

# CSCI/ECEN 3302

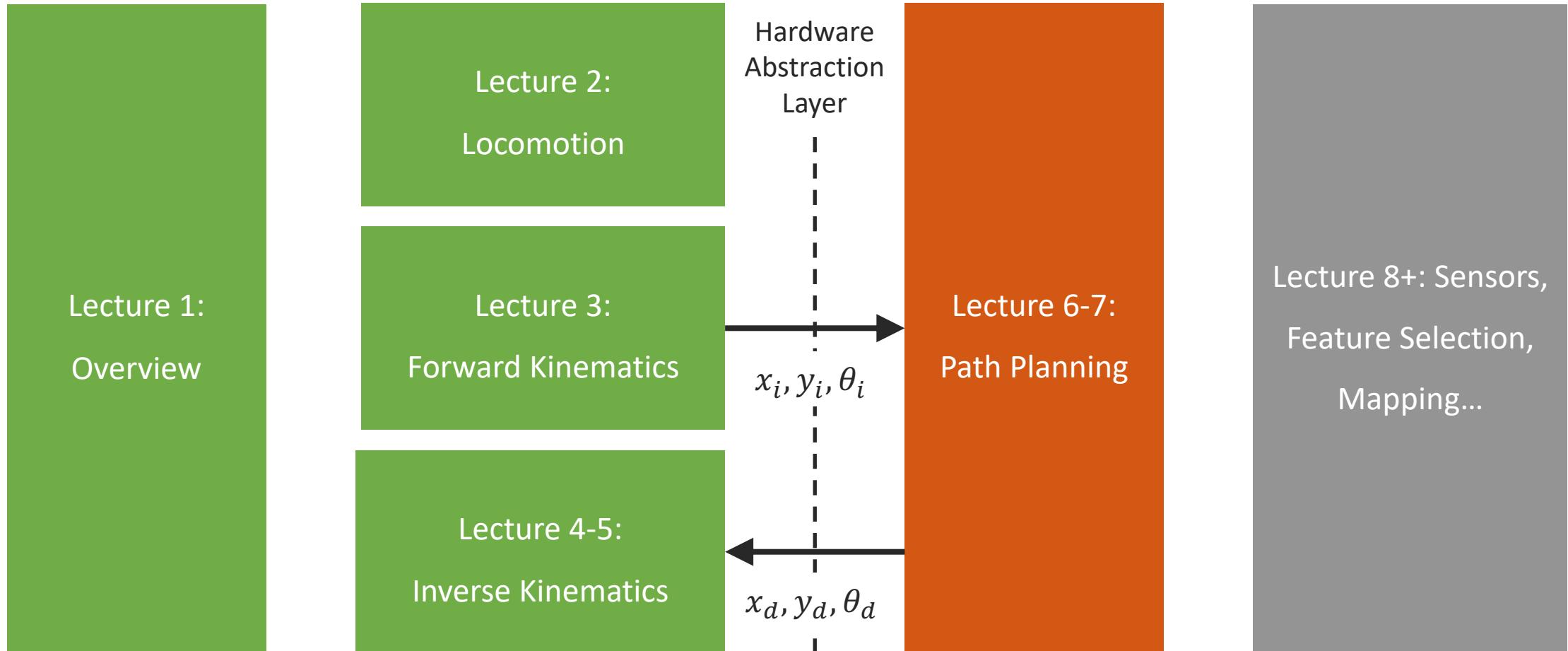
## Introduction to Robotics

Nikolaus Correll, Bradley Hayes, Chris Heckman  
and Alessandro Roncone

# Administrivia

- Lab 3: Inverse Kinematics – Lecture 5 content
  - Deadline **October 4th**
- Lab 4: Mapping – Lecture 6 (today) content
  - One week long
- Homework 2 is out!

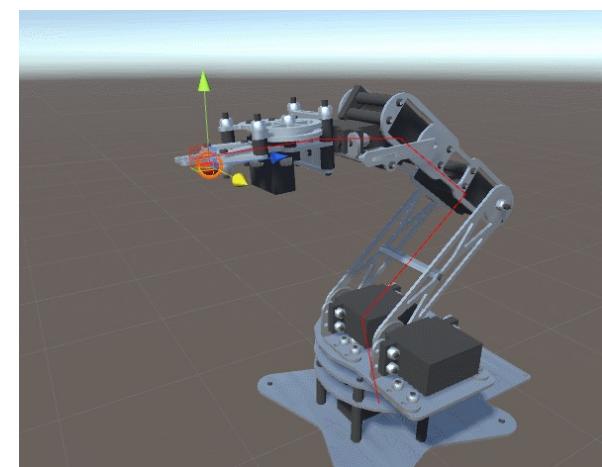
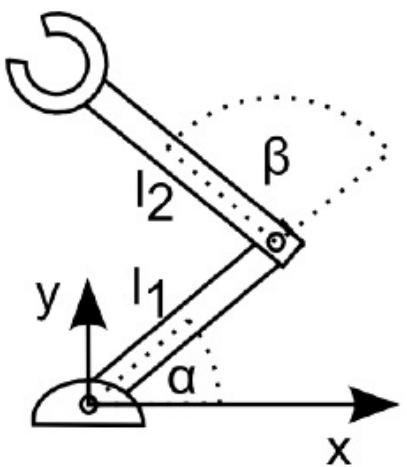
# Roadmap



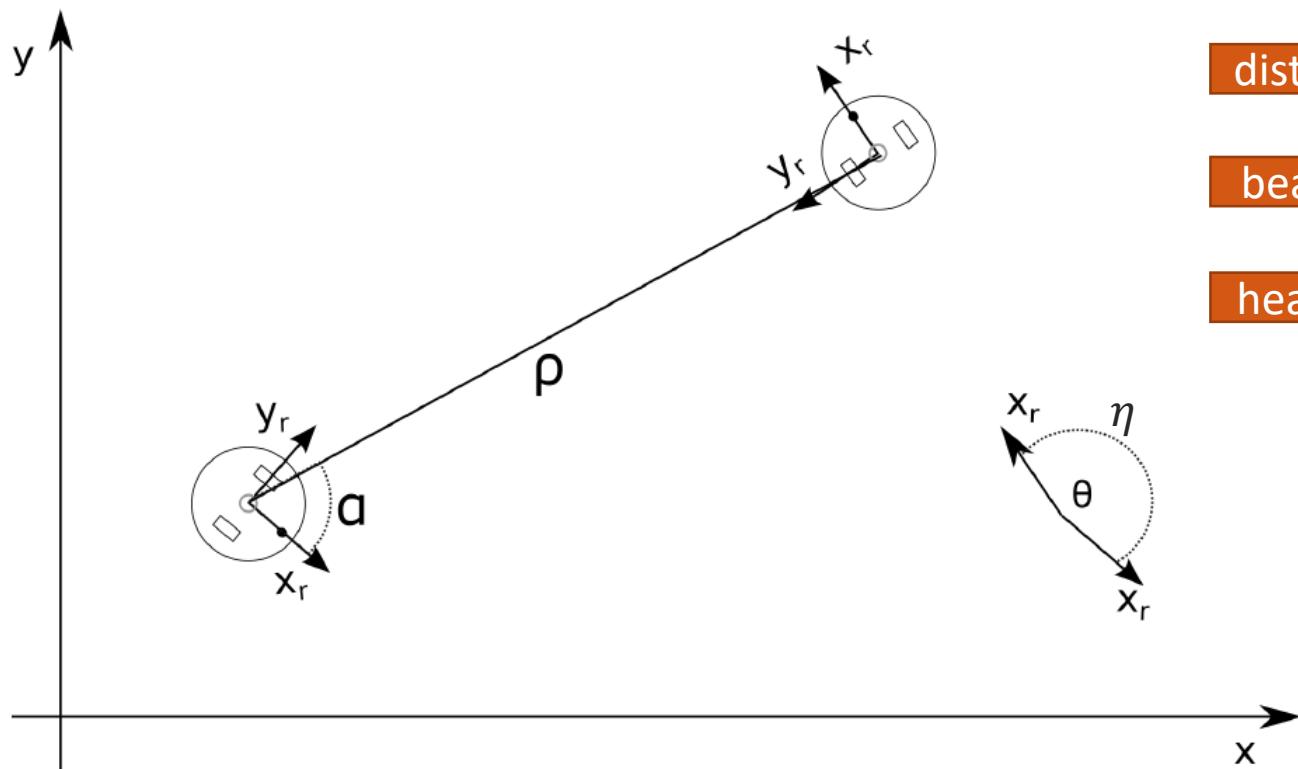
Chapters 12-13

# RECAP

## Motion and Trajectory Planning



# Position Change Using Feedback Control



## Error Terms

**distance**  $\rho = \sqrt{(x_r - x_g)^2 + (y_r - y_g)^2}$

**bearing**  $\alpha = \tan^{-1} \left( \frac{y_g - y_r}{x_g - x_r} \right) - \theta_r$

**heading**  $\eta = \theta_g - \theta_r$

## Update Rules

**translation**  $\dot{x} = p_1 \rho$

**rotation**  $\dot{\theta} = p_2 \alpha + p_3 \eta$

$p_1, p_2, p_3$  are controller gains

# Jacobian: relate joint to operational velocities

$$\begin{bmatrix} \dot{x}_R \\ \dot{\theta}_R \end{bmatrix} = \begin{bmatrix} \frac{r\dot{\phi}_l}{2} + \frac{r\dot{\phi}_r}{2} \\ \frac{\dot{\phi}_r r}{d} - \frac{\dot{\phi}_l r}{d} \end{bmatrix} = \begin{bmatrix} \frac{r}{2} & \frac{r}{2} \\ -\frac{r}{d} & \frac{r}{d} \end{bmatrix} \begin{bmatrix} \dot{\phi}_l \\ \dot{\phi}_r \end{bmatrix} = \begin{bmatrix} \frac{\partial \dot{x}_R}{\partial \dot{\phi}_l} & \frac{\partial \dot{x}_R}{\partial \dot{\phi}_r} \\ \frac{\partial \dot{\theta}_R}{\partial \dot{\phi}_l} & \frac{\partial \dot{\theta}_R}{\partial \dot{\phi}_r} \end{bmatrix} \begin{bmatrix} \dot{\phi}_l \\ \dot{\phi}_r \end{bmatrix}$$

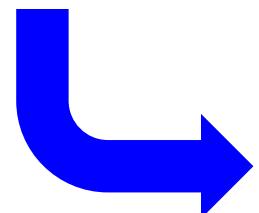
$$\frac{dp_e}{dt} = J \frac{dq}{dt}$$



# Inverse kinematics

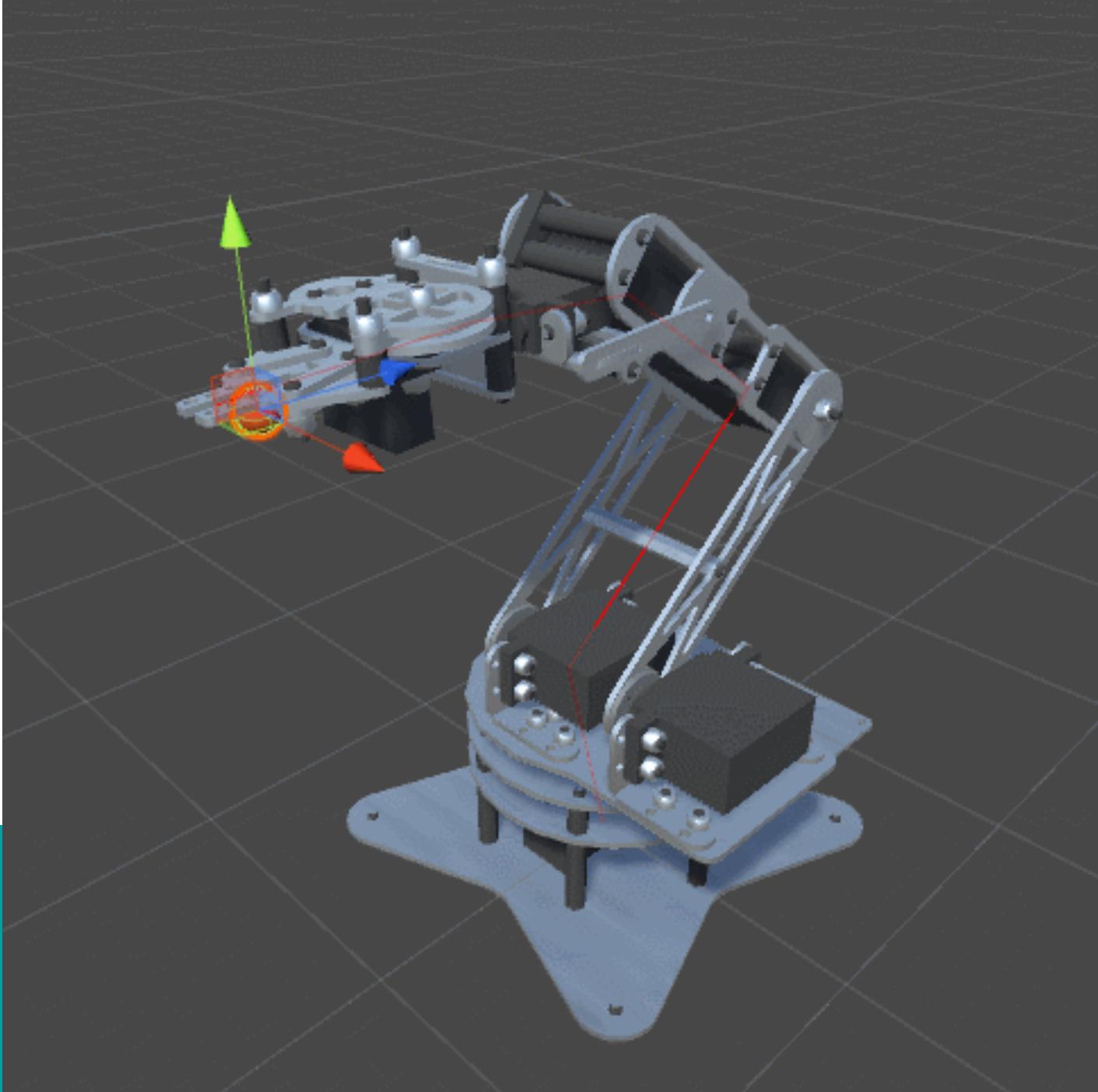
$$\begin{bmatrix} \dot{x}_R \\ \dot{\theta}_R \end{bmatrix} = \begin{bmatrix} \frac{r}{2} & \frac{r}{2} \\ -\frac{r}{d} & \frac{r}{d} \end{bmatrix} \begin{bmatrix} \dot{\phi}_l \\ \dot{\phi}_r \end{bmatrix}$$

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$



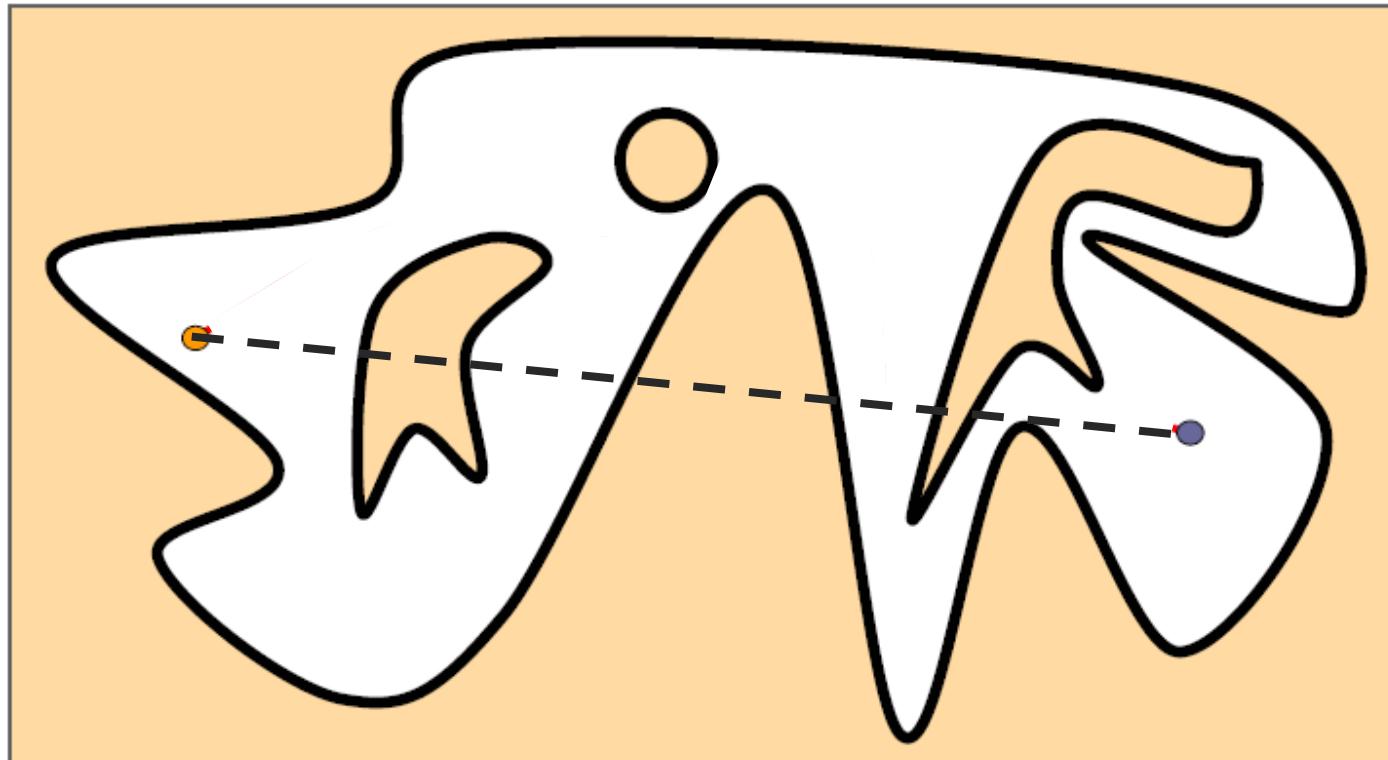
$$\begin{bmatrix} r & r \\ \frac{r}{2} & \frac{r}{2} \\ -\frac{r}{d} & \frac{r}{d} \end{bmatrix}^{-1} \begin{bmatrix} \dot{x}_R \\ \dot{\theta}_R \end{bmatrix} = \begin{bmatrix} \dot{\phi}_l \\ \dot{\phi}_r \end{bmatrix} = \frac{1}{r} \begin{bmatrix} 1 & -d/2 \\ 1 & d/2 \end{bmatrix} \begin{bmatrix} \dot{x}_R \\ \dot{\theta}_R \end{bmatrix}$$

Why we need planning?  
Joint Angle Limitation  
Problems!



