OMPL: The Open Motion Planning Library

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Intended use

Education

Motion planning research

Industry

Design objectives

- Clarity of concepts
- Efficiency
- Simple integration with other software packages
- Straightforward integration of external contributions

Other motion planning software

- MPK, Schwarzer, Saha, Latombe
- **MSL**, LaValle et al.
- **OpenRAVE**, Diankov & Kuffner
- KineoWorks, Laumond et al.
- **OOPSMP**, Plaku et al.

Other related robotics software

- ROS
- Player/Stage, Player/Gazebo
- Webots
- MORSE
- Microsoft Robotics Developer Studio

Main features of OMPL

OMPL in a nutshell

• Common core for sampling-based motion planners

• Includes commonly-used heuristics

• Takes care of many low-level details often skipped in corresponding papers

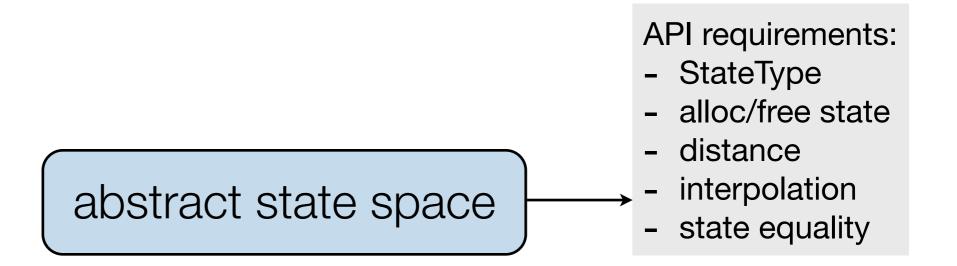
Abstract interface to all core motion planning concepts

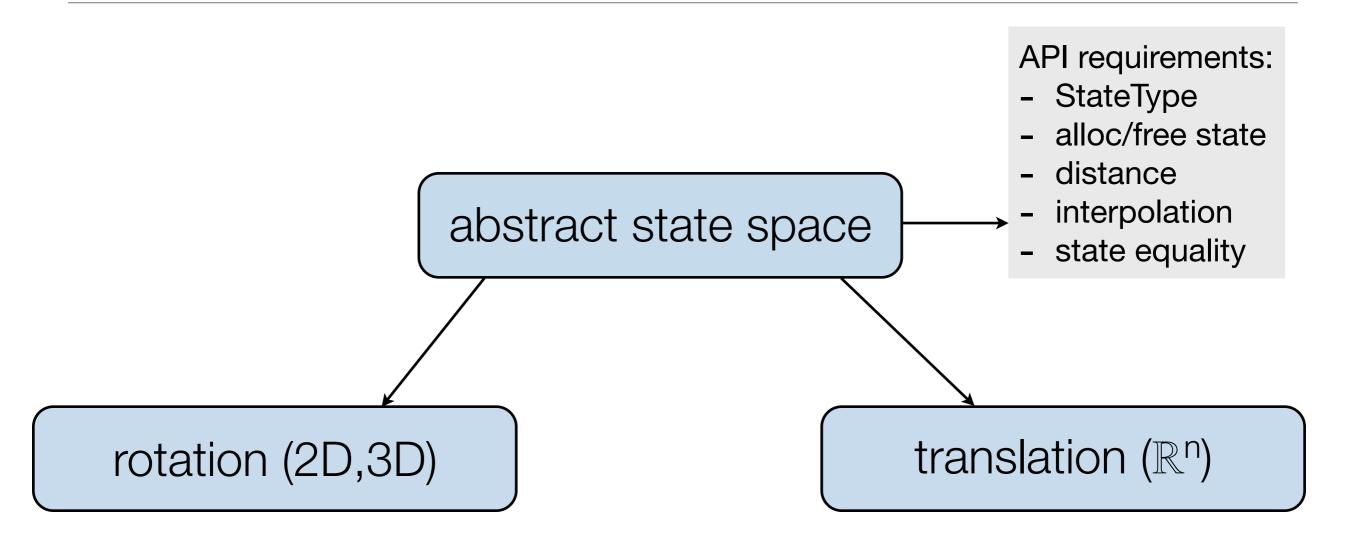
- state space / control space
- state validator (e.g., collision checker)
- sampler
- goal (problem definition)
- planner

