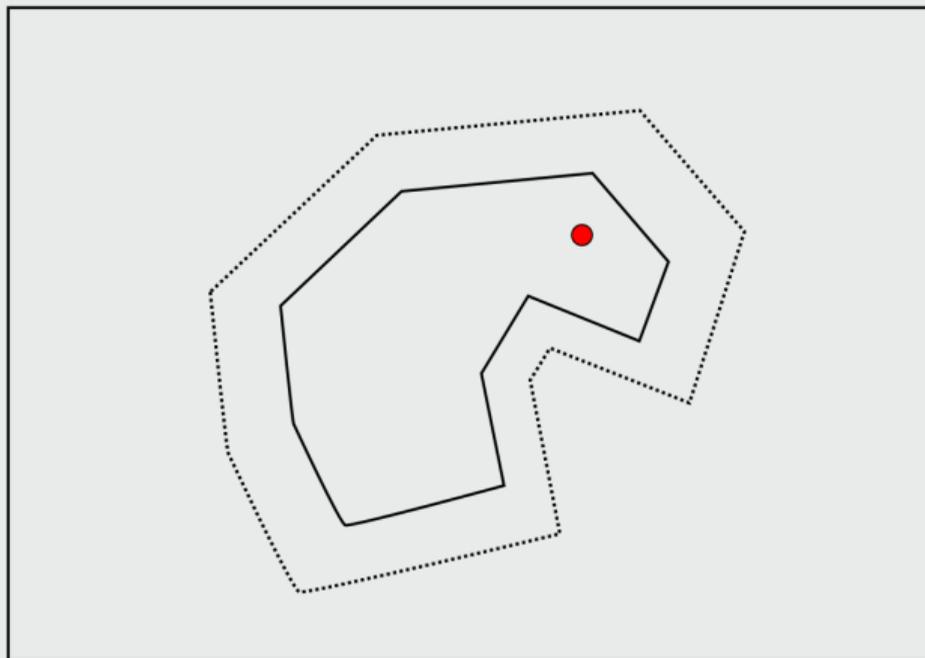
MinimumClearanceValidStateSampler



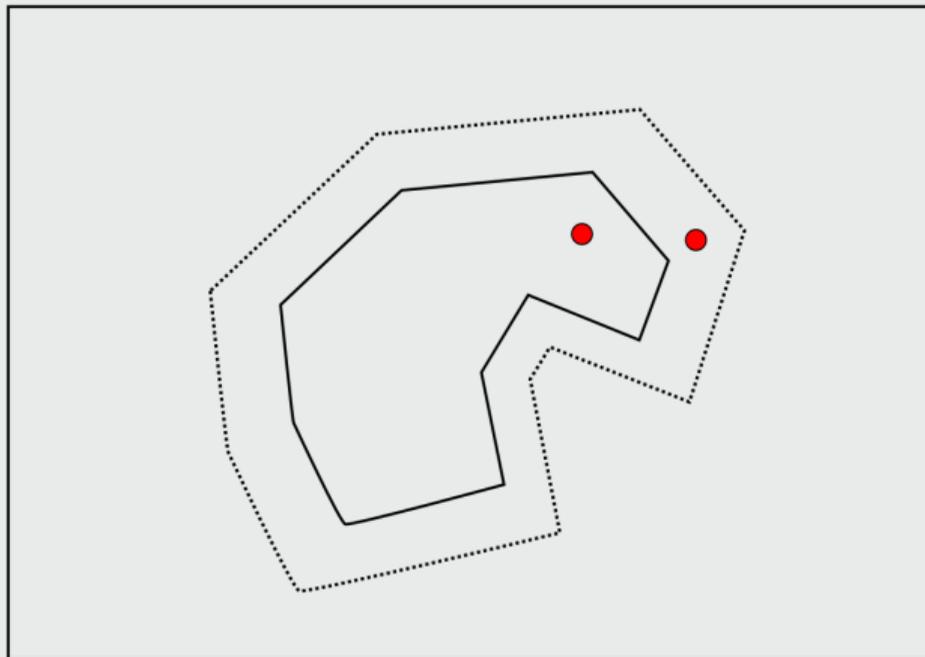
MinimumClearanceValidStateSampler



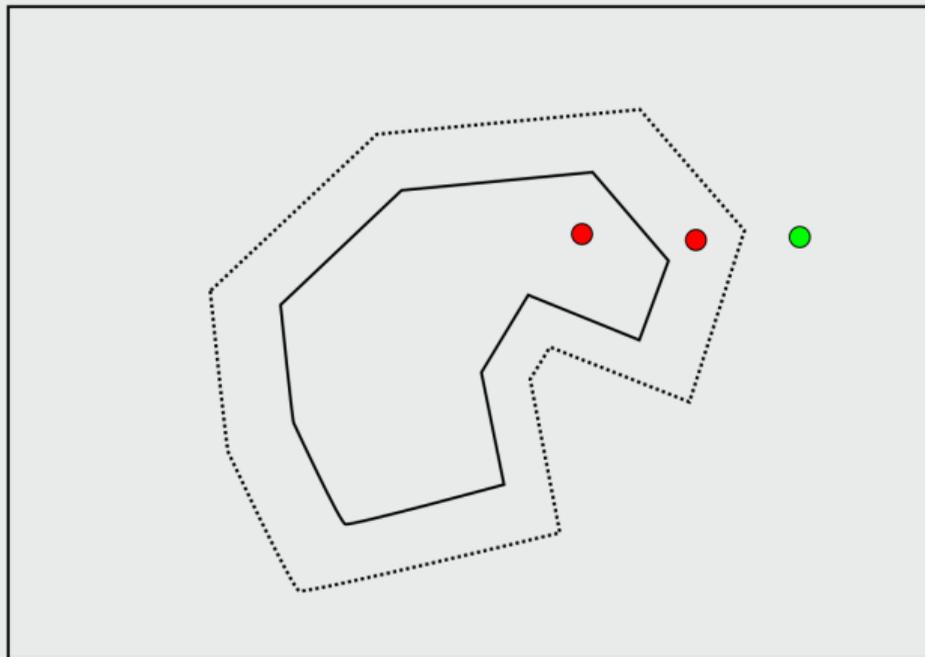
MinimumClearanceValidStateSampler



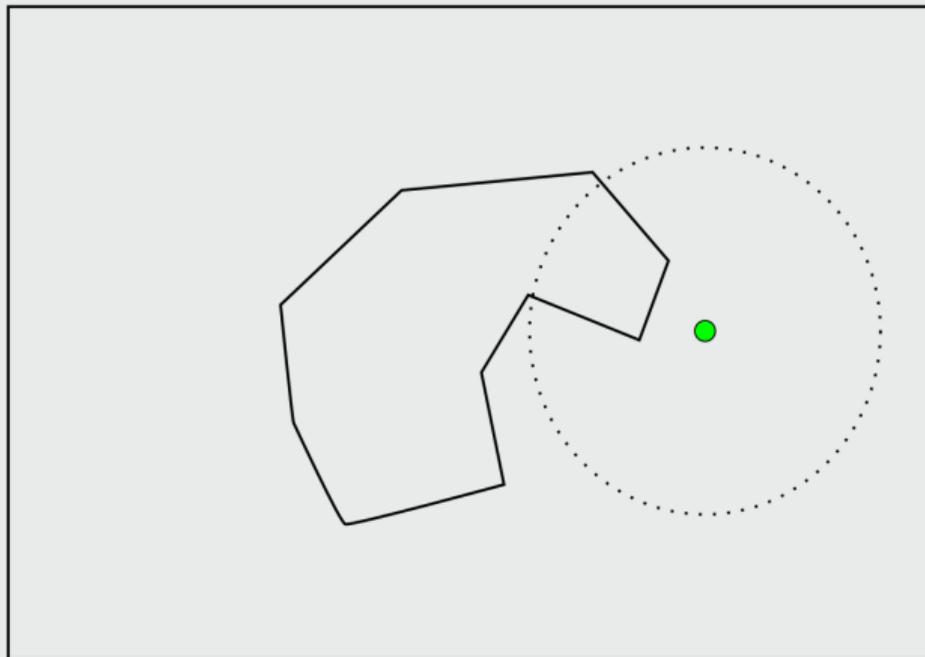
