

# Sampling-Based Methods for Path Planning

With so many slides and ideas from so many people:  
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# Difficulty with classic approaches to path planning

- Running time increases exponentially with the dimension of the configuration space.
  - For a  $d$ -dimension grid with 10 grid points on each dimension, how many grid cells are there?

$$10^d$$

- Several variants of the path planning problem have been proven to be PSPACE-hard.

# Completeness

- Complete algorithm → Slow
  - A **complete** algorithm finds a path if one exists and reports no otherwise in finite time.
  - Example: visibility graph for 2D problems (translation in the plane) and polygonal robot and obstacles
- Heuristic algorithm → Unreliable
  - Example: potential field (we'll see it soon)
- **Probabilistic completeness**
  - Intuition: If there is a solution path, the algorithm will find it with high probability.

# 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
- Facilitates “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 Planning:*

Search for collision-free path  
only by sampling points.

# Probabilistic Roadmaps

# Probabilistic Road Map (PRM)

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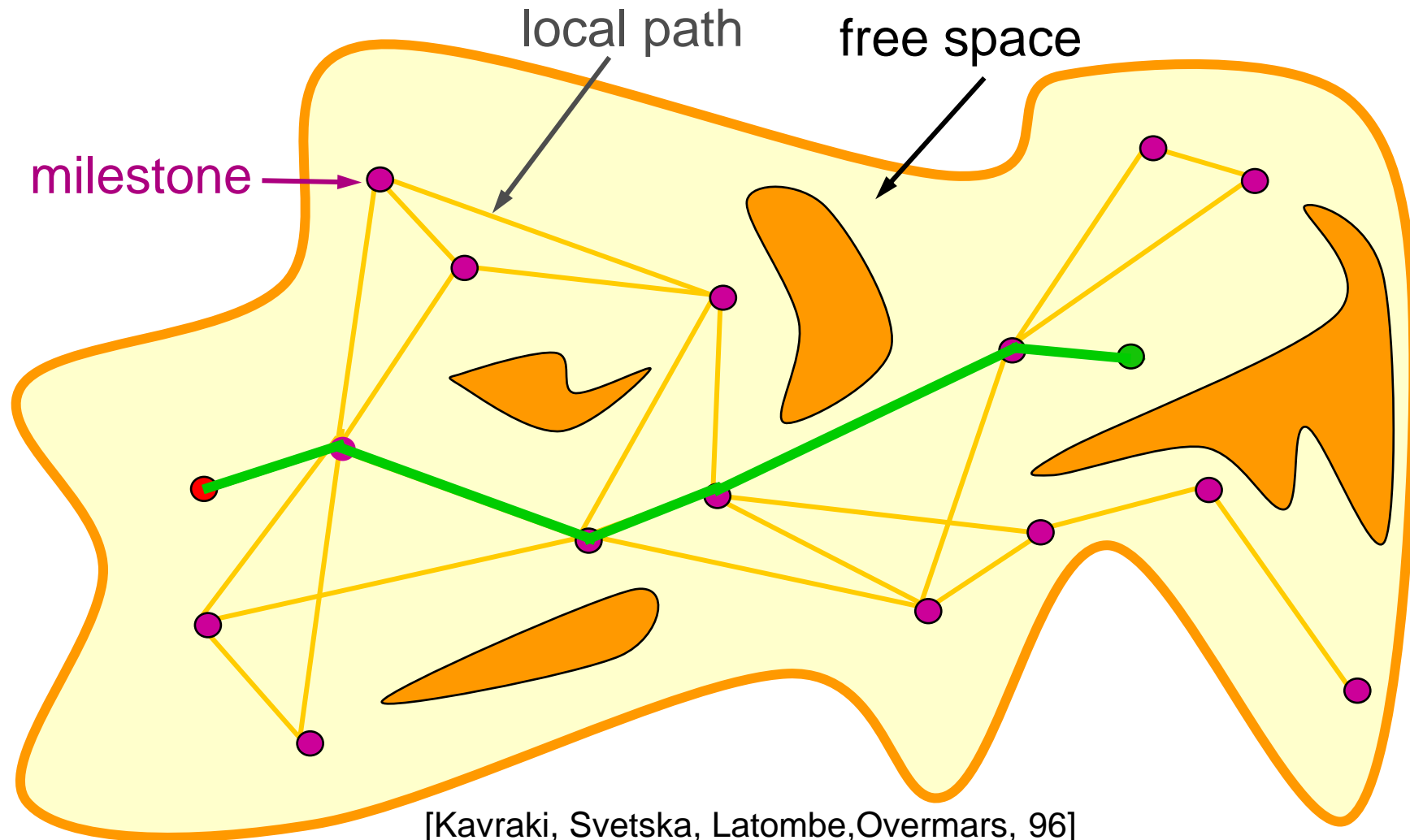
- Probabilistic Roadmap methods proceed in two phases:

1. Preprocessing Phase – to construct the roadmap  $G$

2. Query Phase – to search given  $q_{init}$  and  $q_{goal}$

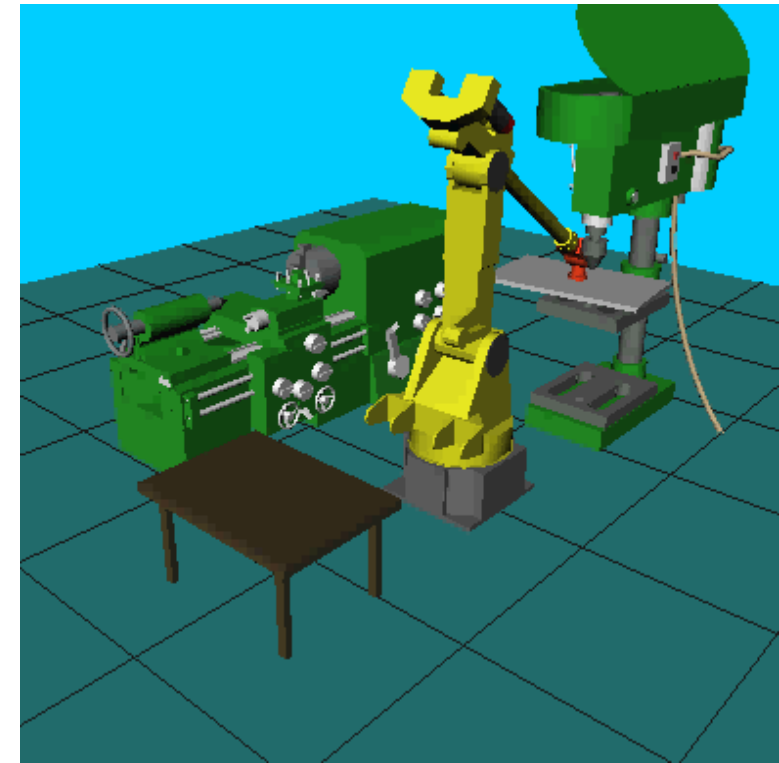
The roadmap is an undirected graph  $G = (N, E)$ . The nodes in  $N$  are a set of configurations of the robot chosen over  $C$ -free. The edges in  $E$  correspond to feasible straight-line paths.

# Probabilistic Roadmap (PRM): multiple queries



# Assumptions

- Static obstacles
- Many queries to be processed in the same environment
- Examples
  - Navigation in static virtual environments
  - Robot manipulator arm in a workcell
- Advantages:
  - Amortize the cost of planning over many problems
  - Probabilistically complete





# Overview

- Precomputation: roadmap construction
  - Uniform sampling
  - Resampling (expansion)
- Query processing

# Uniform sampling

**Input:** geometry of the moving object & obstacles

**Output:** roadmap  $G = (V, E)$

```
1:  $V \leftarrow \emptyset$  and  $E \leftarrow \emptyset$ .
2: repeat
3:    $q \leftarrow$  a configuration sampled uniformly at random from  $C$ .
4:   if CLEAR( $q$ ) then
5:     Add  $q$  to  $V$ .
6:      $N_q \leftarrow$  a set of nodes in  $V$  that are close to  $q$ .
6:     for each  $q' \in N_q$ , in order of increasing  $d(q, q')$ 
7:       if LINK( $q', q$ ) then
8:         Add an edge between  $q$  and  $q'$  to  $E$ .
```

## Some terminology

- The graph  $G$  is called a **probabilistic roadmap**.
- The nodes in  $G$  are called **milestones**.

# How do we determine a *random free configuration*?

- We want the nodes of  $V$  to be a ***uniform*** sampling of  $Q_{\text{free}}$ 
  - Draw each of its coordinates from the interval of values of the corresponding degrees of freedom. (Use the uniform probability distribution over the interval)
  - Check for collision both with robot itself and with obstacles
  - If collision free, add to  $V$ , otherwise discard
  - What about rotations? Strategies for sampling orientation are beyond the scope of this class. Since Duckiebots live in the plane, we could merely sample uniformly in the interval  $[0, 2\pi]$ .

