RBE550
Motion Planning
Learning and Motion Planning I

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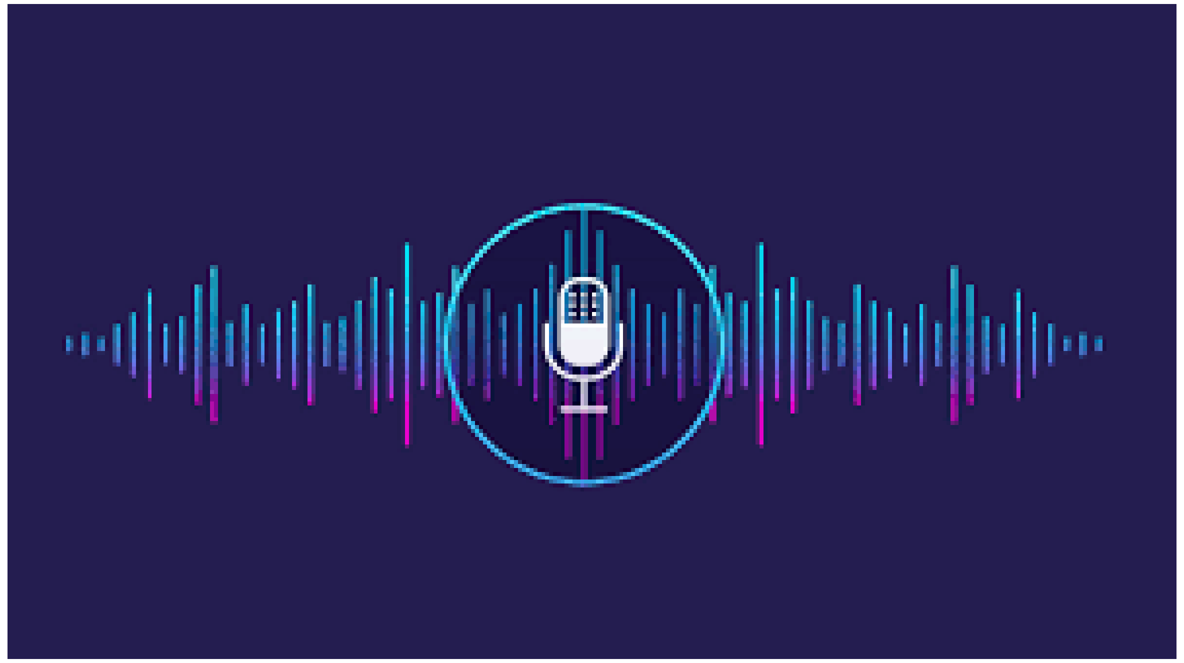
Machine Learning is Everywhere

