



# AuSROS

Australian School of Robotic Systems

## B1 - Motion Planning

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Australian National University

Some content adapted from Hanna Kurniawati's Adv. AI Course



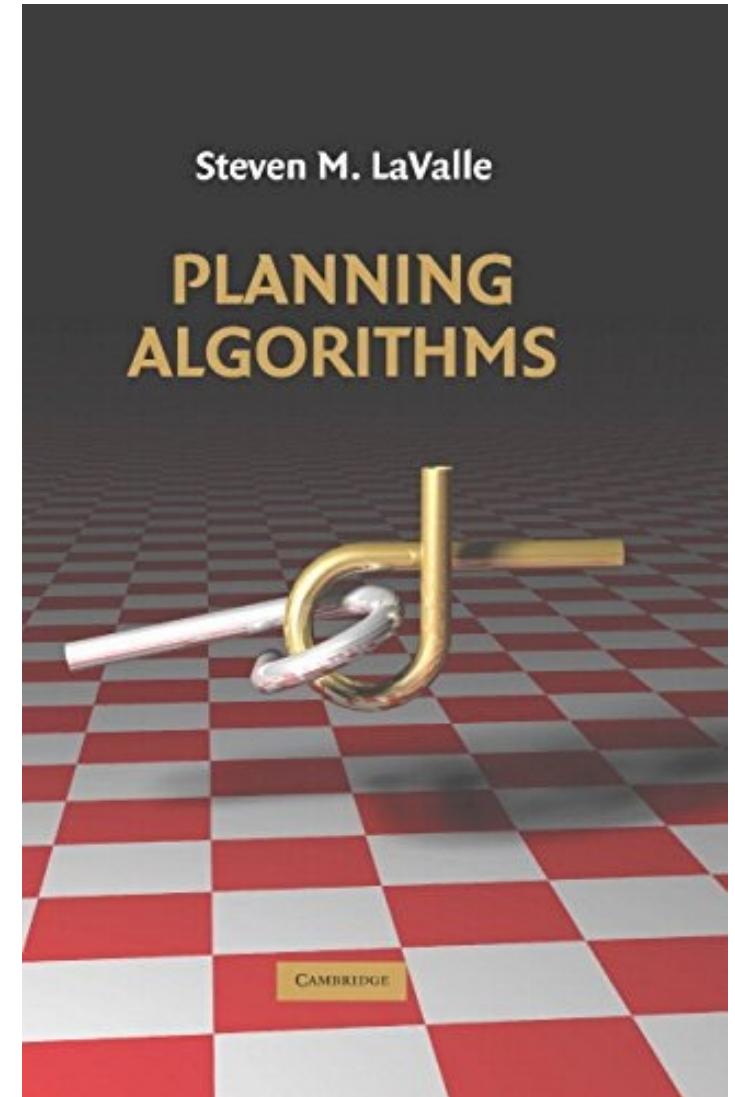




Open Motion Planning Library  
<https://ompl.kavrakilab.org/>



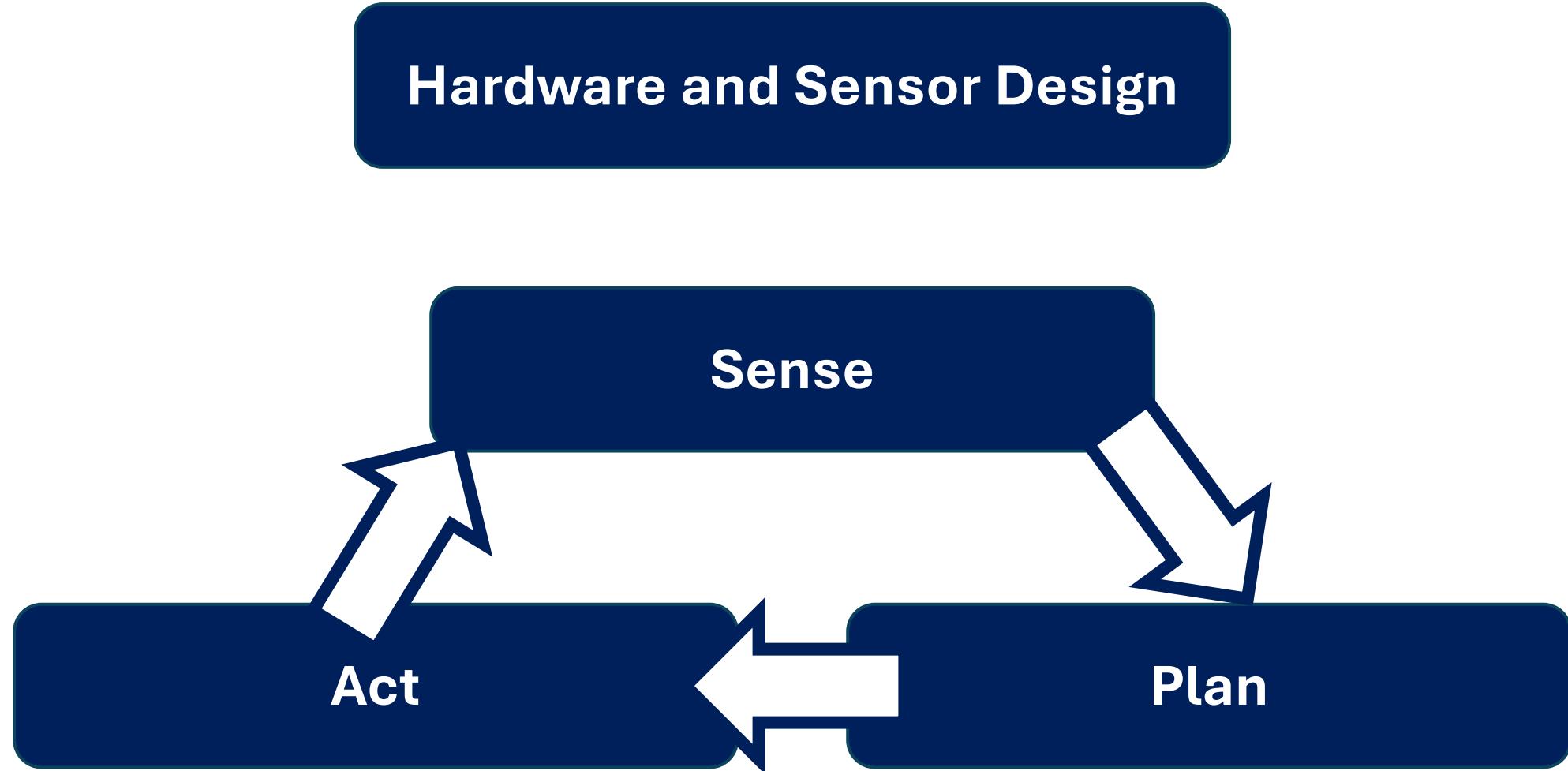
Moveit  
<https://moveit.ros.org/>



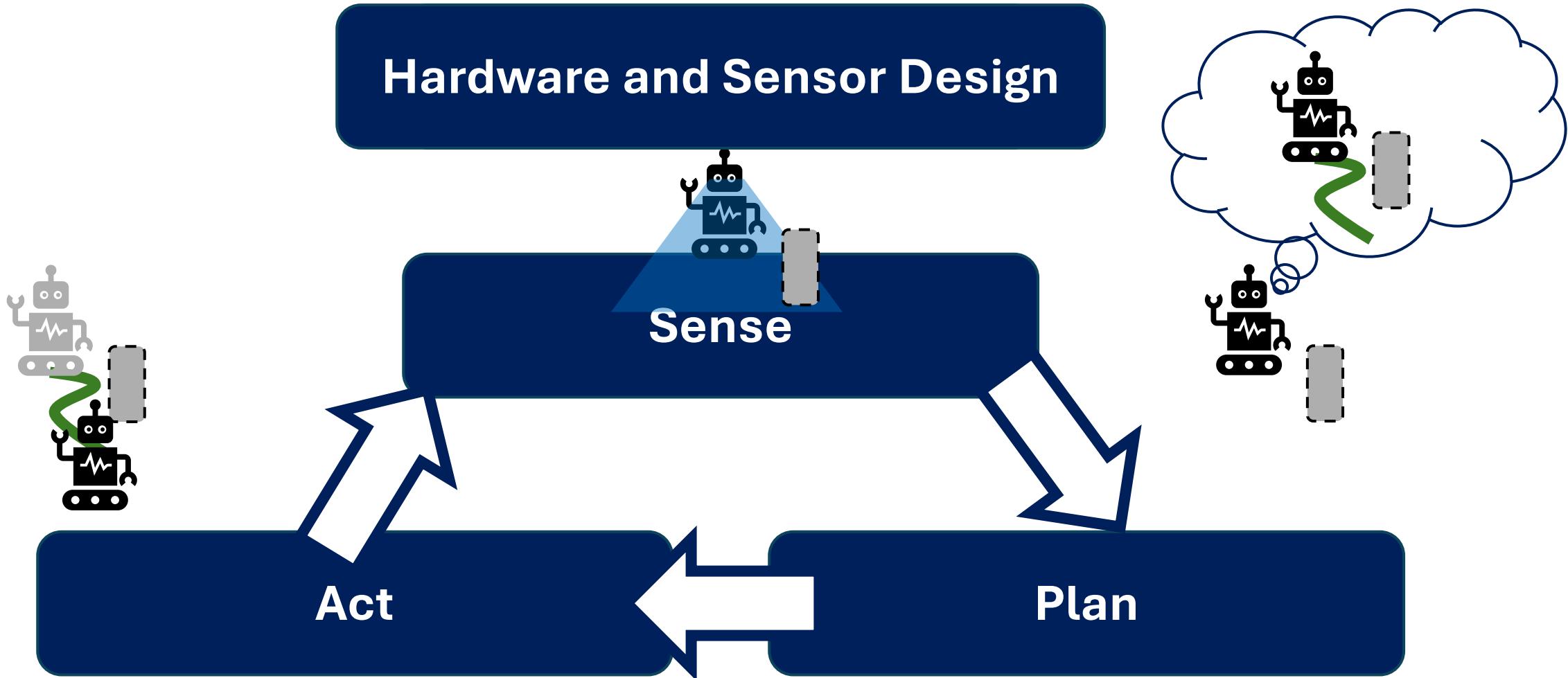
<https://lavalle.pl/planning/>

# Planning

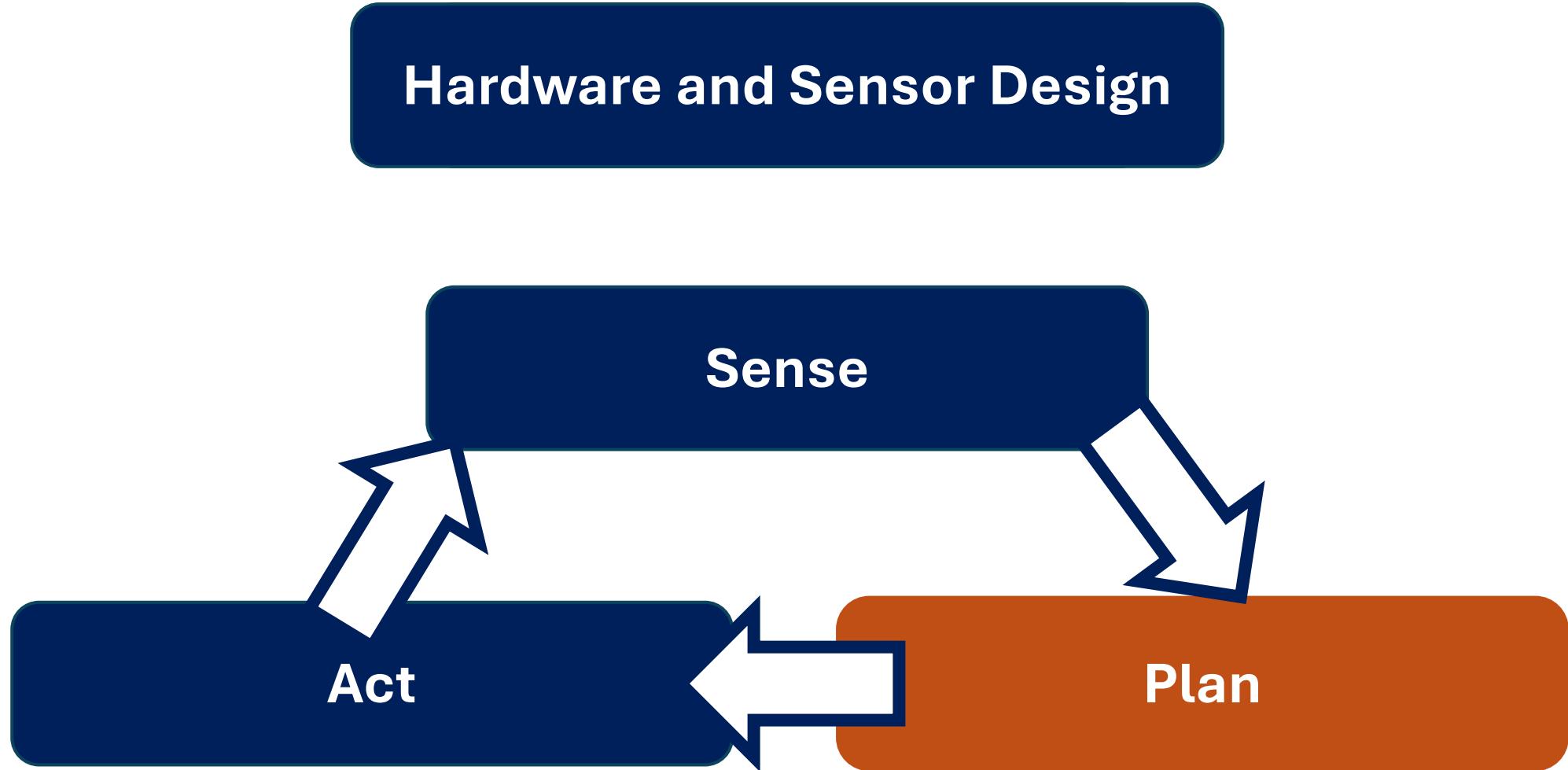
# Robotics



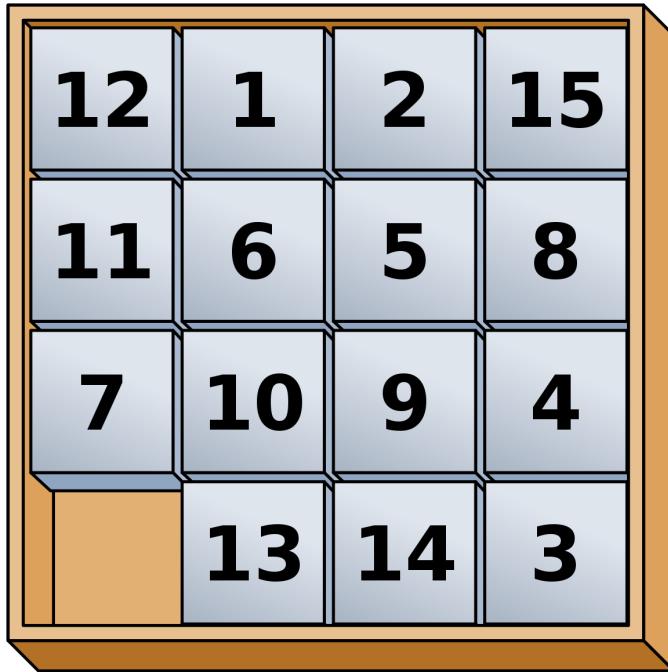
# Robotics



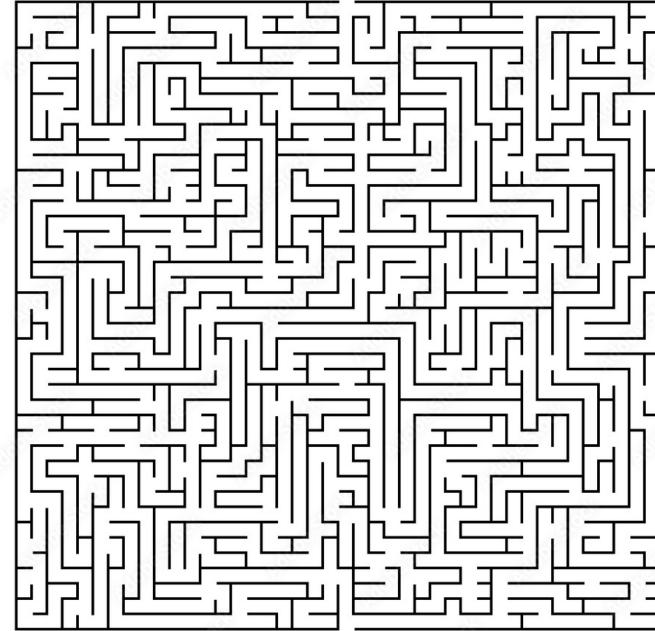
# Robotics



# Computationally Hard Problems



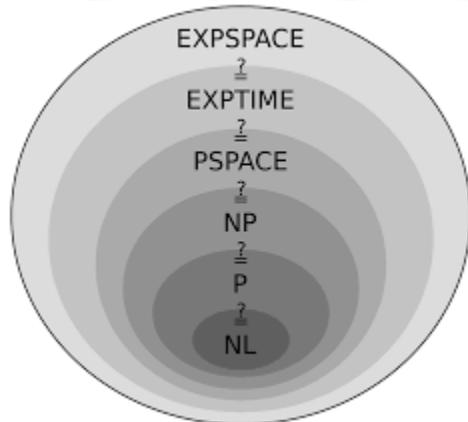
wikipedia 15 puzzle



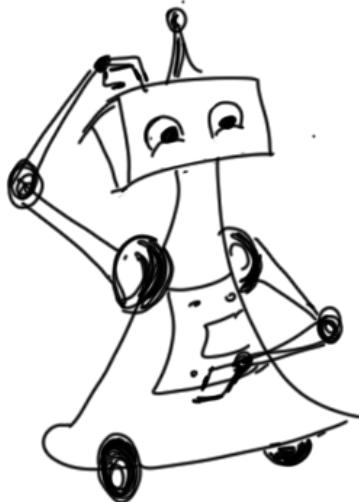
Adobe Stock | #203088304



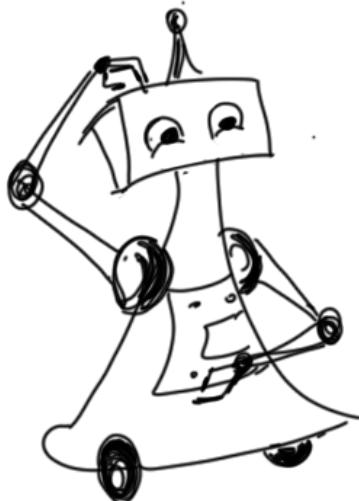
chess.com

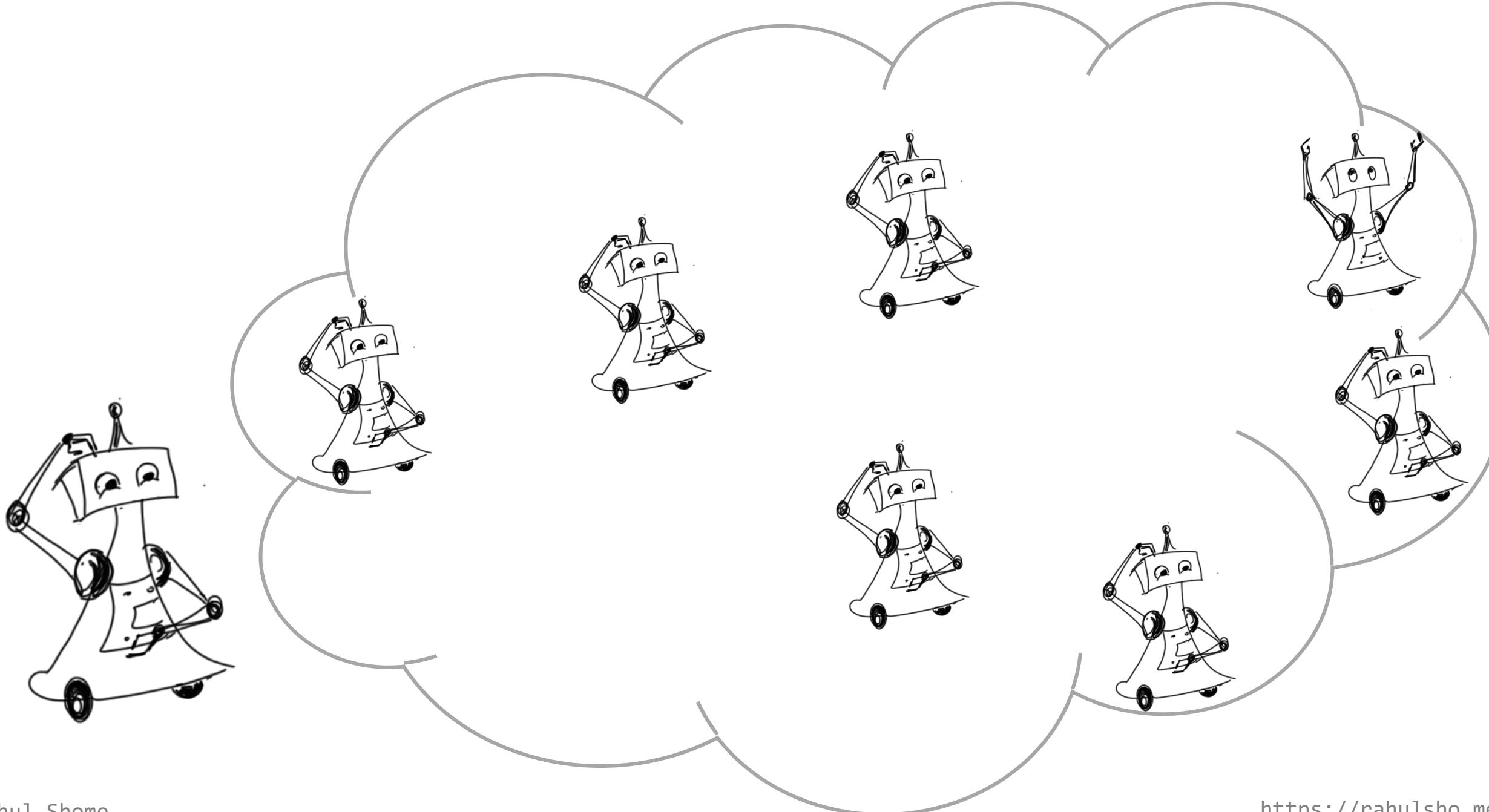


# Two roads diverged in a wood...

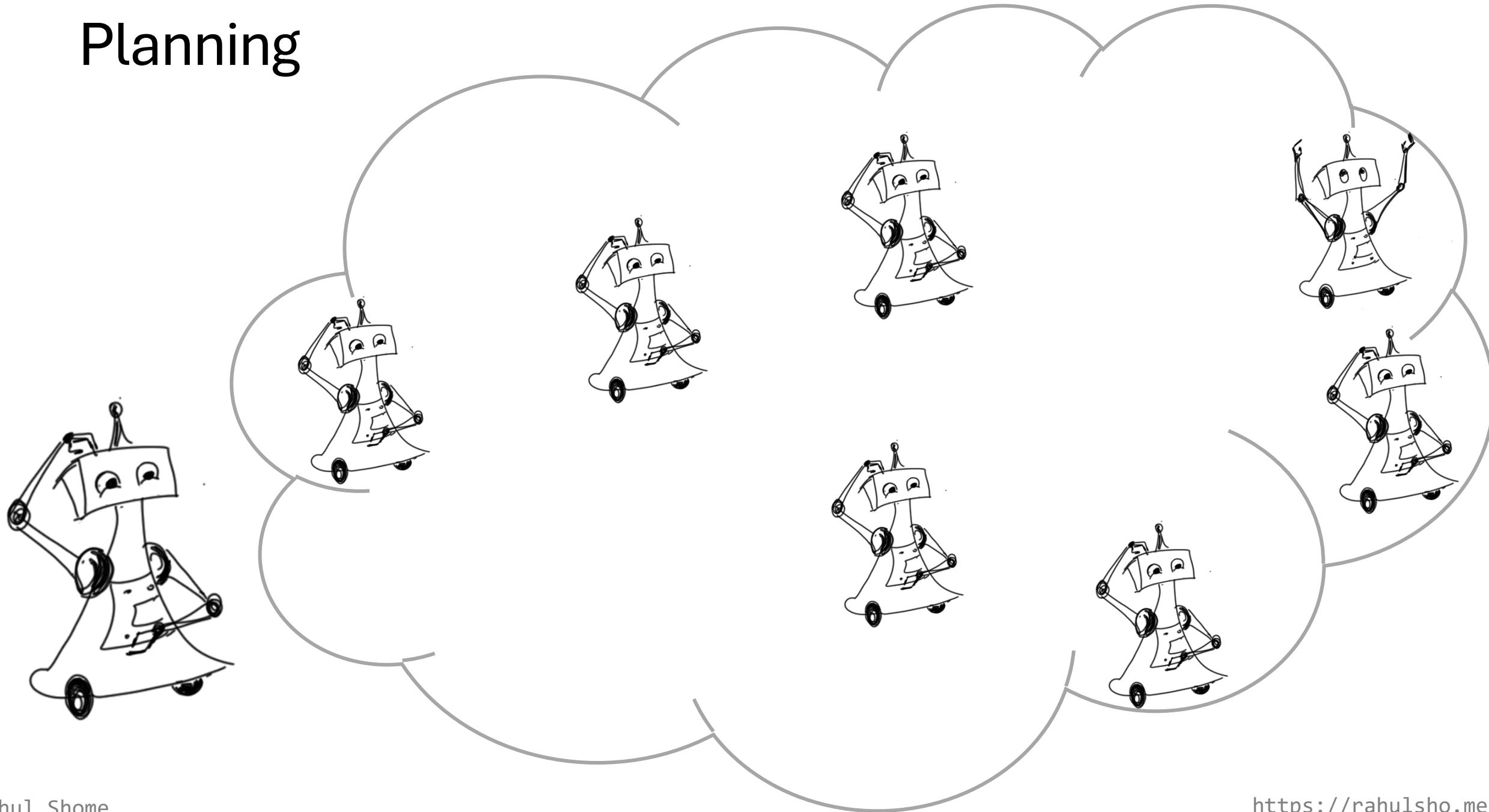


# Many roads diverged in a wood

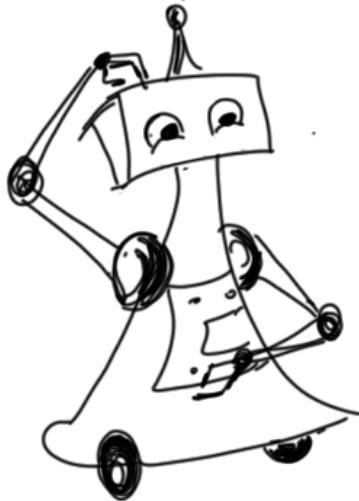




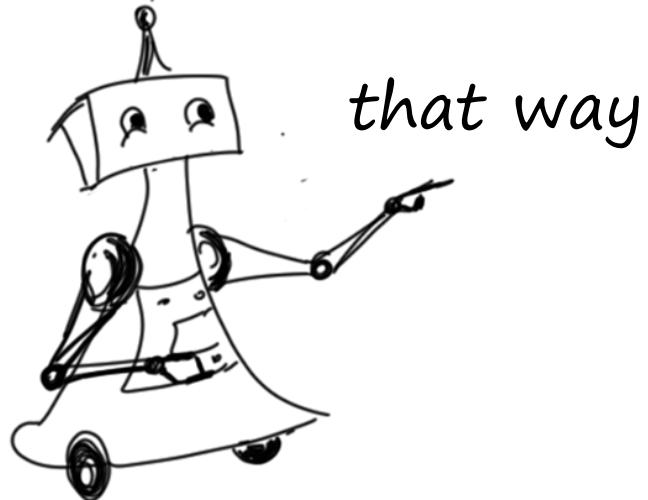
# Planning



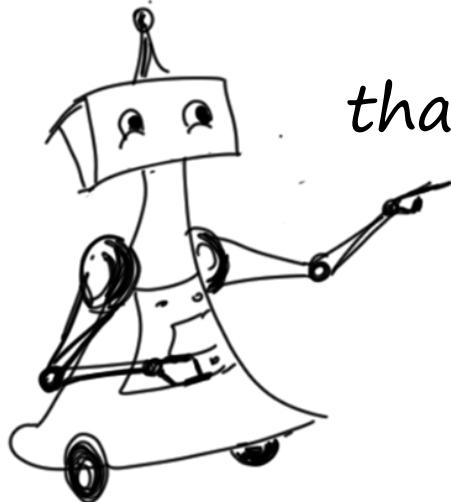
Two roads diverged in a wood, and  
the robot took the one to its goal.



Two roads diverged in a wood, and  
the robot took the one to its goal.



# Planning



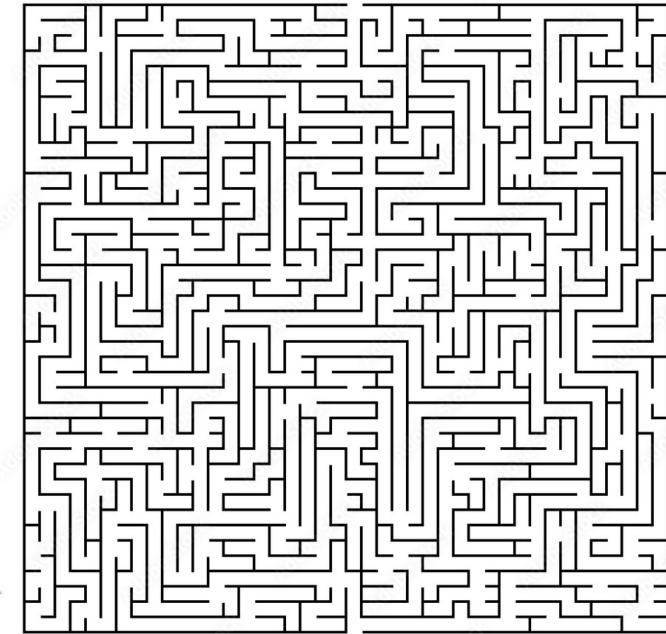
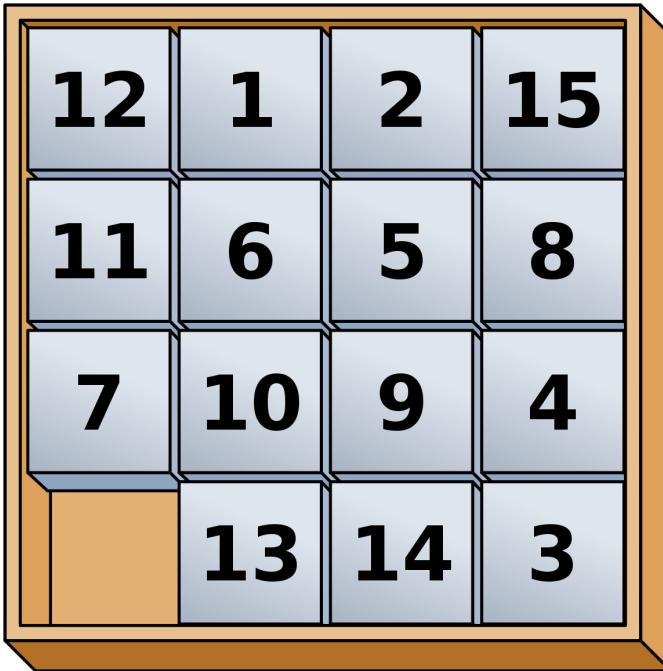
that way

Long-horizon  
goal-directed  
reasoning  
while  
respecting constraints

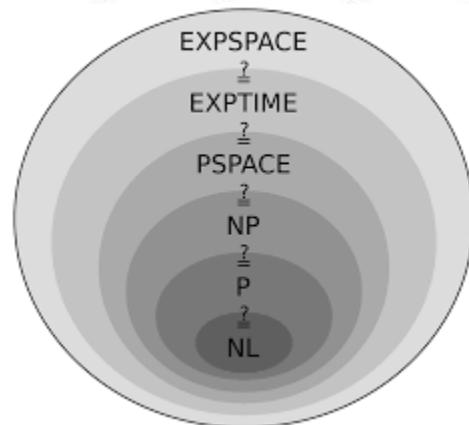
*Think many steps ahead.  
Reach objective.*

*Not every move is valid.*

# How do we represent a robot planning problem?



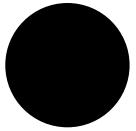
chess.com



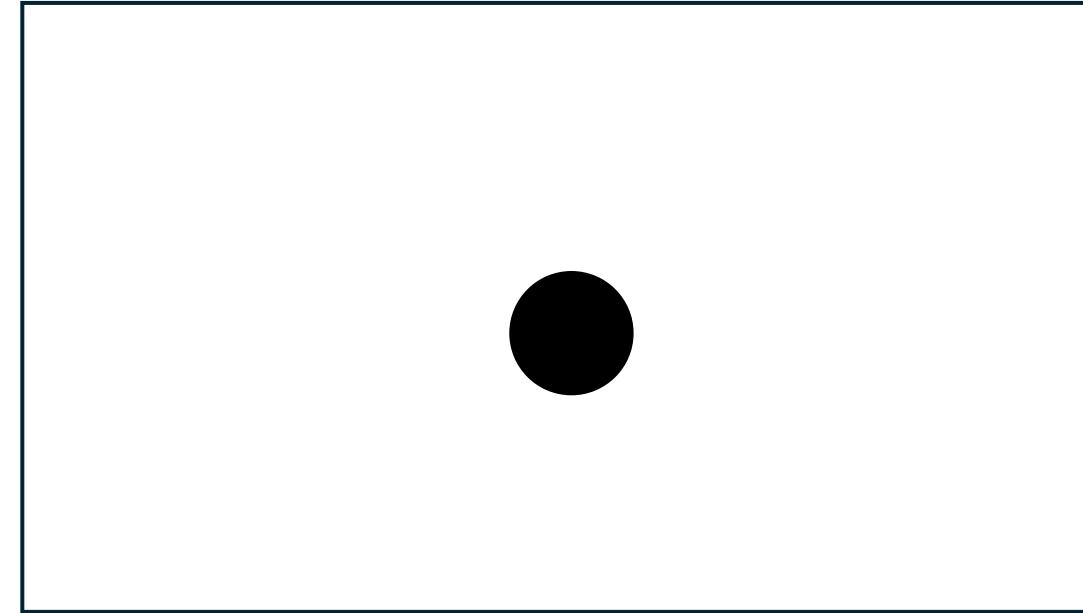
# Representations and Abstractions

# But first, what's the point?

How do we represent or model a robot?