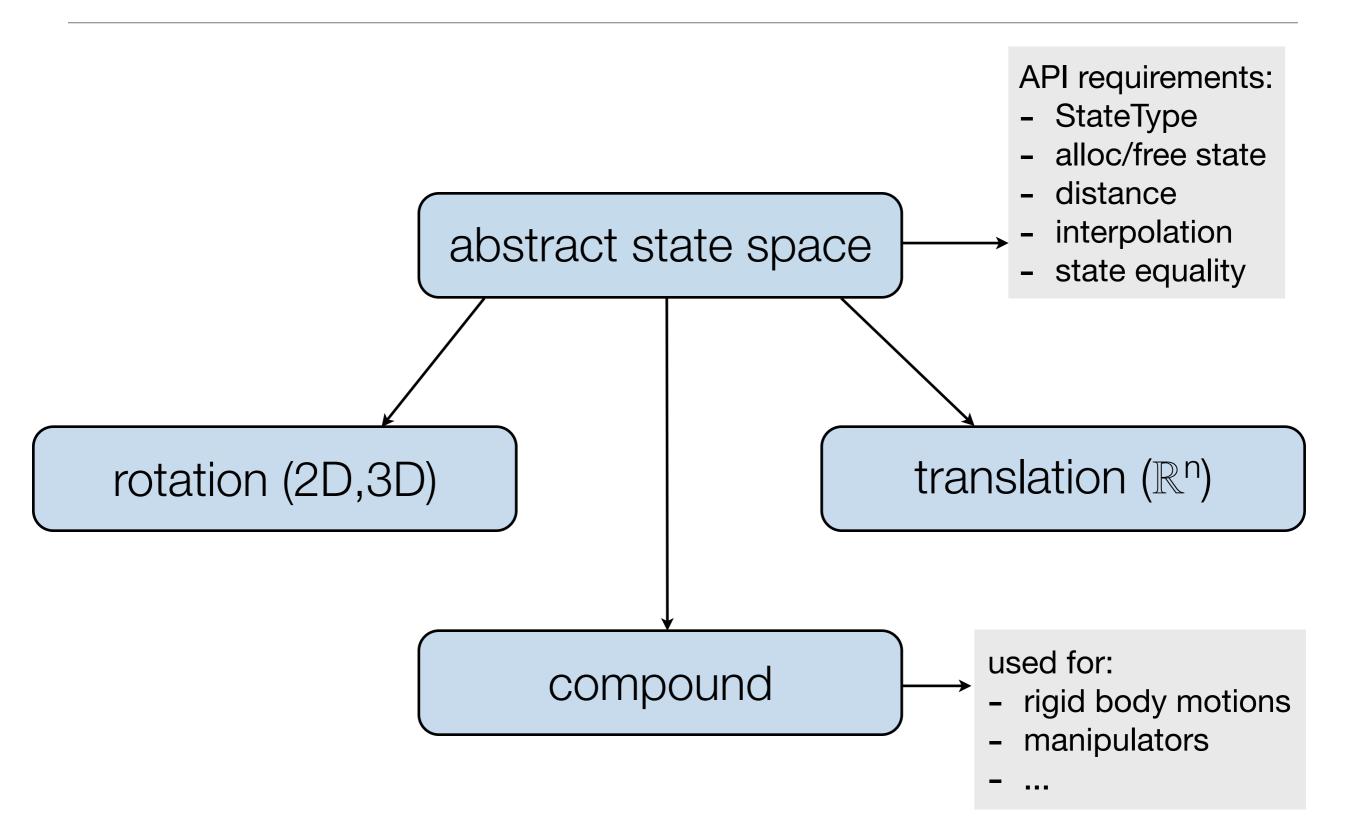


except robot & workspace...

abstract state space

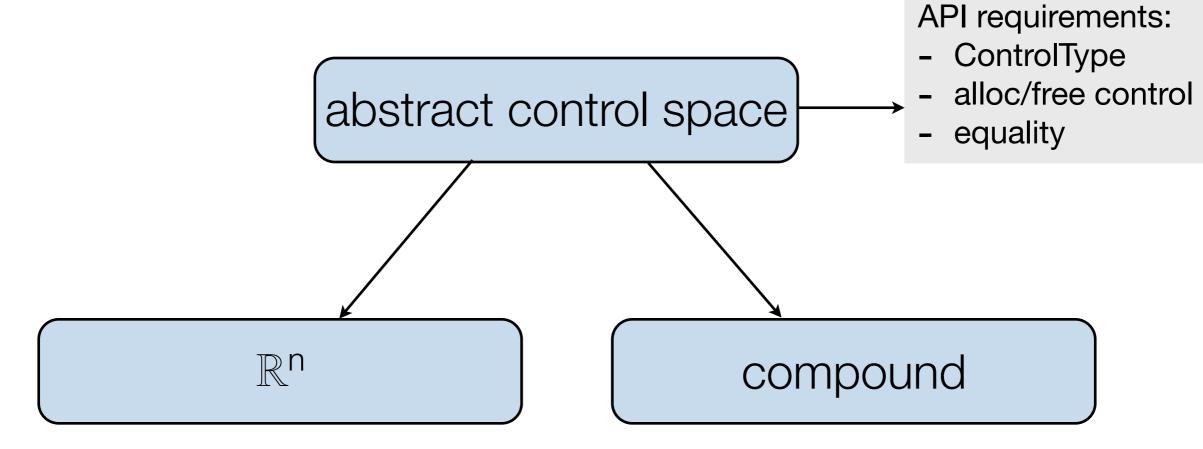






Control spaces & controls

- Needed only for control-based planning
- Analogous to state spaces and states:



State validators

- Problem-specific; must be defined by user or defined by layer on top of OMPL core → ompl_ros_interface
- Checks whether state is collision-free, joint angles and velocities are within bounds, etc.
- Optionally, specific state validator implementations can return
 - distance to nearest invalid state (i.e., nearest obstacle)
 - gradient of distance

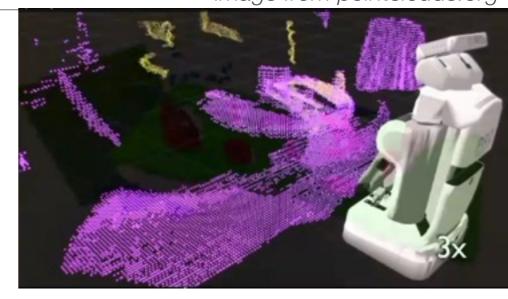
Can be exploited by planners / samplers!

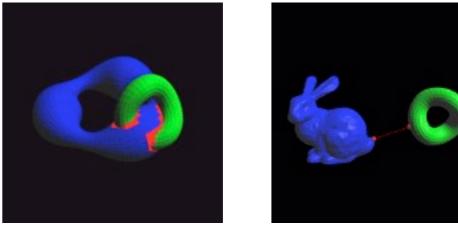
Most common state validator: collision checker

Several options:

- Implemented in ROS on top of sensor-derived world model
- Implemented in OMPL.app for triangle meshes using PQP library
- Easy to add wrappers for other libraries

image from pointclouds.org



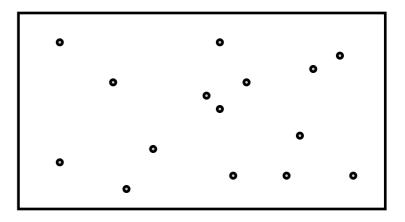


images from PQP web site

Need to define **specific** world representation to implement collision checking

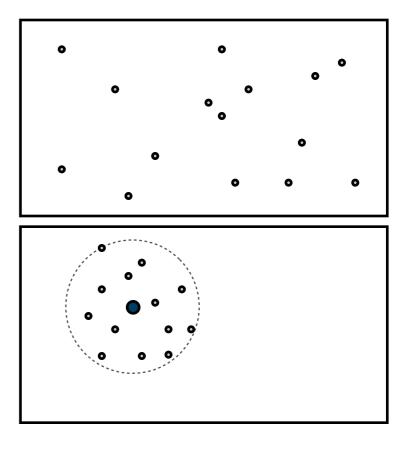
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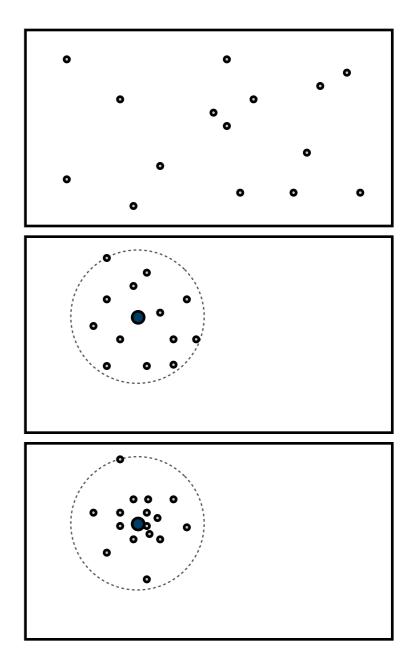
• sample uniform near given state



