CS 287 Advanced Robotics (Fall 2019)
Lecture 9: Motion Planning

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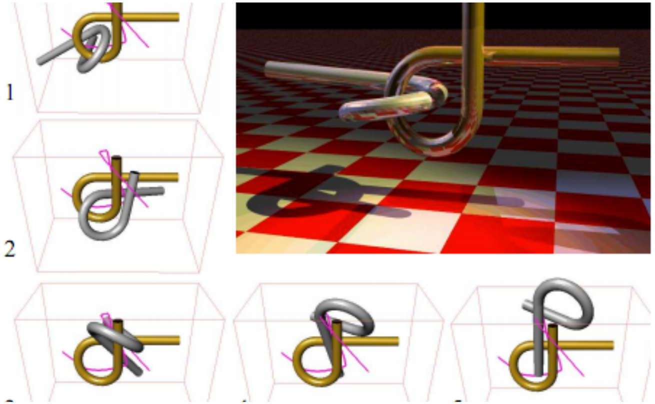
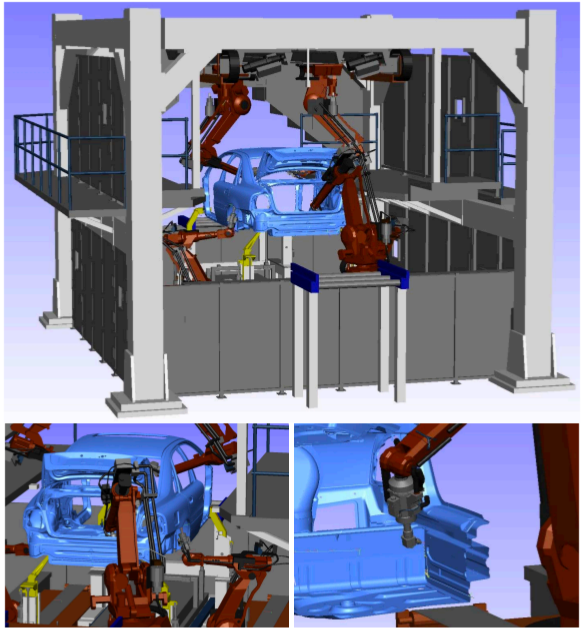
Many images from Lavalle, Planning Algorithms

Motion Planning

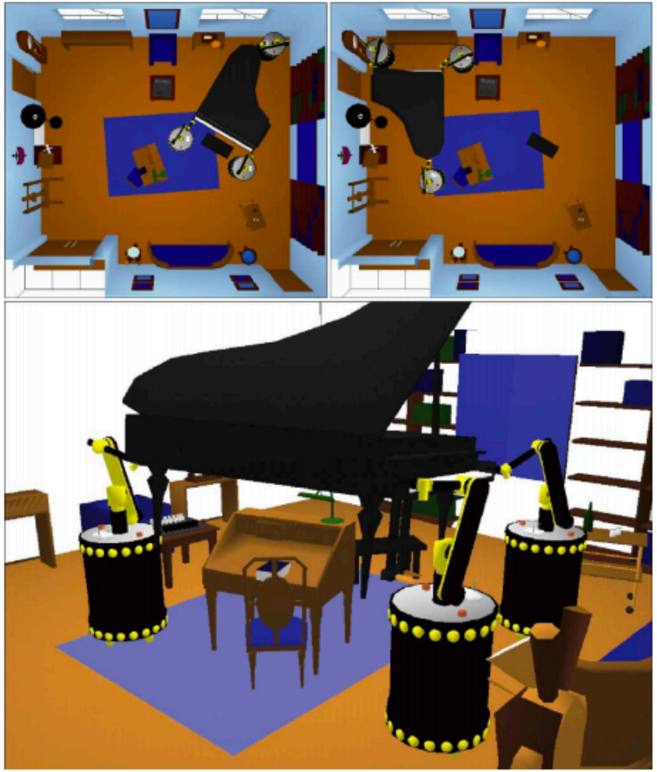
- **Problem**
  - Given start state x_S, goal state x_G
  - Asked for: a sequence of control inputs that leads from start to goal
- Why tricky?
  - Need to avoid obstacles
  - For systems with underactuated dynamics: can't simply move along any coordinate at will
    - E.g., car, helicopter, airplane, but also robot manipulator hitting joint limits

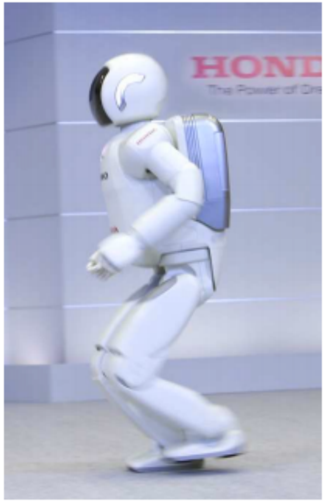
Examples

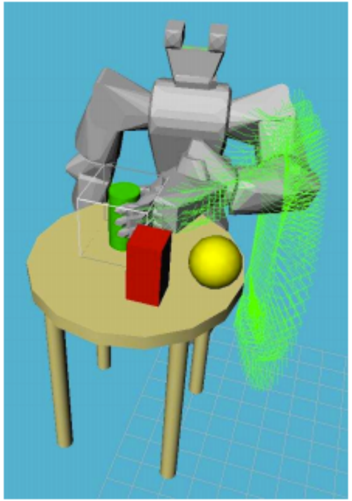




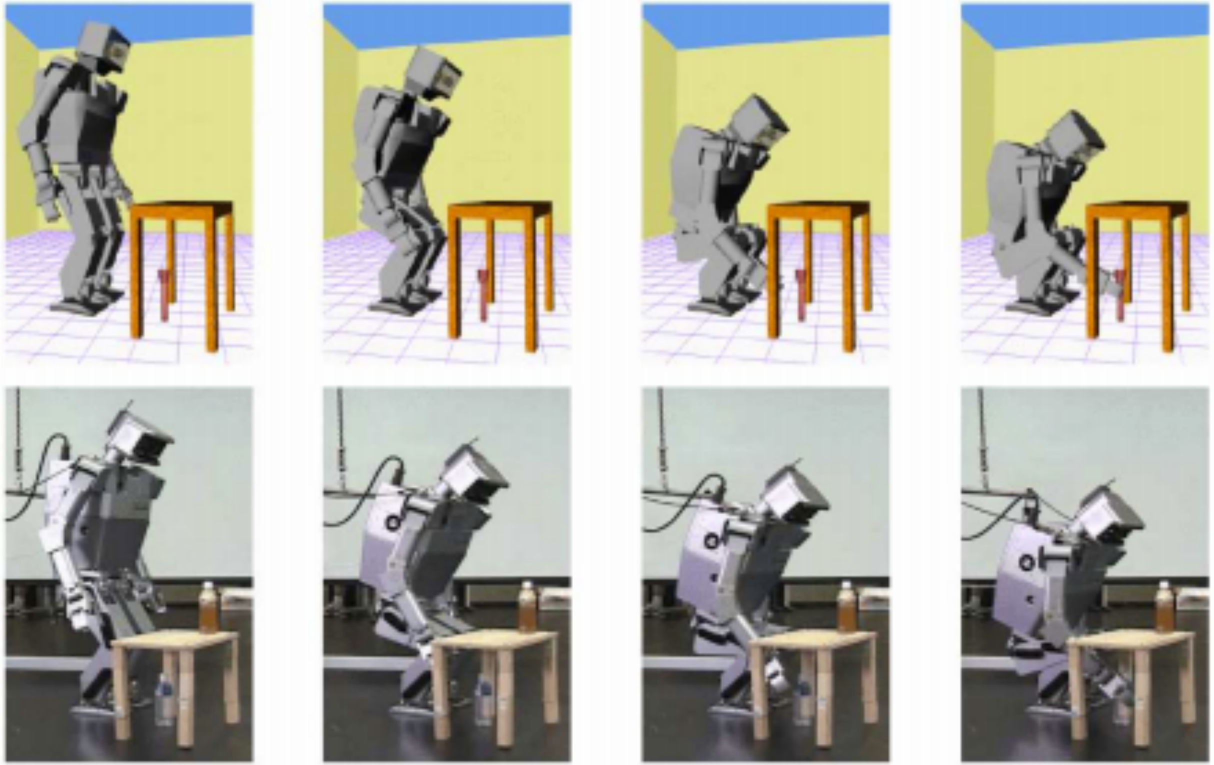
Examples







Examples



Motion Planning: Outline

- Configuration Space
- Optimization-based Motion Planning
- Sampling-based Motion Planning
  - Probabilistic Roadmap
  - Rapidly-exploring Random Trees (RRTs)
  - Smoothing

