



Faster Sample-based Motion Planning using Instance-based Learning

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Abstract

We present a novel approach to improve the performance of sample-based motion planners by learning from prior instances. Our formulation stores the results of prior collision and local planning queries. This information is used to accelerate the performance of planners based on probabilistic collision checking, select new local paths in free space, and compute an efficient order to perform queries along a search path in a graph. We present fast and novel algorithms to perform k -NN queries in high dimensional configuration spaces based on locality-sensitive hashing and derive tight bounds on their accuracy. The k -NN queries are used to perform instance-based learning and have a sub-linear time complexity. Our approach is general, makes no assumption about the sampling scheme, and can be used with various sample-based motion planners, including PRM, Lazy-PRM, RRT and RRT*, by making small changes to these planners. We observe up to 100% improvement in the performance of various planners on rigid and articulated robots.

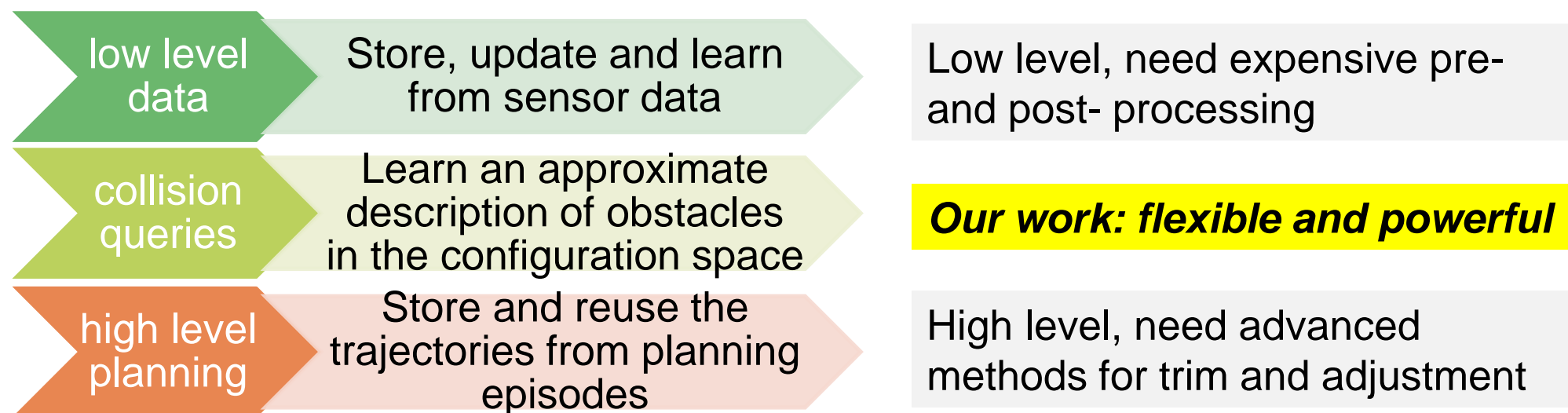
Motivation

Most robots work in environments with small variations over time

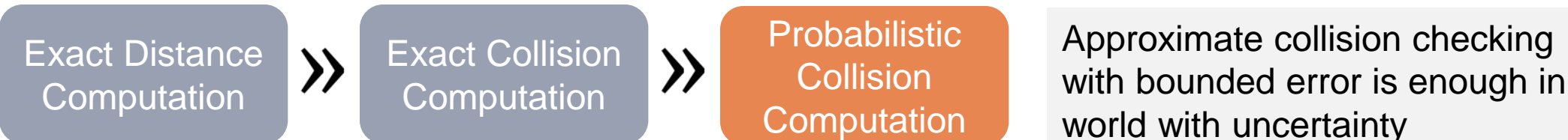
Improve robot's performance by exploiting the knowledge learned from experiences