# What's the local path planner: $\text{Link}(q',q)$ ?

- There are plenty of possibilities
  - Nondeterministic (include a randomized “wandering” component)
    - We'll have to store local paths in roadmap
  - Powerful
    - Slower but maybe we'll need fewer nodes if we do some hard work during roadmap construction?
  - Fast and simple
    - Less powerful, Roadmap will need more nodes

# Go with the fast local planner

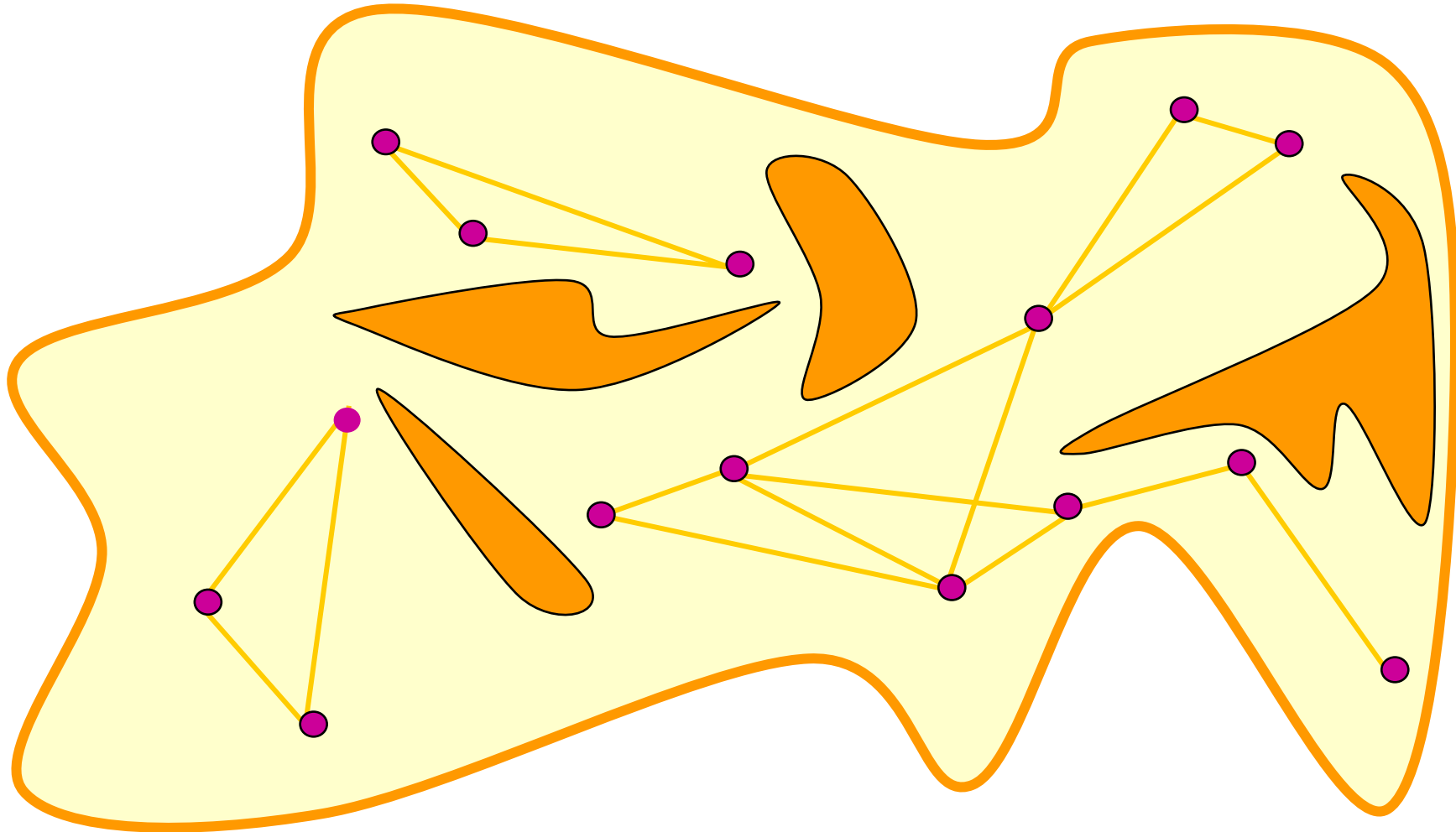
- Need to make sure start and goal configurations can connect to graph, which requires a somewhat dense roadmap
- Can reuse local planner at query time to connect start and goal configurations
- Don't need to memorize local paths