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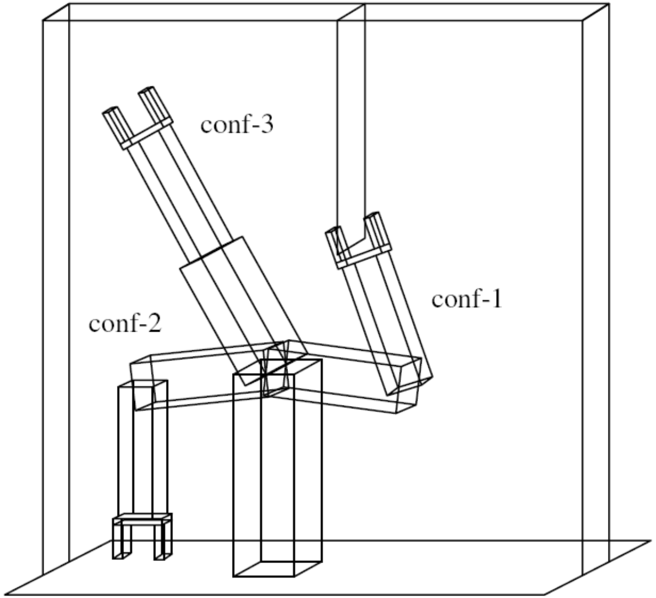
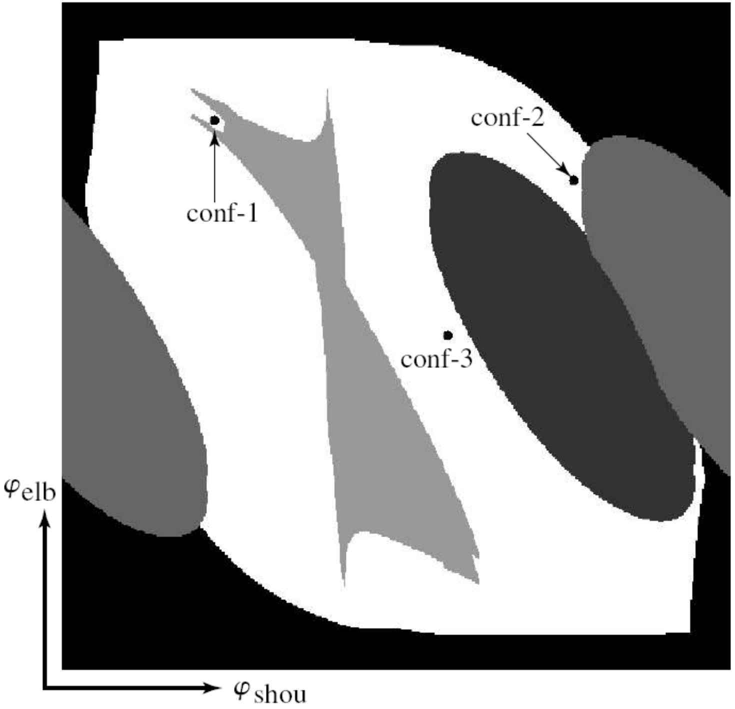
Motion planning

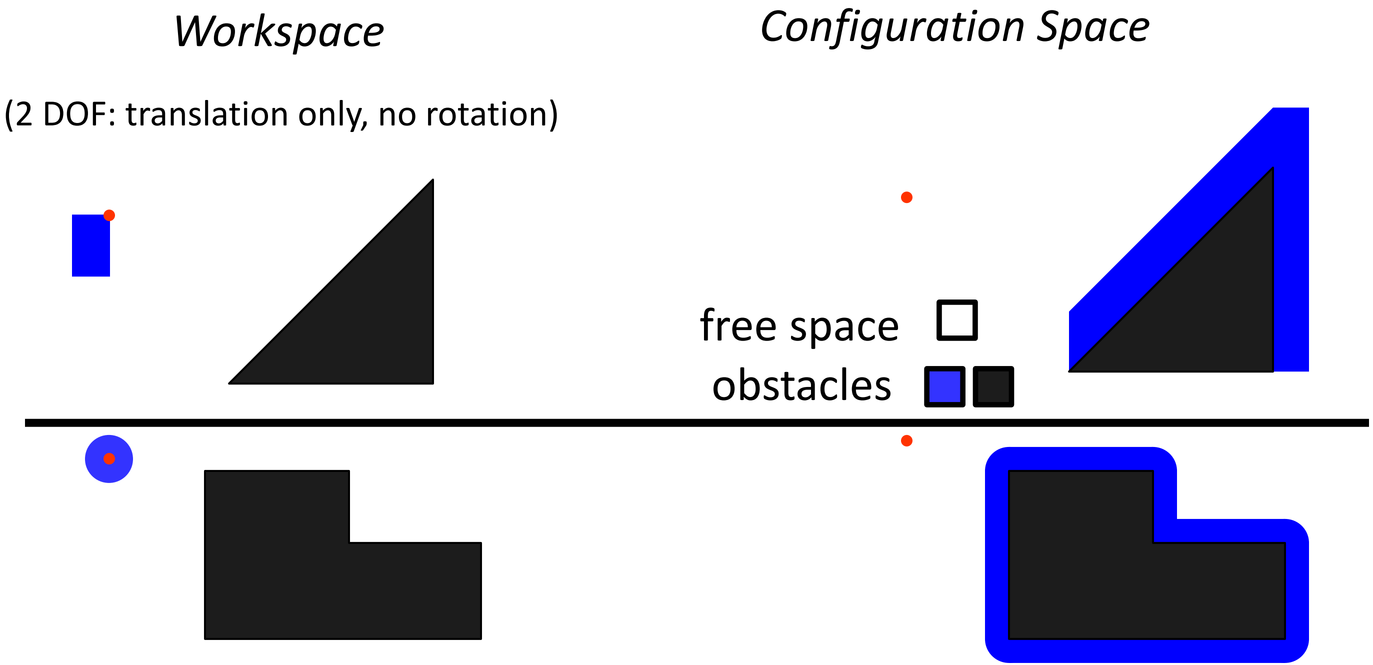




Configuration Space (C-Space)