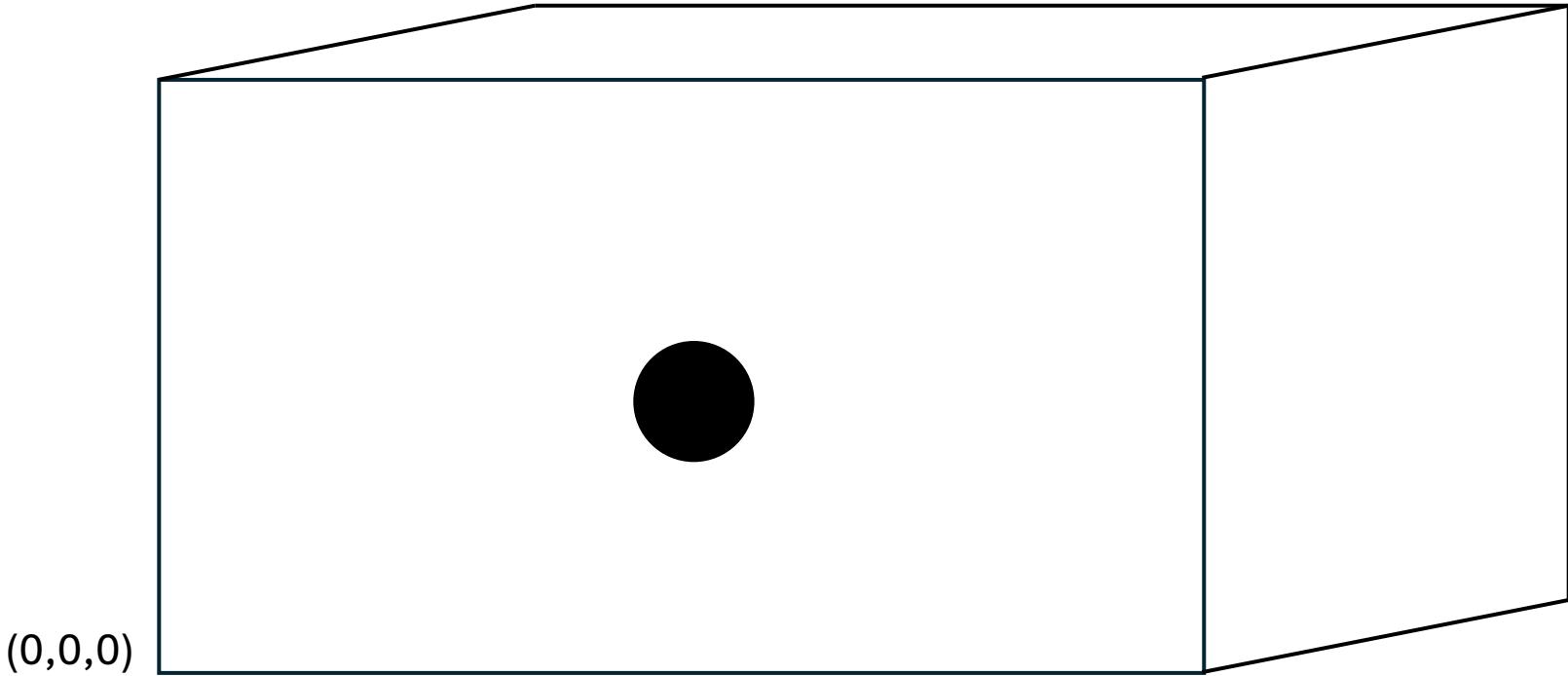


# A point



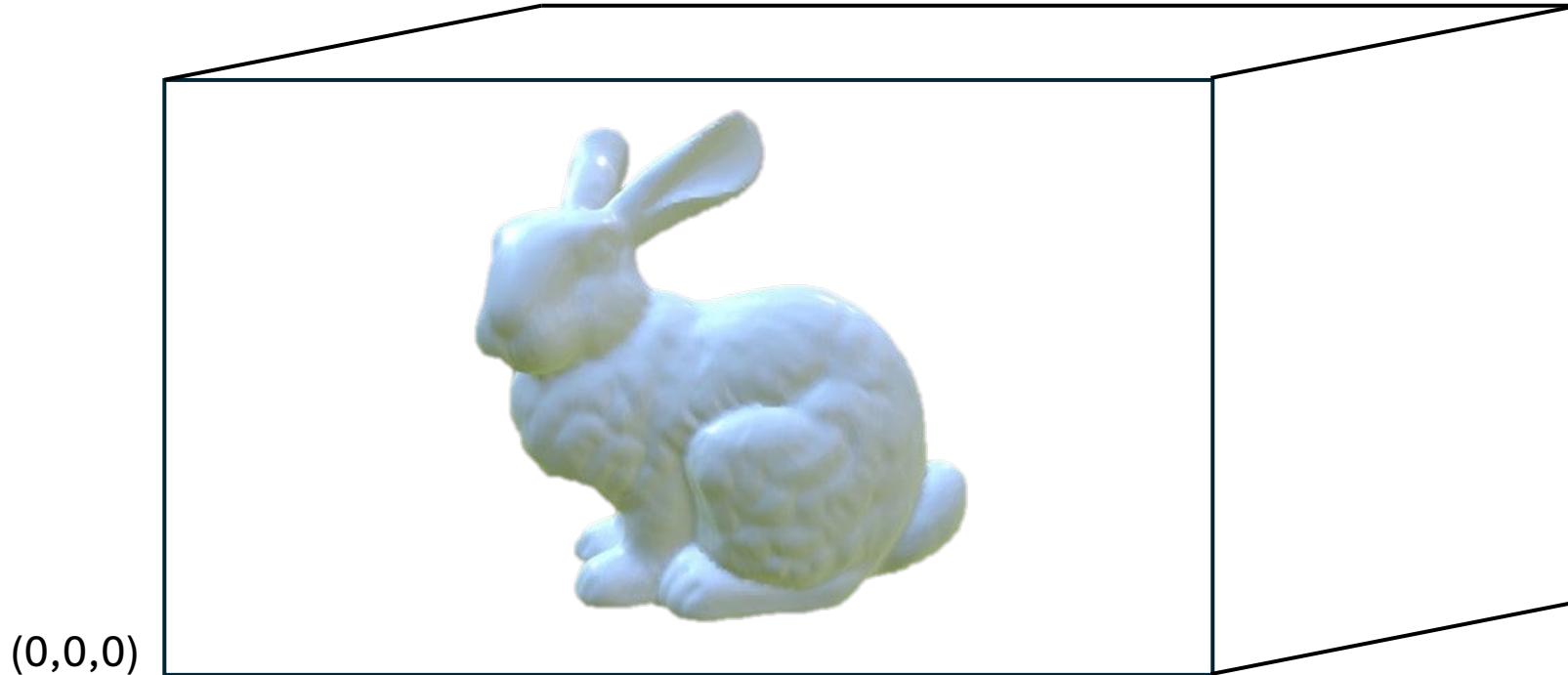
A coordinate in 2D is  $(x,y)$  wrt some origin  $(0,0)$

# A point

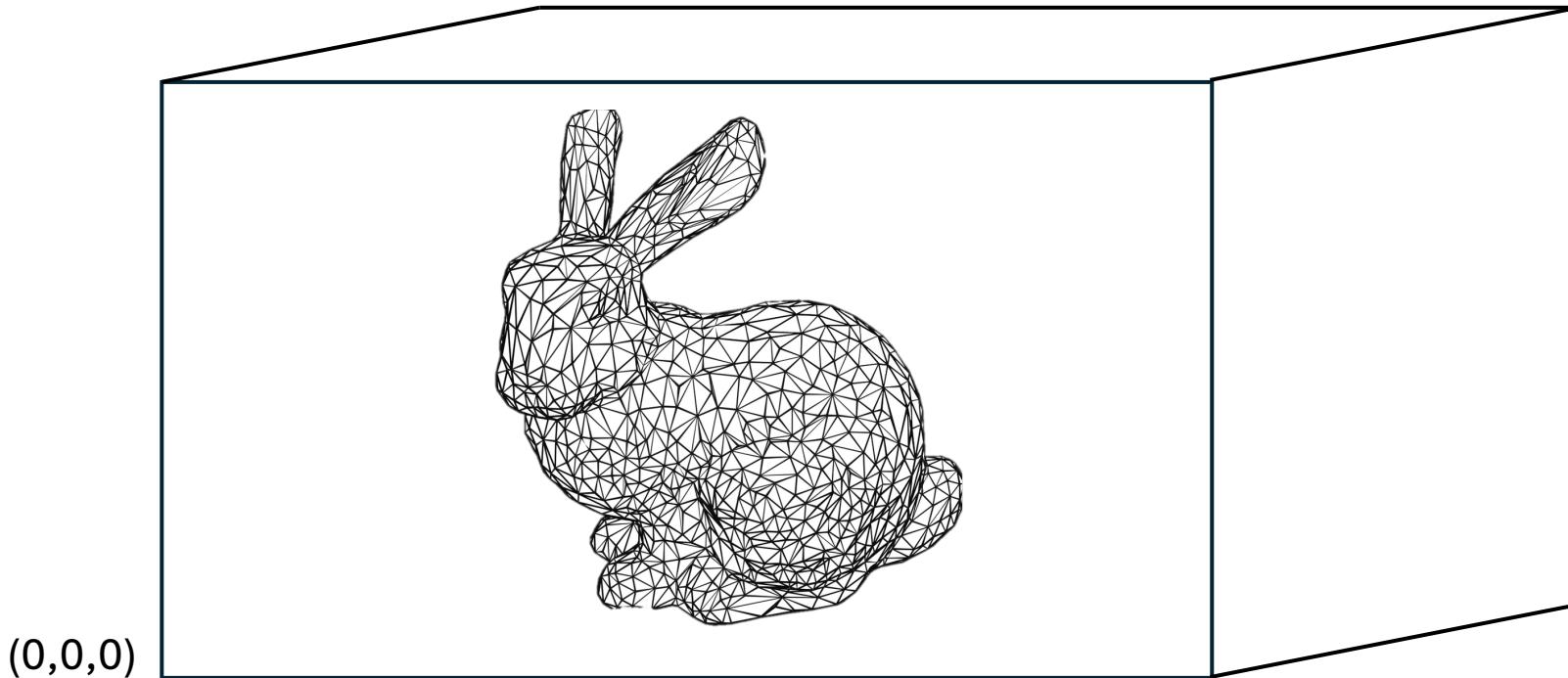


A coordinate in 3D is  $(x,y,z)$  wrt some origin  $(0,0,0)$

# A rigid body

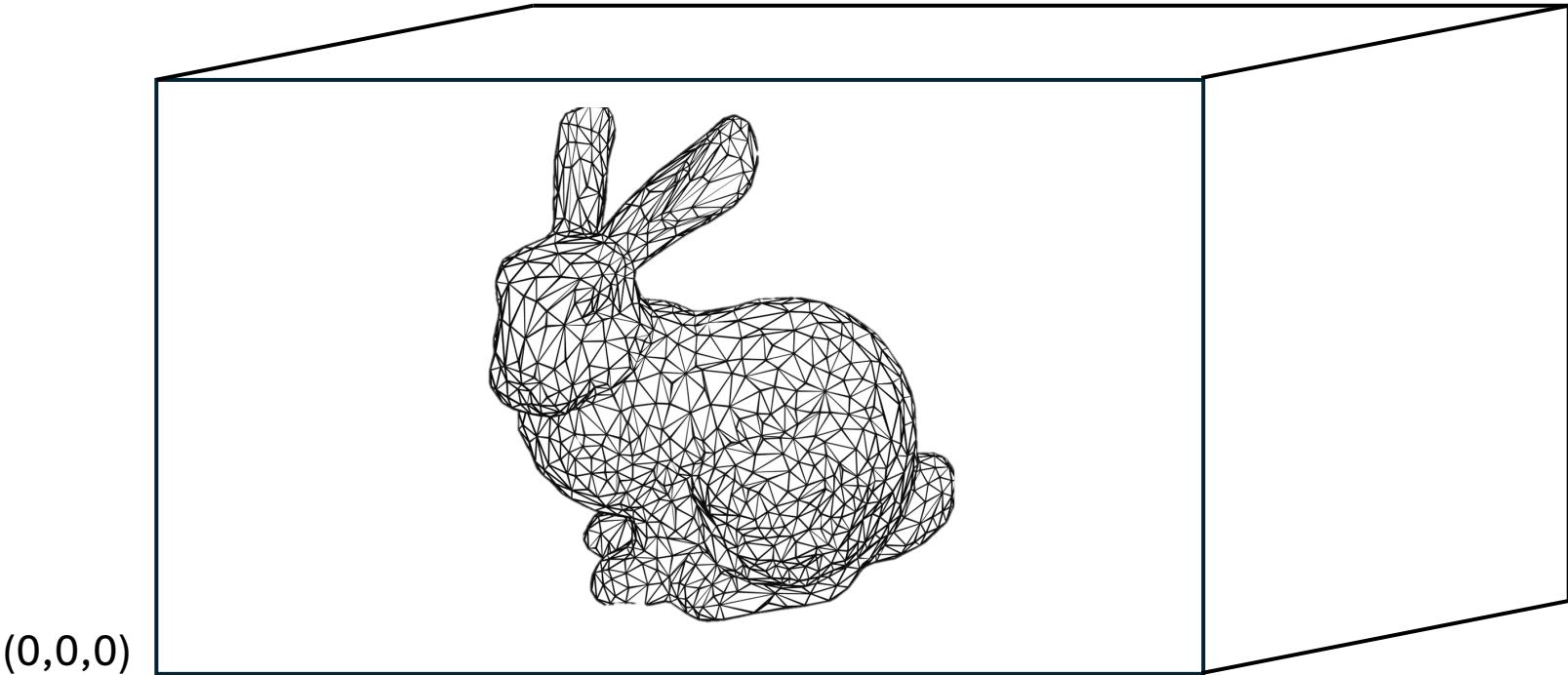


# A rigid body



A set of points

# A rigid body

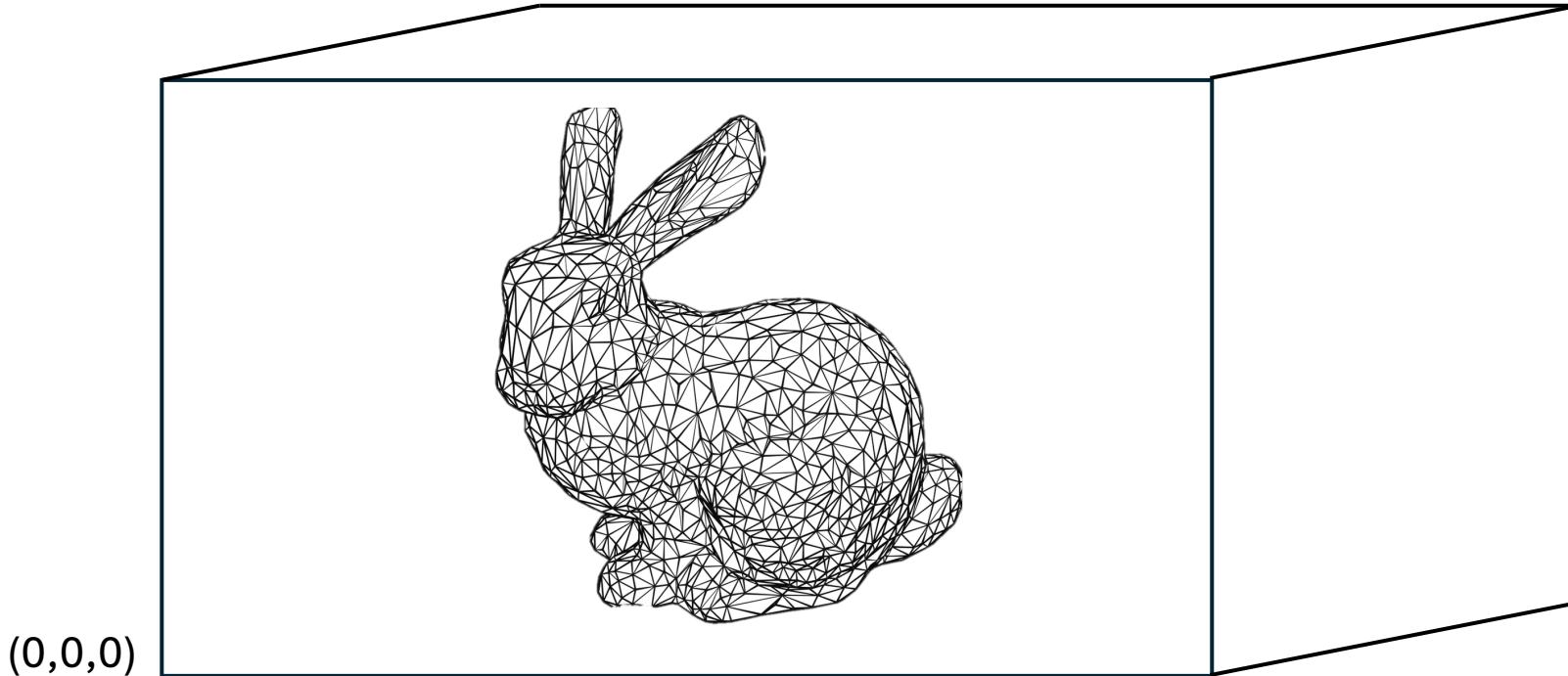


A set of points such that their relative distance does not change



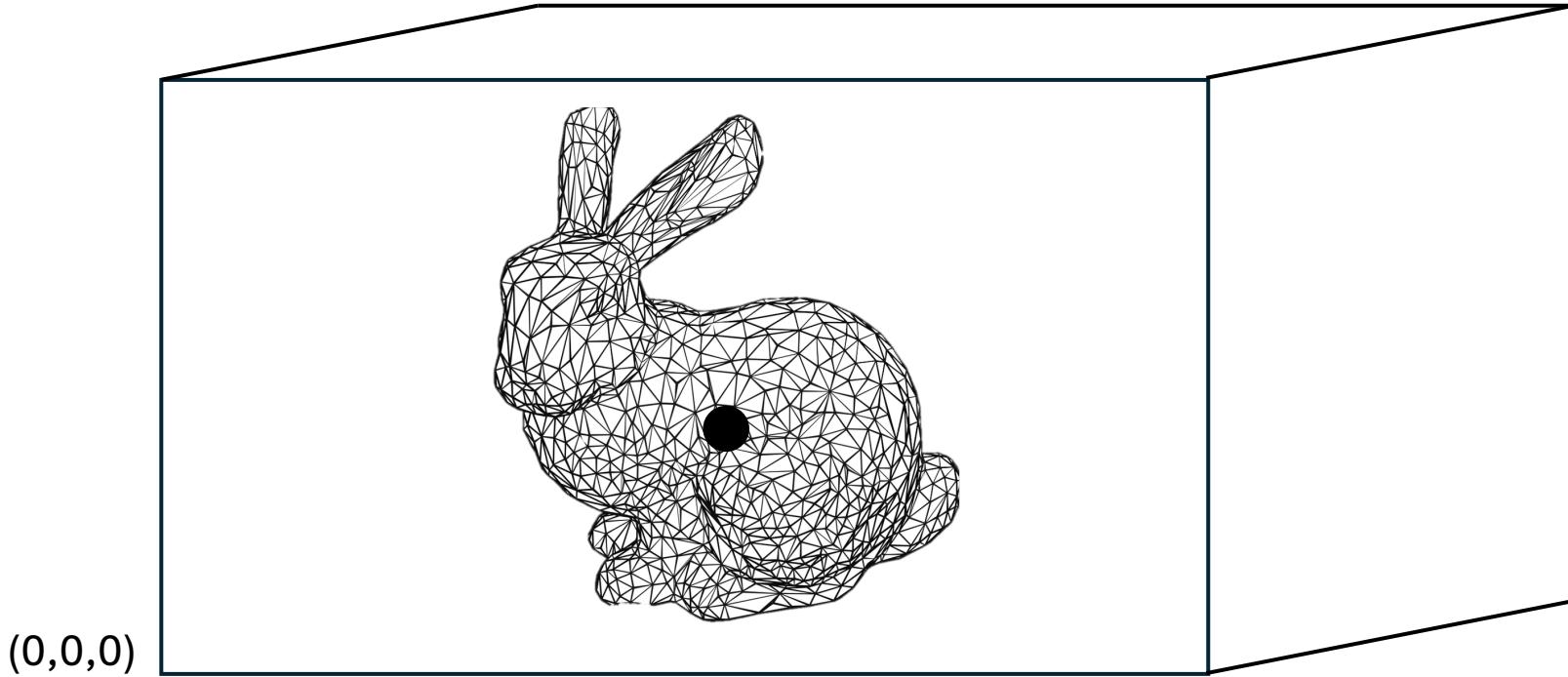
rigid

# How do we represent a rigid body?



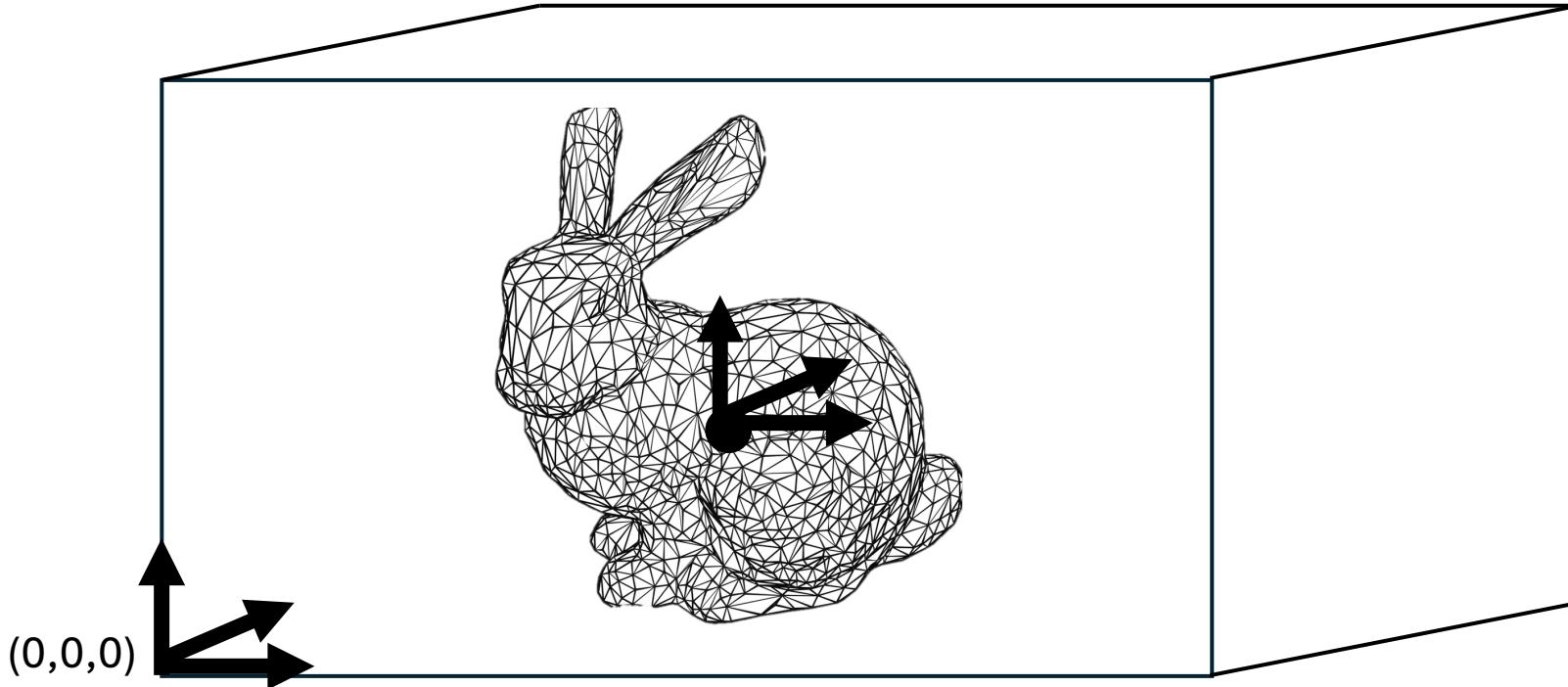
Option 1: A set of points.

# How do we represent a rigid body?



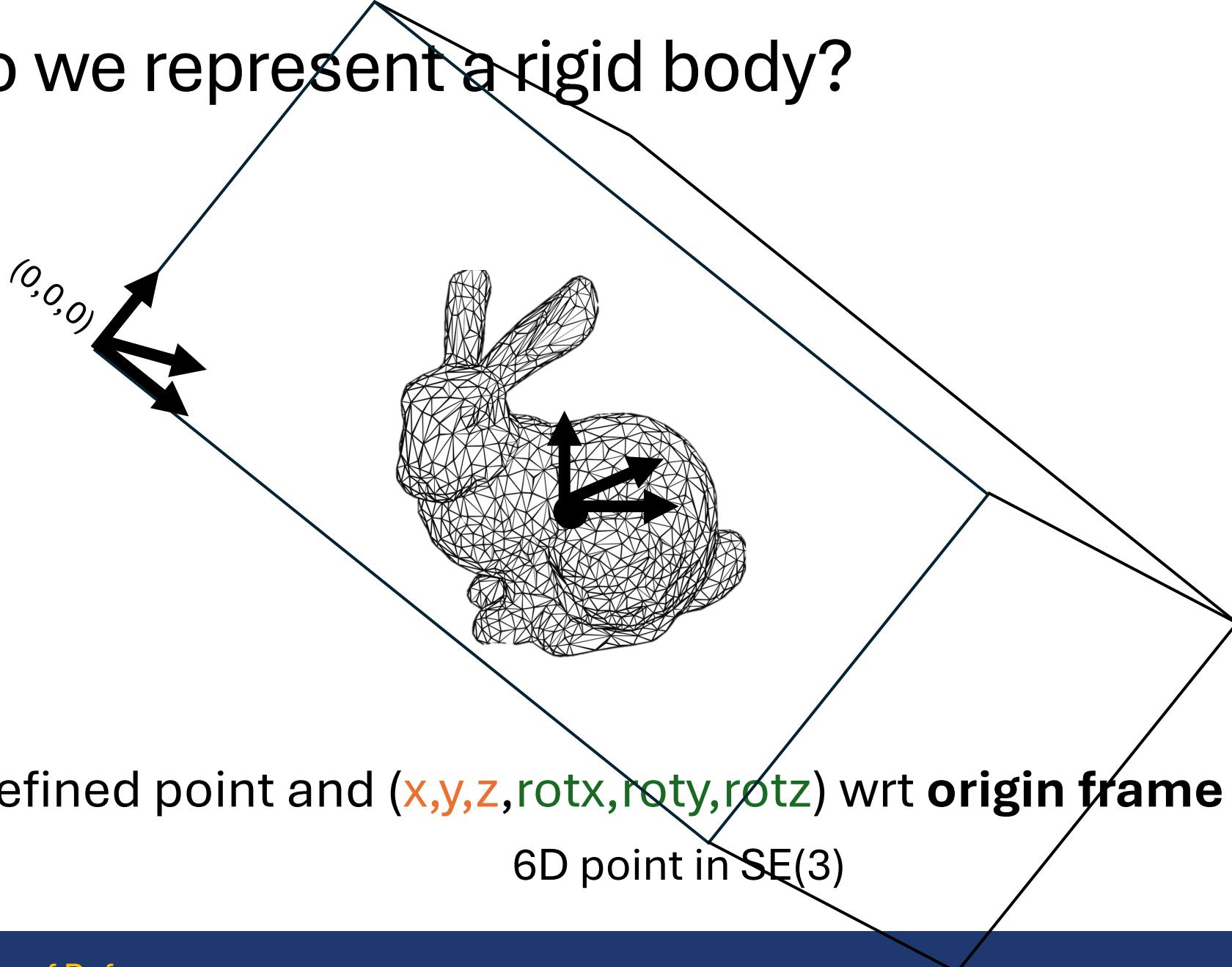
Option 2: One predefined point **and ... ?**

# How do we represent a rigid body?

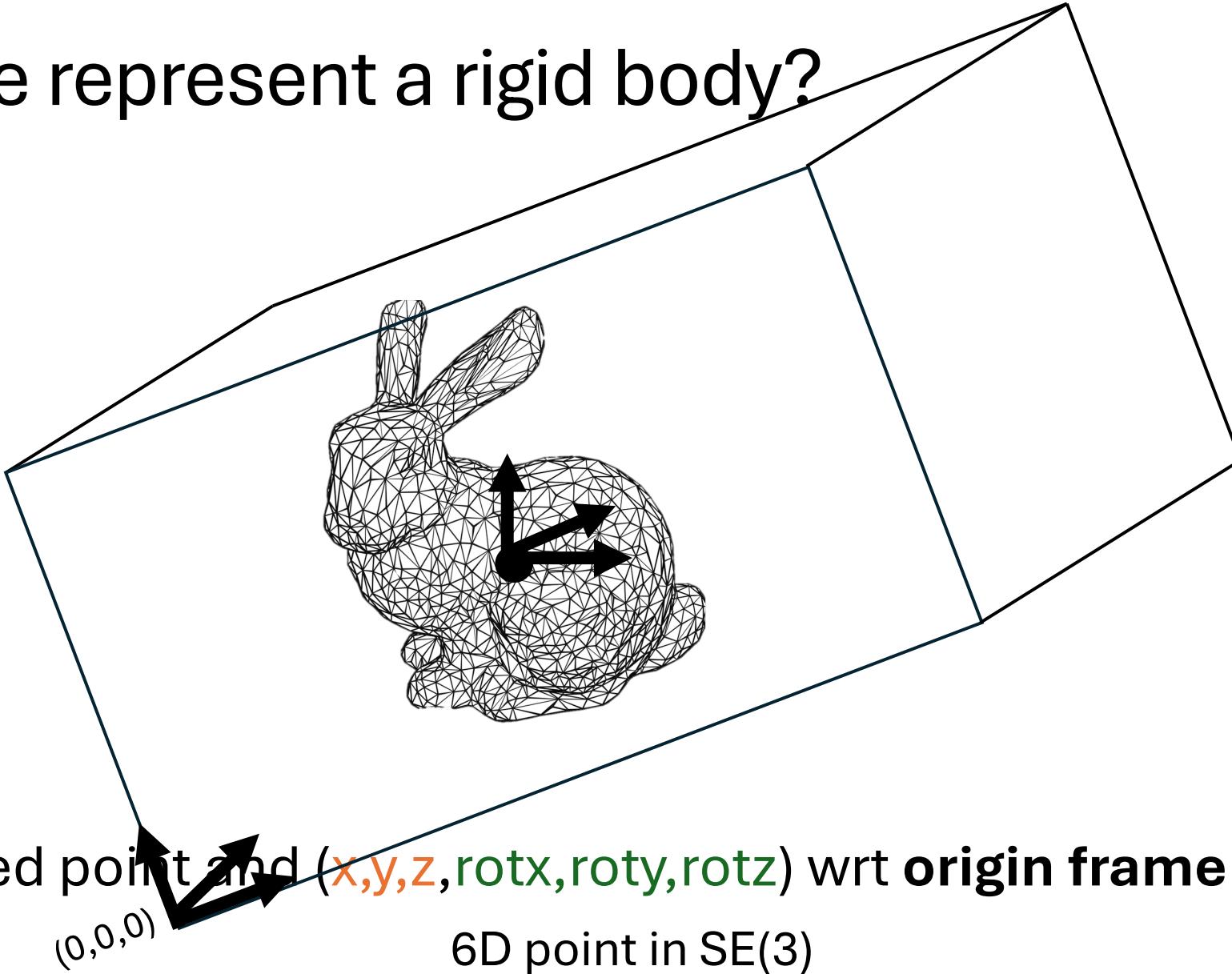


One predefined point and ( $x, y, z, \text{rot}_x, \text{rot}_y, \text{rot}_z$ ) wrt origin frame  
6D point in SE(3)

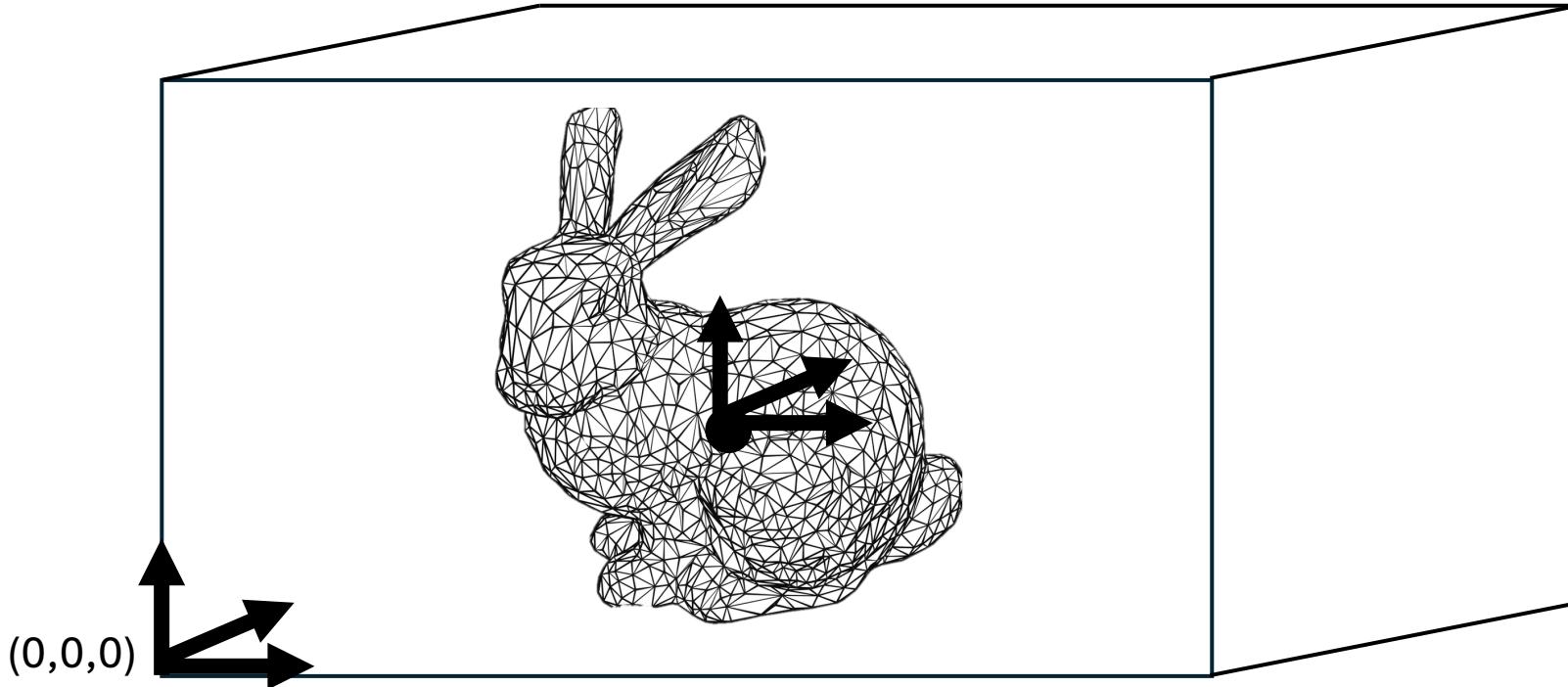
# How do we represent a rigid body?



