



# Summer School Robotics

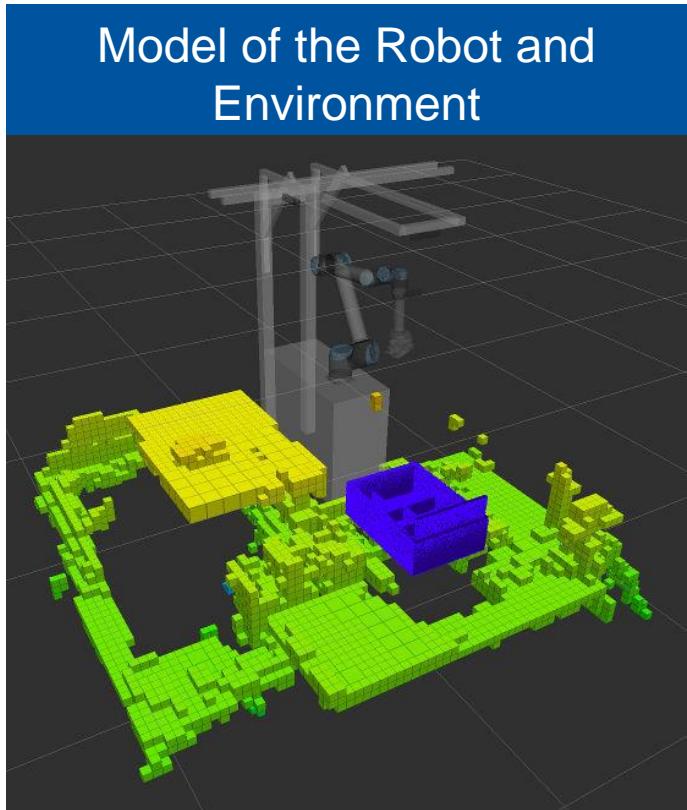
**Week 2 – Motion Planning for Industrial Robots**  
an Comprehensive Introduction

**Haoming Zhang, M.Sc.**

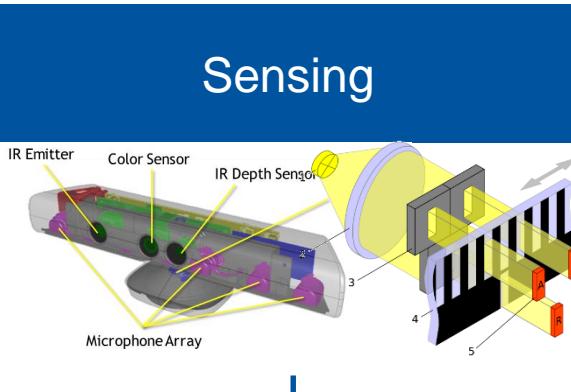
Philipp Ennen, M.Sc.

# Robots as an Example for Intelligent Machines

How do I (the robot) go there?



$$\begin{bmatrix} \ddot{x} \\ \ddot{\dot{x}} \\ \ddot{\phi} \\ \ddot{\dot{\phi}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \frac{-(I+m\ell^2)b}{I(M+m)+Mm\ell^2} & \frac{m^2g\ell^2}{I(M+m)+Mm\ell^2} & 0 \\ 0 & 0 & 0 & 1 \\ 0 & \frac{-mb}{I(M+m)+Mm\ell^2} & \frac{mg\ell(M+m)}{I(M+m)+Mm\ell^2} & 0 \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \phi \\ \dot{\phi} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{I+m\ell^2}{I(M+m)+Mm\ell^2}u \\ 0 \\ \frac{m\ell}{I(M+m)+Mm\ell^2} \end{bmatrix}$$

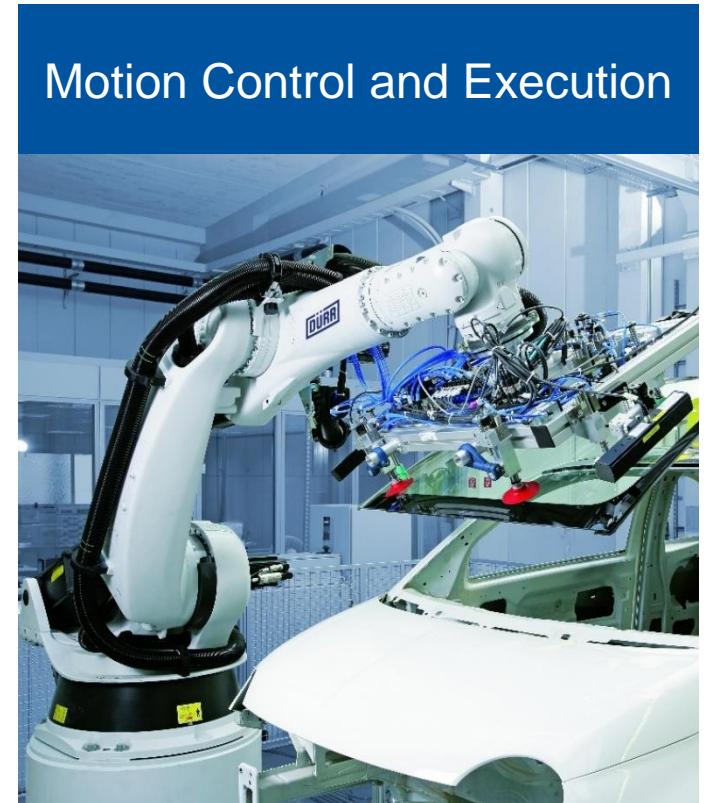


This weeks topic!

Motion Planning

Requires Goalstate:

- i.e. hand-engineered
- i.e. via a cost function



# Outline

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1	Motion Planning	10:00 – 12:10
1.1	Introduction to Motion Planning	10:00 – 10:15
1.2	Configuration Space	10:15 – 10:25
1.3	Classical Approaches	10:25 – 10:55
1.4	Sampling-Based Planning	10:55 – 11:25
1.5	Tree-Based Planning	11:25 – 11:55
1.6	Motion Planning in Practice	11:55 – 12:10
2	Lunch Time	12:10 – 14:30

# Outline

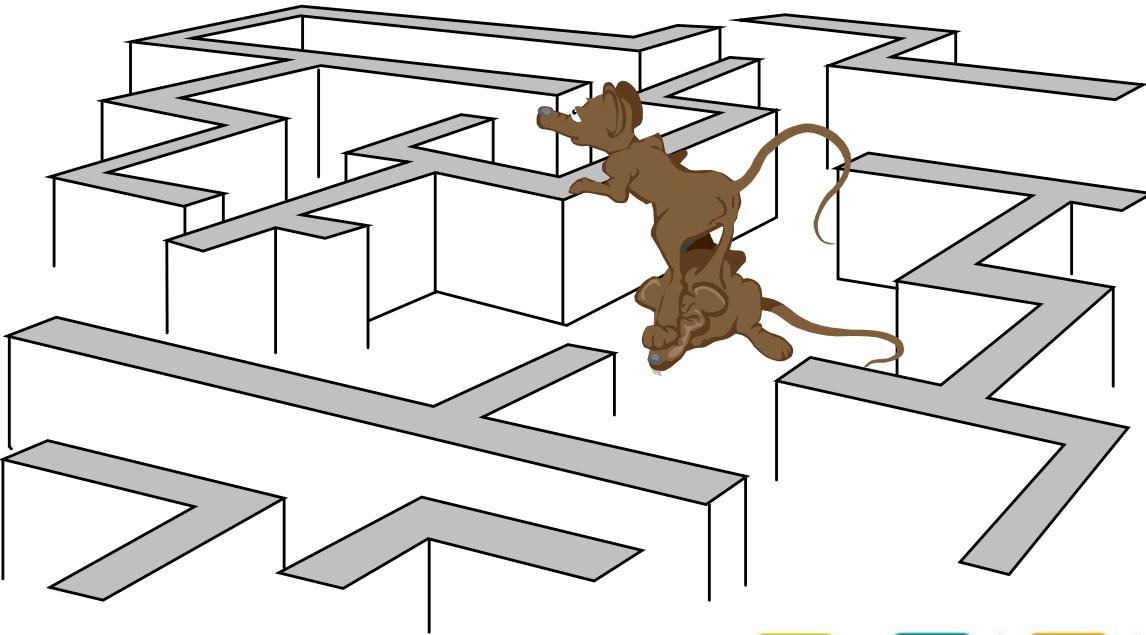
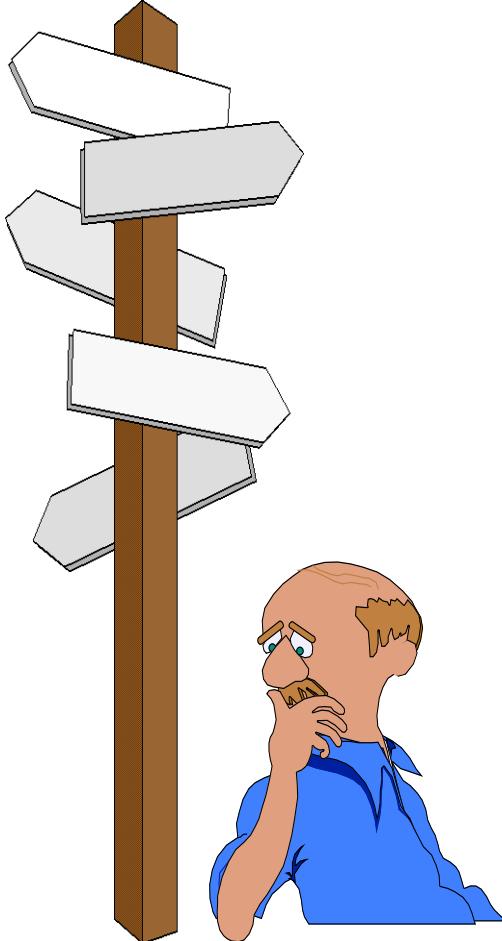
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# Motion Planning: Introduction

## What is Motion Planning?

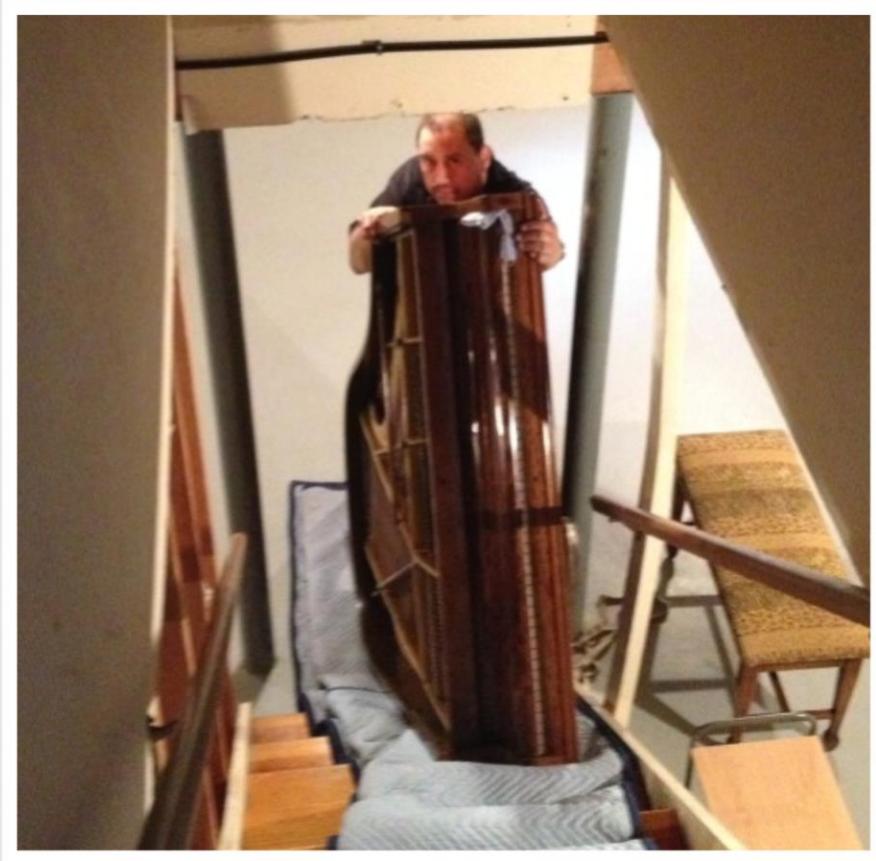
Determining **where to move** without **hit obstacles**.



# Motion Planning: Introduction

## Piano Mover's Problem for you

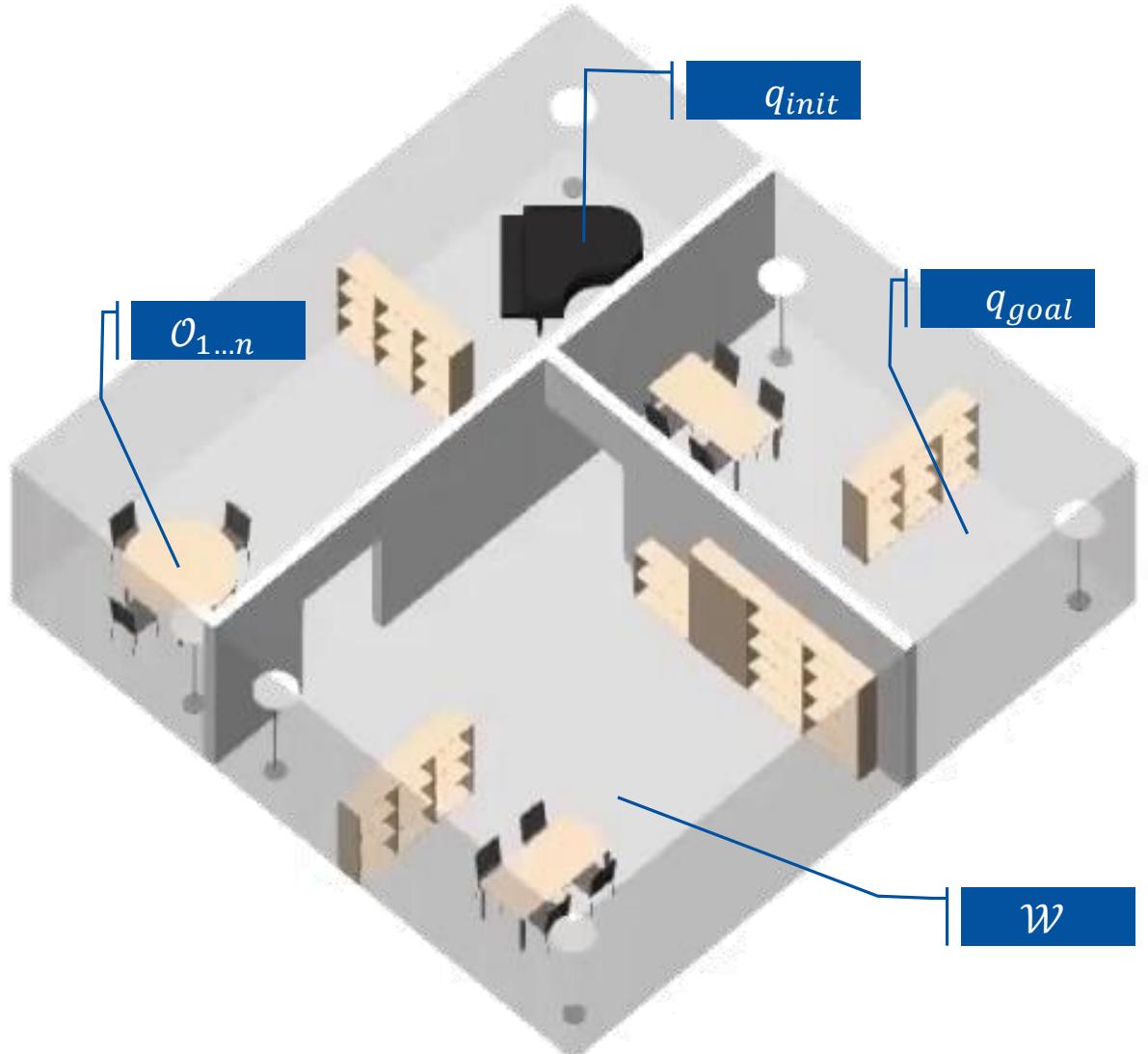
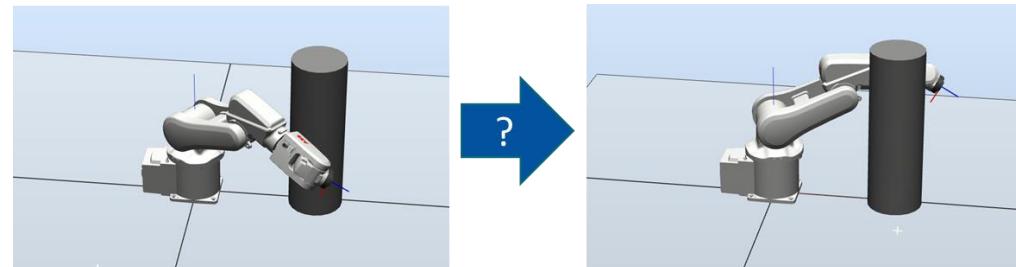
Move the **Piano** in your **house** „**peacefully**“ from **one room** to **another**.



# Motion Planning: Introduction

## Piano Mover 's Problem as a robot

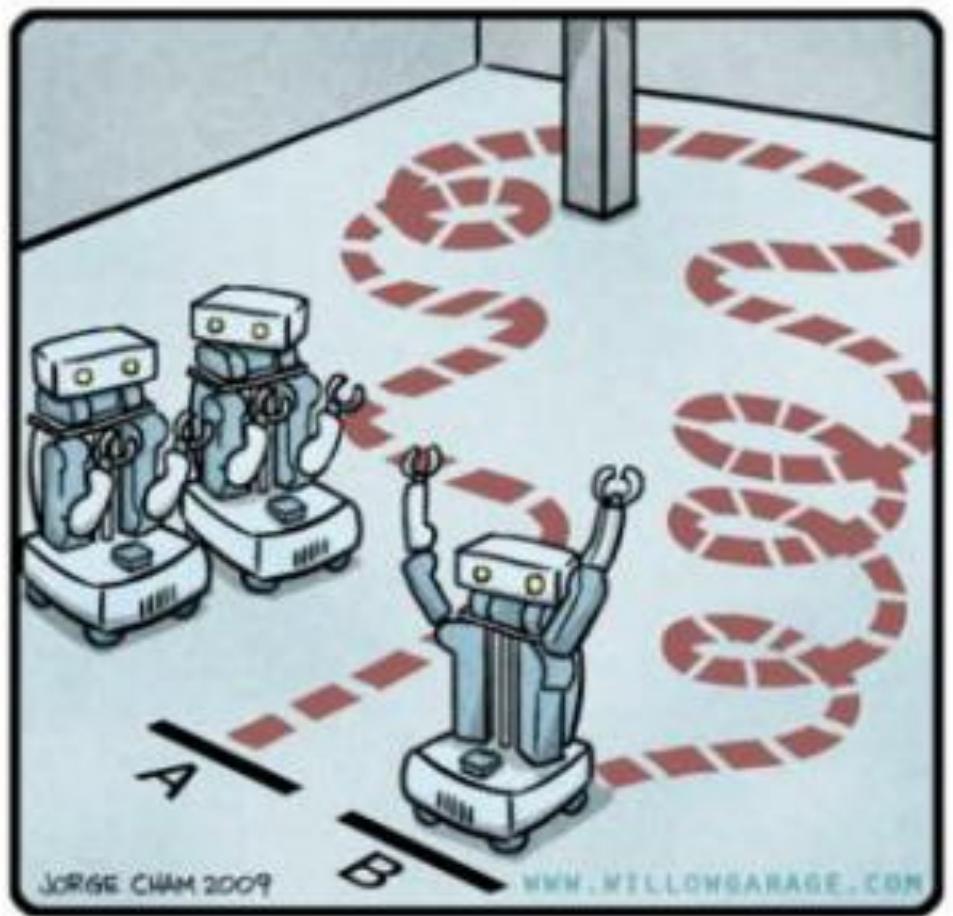
- Problem Formulation: Given
  - A workspace  $\mathcal{W}$  of  $\mathbb{R}^2$  or  $\mathbb{R}^3$
  - A set of (dynamical or statical) obstacles  $\{\mathcal{O}_1, \dots, \mathcal{O}_n\}$
  - A start position  $q_{init}$  and a goal position  $q_{goal}$
  - Geometry and kinematics of the robot
- Problem Formulation: Find a path  $\tau$  from  $q_{init}$  to  $q_{goal}$  that:
  - is (self-) collision-free
  - satisfies (joint, velocity, acceleration) limits
  - ...



# Motion Planning: Introduction

## Goal of Motion Planning

- Compute motion strategies, e.g.:
  - geometric paths
  - time-parameterized trajectories
  - sequence of sensor-based motion commands
- Achieve high-level goals, e.g.:
  - Goto A without colliding with obstacles
  - Assemble product P
  - Build a map of the hallway
  - Find and track the target



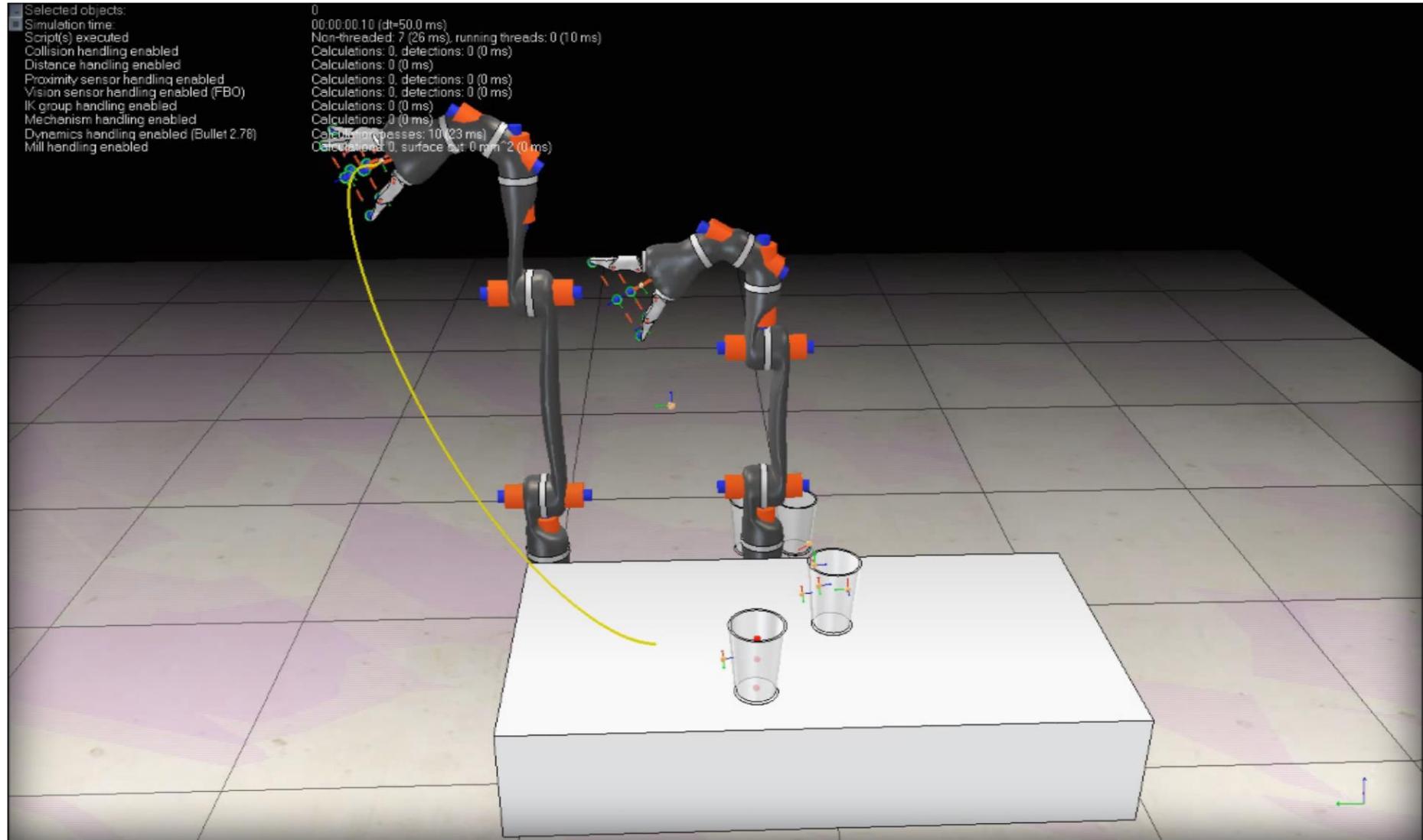
"HIS PATH-PLANNING MAY BE  
SUB-OPTIMAL, BUT IT'S GOT FLAIR."