How do we fix this?

# Why we need planning? Obstacles.



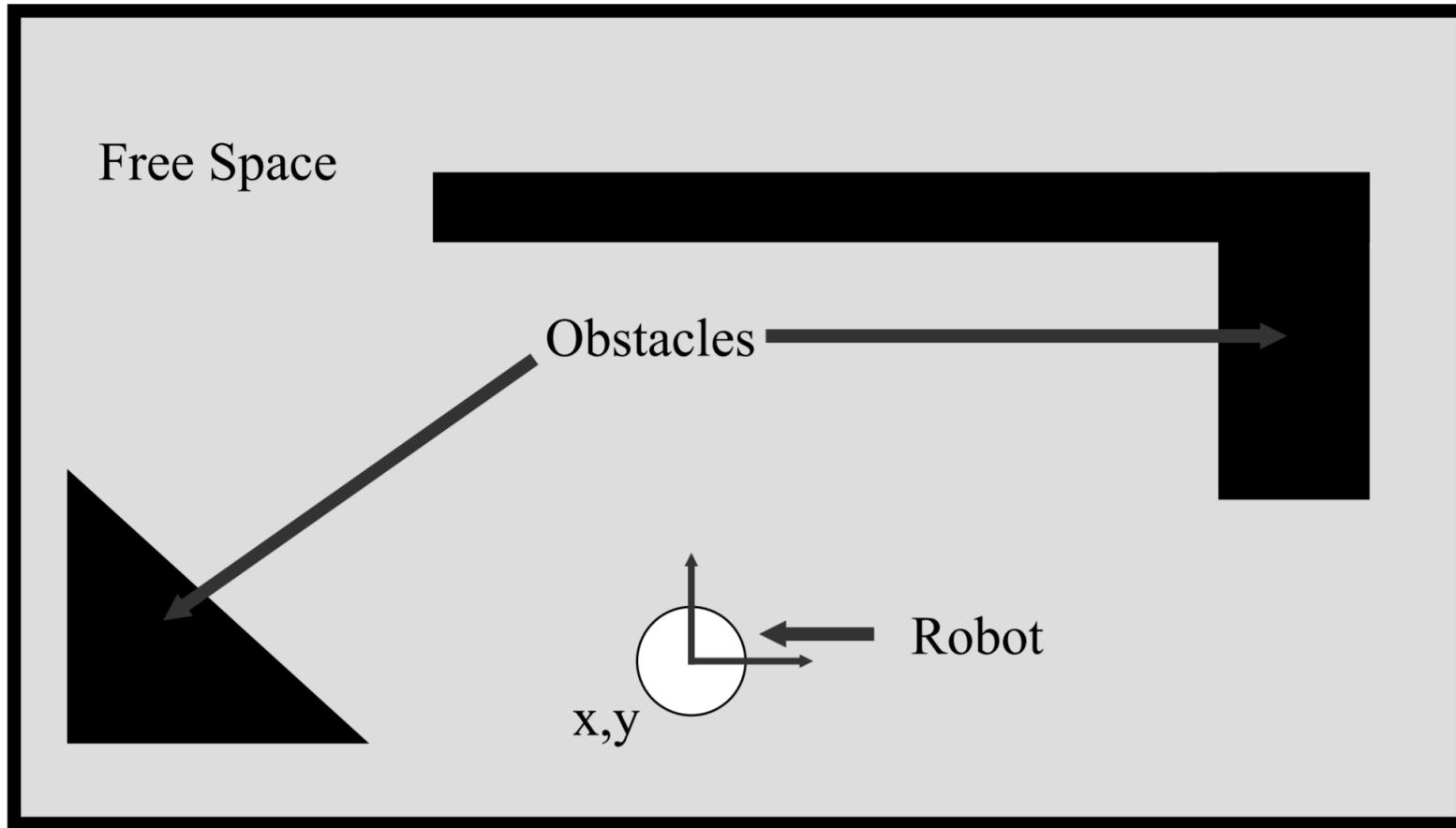
Using distance and angle as "error" is not sufficient anymore.

# Motion Planning

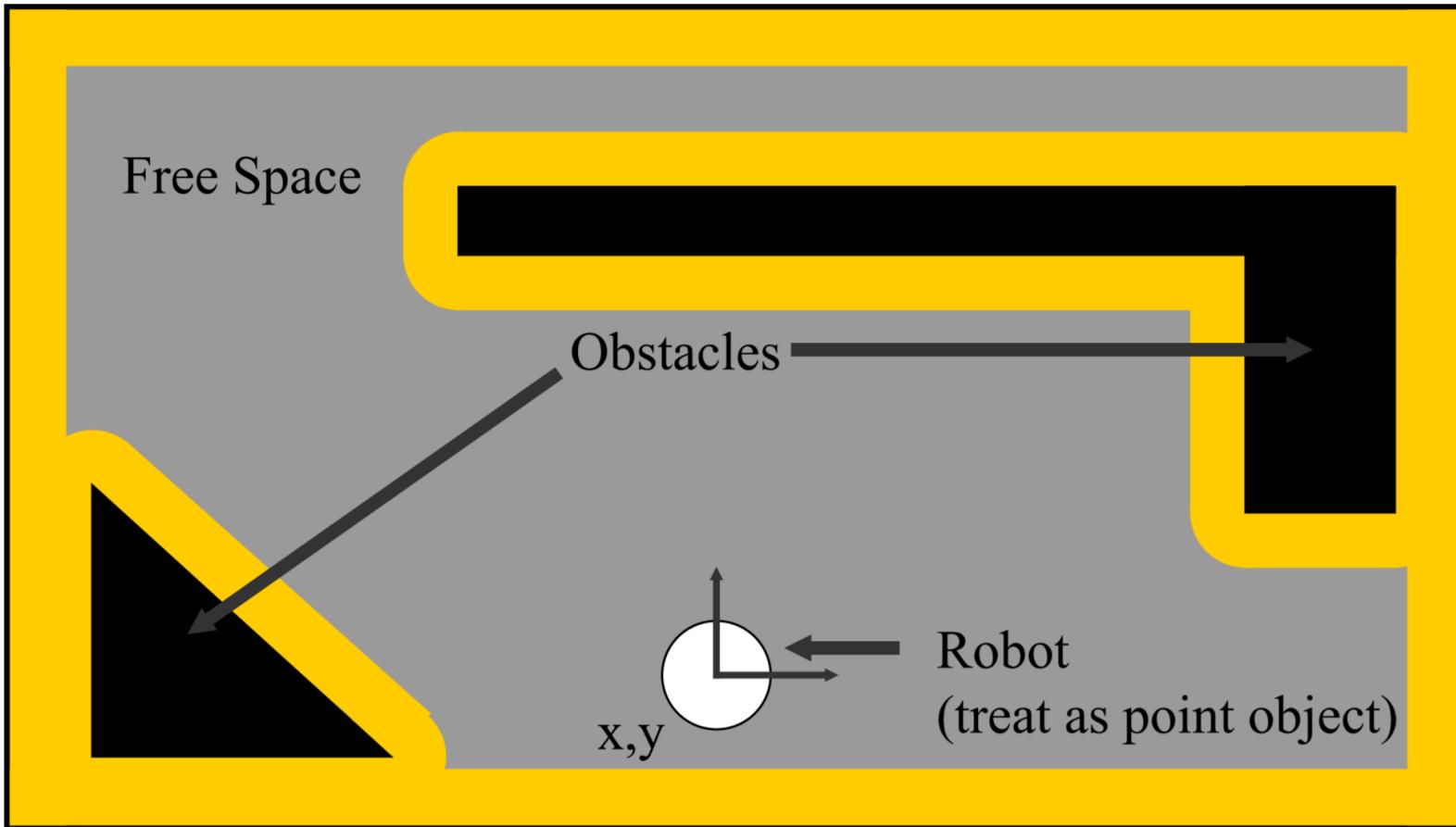
- **Goal:** Find a trajectory in configuration space from one point to another
  - A trajectory is usually denoted as  $\xi: t \in [0, T] \rightarrow C$
  - *(A function mapping time to robot configurations)*
- The Bad News:
  - All complete search algorithms scale exponentially!!
  - Motion planning problems are high dimensional, e.g., big exponent.

Trajectory: execution of path  $r$  over time  $r(t)$

# Configuration Space (operational space)



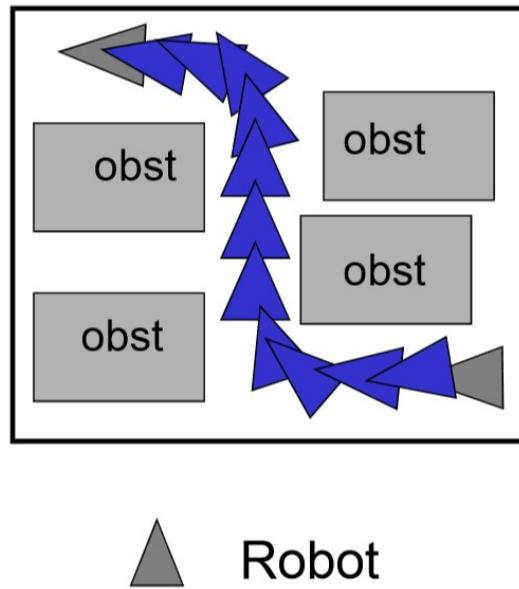
# Configuration Space



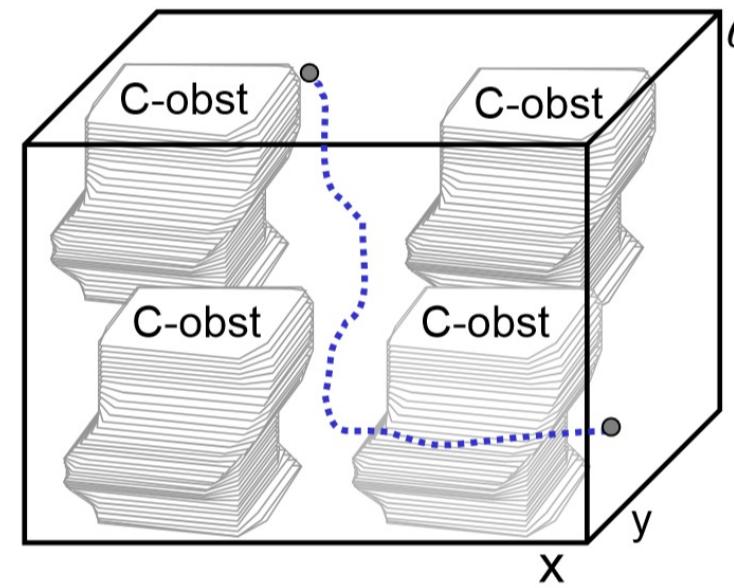
# Configuration Space

## Workspace ( $x, y$ )

Each step has to check for collisions between the robot's body and obstacles!

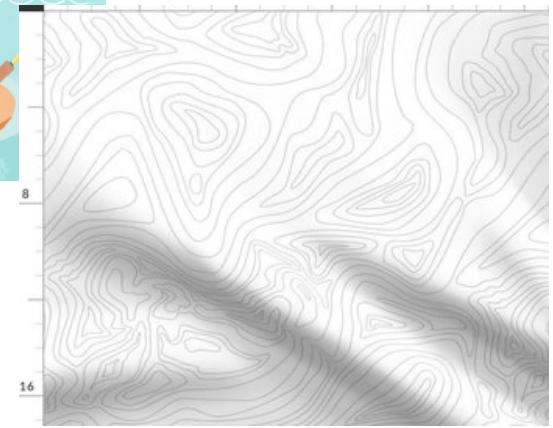
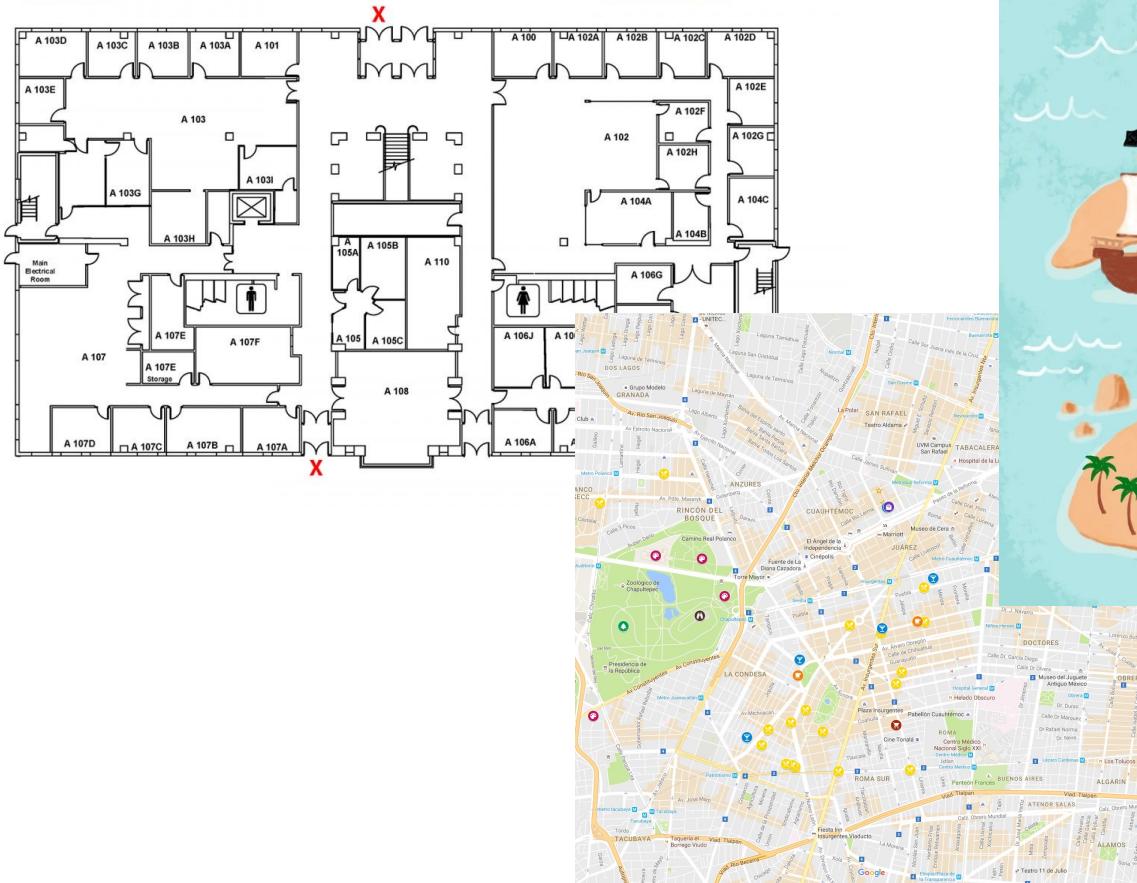


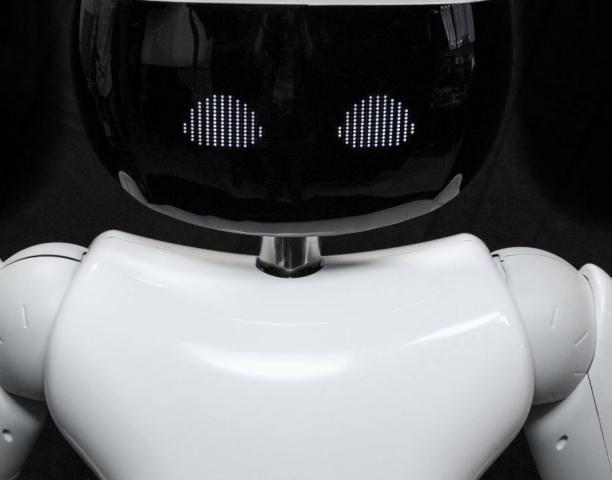
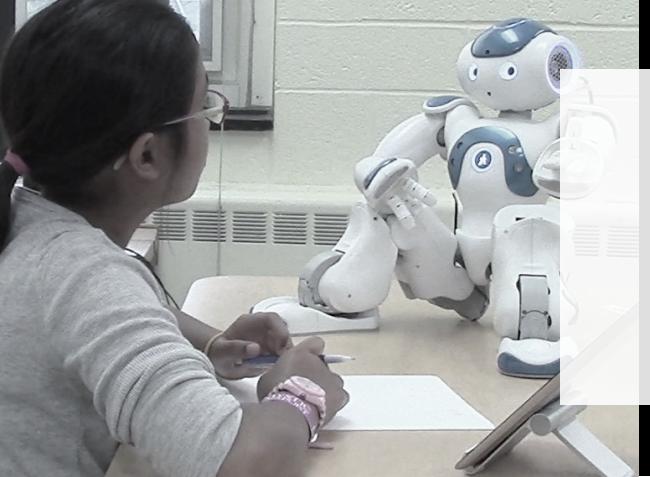
## C-space ( $x, y, \theta$ )



The robot's path is just a path through space – as a single point, collision checks are easy!