= { x | x is a pose of the robot}

- obstacles → configuration space obstacles



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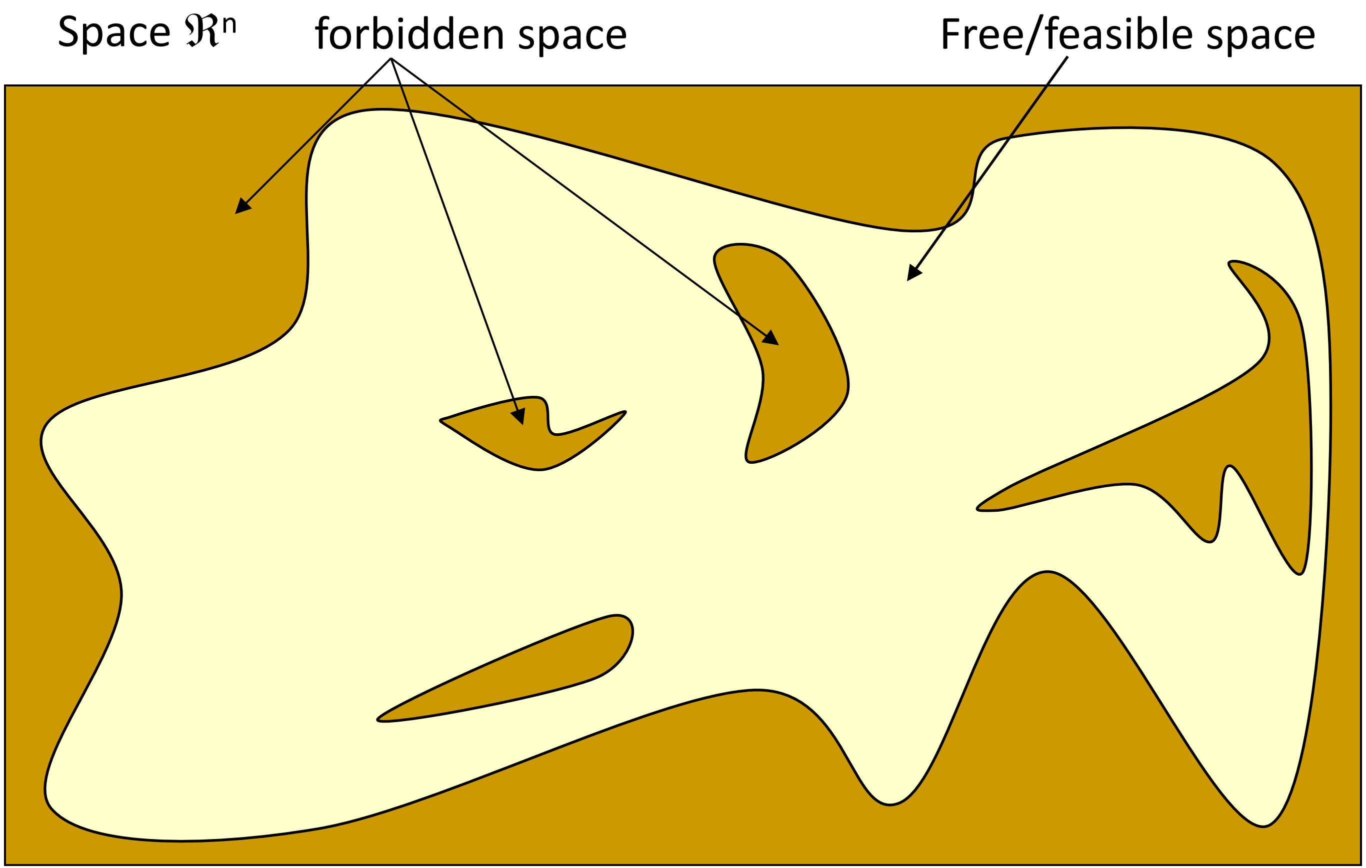
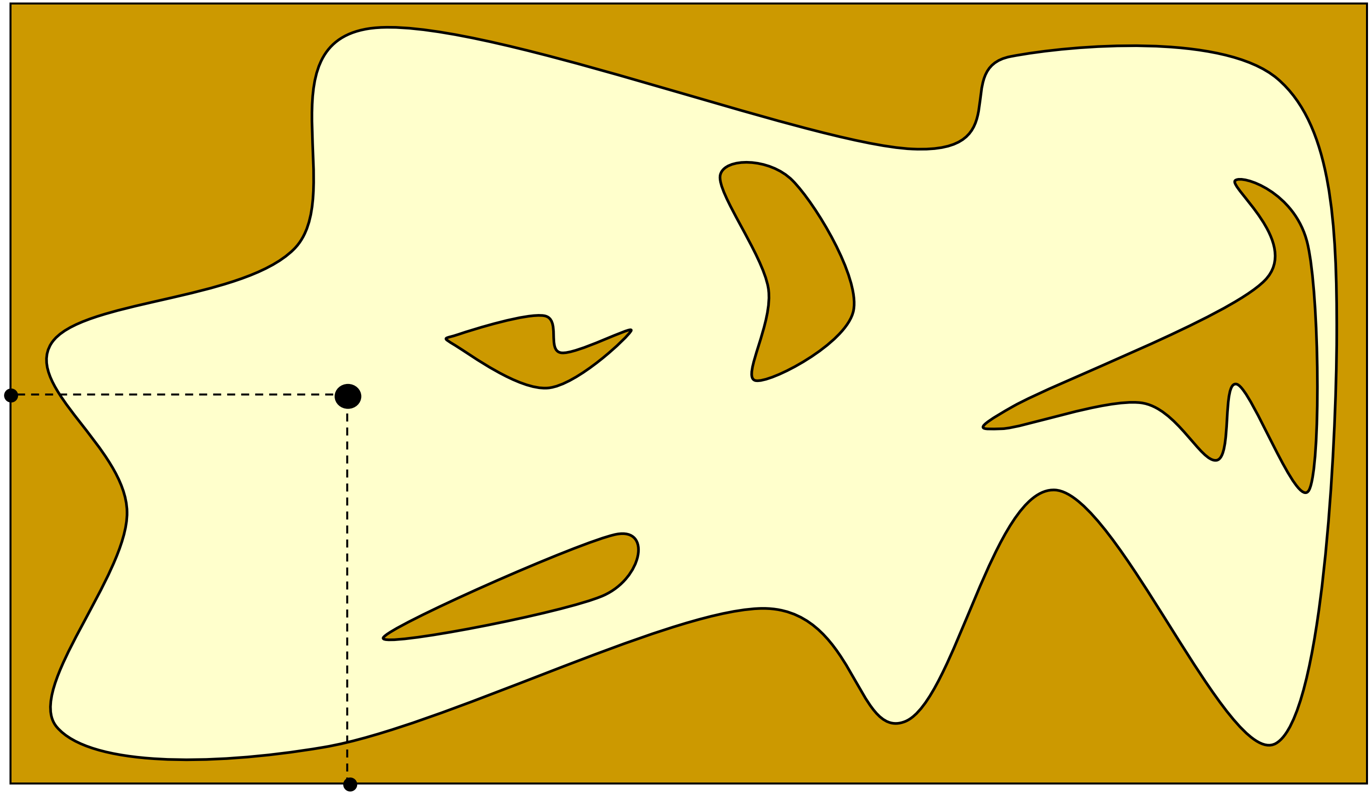
Probabilistic Roadmap (PRM)



Probabilistic Roadmap (PRM)

Configurations are sampled by picking coordinates at random



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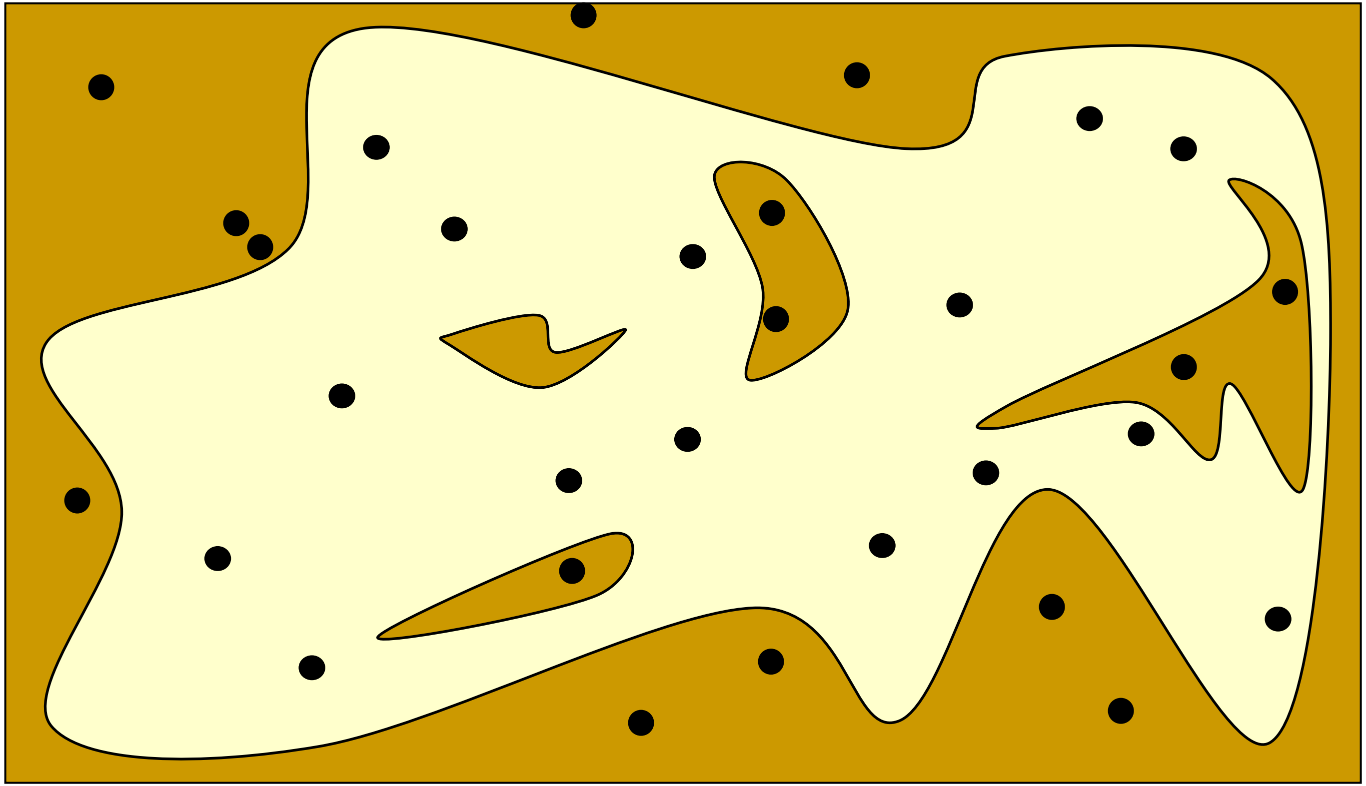
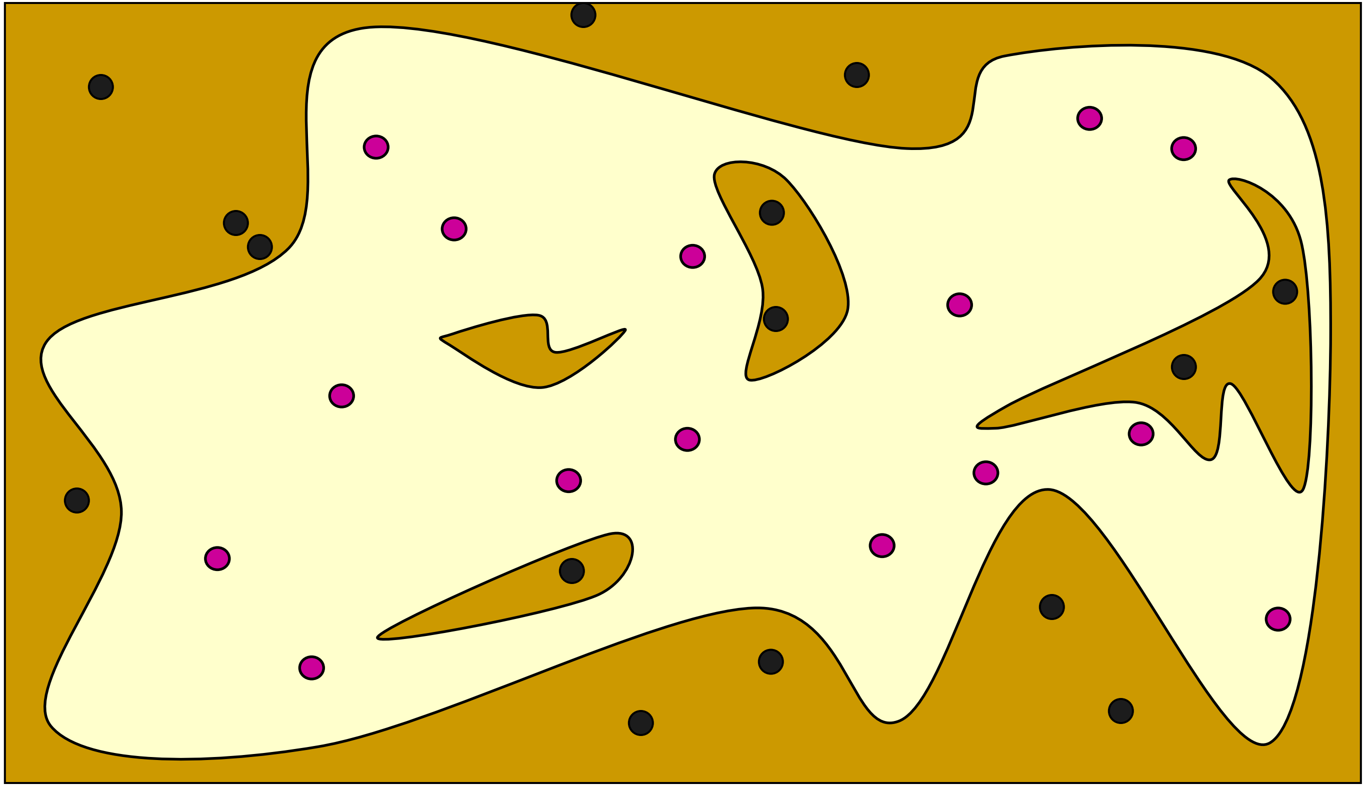