[Source: Willow Garage]

# Motion Planning: Introduction

## Planning involves

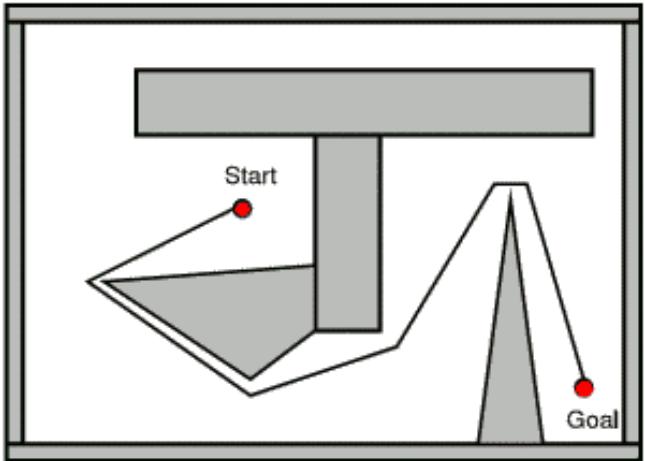
- State Space
- Time
- Action
- Initial and goal state
- A Plan
- A Criterion



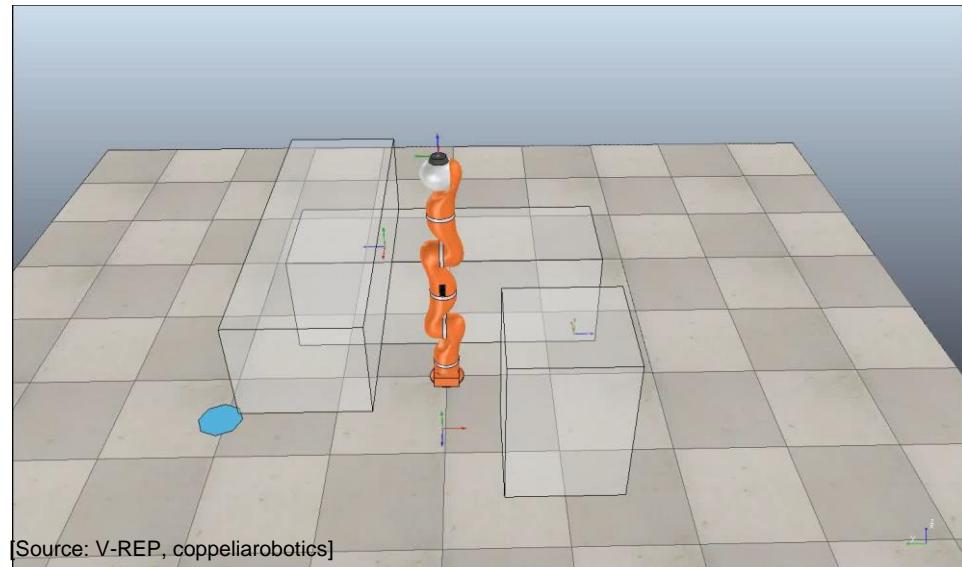
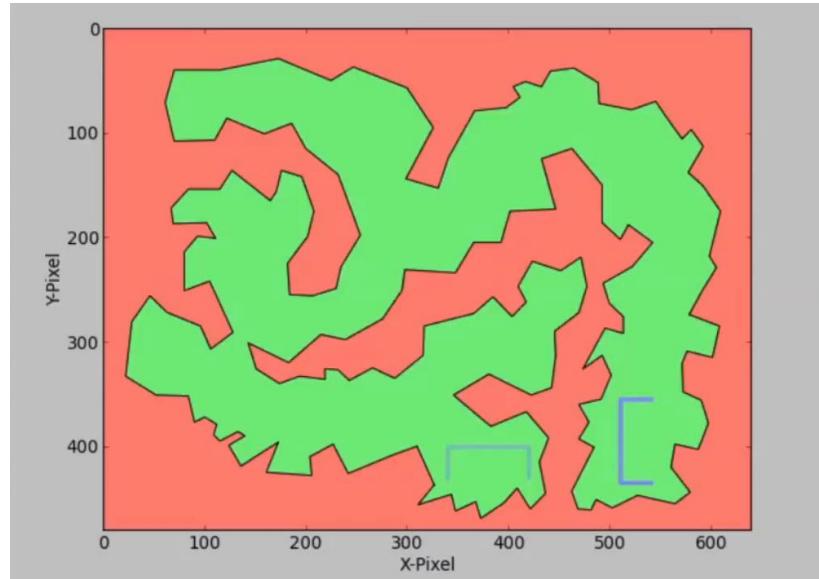
[Source: V-REP, coppeliarobotics]

# Motion Planning: Introduction

## Some Motion Planning Tasks



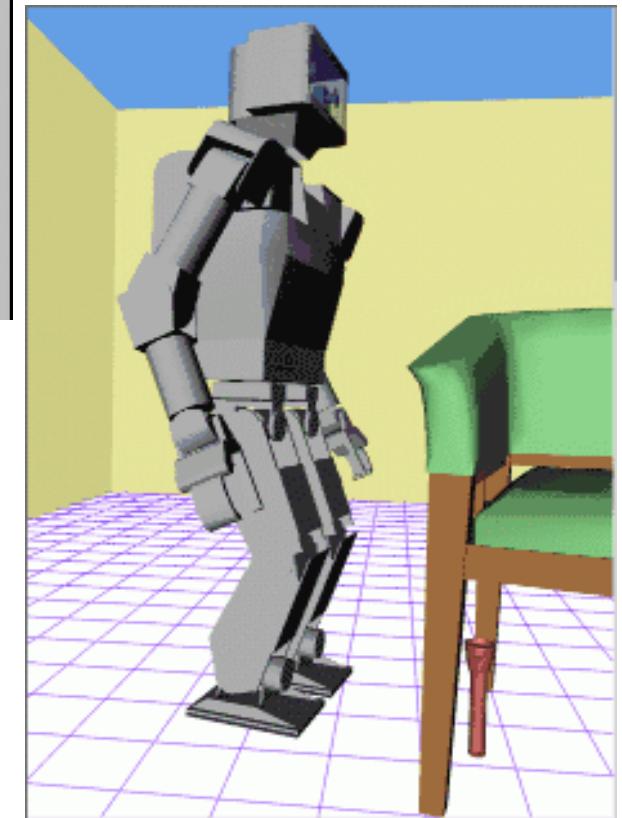
[Source: [http://www.societyofrobots.com/robot\\_arm\\_tutorial.shtml](http://www.societyofrobots.com/robot_arm_tutorial.shtml)]



[Source: V-REP, coppeliarobotics]



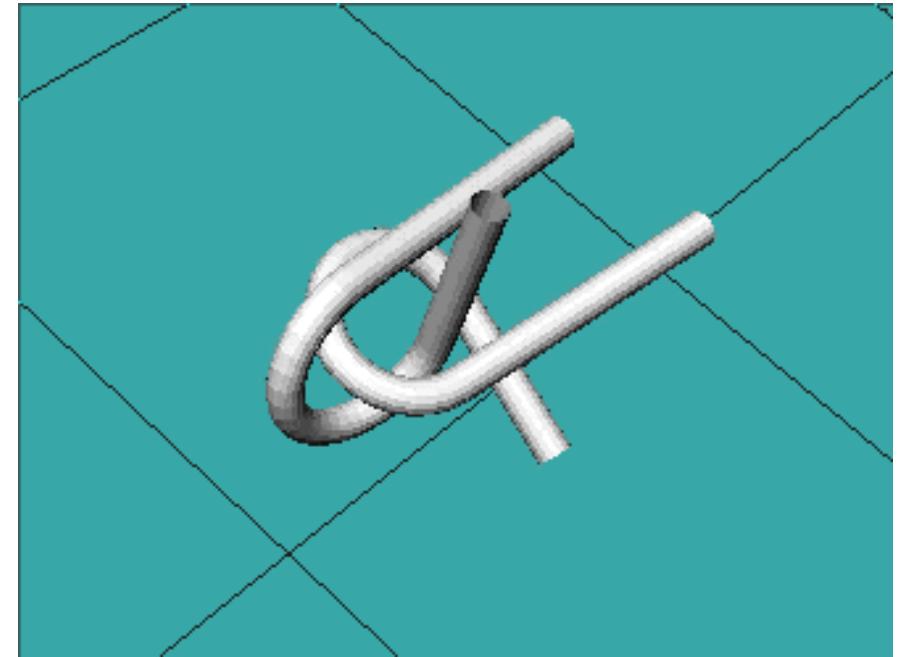
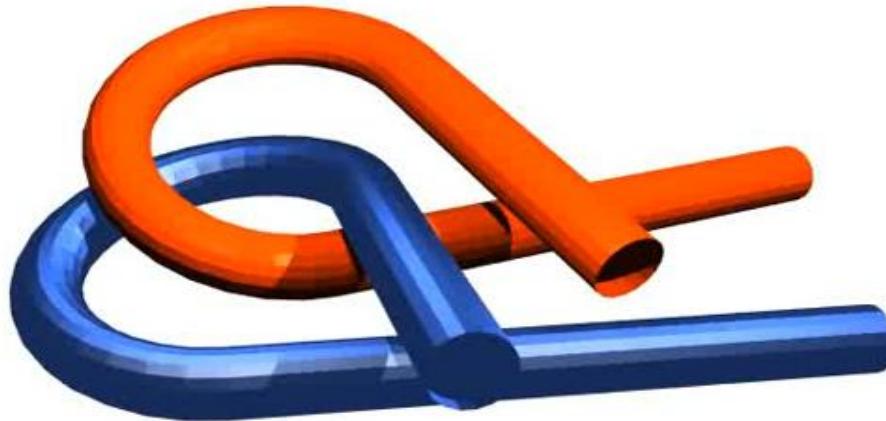
[Source: <https://www.youtube.com/watch?v=UuZWCVxWAsI>]



# Motion Planning: Introduction

## Planning involves: Is it easy?

- State Space
- Time
- Action
- Initial and goal state
- A Plan
- A Criterion



[Source: <https://www.youtube.com/watch?v=UTbiAu8lXas>]

# Outline

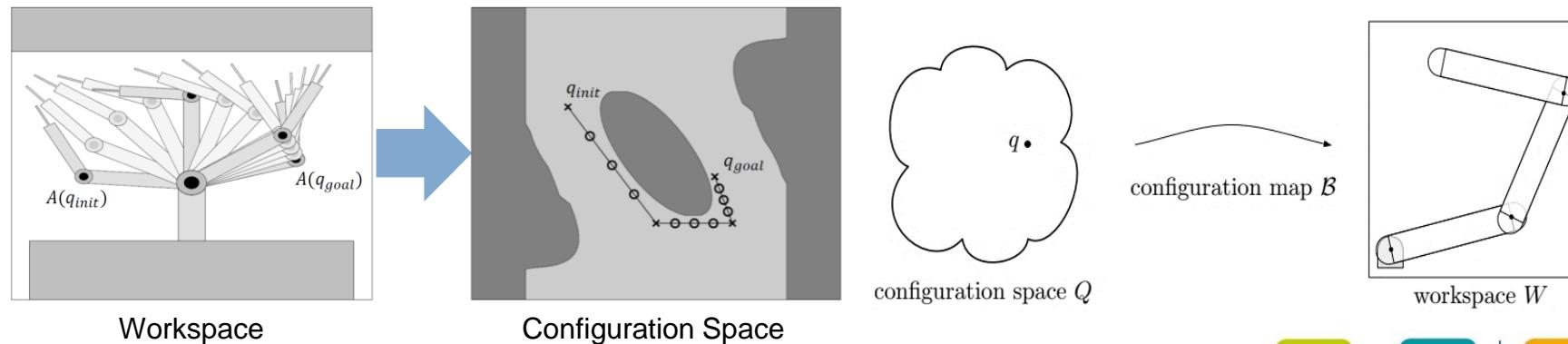
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# Motion Planning: Configuration Space

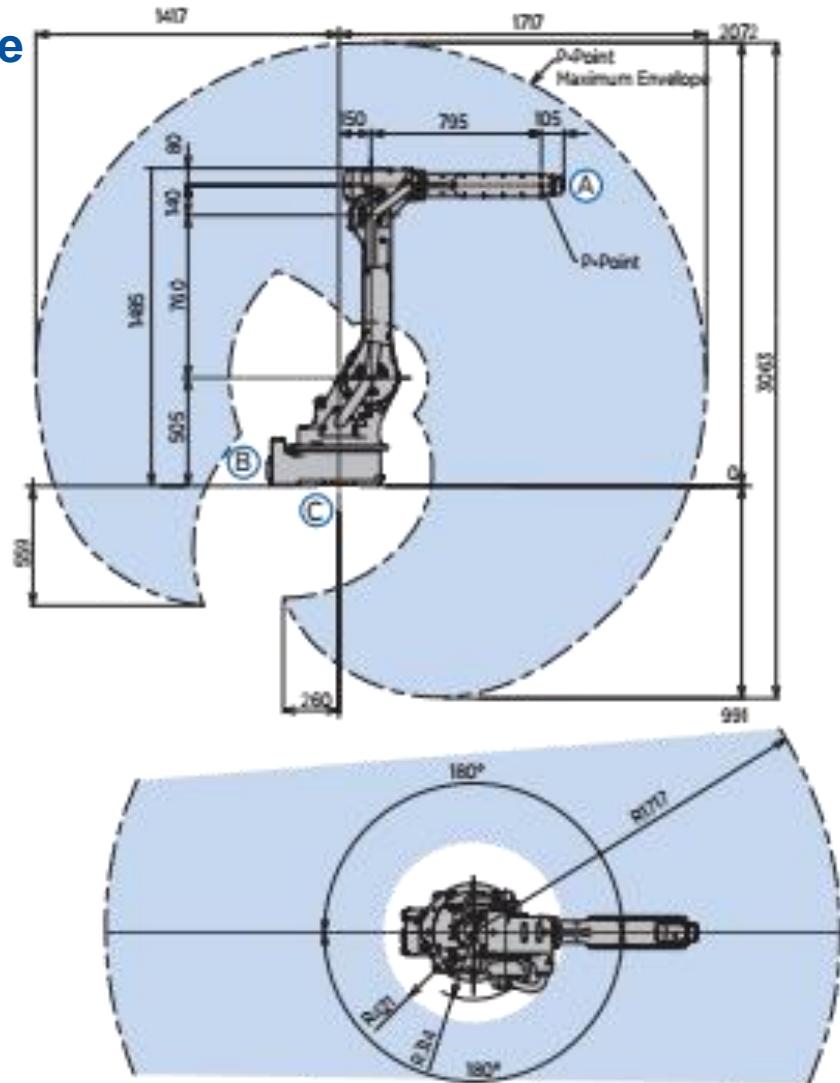
## Context of plan: Workspaces and Configuration Spaces

- Definition of Spaces:
  - Workspace  $\mathcal{W} \in \mathbb{R}^n$ : Environment in which robot operates
  - Obstacle space  $\mathcal{O} \in \mathbb{R}^n$ : Already occupied spaces of the world
  - Free Space  $\mathcal{W}_{free} \in \mathbb{R}^n$ : Unoccupied space of the world
- Projection of robot and workspace into a high dimensional configuration space
  - Configuration  $q$ : A minimal set of variables that describes the position of each rigid body component of a robot, e.g. joint positions and velocities
  - Configuration space  $\mathcal{C}_{space}$ : A set of possible configurations the robot could take
  - C-space obstacle region  $\mathcal{C}_{obs}$ :  $\mathcal{C}_{obs} = \{q \in \mathcal{C}_{space} | \mathcal{B}(q) \cap \mathcal{O} \neq \emptyset\}$
  - C-space without collision  $\mathcal{C}_{free}$ :  $\mathcal{C}_{free} = \mathcal{C}_{space} \setminus \mathcal{C}_{obs}$



# Motion Planning: Configuration Space

## Context of plan: Workspace and Configuration Space



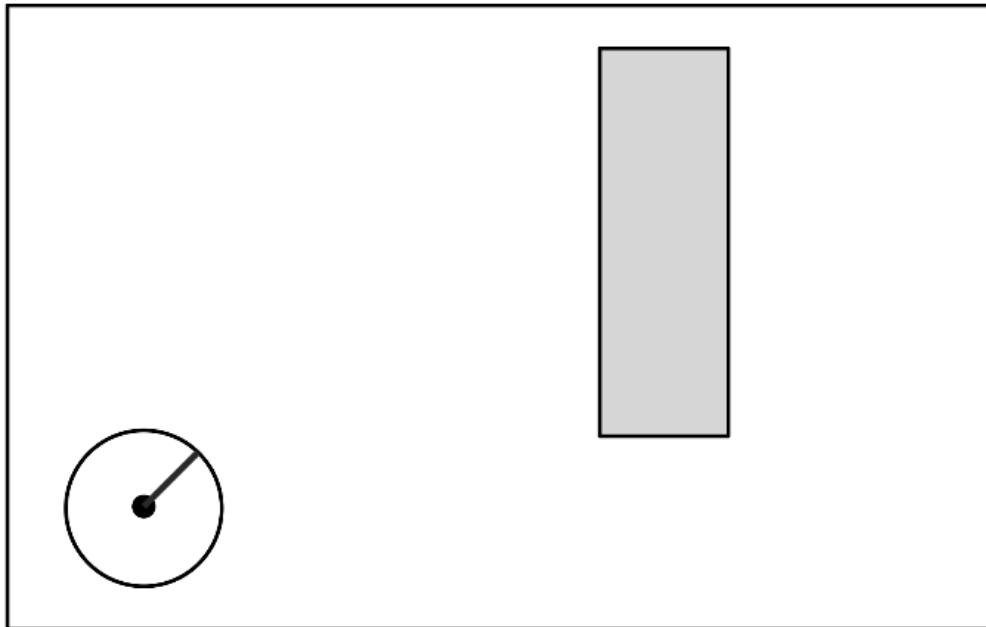
All dimensions are metric (mm) and for reference only.

# Motion Planning: Configuration Space

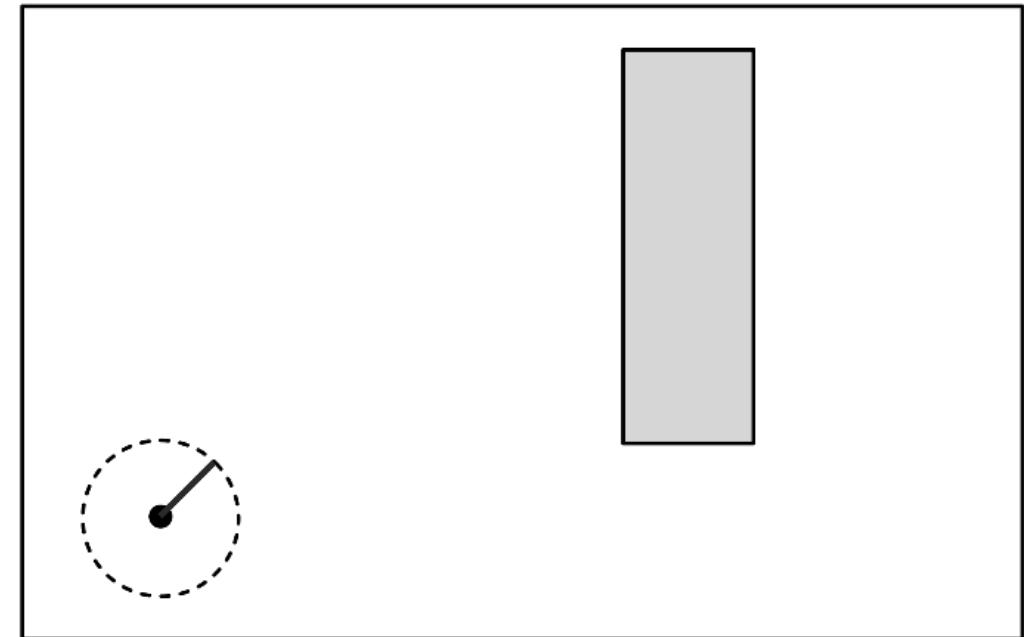
## Context of plan: Workspace and Configuration Space

- Small quiz:
  - Configuration?
  - Free Configuration space?