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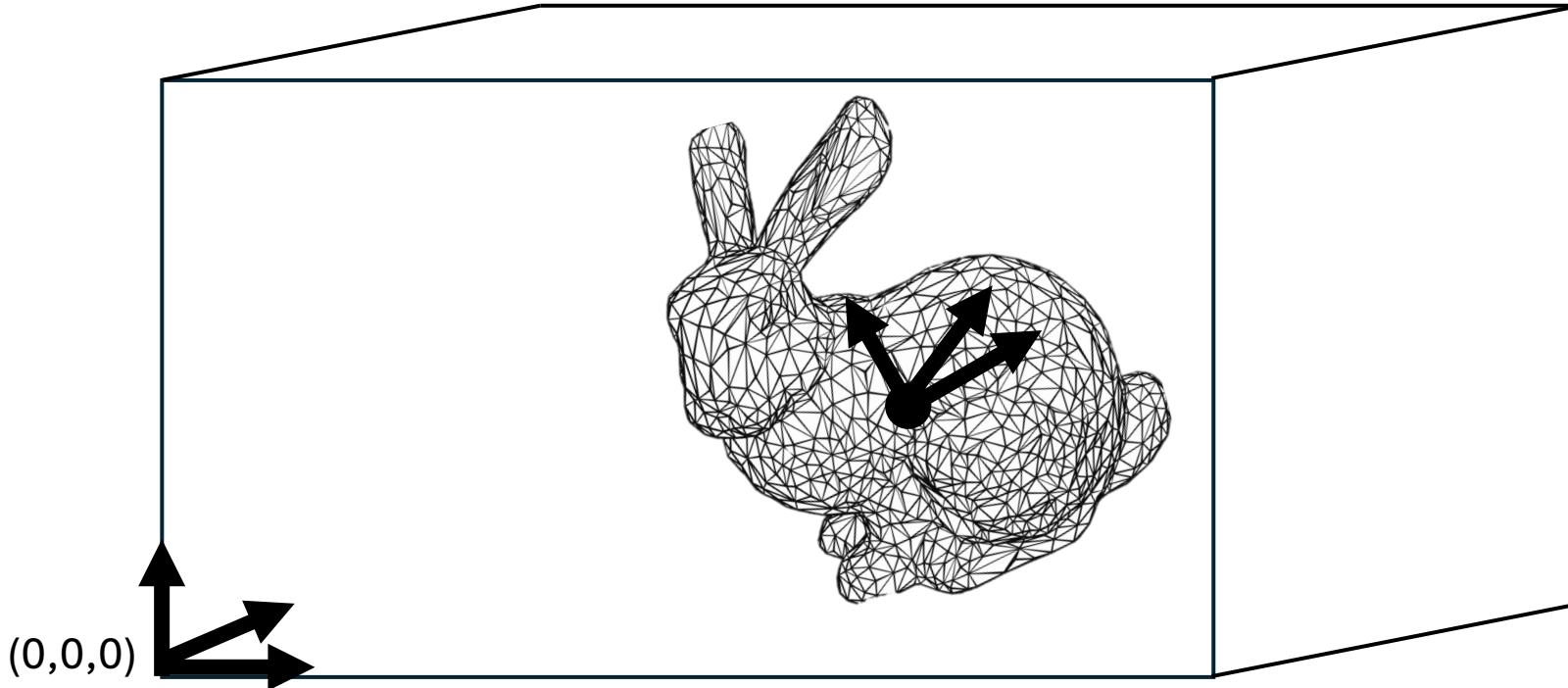


# How do we represent a rigid body?



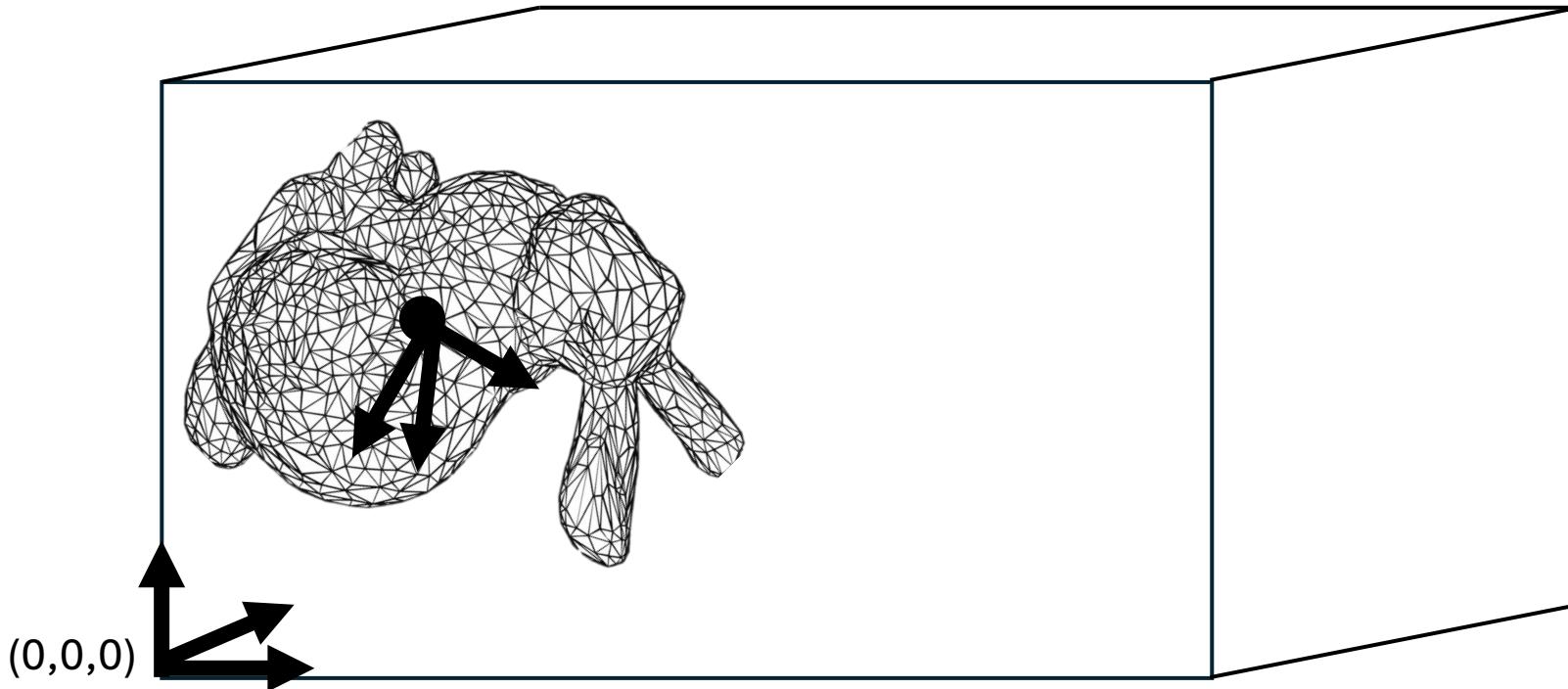
One predefined point and ( $x, y, z, \text{rot}_x, \text{rot}_y, \text{rot}_z$ ) wrt origin frame  
6D point in SE(3)

# How do we represent a rigid body?



One predefined point and ( $x, y, z, \text{rot}_x, \text{rot}_y, \text{rot}_z$ ) wrt origin frame  
6D point in SE(3)

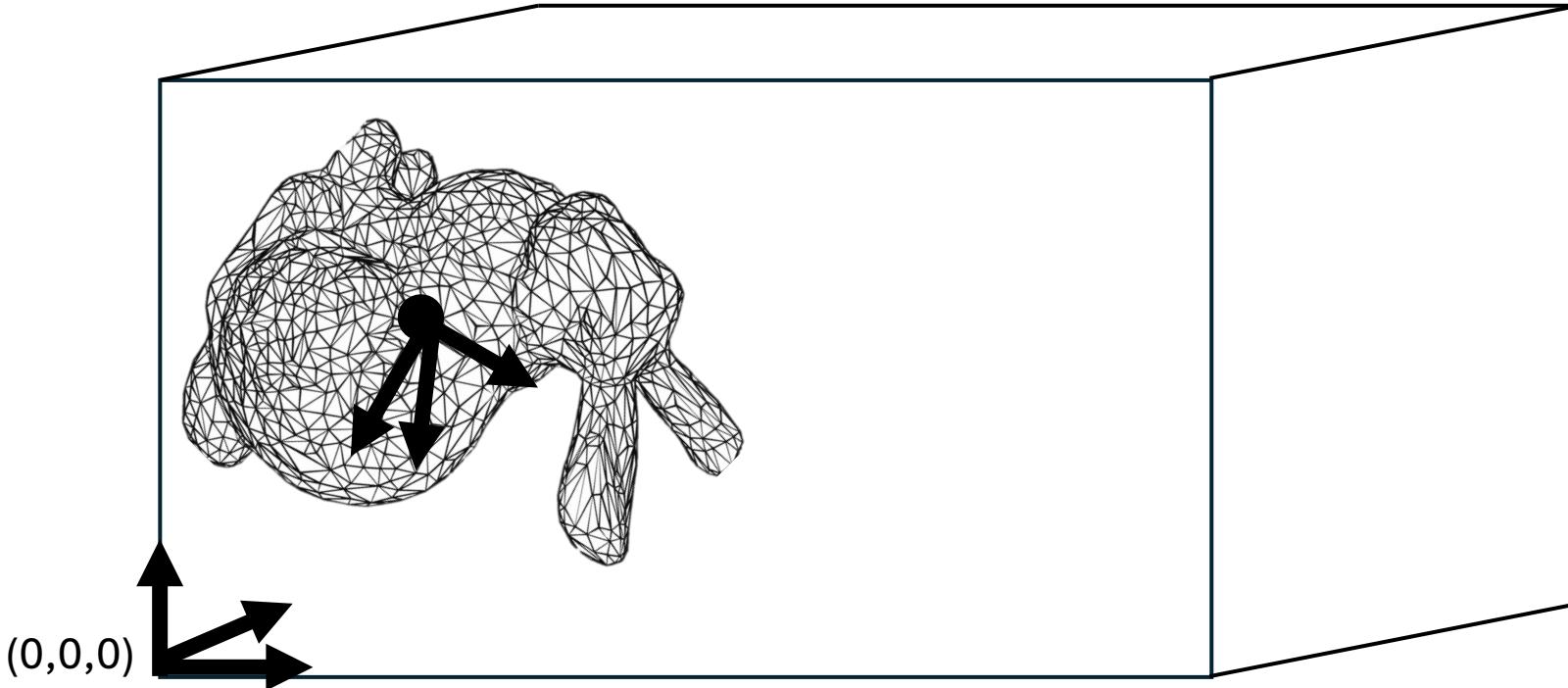
# Rigid Body Poses



One predefined point and ( $x, y, z, \text{rot}_x, \text{rot}_y, \text{rot}_z$ ) wrt origin frame

**Pose in SE(3)**

# Rigid Body Poses

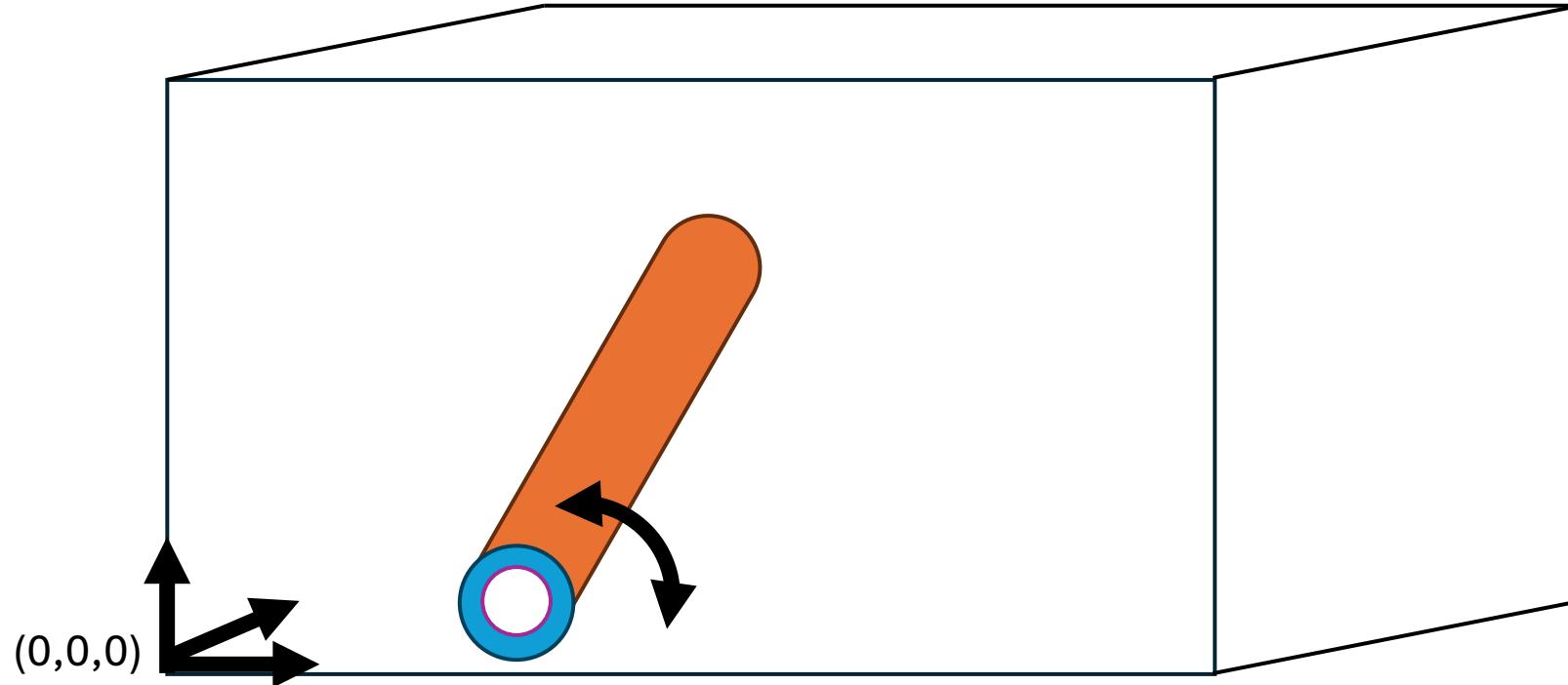


One predefined point and ( $x, y, z, \text{rot}_x, \text{rot}_y, \text{rot}_z$ ) wrt

**Pose in SE(3)**

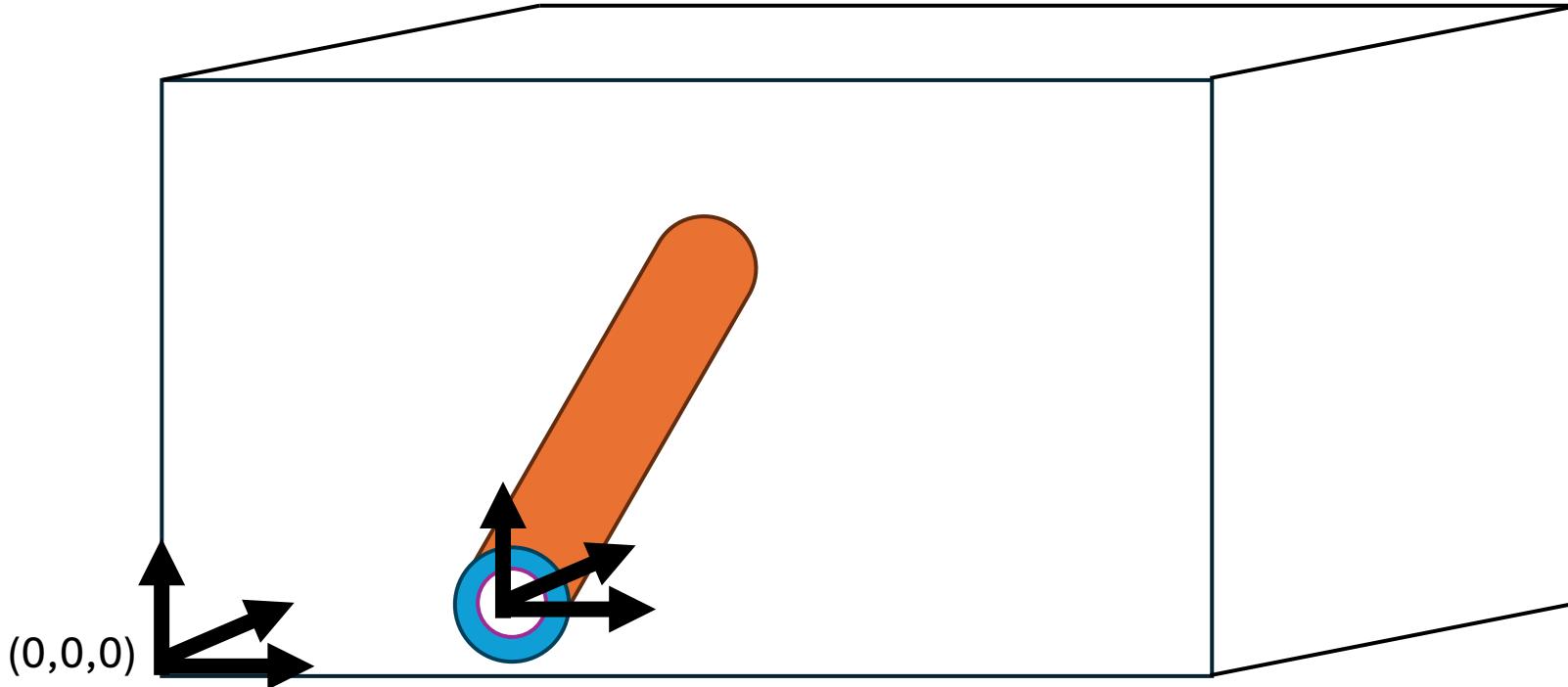
3D rotations can have several representations – Euler angles, axis-angle, rotation matrix, **quaternion**

# How do we represent a single-jointed robot?



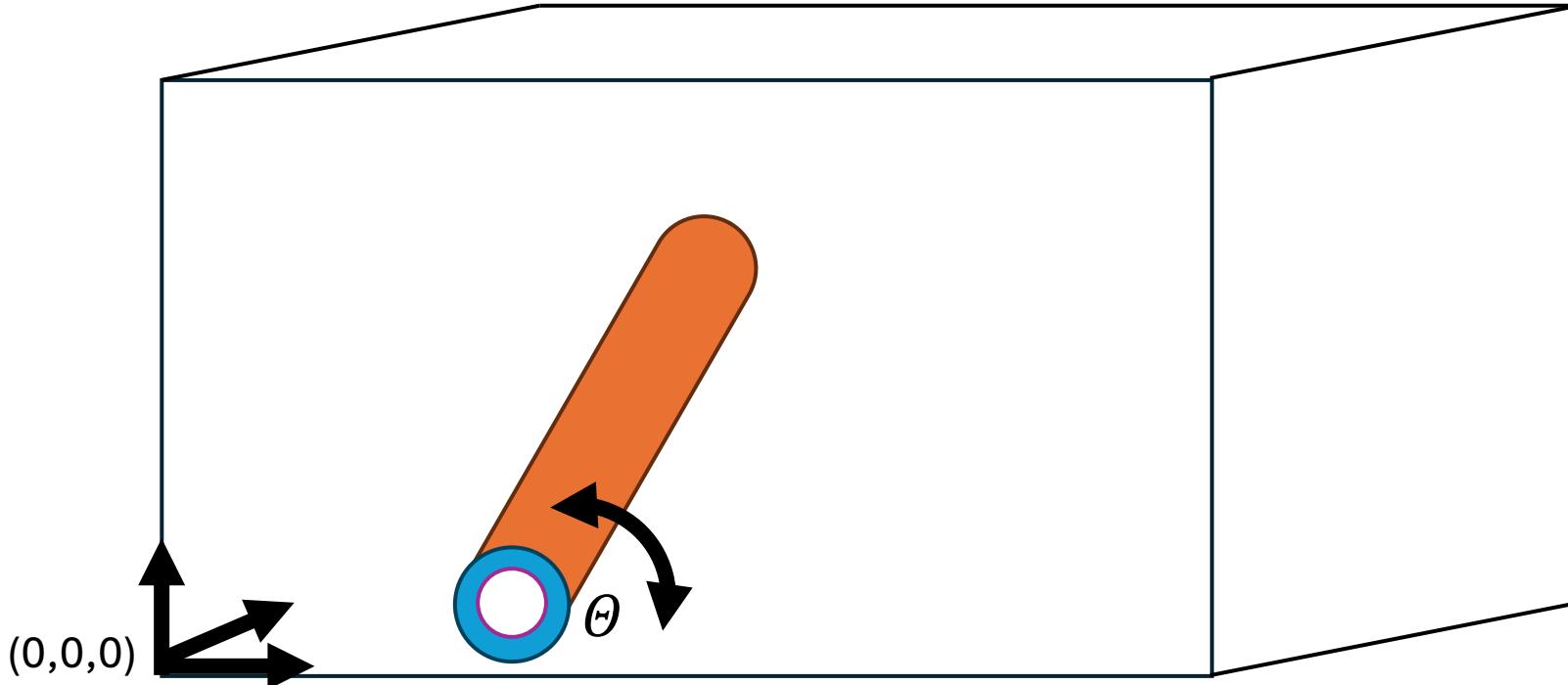
One predefined point and ( $x, y, z, \text{rot}_x, \text{rot}_y, \text{rot}_z$ ) wrt origin frame

# How do we represent a single-jointed robot?



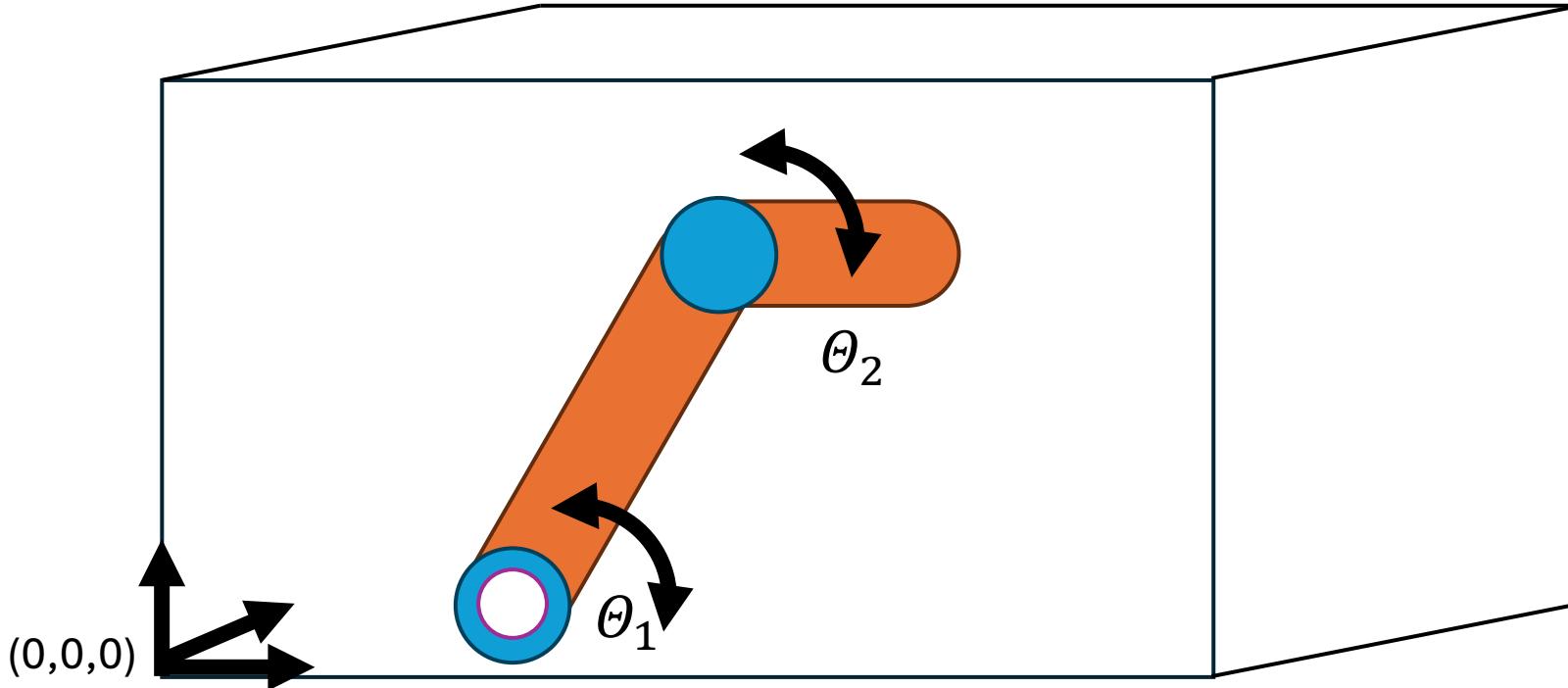
One predefined point and ( $x, y, z, \text{rot}_x, \text{rot}_y, \text{rot}_z$ ) and ...?

# How do we represent a single-jointed robot?



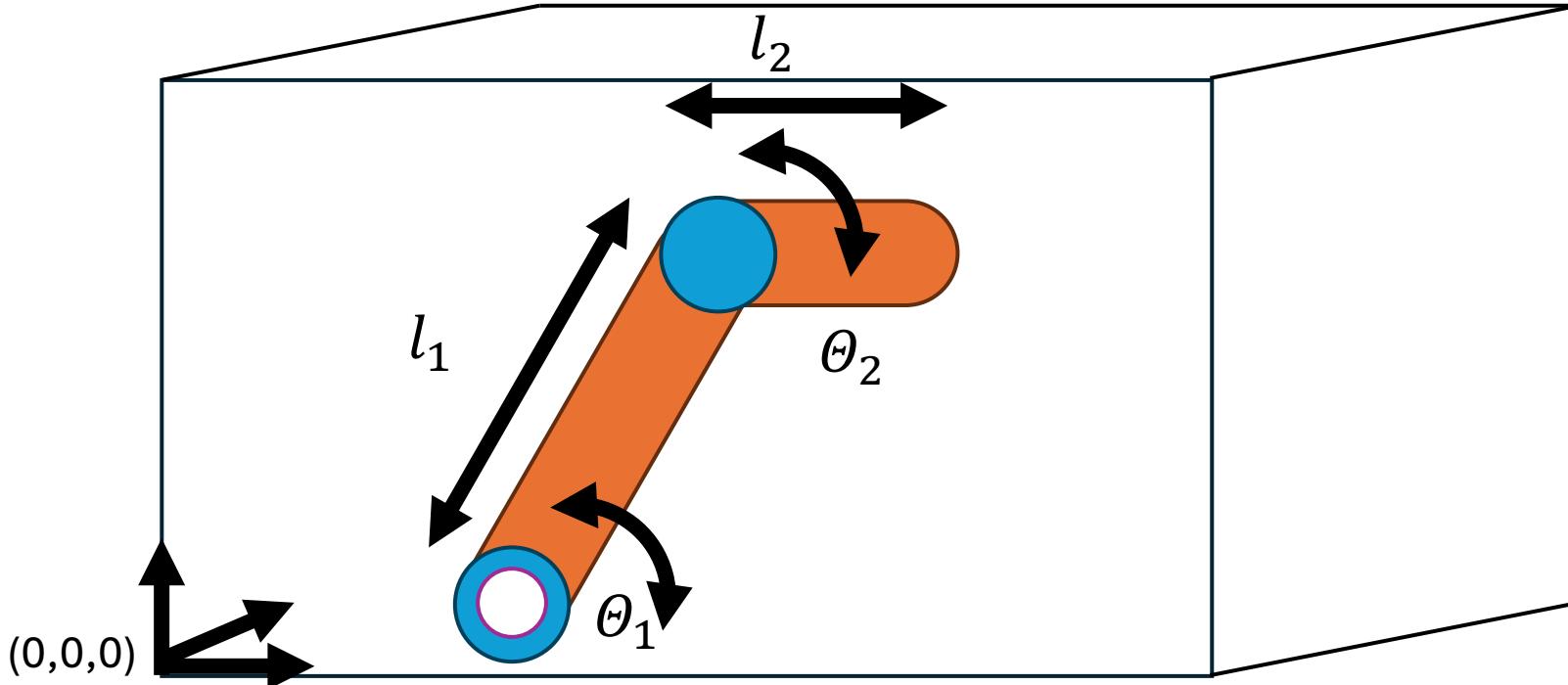
Base frame pose and angle  $\theta$

# More joints



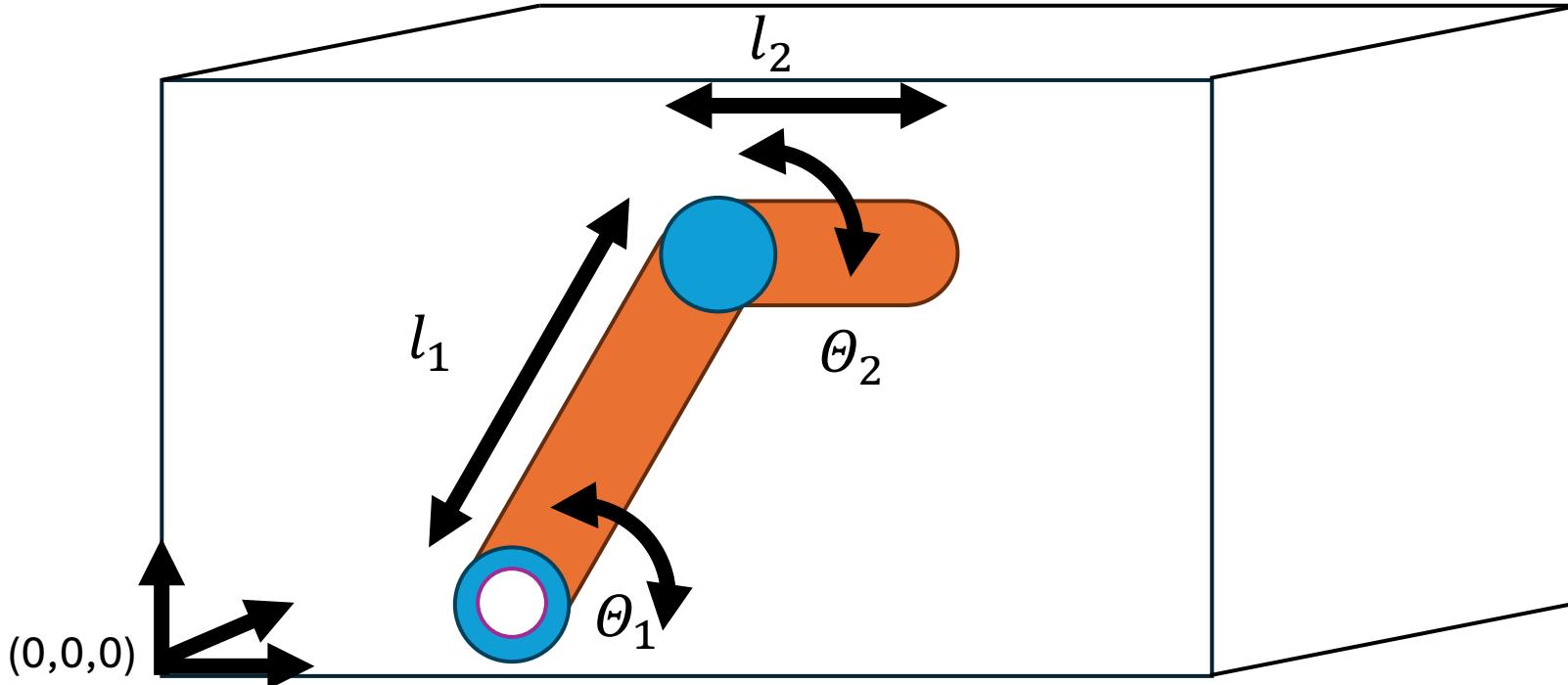
Base frame pose, angle  $\theta_1$  and ...?