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- State samplers need to support the following:
 - sample uniform

• sample uniform near given state

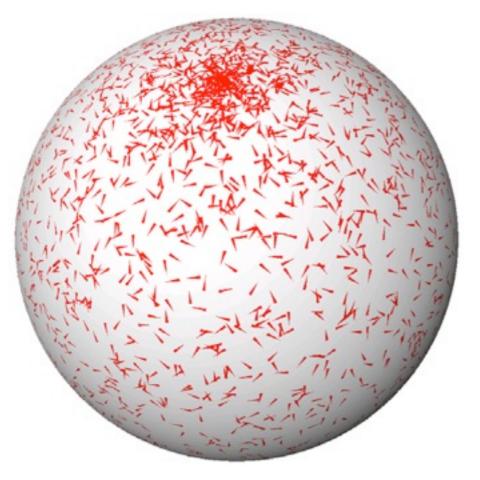
sample from Gaussian centered at given state



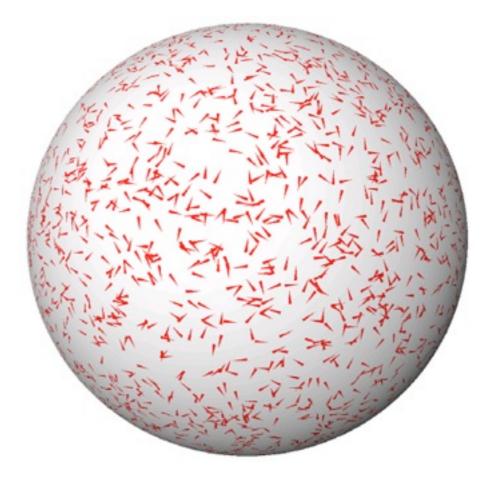
Many ways to get sampling wrong

Example: uniformly sampling 3D orientations

naïve & wrong:



correct:



Images from Kuffner, ICRA '04

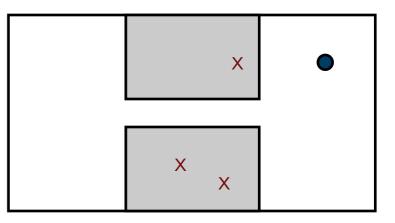
Similar issues occur for nearest neighbors

 k nearest neighbors can be computed efficiently with kd-trees in low-dimensional, Euclidean spaces.

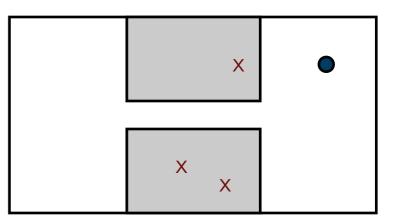
• In high-dimensional spaces **approximate** nearest neighbors much better

 In non-Euclidean spaces (e.g., any space that includes rotations), other data structures are necessary

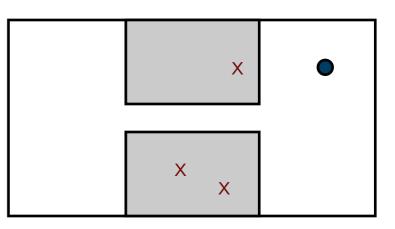
- Valid state samplers combine low-level state samplers with the validity checker
- Simplest form: sample at most *n* times to get valid state or else return failure

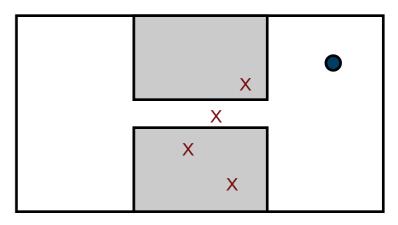


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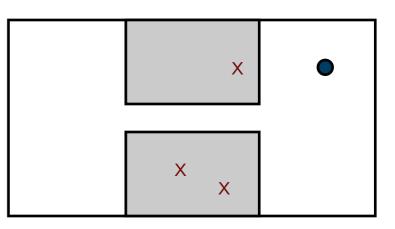


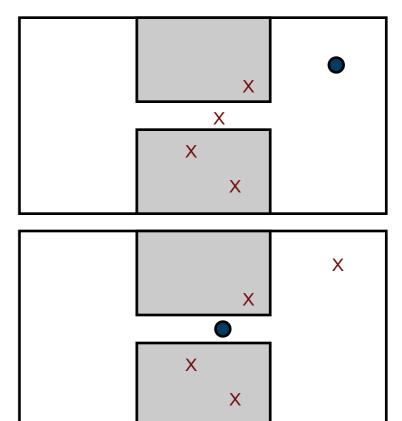
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- Other sampling strategies:
 - Try to find samples with a large clearance