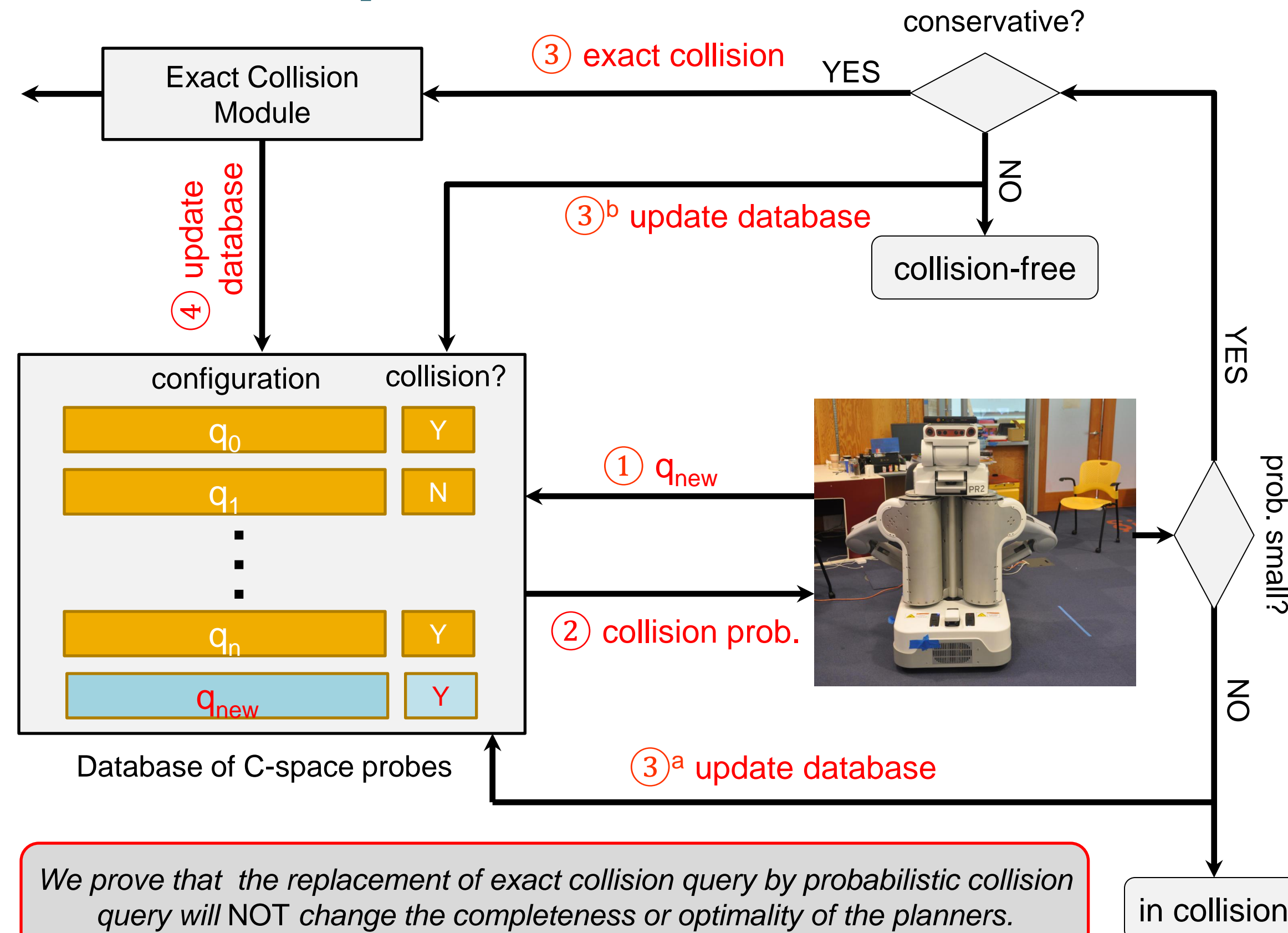
Three levels of Learning from Experience