# More joints



Base frame pose,  $l_1$ ,  $l_2$ , angles  $\theta_1$ ,  $\theta_2$

# More joints

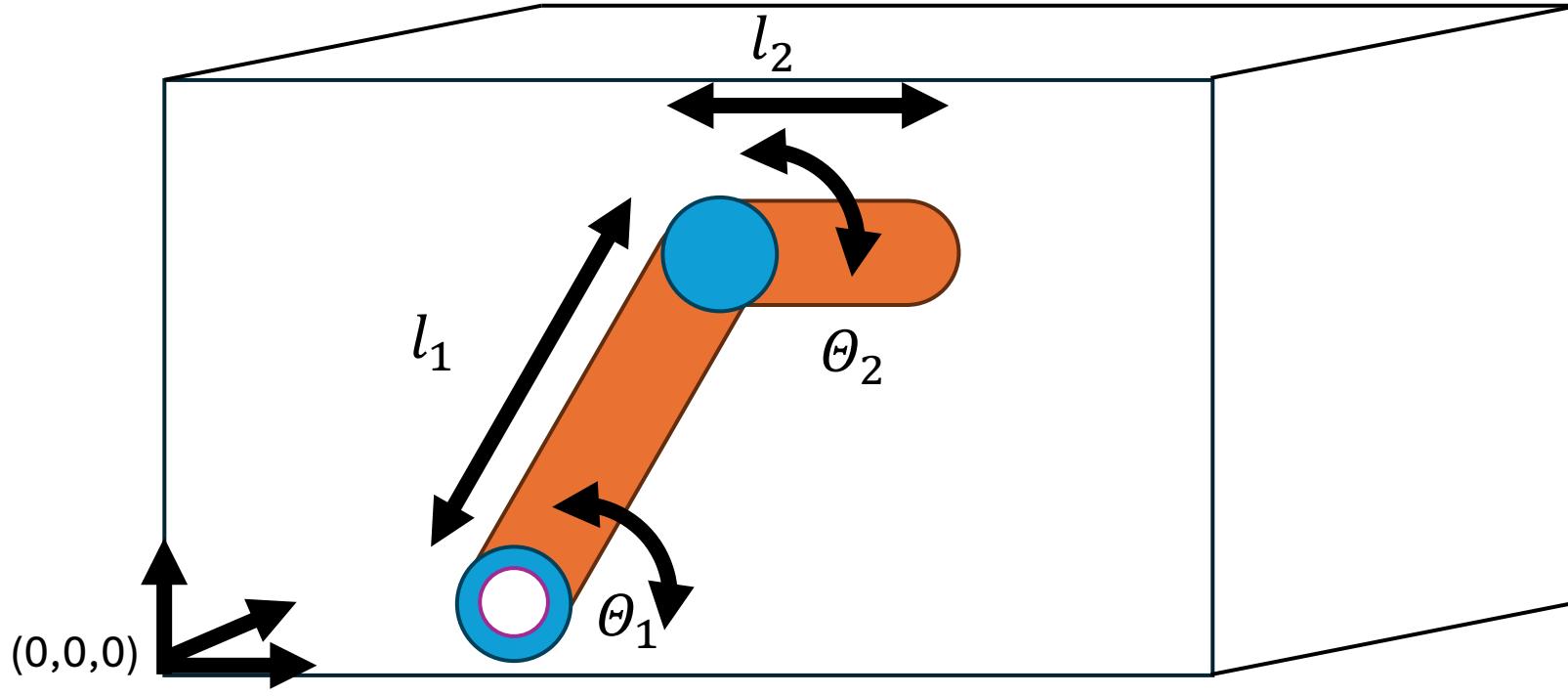


Base frame pose,  $l_1, l_2$

angles  $\theta_1, \theta_2$

Model of robot, DH Parameters,  
URDF, Simulation

# More joints



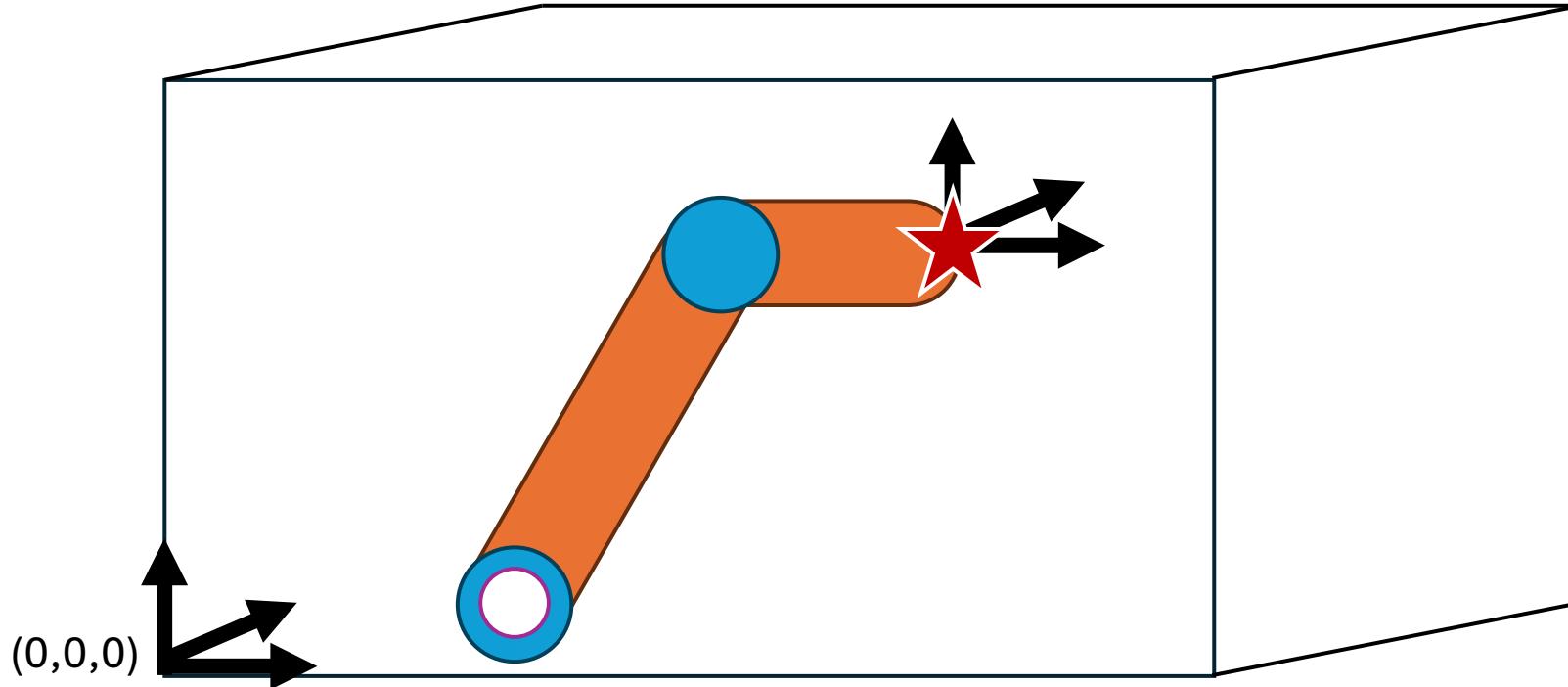
Base frame pose,  $l_1, l_2$

Model of robot, DH Parameters,  
URDF, Simulation

angles  $\theta_1, \theta_2$

Degrees of freedom (DoF)

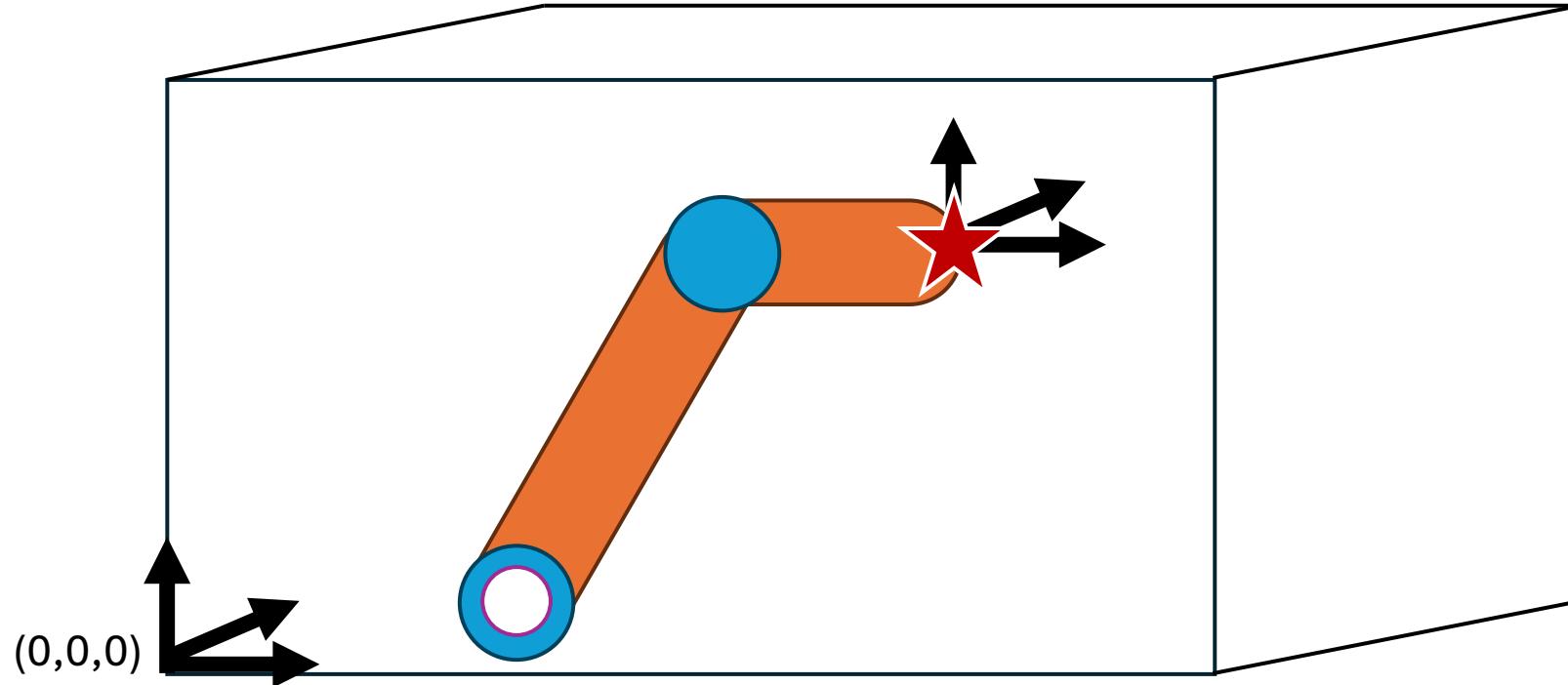
# Forward Kinematics



Forward Kinematics – given joint angles what is the pose of a part of the robot?

$$\theta_1, \theta_2 \xrightarrow{\text{FK}} \star$$

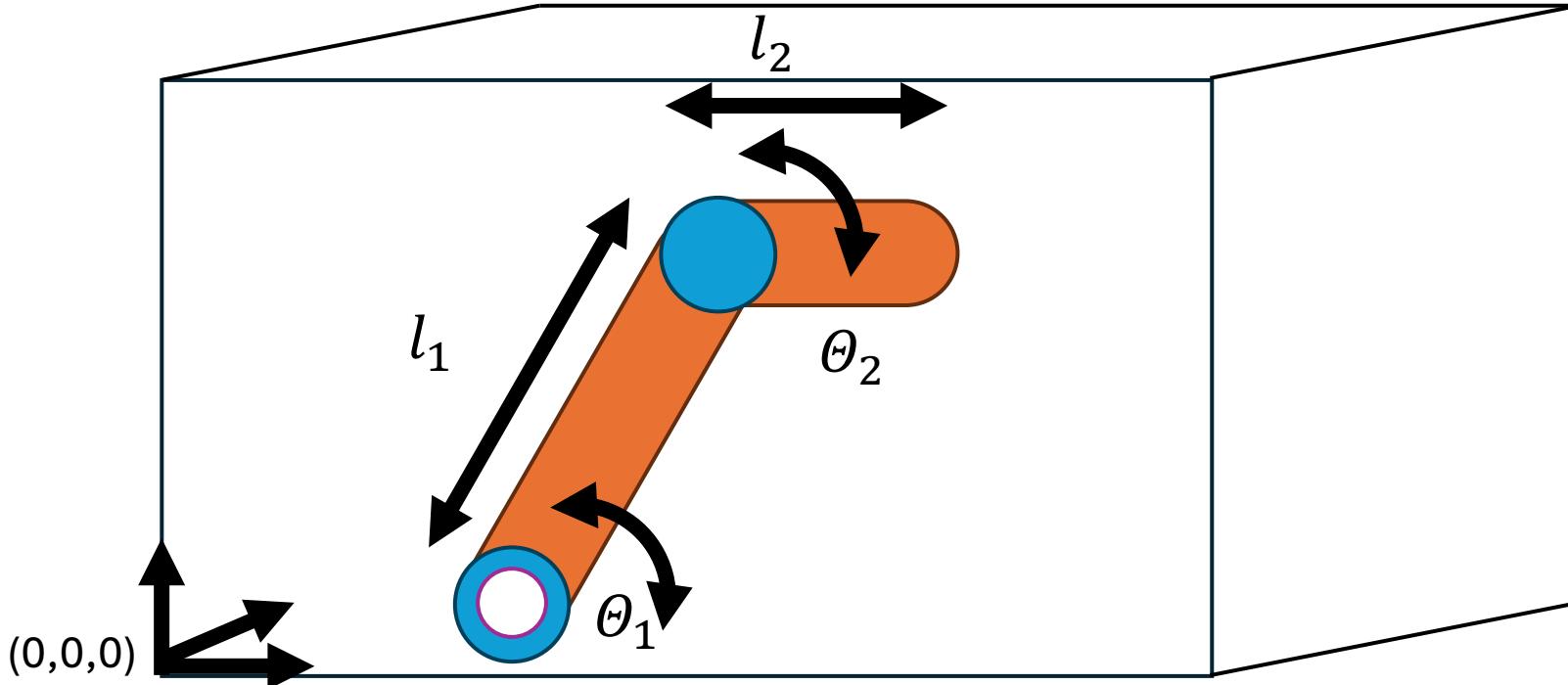
# Inverse Kinematics



Inverse Kinematics – given pose of a part of the robot what are joint angles?

$$\theta_1, \theta_2 \leftarrow \text{IK}$$

# What changes in the robot?



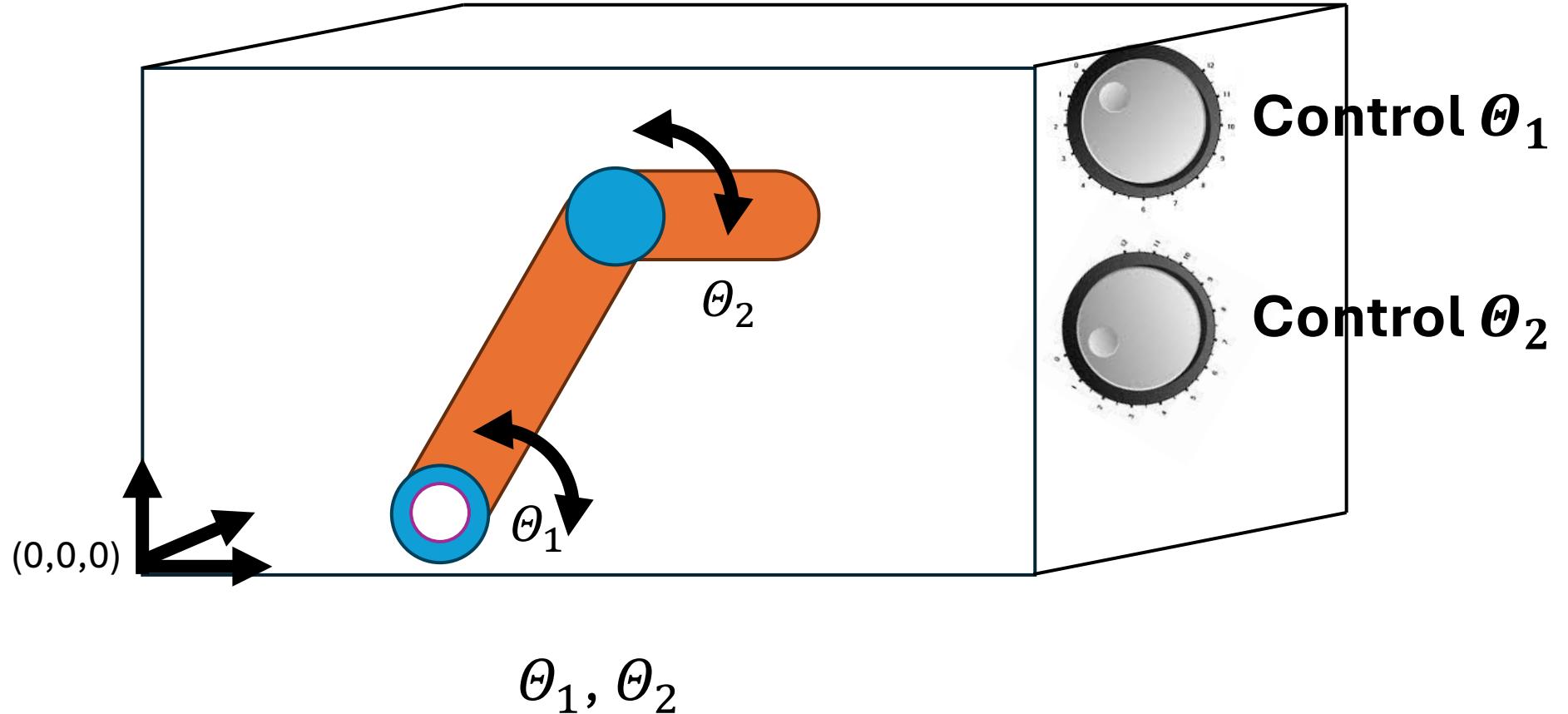
Base frame pose,  $l_1, l_2$

Model of robot, DH Parameters,  
URDF, Simulation

angles  $\theta_1, \theta_2$

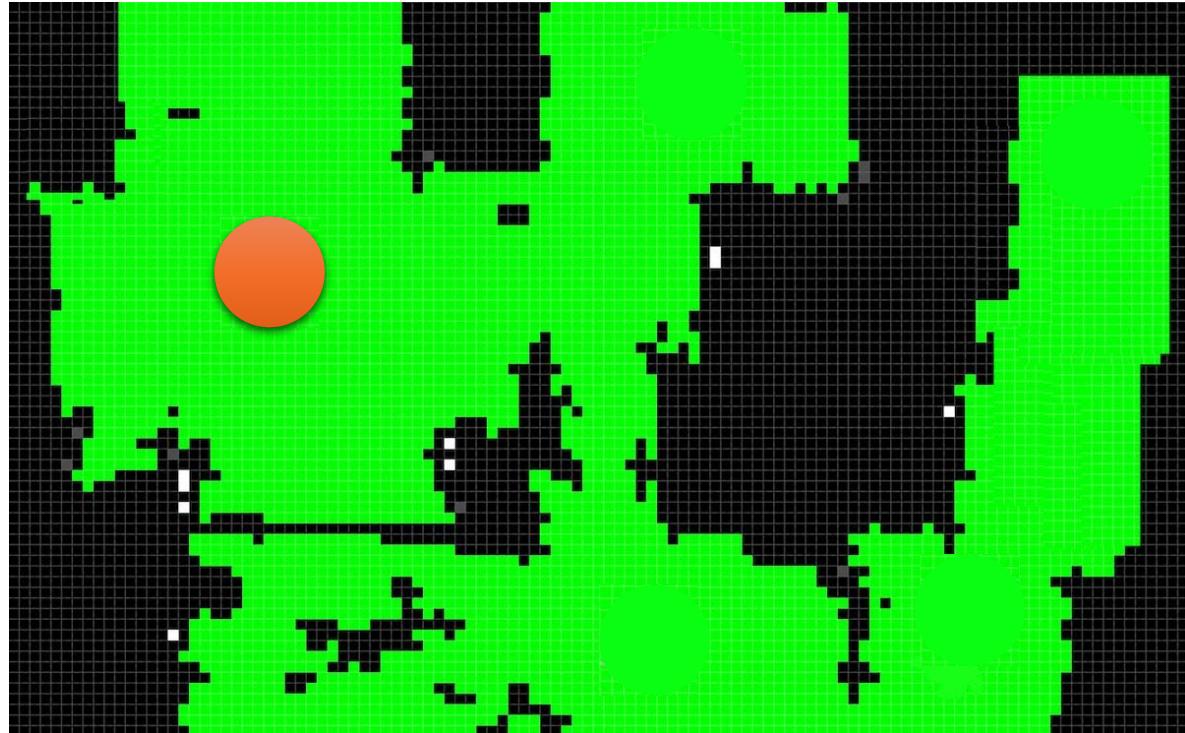
**Degrees of freedom (DoF)**

# 2D configuration of a robot



$\theta_1, \theta_2$

# 2D configuration of a robot



A circular robot on a floorplan

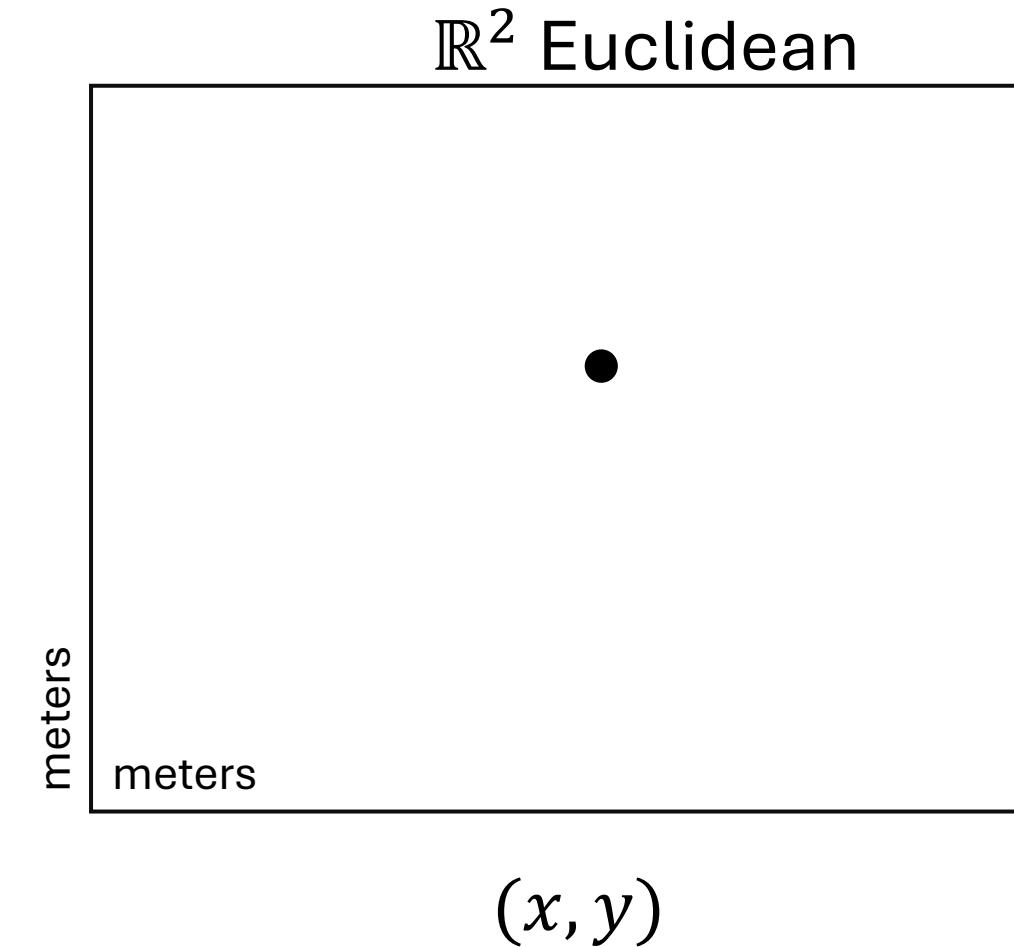
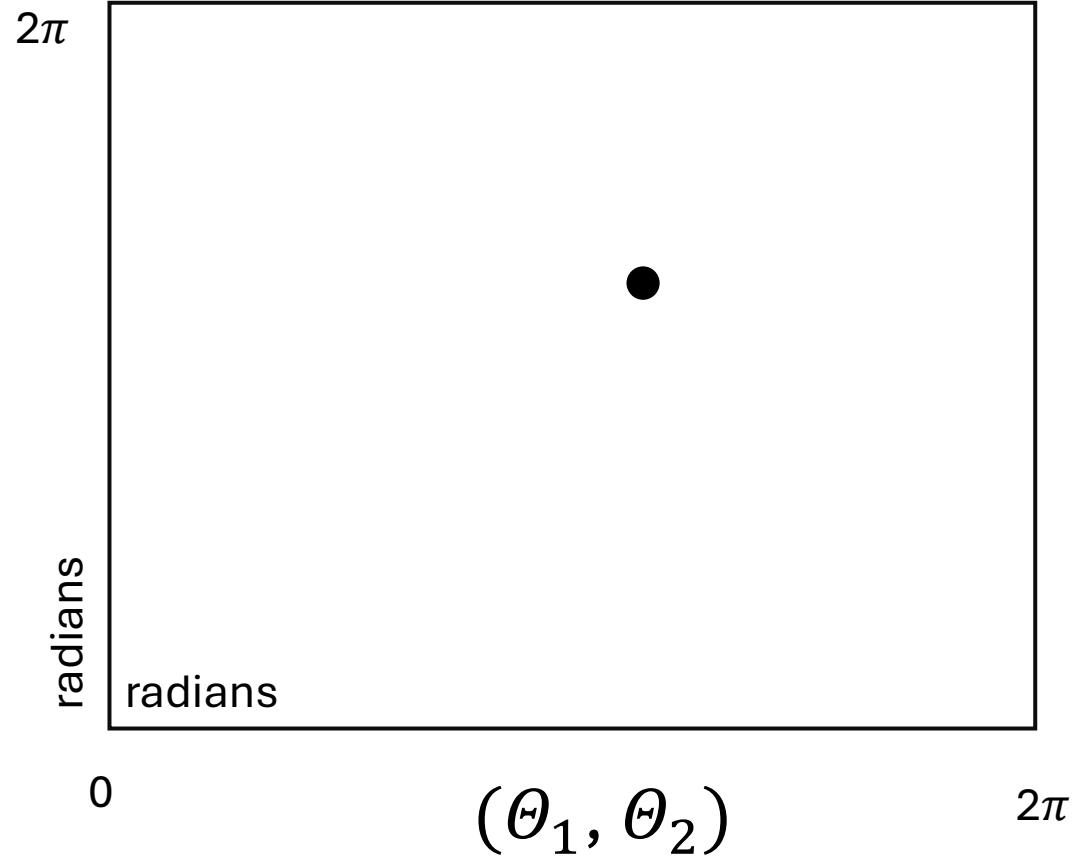