Free Workspace

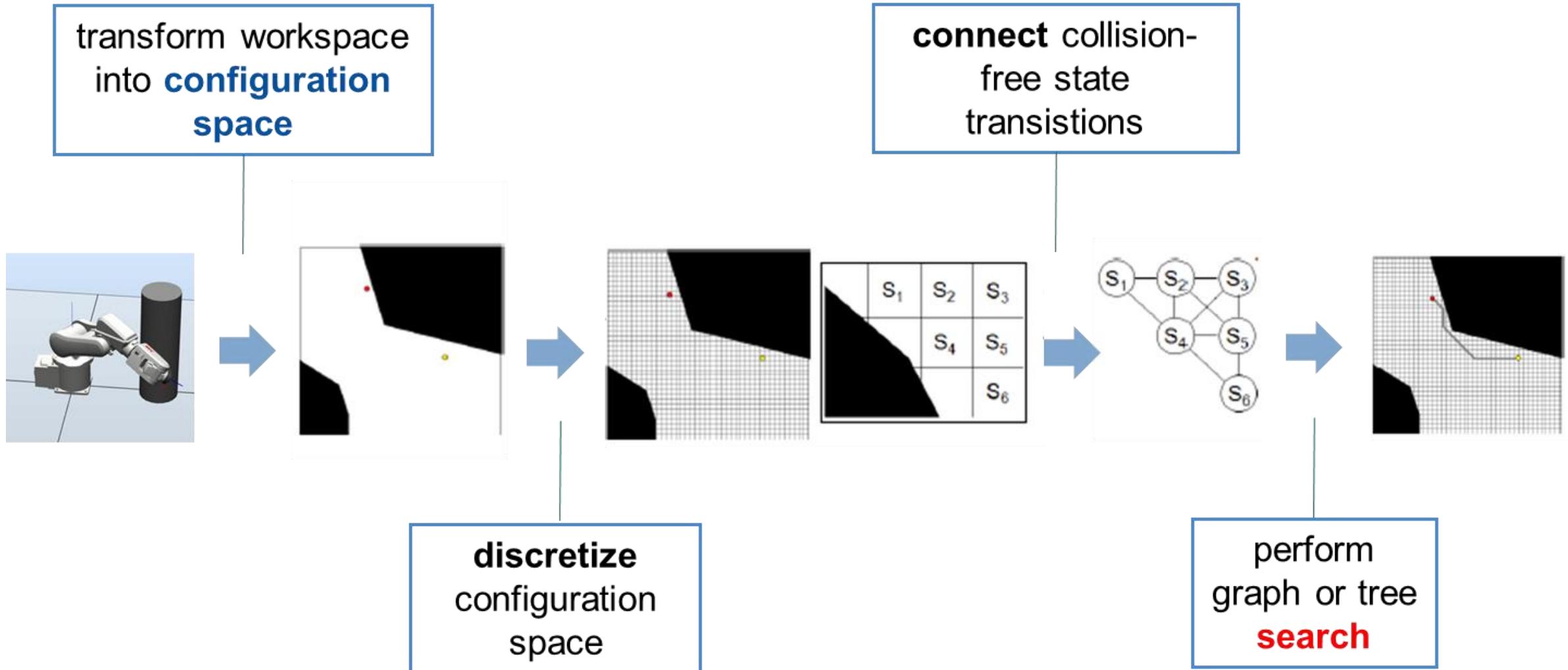


Free Configuration space



# Motion Planning: Configuration Space

## Motion Planning Pipeline within $\mathcal{C}_{space}$



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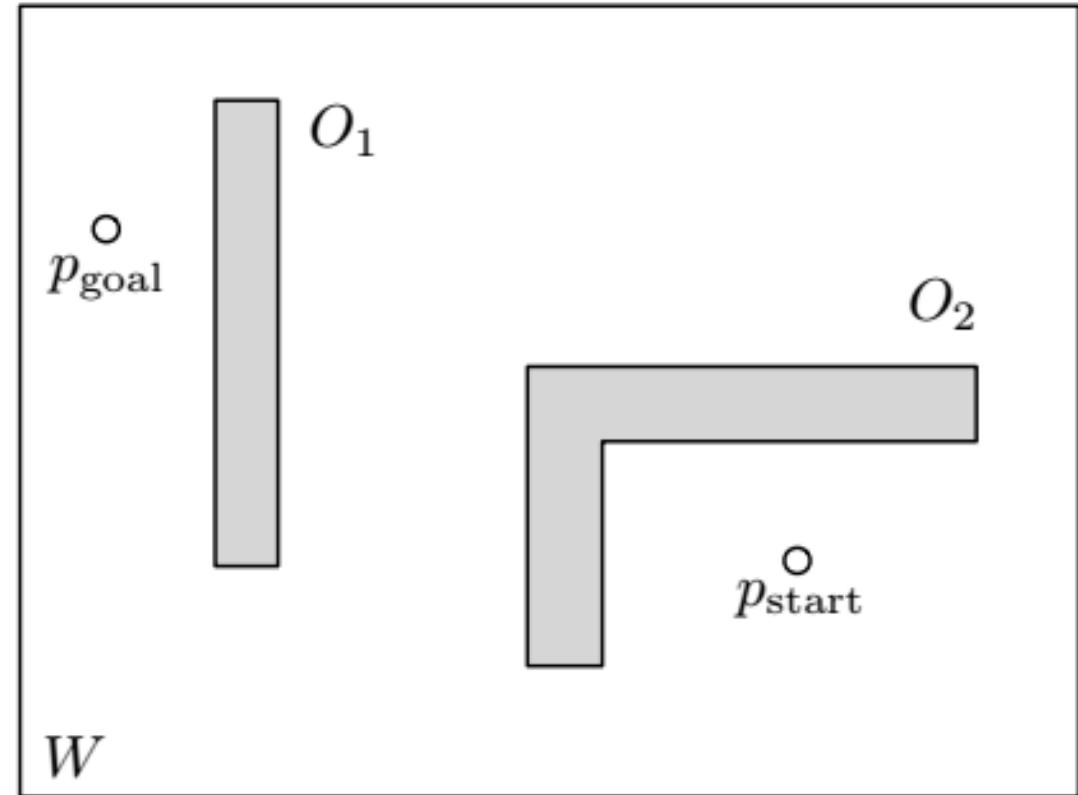
# Motion Planning: Classical Approaches

## Sensor-based Planning: the Bug Algorithms

- Problem setup:
  - A workspace  $\mathcal{W}$  of  $\mathbb{R}^2$  or  $\mathbb{R}^3$
  - Some obstacles  $\{O_1, \dots, O_n\}$
  - A state position  $q_{init}$  and a goal position  $q_{goal}$
  - A robot described by a moving point (no size)

- Assumptions

- Robot Assumptions:
  - Knows the direction towards the goal and distance to goal
  - Does not know anything about the obstacles (without map)
  - A (contact) Sensor to detect obstacles
  - Move either in a straight line or follow an obstacle boundary
  - Limited memory to store distances and angles
- Environment Assumptions:
  - The workspace is bounded
  - Finite number of obstacles
  - Start and goal position in free Workspace  $\mathcal{W}_{free}$



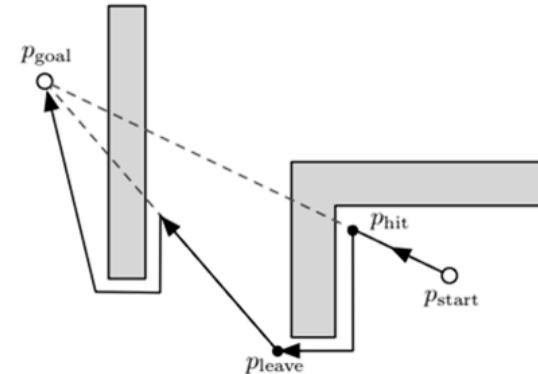
# Motion Planning: Classical Approaches

## Sensor-based Planning: the Bug Algorithms

- Bug 0:

### Algorithm: Bug 0

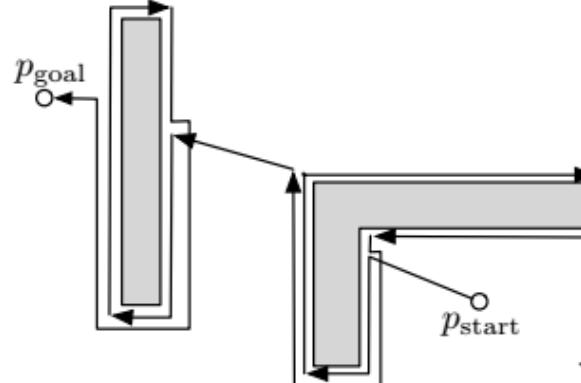
```
while not at goal:  
    move towards the goal  
    if hit an obstacle:  
        while not able to move towards the goal:  
            follow the obstacle's boundary moving to the left
```



- Bug 1:

### Algorithm: Bug 1

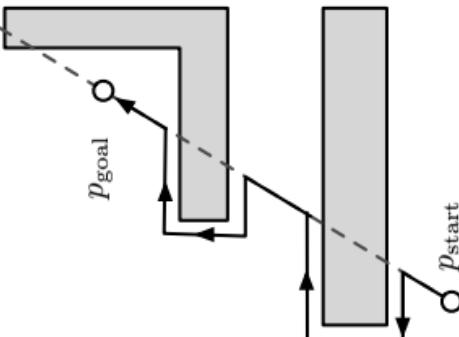
```
while not at goal:  
    move towards the goal  
    if hit an obstacle:  
        circumnavigate it.  
        store in memory the minimum distance from the obstacle boundary to the goal  
        follow the boundary back to the boundary point with minimum distance to goal
```



- Bug 2:

### Algorithm: Bug 2

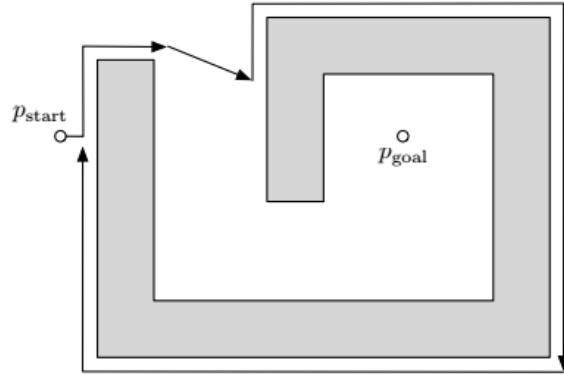
```
while not at goal:  
    move towards the goal (along the start – goal line)  
    if hit an obstacle:  
        follow the boundary (either left or right)  
        leave the boundary until you encounter the start - goal line
```



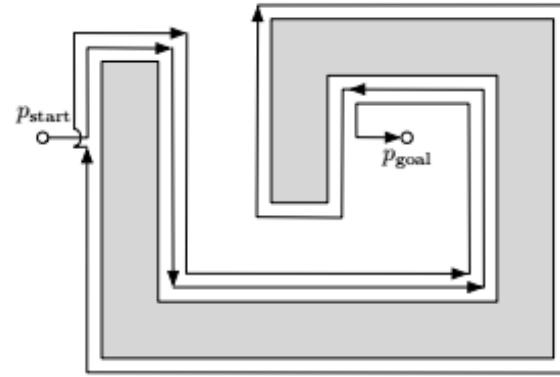
# Motion Planning: Classical Approaches

## Sensor-based Planning: the Bug Algorithms, could they work well?

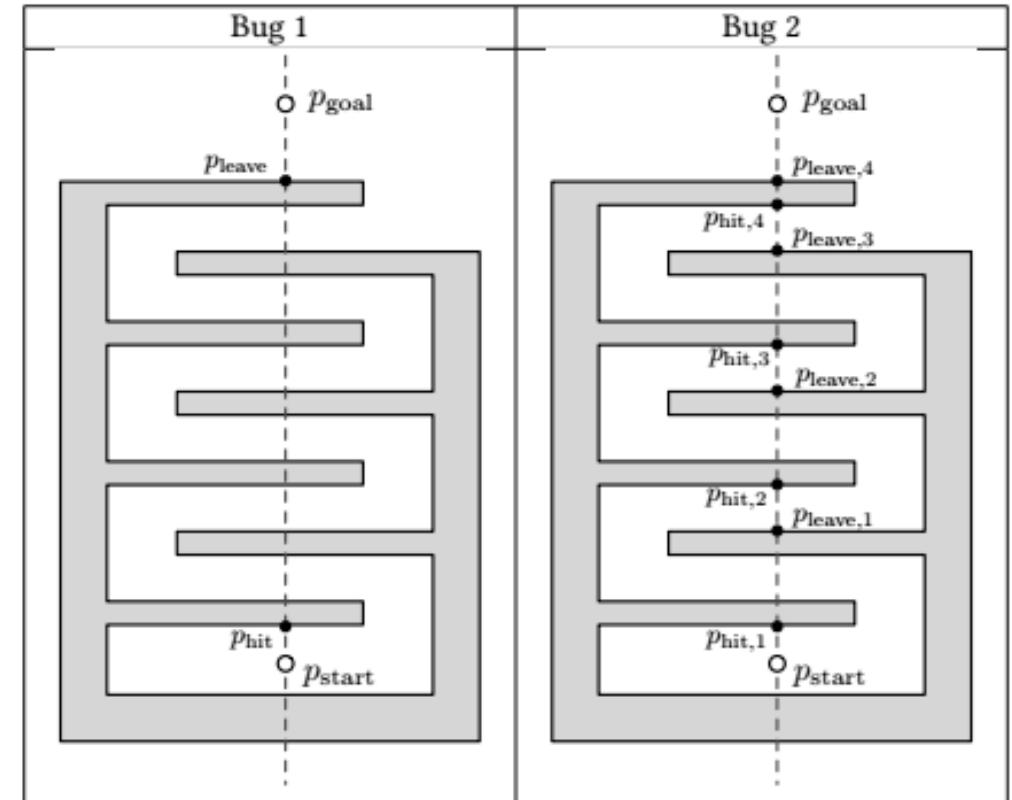
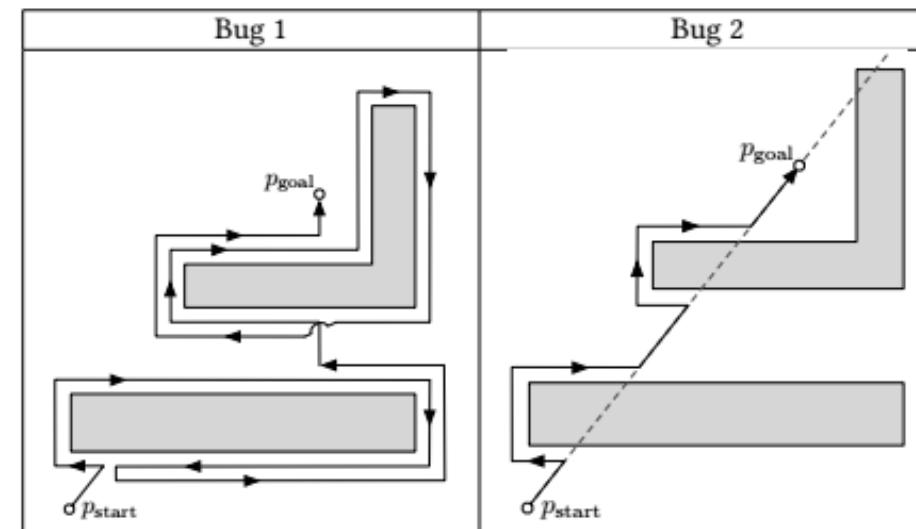
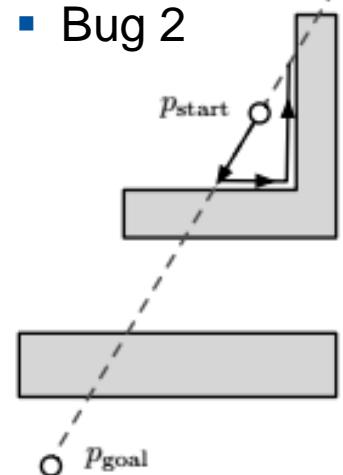
- Bug 0



- Bug 1



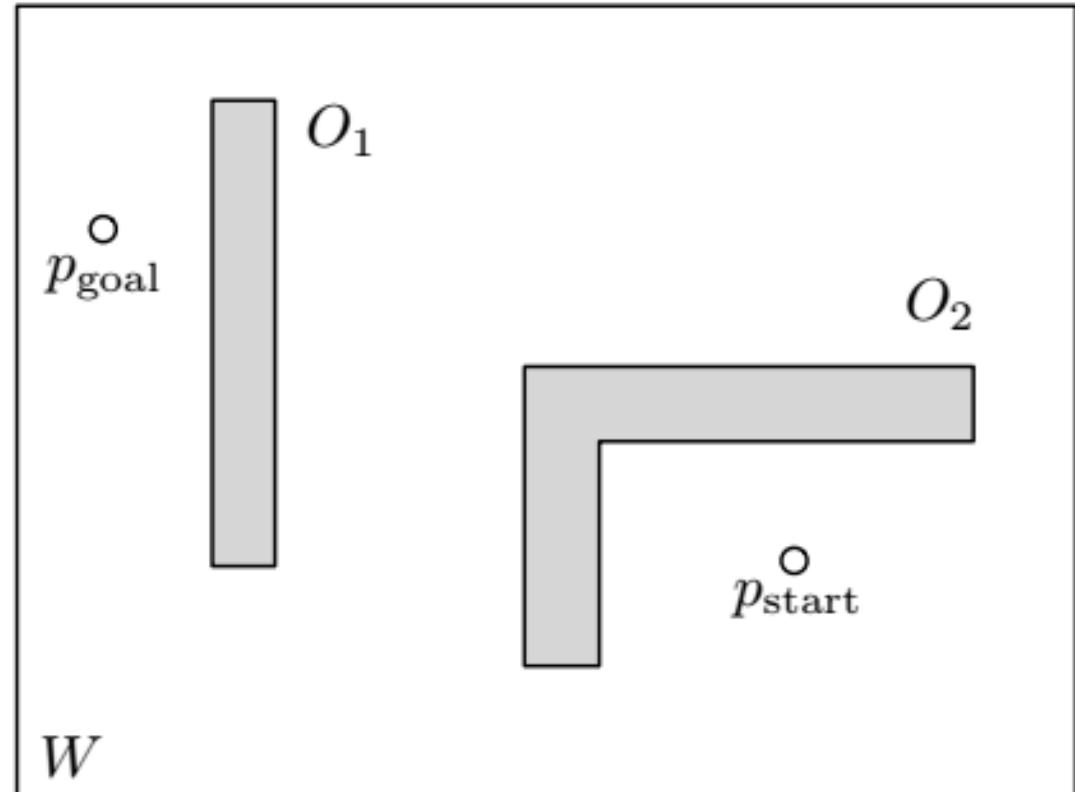
- Bug 2



# Motion Planning: Classical Approaches

## Potential-based Planning

- Problem setup:
  - A workspace  $\mathcal{W}$  of  $\mathbb{R}^2$  or  $\mathbb{R}^3$
  - Some obstacles  $\{\mathcal{O}_1, \dots, \mathcal{O}_n\}$
  - A state position  $q_{init}$  and a goal position  $q_{goal}$
  - A robot described by a moving point (no size)
  
- Assumptions
  - Robot Assumptions:
    - Knows the direction towards the goal and distance to goal
    - Know something about the obstacles (map)
  
  - Environment Assumptions:
    - The workspace is bounded
    - Finite number of obstacles
    - Start and goal position in free Workspace  $\mathcal{W}_{free}$



# Motion Planning: Classical Approaches

## Potential-based Planning: Idea

- No explicit representation of the Configuration space

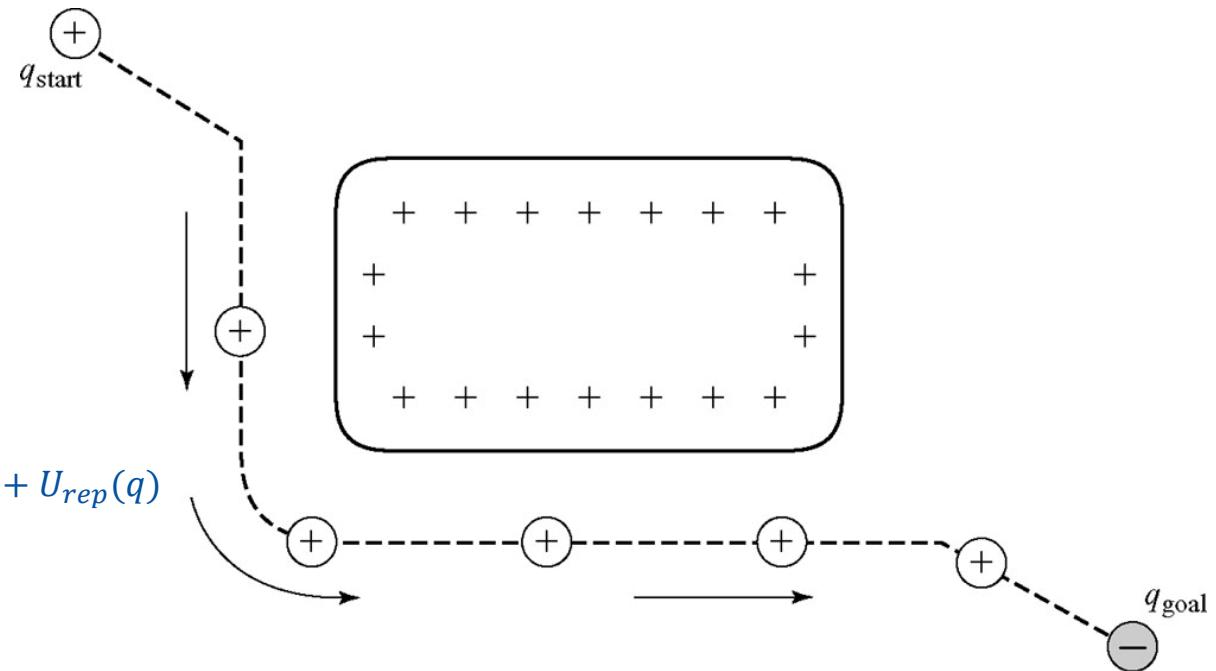
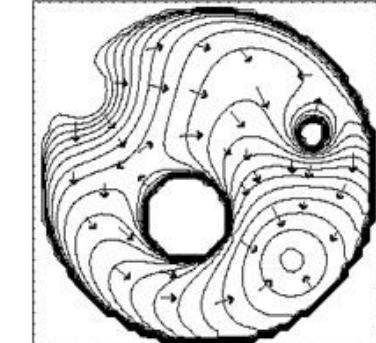
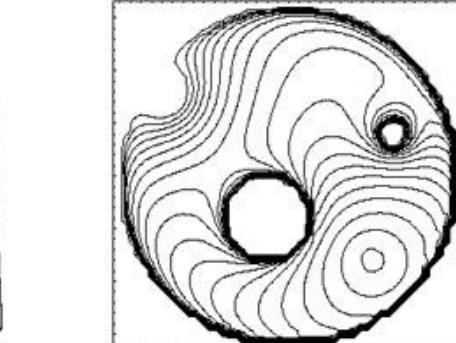
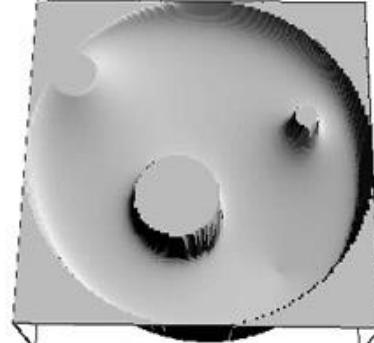
- Potential function:

- Differentiable real-valued function  $U: \mathbb{R}^m \rightarrow \mathbb{R}$
  - Motion Direction towards to the goal using gradient:

$$\nabla U(q) = DU(q)^T = \left[ \frac{\partial U}{\partial q_1}(q), \dots, \frac{\partial U}{\partial q_m}(q) \right]^T$$

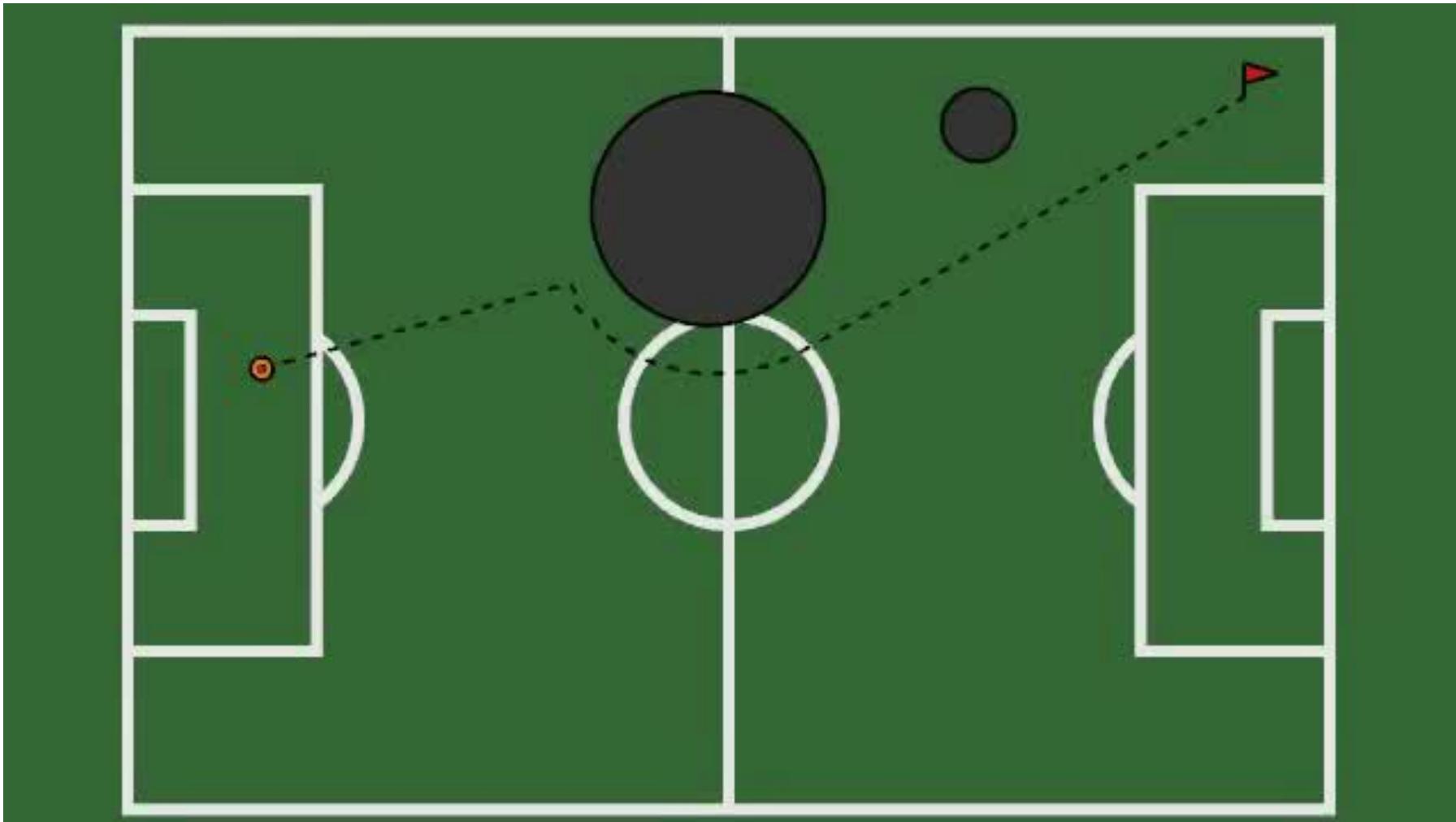
- Gradient descent: „downhill“:  $\dot{q} = -\nabla U(q)$
  - Attractive / Repulsive potential