MinimumClearanceValidStateSampler



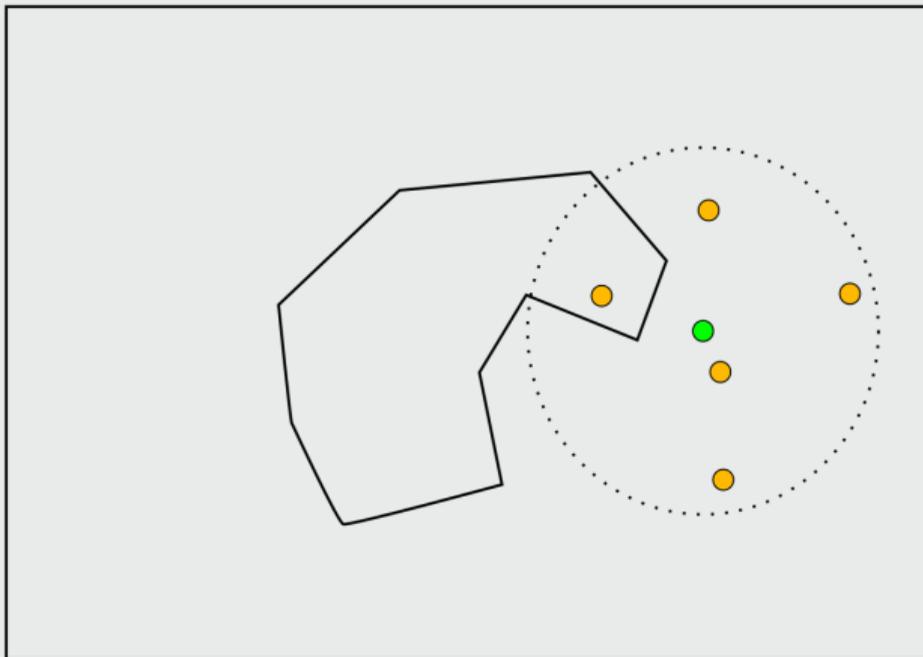
MinimumClearanceValidStateSampler



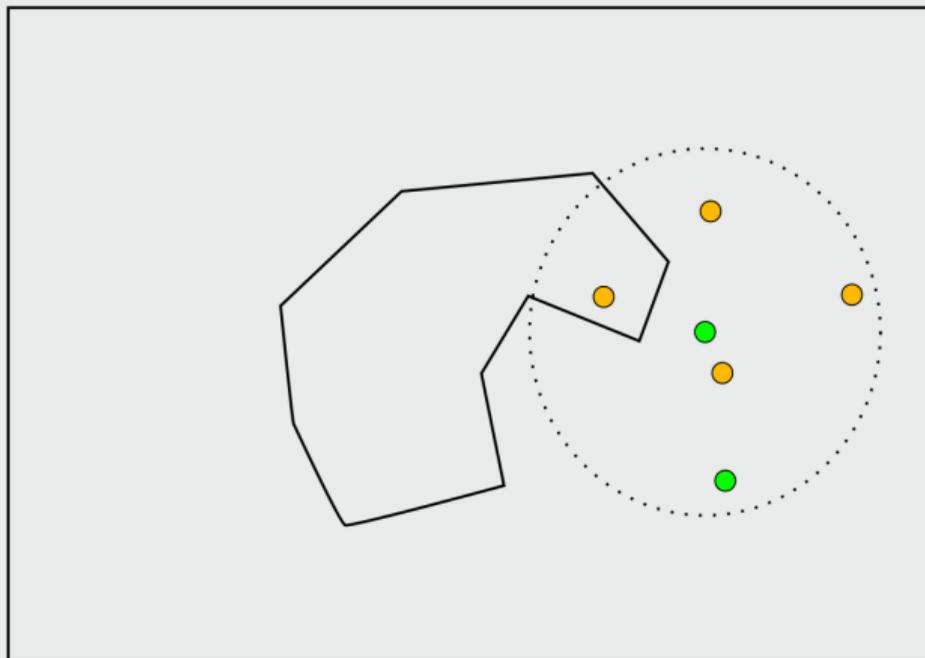
MaximizeClearanceValidStateSampler



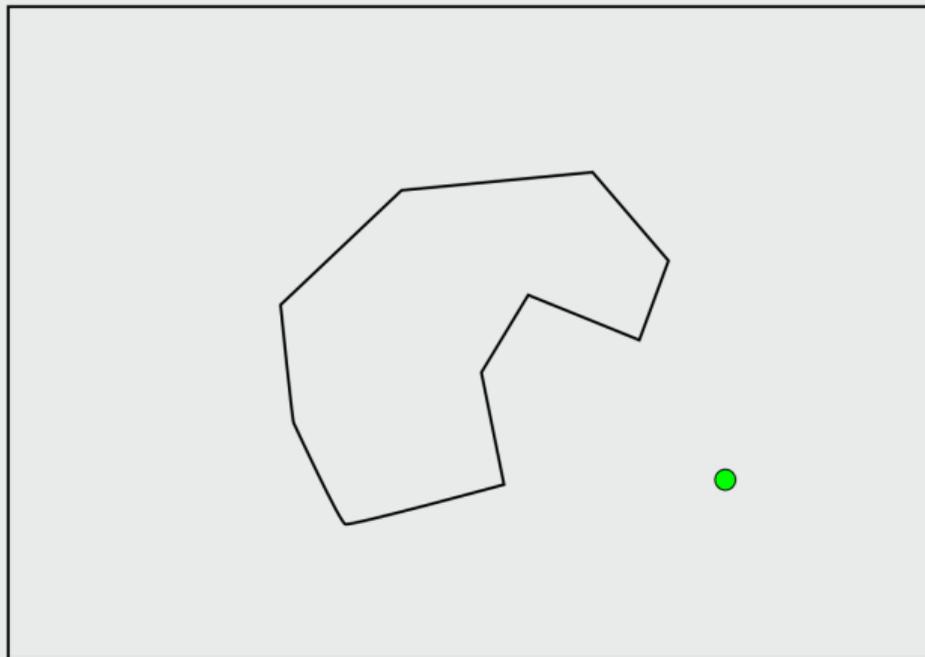
MaximizeClearanceValidStateSampler