**Control X**

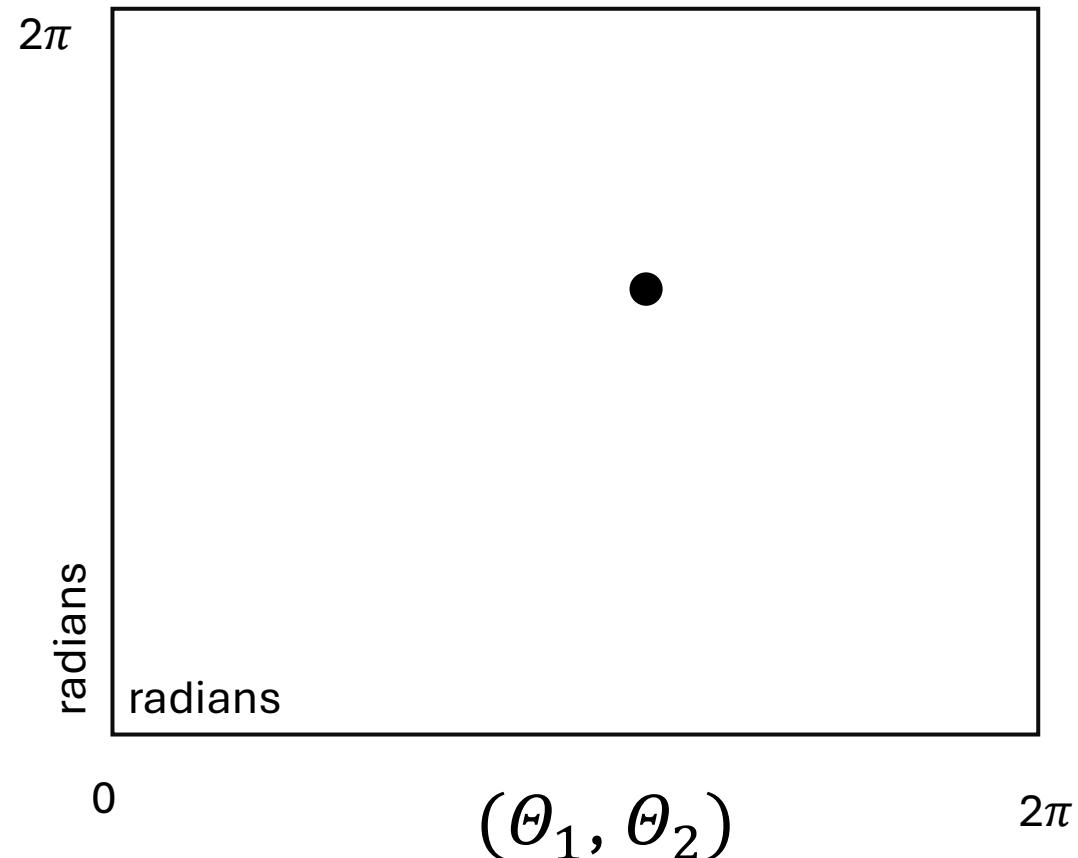


**Control Y**

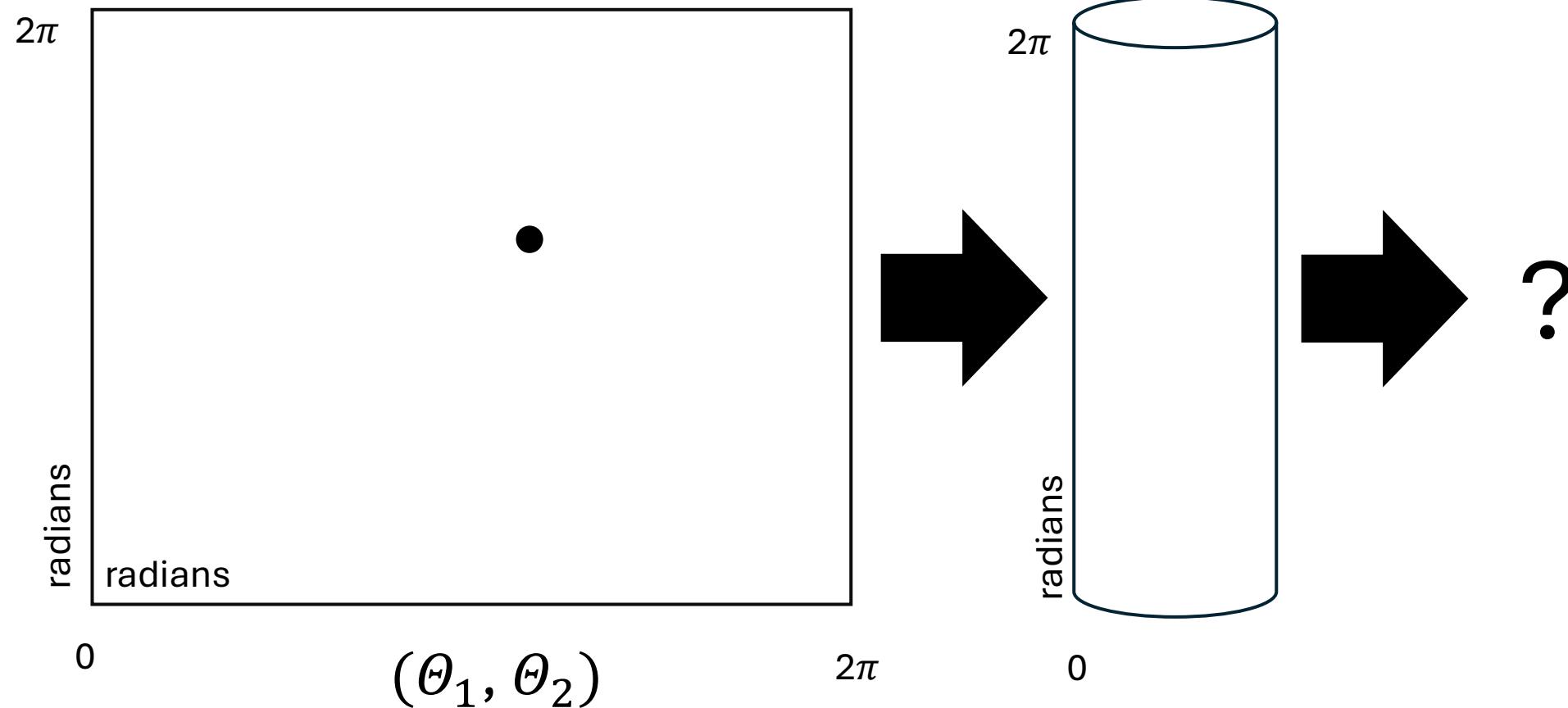
# Topology of the Space



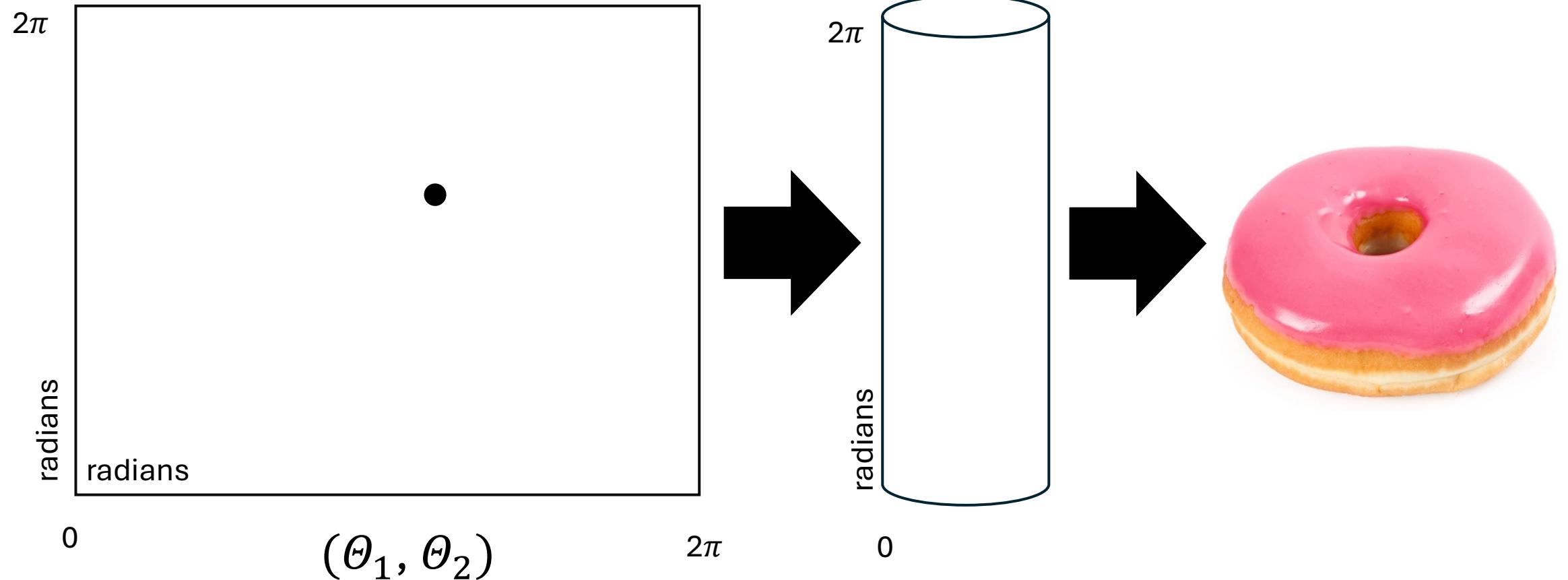
# Topology of the Space



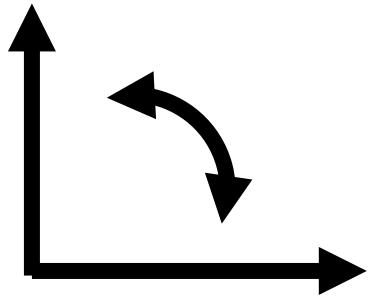
# Topology of the Space



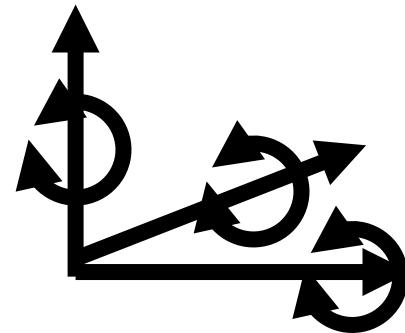
# Topology of the Space



# More Spaces

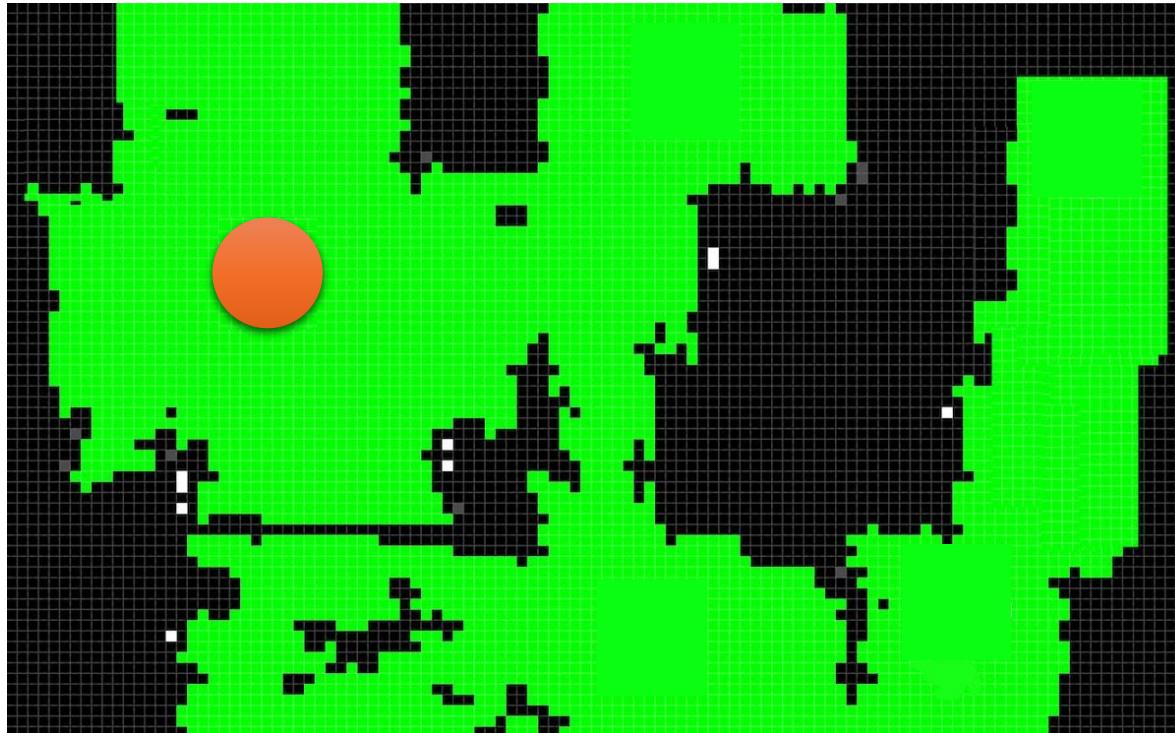


$(x, y, \theta)$  SE(2)



$(x, y, z, \theta_x, \theta_y, \theta_z)$  SE(3) poses

# Configuration Spaces

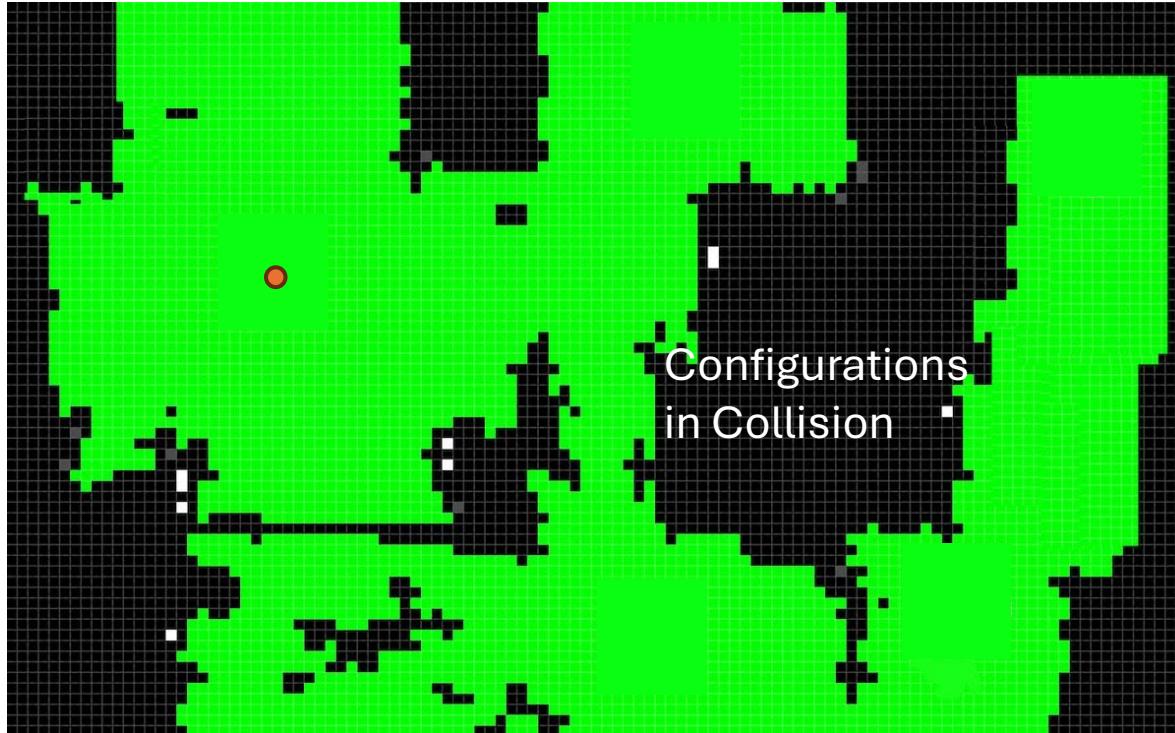


Is this a configuration space?  
What are the dark regions?

A robot configuration is a **point** in the configuration space.

Lozano-Perez, Tomas. *Spatial planning: A configuration space approach*. Springer New York, 1990.

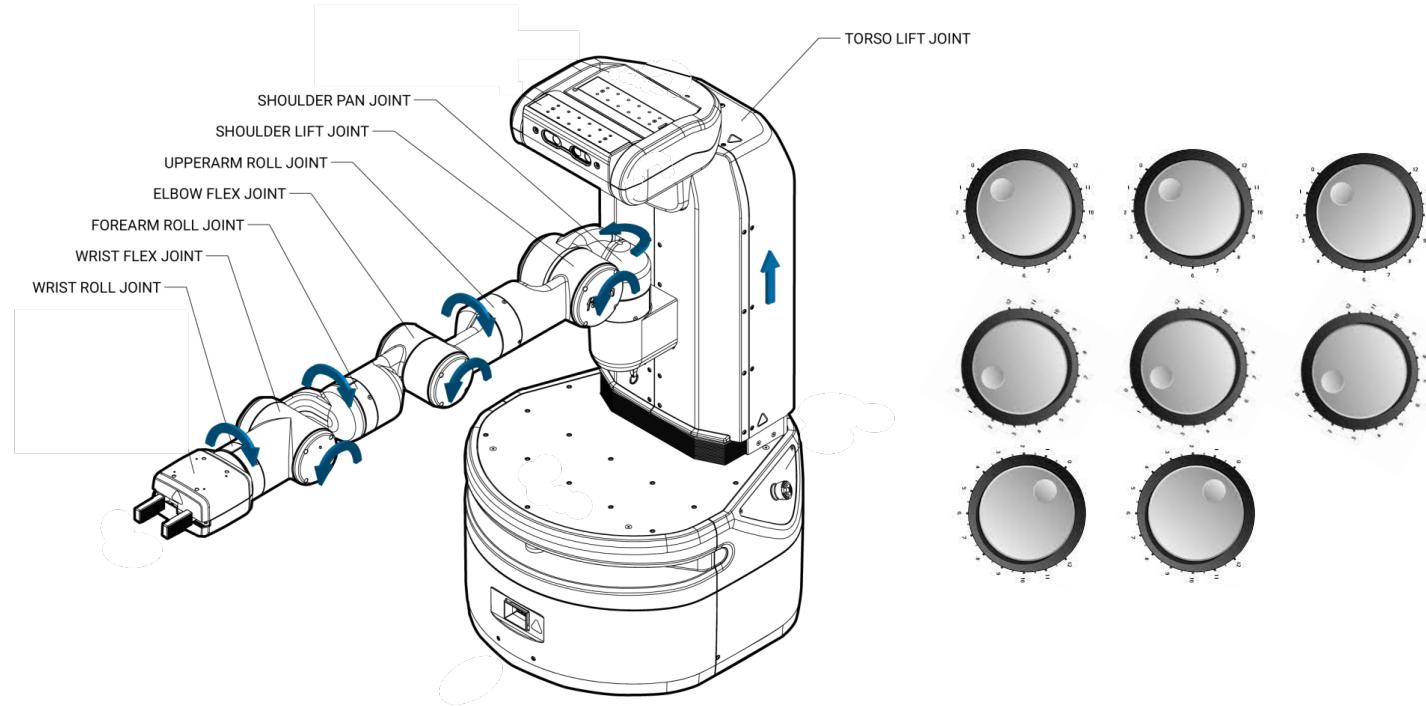
# Configuration Spaces



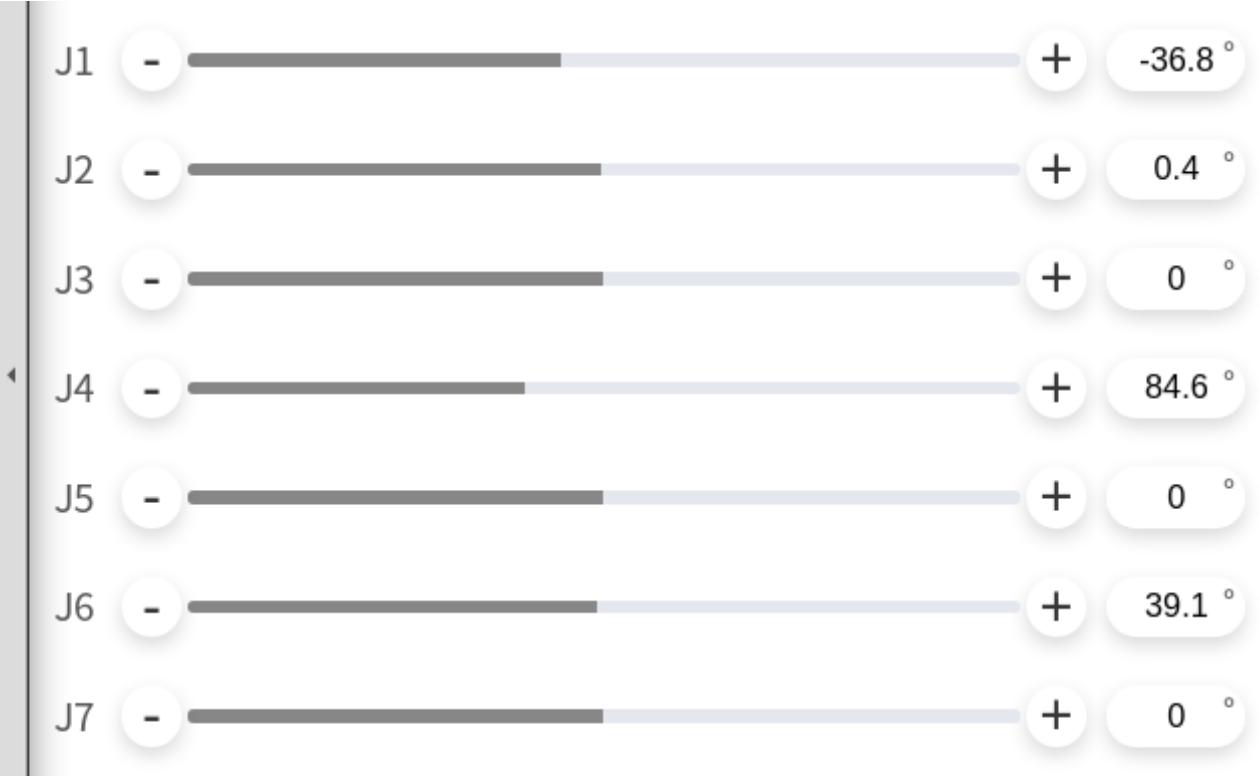
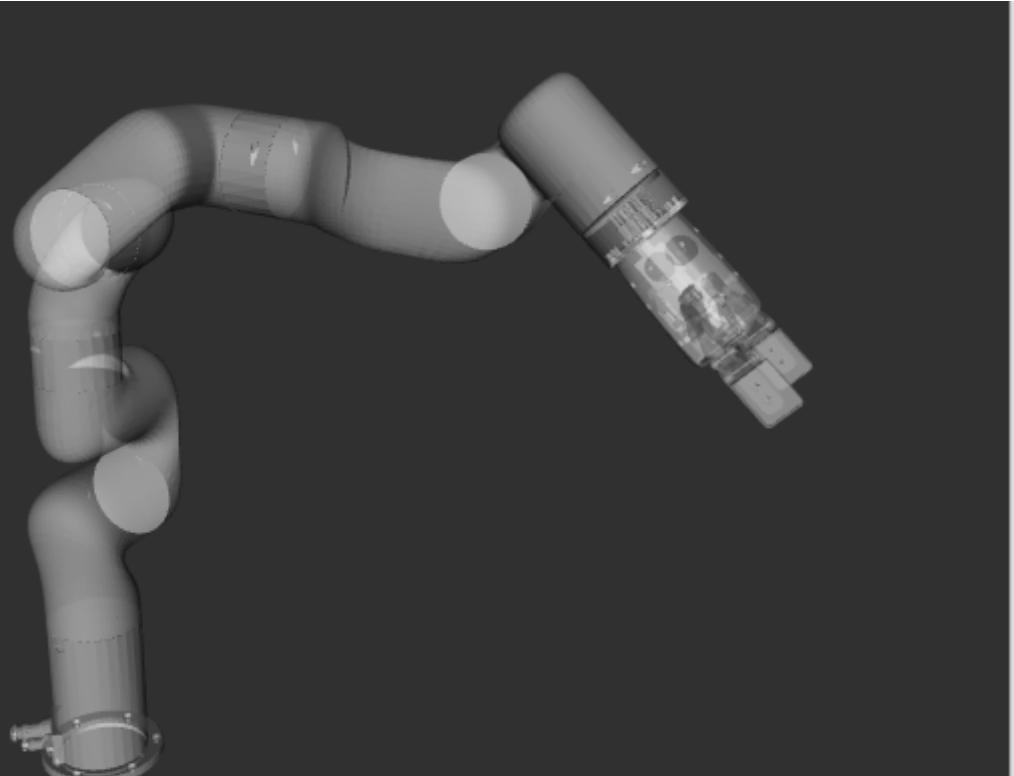
**Feasible** subset of configuration space.

A robot configuration is a point in the configuration space.

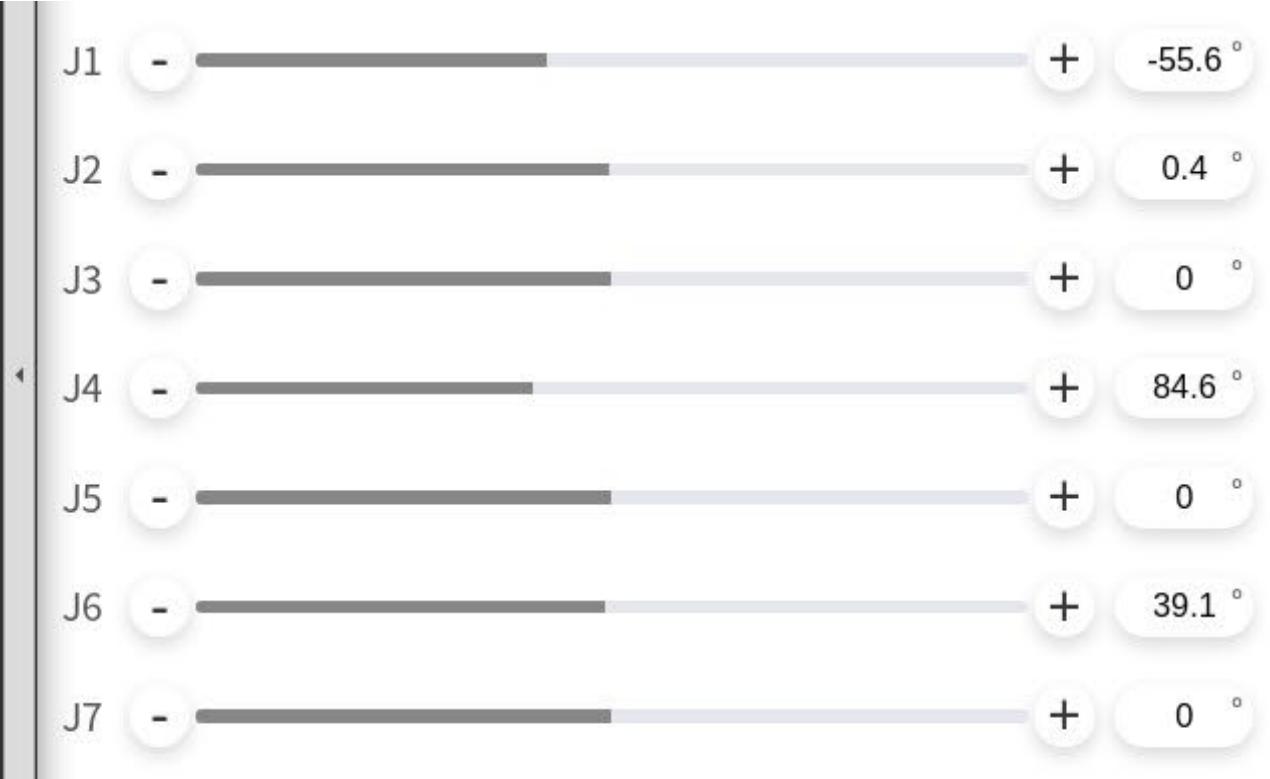
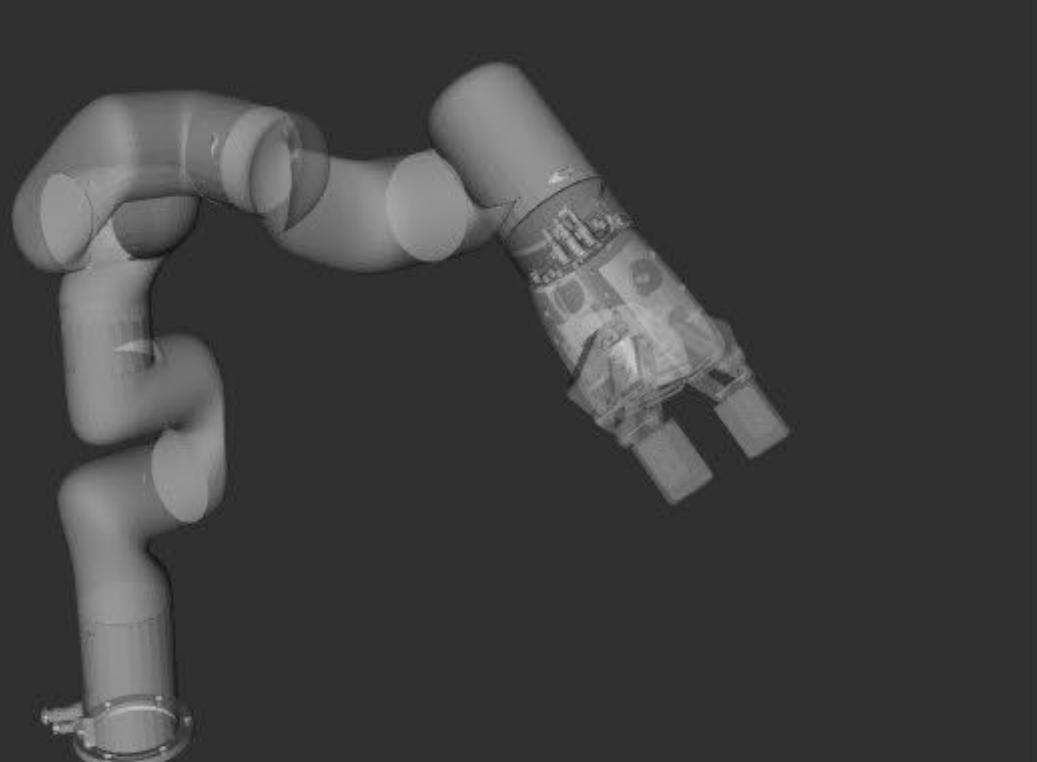
# Dimensionality of Configuration Spaces



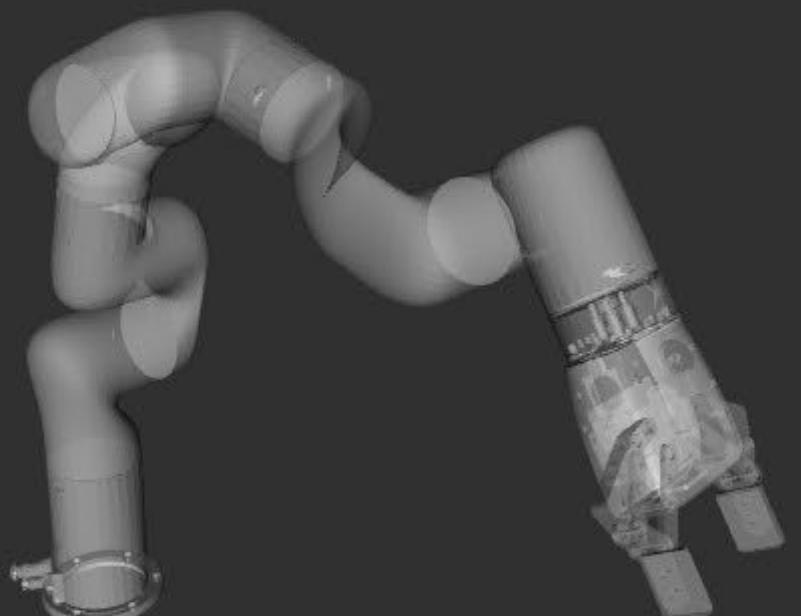
More the joints, more the dimensions.