Reduce the cost of collision detection



Overall Pipeline

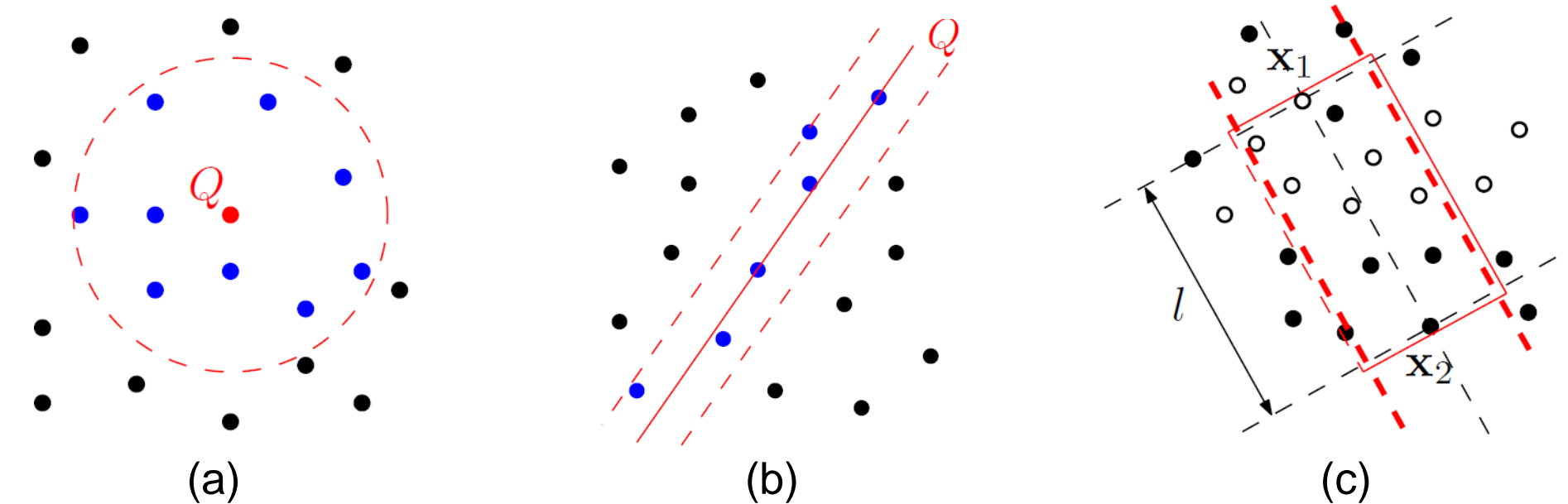


Probabilistic Collision Query

The collision probability computation is based on two kinds of k -nearest neighbor algorithms:

- 1) Find points that are nearest to a given point query;
- 2) Find points that are nearest to a given line query;

We use locality-sensitive hashing (LSH) based k -NN to provide almost *constant* query cost.



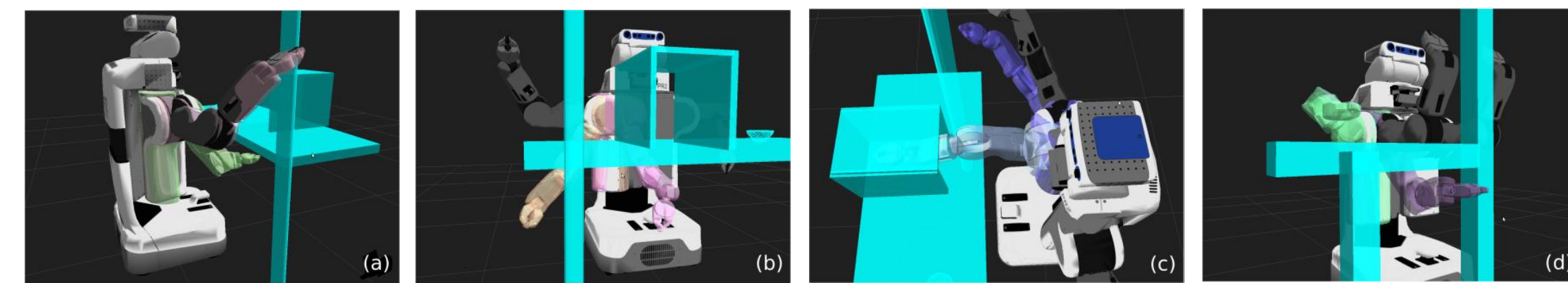
<http://gamma.cs.unc.edu/IBL>

Experiments

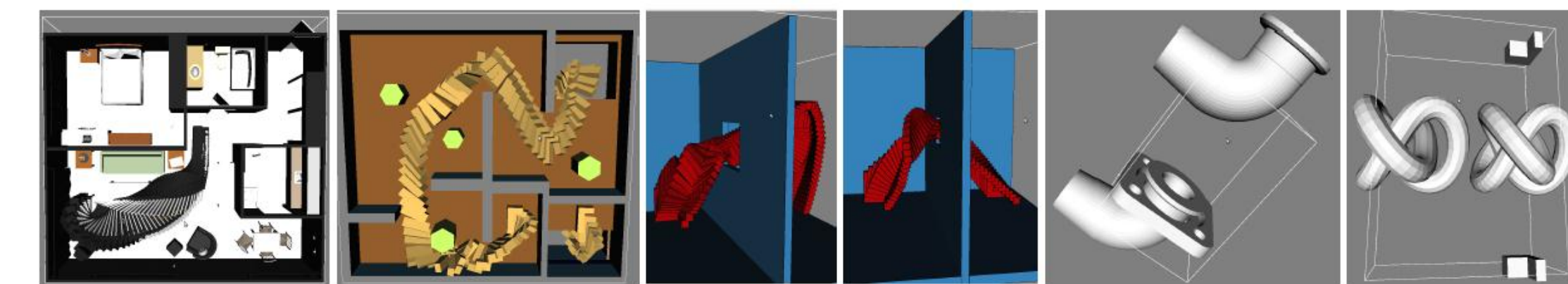
The instance-based learning algorithm is Integrated into OMPL as an alternative collision detection call. Our method is a general approach and does not change the sampling or planning strategies used by the underlying planners.