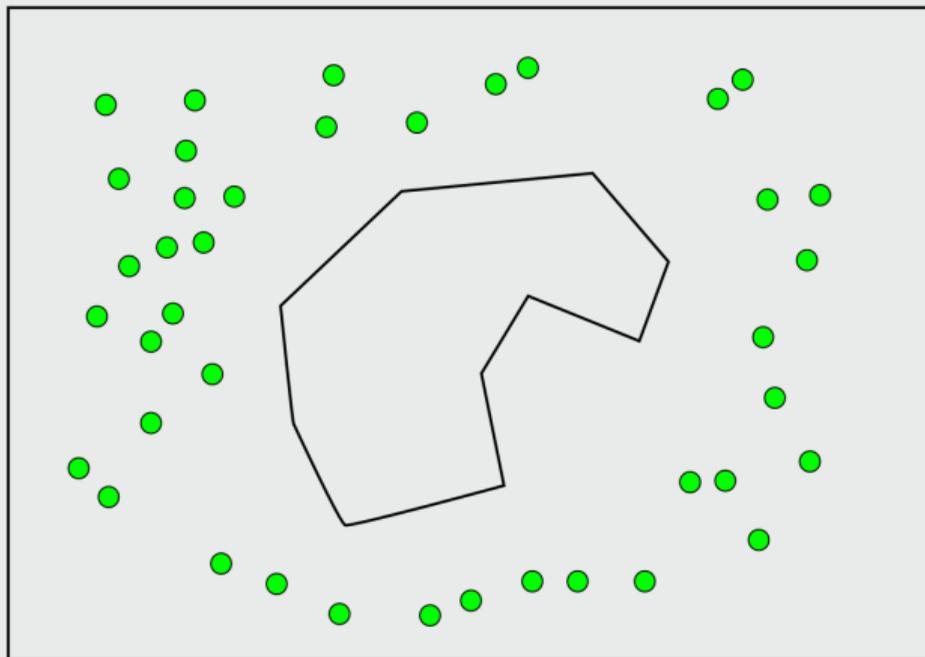
MaximizeClearanceValidStateSampler



MaximizeClearanceValidStateSampler



MaximizeClearanceValidStateSampler



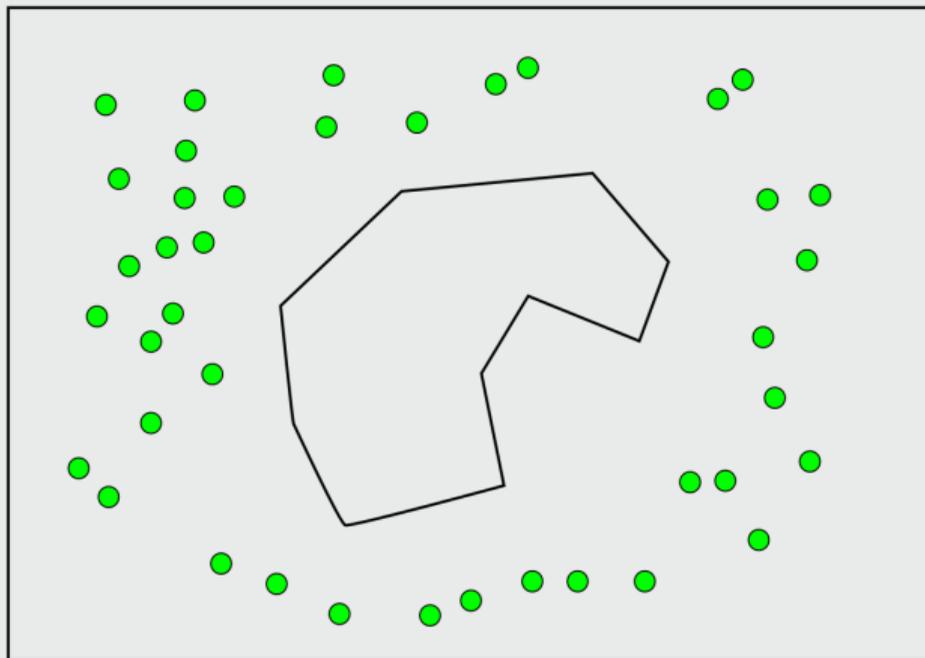
Question

What are the disadvantages of using clearance-based sampling?