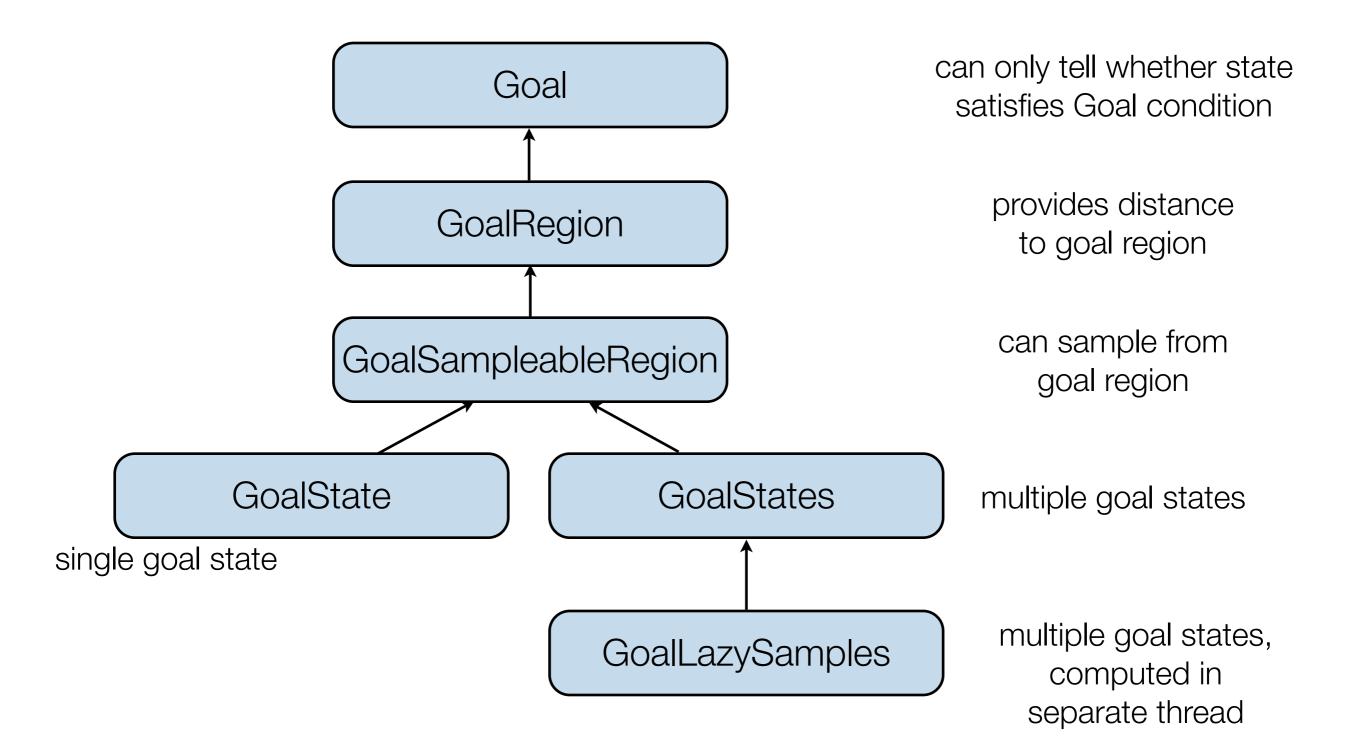


- Valid state samplers combine low-level state samplers with the validity checker
- Simplest form: sample at most *n* times to get valid state or else return failure
- Other sampling strategies:
 - Try to find samples with a large clearance
 - Try to find samples near obstacles (more dense sampling in/near narrow passages)





Goals



Planners

- Take as input a **problem definition**: object with one or more **start states** and a **goal object**
- Planners need to implement two methods:

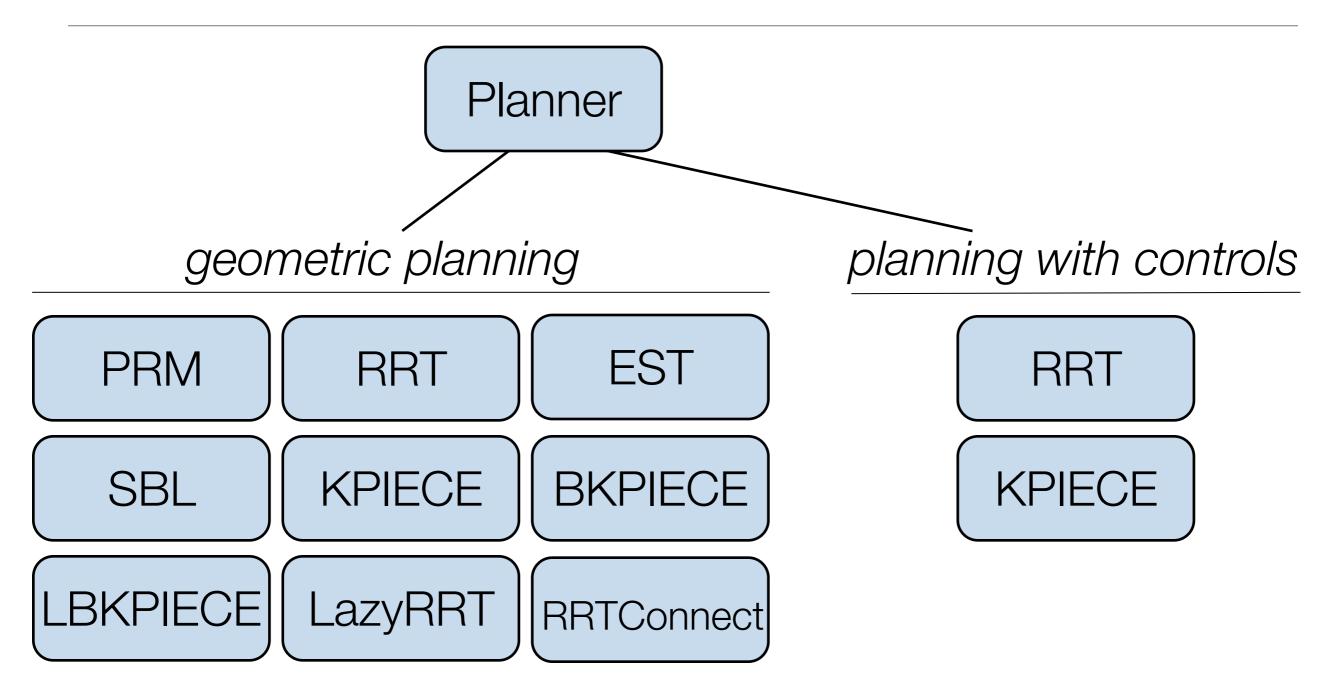
• solve:

- takes PlannerTerminationCondition object as argument
- termination can be based on timer, external events, ...