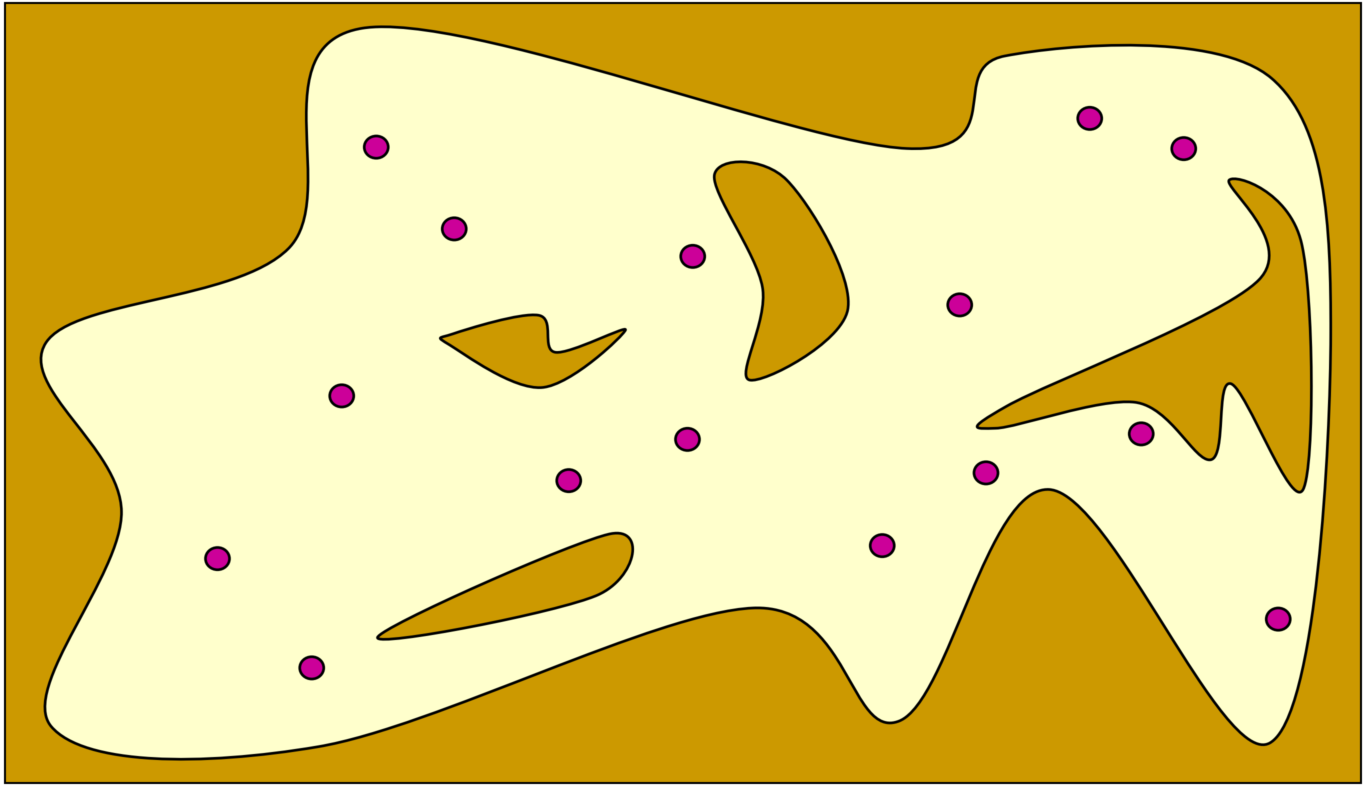
Probabilistic Roadmap (PRM)