- $$U(q) = U_{att}(q) + U_{rep}(q)$$
- Attractive potential: w.r.t. Goal, e.g.  $U_{att} = \frac{1}{2}\xi d^2(q, q_{goal})$
  - Repulsive potential: w.r.t. Obstacles, e.g.  $U_{rep} = \frac{1}{2}\eta \left( \frac{1}{D(q)} - \frac{1}{Q^*} \right)^2$



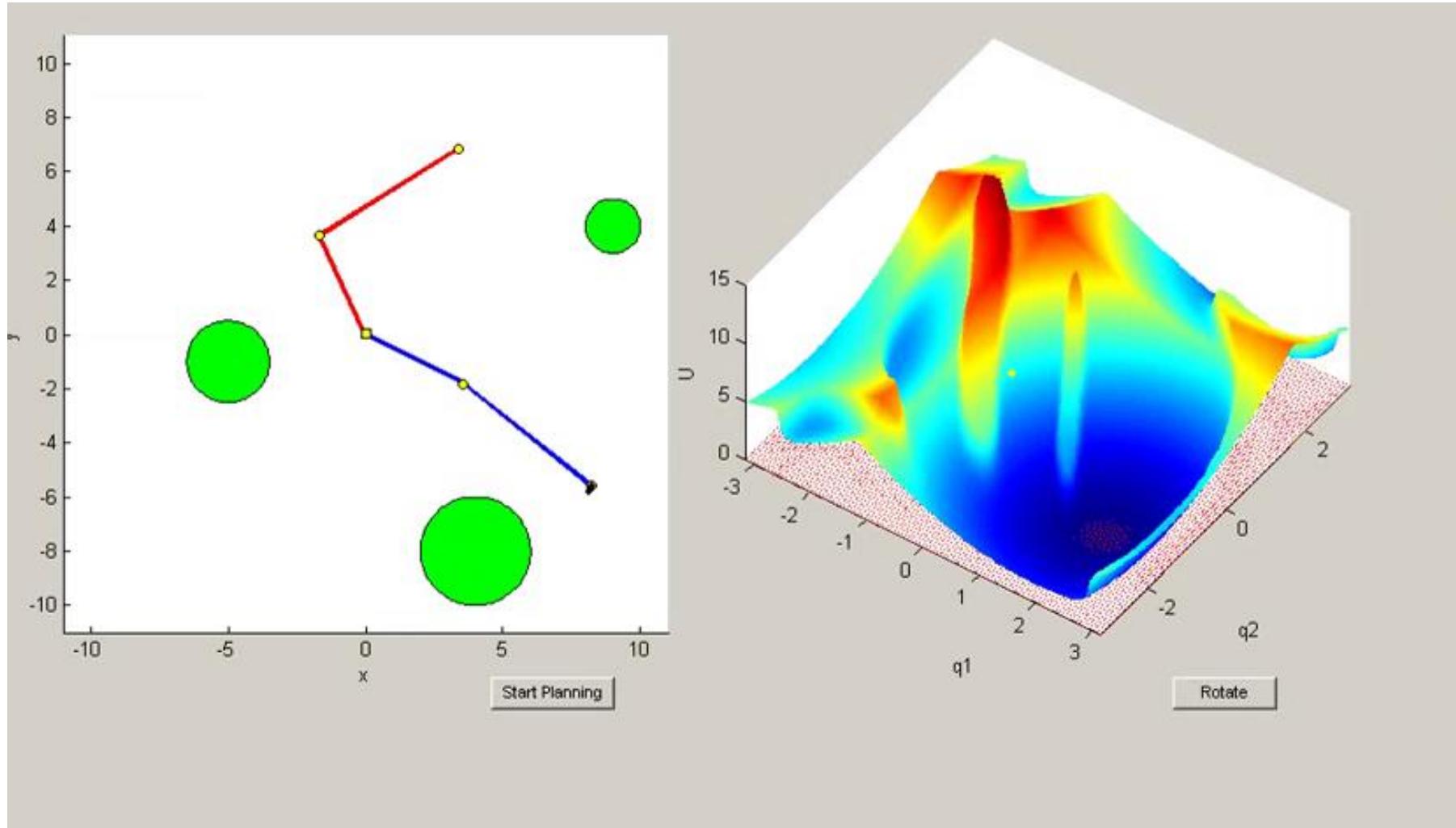
# Motion Planning: Classical Approaches

## Potential-based Planning: Illustration I



# Motion Planning: Classical Approaches

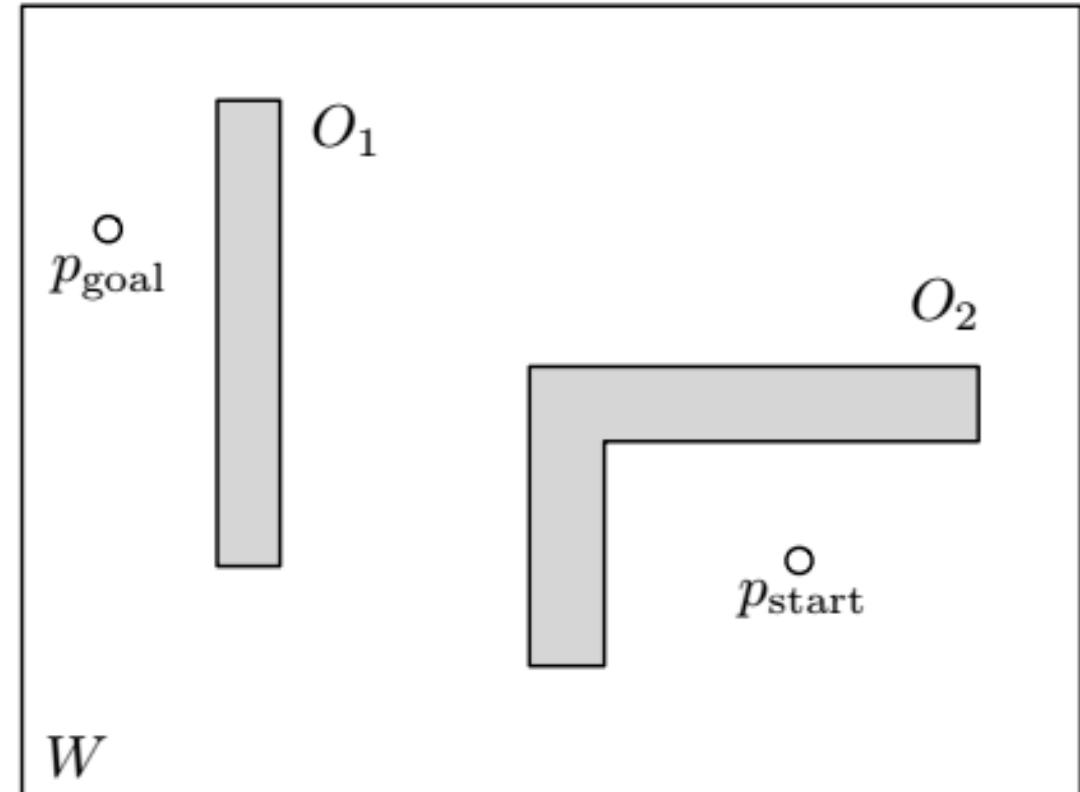
## Potential-based Planning: Illustration II



# Motion Planning: Classical Approaches

## Cell Decompositions

- Problem setup:
  - A workspace  $\mathcal{W}$  of  $\mathbb{R}^2$  or  $\mathbb{R}^3$
  - Some obstacles  $\{\mathcal{O}_1, \dots, \mathcal{O}_n\}$
  - A state position  $q_{init}$  and a goal position  $q_{goal}$
  - A robot described by a moving point (no size)
  
- Assumptions
  - Robot Assumptions:
    - Knows the direction towards the goal and distance to goal
    - **Know the workspace and obstacles (map)**
  
  - Environment Assumptions:
    - The workspace is bounded
    - Finite number of obstacles
    - Start and goal position in free Workspace  $\mathcal{W}_{free}$



# Motion Planning: Classical Approaches

## Cell Decompositions: Idea

- Decompose the free space into simple cells
- Represent the connectivity of the free space by the adjacency graph of cells
- Decomposition into e.g. Triangles and **Trapezoids**

### Algorithm: The roadmap-from-decomposition algorithm

**Input:** the trapezoidation of a polygon

**Output:** a roadmap

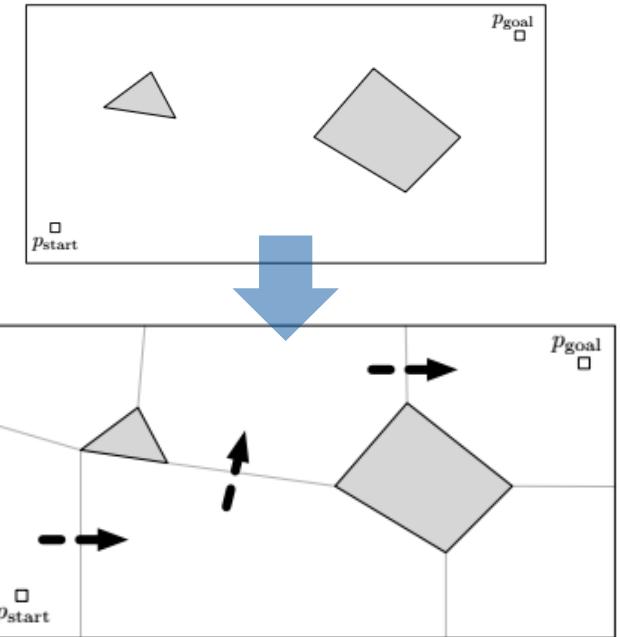
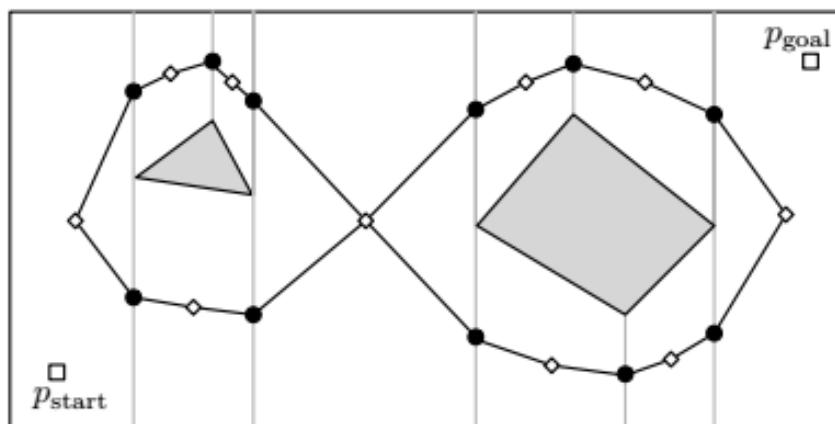
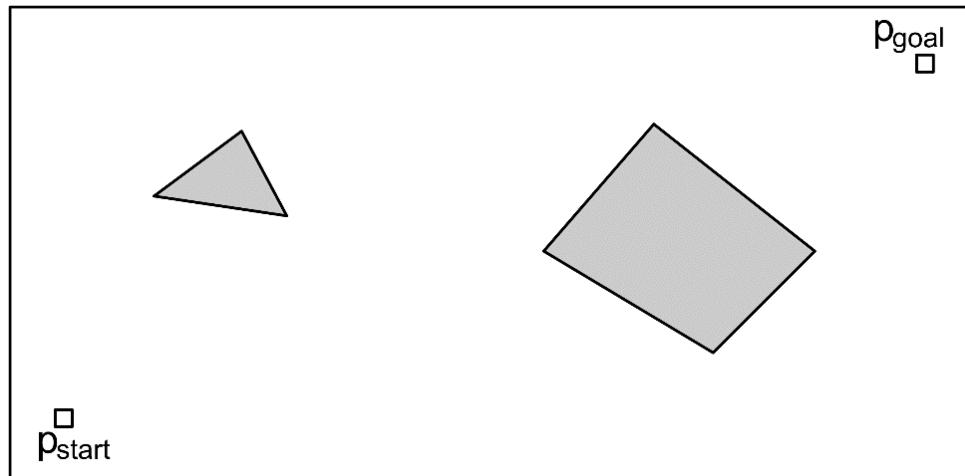
label the center of each trapezoid with the symbol  $\diamond$

label the midpoint of each vertical separating segment with the symbol  $\bullet$

**for** each trapezoid:

    connect the center to all the midpoints in the trapezoid

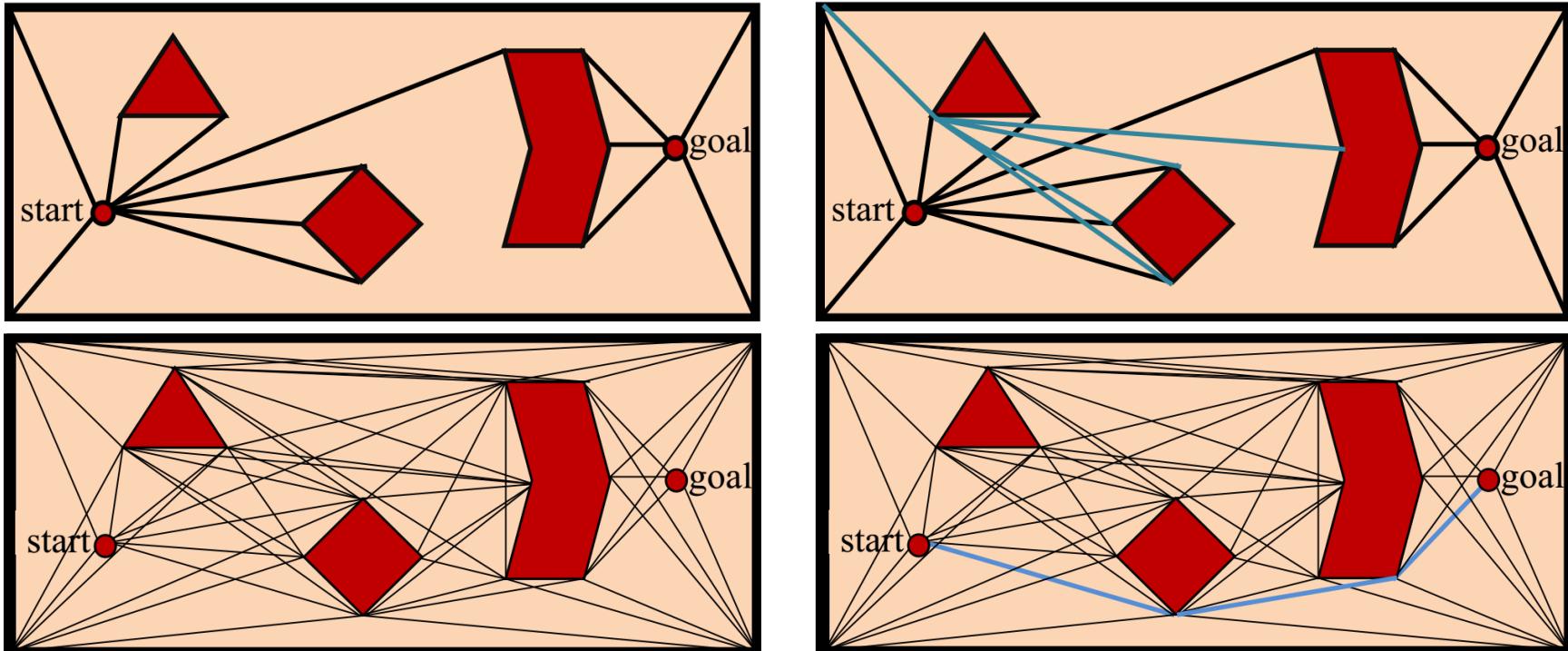
**return** the roadmap consisting of centers and connections between them through midpoints



# Motion Planning: Classical Approaches

## Roadmaps

- Map: a data structure, topological, geometric, and grids
- Represent the connectivity of a free space by a network of 1-D curves
- Many types: visibility maps, deformation retracts, *retract-like structures*, *piecewise retracts* and *silhouettes*
- Visibility Maps:

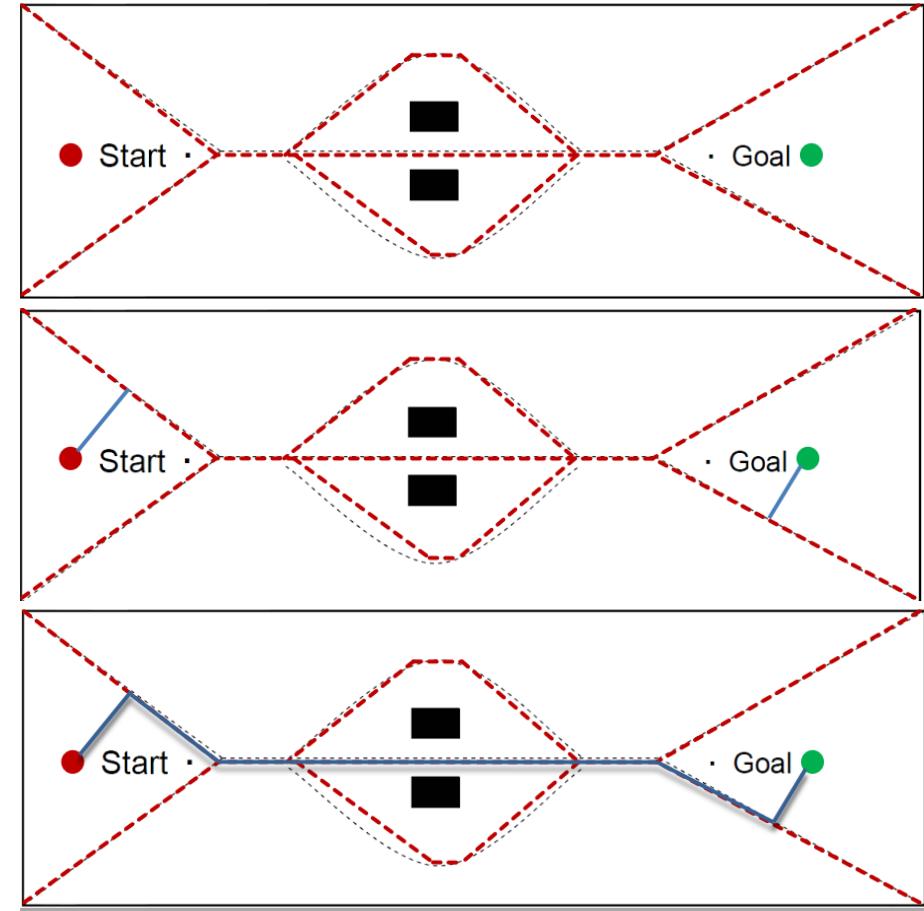
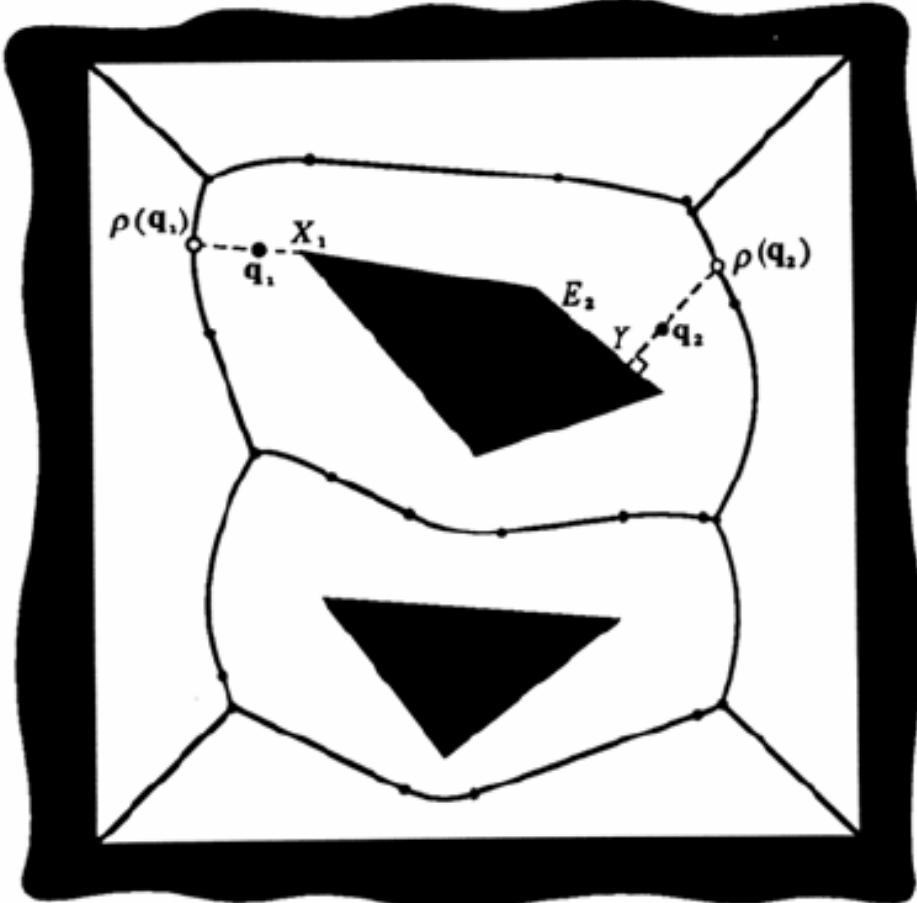


# Motion Planning: Classical Approaches

## Roadmaps

- Deformation reacts: **Generalized Voronoi Diagram (GVD)**

The set of points where the distance to the two closest obstacles is the same.