Disadvantages clearance-based sampling

- Narrow passages
- Clearance cost

Deterministic sampling



Question

What are the advantages of using deterministic sampling?

Advantages deterministic sampling

- Predictability
- Better distributed
- Low-discrepancy

Halton sampling



Halton sampling



Halton sampling



Halton sampling



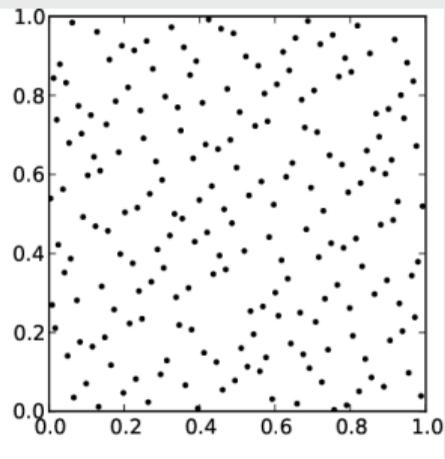
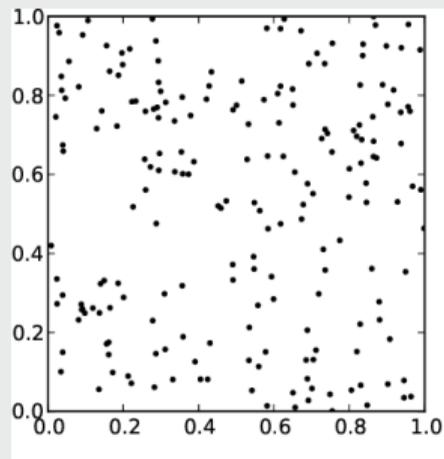
Halton sampling



Halton sampling



Halton sampling



Question

What are the disadvantages of using deterministic sampling?