Sampled configurations are tested for collision



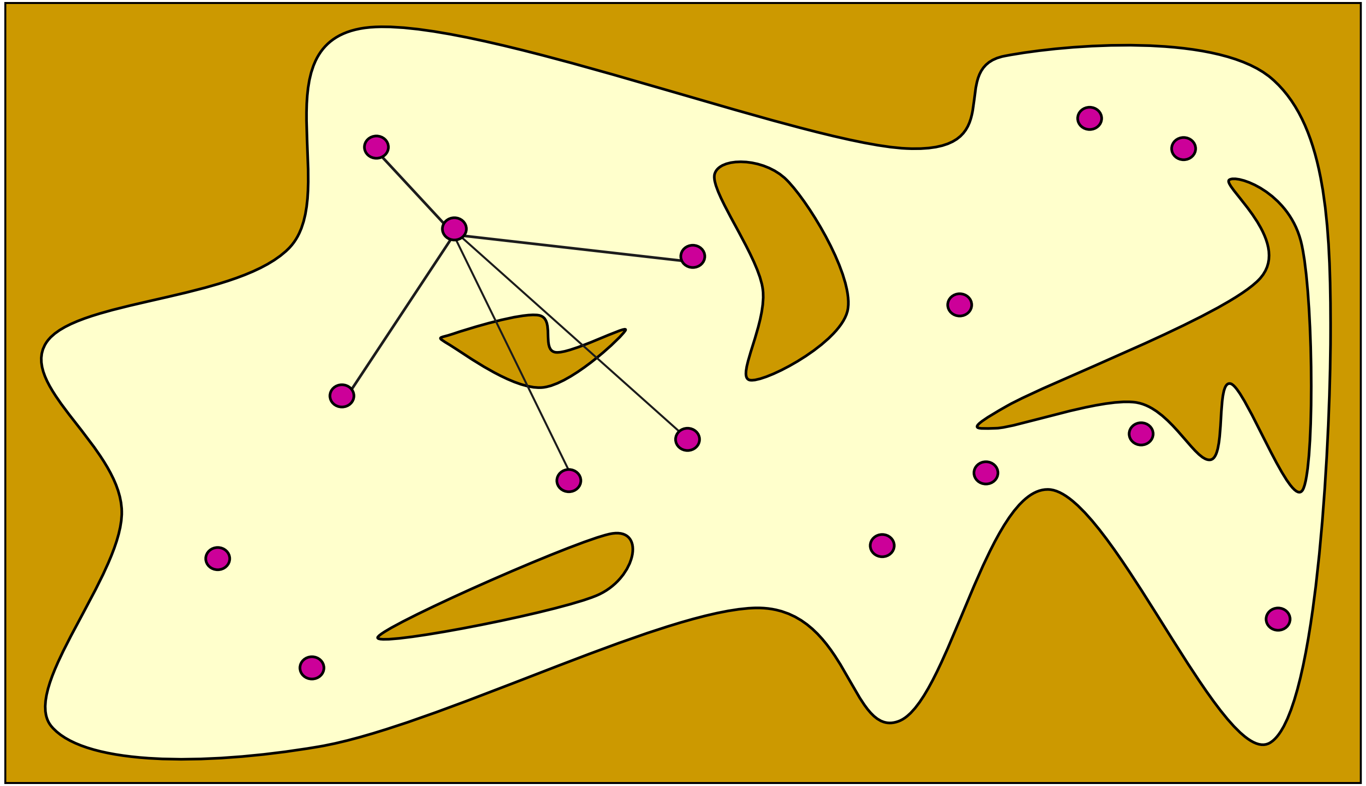
Probabilistic Roadmap (PRM)

The collision-free configurations are retained as milestones



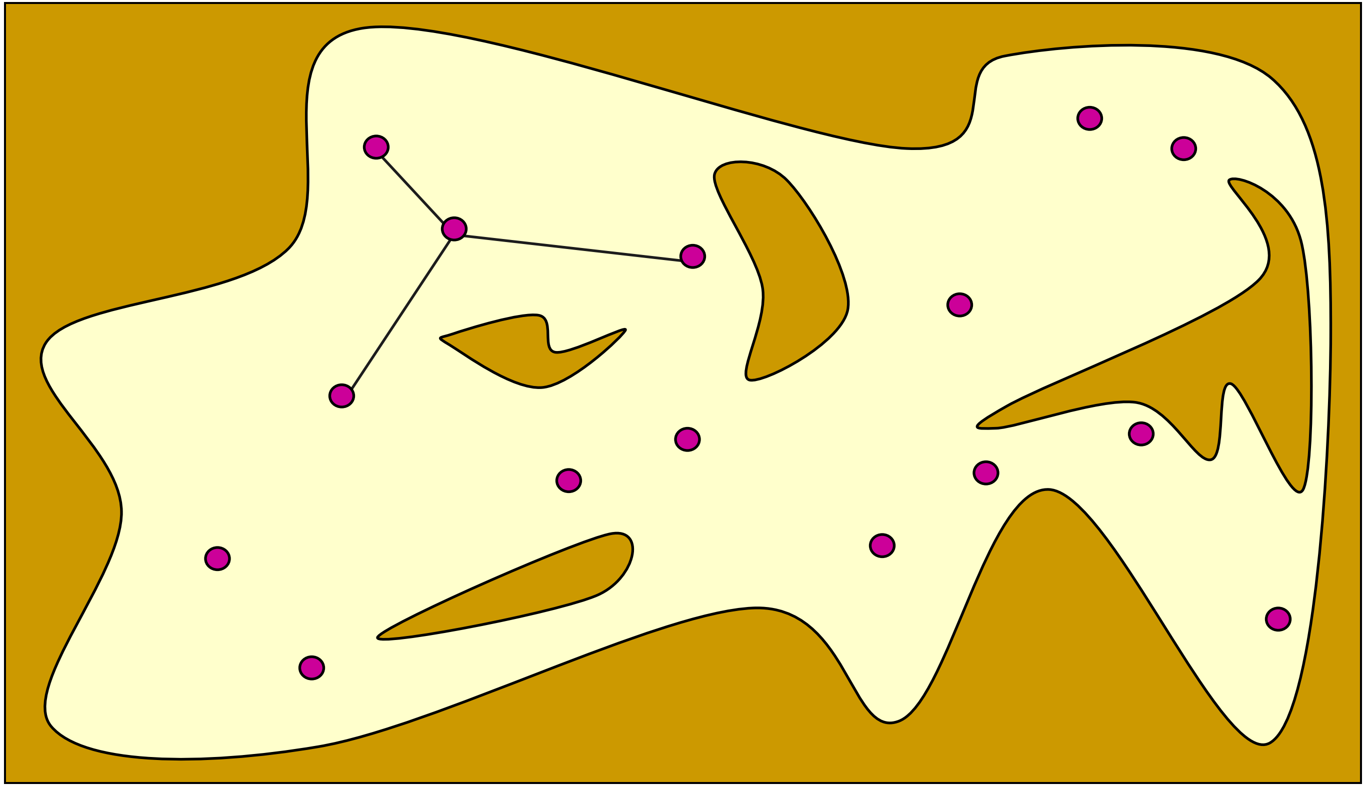
Probabilistic Roadmap (PRM)

Each milestone is linked by straight paths to its nearest neighbors



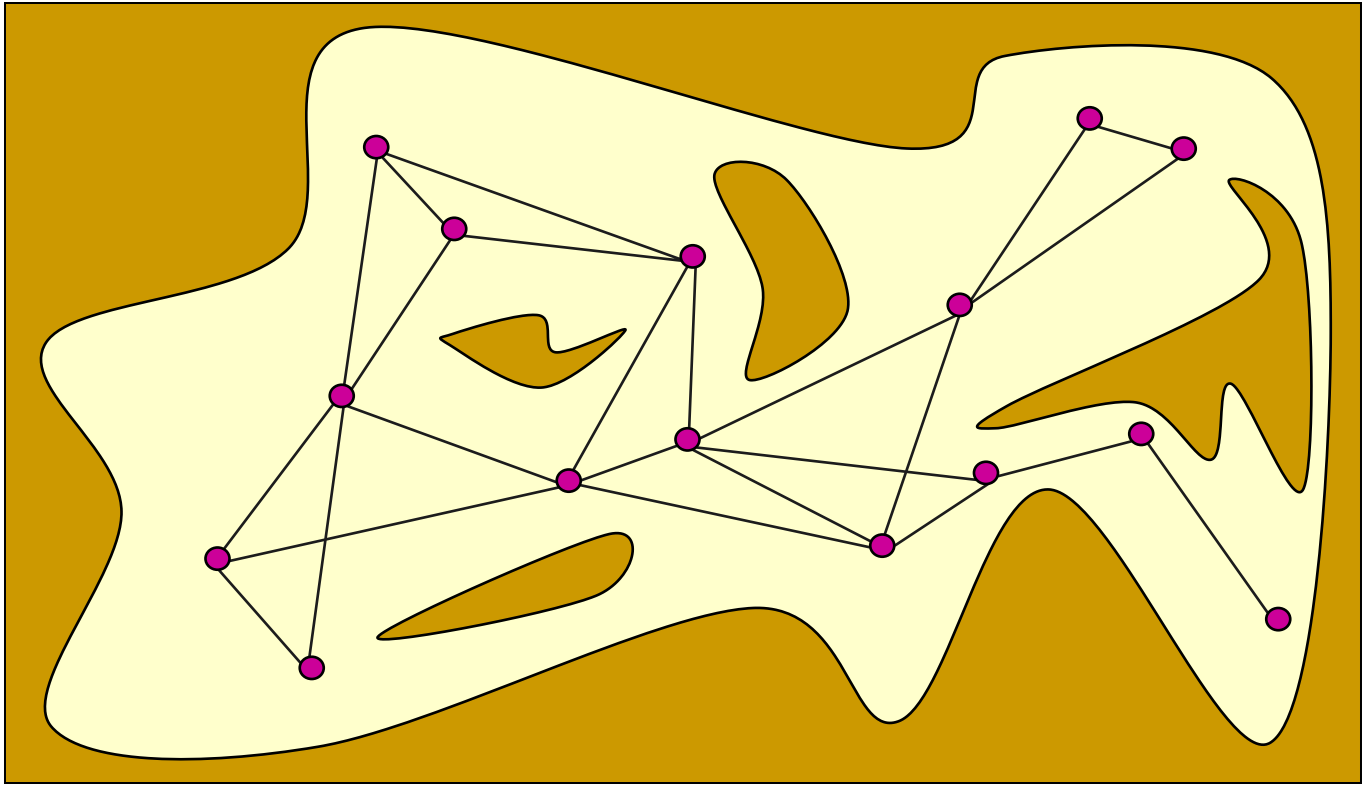
Probabilistic Roadmap (PRM)