Strategy Algorithms

Assistive Driving

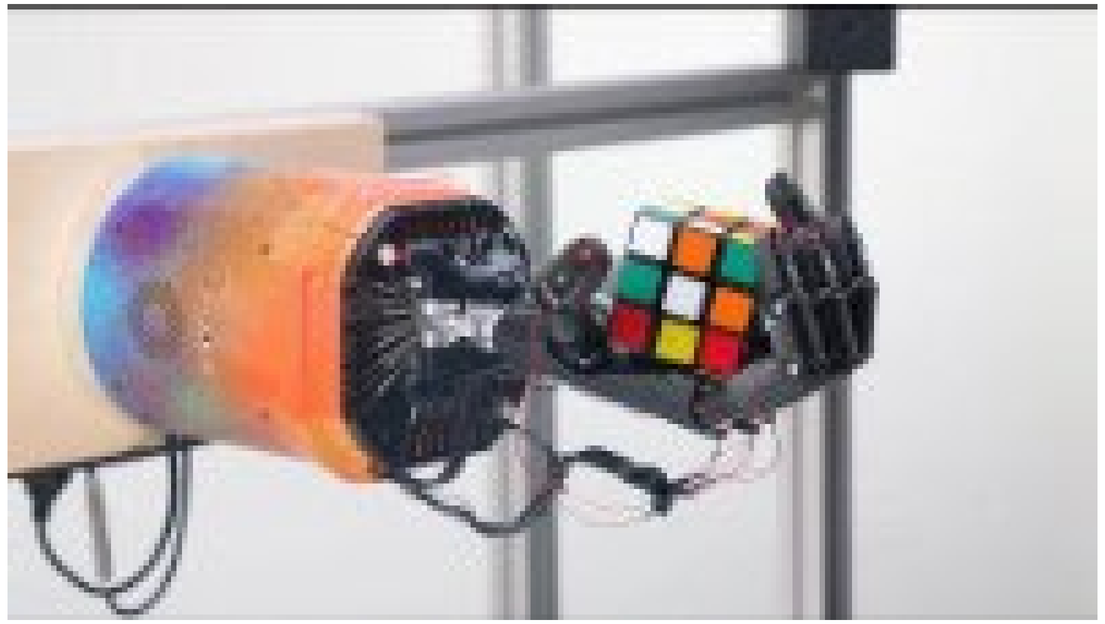
NETFLIX

Recommendation Algorithms



Voice recognition/assistants

Machine Learning in Robotics



Learn Dexterous Manipulation

Learn Grasping Poses

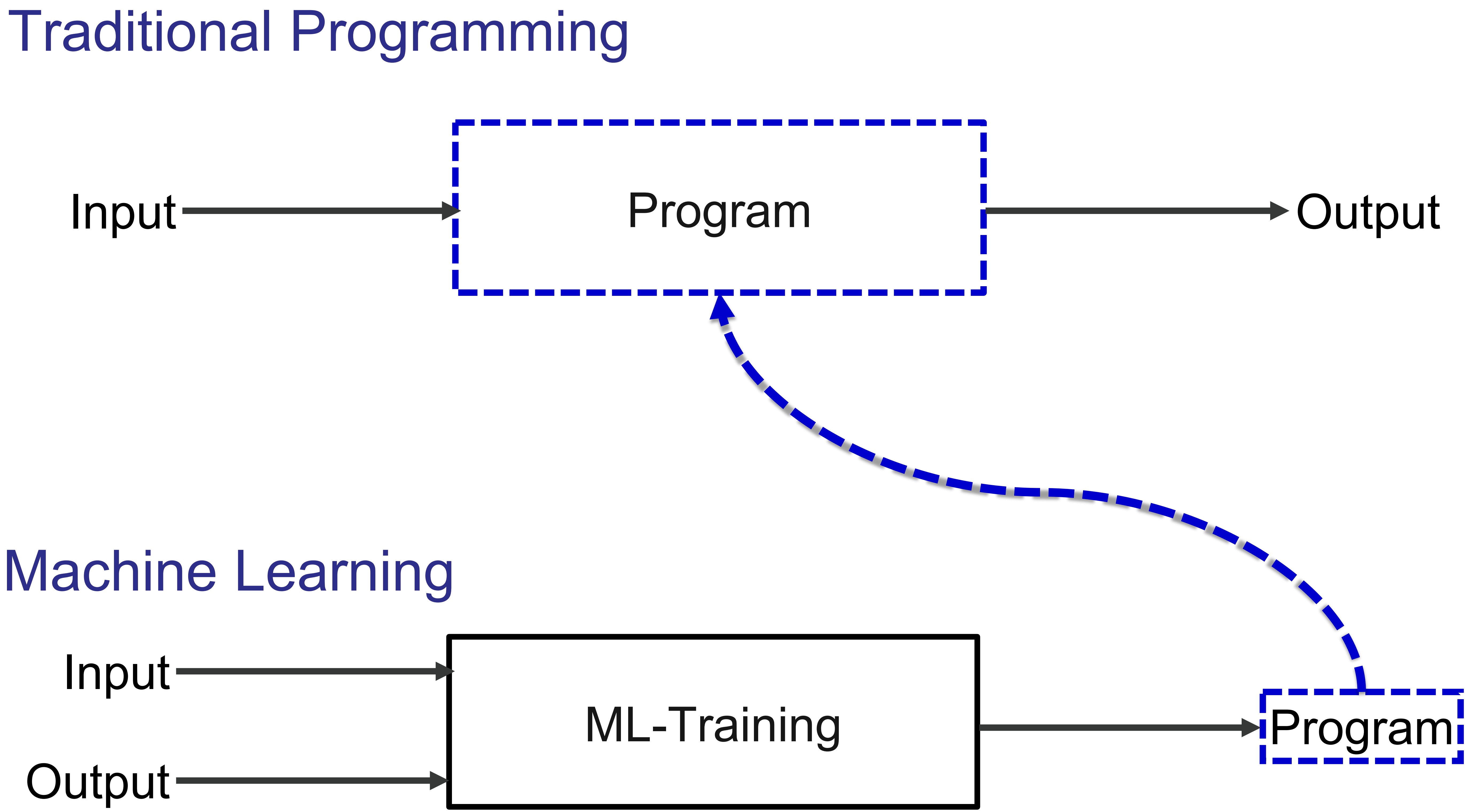
Learn Walking Gaits

What is Machine Learning?

Traditional Programming

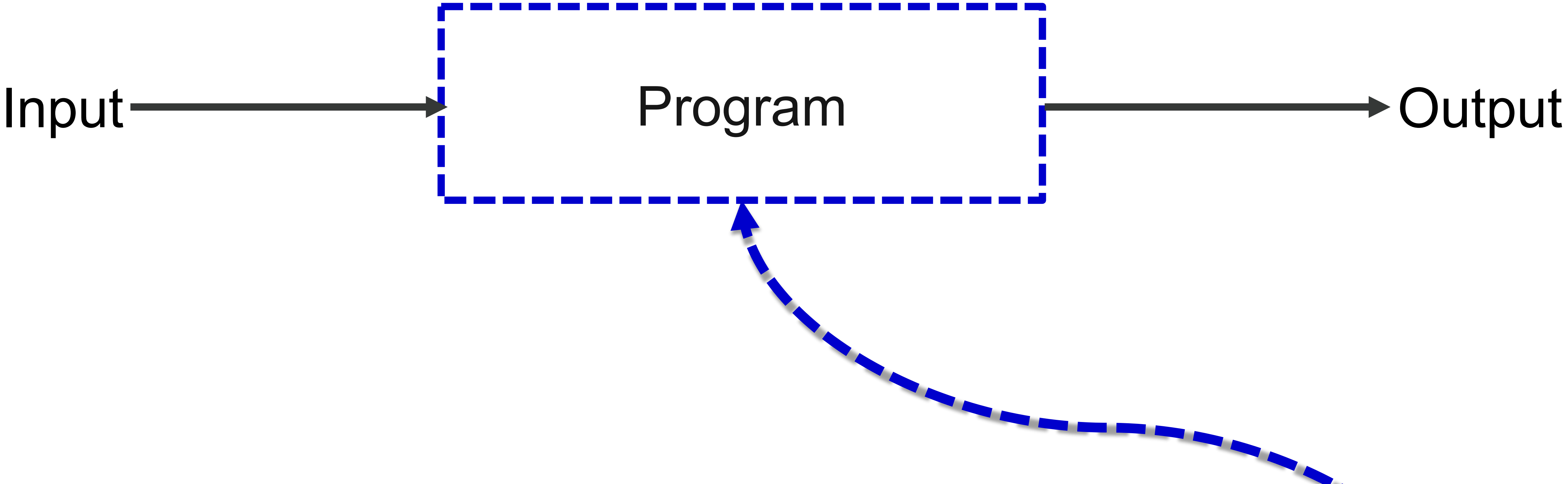
Machine Learning

What is Machine Learning?