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# Motion Planning: Sampling-Based Planning

- Ideal: Build a **complete motion planner** (complete configuration space)
- Complete motion planner: always returns a solution when one exists and indicates that no such solution exists otherwise.
- Problem:
  - Challenges of High Dimensions
  - Motion Planning is **PSPACE-hard**
  - Complexity is **exponential** in the dimension of the robot's configuration space
- Practical Algorithmus:
  - Theoretical: algorithms strive for completeness and minimal worst-case complexity  
Difficult to implement and not robust
  - **Heuristic**: algorithms strive for efficiency in commonly encountered situations
    - Trade off completeness for practical efficiency
    - Weaker performance guarantee
- Ways to simplify problem:
  - Project search to lower-dimensional space
  - Limit the number of possibilities
    - Add constraints
    - Reduce “volume” of free space
  - Sacrifice optimality and completeness



# Motion Planning: Sampling-Based Planning

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## The Rise of Monte Carlo Techniques

- Key Idea
  - Rather than exhaustively explore ALL possibilities, randomly explore a smaller subset of possibilities while keeping track of progress
  - Facilities “probing” deeper in a search tree much earlier than any exhaustive algorithm can
  
- What’s the catch?
  - Typically we must sacrifice both *completeness* and *optimality*
  - Classic tradeoff between solution quality and runtime performance

## ➤ Sampling-based Motion Planning

# Motion Planning: Sampling-Based Planning

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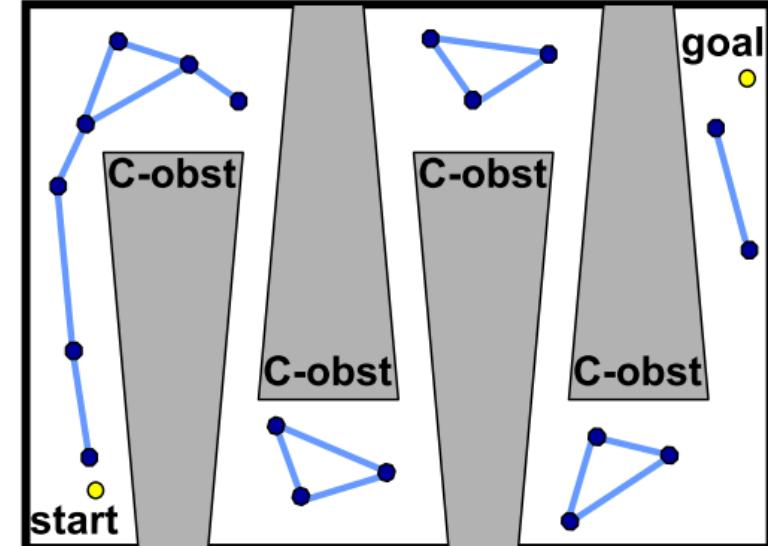
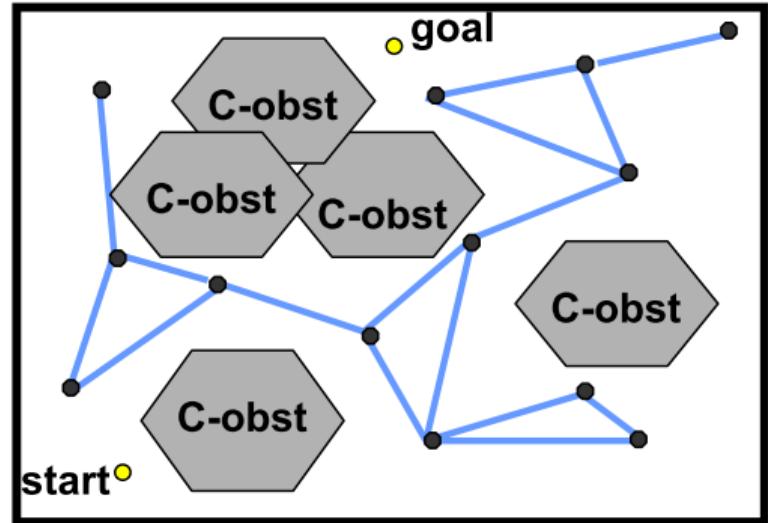
## Concept

- Efficiently handling of planning problems
  - Good for systems with many Degrees of Freedom (DoF)
  - Idea:
    - Generate random sample points in configuration space
    - Connect start and goal state by connecting samples via collision free paths
- it is not necessary to reason about the whole configuration space (only about a finite number of sample configurations)

# Motion Planning: Sampling-Based Planning

## Good news, but bad news too

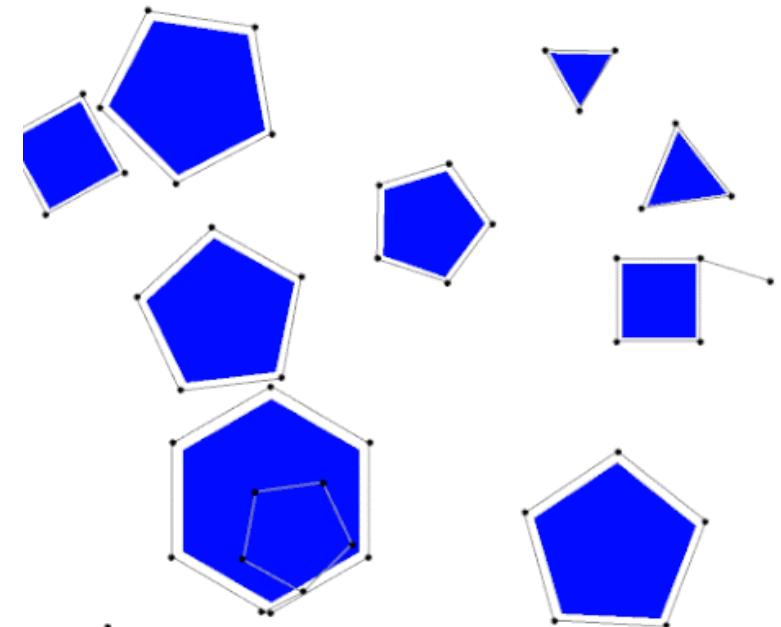
- Sample-based: **The Good News**
  - *probabilistically complete*
  - Do not construct the C-space
  - Apply easily to high dimensional C-space
  - Support fast queries with enough preprocessing
- Many success stories where Sampling-based Motion Planning solve previously unsolved problems
- Sample-based: **The Bad News**
  1. don't work as well for some problems
    - unlikely to sample nodes in *narrow passages*
    - Hard to sample/connect nodes on constraint surfaces
  2. No optimality or completeness



# Motion Planning: Sampling-Based Planning

## Methods

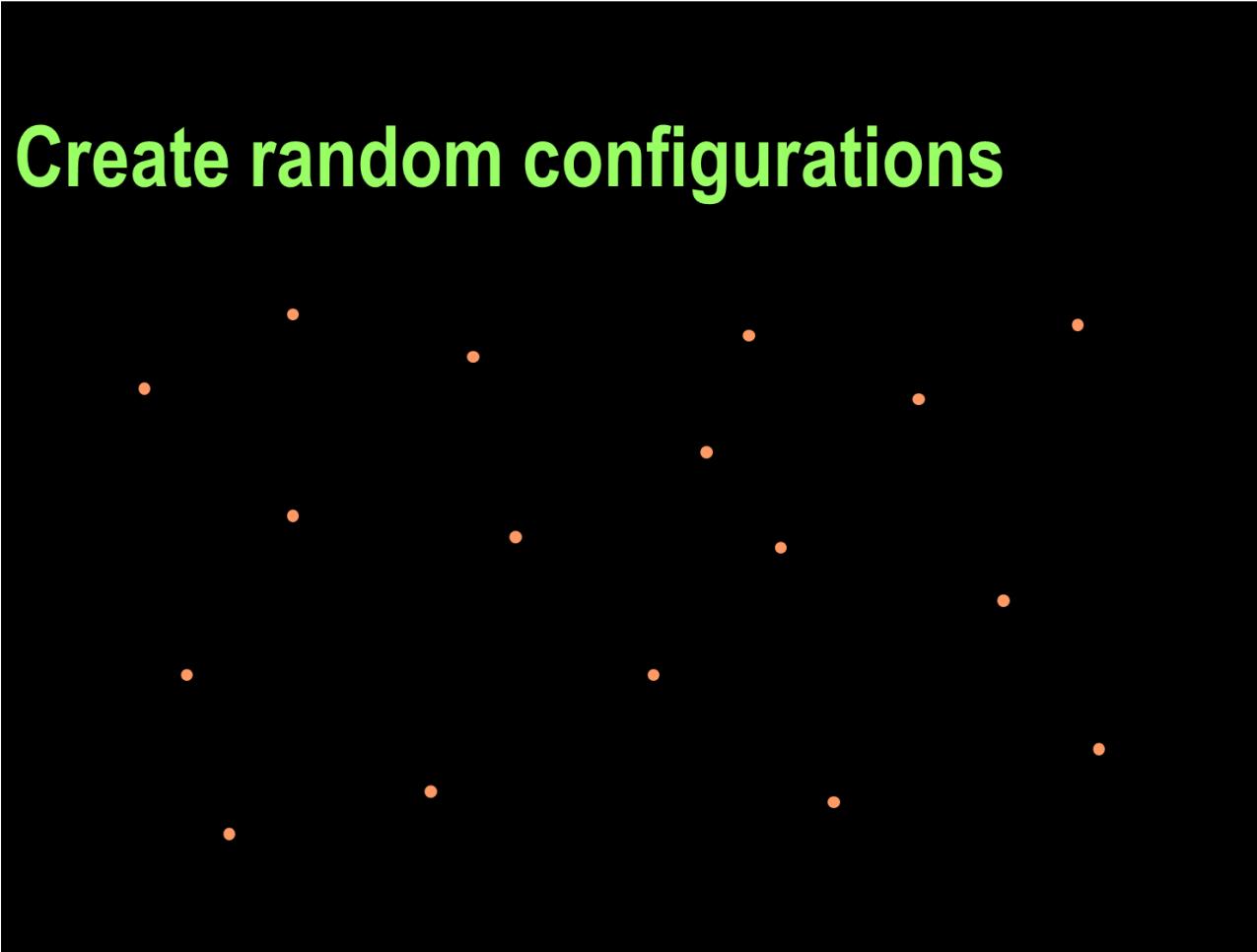
- Probabilistic Roadmaps (PRM)
  - Uses sampled states to create a **roadmap** of the free state space
  - Each sample point is connected to an amount of nearby samples via collision free paths
  - Collision free paths between samples are determined by a local planner (i.e. linear interpolation)
  - Learning Phase
    - Construction Step:  
Construct a probabilistic roadmap by generating random free configurations  
of the robot and Connecting them using a **local planner**
    - Expansion Step: Supplement and refine the Roadmap
  - Query Phase: find a path



# Motion Planning: Sampling-Based Planning

## Methods

- Probabilistic Roadmaps (PRM)

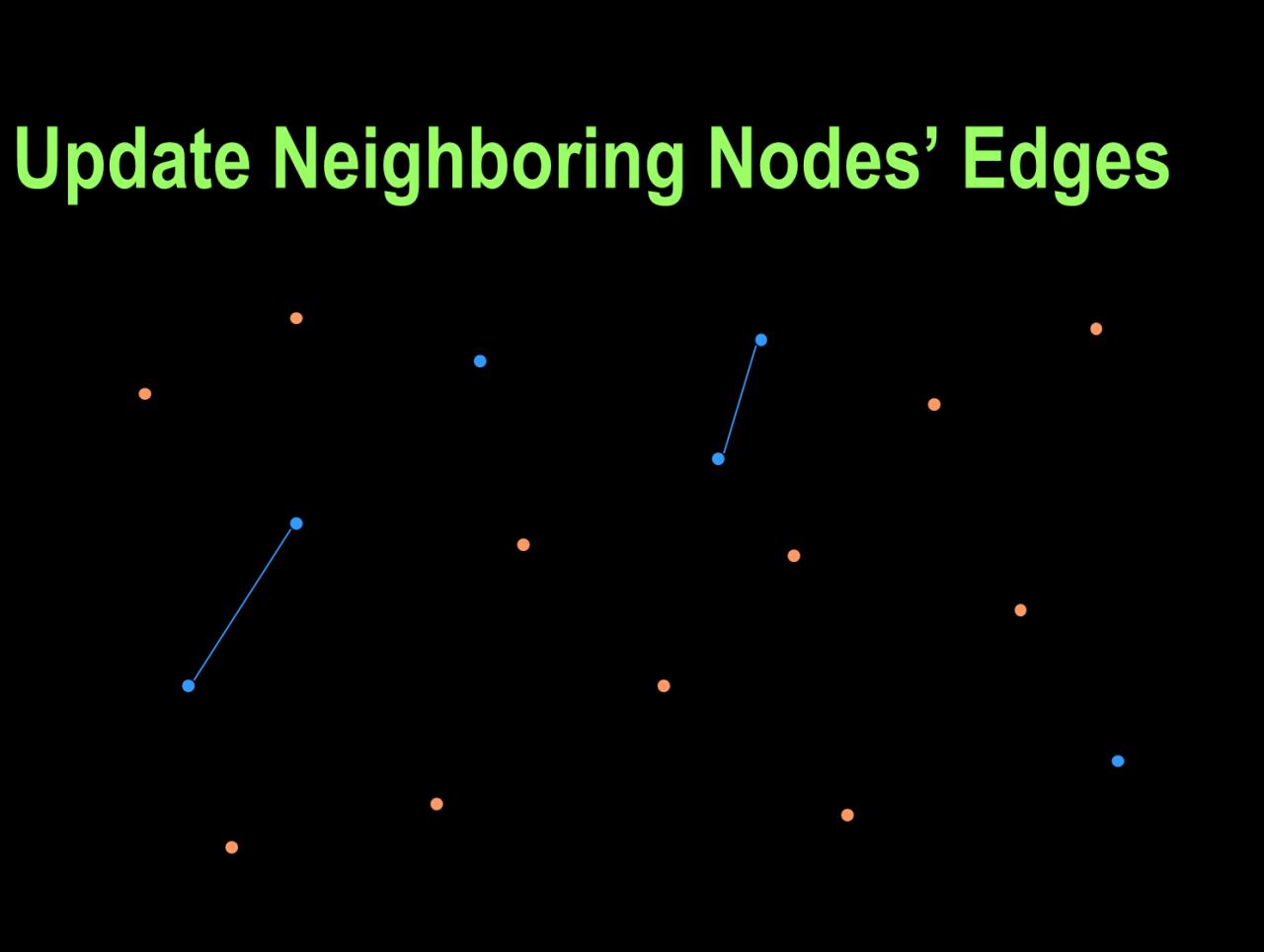


Slides from Nancy Amato, Sujay Bhattacharjee, G.D. Hager, S. LaValle, and a lot from James Kuffner

# Motion Planning: Sampling-Based Planning

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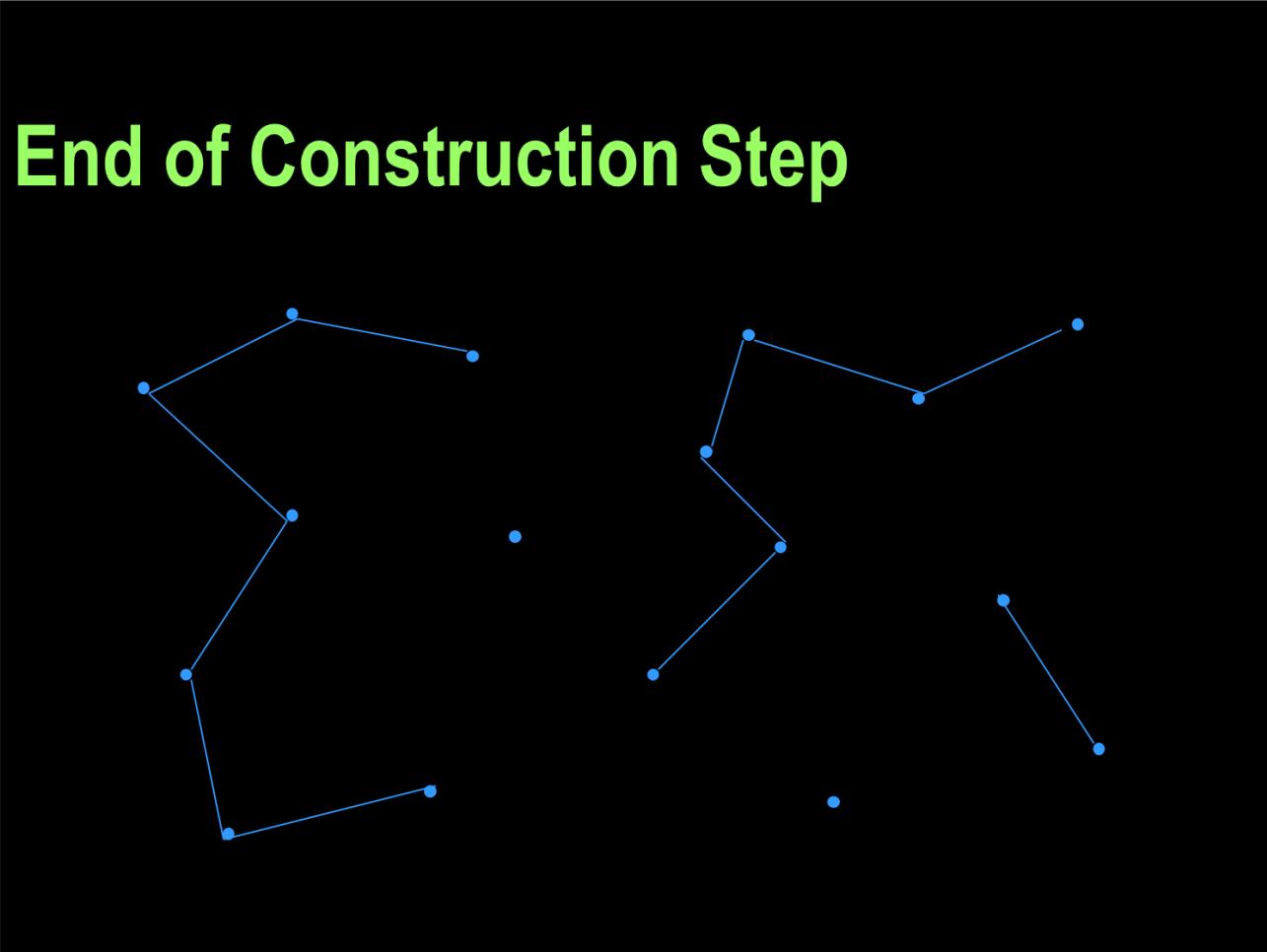


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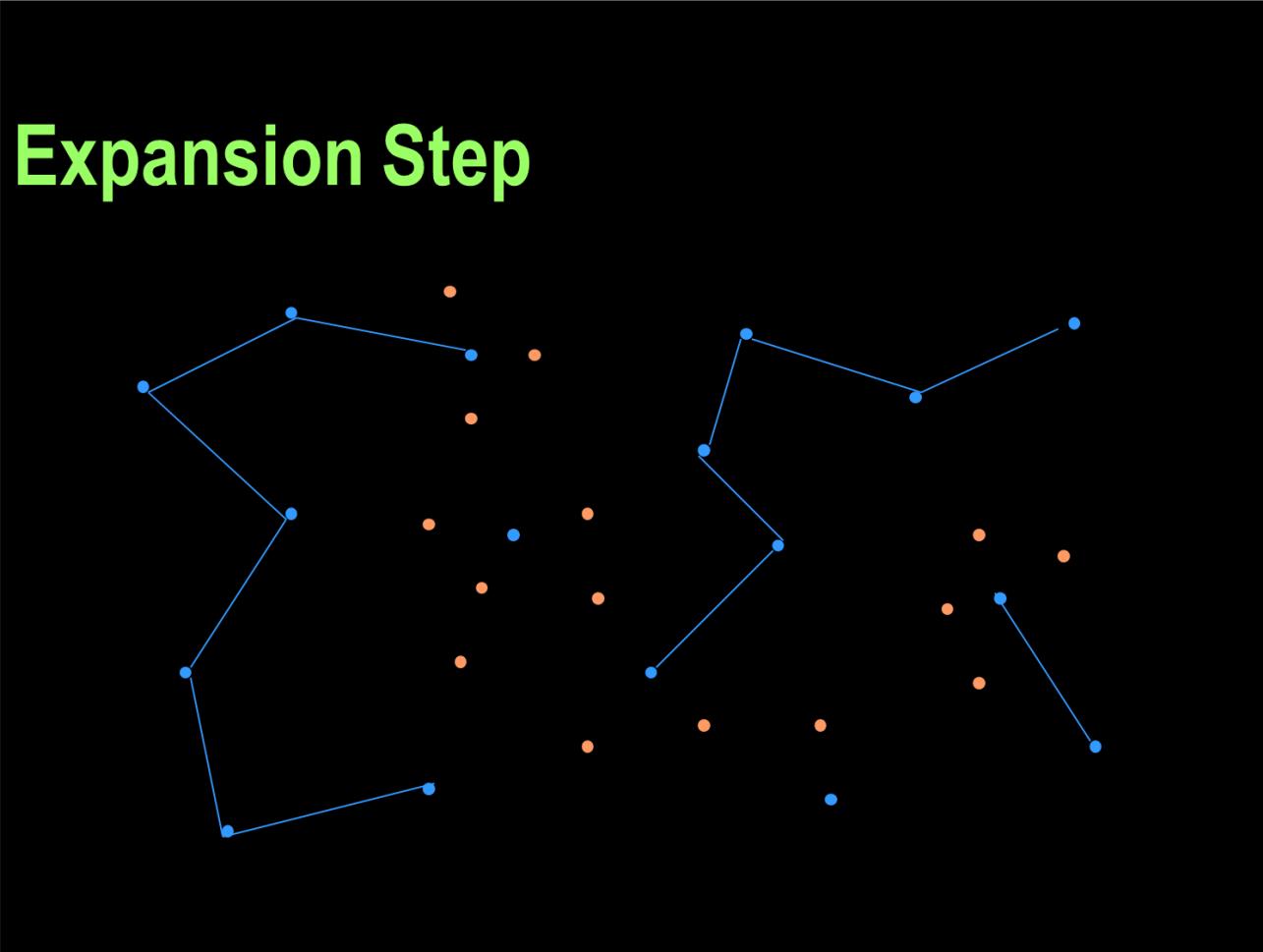


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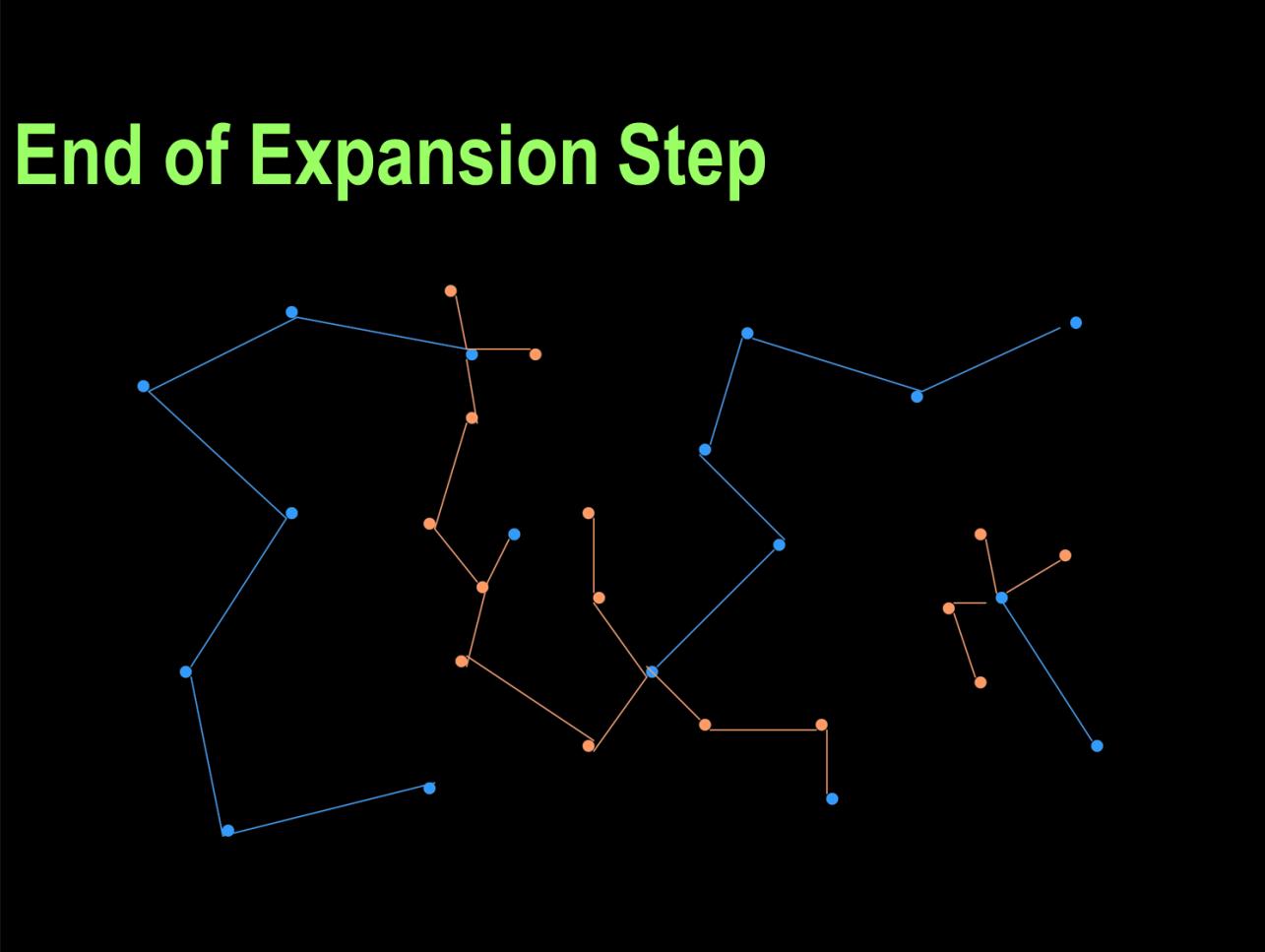


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- Probabilistic Roadmaps (PRM)