Each milestone is linked by straight paths to its nearest neighbors



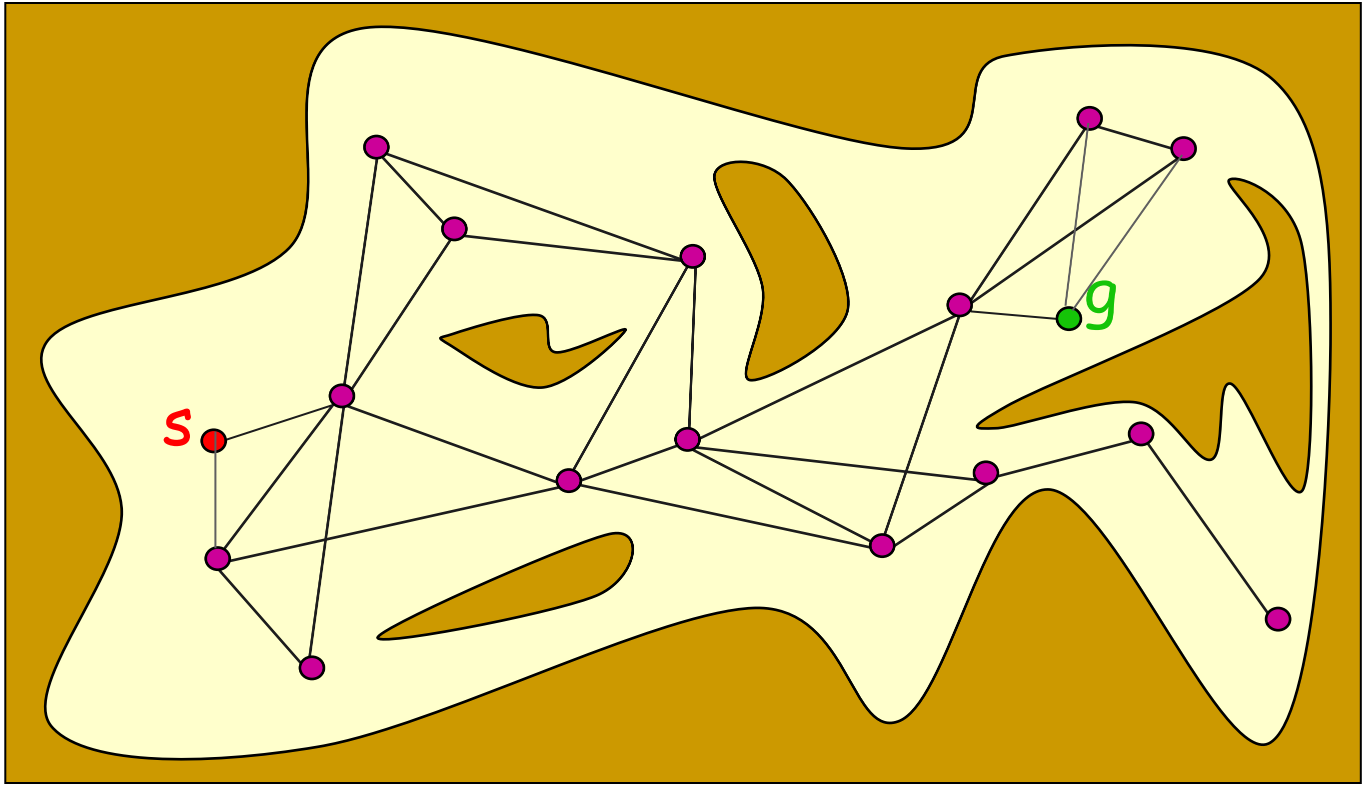
Probabilistic Roadmap (PRM)

The collision-free links are retained as local paths to form the PRM



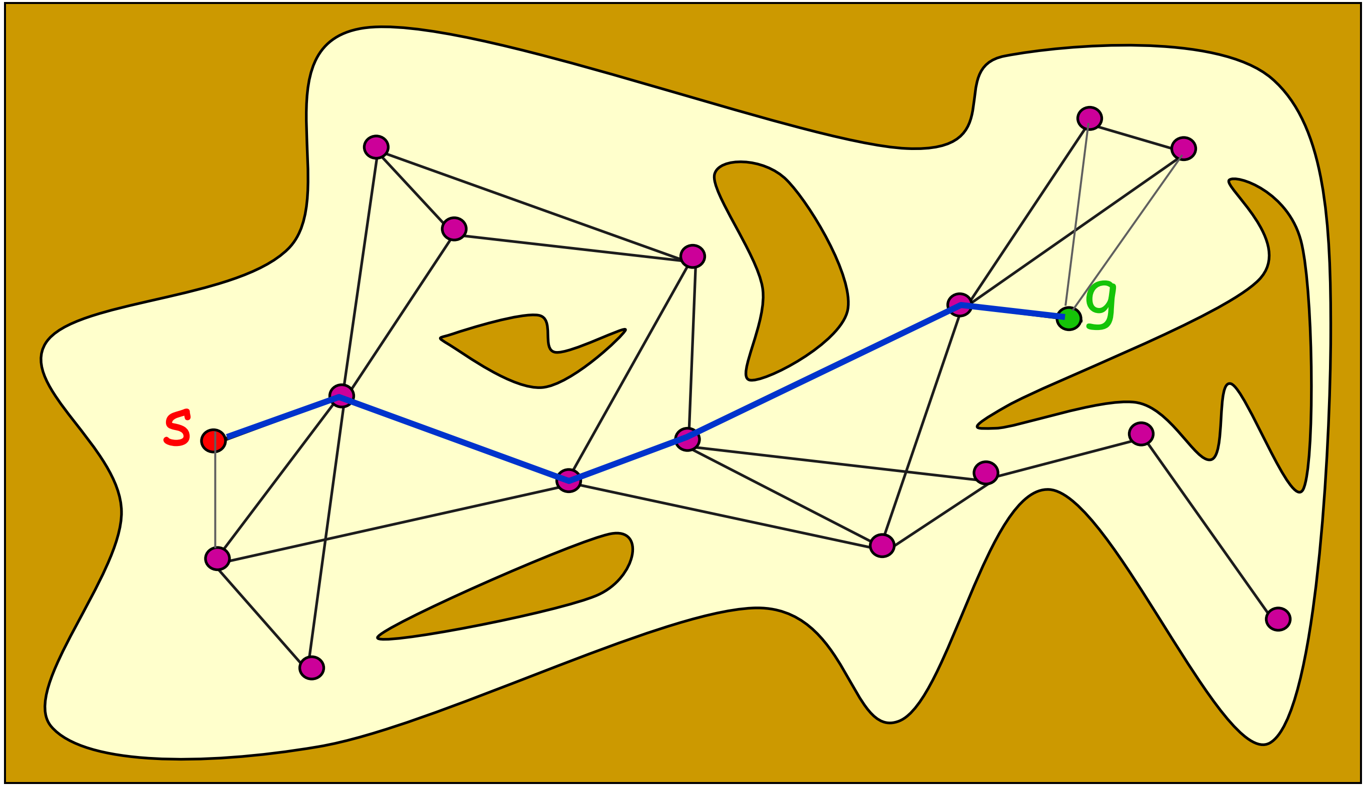
Probabilistic Roadmap (PRM)

The start and goal configurations are included as milestones



Probabilistic Roadmap (PRM)

The PRM is searched for a path from s to g



Probabilistic Roadmap

- Initialize set of points with x_S and x_G
- Randomly sample points in configuration space
- Connect nearby points if they can be reached from each other
- Find path from x_S to x_G in the graph

  - Alternatively: keep track of connected components incrementally, and declare success when x_S and x_G are in same connected component

PRM: Challenges

1. Connecting neighboring points: Only easy for holonomic systems (i.e., for which you can move each degree of freedom at will at any time). Generally requires solving a Boundary Value Problem

$$\begin{aligned} \min_{u,x} \quad & \|u\| \\ \text{s.t.} \quad & x_{t+1} = f(x_t, u_t) \quad \forall t \\ & u_t \in \mathcal{U}_t \\ & x_t \in \mathcal{X}_t \\ & x_0 = x_S \\ & X_T = x_G \end{aligned}$$

Typically solved without collision checking; later verified if valid by collision checking

2. Collision checking:

Often takes majority of time in applications (see Lavalle)

PRM’s Pros and Cons

- Pro:
  - Probabilistically complete: i.e., with probability one, if run for long enough the graph will contain a solution path if one exists.