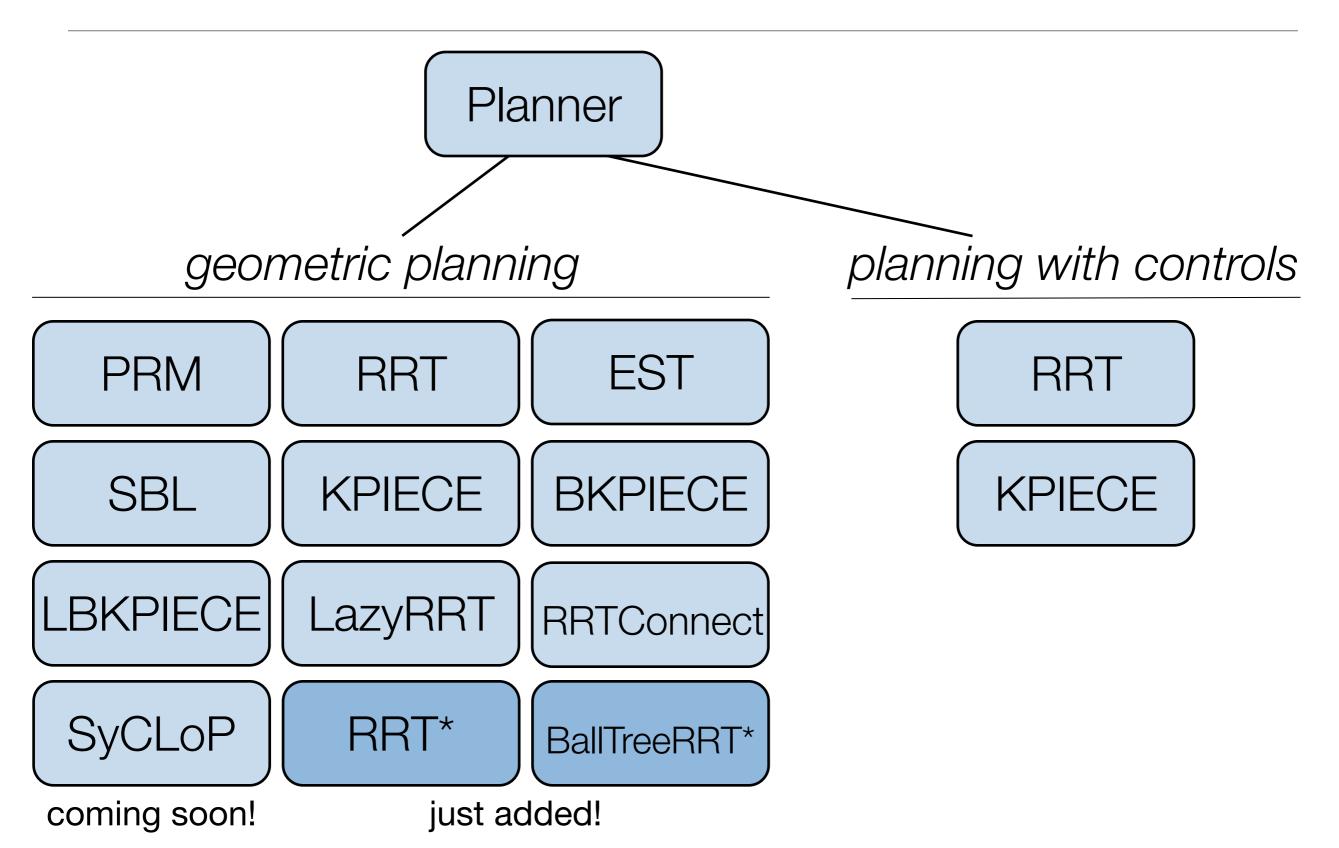
• clear:

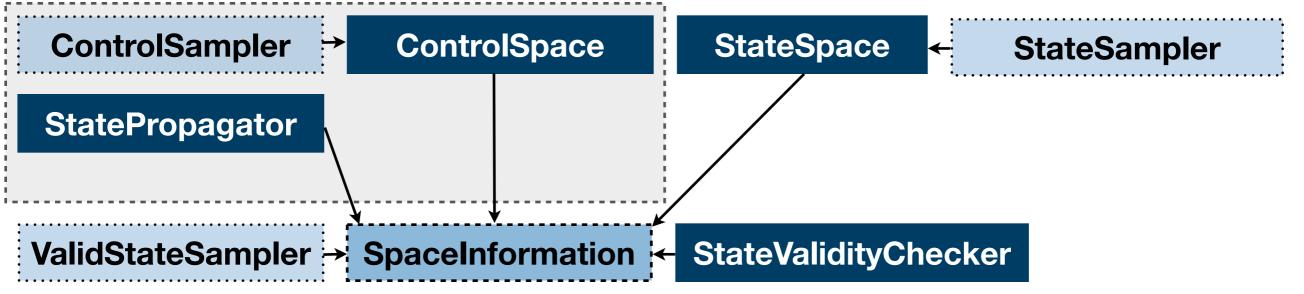
clear internal data structures, free memory, ready to run solve again