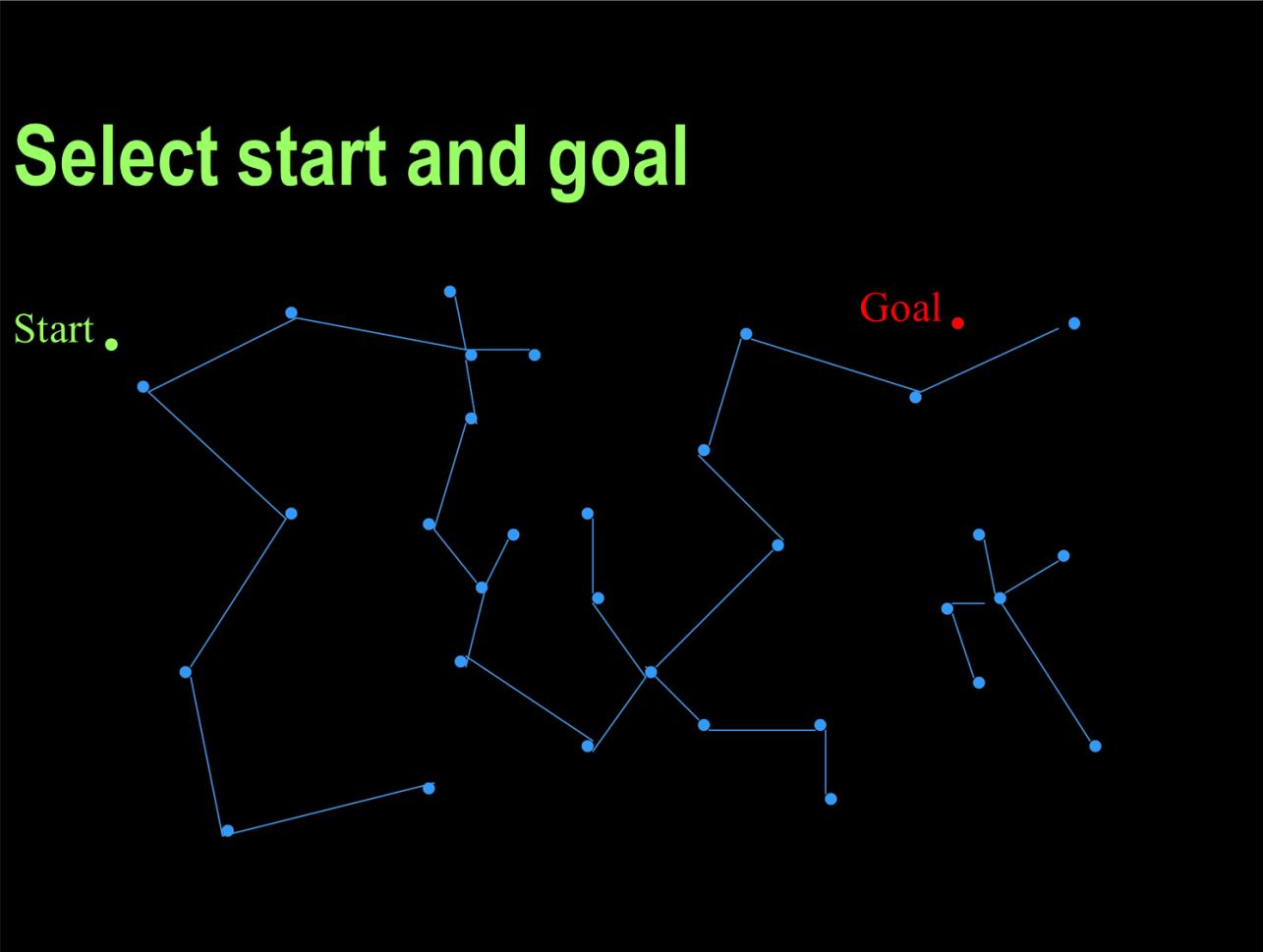


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# Motion Planning: Sampling-Based Planning

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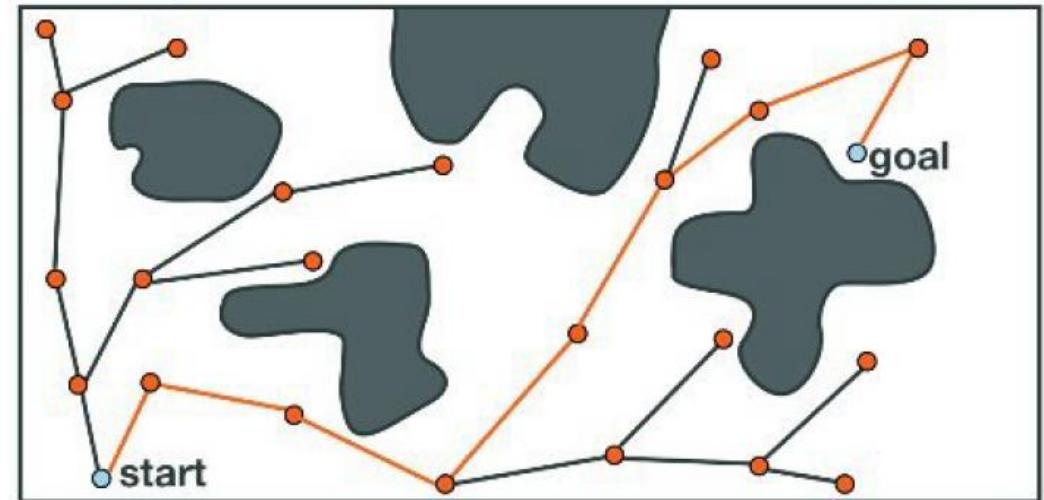
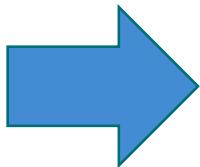


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# Motion Planning: Sampling-Based Planning

## Methods

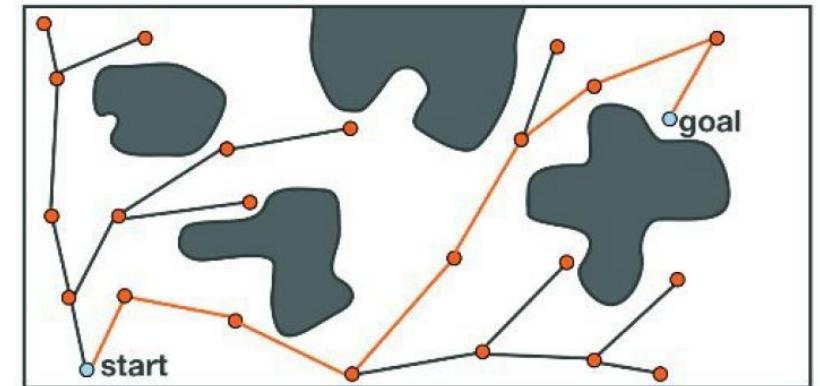
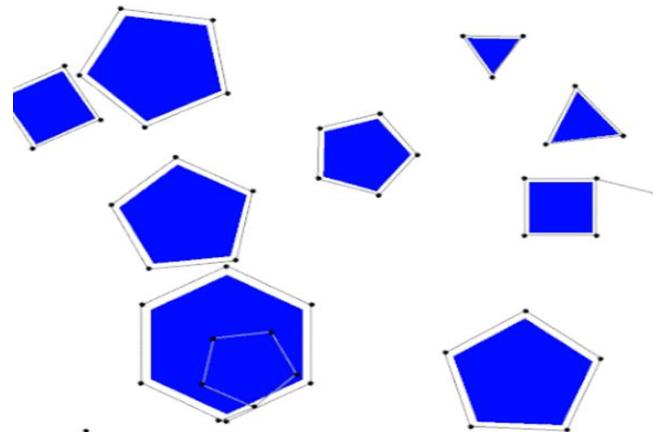
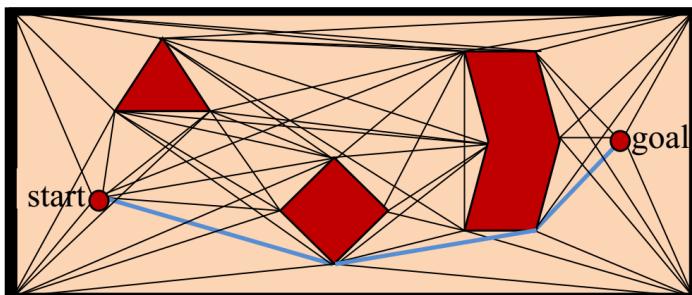
- Tree-based Planners
  - Uses sampled states to create a **tree** of the free state space
  - Root of the tree is the start state (i.e. A)
  - Based on this, the tree is expanded towards the goal state by creating collision free connections between samples



# Motion Planning: Sampling-Based Planning

## Compare

- Complete Motion Planning
  - Always terminate
  - Not efficient
  - Not robust even for low DoF
- Probabilistic Roadmap
  - Construction and query phase
  - Can be reused for subsequent queries
  - Efficient
  - Work for complex problems with many DoFs
  - Difficult for narrow passages
  - May not terminate when no path exists
- Tree-based Planners
  - Good for *single query planning*
  - Does not cover the whole free state space
  - Many up to date methods are tree-based planners



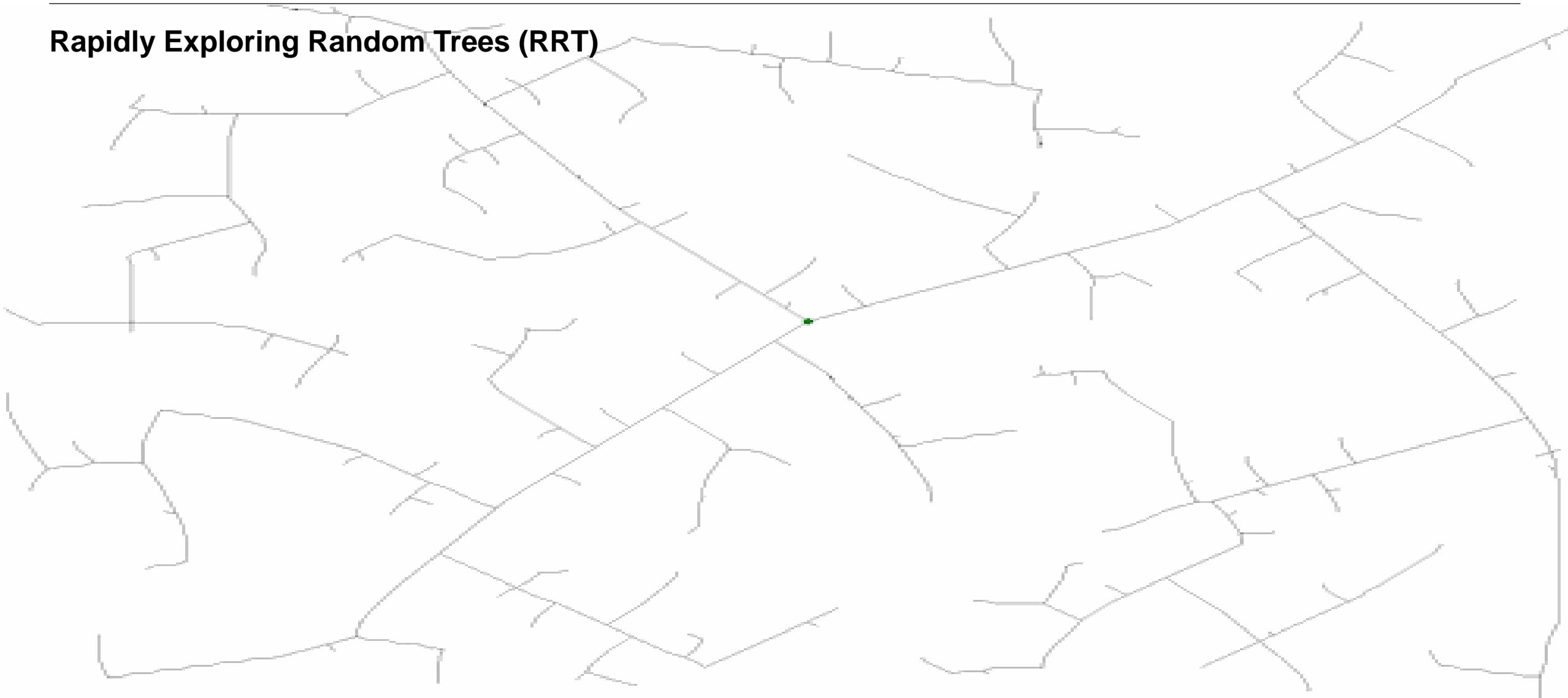
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1	Motion Planning	10:00 – 12:10
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# Motion Planning: Tree-based Planners

## Rapidly Exploring Random Trees (RRT)



# Motion Planning: Tree-based Planners

## Rapidly Exploring Random Trees (RRT)

### Algorithm: Build RRT

**Input:** Initial configuration  $q_{init}$ , number of vertices in RRT  $K$ , incremental distance  $\Delta q$

**Output:** RRT tree  $T$

Initialize tree  $T$  with initial configuration  $q_{init}$

for  $k=1$  to  $K$ :

$q_{rand} \leftarrow$  random point in configuration space

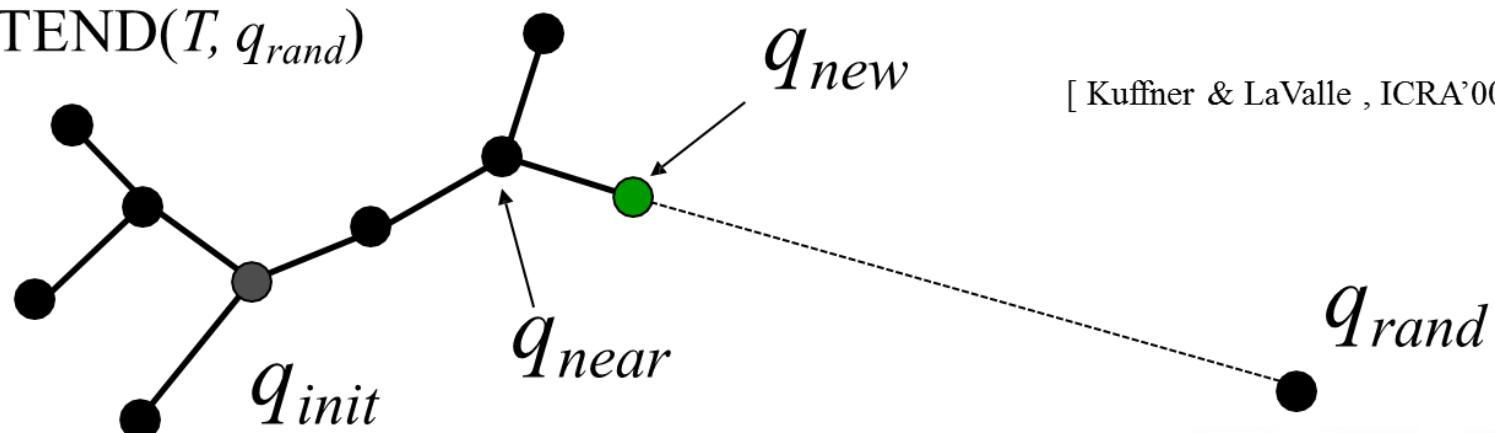
$q_{near} \leftarrow$  nearest vertex in tree  $T$  of  $q_{rand}$

$q_{new} \leftarrow$  new config by moving an incremental dist  $\Delta q$  from  $q_{near}$  in the direction of  $q_{rand}$

    Add vertex  $q_{new}$  to tree  $T$

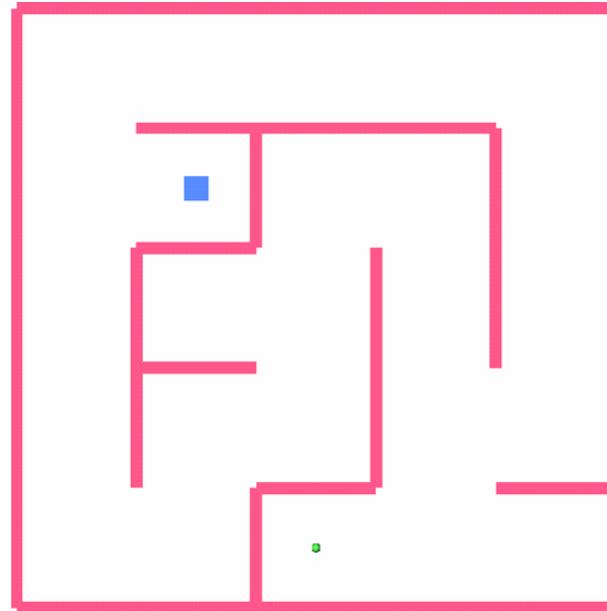
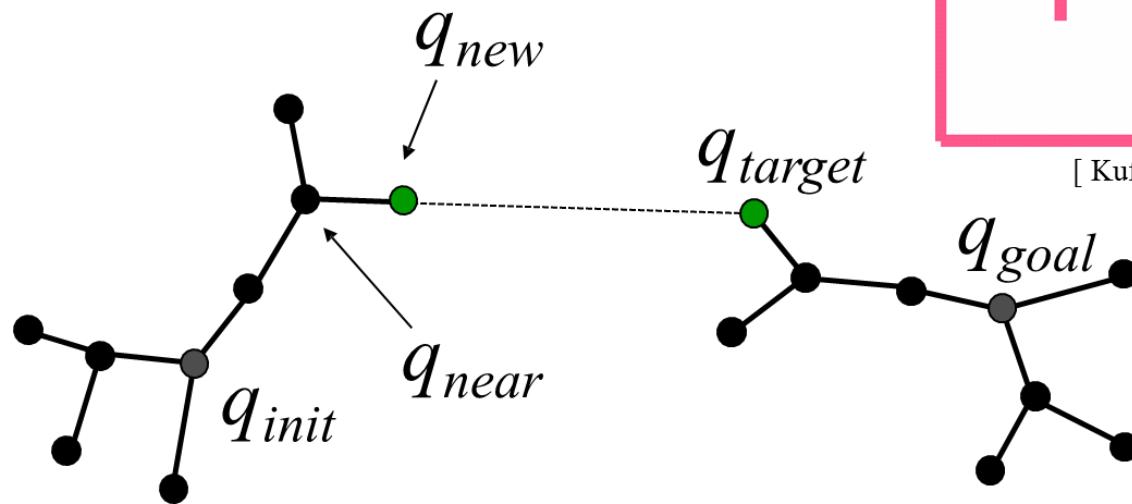
    Add edge  $(q_{near}, q_{new})$  to tree  $T$

$\text{EXTEND}(T, q_{rand})$



## Motion Planning: Tree-based Planners

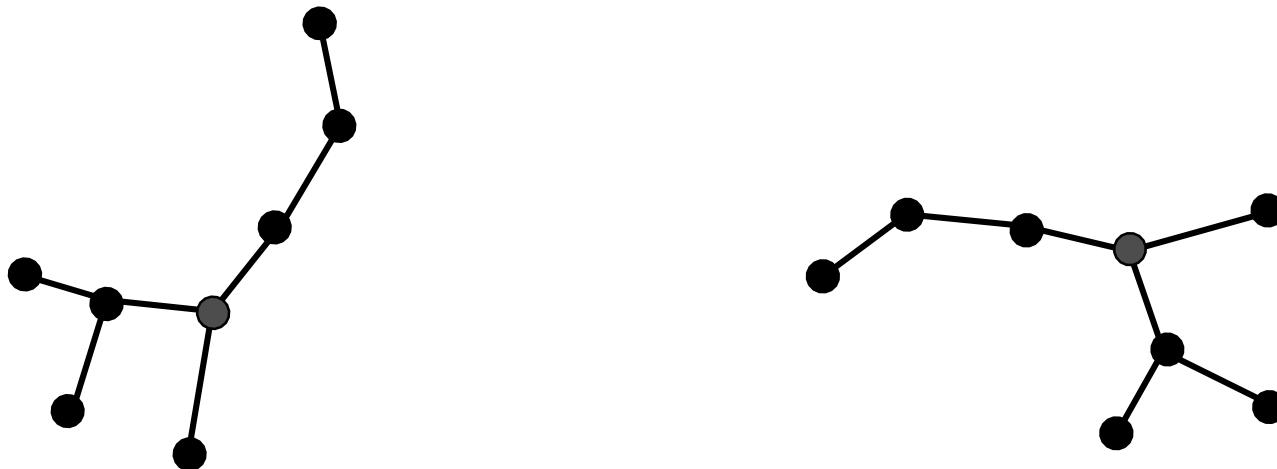
- Grow two RRTs towards each other



## Motion Planning: Tree-based Planners

- Grow two RRTs towards each other

A single RRT-Connect iteration..

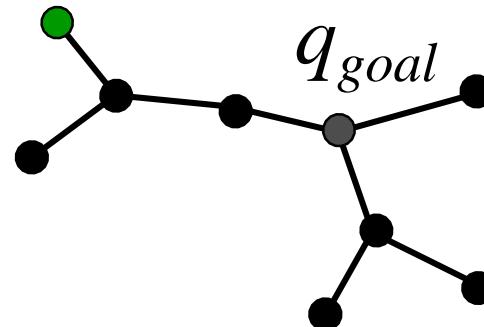
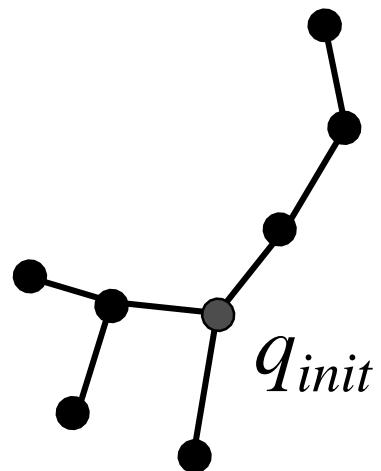


[ Kuffner & LaValle , ICRA'00]

# Motion Planning: Tree-based Planners

- Grow two RRTs towards each other

1) One tree grown using random target

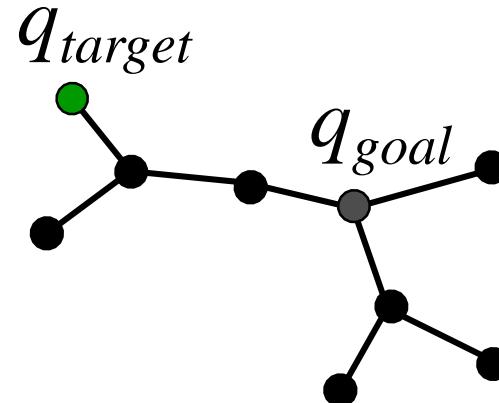
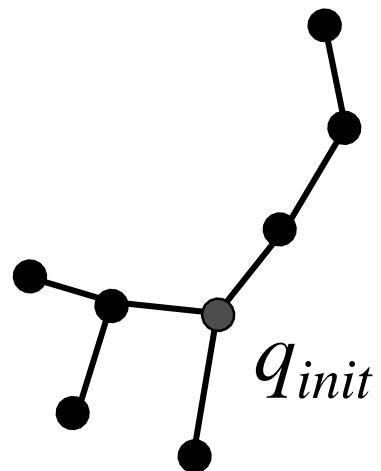


[ Kuffner & LaValle , ICRA'00]

## Motion Planning: Tree-based Planners

- Grow two RRTs towards each other

2) New node becomes target for other tree

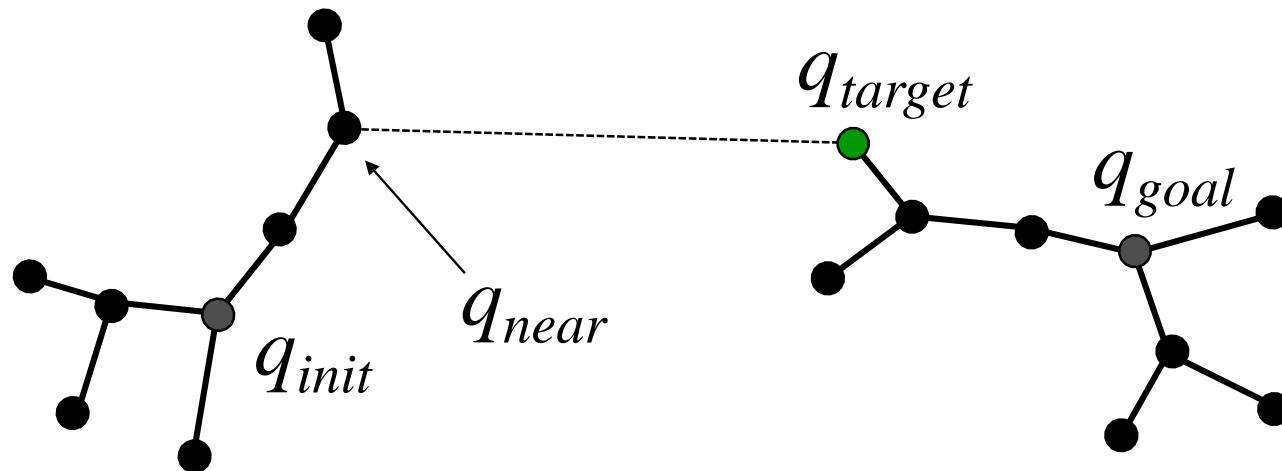


[ Kuffner & LaValle , ICRA'00]