- Cons:
  - Required to solve 2-point boundary value problem
  - Build graph over entire state space, which might be unnecessarily expensive when what’s needed is connecting specific start and goal

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  - ***Rapidly-exploring Random Trees (RRTs)***
  - Smoothing

Rapidly exploring Random Tree (RRT)

Steve LaValle (98)

- Basic idea:
  - Build up a tree through generating “next states” in the tree by executing random controls
  - However: not exactly above to ensure good coverage

Rapidly exploring Random Tree (RRT)

GENERATE_RRT($x_{init}, K, \Delta t$)

$\mathcal{T}$.init(x_{init});

for $k = 1$ **to** K **do**

  $x_{rand} \leftarrow$ RANDOM_STATE();

  $x_{near} \leftarrow$ NEAREST_NEIGHBOR($x_{rand}, \mathcal{T}$);

  $u \leftarrow$ SELECT_INPUT(x_{rand}, x_{near});

  $x_{new} \leftarrow$ NEW_STATE($x_{near}, u, \Delta t$);

  $\mathcal{T}$.add_vertex(x_{new});

  $\mathcal{T}$.add_edge(x_{near}, x_{new}, u);

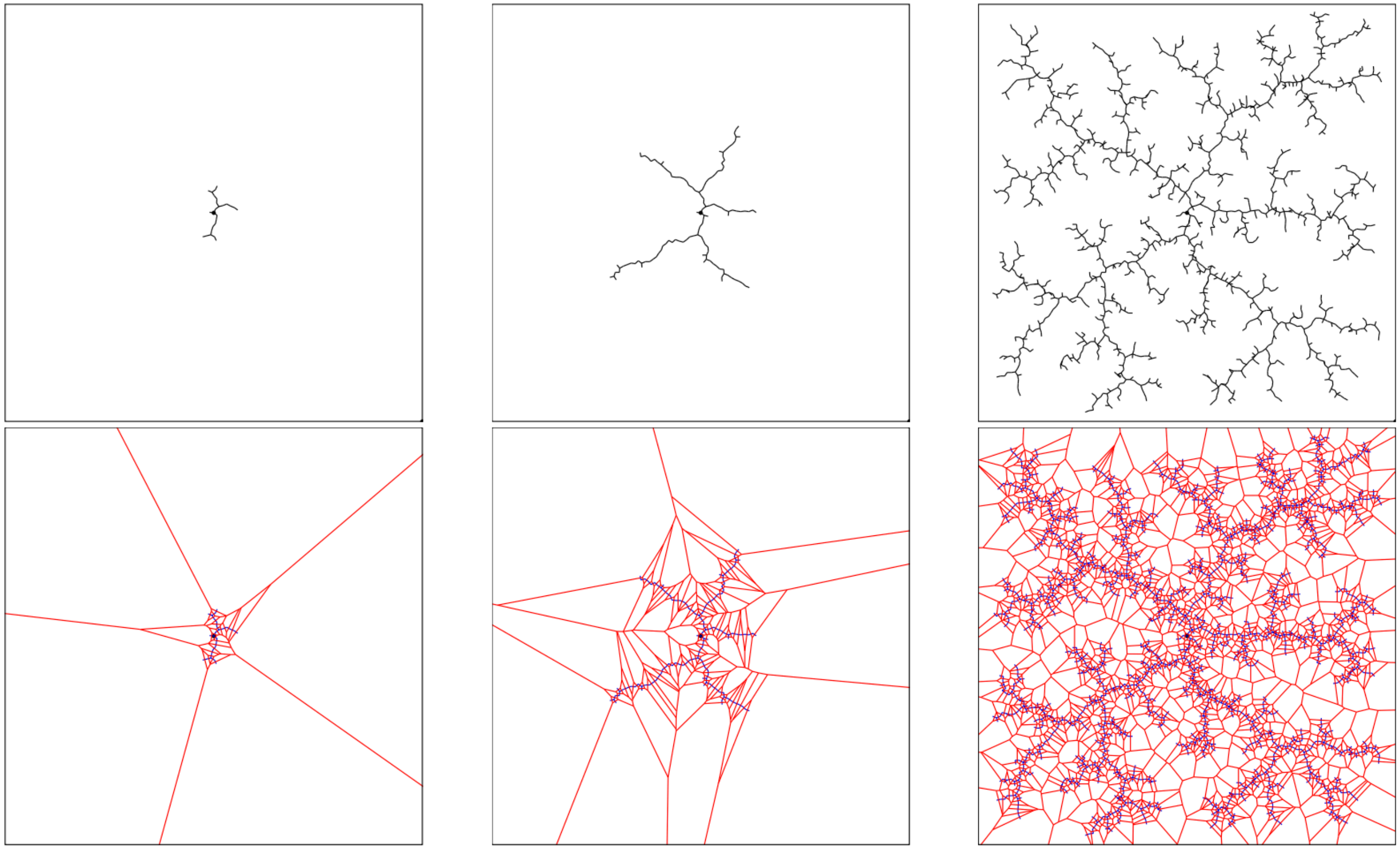
Return $\mathcal{T}$

RANDOM_STATE(): often uniformly at random over space with probability 99%, and the goal state with probability 1%, this ensures it attempts to connect to goal semi-regularly
SELECT_INPUT(): often a few inputs are sampled, and one that results in x_new closest to x_rand is retained; sometimes optimization is run to find the best input

Rapidly exploring Random Tree (RRT)

- Select random point, and expand nearest vertex towards it
  - Biases samples towards largest Voronoi region

Rapidly exploring Random Tree (RRT)



Source: LaValle and Kuffner 01

RRT Practicalities

- NEAREST_NEIGHBOR(x_{rand}, T): need to find (approximate) nearest neighbor efficiently
  - KD Trees data structure (upto 20-D) [e.g., FLANN]
  - Locality Sensitive Hashing

- SELECT_INPUT(x_{rand}, x_{near})
  - Two point boundary value problem
    - If too hard to solve, often just select best out of a set of control sequences. This set could be random, or some well chosen set of primitives.

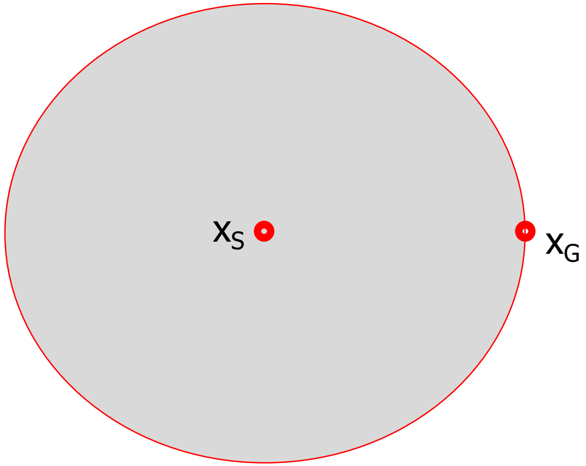
Growing RRT

45 iterations   390 iterations

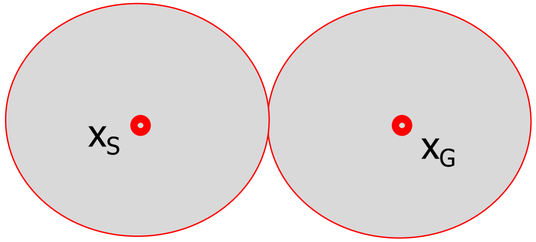
Demo: http://en.wikipedia.org/wiki/File:Rapidly-exploring_Random_Tree_(RRT)_500x373.gif

Bi-directional RRT

- Volume swept out by unidirectional RRT:



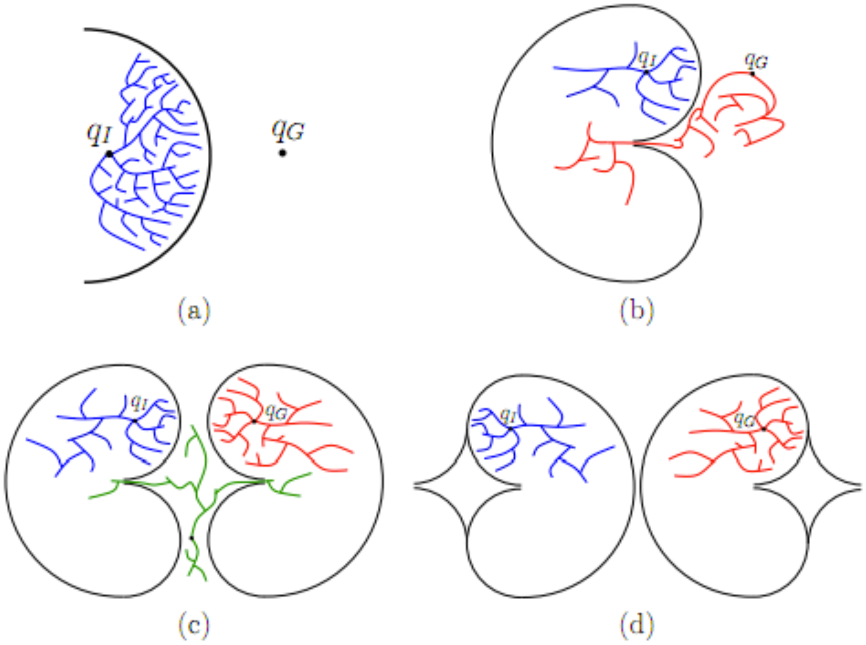
- Volume swept out by bi-directional RRT:



- Difference more and more pronounced as dimensionality increases

Multi-directional RRT

- Planning around obstacles or through narrow passages can often be easier in one direction than the other



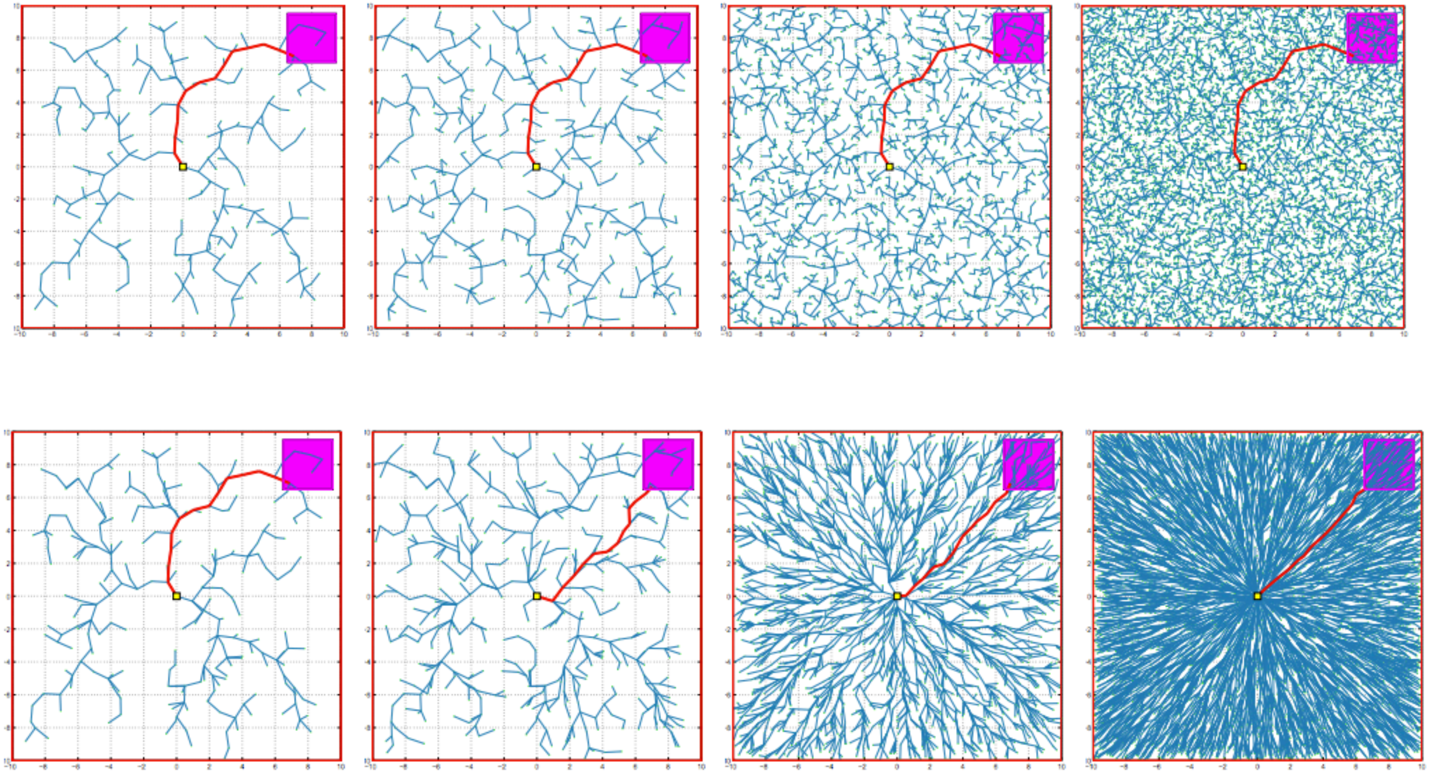
RRT*

- Asymptotically optimal
- Main idea:
  - Swap new point in as parent for nearby vertices who can be reached along shorter path through new point than through their original (current) parent

RRT*

RRT

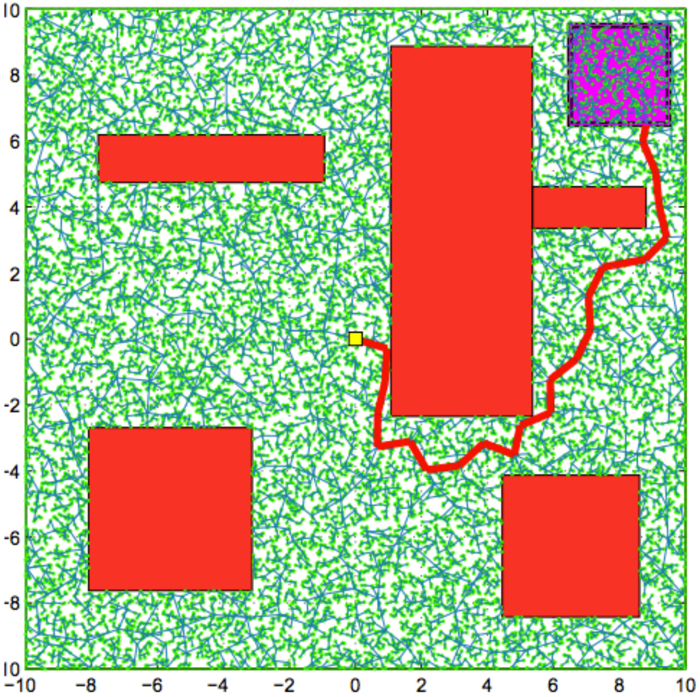
RRT*



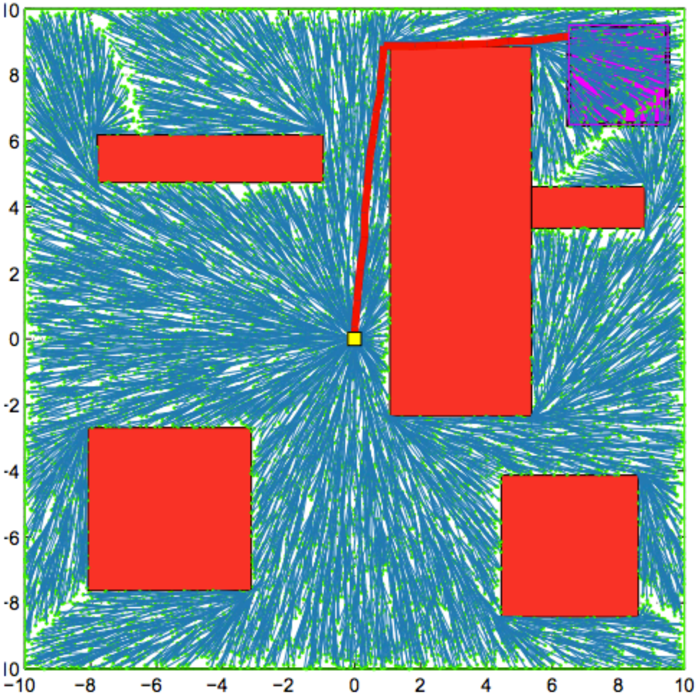
Source: Karaman and Frazzoli

RRT*

RRT



RRT*



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Smoothing

Randomized motion planners tend to find not so great paths for execution: very jagged, often much longer than necessary.

→ In practice: do smoothing before using the path

- *Shortcutting:*
  - along the found path, pick two vertices x_{t1}, x_{t2} and try to connect them directly (skipping over all intermediate vertices)
- *Nonlinear optimization for optimal control (trajopt)*
  - Allows to specify an objective function that includes smoothness in state, control, small control inputs, etc.