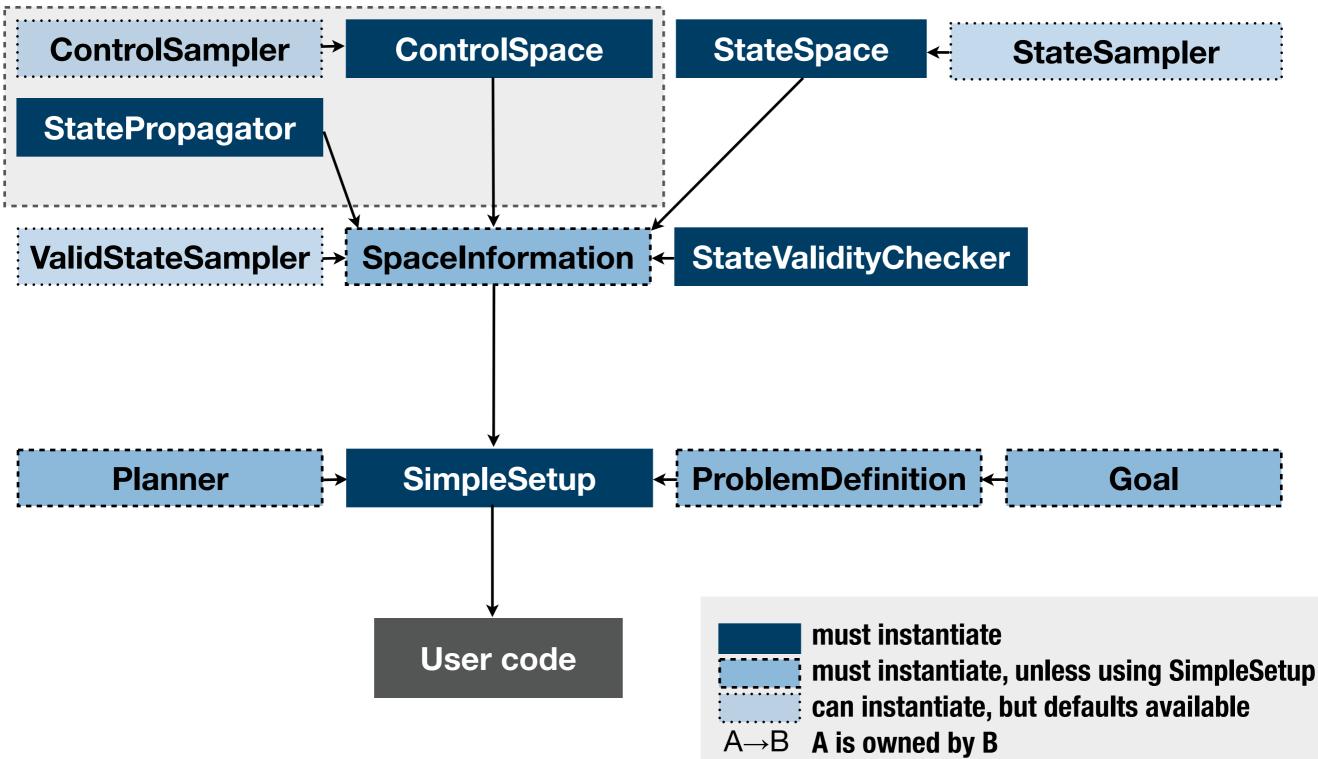
Many planners available in OMPL

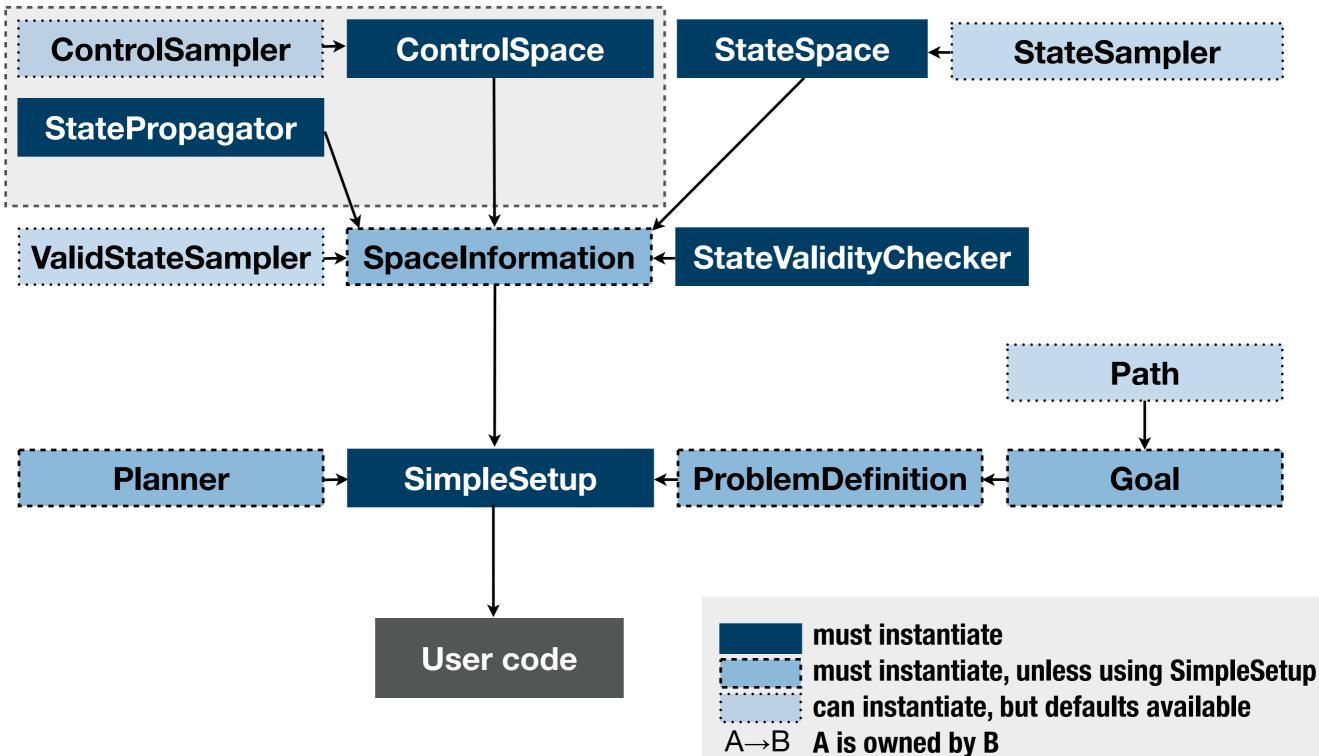


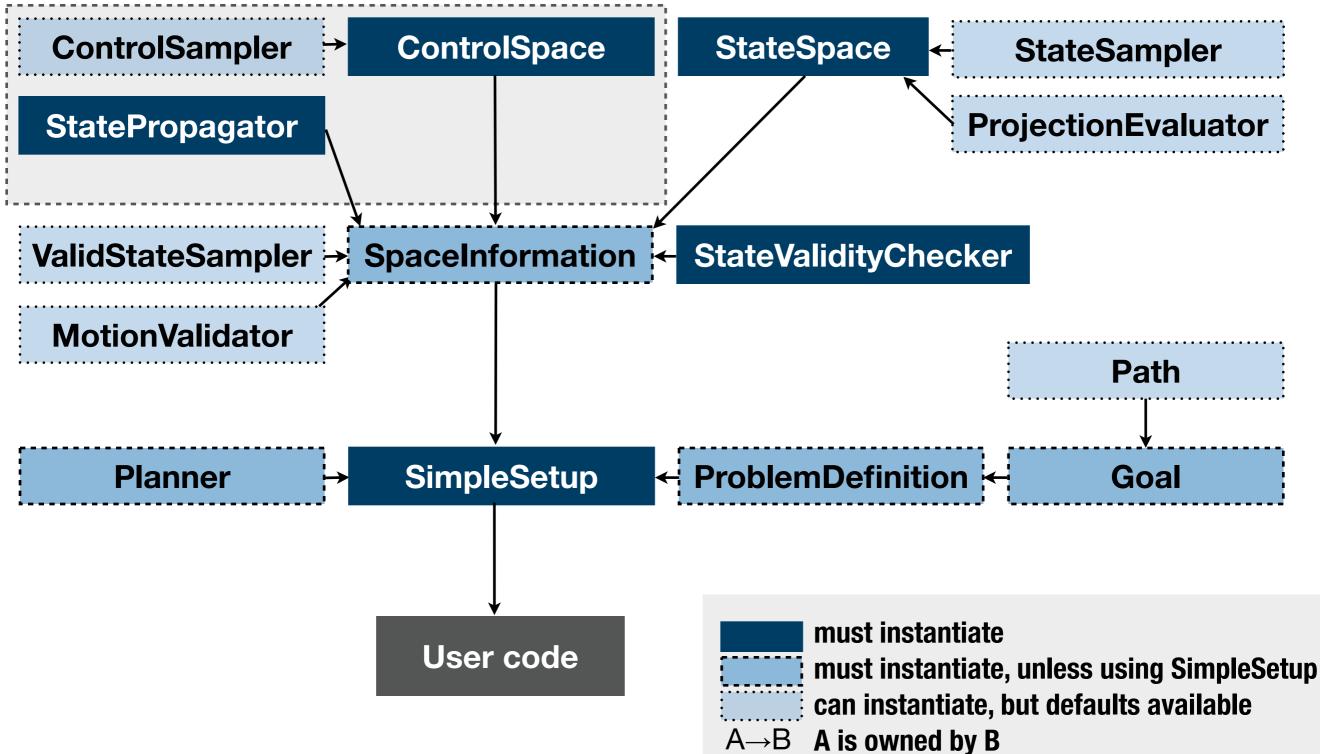
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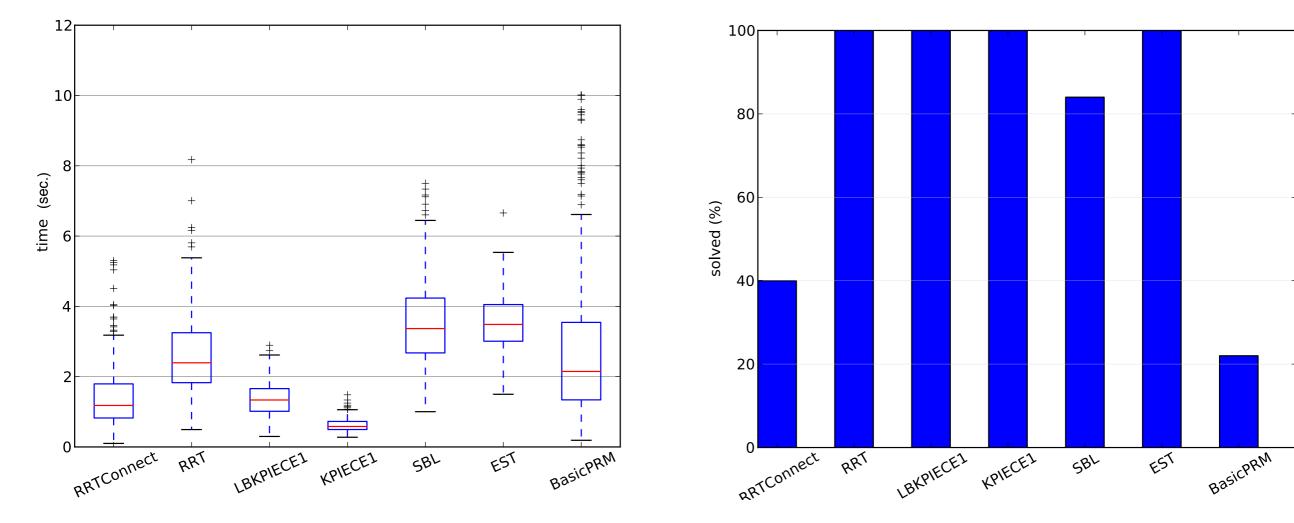
Minimal code example

```
space = SE3StateSpace()
1
2 # set the bounds (code omitted)
3
   ss = SimpleSetup(space)
4
   # "isStateValid" is a user-supplied function
5
   ss.setStateValidityChecker(isStateValid)
6
7
   start = State(space)
8
   goal = State(space)
9
   # set the start & goal states to some values
10
   # (code omitted)
11
12
   ss.setStartAndGoalStates(start, goal)
13
   solved = ss.solve(1.0)
14
   if solved:
15
       print setup.getSolutionPath()
16
```

Minimal code example

```
StateSpacePtr space(new SE3StateSpace());
1
  // set the bounds (code omitted)
2
3
   SimpleSetup ss(space);
4
   // "isStateValid" is a user-supplied function
5
   ss.setStateValidityChecker(isStateValid);
6
7
   ScopedState<SE3StateSpace> start(space);
8
   ScopedState<SE3StateSpace> goal(space);
9
   // set the start & goal states to some values
10
  // (code omitted)
11
12
   ss.setStartAndGoalStates(start, goal);
13
   bool solved = ss.solve(1.0);
14
   if (solved)
15
       setup.getSolutionPath().print(std::cout);
16
```

Benchmarking



Benchmarking

SimpleSetup setup;
// motion planning problem setup code omitted
Benchmark b(setup, "My First Benchmark");