# Maps

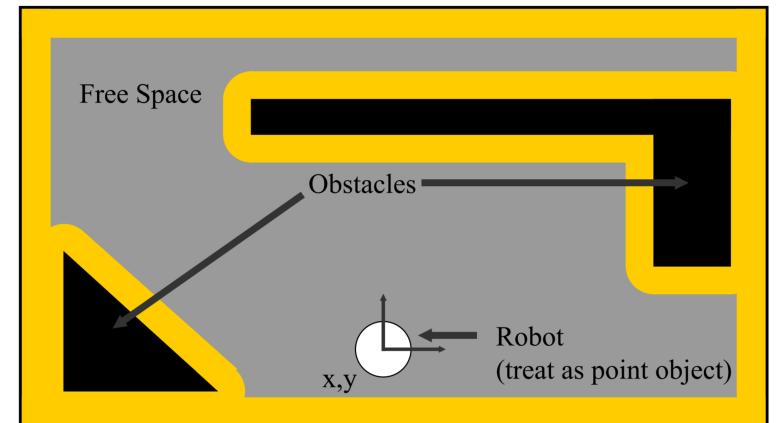
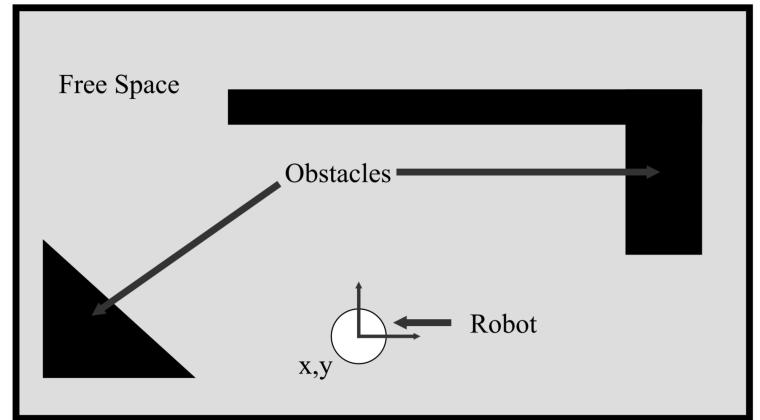




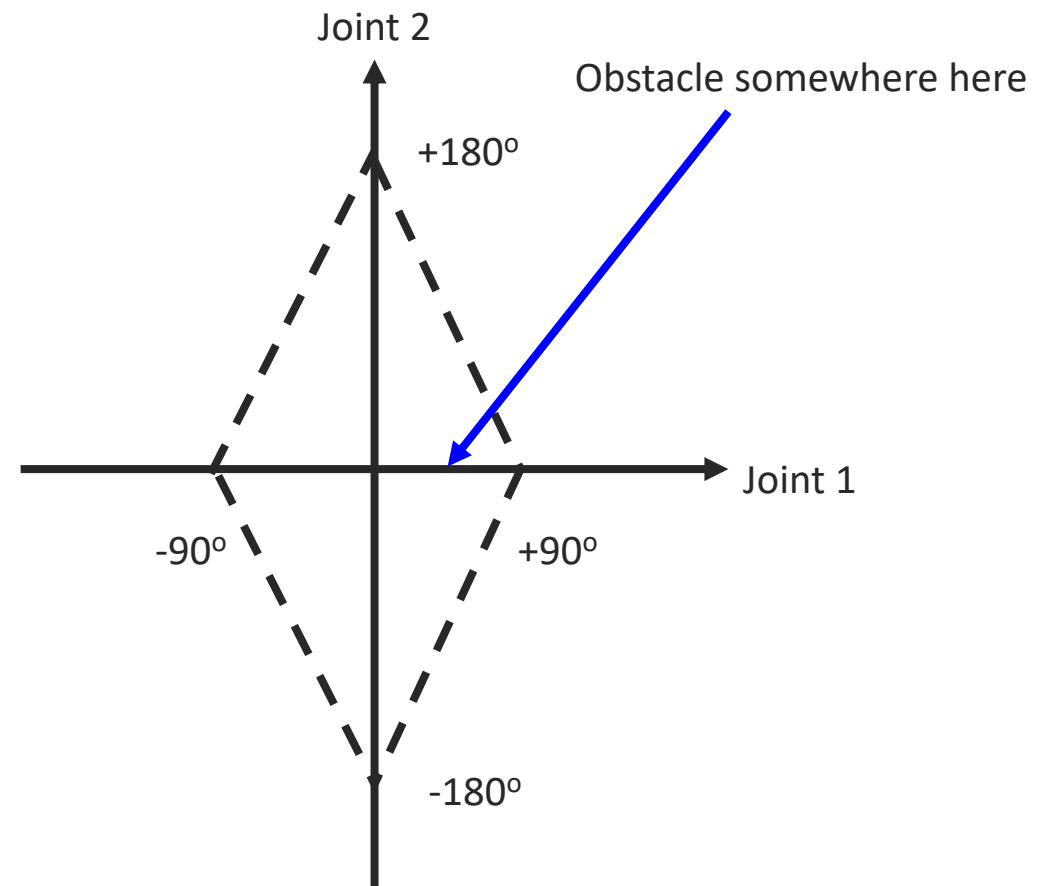
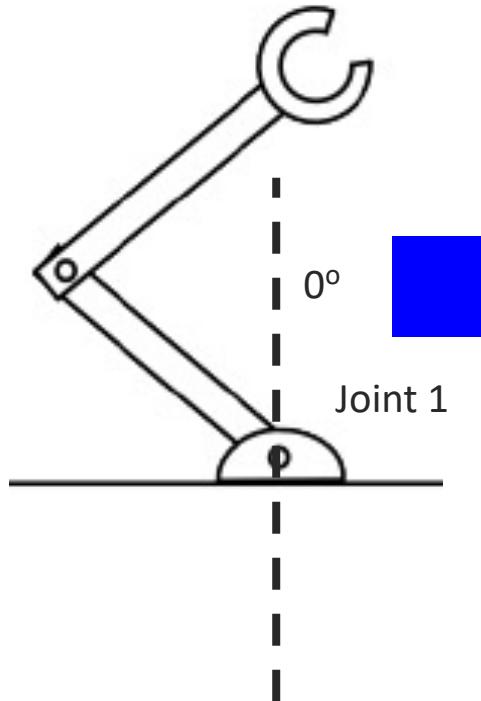
# Questions?

# In practice...

- Optimally, maps are in configuration space
- In practice: combination of c-space representation and on-the-spot checking



# Example: C-Space for Robotic Arm

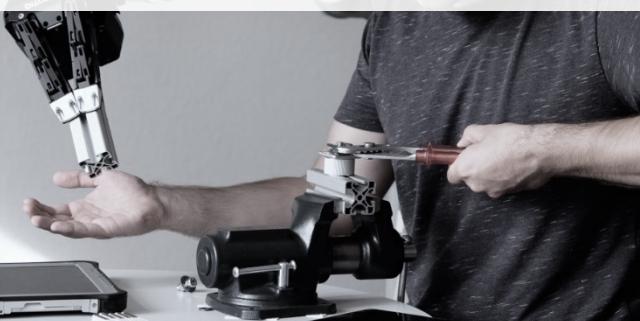
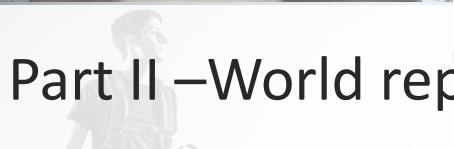
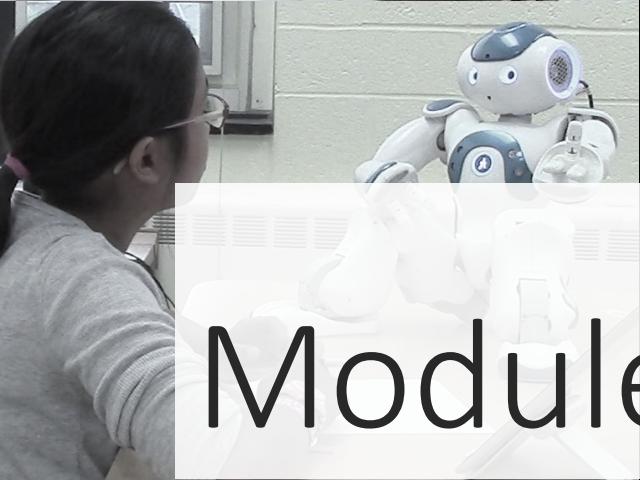


C-Space without obstacles

# Chapter 4

## Module 2 – COMPUTATION

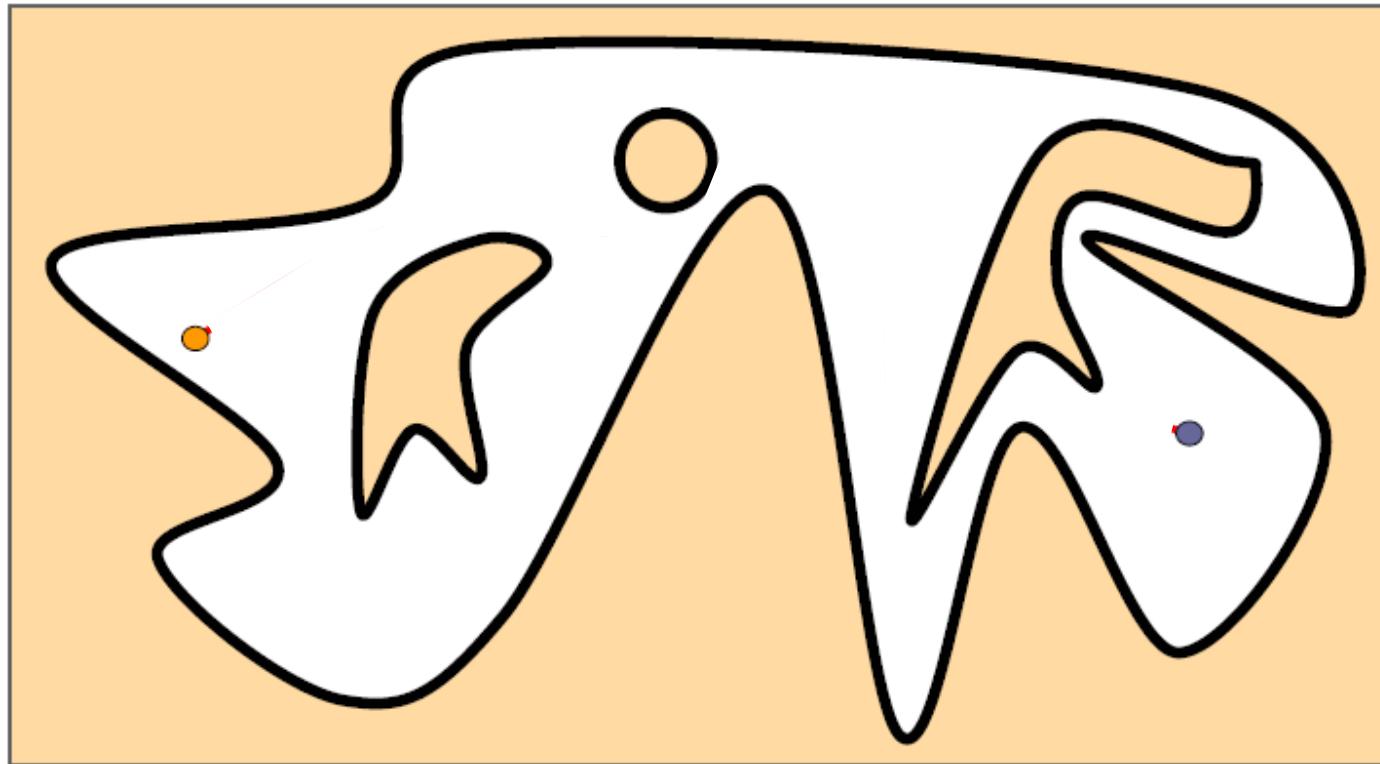
Part II –World representations



# Objective: Compute a collision-free path for a mobile robot among static obstacles

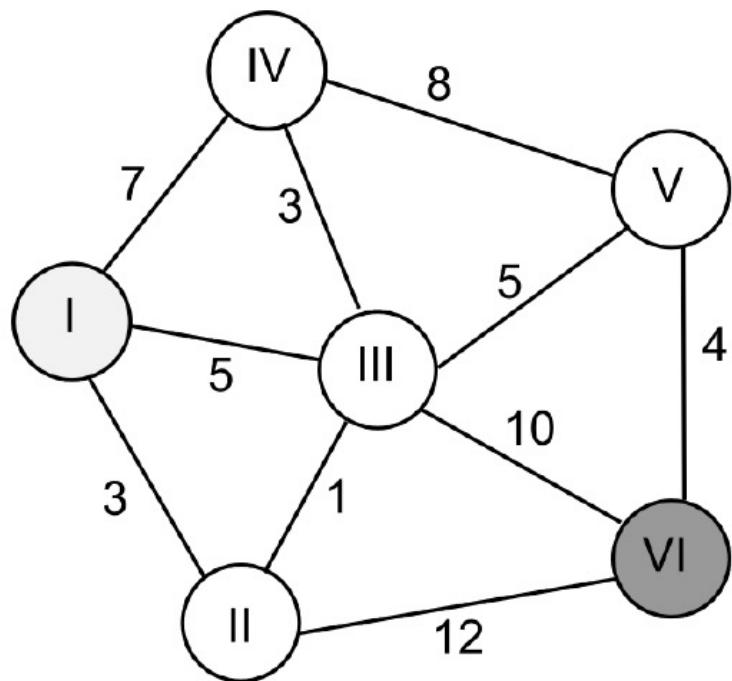
- Inputs required
  - **Geometry** of the robot, any obstacles in the environment
  - **Kinematics** of the robot (DoF, Joint links and types)
  - Initial and goal robot **configurations** (positions & orientations)
- Expected Result
  - Continuous **sequence of collision-free** robot configurations
  - The sequence **connects** the initial and goal configurations
  - We can **follow** this sequence of configurations to traverse the path

# Moving from Start to Goal state

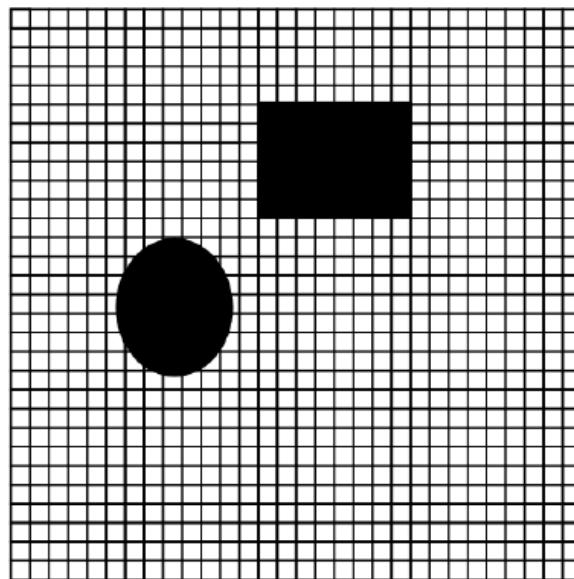


- General approach: Reduce what amounts to an intractable problem in continuous C-space to a tractable problem in a discrete space.
- Tools:
  - Environment Representations
  - Search Algorithms (next lectures)