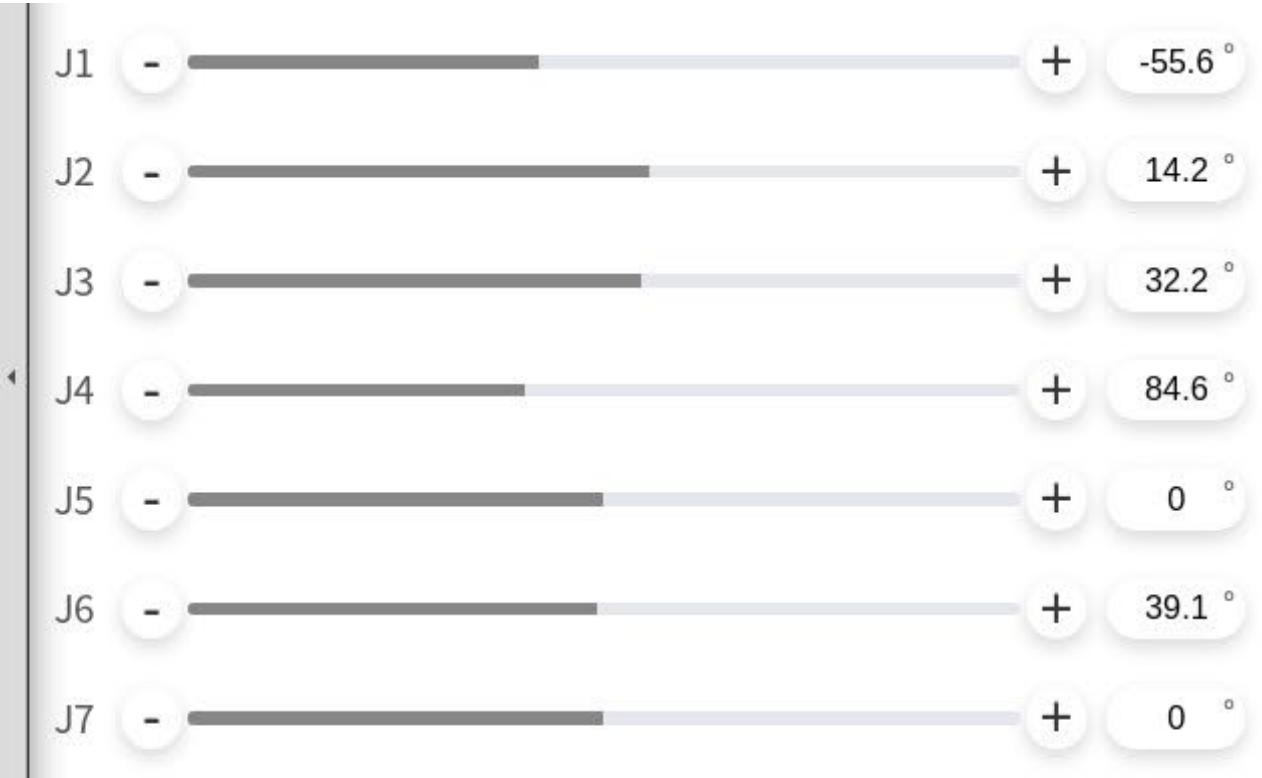
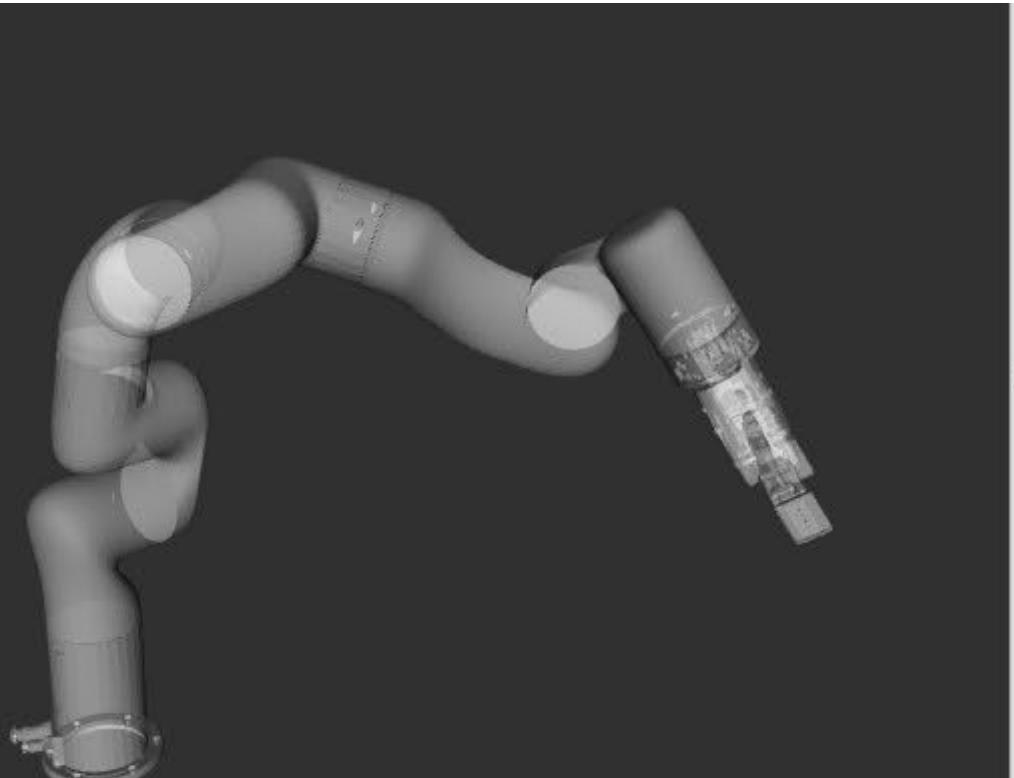
7-dim configuration: (J1,J2,J3,J4,J5,J6,J7)



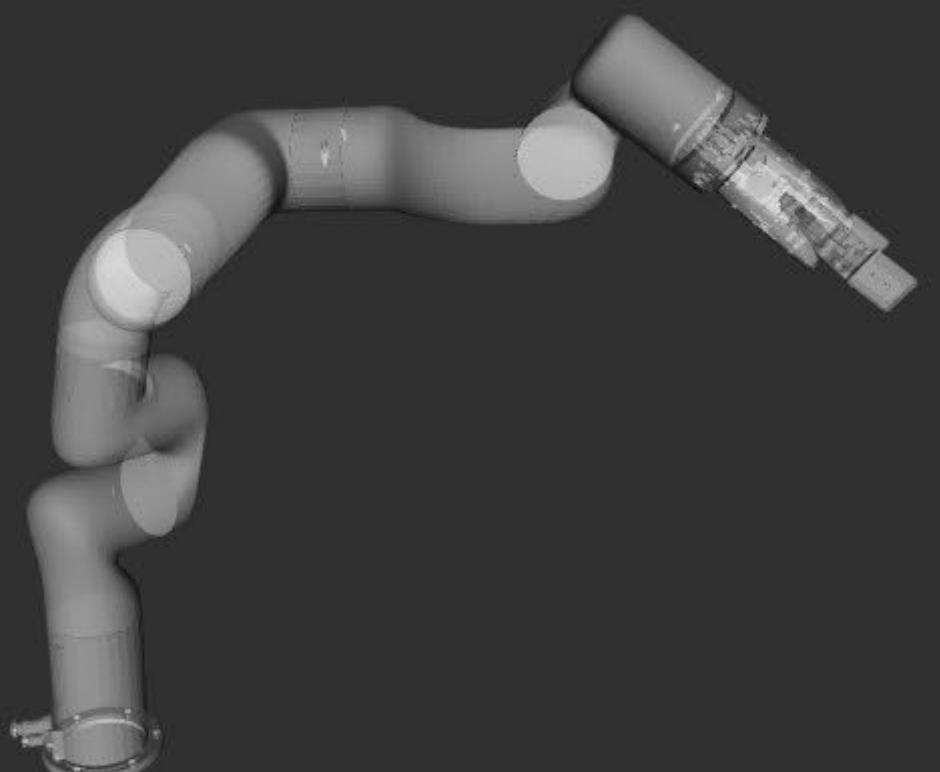
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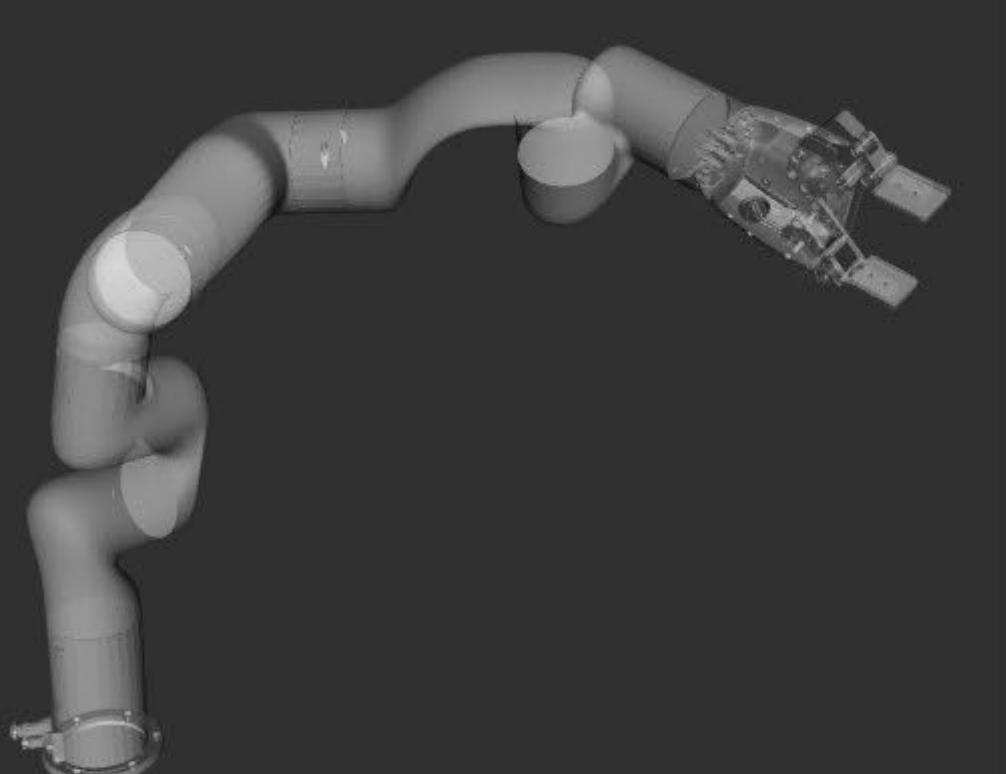
7-dim configuration: (J1,J2,J3,J4,J5,J6,J7)



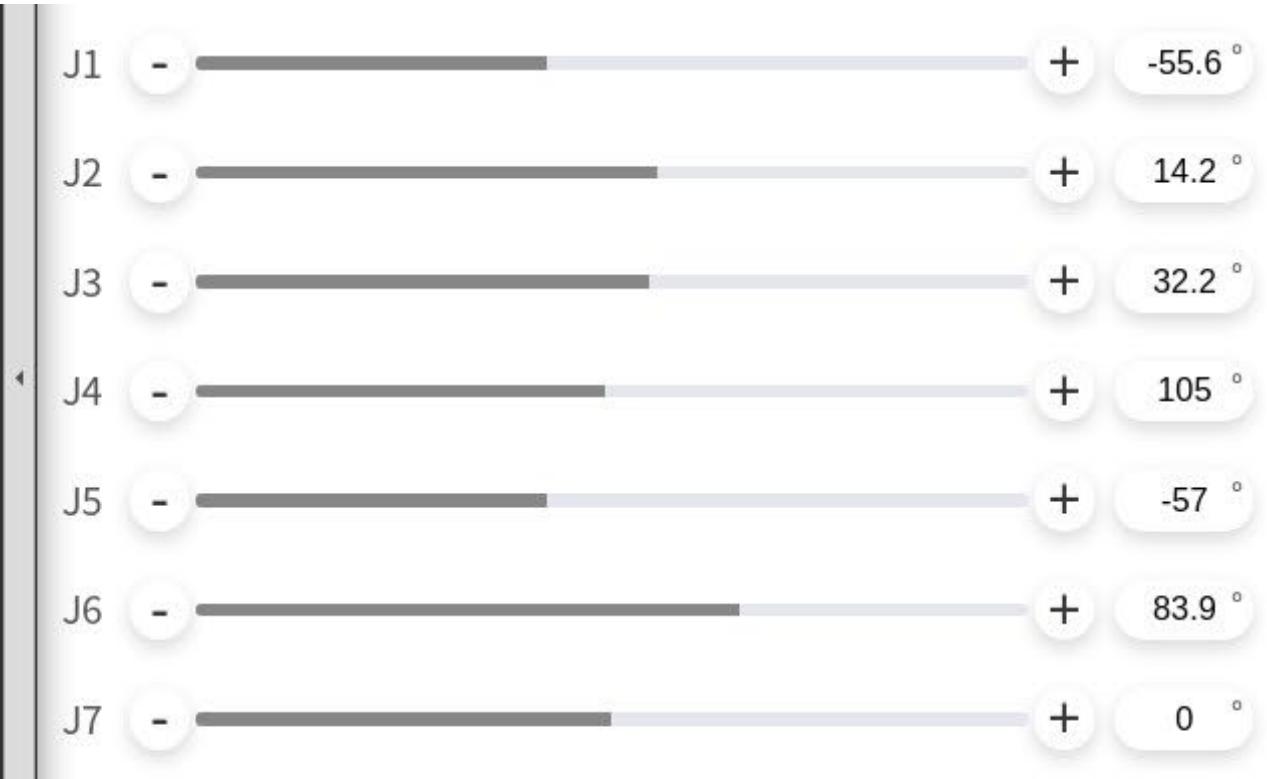
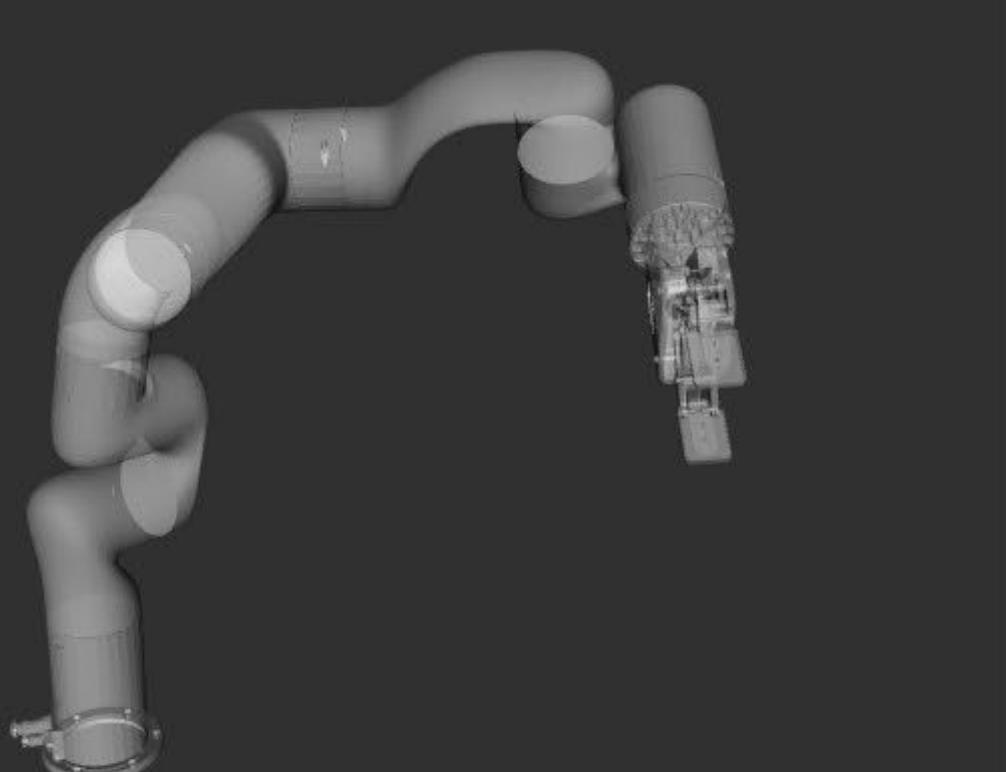
7-dim configuration: (J1,J2,J3,J4,J5,J6,J7)



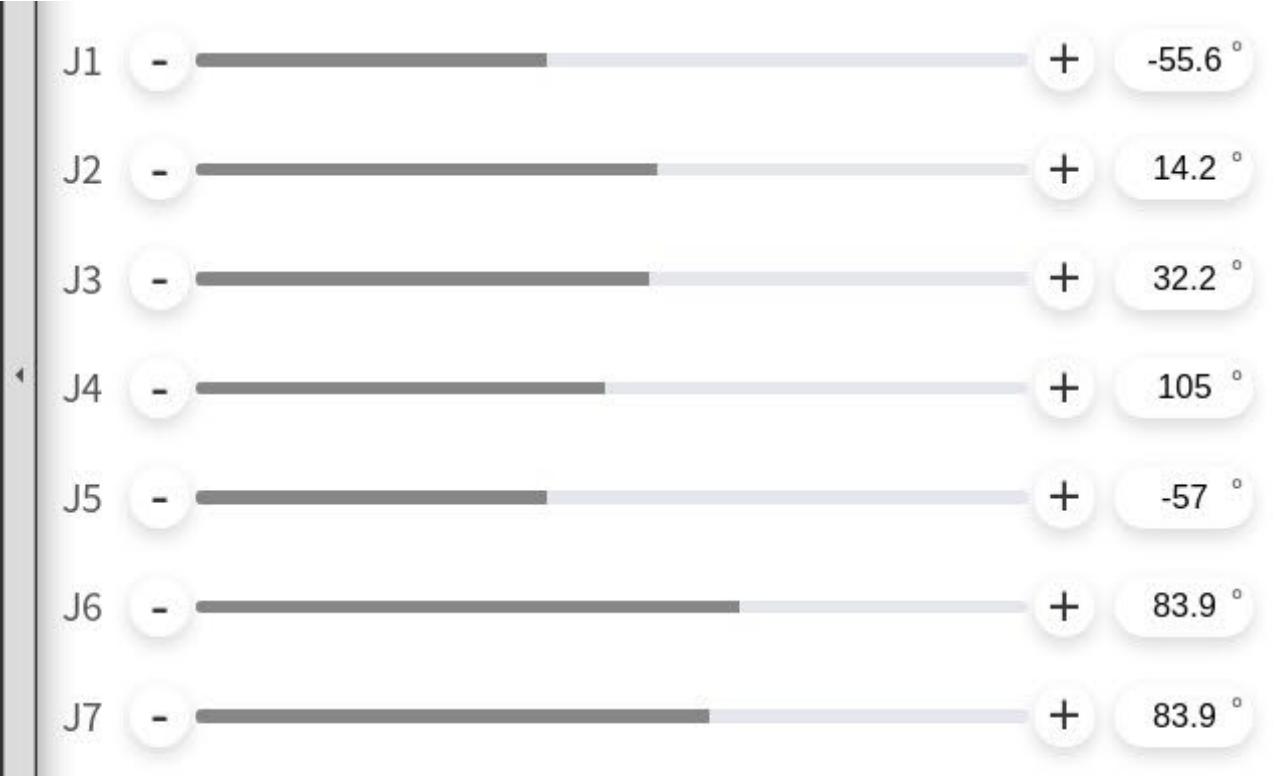
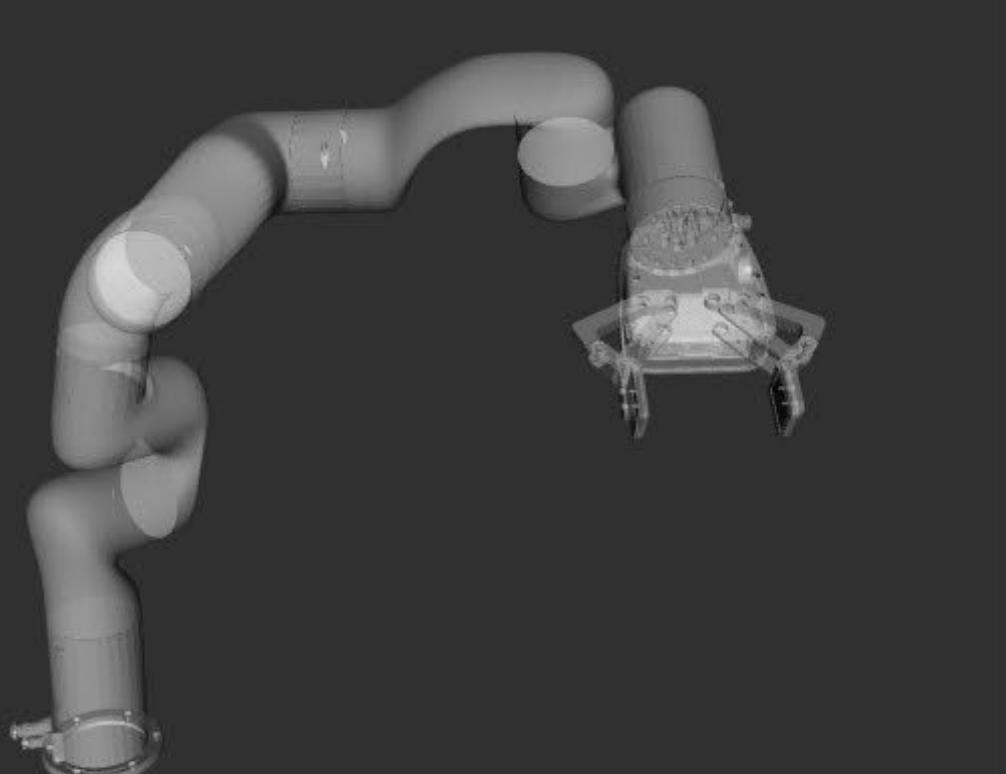
7-dim configuration: (J1,J2,J3,J4,J5,J6,J7)



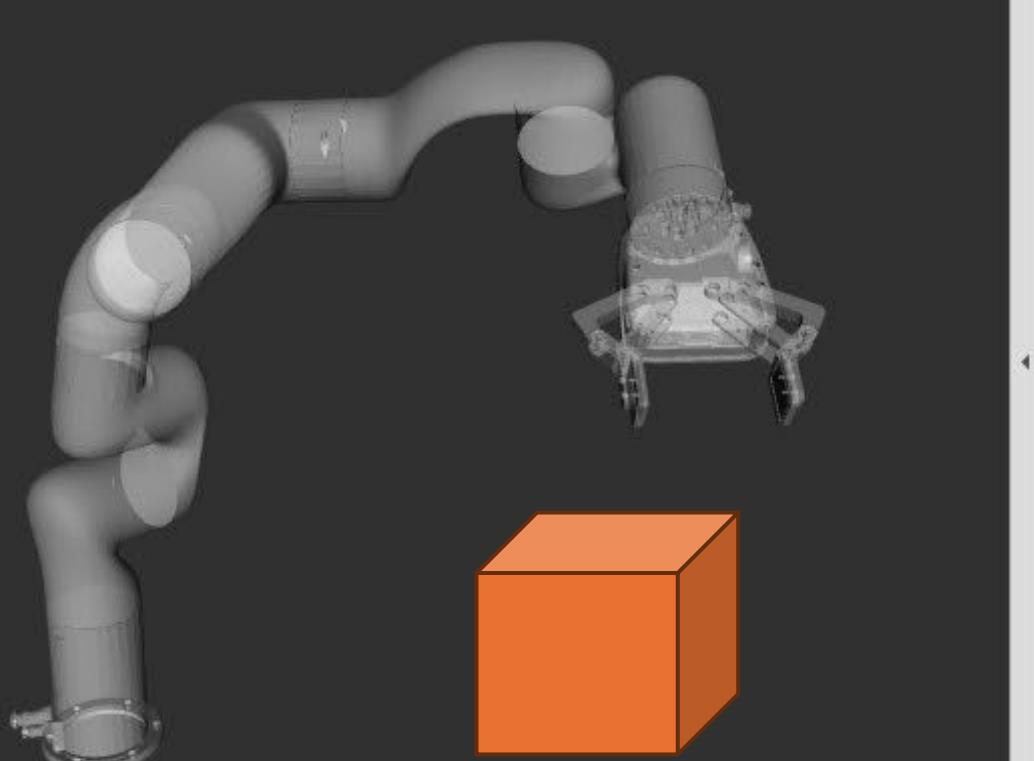
7-dim configuration: (J1,J2,J3,J4,J5,J6,J7)



7-dim configuration: (J1,J2,J3,J4,J5,J6,J7)

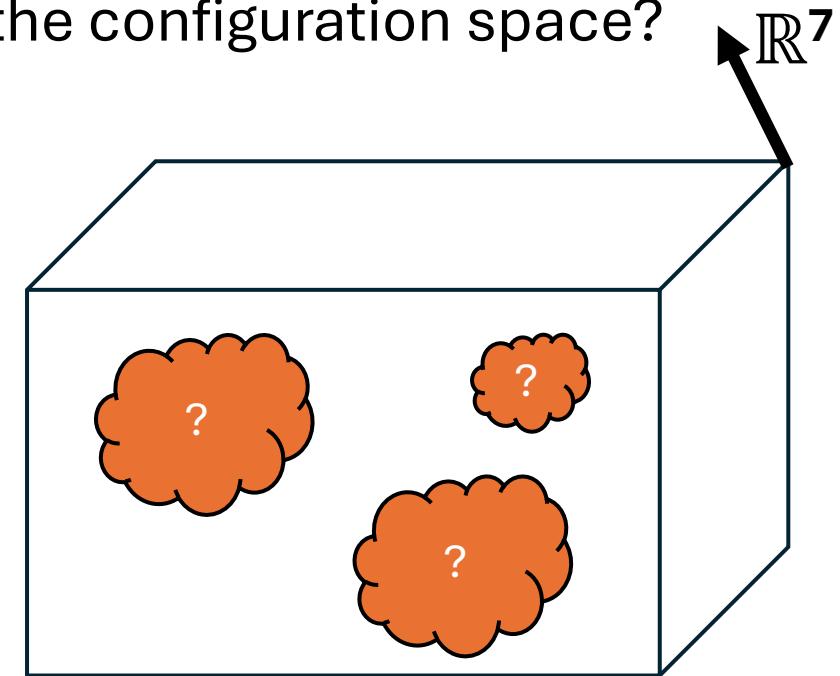


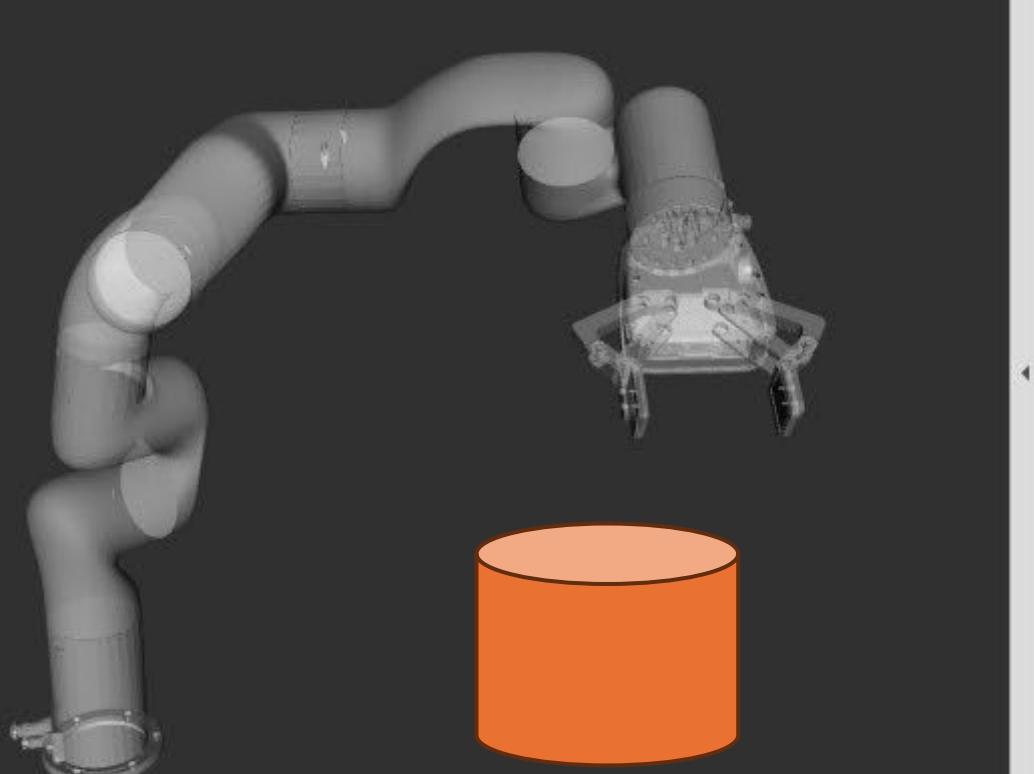
High dimensions cause combinatorial explosion of search space



Set of colliding configurations in high-dimensional configuration spaces.

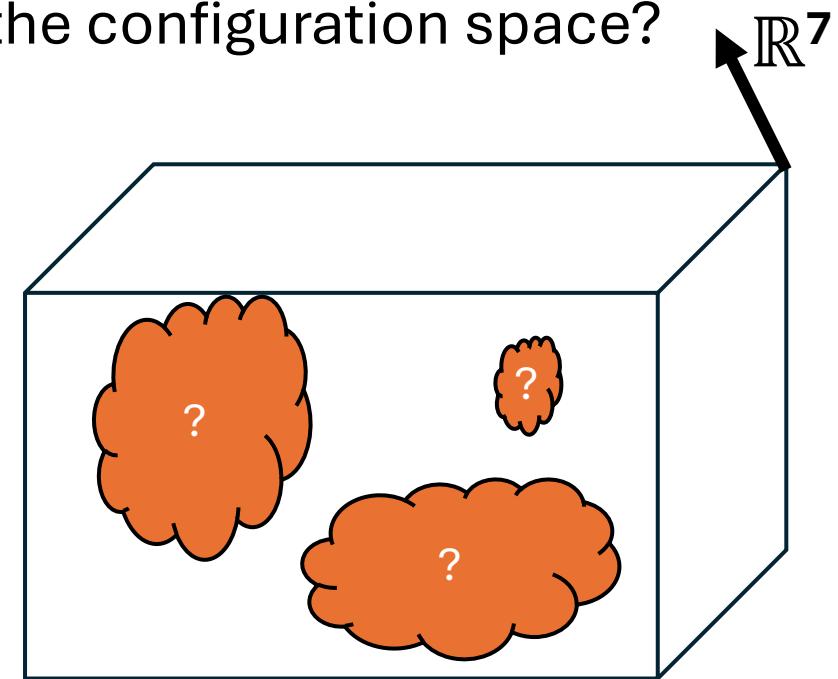
What does the cube look like in the configuration space?





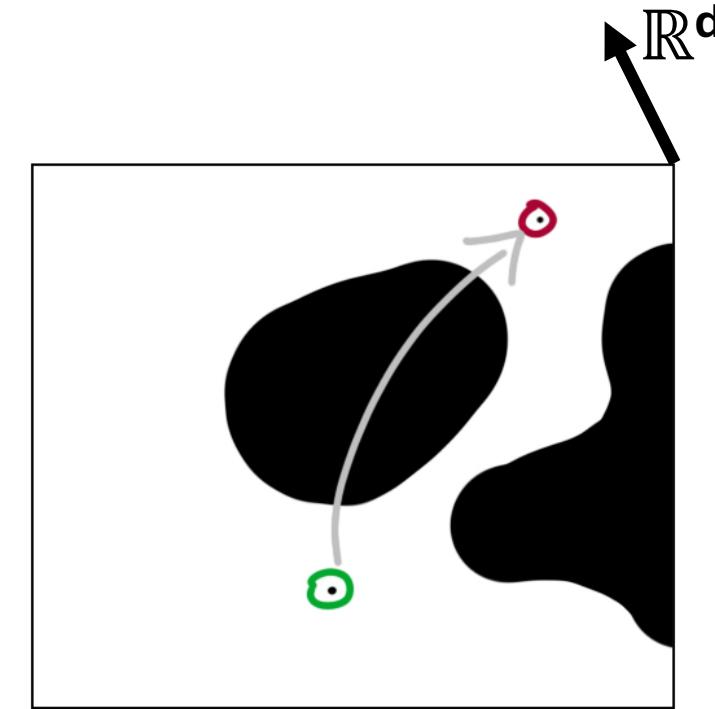
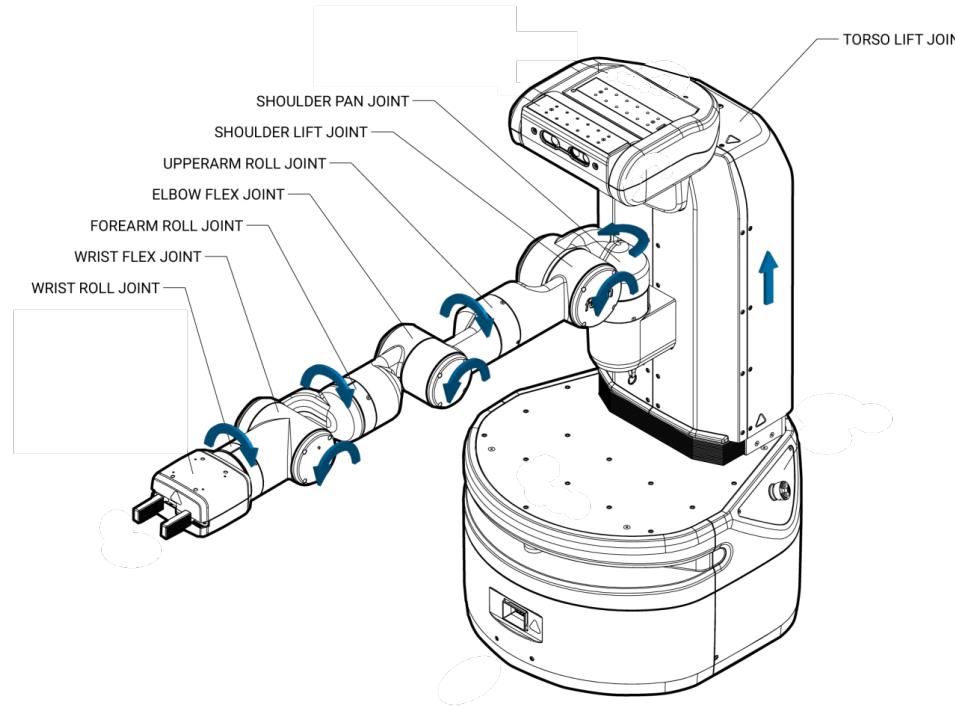
Set of colliding configurations in high-dimensional configuration spaces.

What does the cylinder look like in the configuration space?