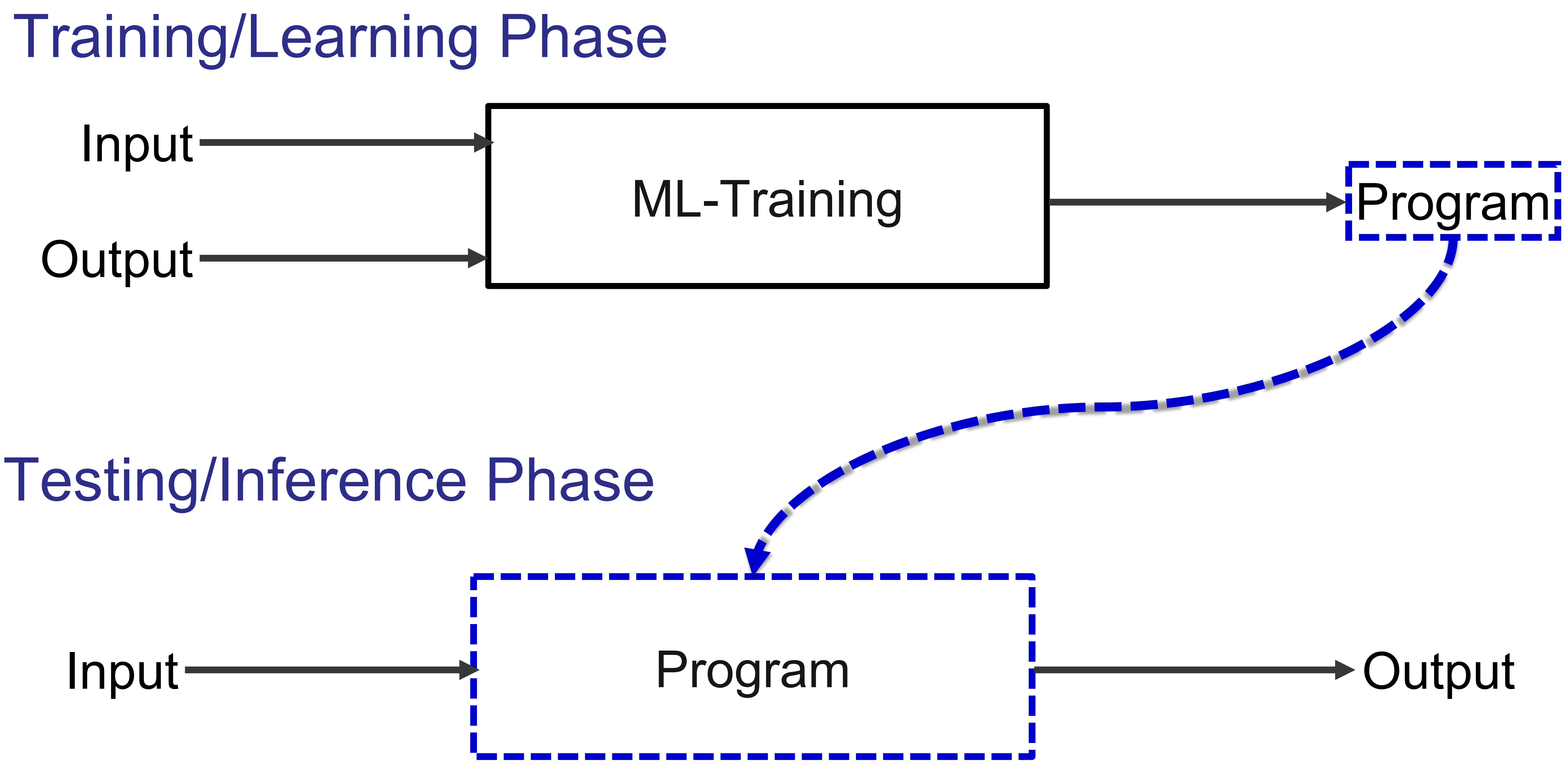
What is Machine Learning?

Testing/Inference Phase

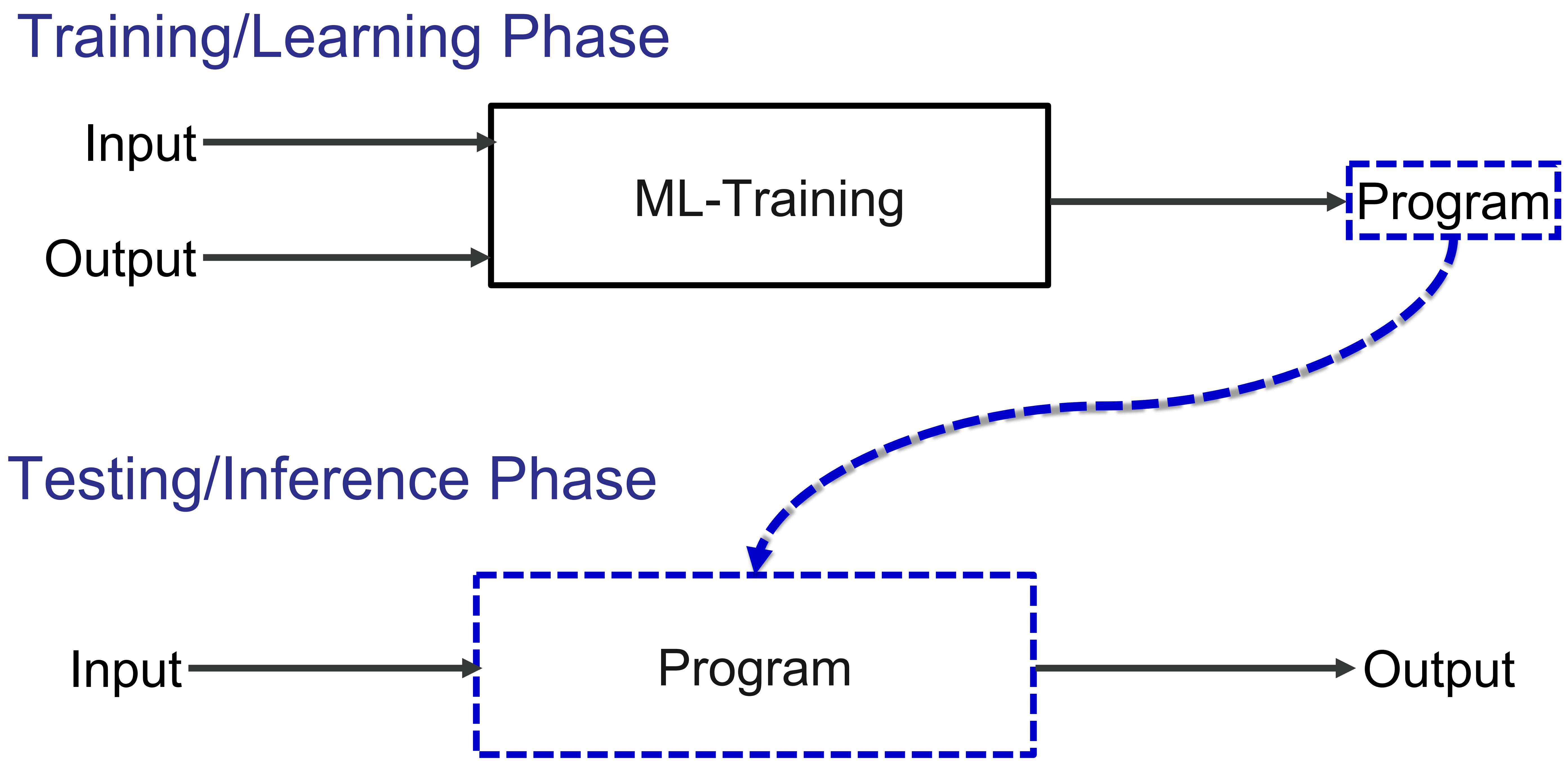


Training/Learning Phase

What is Machine Learning?