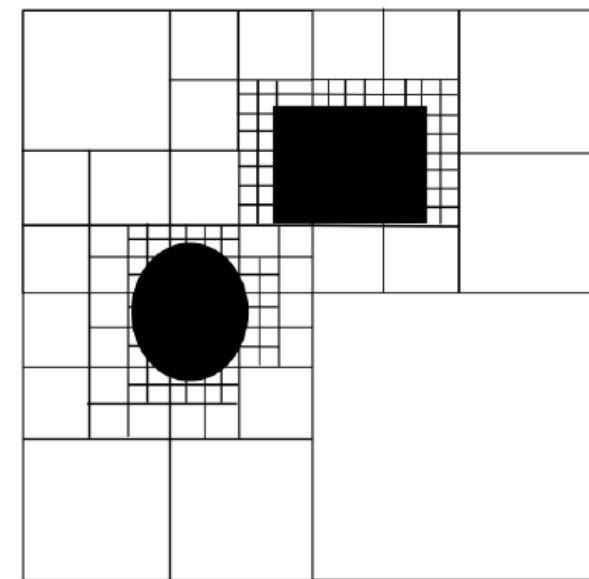
# Map Representations



Topological Map  
(Graph)



Grid Map  
(Discrete Coordinates)



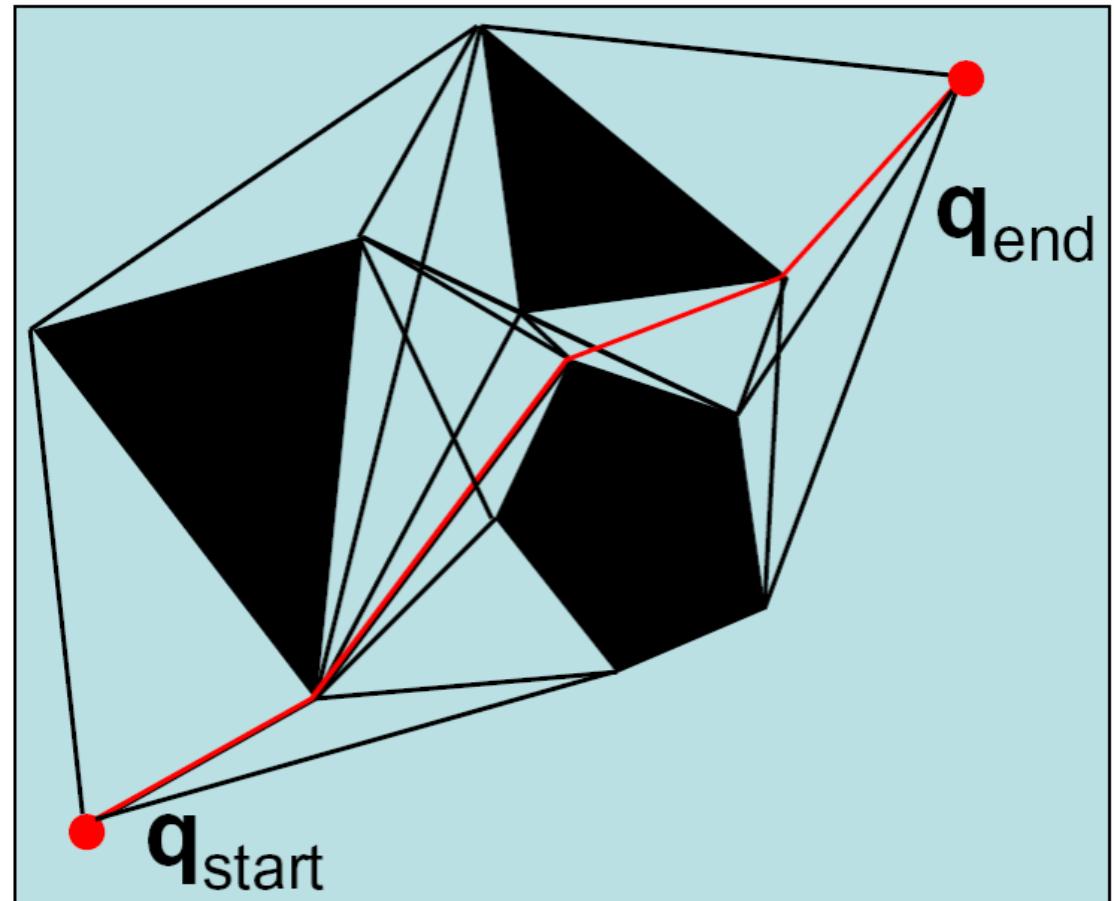
K-d Tree  
(Quadtree)



Planning across  
length scales

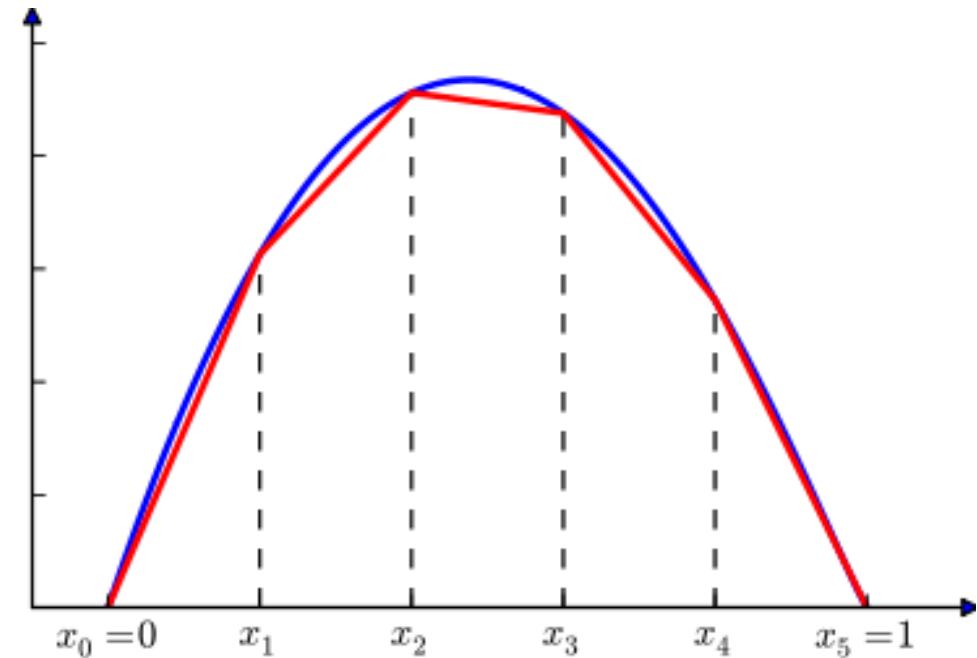
# Some Well-Known Representations

- **Visibility Graphs**
- Cell Decomposition
- Probabilistic Road Map



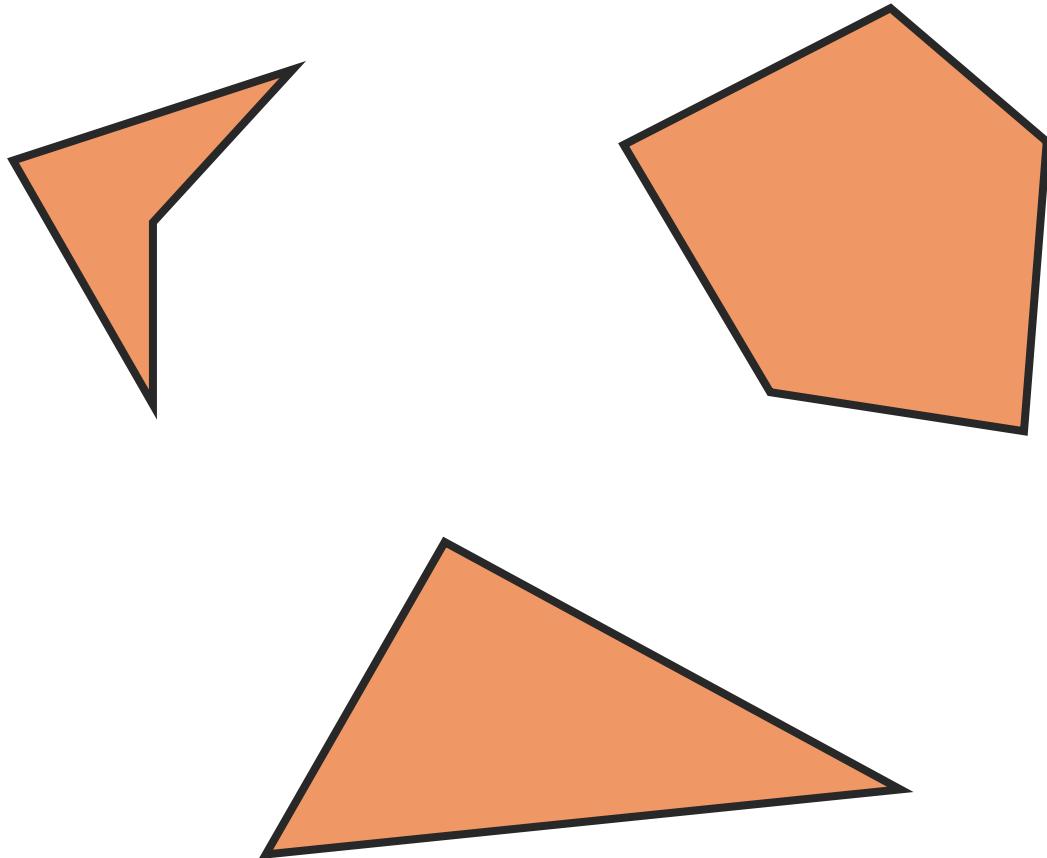
# Visibility Graph Method

- If there is a collision-free path between two points, then there is a polygonal path that bends only at the obstacles vertices.
- A polygonal path is a piecewise linear curve:



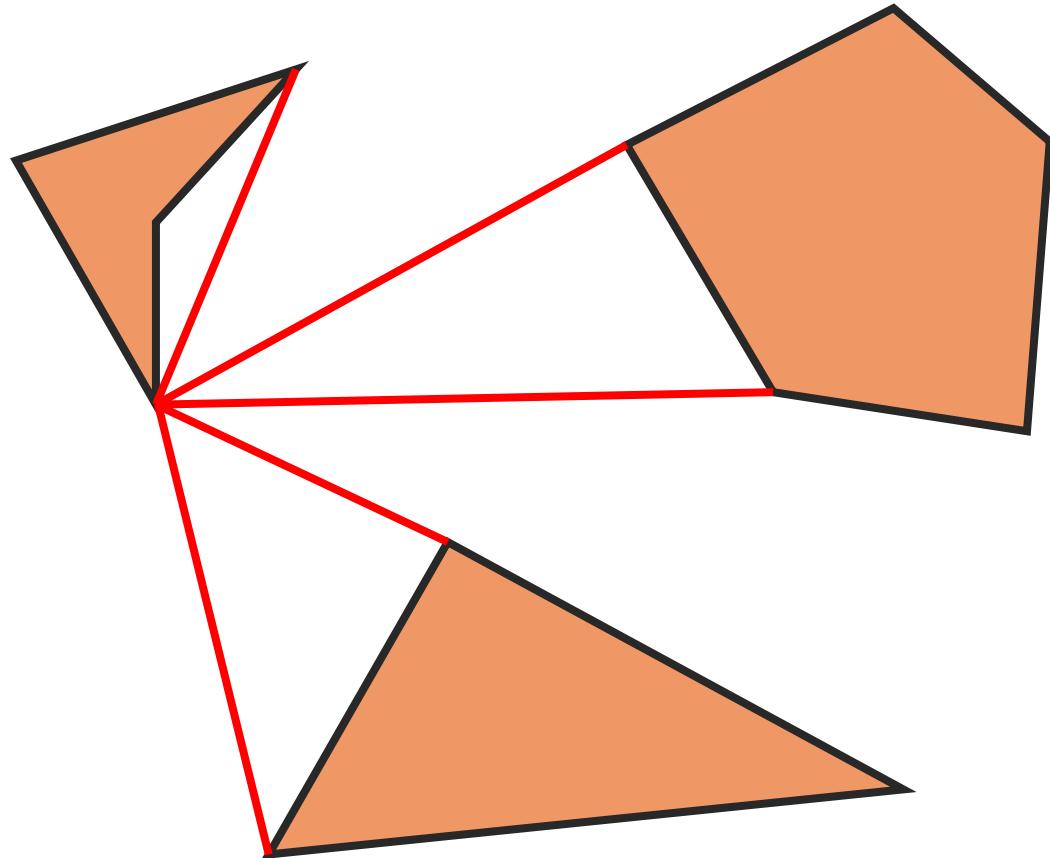
# Visibility Graph Method

- Create edges to all polygon corners that are “visible” from each other



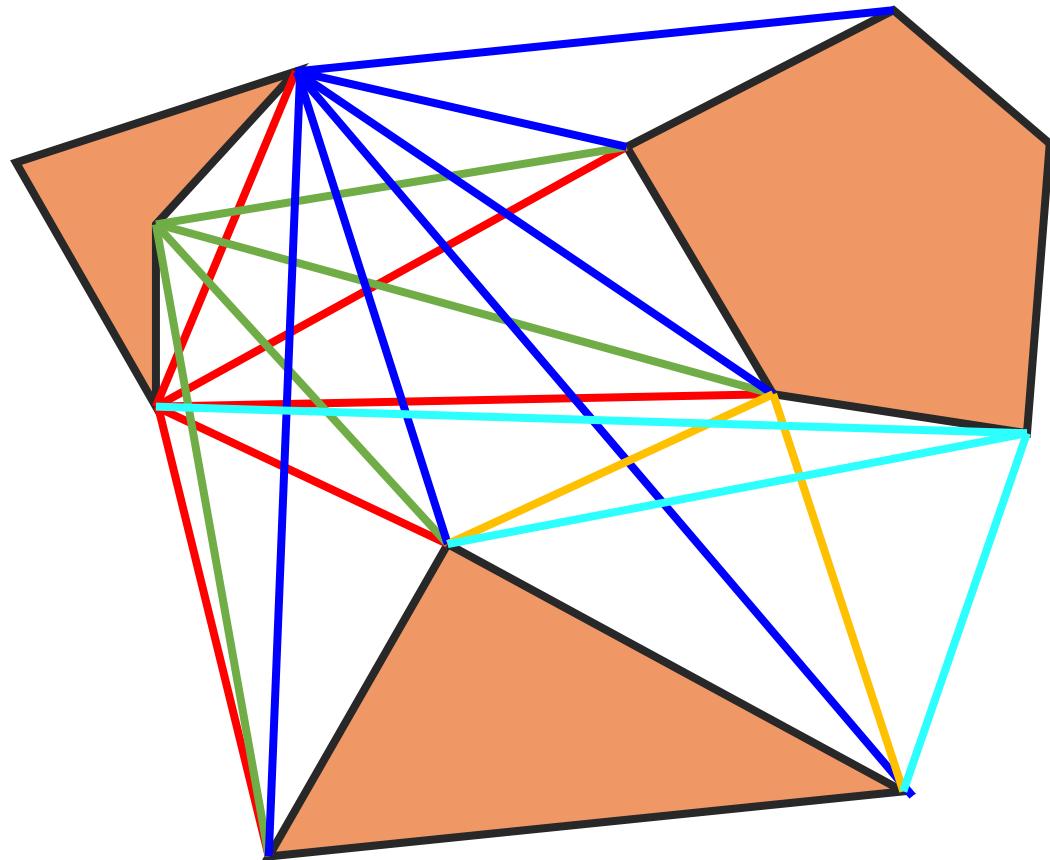
# Visibility Graph Method

- Create edges to all polygon corners that are “visible” from each other
- Include edges along polygons



# Visibility Graph Method

- Create edges to all polygon corners that are “visible” from each other
- Include edges along polygons