Overview OMPL

Goal

Goal

- GoalState: State plus an ϵ neighborhood
- GoalStates: Multiple states (e.g. grasping)
- GoalRegions: Subspace of state space (manipulator arm on mobile base)

Primitives

- `bool isSatisfied(x)`: Check if a state satisfies the goal constraints

Overview OMPL

OptimizationObjective

OptimizationObjective

- PathLength
- MaximizeMinClearance
- MinimizeArrivalTime

Primitives

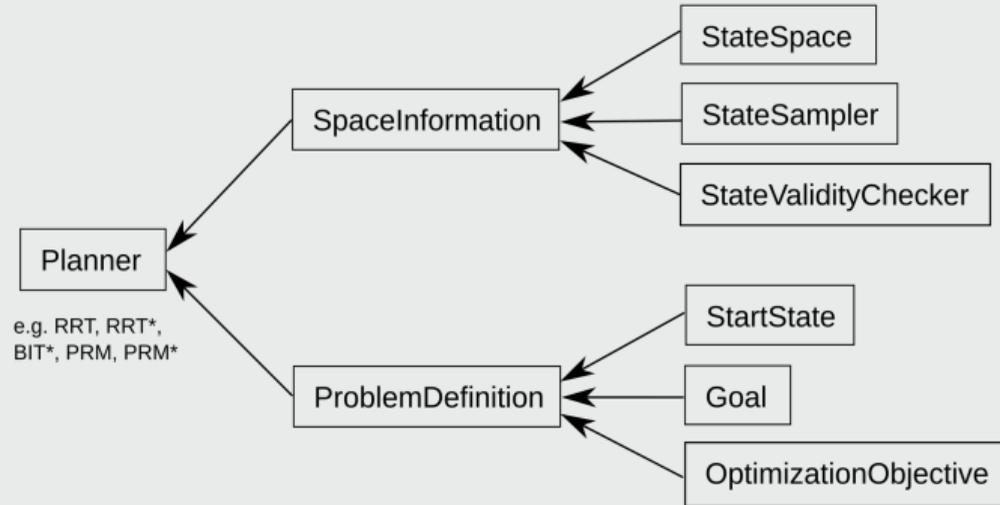
- `float motionCost(x, y):` Compute the cost to go from x to y .

Overview OMPL

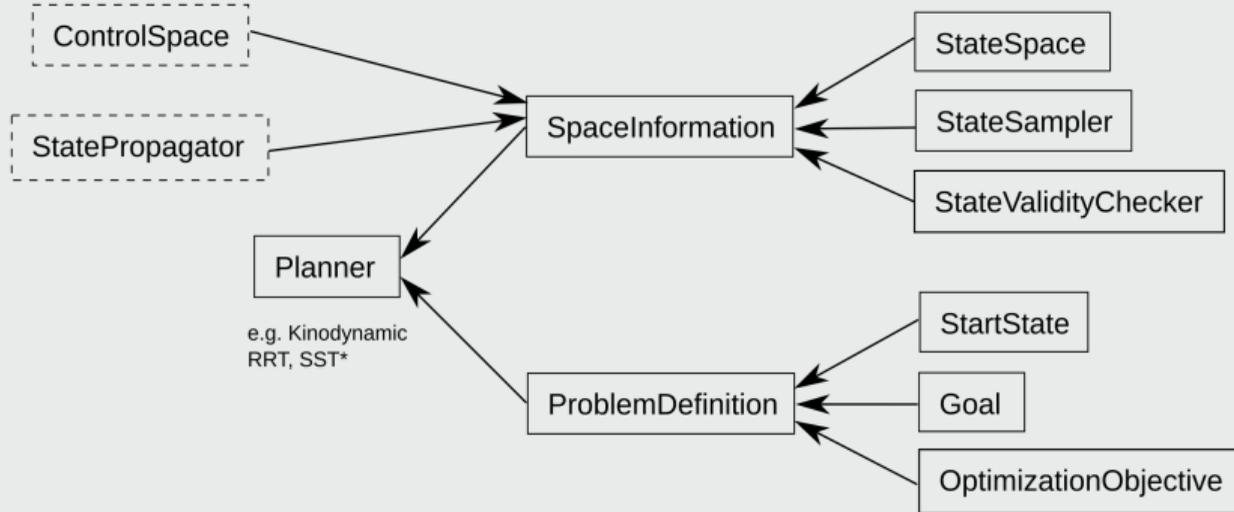
Coding Demo VL8-demo1.py

Kinodynamic Planning in OMPL

Kinodynamic planning



Kinodynamic planning



Kinodynamic Planning in OMPL

Control Space

Control Space

- RealVectorControlSpace: R^n plus bounds
- DiscreteControlSpace: Predefined set of controls (motion primitives)