Machine Learning and Motion Planning

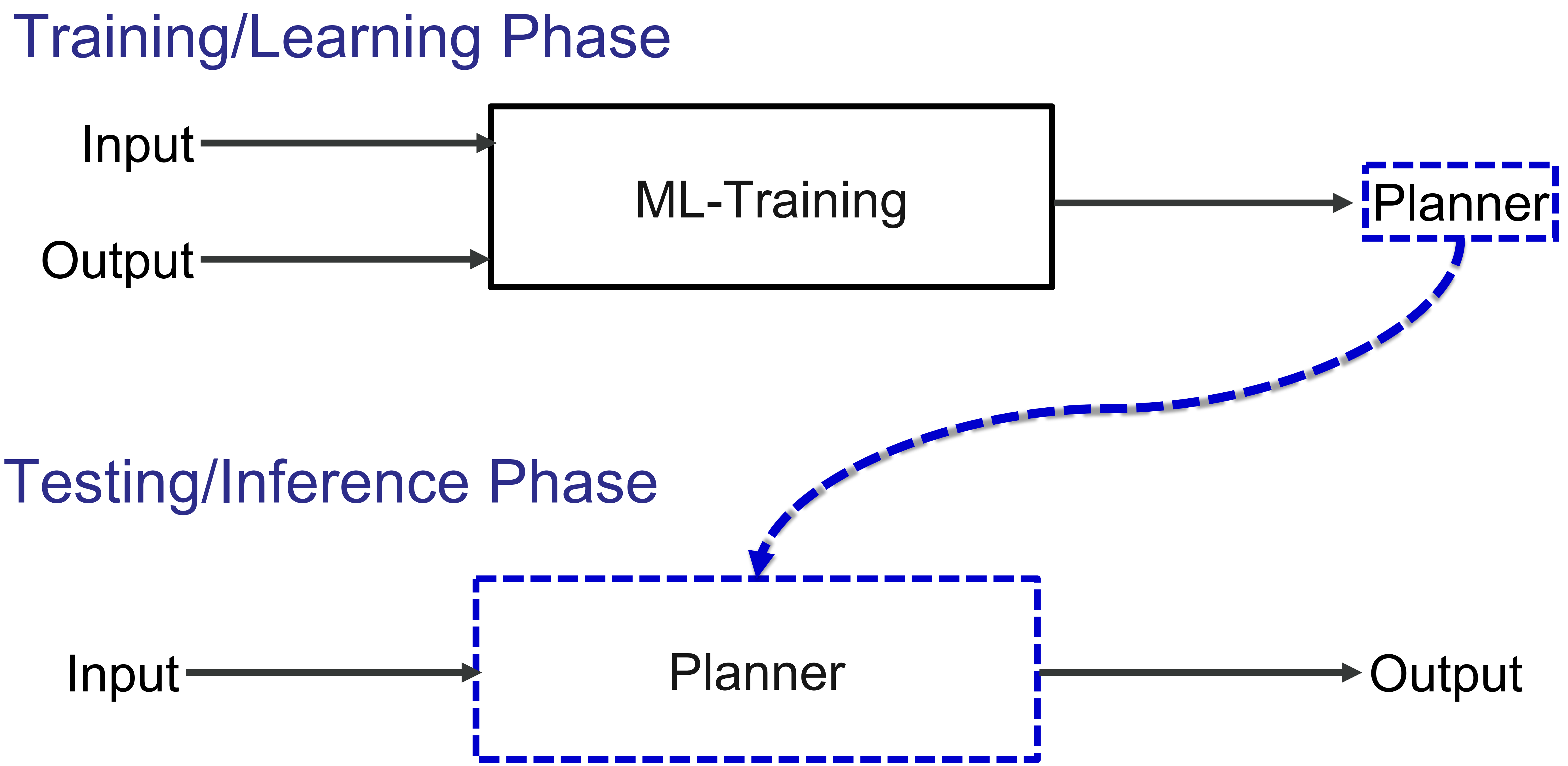


What is the "Program" called in Motion Planning ?

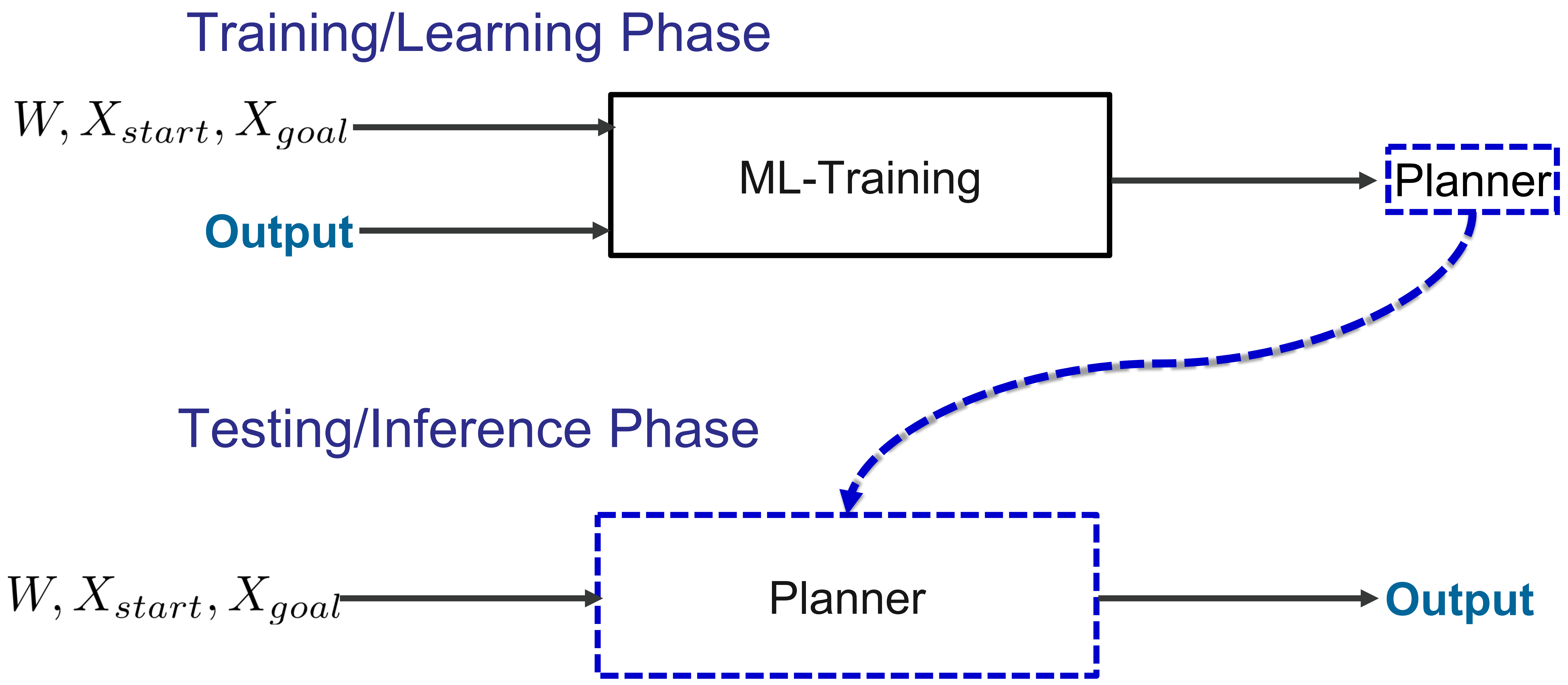
Nobody has responded yet.