# Motion Planning in High-Dimensional Configuration Spaces

# Motion Planning in High-dimensional Configuration Spaces



Start configuration,  
goal,  
configuration space

Motion Planning

Continuous curve  
in feasible configuration space  
connecting start and goal

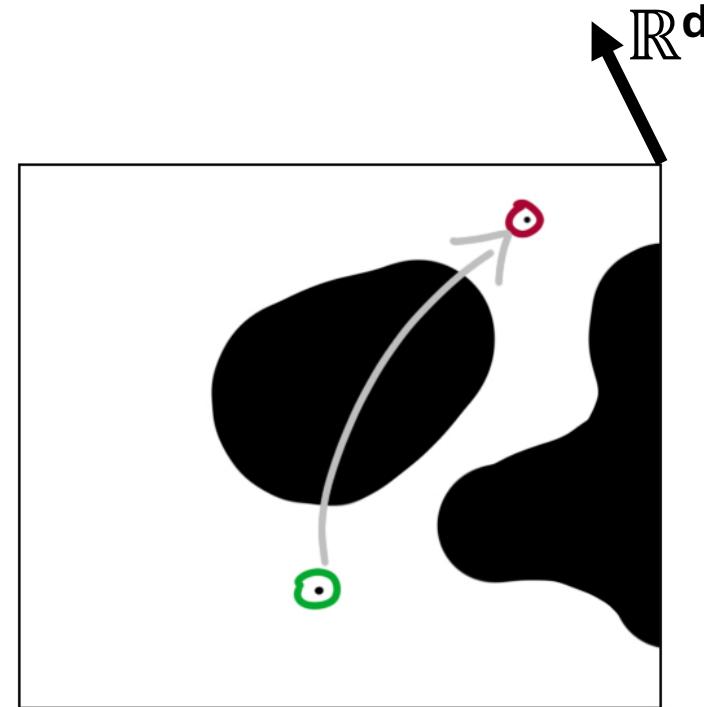
# Properties and Notes: Theoretical Guarantees

## **Completeness:**

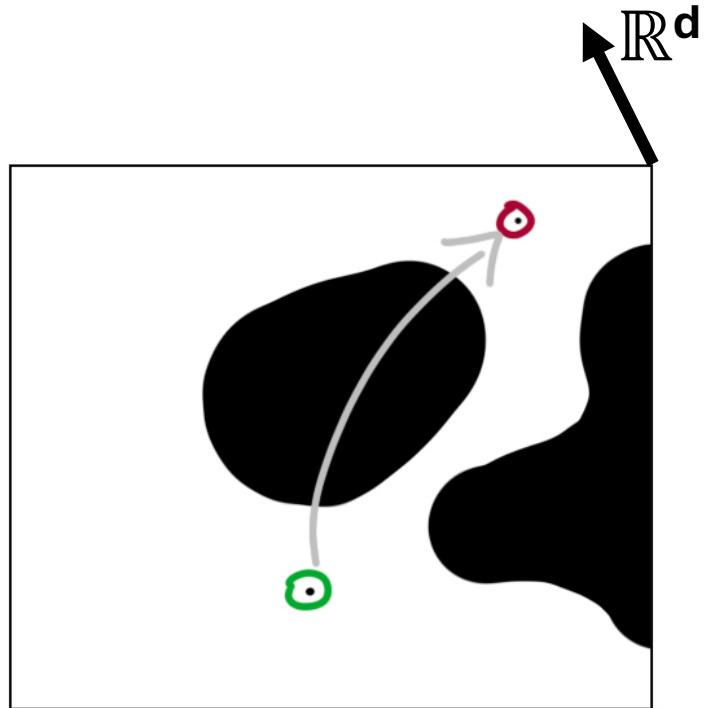
*Guarantee a feasible solution  
if one exists*

## **Optimality:**

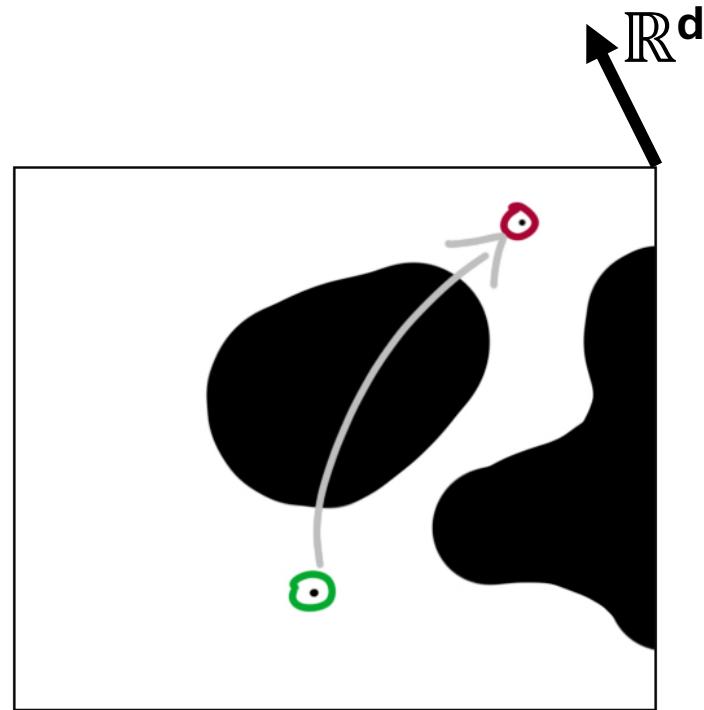
*Guarantee a cost-optimal solution  
if one exists*



# Properties and Notes: Plans or Policies?



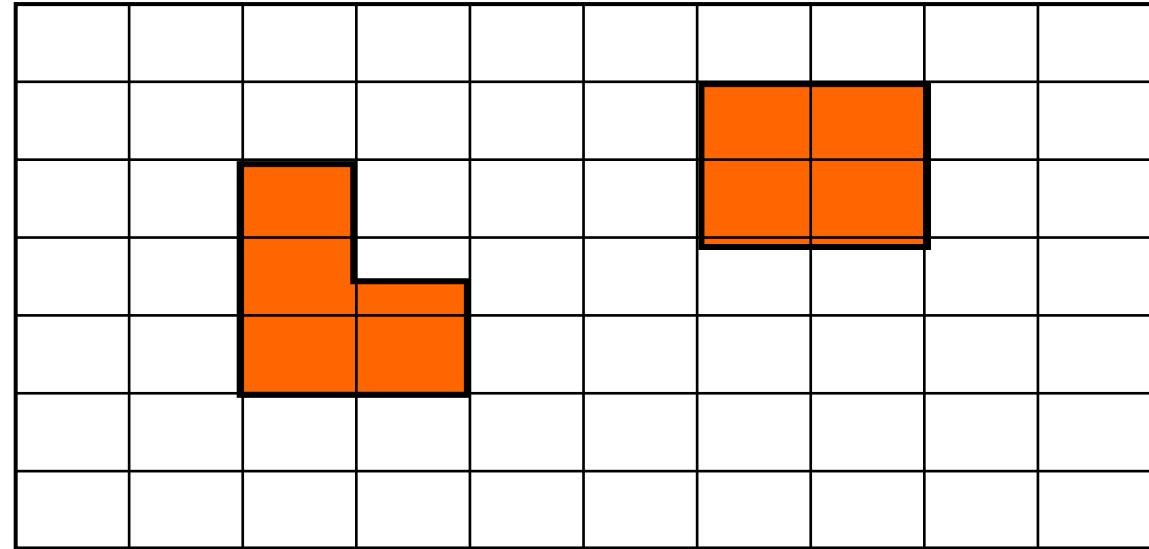
Plan: start to goal



Policy: next action from any state

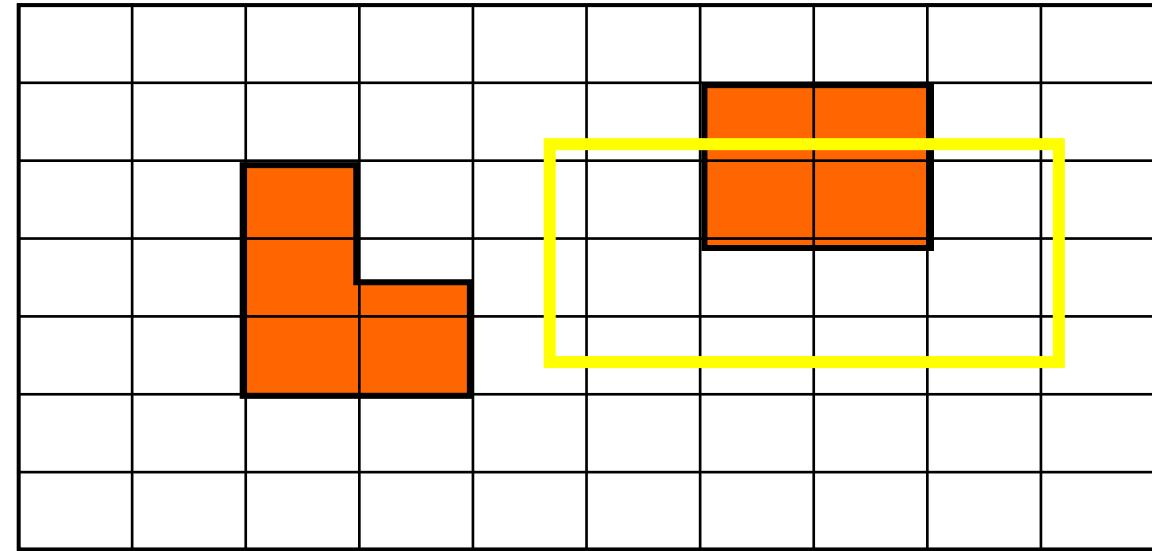
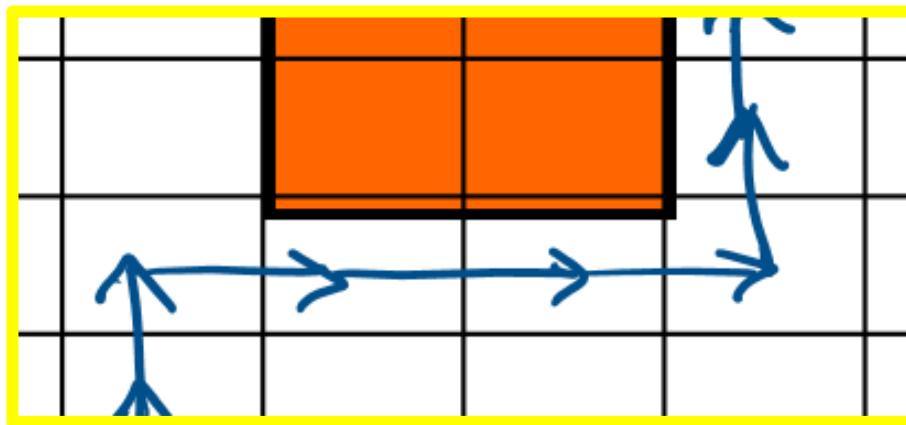
# Solution Strategies: Discretizing the Space

Connect a sequence of adjacent discretization cells from start to goal



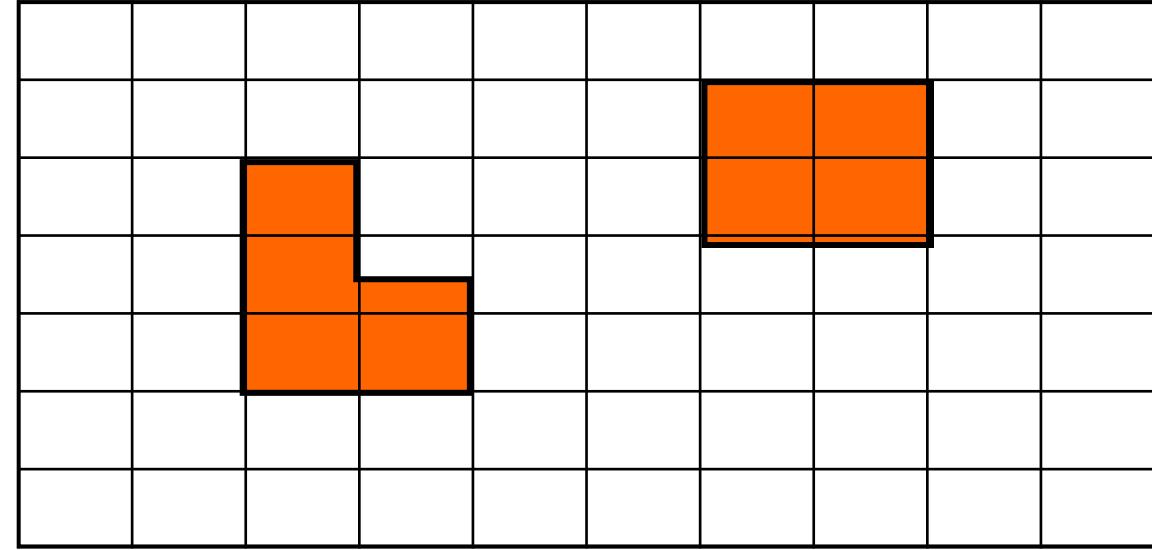
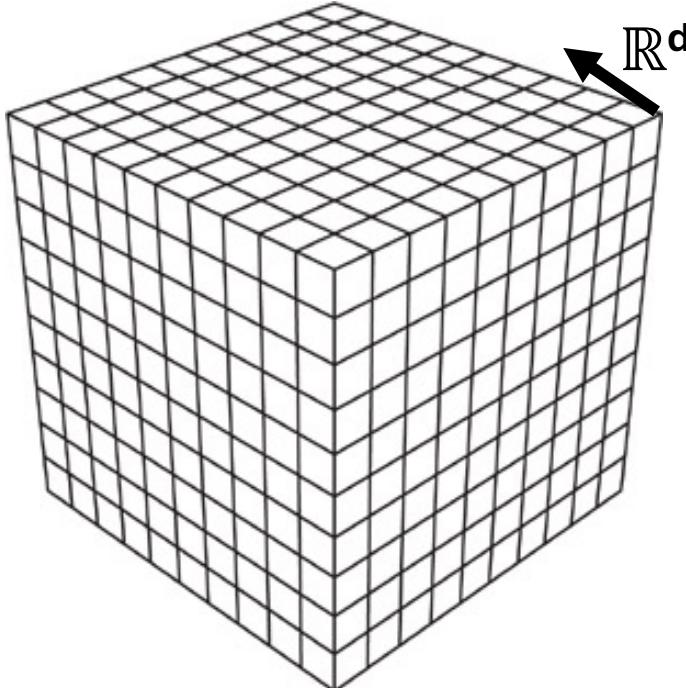
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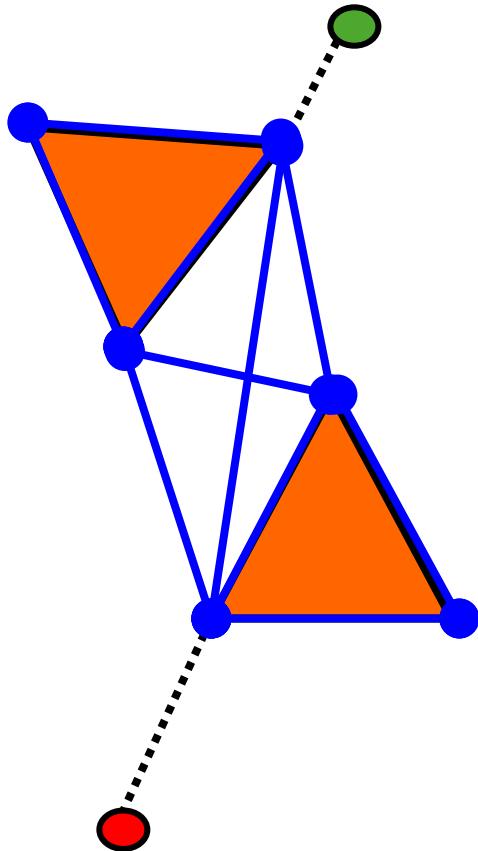


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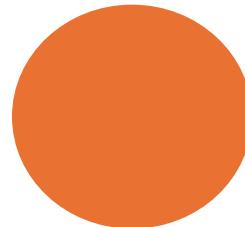


# Other Solution Strategies



## Visibility Graphs

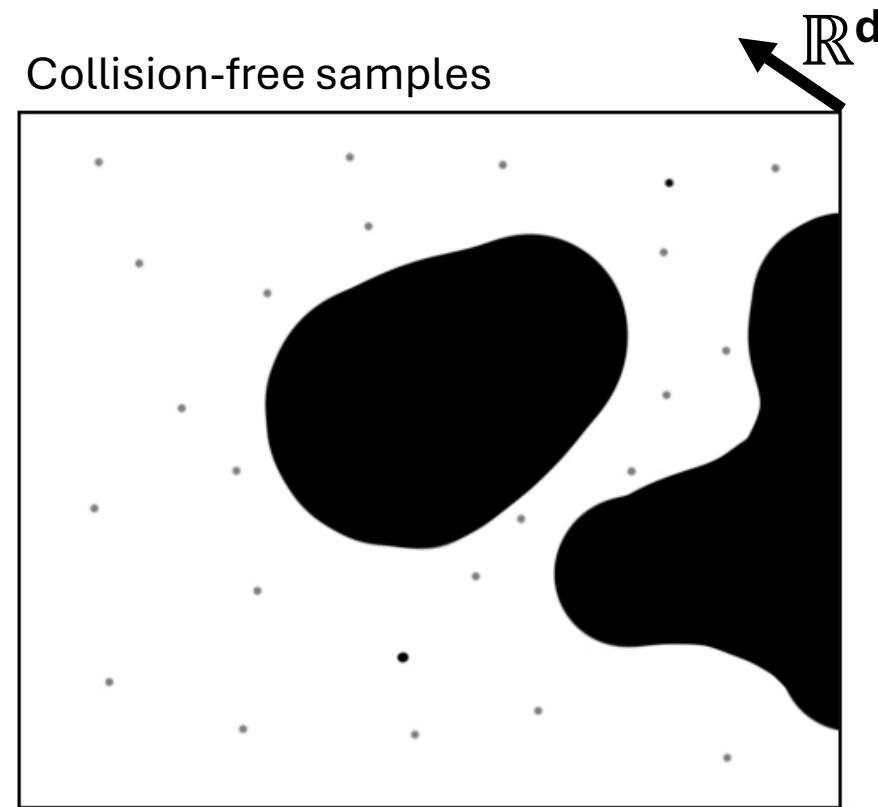
Reasoning about geometry of obstacles does not scale to high dimensions.



## Navigation Functions

Potential fields can have local minima.

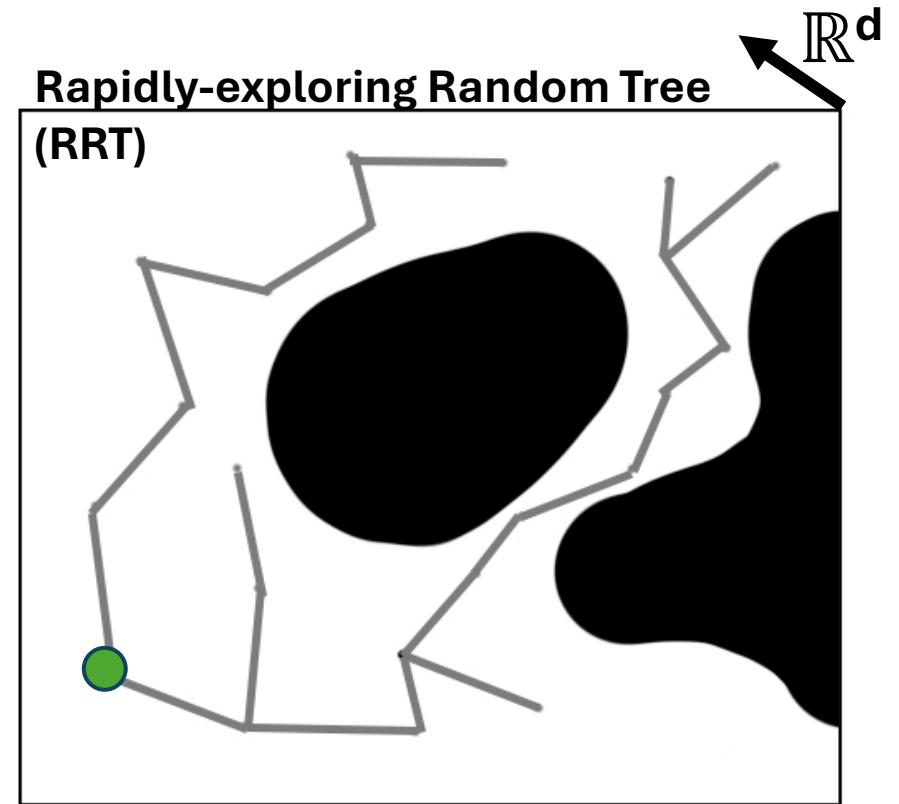
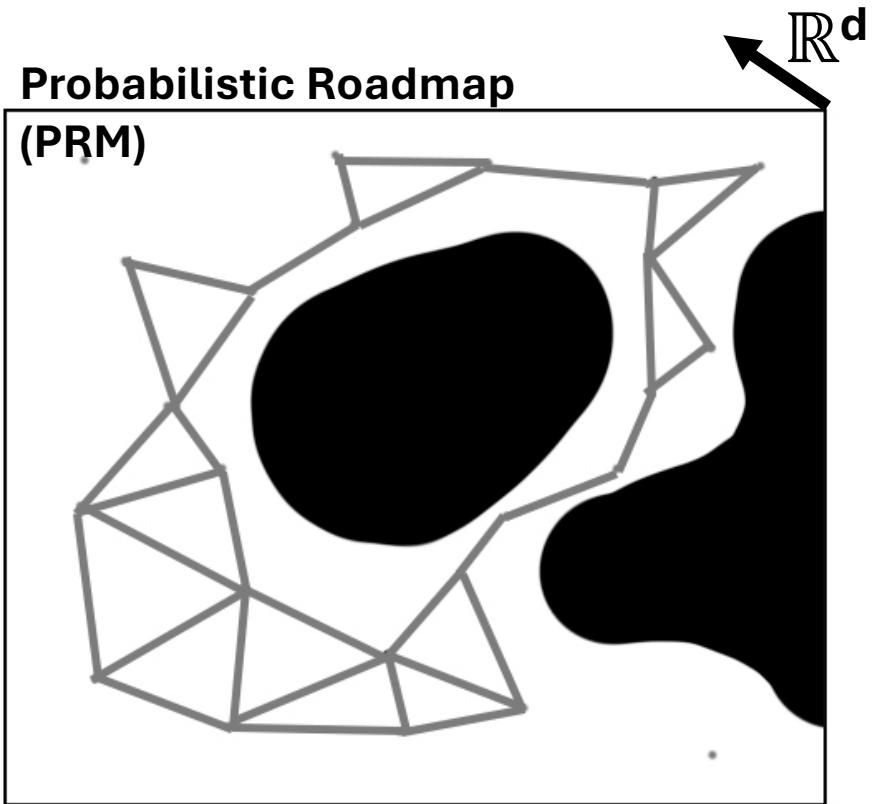
# Sampling-based Motion Planning



A sampling-based motion planner samples configurations

Kavraki et al 1996. Probabilistic roadmaps for path planning in high-dimensional configuration spaces."

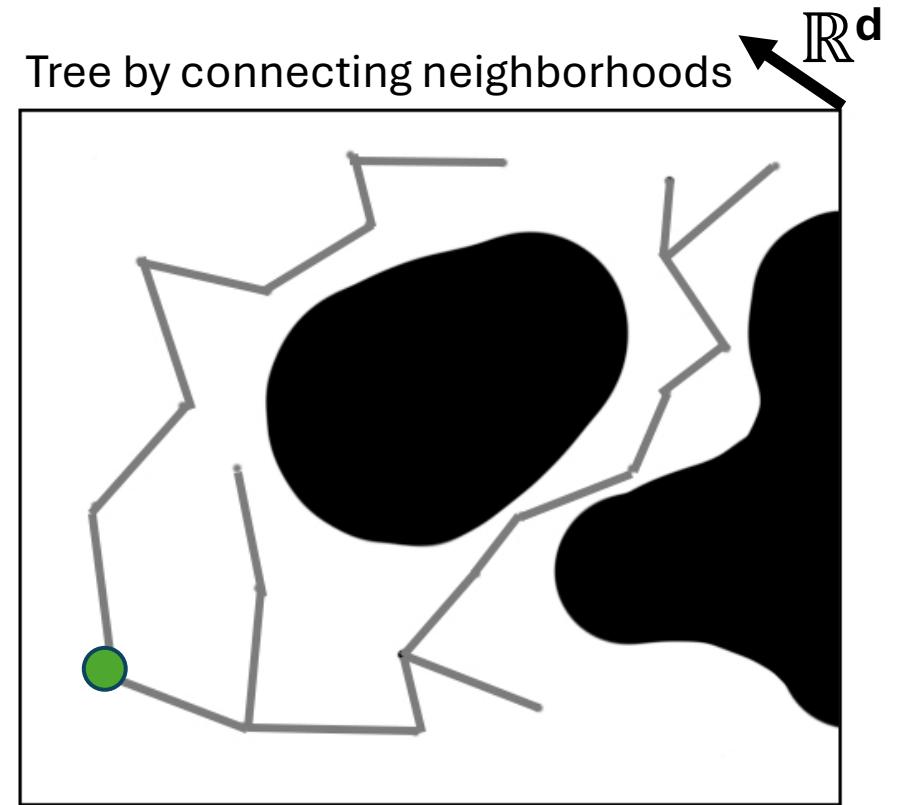
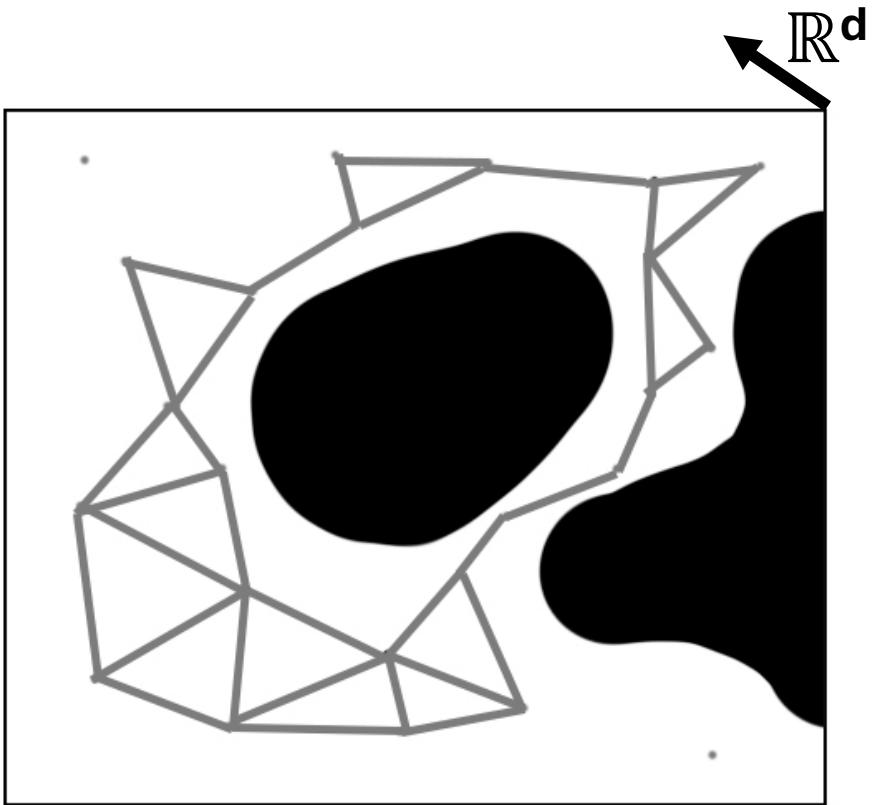
# Sampling-based Motion Planning



A roadmap or a tree is created by connecting neighborhoods in the collision-free or feasible configuration space.

Kavraki et al 1996. Probabilistic roadmaps for path planning in high-dimensional configuration spaces.“  
LaValle et al 2001, "Randomized kinodynamic planning."

# Sampling-based Motion Planning



A planning data structure is created by connecting neighborhoods in the collision-free or feasible configuration space.