# Distance Functions: $d(q, q')$

- Really,  $d$  should reflect the likelihood that the planner will fail to find a path
  - close points, likely to succeed
  - far away, less likely
- This is often related to the area swept out by the robot along the local path:
  - very hard to compute exactly
  - usually heuristic distance is used
- Typical approaches
  - Euclidean distance on some embedding of c-space
  - Create a weighted combination of translation and rotational “distances”
  - Weighted sum of distances for a set of “control points” on the robot

# Difficulty

- Many small connected components





# Resampling (expansion)

□ Failure rate

$$r(q) = \frac{f(q)}{n(q) + 1}$$

□ Weight

$$w(q) = \frac{r(q)}{\sum_p r(p)}$$

□ Resampling probability  $\Pr(q) = w(q)$

- $f(q)$  = # of failed attempts to connect  $q$  to the roadmap
- $n(q)$  = total # of attempts to connect  $q$  to the roadmap

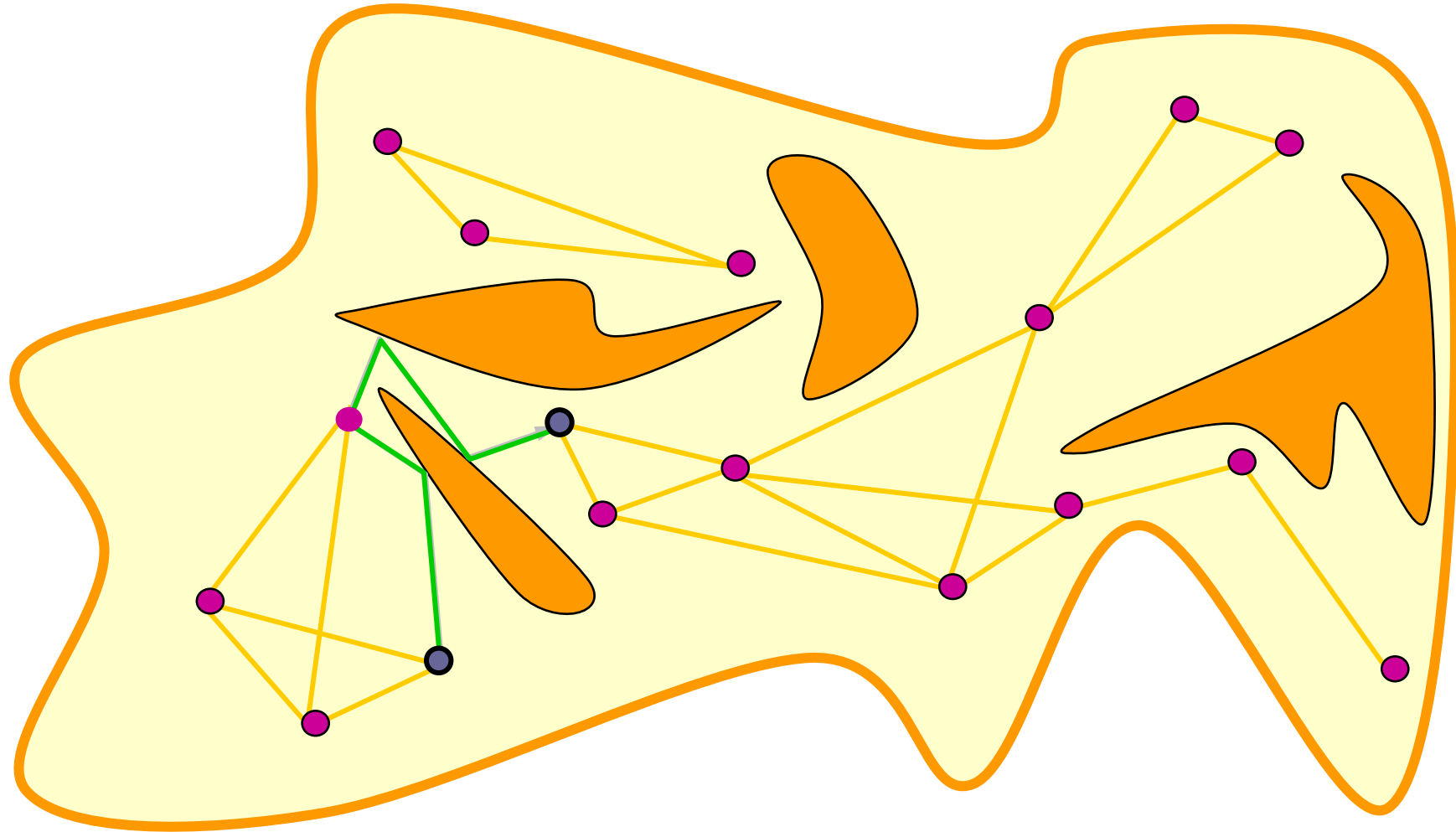
# Now that we have weights...