Hang tight! Responses are coming in.

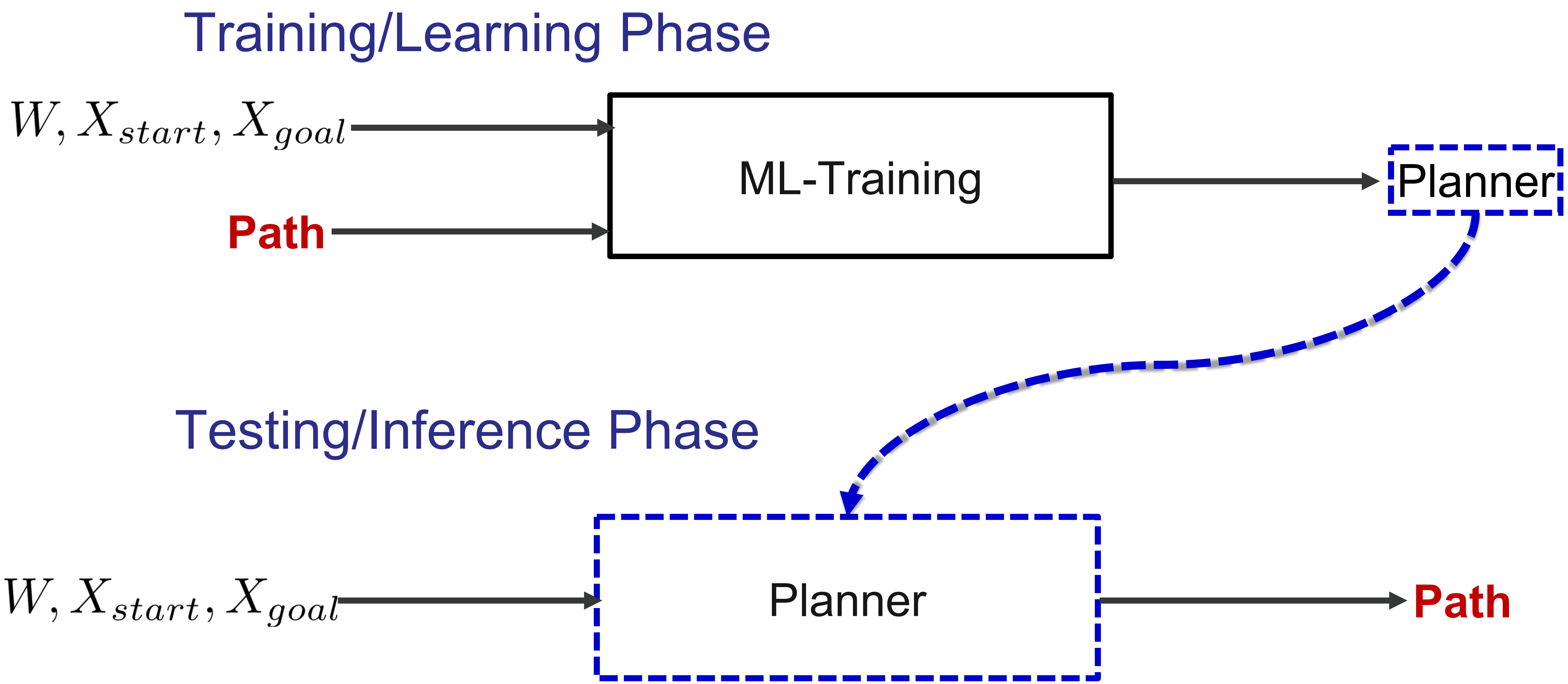
Machine Learning and Motion Planning



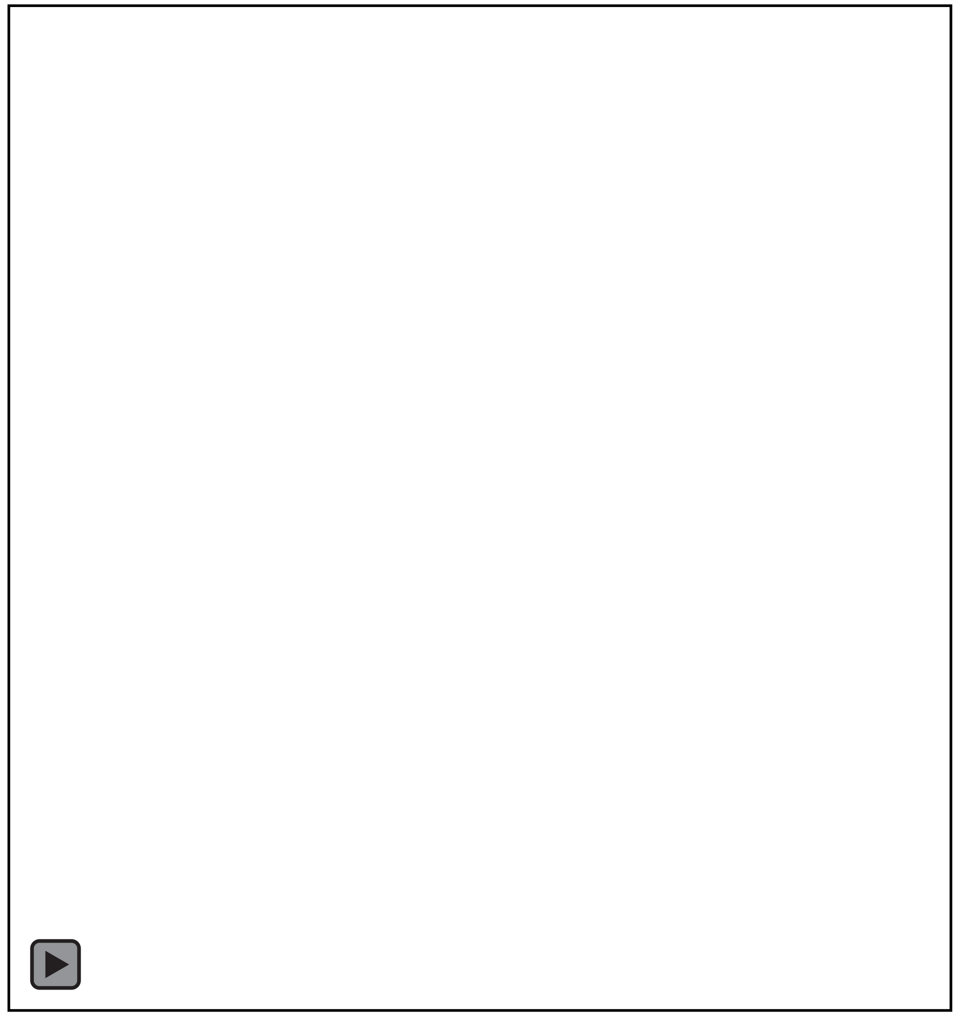
Machine Learning and Motion Planning



Machine Learning and Motion Planning



Why Machine Learning and Motion Planning?



High planning time☹

State-of-the-art planners still struggle in complex environments!

Can we use learning to solve motion planning problems **faster**?

Using Learning for Motion Planning

I have no memory of this,
I will need some time.

I know this,
I can do it **fast**!

High planning time☹