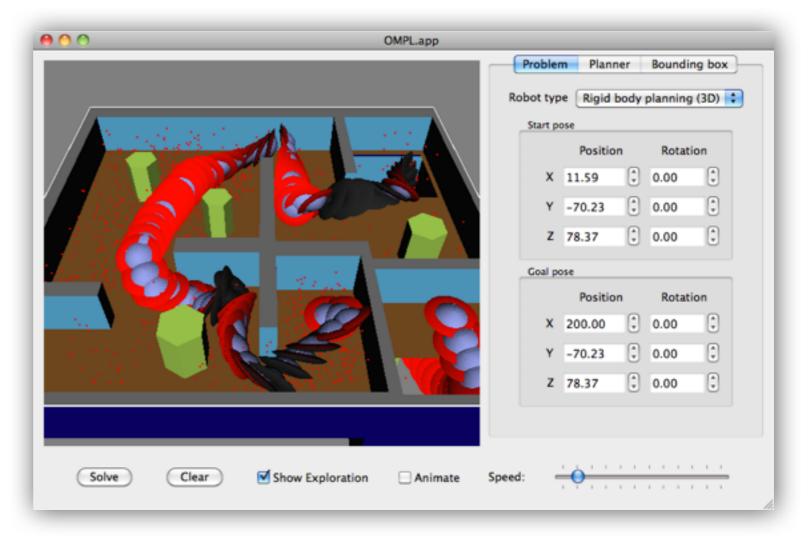
b.addPlanner(base::PlannerPtr(new geometric::RRT(setup.getSpaceInformation())); b.addPlanner(base::PlannerPtr(new geometric::KPIECE1(setup.getSpaceInformation())); b.addPlanner(base::PlannerPtr(new geometric::SBL(setup.getSpaceInformation())); b.addPlanner(base::PlannerPtr(new geometric::EST(setup.getSpaceInformation())); b.addPlanner(base::PlannerPtr(new geometric::PRM(setup.getSpaceInformation()));

```
b.benchmark(runtime_limit, memory_limit, run_count, true);
b.saveResultsToFile();
```

Script post-processes benchmark log files to create/update SQLite database and plots

OMPL.app

- Front-end that demonstrates integration with libraries for collision checking, 3D mesh loading, GUI toolkit
- Easy-to-use tool for novices to get started
- Alternative to ompl_ros_interface



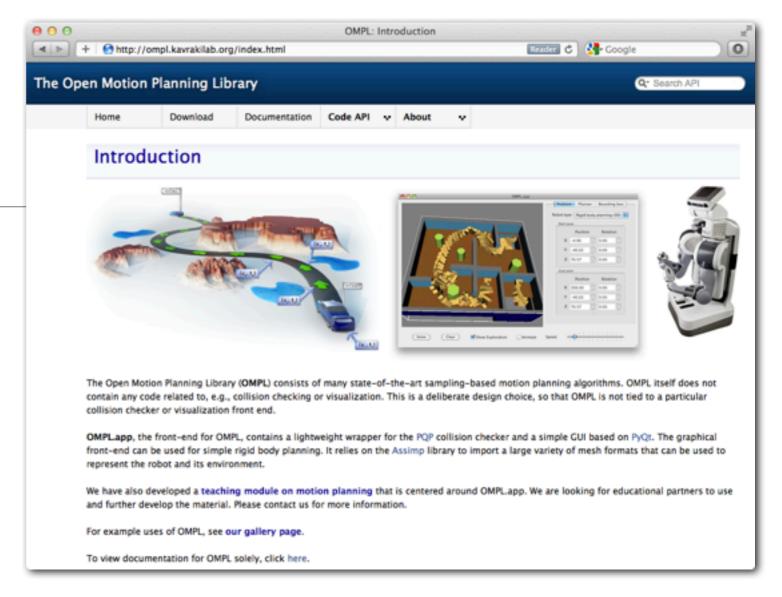
OMPL.app demo / screencast

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Resources to get started with OMPL

OMPL online

Web site:
 <u>http://ompl.kavrakilab.org</u>



- Mailing lists:
 - Developers: <u>ompl-devel@lists.sourceforge.net</u>
 - Users: <u>ompl-users@lists.sourceforge.net</u>
- Public Mercurial repository: <u>http://ompl.hg.sourceforge.net:8000/hgroot/ompl/ompl</u>

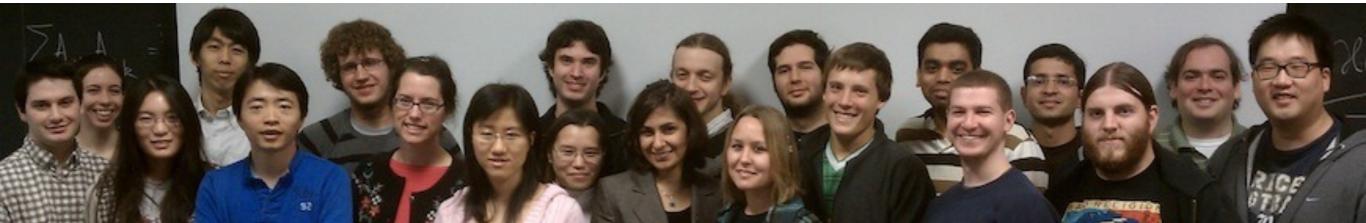
OMPL for education

• Programming assignments centered around OMPL, available upon request.

• Ongoing educational assessment.

• Already in use in several robotics / motion planning classes.

Happy OMPL users: students in the Algorithmic Robotics class at Rice, Fall 2010



OMPL tutorials

Step-by-step walkthroughs for:

- geometric planning for rigid body in 3D
- working with states and state spaces
- representing goals
- benchmarking
- creating new planning algorithms

OMPL examples

- Many demos for basic usage patterns, often available in both C++ and Python
- Demos for advanced features:
 - 1. Lazy goal sampler, generic numerical IK solver
 - 2. Using the Open Dynamics Engine

Example 1: lazy goal sampler + IK

- Spawn thread responsible for generating goal states
 - generate as many goal states as user wants
 - OMPL comes with Genetic Algorithm-based IK solver, but other types of solvers can be used
- Planner waits until at least one goal state is available
- Can use bi-directional planner with implicit goal region in state space
- Same approach is used in ROS for end-effector constraints

Example 2: OMPL + ODE

- Treat ODE physics engine as a black box state propagation function: Given state, controls, and time duration, ODE produces new state
- Can plan for systems with movable objects, various contact modes, etc.
- Same approach can be used for other physics engines



Discussion

- OMPL actively developed, but ready for general use
- Can easily implement new algorithms from many reusable components
- Simple high-level interface:
 - Can treat motion planner almost as a black box
 - Easy enough that non-experts can use it
- Interface generic enough to be extensible in many ways

We want your contributions!

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