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# Sampling-based Motion Planning

```
while problem not solved grow planning data structure
    sample collision-free configurations
    connect neighborhoods with local collision-free edges
    if start and goal are connected
        report path from start to goal
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Key modules:

**Sampler:** Sampling strategies – uniform, goal-biased, etc.

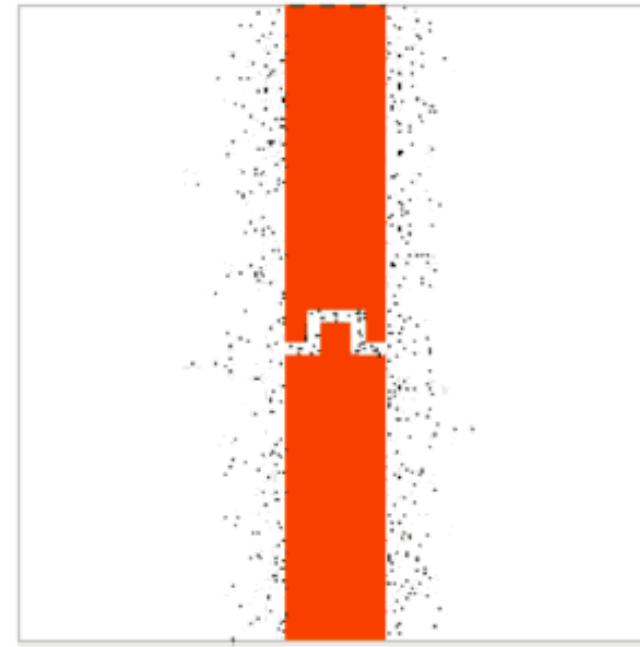
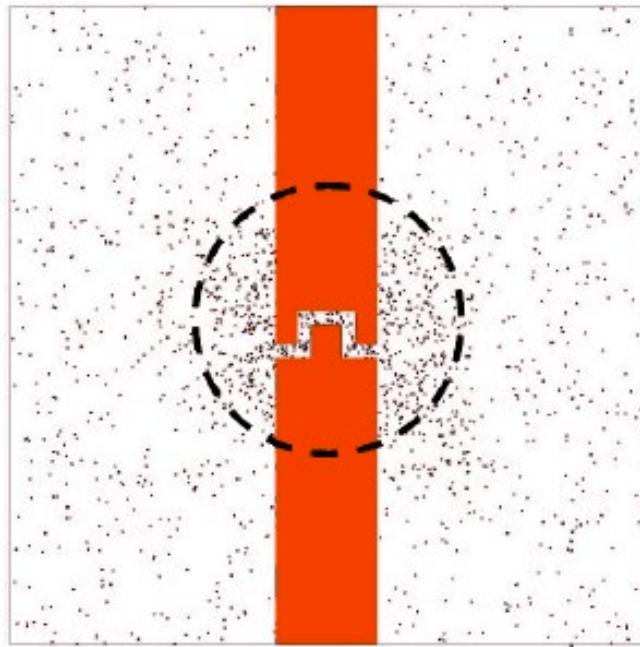
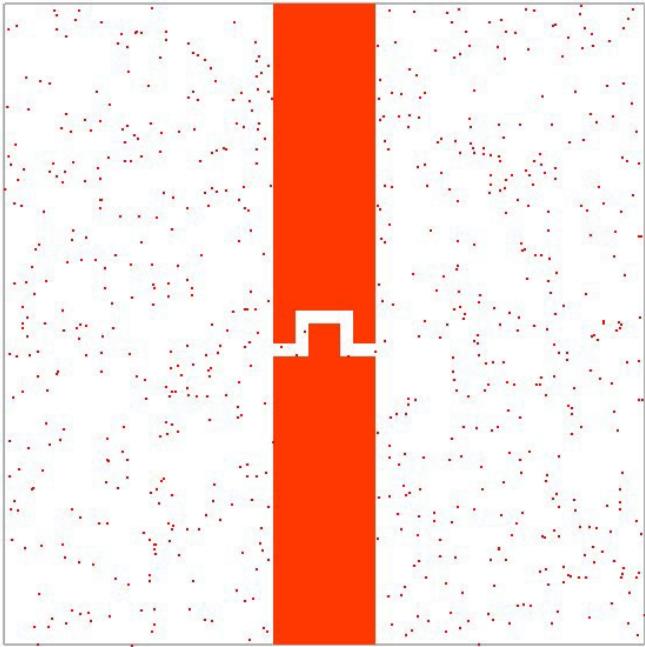
**Collision-checker:** Evaluate configurations and motions (*hint: FK is involved*)

**Nearest Neighbor:** NN data structures – KD Trees, Approximate NN (ANN), etc

**Local Planner:** Connecting nearby configurations – steering, forward propagation

**Search:** Heuristic search - A\*, Dijkstra, Tree traversal

# Samplers



Sample from a distribution in the configuration space.  
Tree-based methods can goal-bias by growing tree towards goal.

# Local Planning: Kinematic versus Kinodynamic

Select nearby configuration and  
connect to it

## Kinematic

PRM, k-PRM, RRT-Connect  
PRM\*, RRT\*, FMT\*, RRG

Select a control input and connect  
to forward propagated state

## Kinodynamic

EST, RRT, KPIECE,  
SST, AO-RRT, BoE

A steering function can connect to a nearby configuration  
by solving a two-point boundary value problem.

# Local Planning: Graphs versus Trees

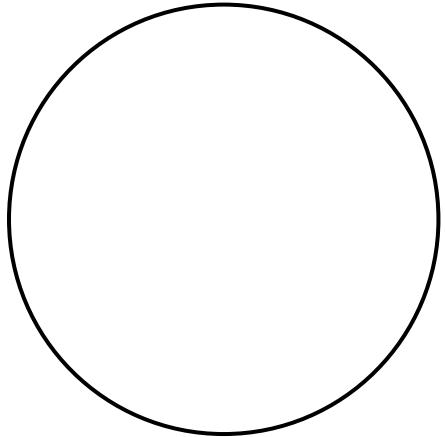
## Kinematic

Properties of configuration space and geodesics connecting configurations.

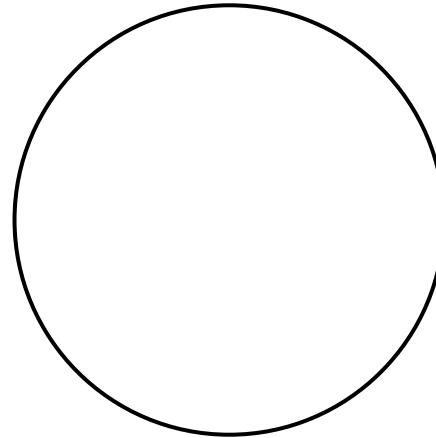
## Kinodynamic

The space is typically referred to as state space.  
The dynamics of the system can be simulated in a forward search tree.

# Connection Strategies



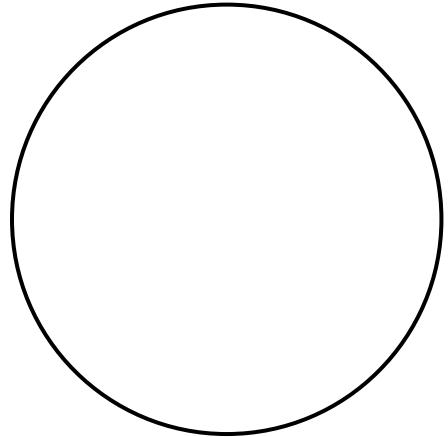
**Neighborhood radius**



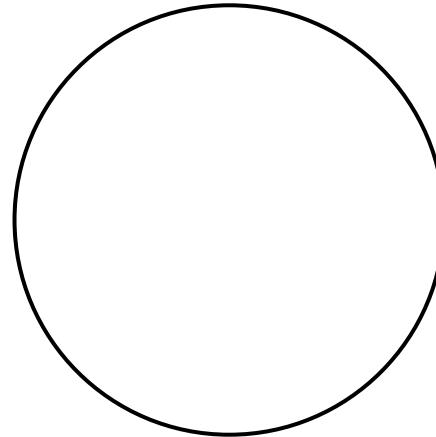
**Nearest k**

**Grow trees  
up to maximum extension**

# Can we choose any radius or k?



**Neighborhood radius**



**Grow trees  
up to maximum extension**

**Nearest k**

# Probabilistic Guarantees

## Probabilistic Completeness:

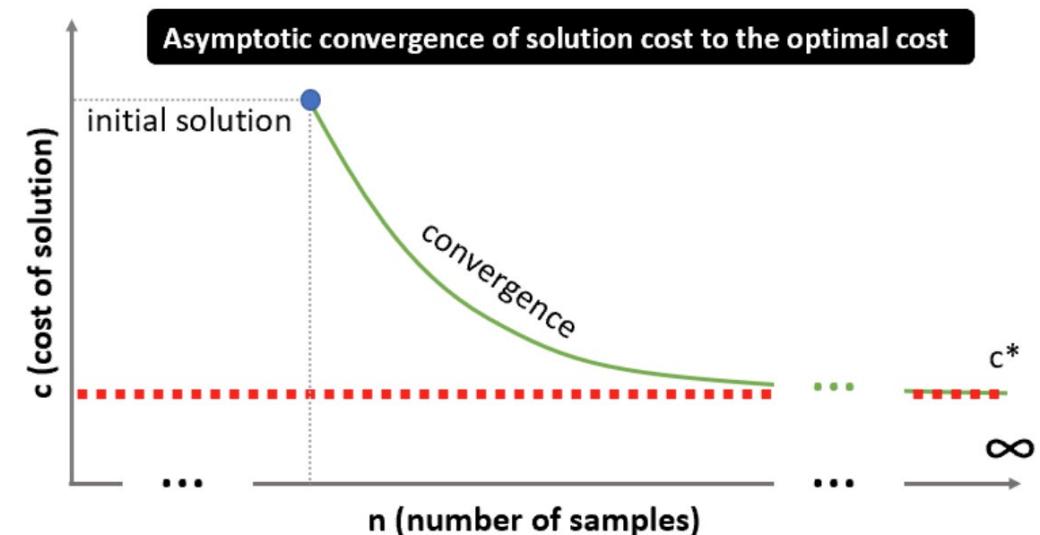
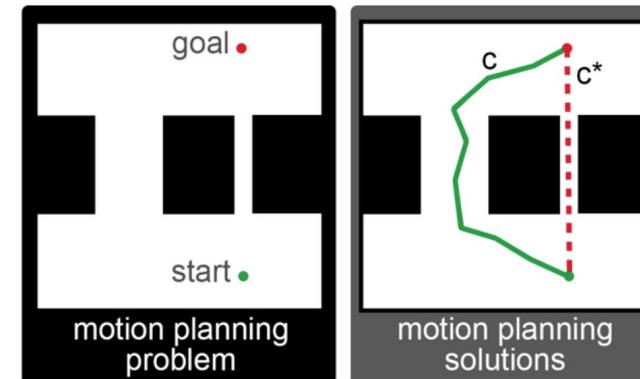
Asymptotically, in probability guarantee a feasible solution if one exists

## Asymptotic Optimality:

Asymptotically, in probability guarantee a cost-optimal solution if one exists

Kinematic: e.g., PRM\*, FMT\*, RRT\*

Kinodynamic: e.g., SST, AO-RRT



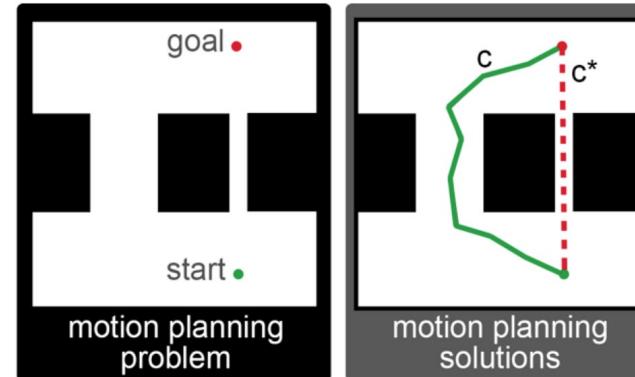
Bekris, K. E., & Shome, R. (2021). Asymptotically optimal sampling-based planners. Encyclopedia of Robotics.

Karaman, Sertac, and Emilio Frazzoli. "Sampling-based algorithms for optimal motion planning." *IJRR* 30, (2011).

# Probabilistic Guarantees

## Probabilistic Completeness:

Asymptotically, in probability guarantee a feasible solution if one exists

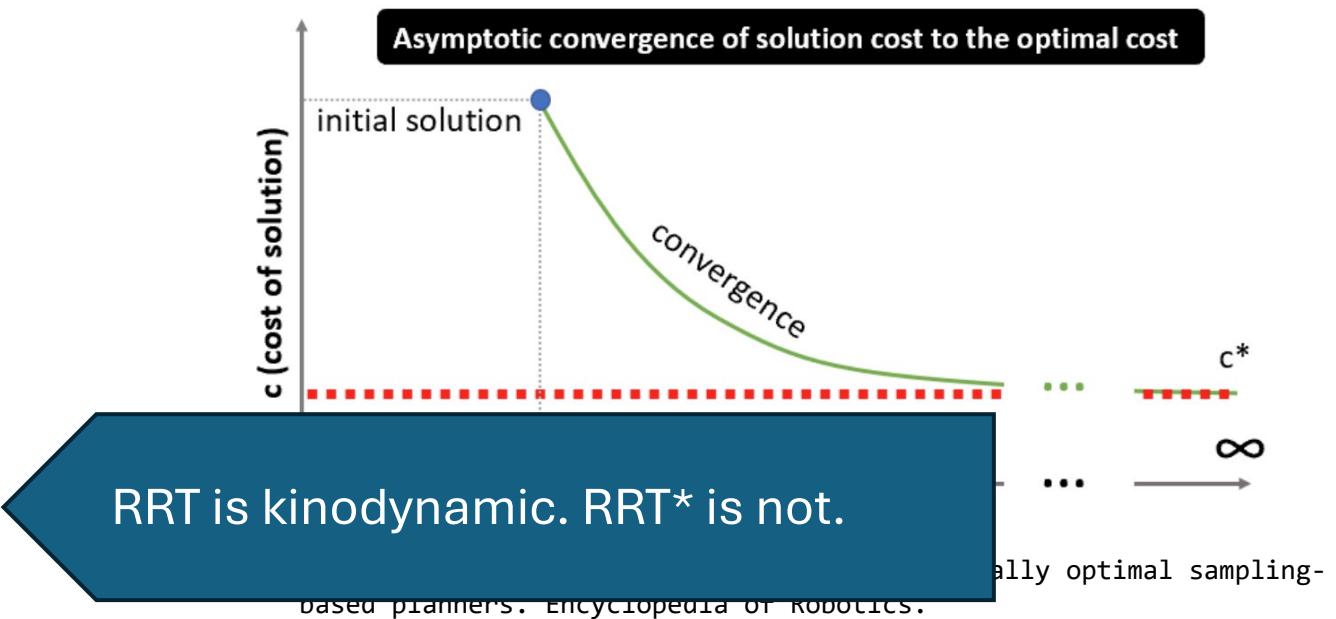


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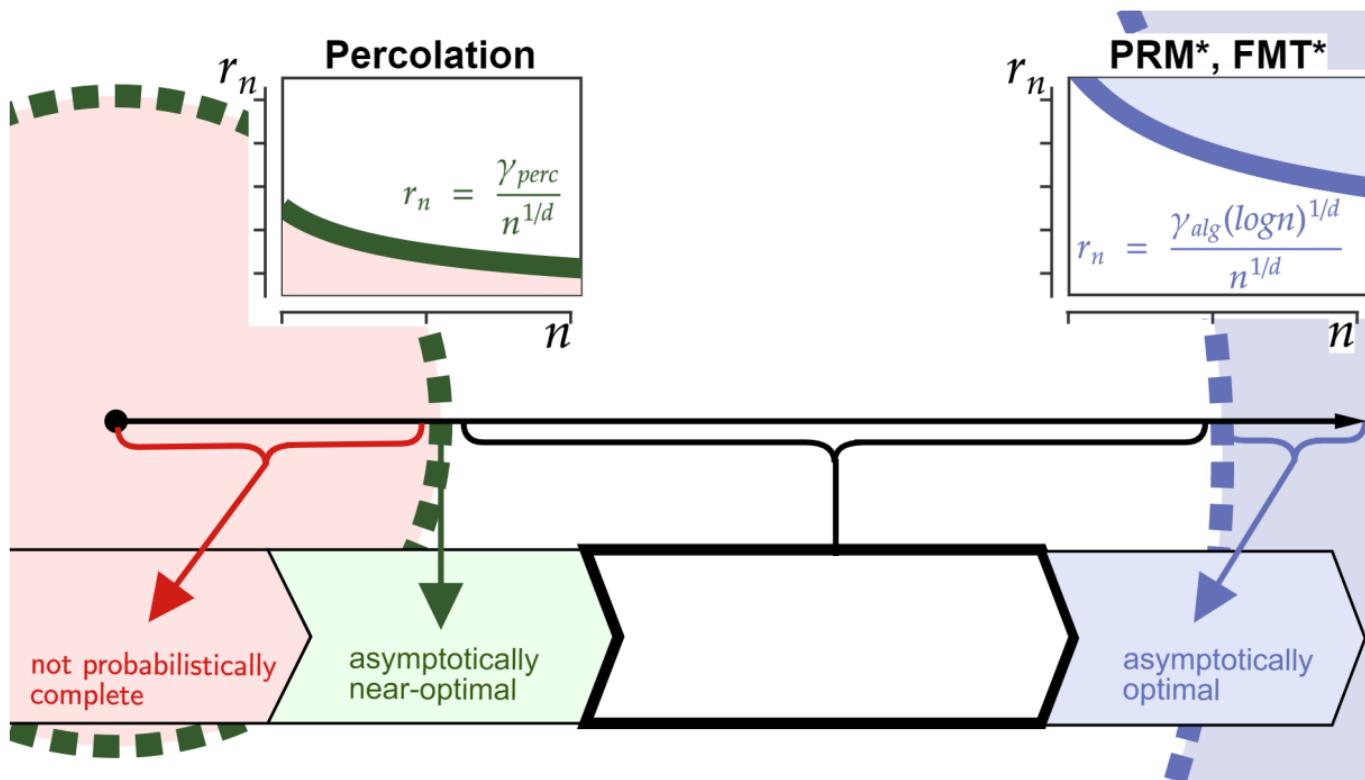
Kinematic: e.g., PRM\*, FMT\*, **RRT\***

Kinodynamic: e.g., SST, AO-RRT

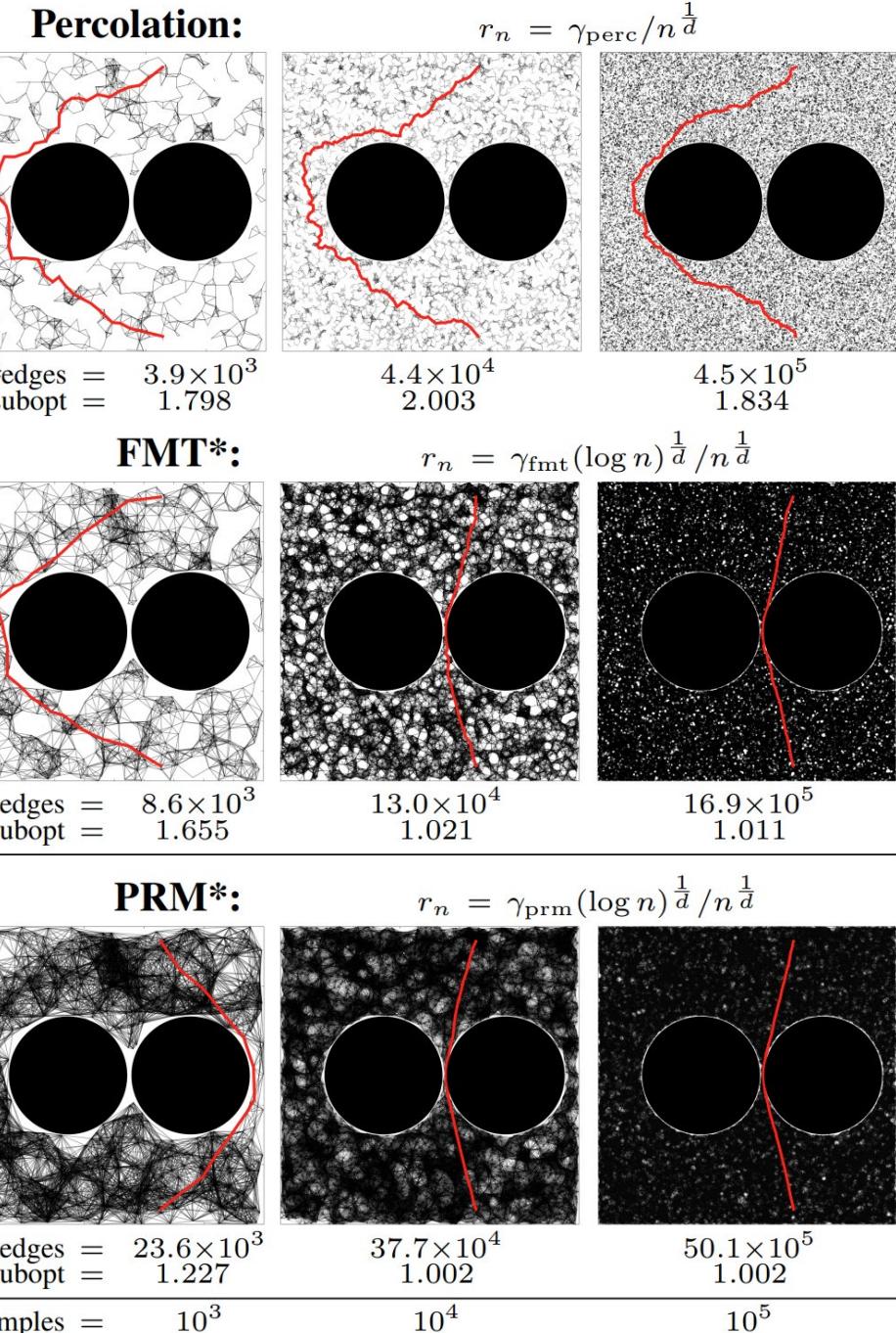
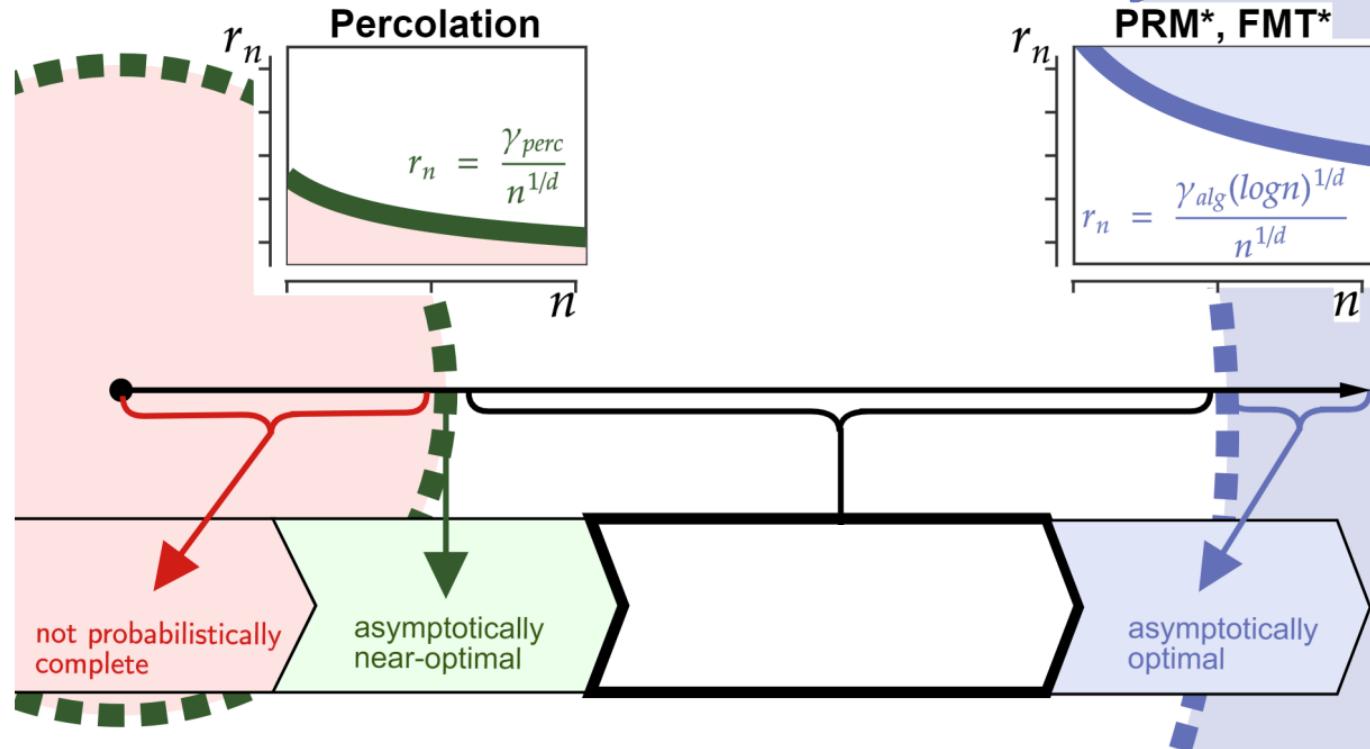


Karaman, Sertac, and Emilio Frazzoli. "Sampling-based algorithms for optimal motion planning." *IJRR* 30, (2011).

# Choice of Connection Radius



# Choice of Connection Radius



# Sampling-based Motion Planning

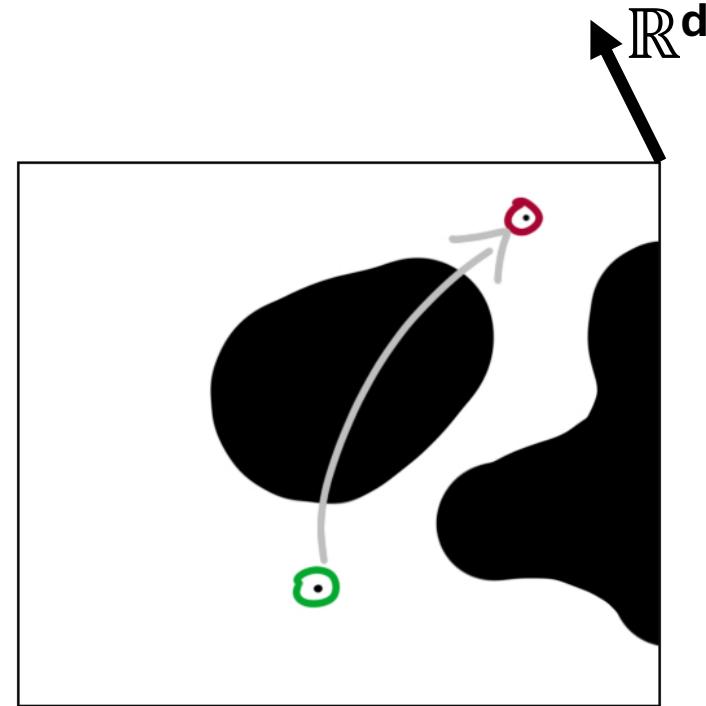
Scales to high dimensions.

Kinematic and kinodynamic.

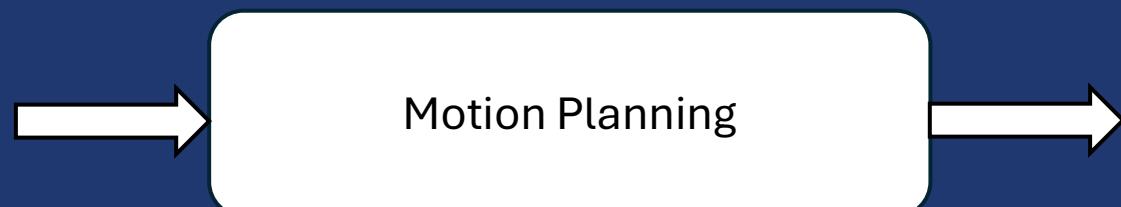
Probabilistic completeness and asymptotic optimality.

*Some categories of high-dimensional planning problems can now be solved in microseconds.*

Thomason, Wil, Zachary Kingston, and Lydia E. Kavraki. "Motions in microseconds via vectorized sampling-based planning." ICRA (2024).



Start configuration,  
goal,  
configuration space



Continuous curve  
in feasible configuration space  
connecting start and goal

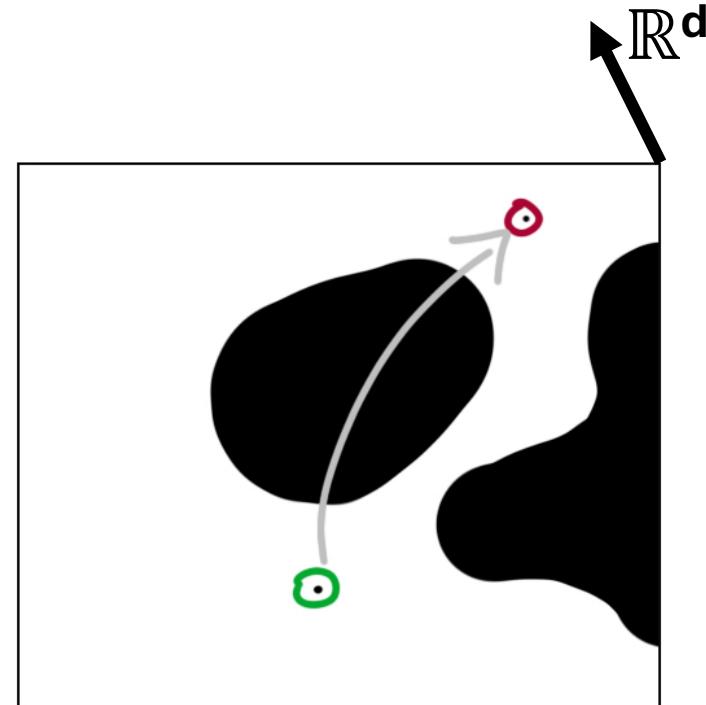
# The general problem is still hard

The space is still high-dimensional.

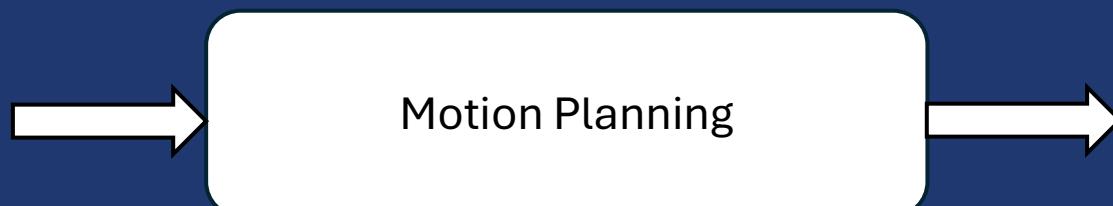
Easier spaces (end-effector pose control) do not generalize.

The infeasible subset of space is not known beforehand.

Kinodynamic state spaces are typically more complex.



Start configuration,  
goal,  
configuration space



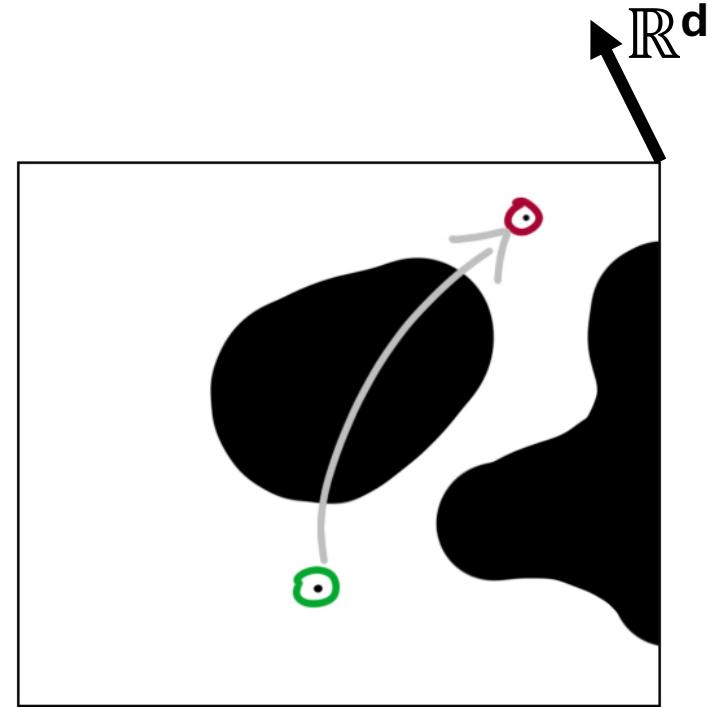
Continuous curve  
in feasible configuration space  
connecting start and goal

# Wrapping Up

# Other Strategies: Trajectory Optimization

Trajectory optimization samples a trajectory representation and optimizes it subject to constraints and costs.

(CHOMP, TrajOPT, cuRobo, etc.)



# Other Variants

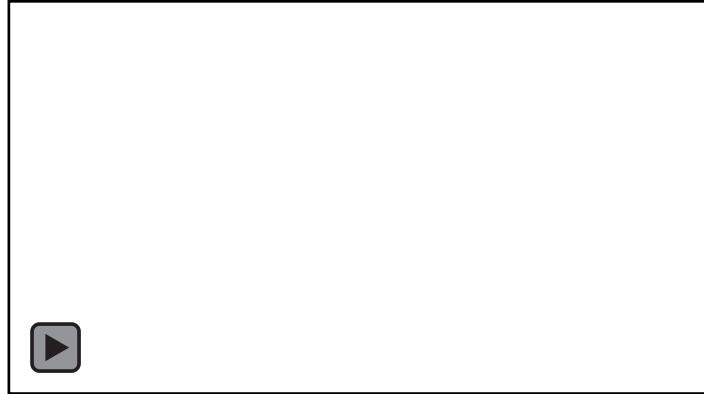
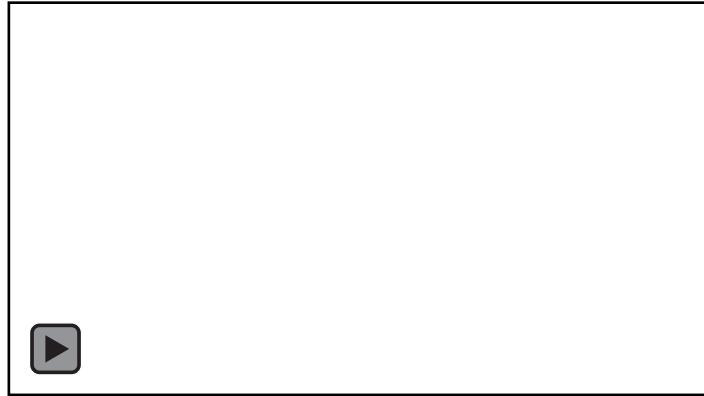
Motions over constraint manifolds.

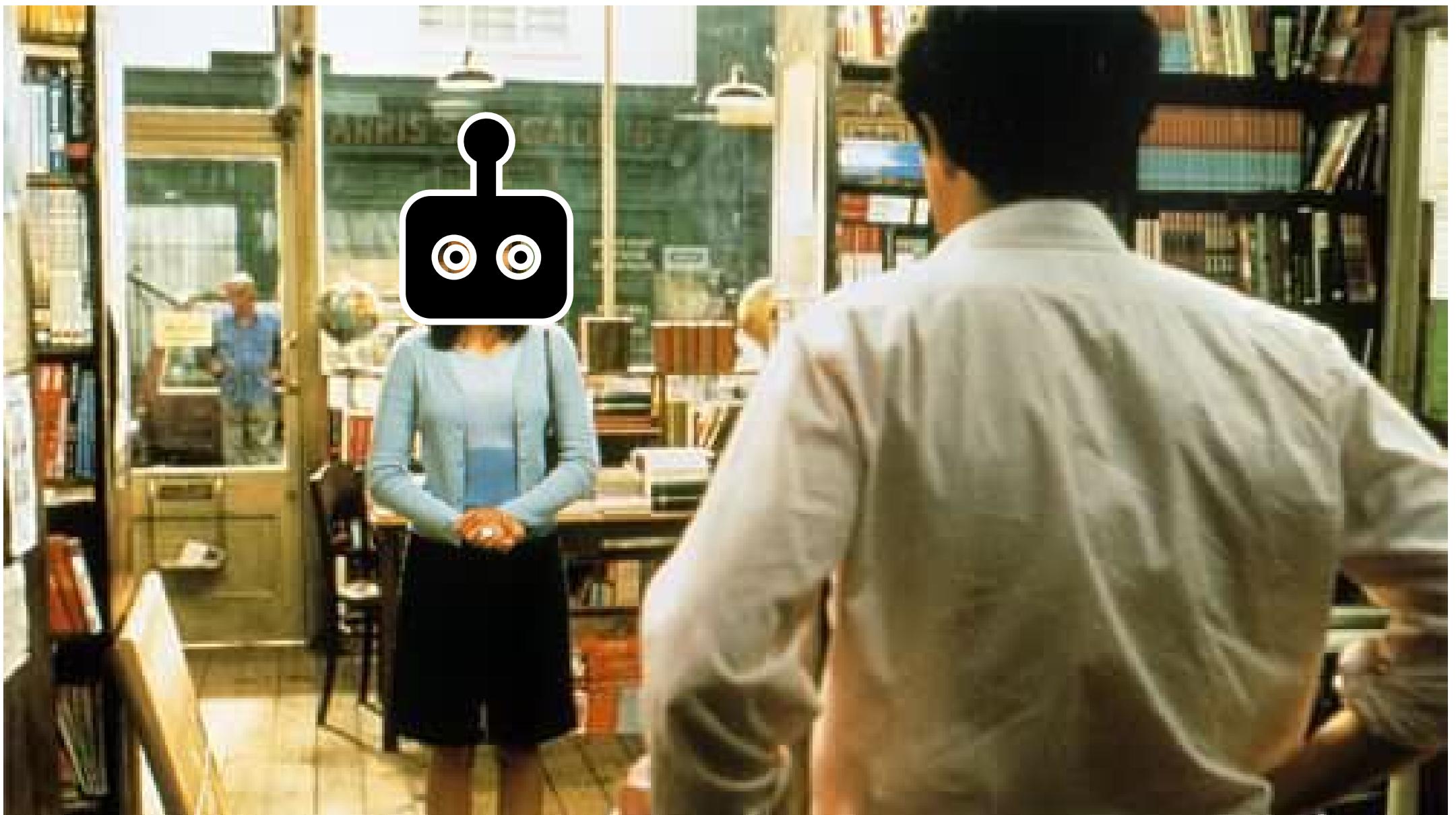
Multi-robot motions.

Motions under uncertainty.

Motions learned from demonstration.

...





I'm just a point in a high-dimensional space trying to reach the goal.