# Visibility Graph

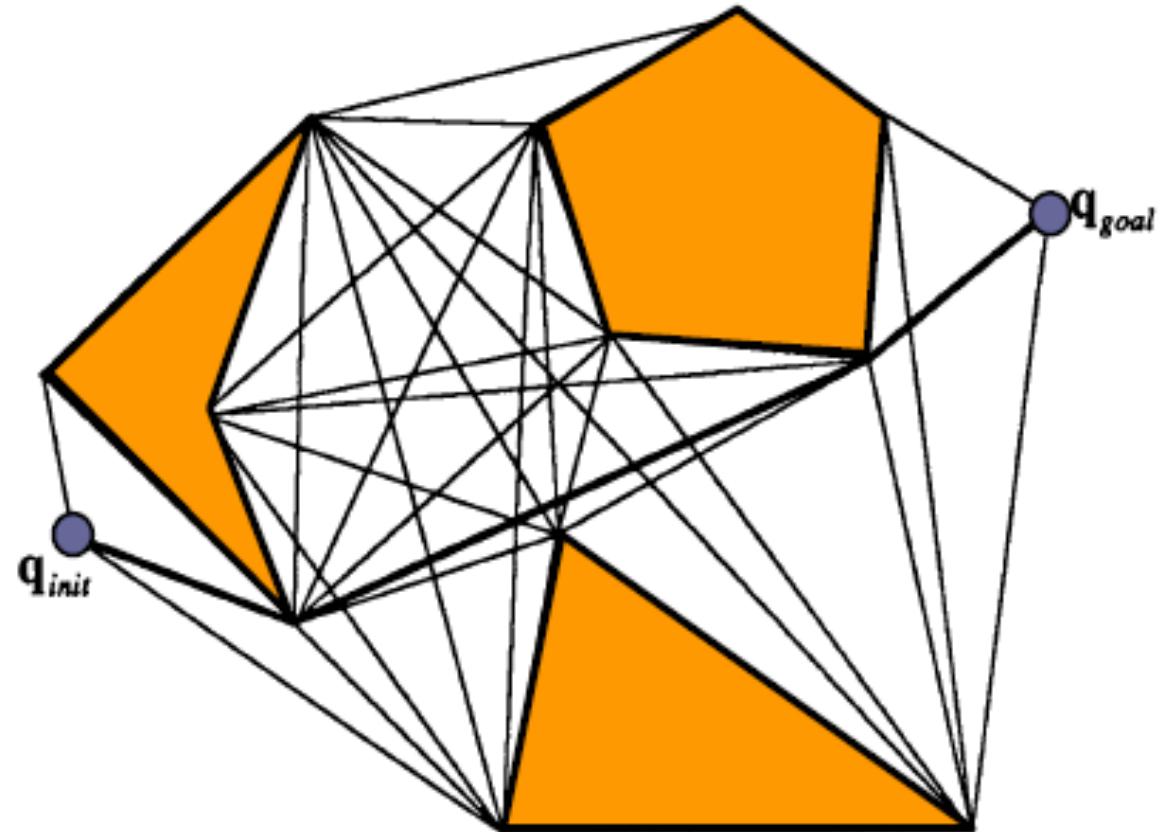
- A visibility graph is a graph such that
  - **Nodes**:  $q_{init}$ ,  $q_{goal}$ , or an obstacle vertex.
  - **Edges**: An edge exists between nodes  $u$  and  $v$  if the line segment between  $u$  and  $v$  is an obstacle edge or it does not intersect the obstacles.

# Visibility Graph Algorithm

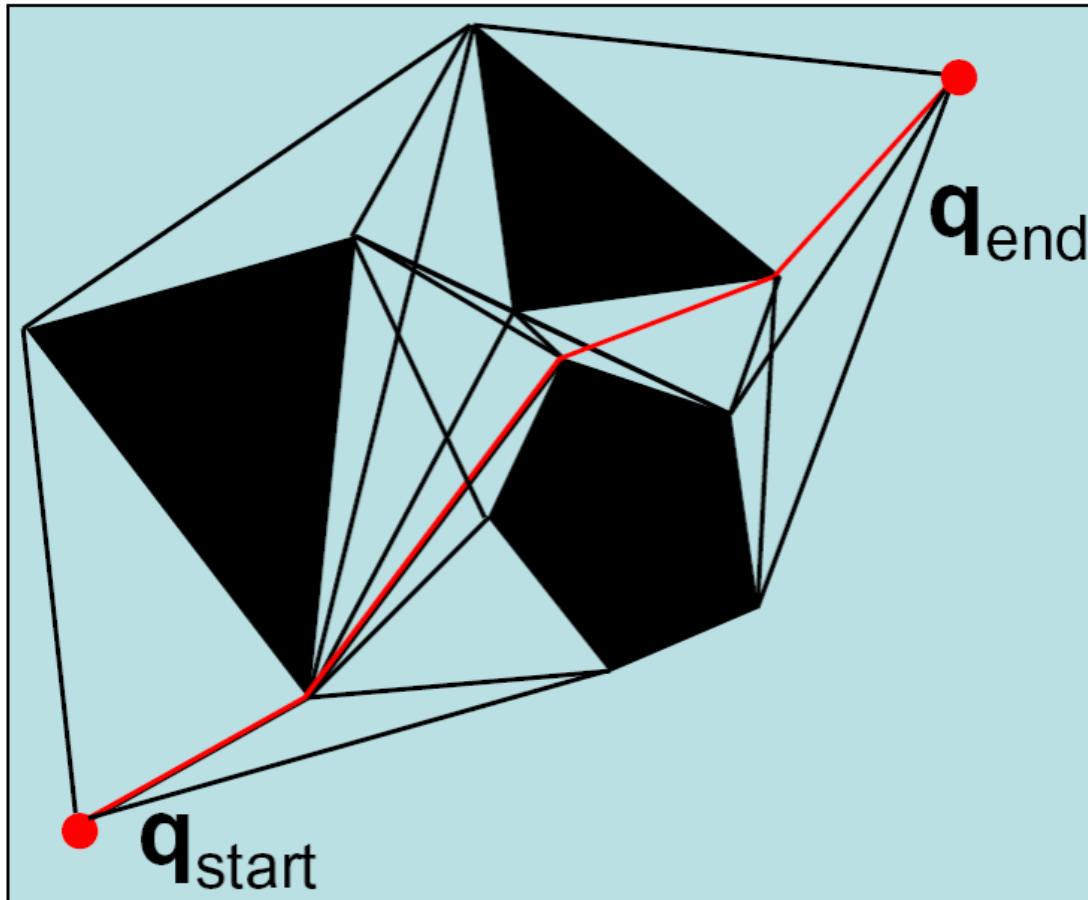
**Input:**  $q_{init}$ ,  $q_{goal}$ , polygonal obstacles

**Output:** visibility graph G

1. **for** every pair of nodes  $u, v$
2.   **if** segment  $(u, v)$  is an obstacle edge **then**
3.     insert edge  $(u, v)$  into G;
4.   **else**
5.     **for** every obstacle edge e
6.       **if** segment  $(u, v)$  intersects e
7.         go to (1);
8.     insert edge  $(u, v)$  into G.

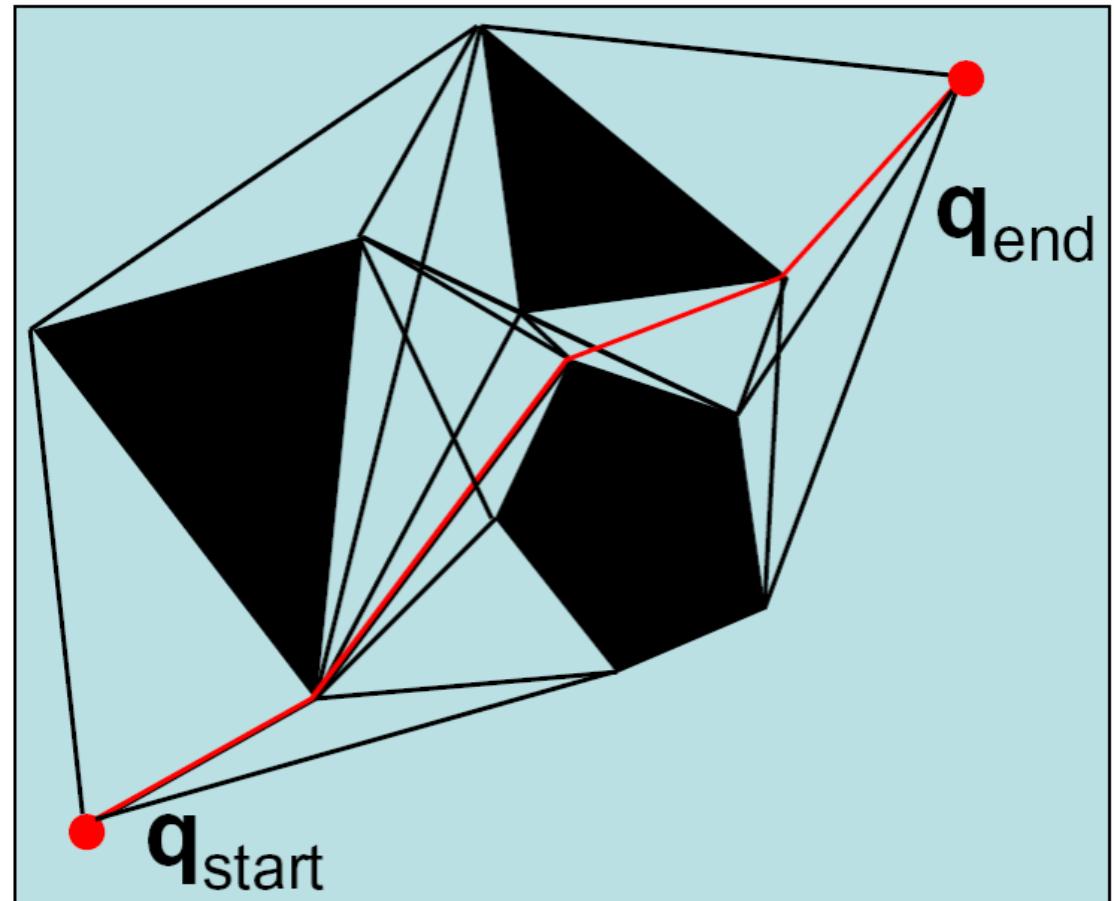


# Visibility Graph: Strengths/Weaknesses?

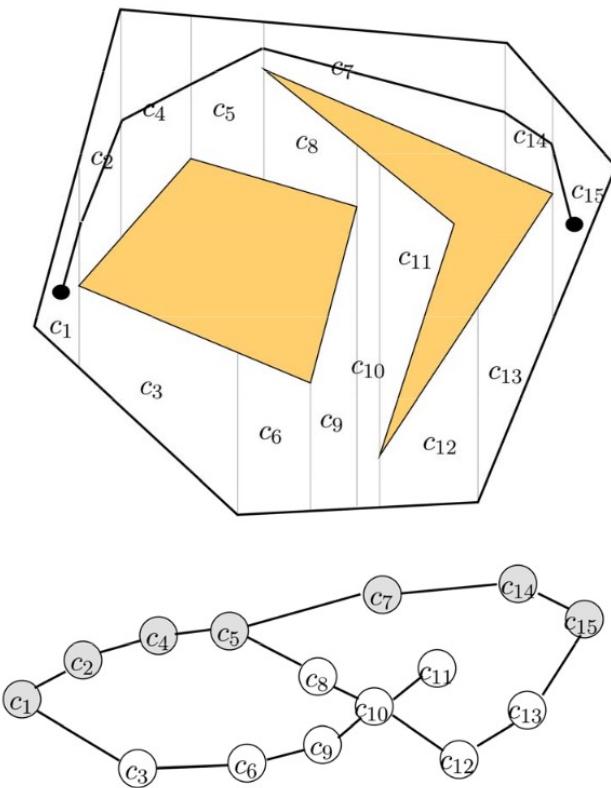


# Some Well-Known Representations

- Visibility Graphs
- Cell Decomposition
- Probabilistic Road Map



# Cell Decomposition



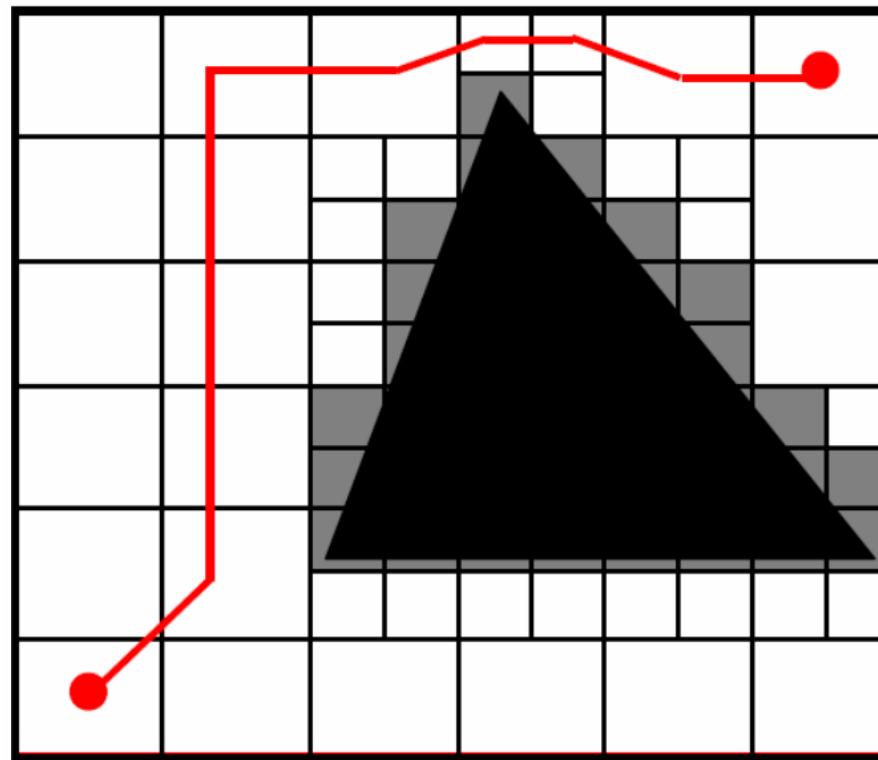
## Exact cell decomposition

- Divides a space  $F$  precisely into sub-units

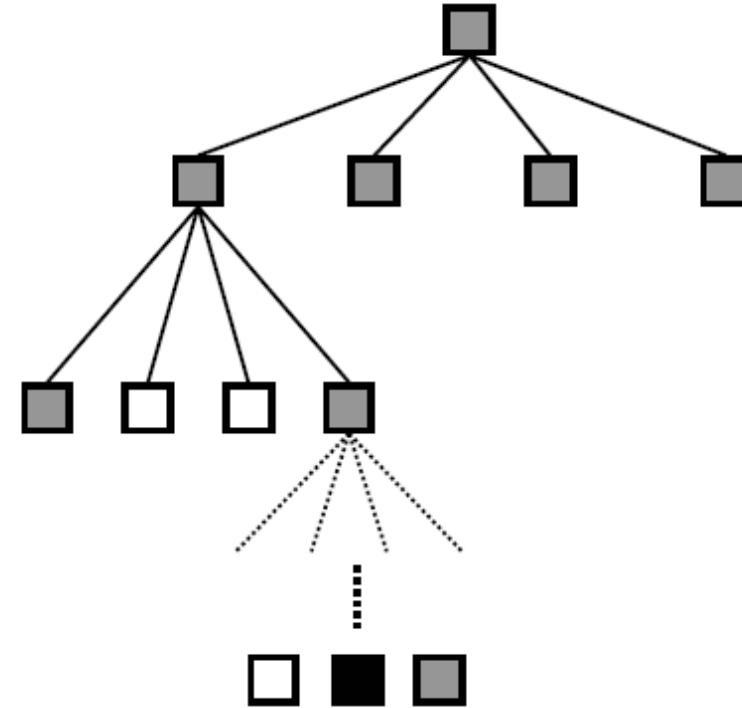
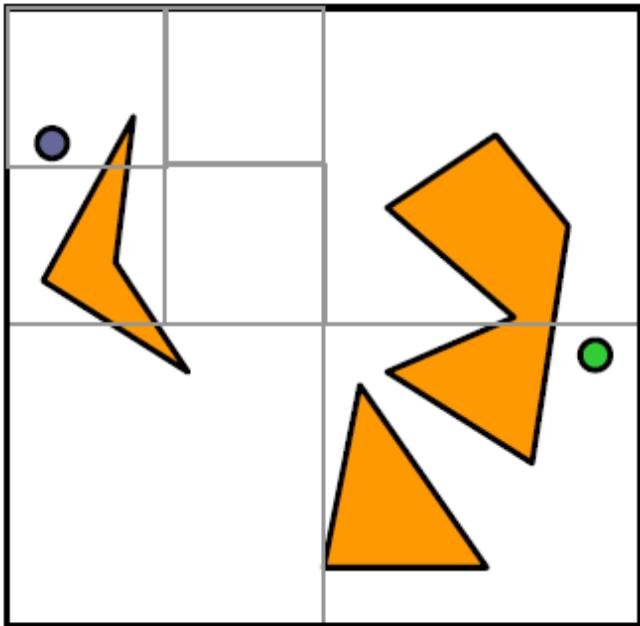
## Approximate cell decomposition