## Motion Planning: Tree-based Planners

- Grow two RRTs towards each other

3) Calculate node “nearest” to target

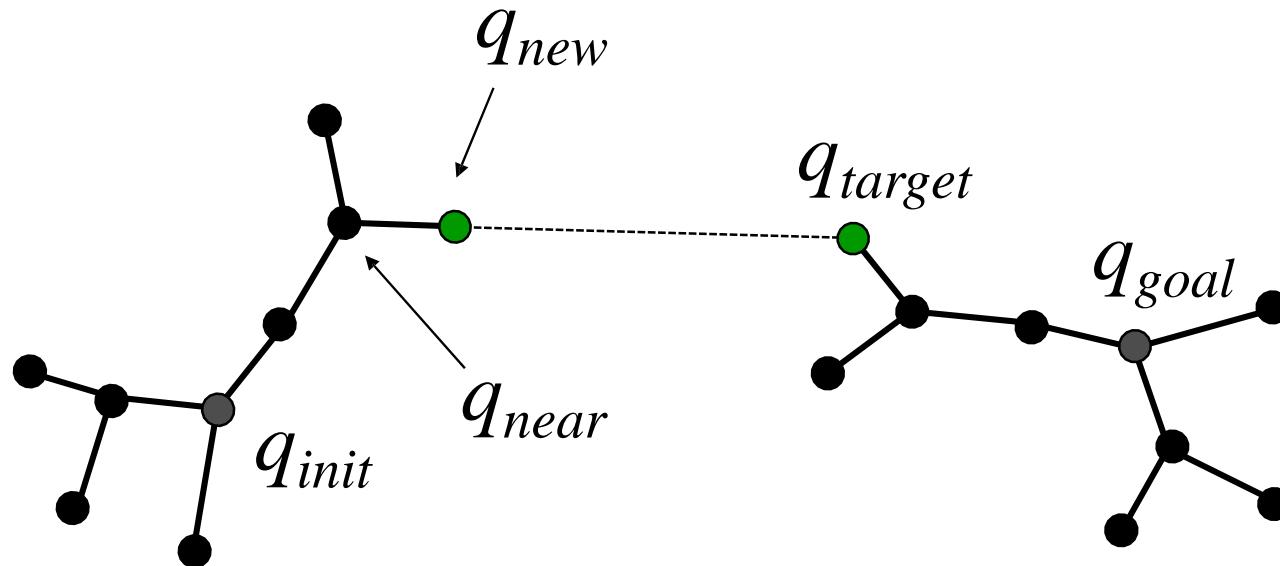


[ Kuffner & LaValle , ICRA'00]

## Motion Planning: Tree-based Planners

- Grow two RRTs towards each other

4) Try to add new collision-free branch

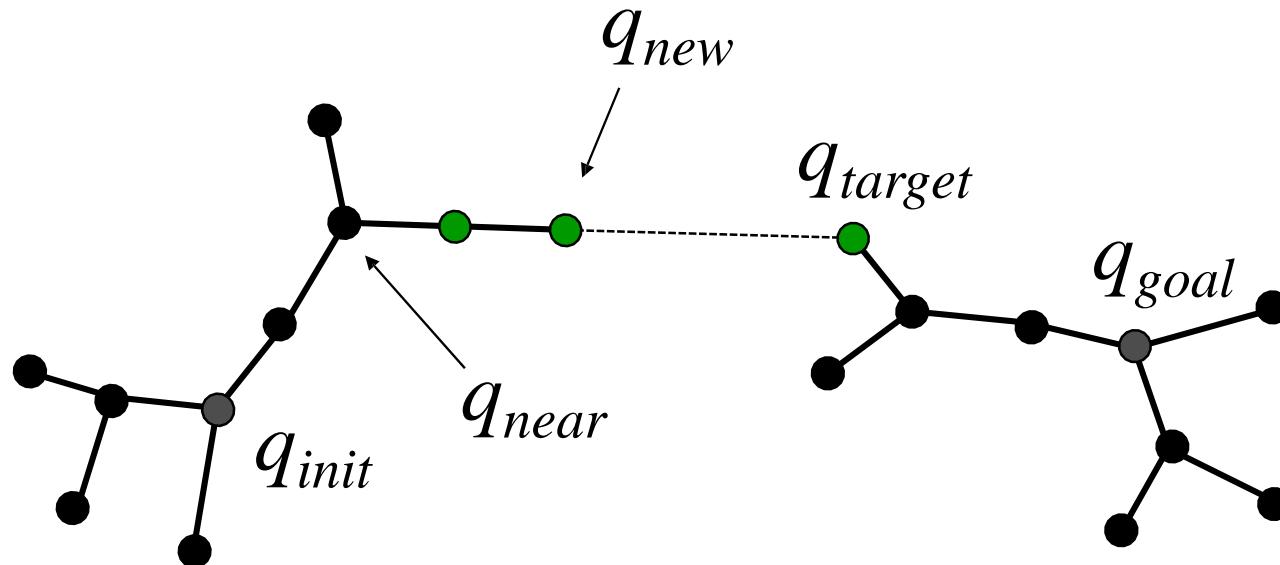


[ Kuffner & LaValle , ICRA'00]

## Motion Planning: Tree-based Planners

- Grow two RRTs towards each other

5) If successful, keep extending branch

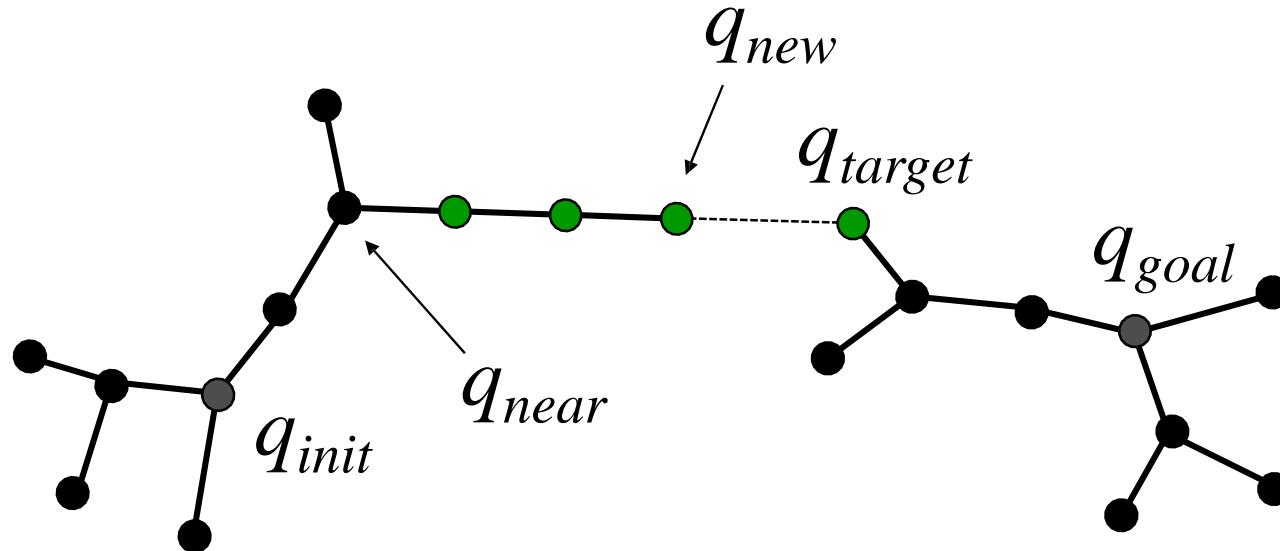


[ Kuffner & LaValle , ICRA'00]

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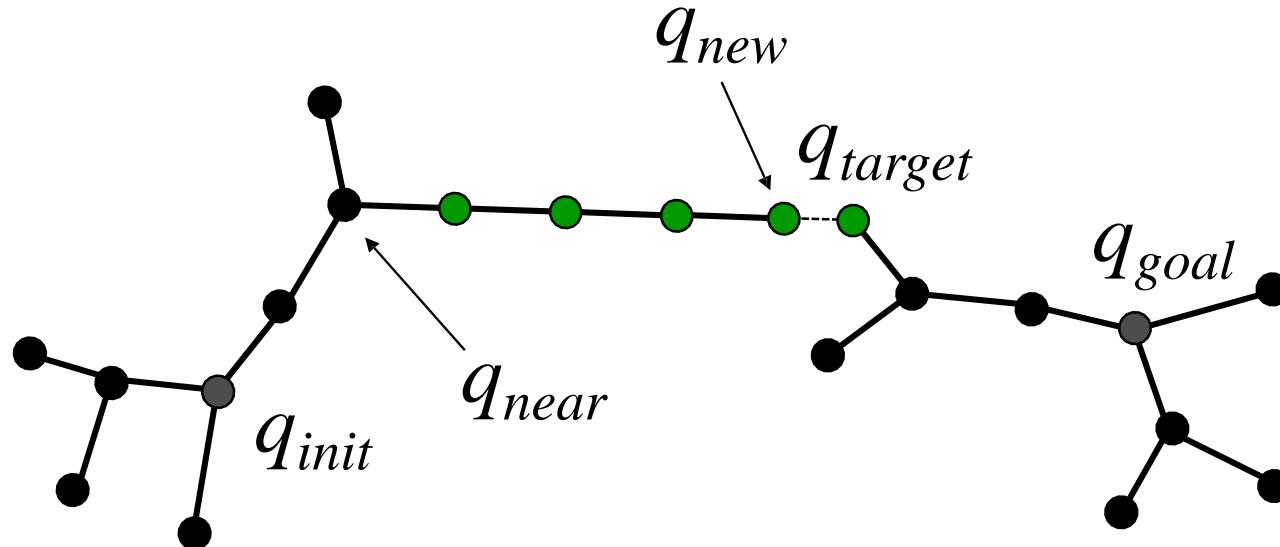


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## Motion Planning: Tree-based Planners

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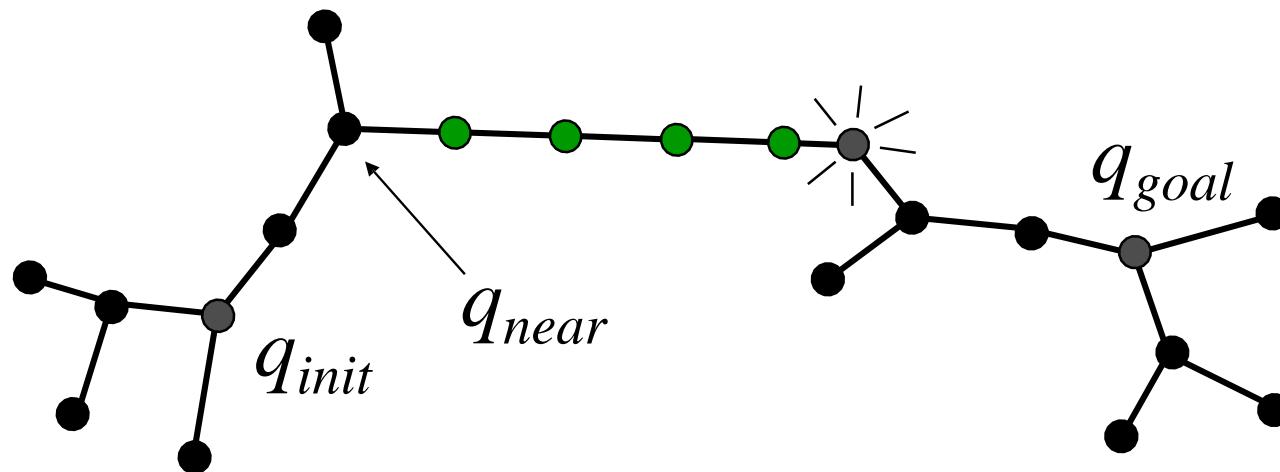


[ Kuffner & LaValle , ICRA'00]

## Motion Planning: Tree-based Planners

- Grow two RRTs towards each other

6) Path found if branch reaches target

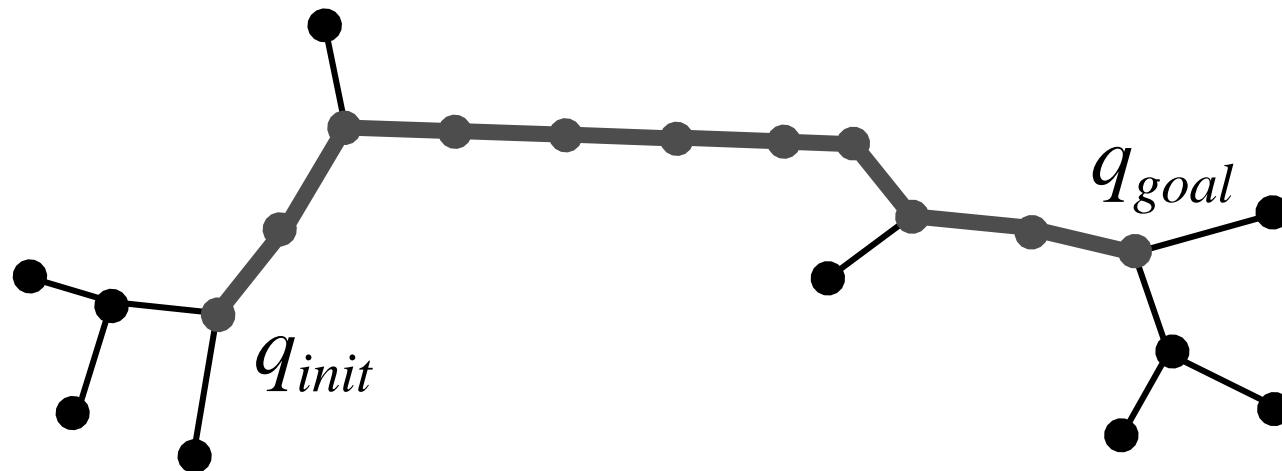


[ Kuffner & LaValle , ICRA'00]

## Motion Planning: Tree-based Planners

- Grow two RRTs towards each other

7) Return path connecting start and goal



[ Kuffner & LaValle , ICRA'00]

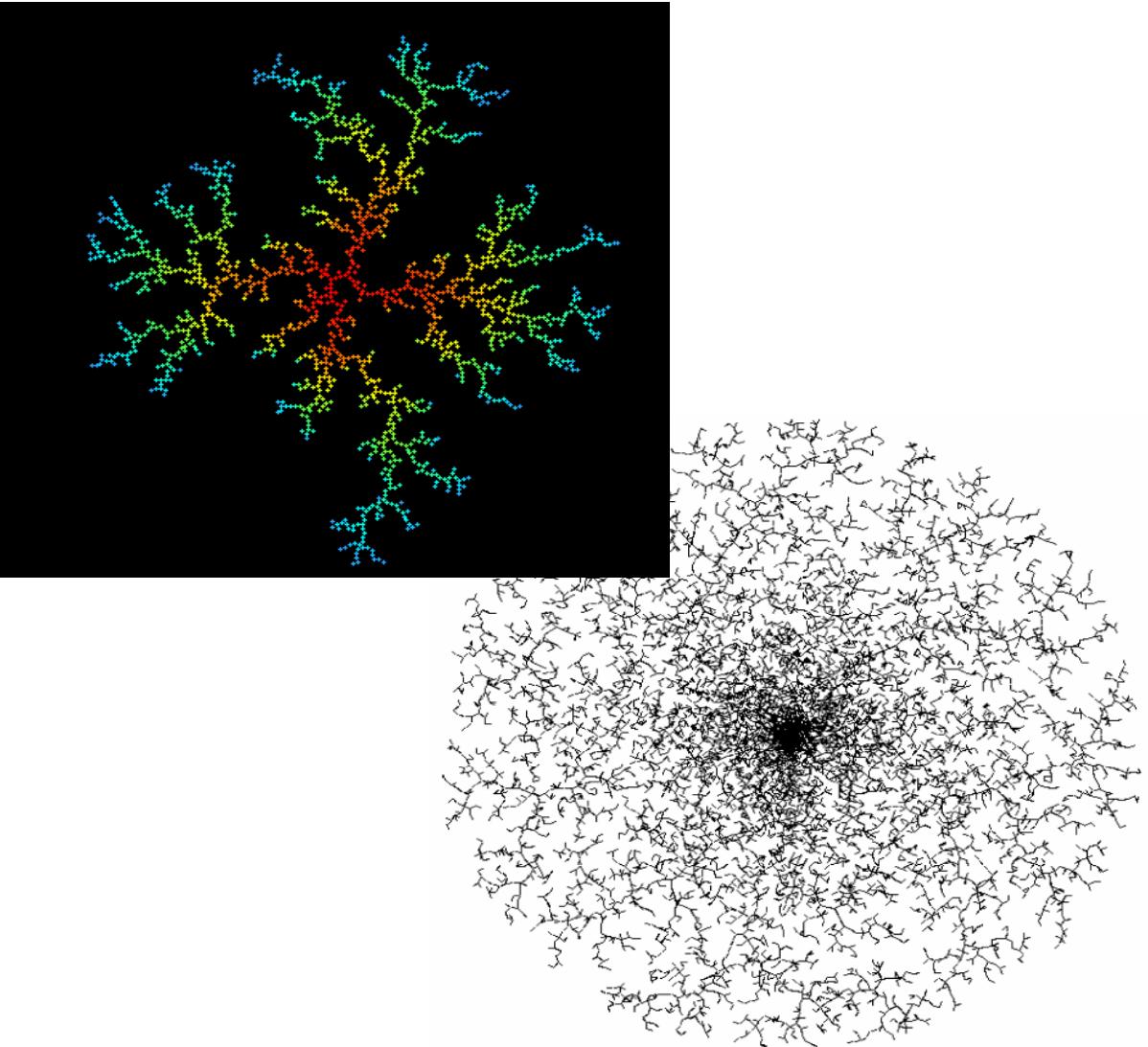
# Motion Planning: Tree-based Planners

## ■ Applications of RRTs

- Robotics Applications
  - mobile robotics
  - manipulation
  - Humanoids
- Other Applications
  - biology (drug design)
  - manufacturing and virtual prototyping (assembly analysis)
  - verification and validation
  - computer animation and real-time graphics aerospace

## ■ RRT Extensions

- discrete planning (STRIPS and Rubik's cube)
- real-time RRTs
- anytime RRTs
- dynamic domain RRTs
- deterministic RRTs
- parallel RRTs
- hybrid RRTs



## Review of Piano Mover's Problem

### Balancing Exploration and Exploitation in Sampling-Based Motion Planning

*"The piano mover's problem"*

Markus Rickert, Arne Sieverling, and Oliver Brock

fortiss GmbH, An-Institut Technische Universität München, München, Germany  
Robotics and Biology Laboratory, Technische Universität Berlin, Berlin, Germany

*IEEE Transactions on Robotics*

# Motion Planning: Tree-based Planners

## Did we concern the Real World? Not Really!

- Robots in Real World
  - Have inertia (not a point)
  - Have limited controllability (nonholonomic motion)
  - Have limited sensors
  - Face a dynamic environment
  - Face an unreliable environment



# Motion Planning: Tree-based Planners

## Kinodynamic Motion Planning

- **Kinodynamic Motion Planning:** Takes dynamic constraints into account (i.e. velocity, acceleration, friction, bounded forces)
  - Important for realistic robots
  - Enables motion planning for complex dynamics (e.g. complex environment)
- Challenges
  - Dimensionality of the state space is typically higher because dynamics (velocity, acceleration, ...) are included in the state space
  - State space may not be entirely reachable from the robot's initial state
  - Difficult to define a meaningful metric for these complex state spaces



# Motion Planning: Tree-based Planners

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## Kinodynamic Motion Planning by Interior-Exterior Cell Exploration (KPIECE)

- **KPIECE:**

- Addresses previously mentioned challenges
  - Uses a physic simulation to create motion samples

- Design goals

- Ease of use for systems where only forward propagation is available (simulation can be done forward in time)
  - No state sampling and distance metric is required
  - For complex systems, described by physical models (instead of equations of motions)

- Advantages

- Fast and accurate
  - Is applicable in real-time motion planning

## Kinodynamic Motion Planning by Interior-Exterior Cell Exploration (KPIECE)

### Definition: KPIECE Motion Planning P

A KPIECE motion planning problem is defined as a tuple  $\langle Q, U, I, F, f \rangle$

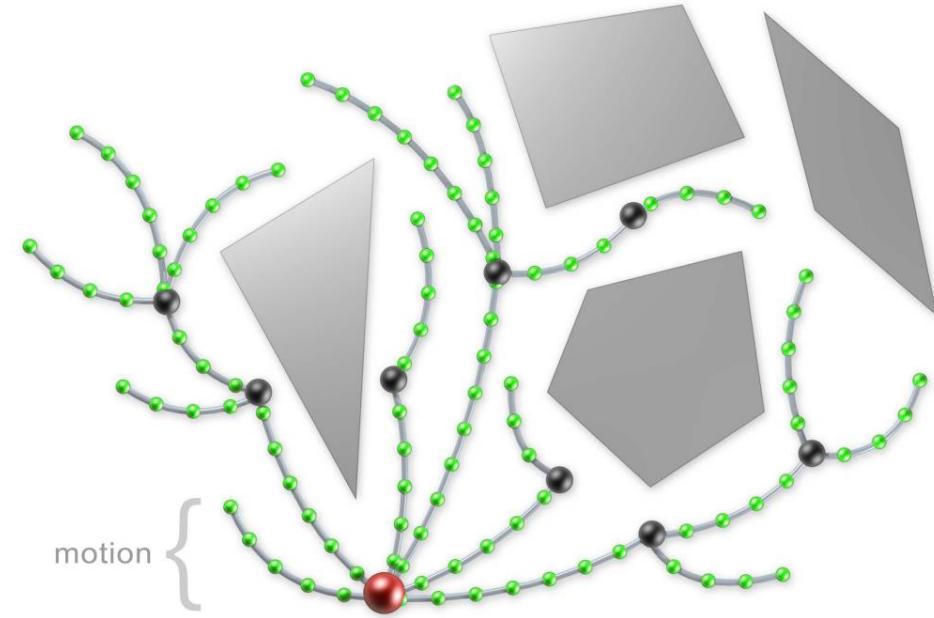
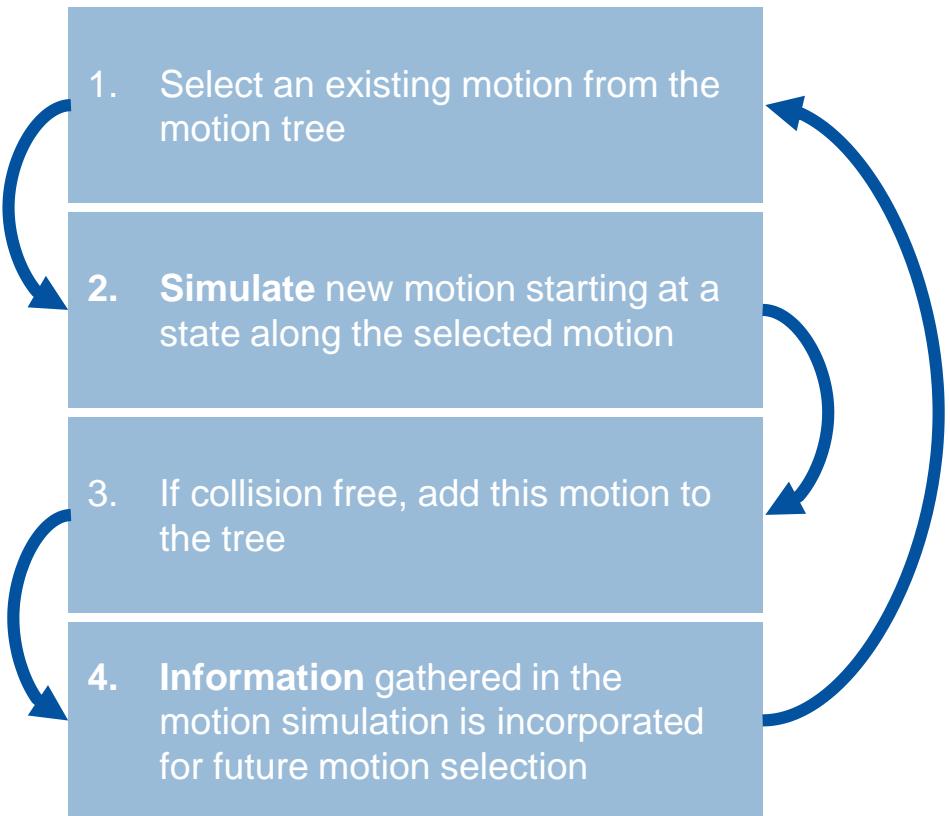
- $Q$  is the state space
- $U$  is the control space
- $I \in Q$  is the set of initial states
- $F \in Q$  is the set of final states
- $f$  is the dynamics (forward propagation routine)