- To expand a node  $c$ , we compute a short random-bounce walk starting from  $c$ .

This means

- Repeatedly pick at random a direction of motion in C-space and move in this direction until an obstacle is hit.
- When a collision occurs, choose a new random direction.
- The final configuration  $n$  and the edge  $(c,n)$  are inserted into the roadmap and the path is memorized.
- Try to connect  $n$  to the other connected components like in the construction step.
- Weights are only computed once at the beginning and not modified as nodes are added to the roadmap.

# Resampling (expansion)



# Query processing

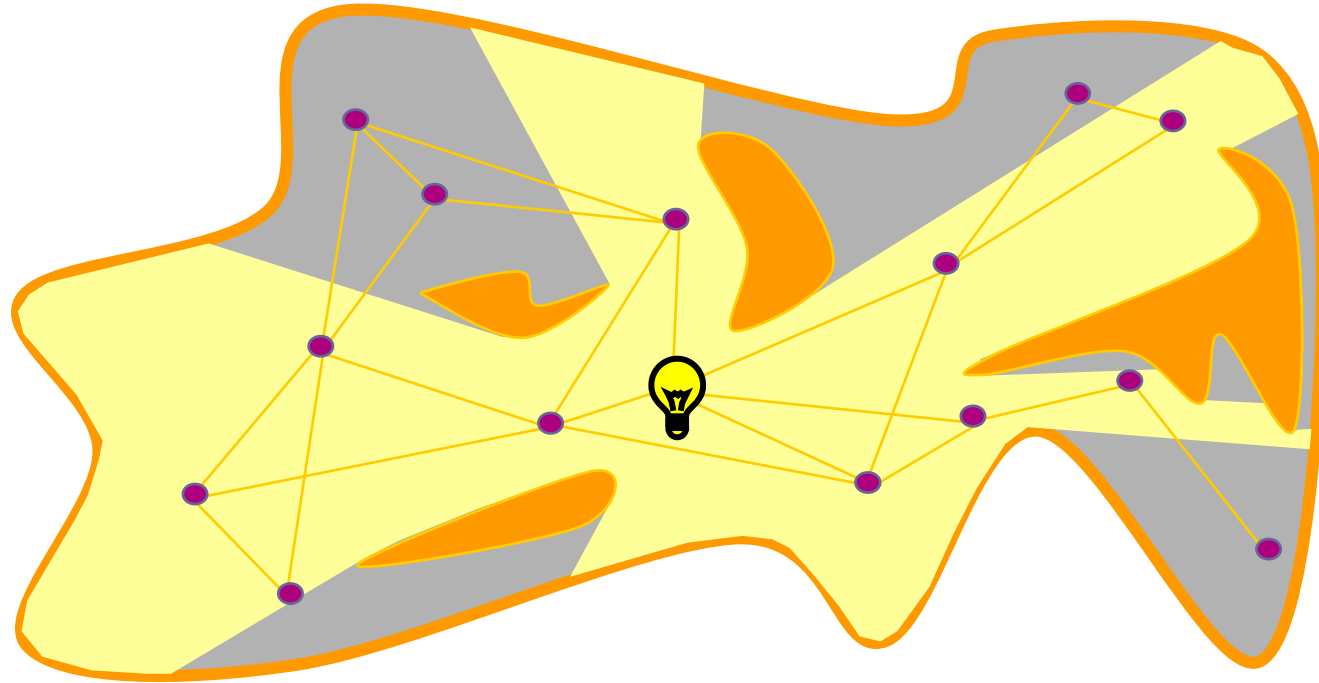
- Connect  $q_{init}$  and  $q_{goal}$  to the roadmap
- Start at  $q_{init}$  and  $q_{goal}$ , perform a random walk, and try to connect with one of the milestones nearby
- Try multiple times

# Error

- If a path is returned, the answer is always correct.
- If no path is found, the answer may or may not be correct. We hope it is correct with high probability.

# Why does it work? Intuition

- A small number of milestones **almost** “cover” the **entire** configuration space.



- Rigorous definitions and exist (of course!)