- $F$  is represented by a collection of non-overlapping cells whose union is contained in  $F$ .
- Cells usually have simple, regular shapes, e.g., rectangles, squares.
- Facilitates hierarchical space decomposition

# Grid-based Cell Decomposition



# Quadtree Decomposition

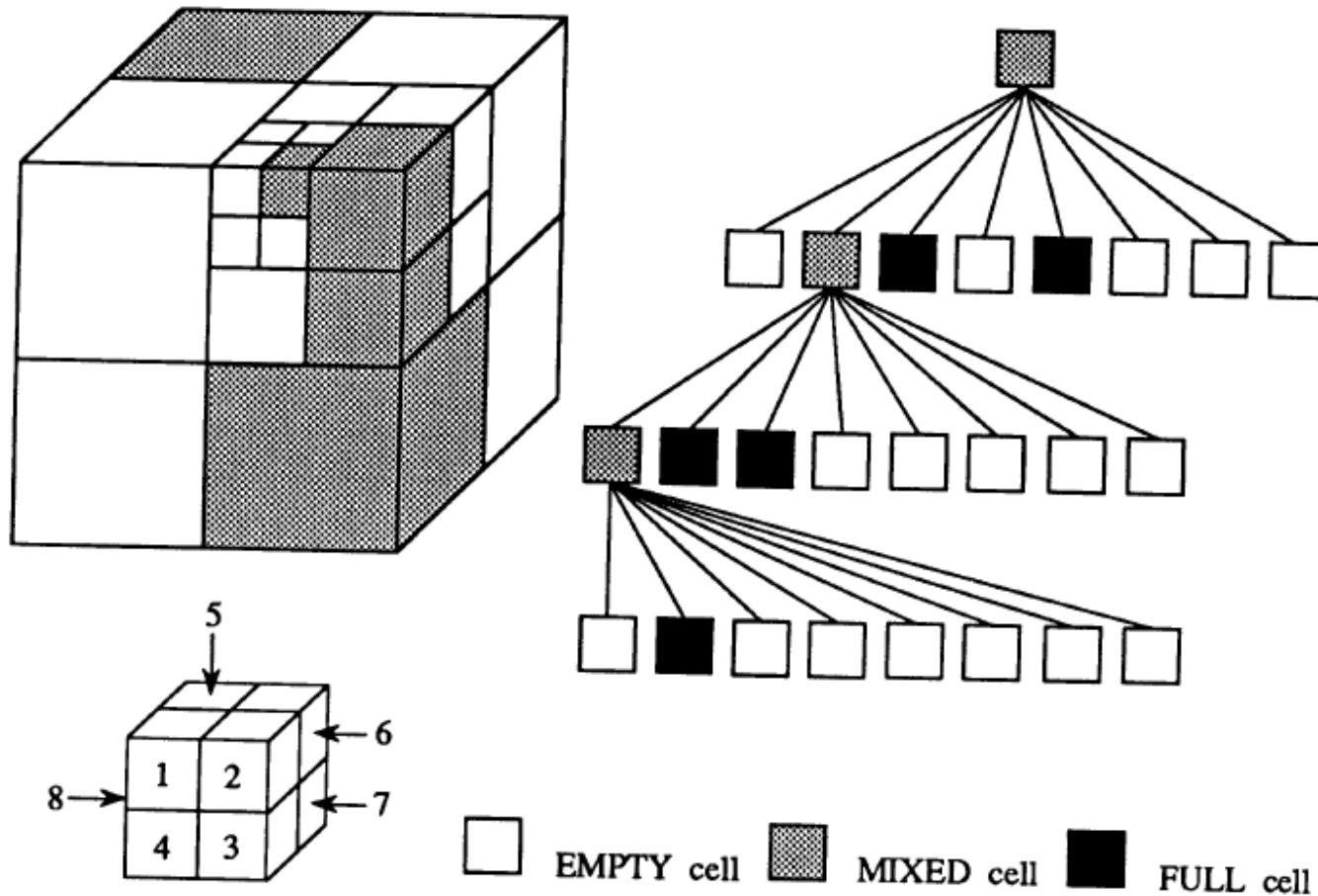


□ empty

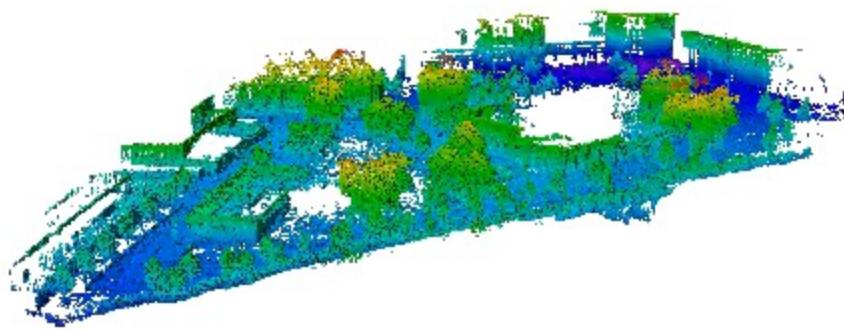
■ mixed

■ full

# Octree Decomposition

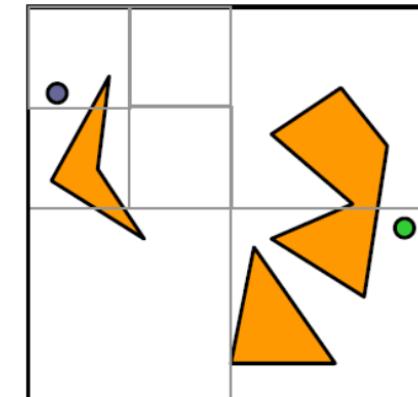


# Octree

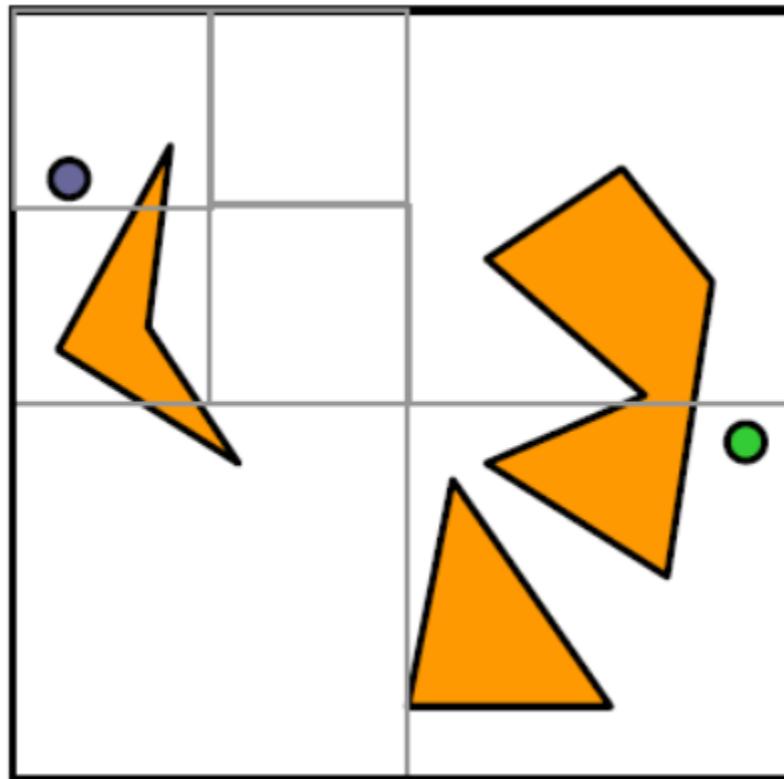


# Cell Decomposition Path Planning Algorithm Outline

1. Decompose the free space  $F$  into cells.
2. Search for a sequence of **mixed** or **free** cells that connect the initial and goal positions.
3. Further decompose the mixed.
4. Repeat (2) and (3) until a sequence of **free** cells is found.

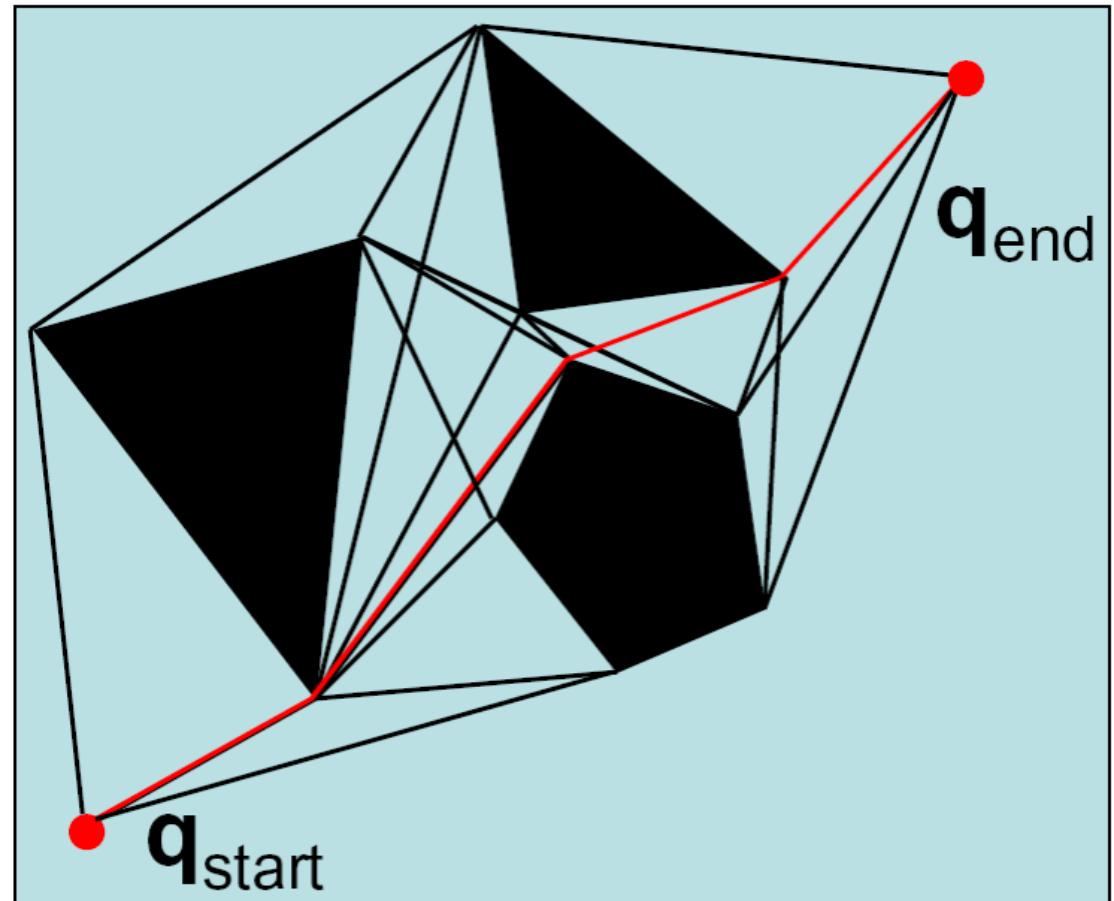


# Cell Decomposition: Strengths/Weaknesses

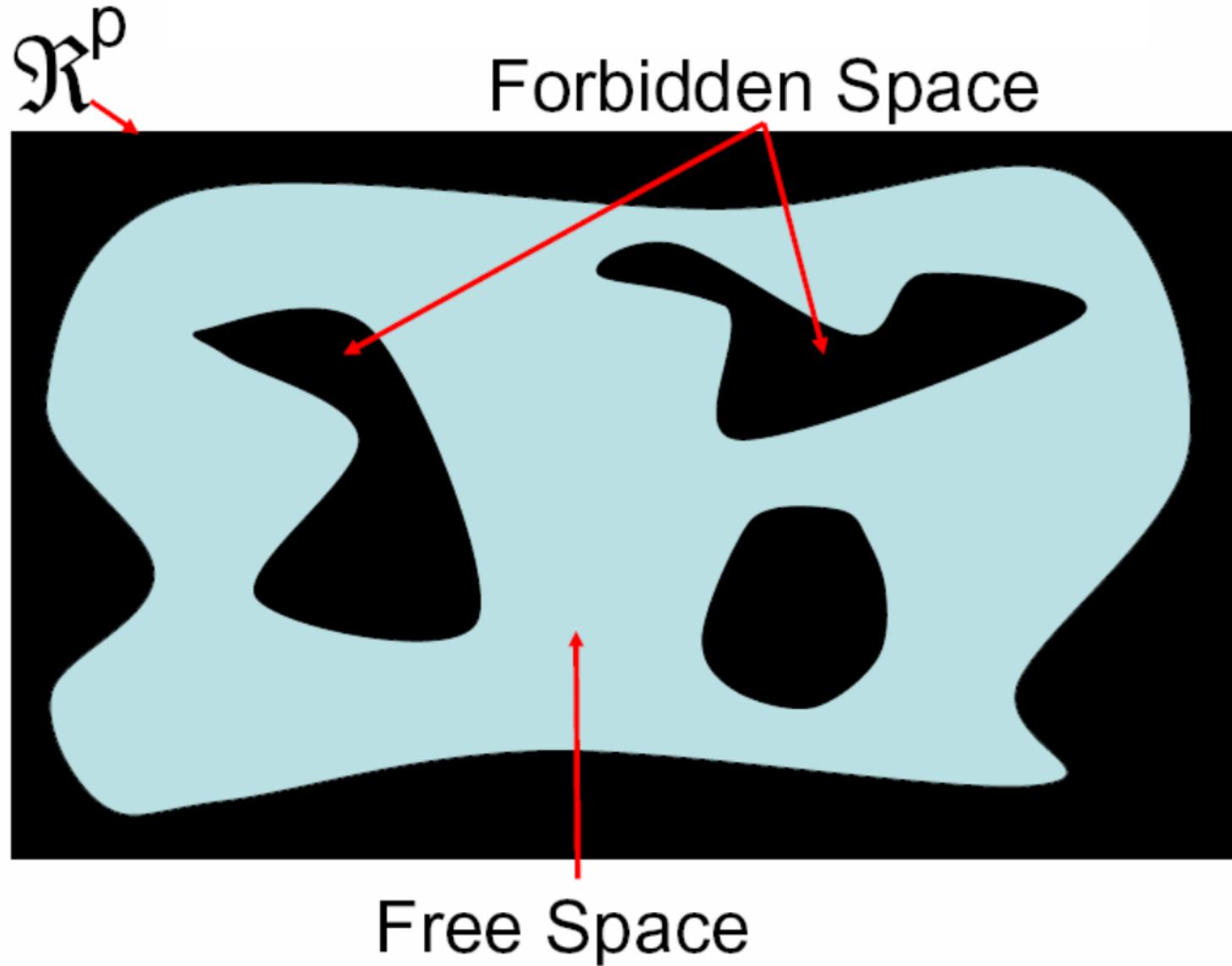


# Some Well-Known Representations

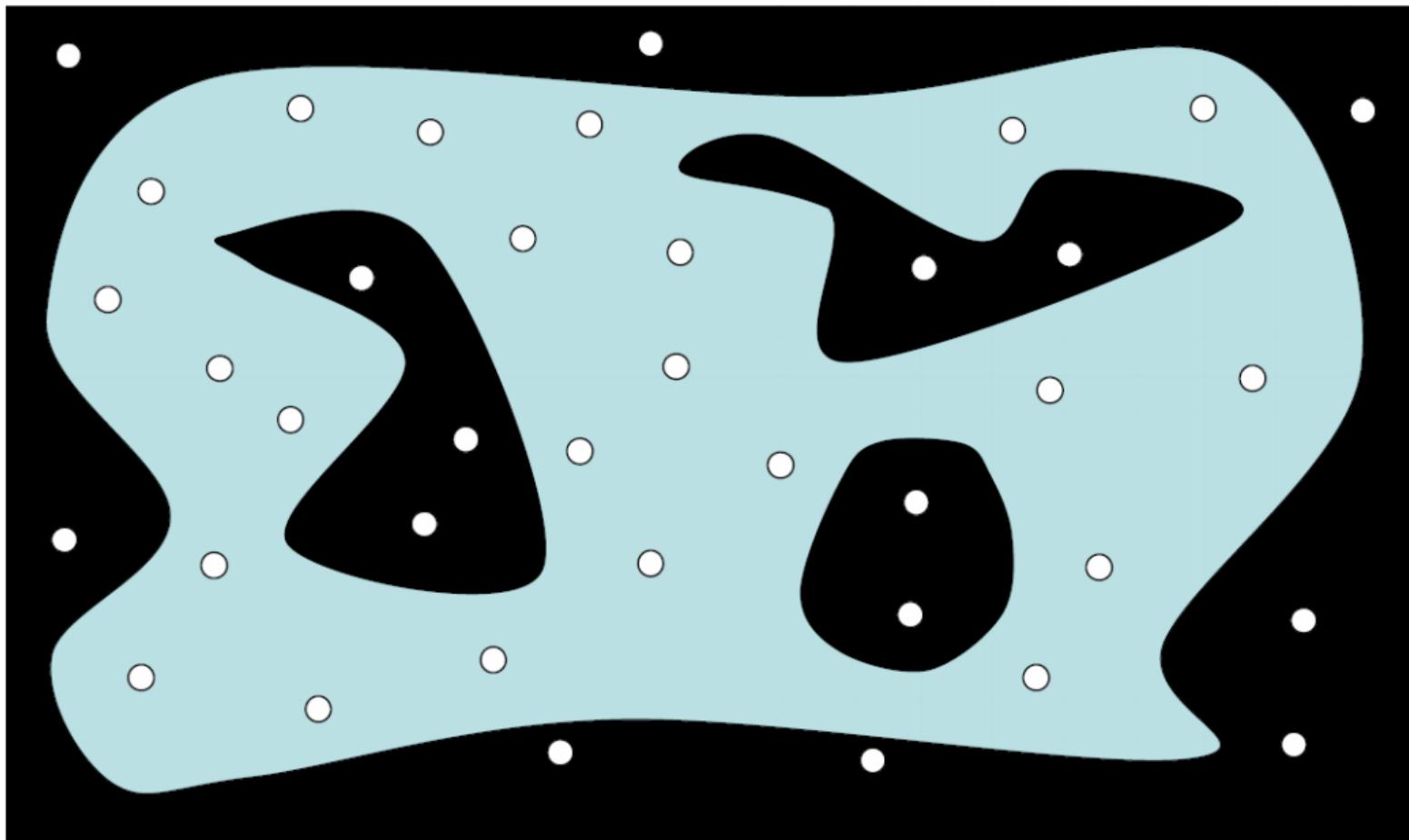
- Visibility Graphs
- Cell Decomposition
- Probabilistic Road Map