Low planning time☺

Robots solve similar problems (W, X_{start}, X_{goal})

Existing planners can generate data (Paths)

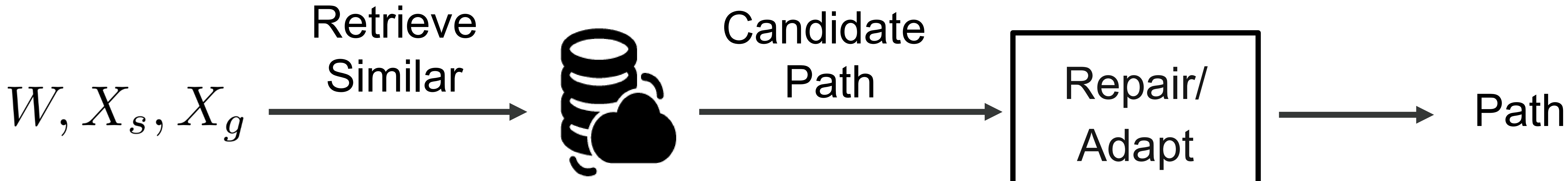
Learning Archetypes (Methodologies)

Learning Archetypes	Corresponding Papers
1. Retrieve and Repair	**Lightning[1]**, **Thunder [2],** ERT[3], Sim-Obstacles[4], Traj-Pred[5]
2. Biased Samplers	**Rep-Sampling[6]**,**Rep-Roadmaps[7],** AWS[8], SPARK2D[9], CVAE[10], FLAME[11], FIRE[12]

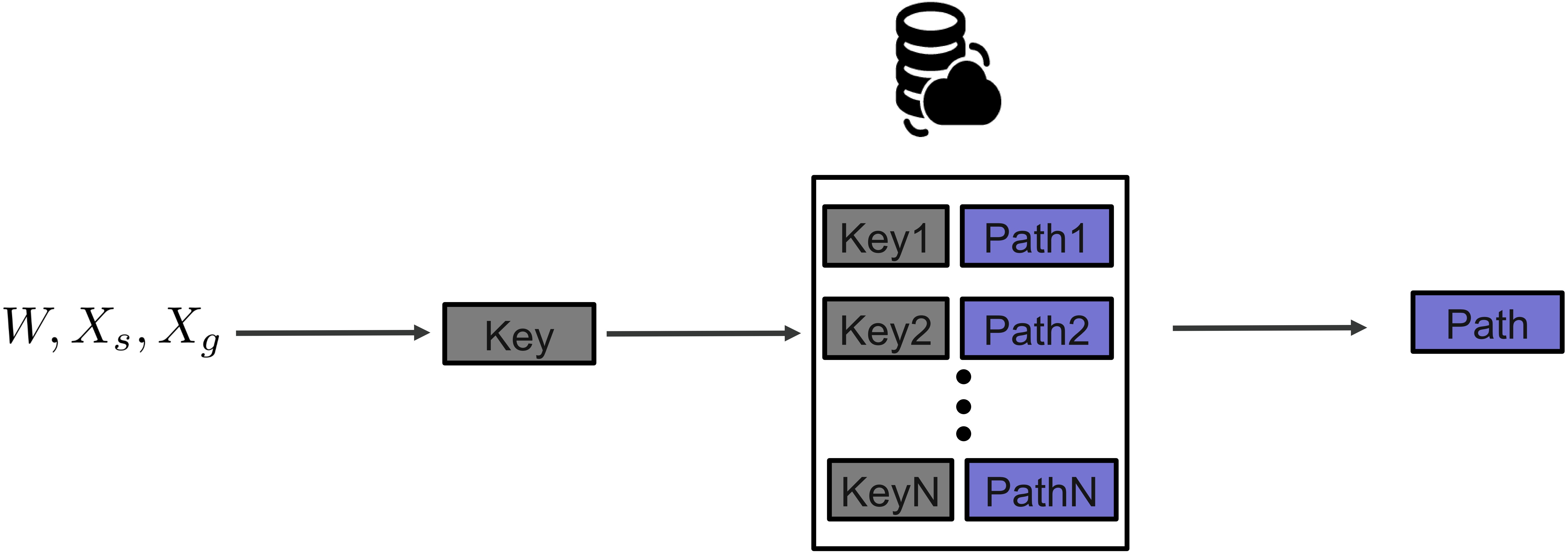
1. Retrieve and Repair Archetype

Training/Learning Phase

Testing/Inference



What is an experience Database?