A solution to this motion planning problem consists of a sequence of controls  $u_1, \dots, u_n$  and time  $t_1, \dots t_n$

# Motion Planning: Tree-based Planners

## KPIECE: High-Level Description of the algorithm

- Iterative Construction of a tree of motions in state space of the robot.
- Motion  $\mu = (s, u, t)$ ,  $s \in Q, u \in U, t \in \mathbb{R}^{\geq 0}$



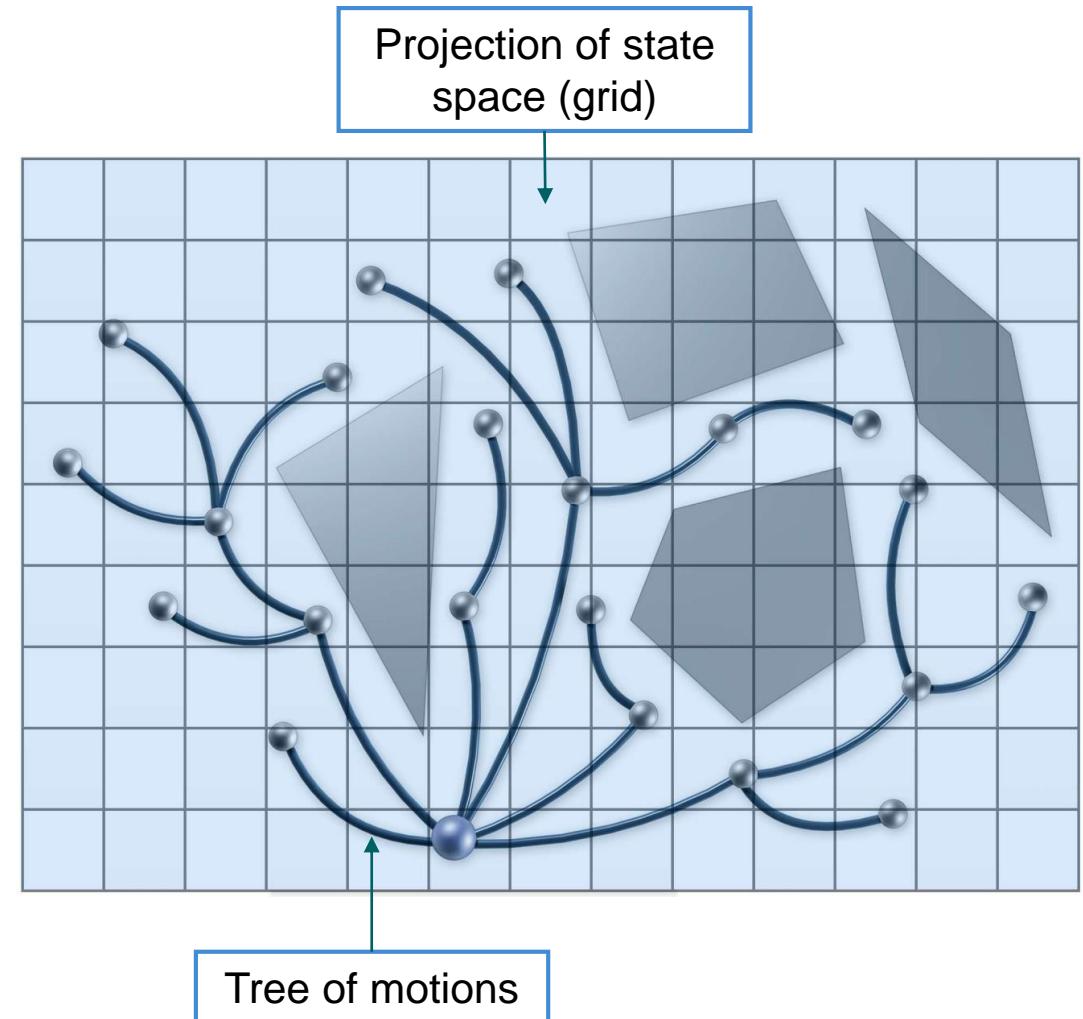
Tree of motions as grown by KPIECE. The states of the start of motions are depicted as larger vertices. The motion is computed by forward integration at fixed step size.

# Motion Planning: Tree-based Planners

## KPIECE: Estimating State Space Coverage

Which samples to create?

- Key difficulty
  - Avoiding over-exploration of certain regions
  - Avoiding under-exploration of other regions
- **Idea:** Employ a projection of the state space  
Assumption: if the tree of motions covers the projection well, it also covers the state space
- How to define the projection?



# Motion Planning: Tree-based Planners

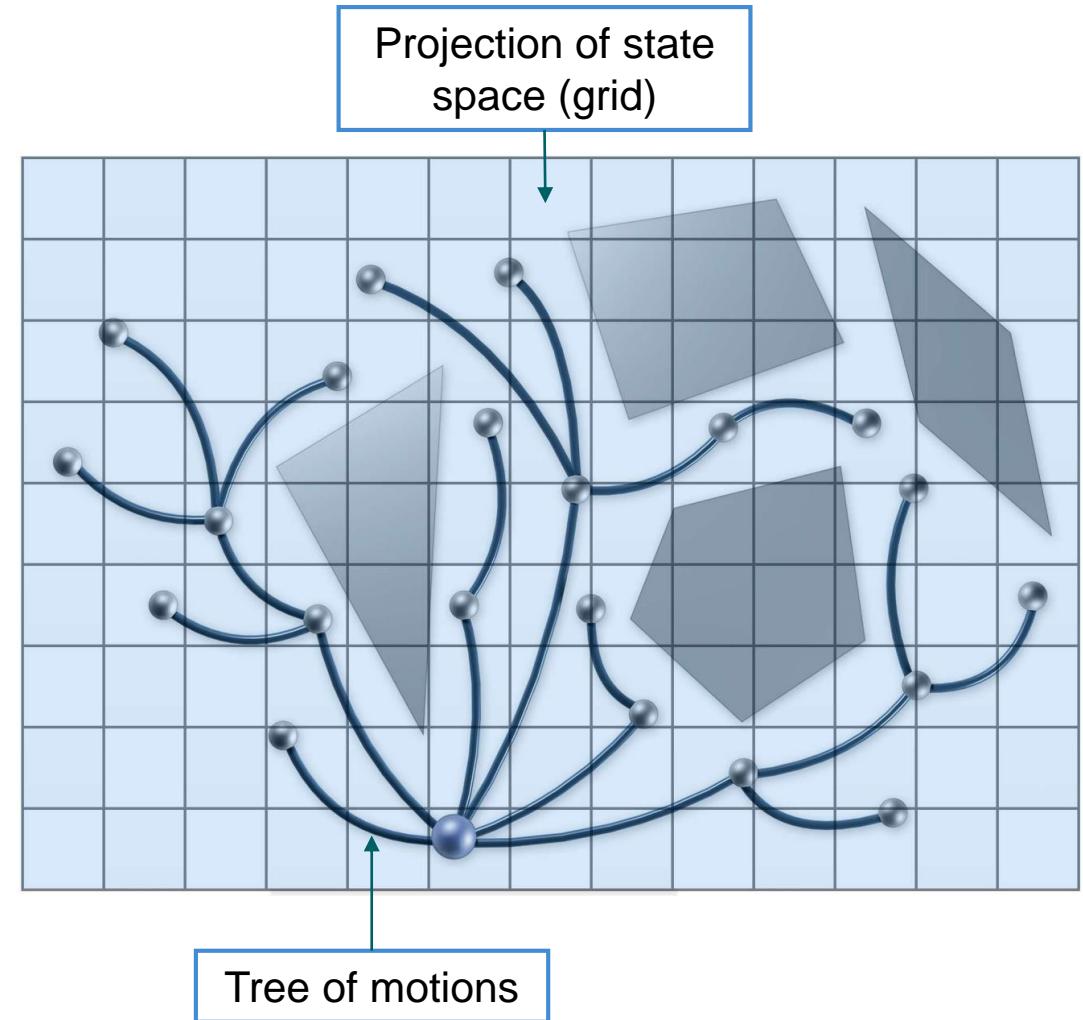
## KPIECE: State Space Coverage

- KPIECE carefully selects motions for further expansion

Selection strategy is based on estimating the **coverage** of the state space that the tree of motions achieves

- Experiments shown that projection is often easy to specify manually
- An algorithm for calculating the projection is also available

[Sucan, Ioan Alexandru. Task and motion planning for mobile manipulators. Diss. Rice University Houston, 2011]

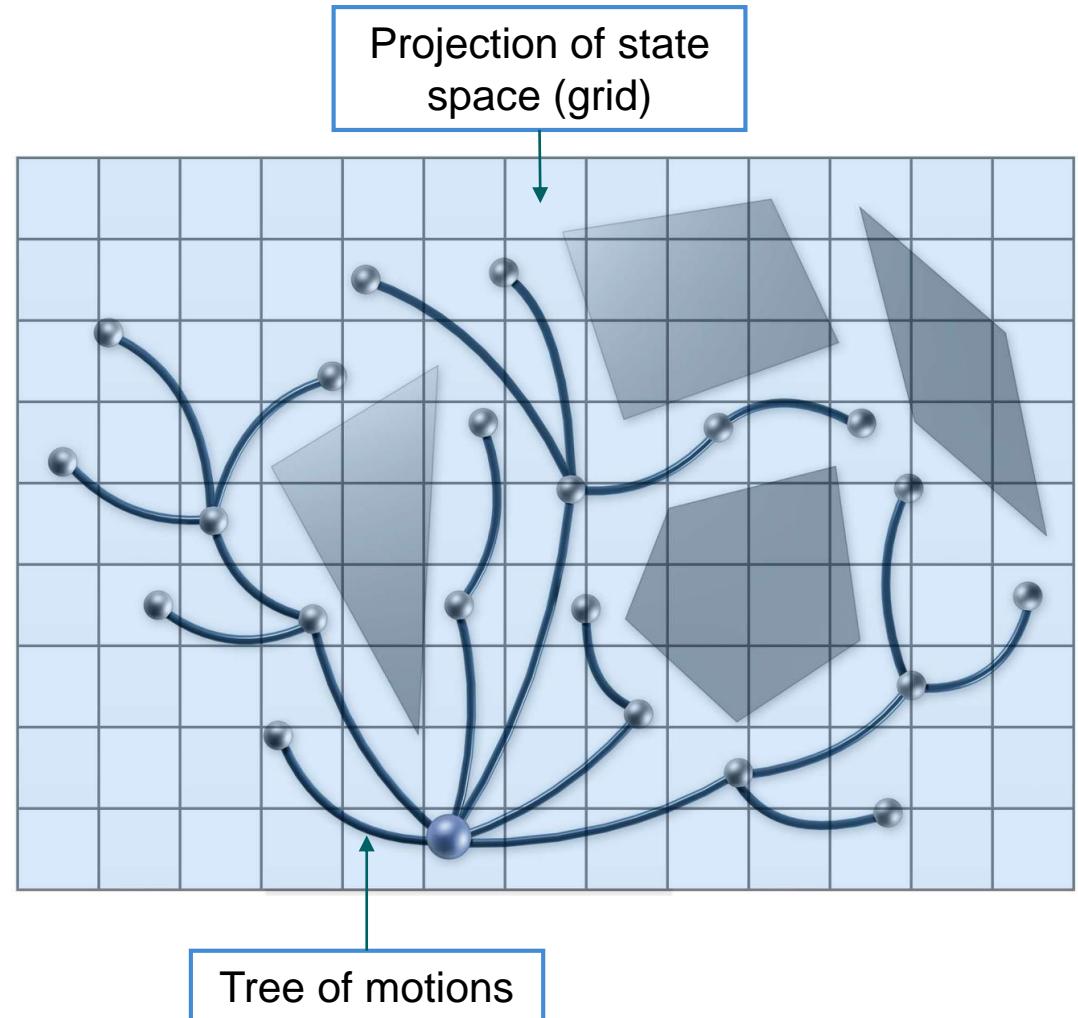


# Motion Planning: Tree-based Planners

## Find the shortest path between two points

We assume to have a motion tree

- How to find a path starting at the current state to a goal state?
- This is done by standard search algorithms (similar to navigation system in cars)
  - Breadth- and depth-search
  - Variant of A\*-Algorithm
  - ...



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# Motion Planning in Practical

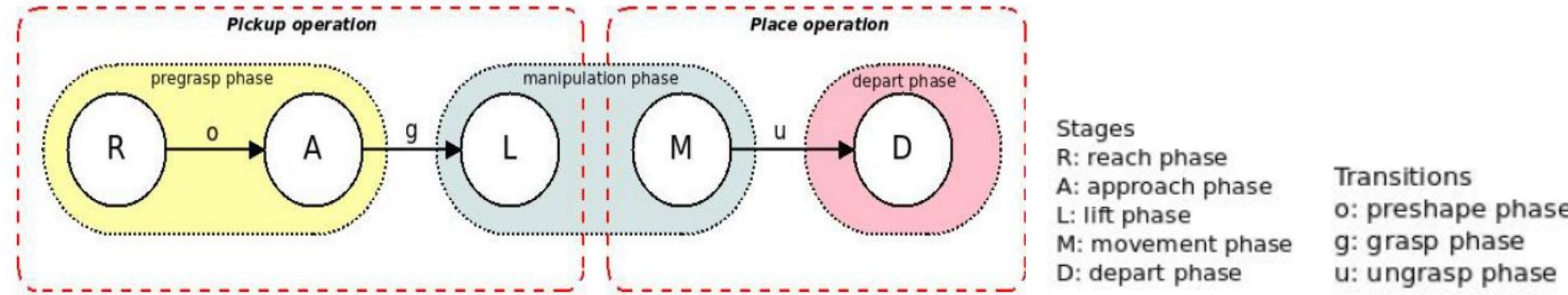
## Pick and Place Tasks

- Common task in industry
- Take an object at position A and bring it to position B



# Motion Planning in Practical

## Pick and Place Tasks: Robot vs. Human



### 1. Pregrasp phase

- Phase starts at an arbitrary robot configuration
- Gripper is moved towards the grasp location

### 2. Grasp phase

- The gripper gets in contact with the object and closes

### 3. Manipulation phase

- The grasped object is enclosed by the gripper
- The object is translated towards the place location by enforcing path constraints

### 4. Ungrasp phase

- The gripper releases the object

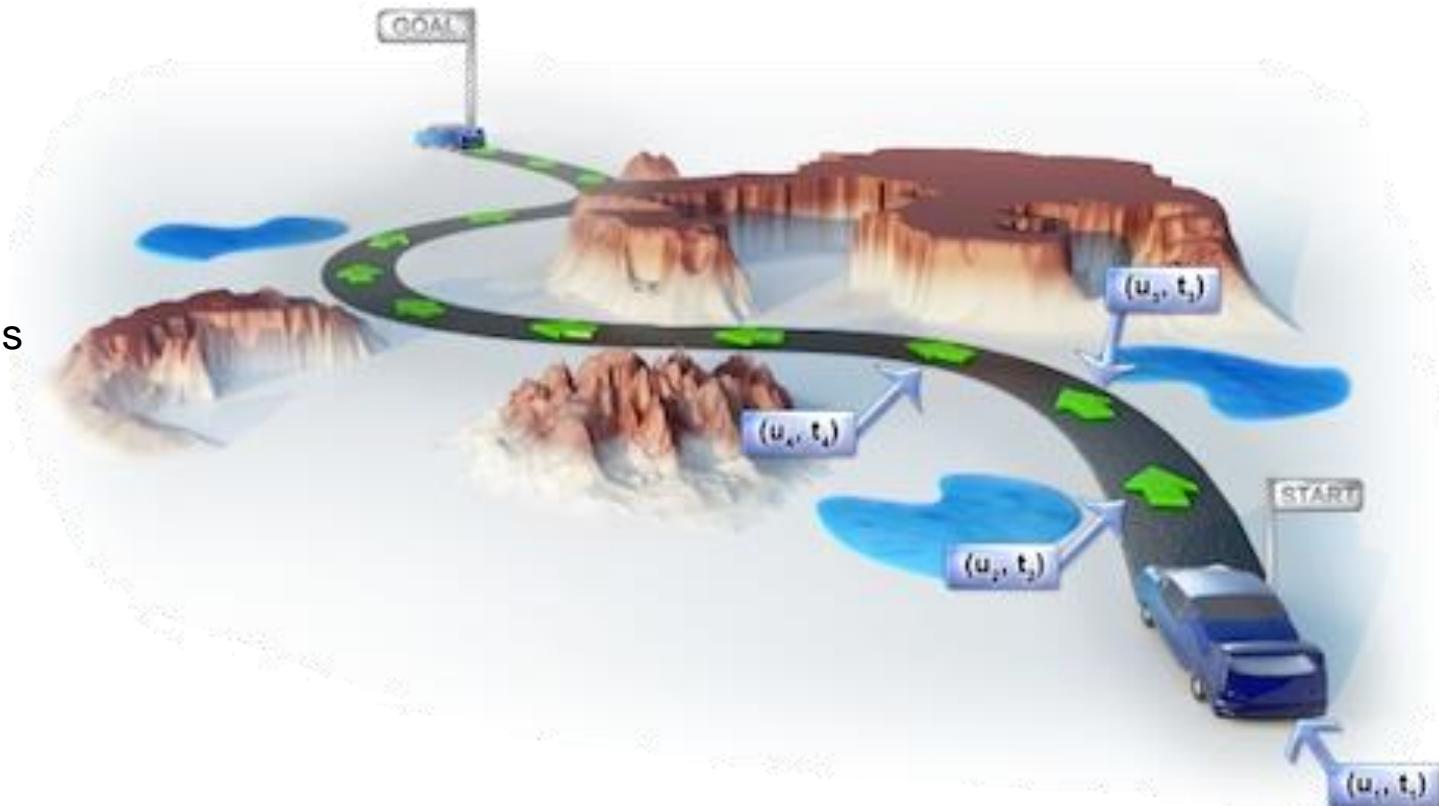
### 5. Depart phase

- The manipulator retreats from the object

# Motion Planning in Practical

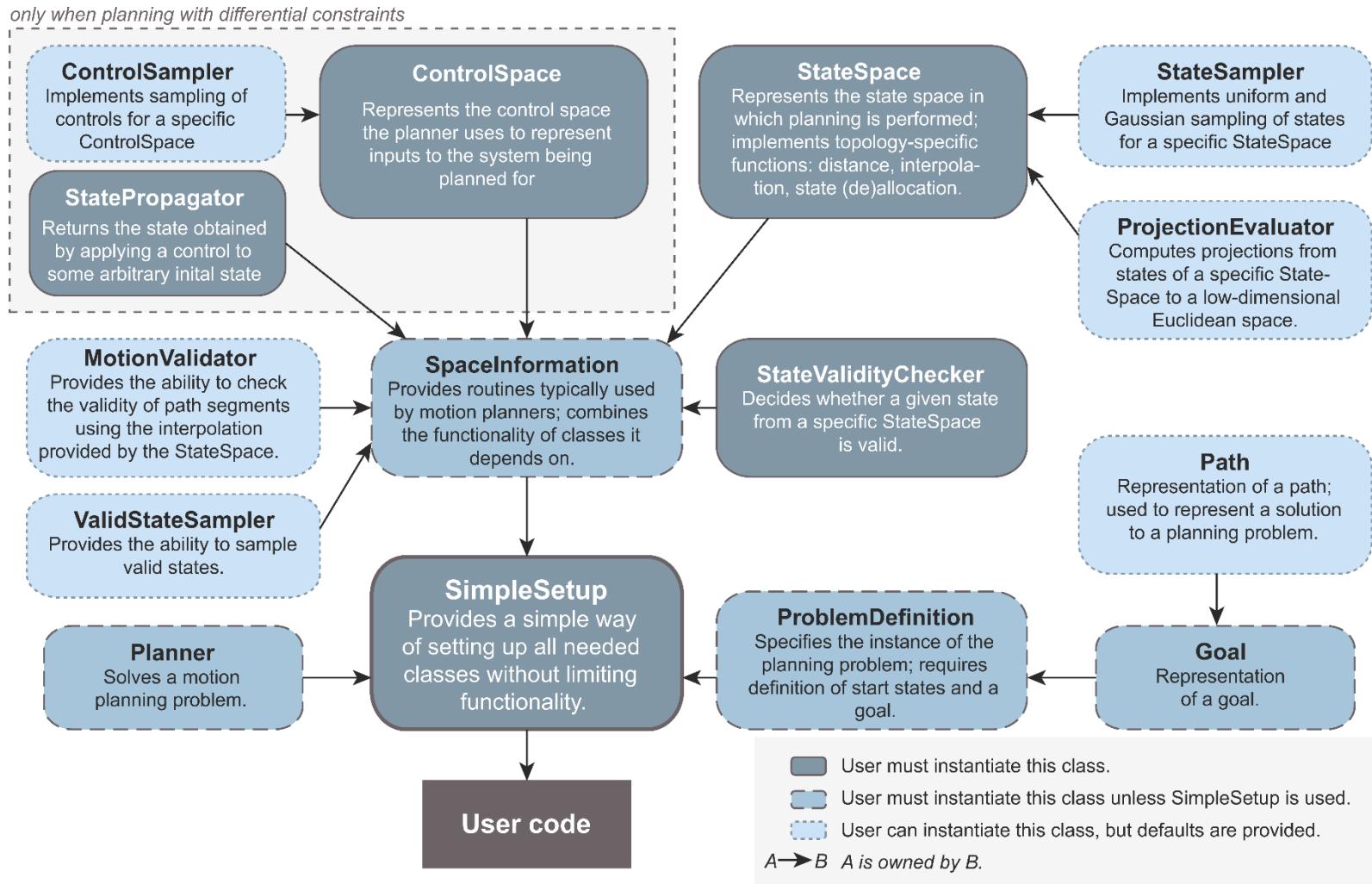
## The Open Motion Planning Library (OMPL)

- Open Source Implementation of many sampling-based algorithms and core low-level data structures
- C++ with Python Bindings
- For Academic and industrial Settings
  
- Conceptual Overview of OMPL:
  - Efficiency
  - Simple integration with other software packages
  - Straightforward integration of external contributions
  - Clarity of Concepts



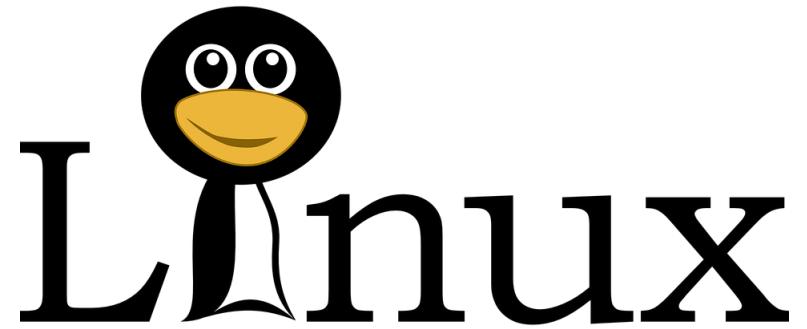
# Motion Planning in Practical

# The Open Motion Planning Library (OMPL)



## What is coming?

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ROS



Open Source Robotics Foundation

 **MoveIt!**  
*moving robots into the future*  
[moveit.ros.org](http://moveit.ros.org)



## Outline

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2 Lunch Time	12:10 – 14:30

**Enjoy your Lunch  
and  
See you later!**