# Probabilistic Road Map (PRM)

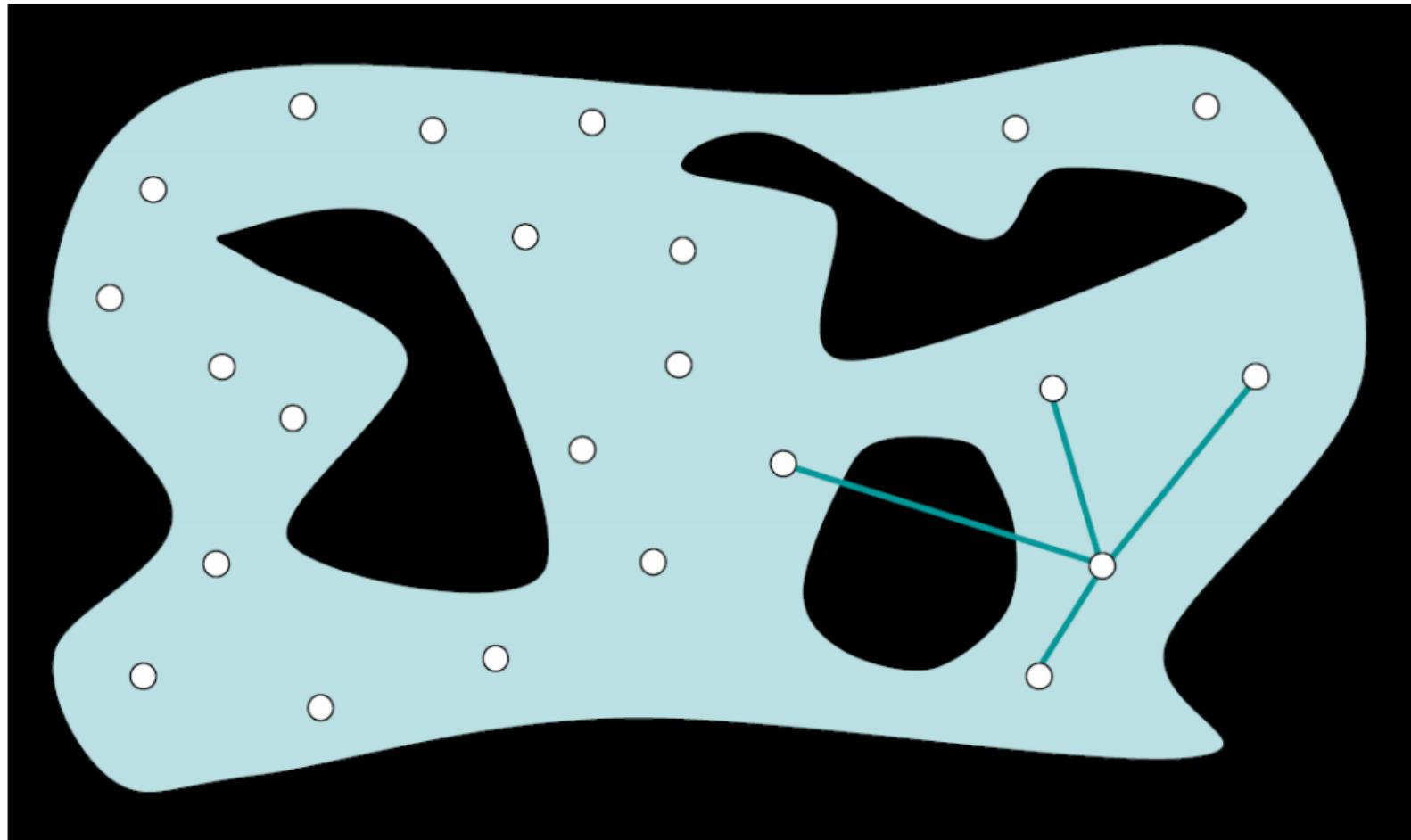


# Probabilistic Road Map (PRM)



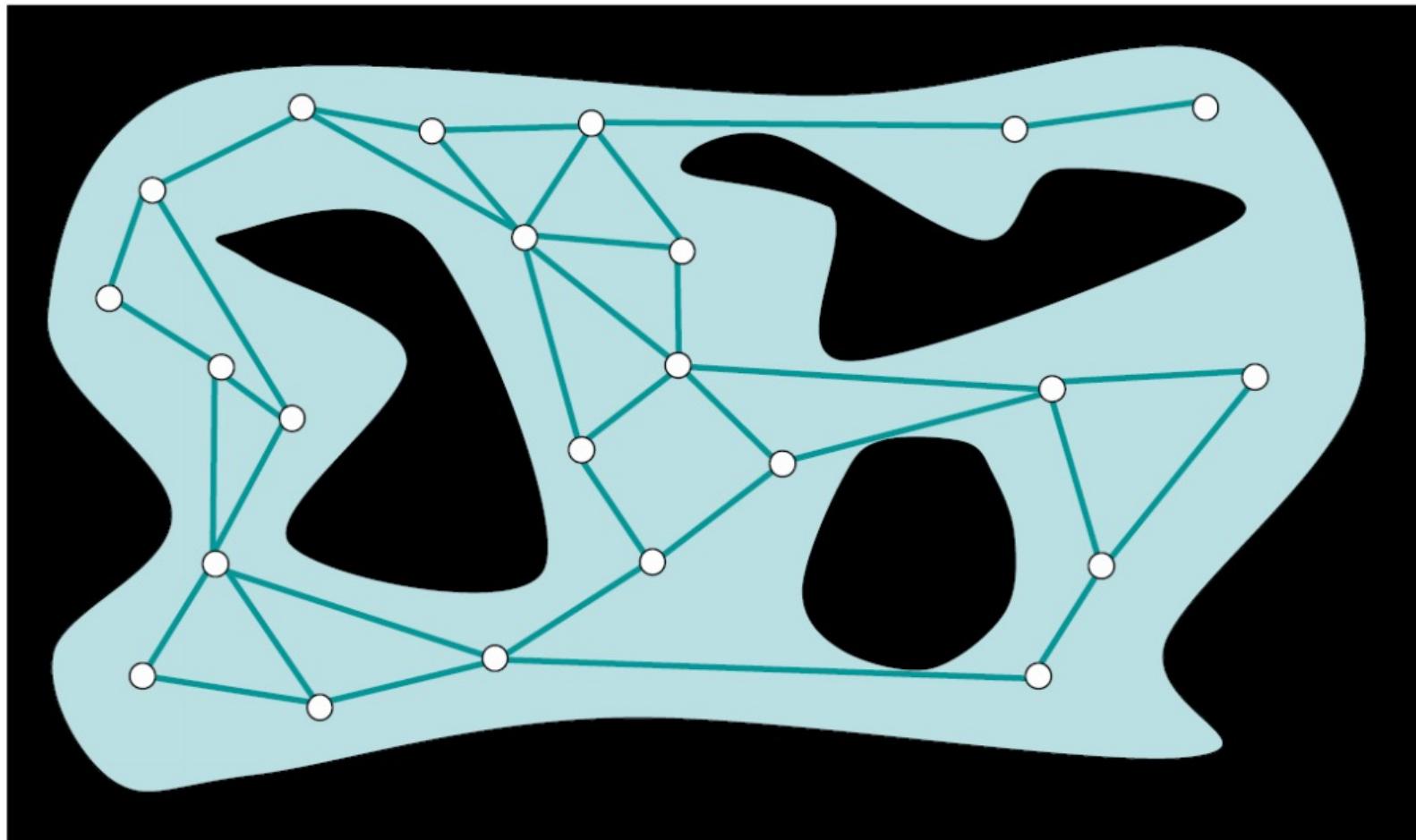
Sample random locations!

# Probabilistic Road Map (PRM)



Remove points in forbidden areas  
Link each point to its K nearest neighbors

# Probabilistic Road Map (PRM)

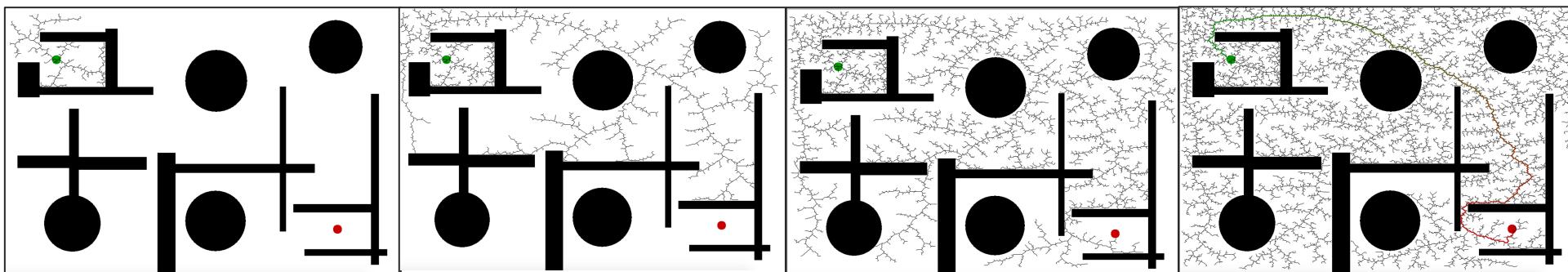


Remove edges crossing forbidden areas

# How to sample points?

- Uniformly randomly
- Sample more near places with few neighbors
- Bias samples to exist near obstacles
- Use human-provided waypoints
- Something better?

Rapidly-exploring Random Trees (RRT)



# Rapidly-exploring Random Trees

```
Algorithm BuildRRT
    Input: Initial configuration  $q_{init}$ , number of vertices in RRT  $K$ , incremental distance  $\Delta q$ )
    Output: RRT graph  $G$ 
```

```
    G.init( $q_{init}$ )
    for  $k = 1$  to  $K$ 
```

**How can we make use of these representations?**  
Search algorithms provide a way to find a path!

```
        G.add_edge( $q_{near}$ ,  $q_{new}$ )
    return  $G$ 
```



# Rapidly Exploring Random Trees [RRT]

Basic idea:

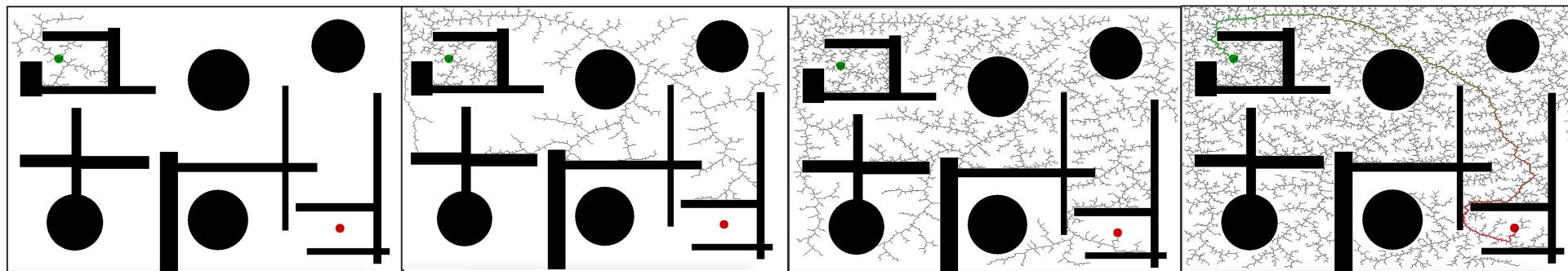
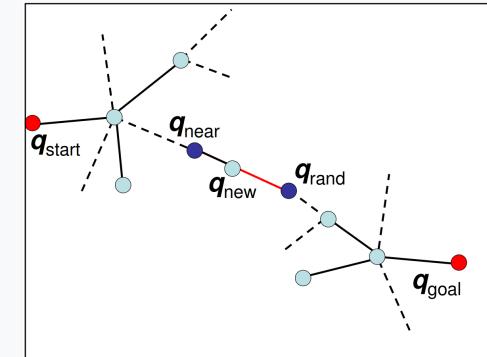
- Build up a tree through generating “next states” in the tree by executing random controls
- However: to ensure good coverage, we need something better than the above

# Rapidly-exploring Random Trees

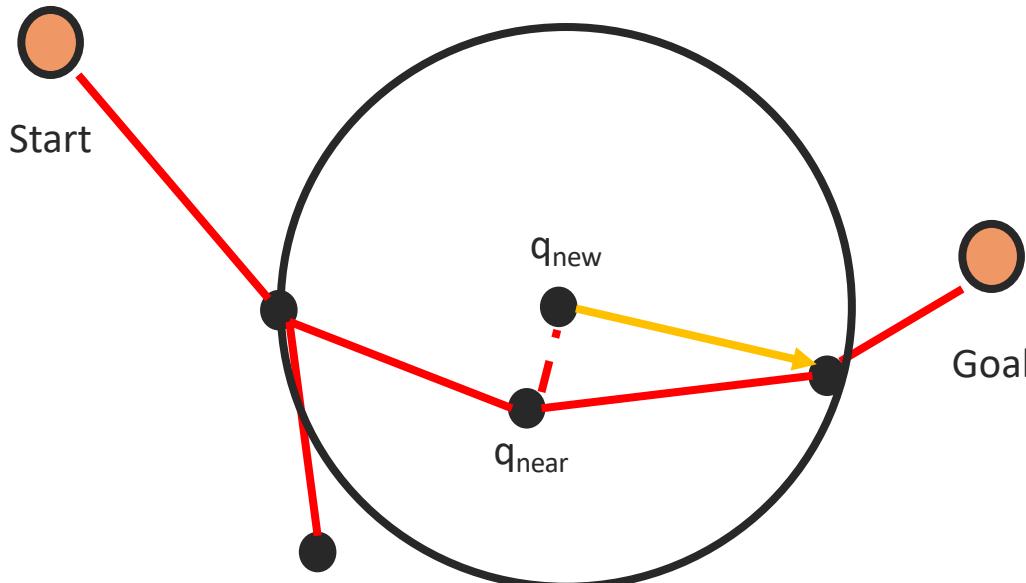
**Algorithm BuildRRT**

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

```
G.init( $q_{init}$ )
for  $k = 1$  to  $K$ 
     $q_{rand} \leftarrow \text{RAND\_CONF}()$ 
     $q_{near} \leftarrow \text{NEAREST\_VERTEX}(q_{rand}, G)$ 
     $q_{new} \leftarrow \text{NEW\_CONF}(q_{near}, q_{rand}, \Delta q)$ 
    G.add_vertex( $q_{new}$ )
    G.add_edge( $q_{near}, q_{new}$ )
return G
```