Methods

- Uniform sampling

Requirements

- Bounds
- Dimensionality
- Set of controls

Kinodynamic Planning in OMPL

State propagator

State propagator

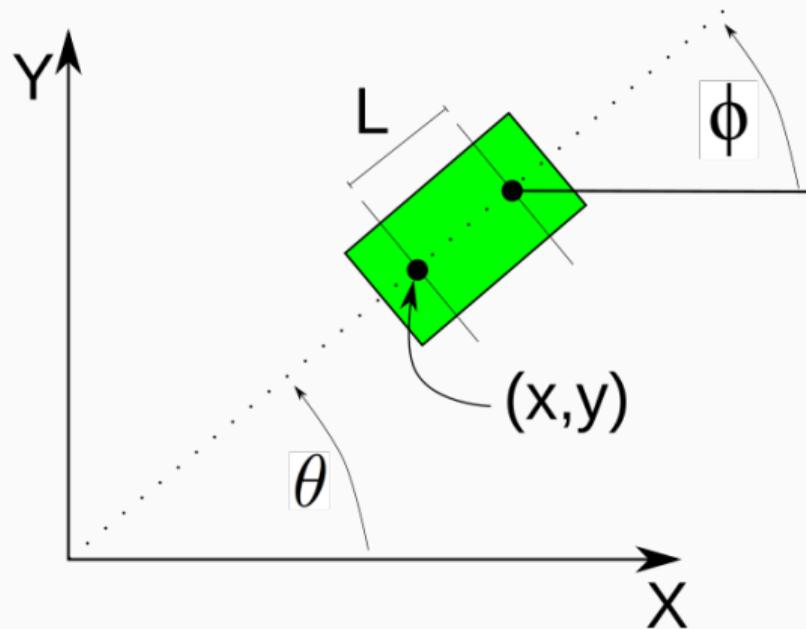
- State `propagate(x, c, t)`: Start at x , and propagate system forward with control c for duration t .
- Control `steer(x, y)`: Compute control c and duration t to move state from x to y [Optional]

Kinodynamic Planning in OMPL

Kinematic Car

Kinematic car

- State space $SE(2) = (x, y, \theta)$
- Control space $U = [-1, +1] \times (\phi_{\min}, \phi_{\max}) = (u_1, u_2)$
- Dynamics $\dot{x} = f(x, y, \theta, u_1, u_2)$



Kinematic car

$$\dot{x} = \begin{bmatrix} u_1 \cos(\theta) \\ u_2 \sin(\theta) \\ \frac{\tan(u_2)}{L} u_1 \end{bmatrix}$$

OMPL

- Overview of OMPL
- Class structures, options
- Setting up kinodynamic problems
- Coding examples

Links

- OMPL <https://ompl.kavrakilab.org/>: Main website
- OMPL on github <https://github.com/ompl/ompl>: Main repository on github
- Planner Arena <https://plannerarena.org/>: Can open database (db) files to display performance of planners
- Webapp <http://omplapp.kavrakilab.org/>: Run planners on a set of classical scenarios

- [1] Zachary Kingston, Mark Moll, and Lydia E. Kavraki. “Exploring Implicit Spaces for Constrained Sampling-Based Planning”. In: *Intl. J. of Robotics Research* 38.10–11 (Sept. 2019), pp. 1151–1178. DOI: 10.1177/0278364919868530.
- [2] Mark Moll, Ioan A. Şucan, and Lydia E. Kavraki. “Benchmarking Motion Planning Algorithms: An Extensible Infrastructure for Analysis and Visualization”. In: *IEEE Robotics & Automation Magazine* 22.3 (Sept. 2015), pp. 96–102. DOI: 10.1109/MRA.2015.2448276.
- [3] Ioan A. Şucan, Mark Moll, and Lydia E. Kavraki. “The Open Motion Planning Library”. In: *IEEE Robotics & Automation Magazine* 19.4 (Dec. 2012). <https://ompl.kavrakilab.org>, pp. 72–82. DOI: 10.1109/MRA.2012.2205651.

Kinodynamic Planning in OMPL

Coding Demo VL8-demo2.py