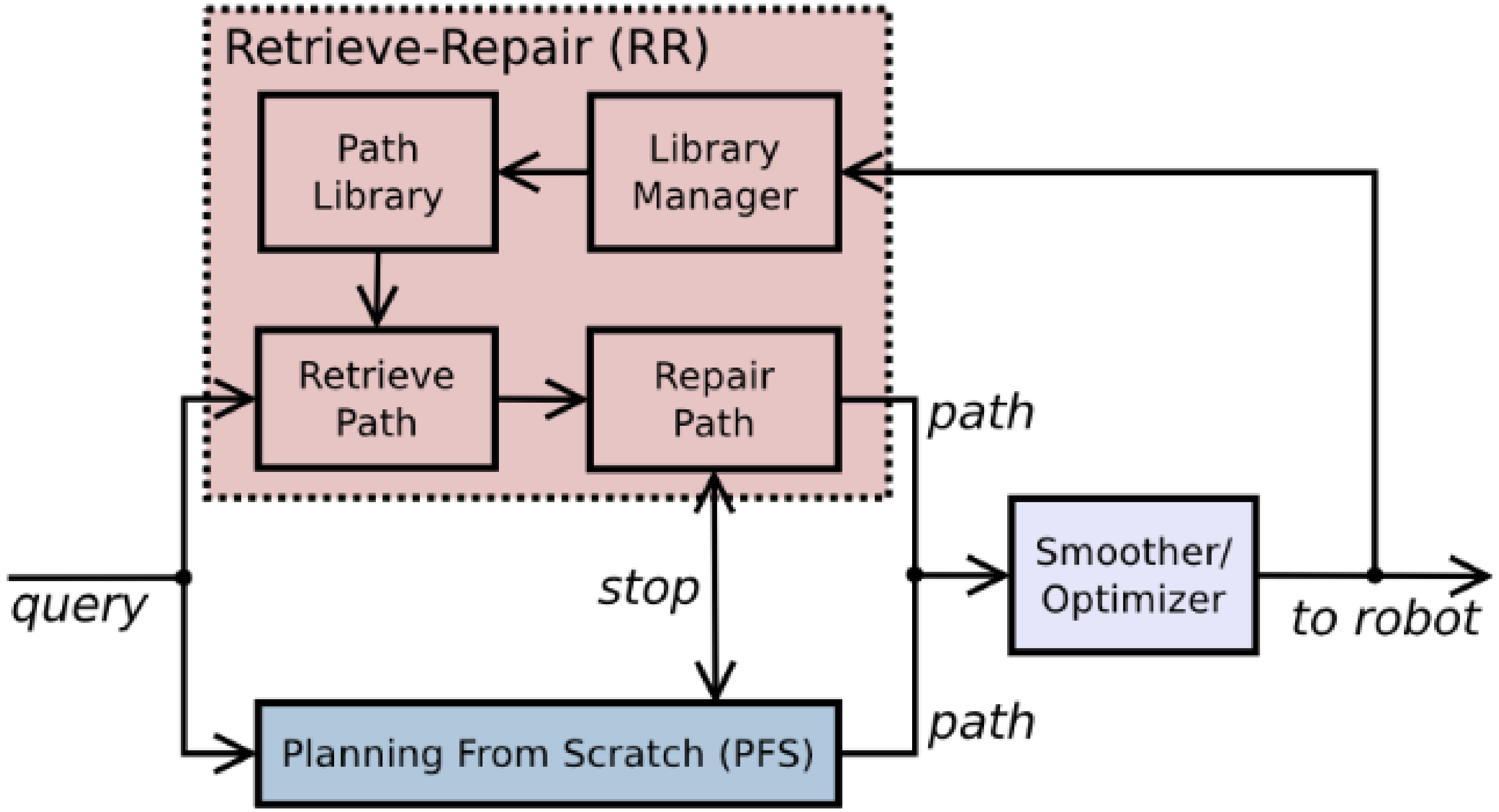


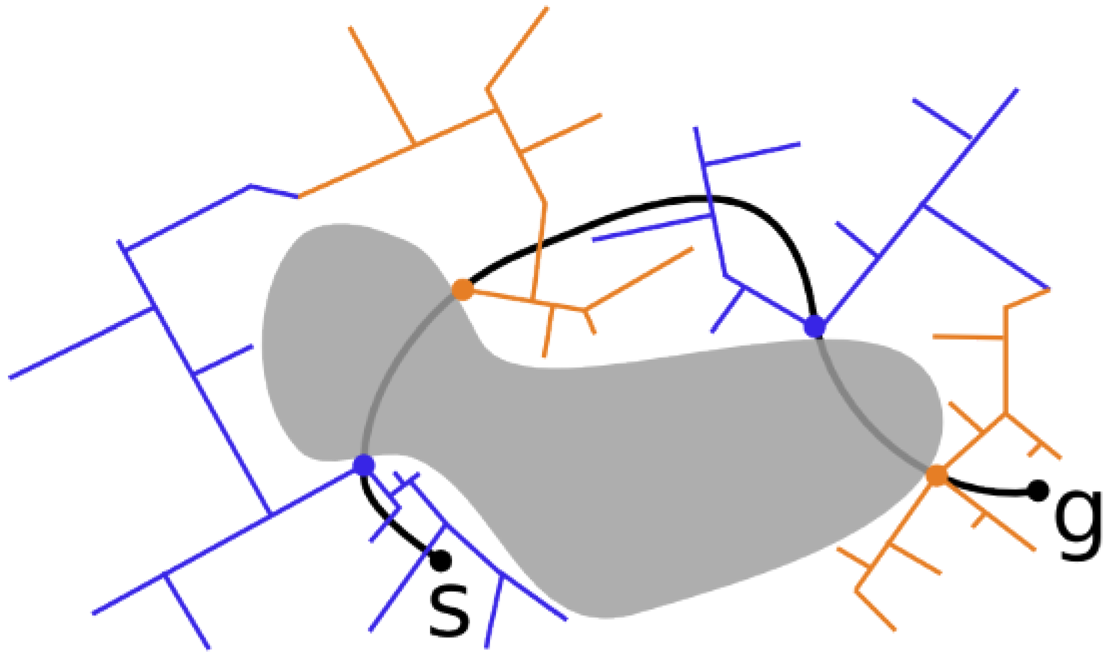
An experience is usually stored as a pair (key:path) that can be retrieved later

Lightning Framework [1]

Training/Testing:
Simultaneous Retrieve-Repair (RR) and Planning from Scratch (PFS)