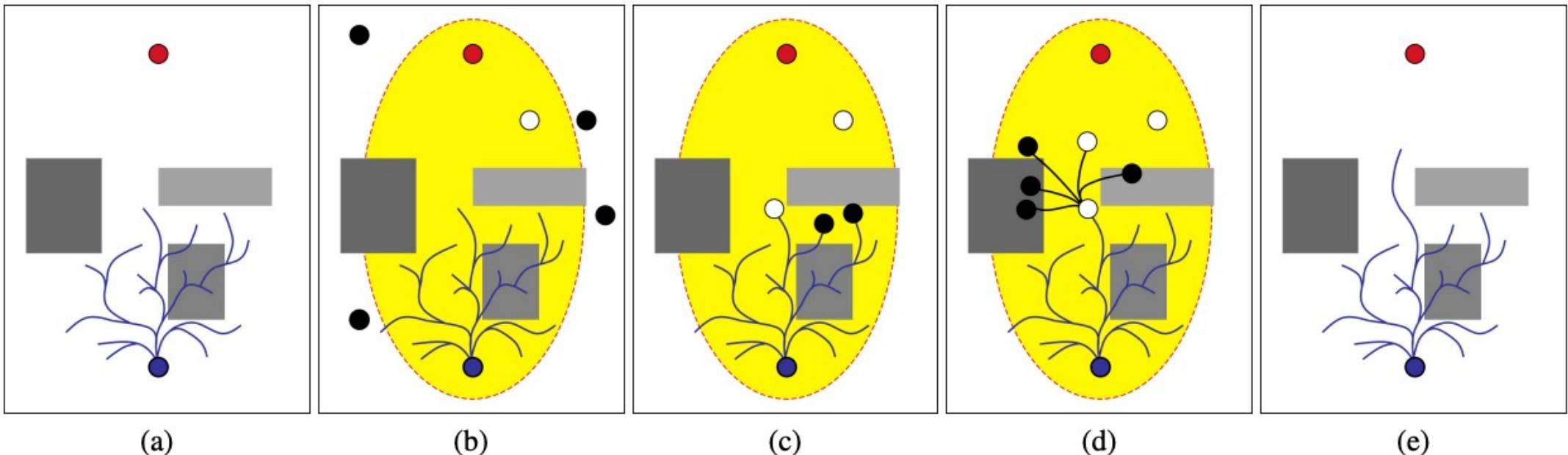


# Making RRT optimal – RRT\*



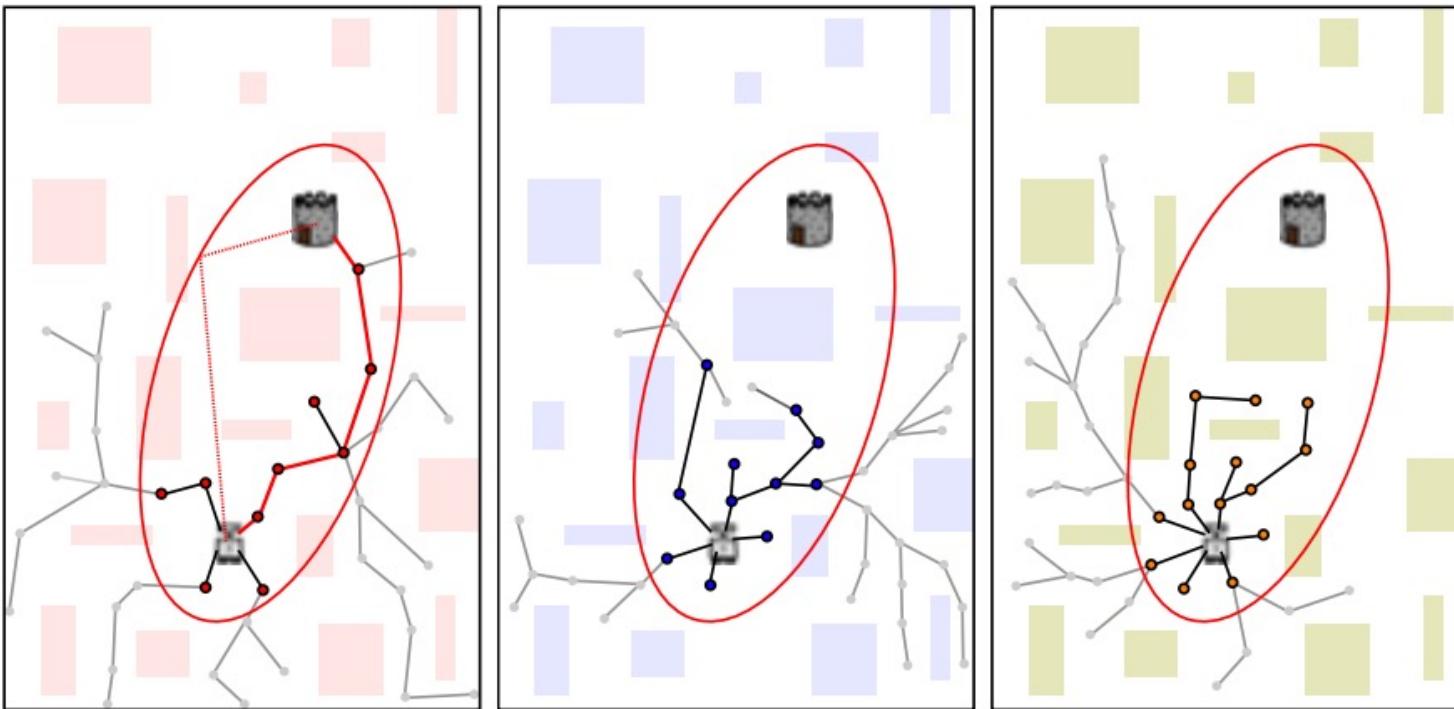
Karaman, Sertac, and Emilio Frazzoli. "Sampling-based algorithms for optimal motion planning." *The international journal of robotics research* 30, no. 7 (2011): 846-894.

# Making RRT faster....



Ferguson, D. and Stentz, A., 2006, October. Anytime RRTs. In *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 5369-5375).

# Parallelizing RRT



Otte, Michael, and Nikolaus Correll. "C-FOREST: Parallel shortest path planning with superlinear speedup." *IEEE Transactions on Robotics* 29, no. 3 (2013): 798-806.

# Putting it together: Informed RRT\*



## Informed RRT\*

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Optimal Sampling-based Path Planning Focused via  
Direct Sampling of an Admissible Ellipsoidal Heuristic

Jonathan D. Gammell<sup>1</sup>

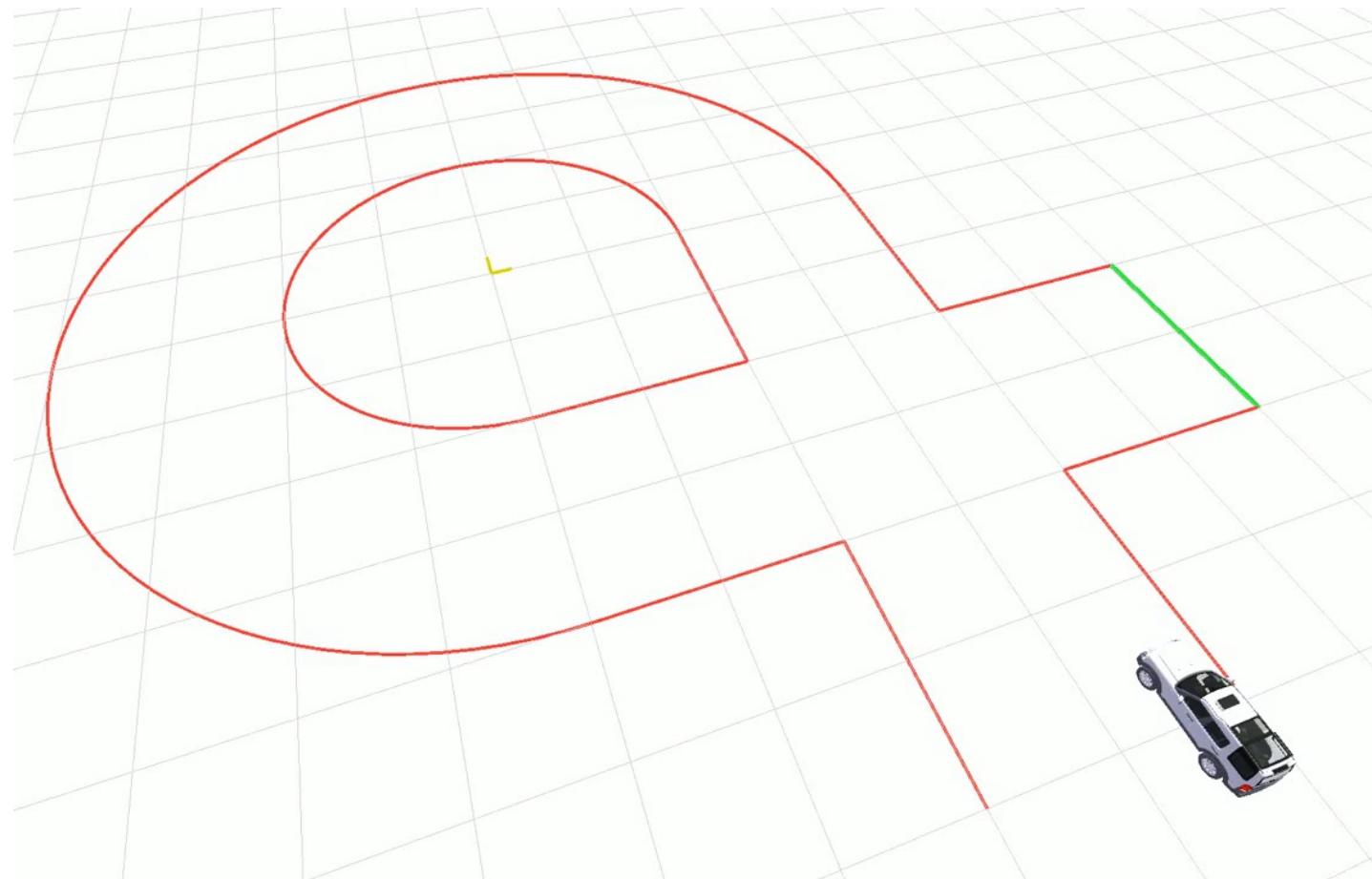
Siddhartha S. Srinivasa<sup>2</sup>

Timothy D. Barfoot<sup>1</sup>

<sup>1</sup>  Institute for Aerospace Studies  
UNIVERSITY OF TORONTO

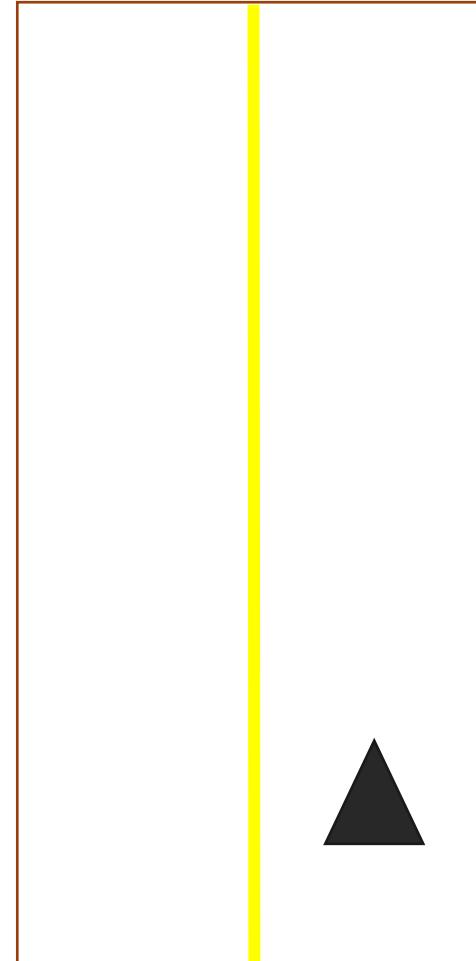
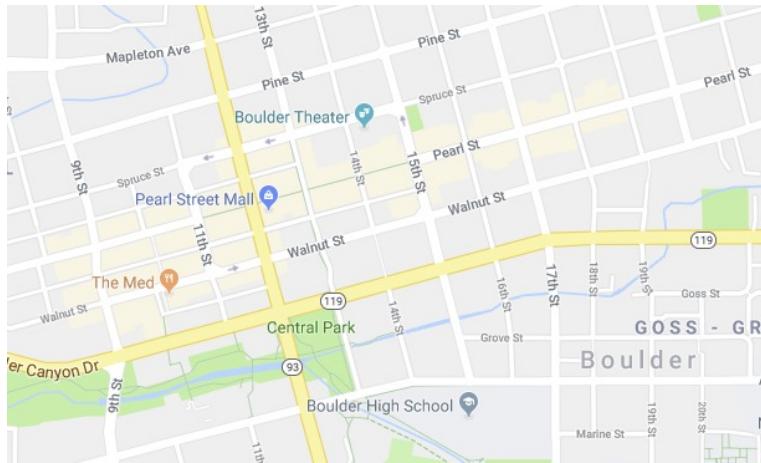
<sup>2</sup>  Carnegie Mellon  
THE ROBOTICS INSTITUTE

# RRT with dynamics



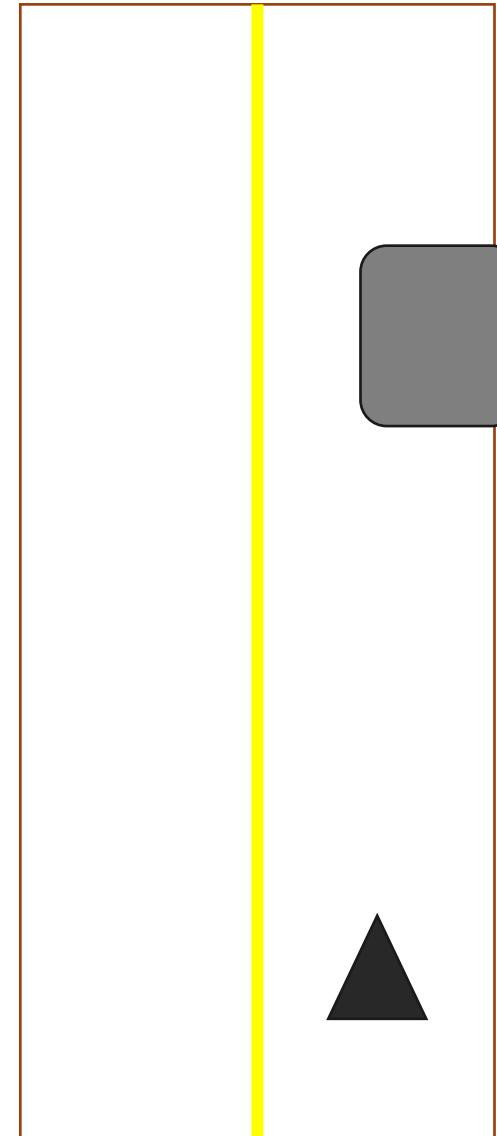
# Exercise: Building an Autonomous Car

1. World Representation
2. Planning System

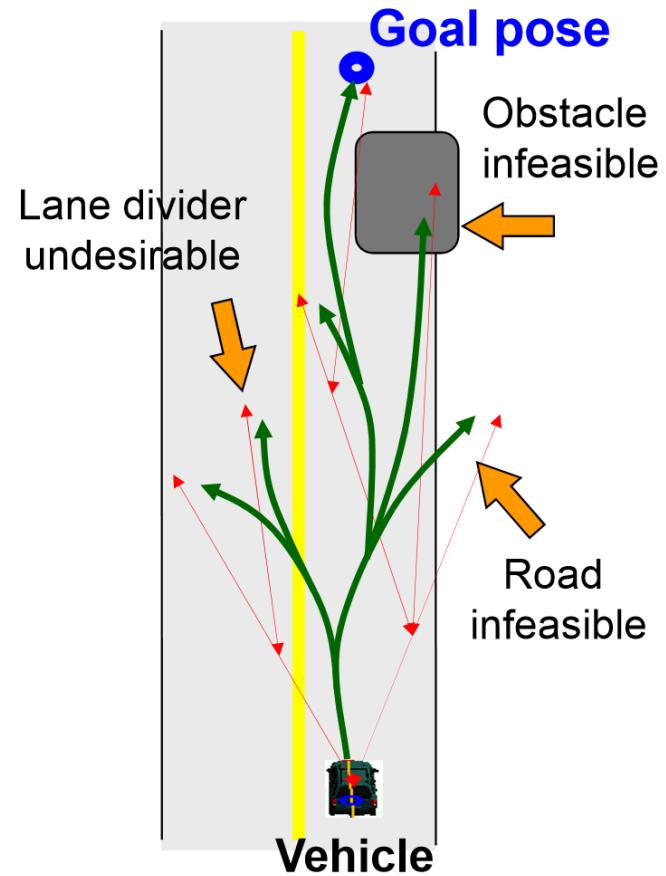


# Exercise: Building an Autonomous Car

How can we get our  
agent to accommodate  
obstacles?



# Exercise: Building an Autonomous Car



# RRT for Autonomous Parking



**How can we make use of these representations?**  
Search algorithms provide a way to find a path!