All motion planners can benefit it without any programming overhead!

Benchmarks



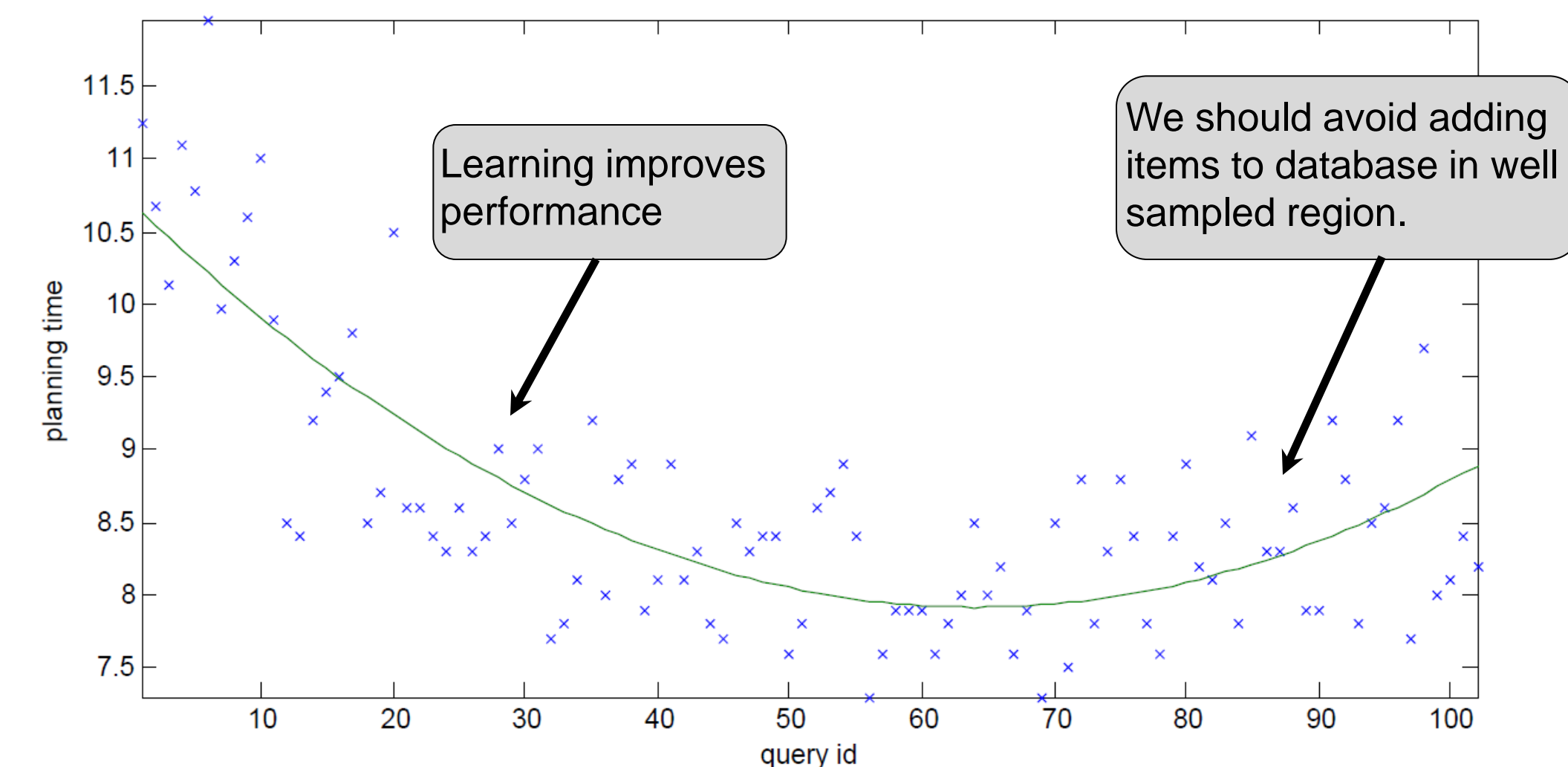
ROS planning wizard benchmarks



OMPL benchmarks

Results

- 1) Up to 100% acceleration on various planners.
- 2) The variation of the planning time is a bit smaller than original planner.
- 3) The robot is more efficient when it learns more and more:



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