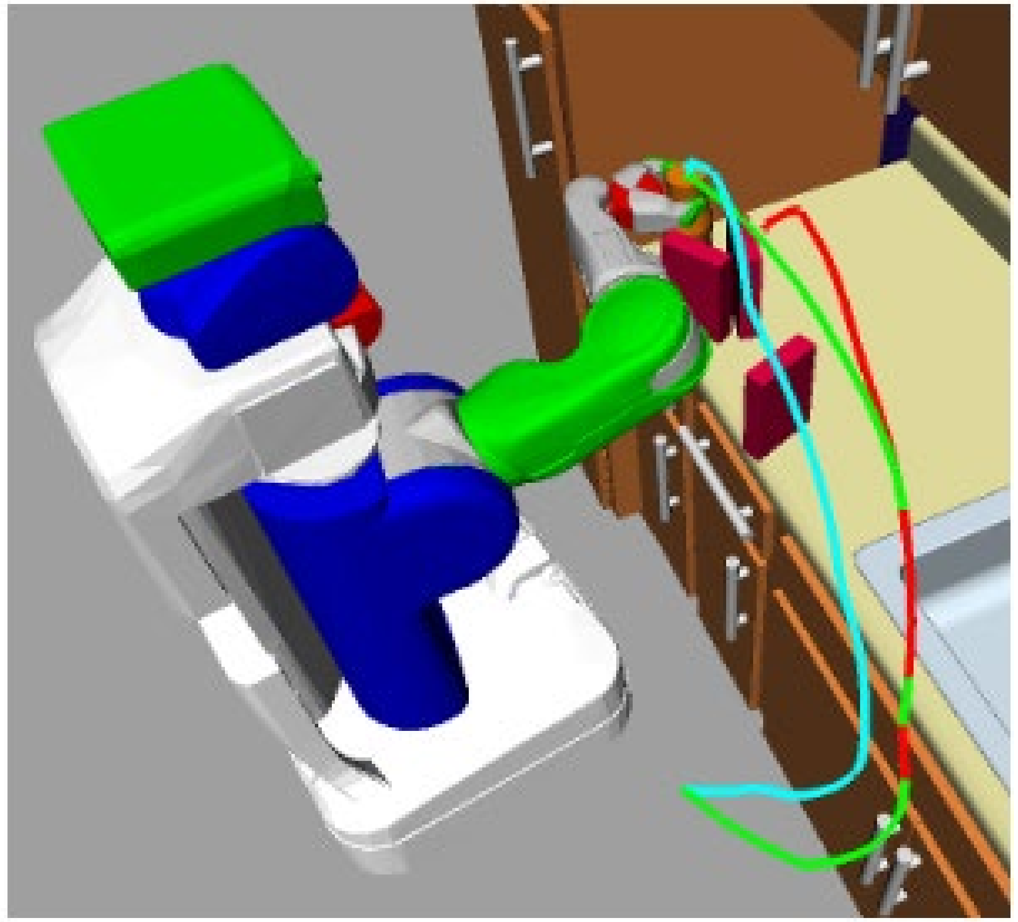
Adapt/Repair:
Use Multiple Bi-RRTs from the ends of invalid segments





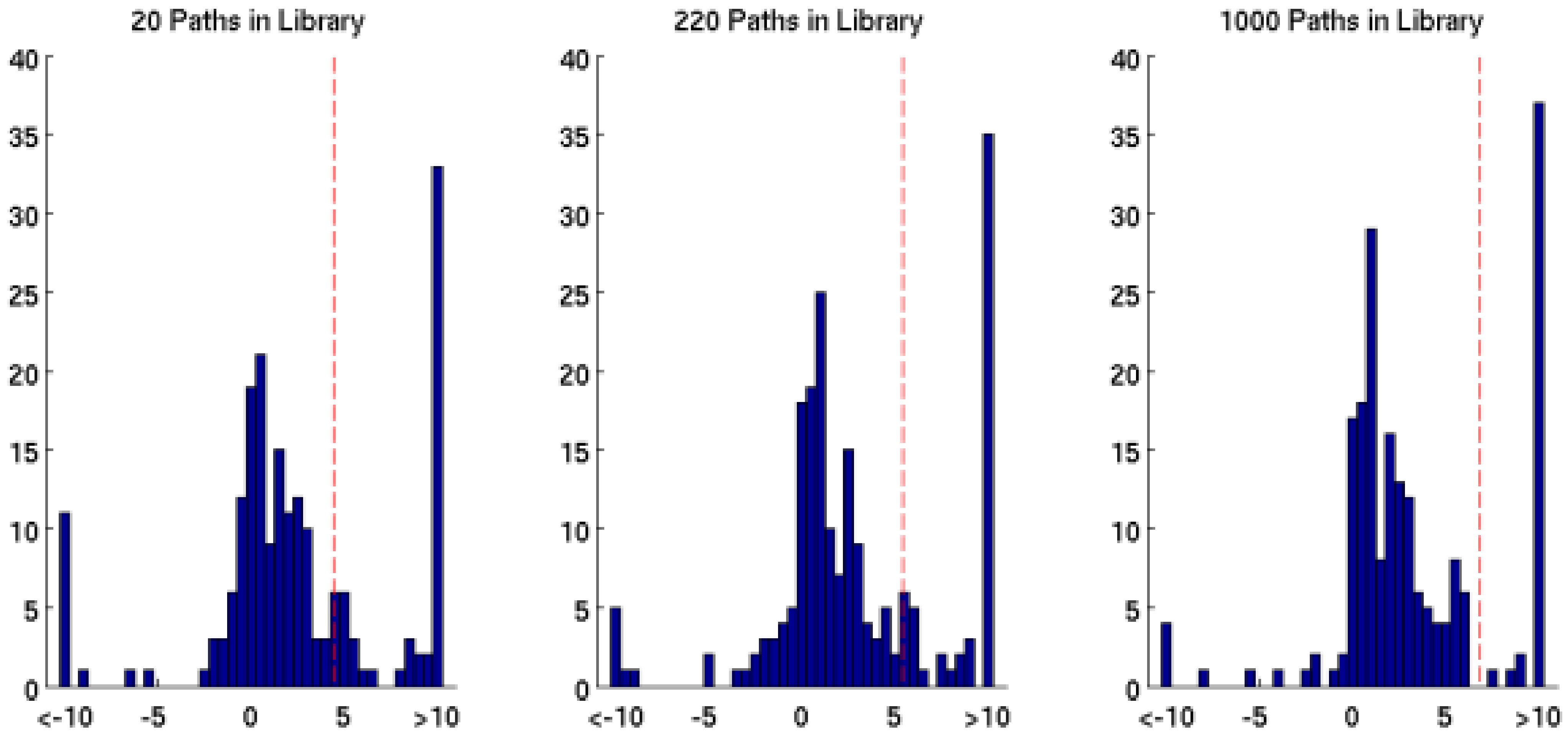
[1] Berenson, Dmitry, Pieter Abbeel, and Ken Goldberg. "A robot path planning framework that learns from experience."*International Conference on Robotics and Automation*. IEEE, 2012.

Lightning Framework – Kitchen Task

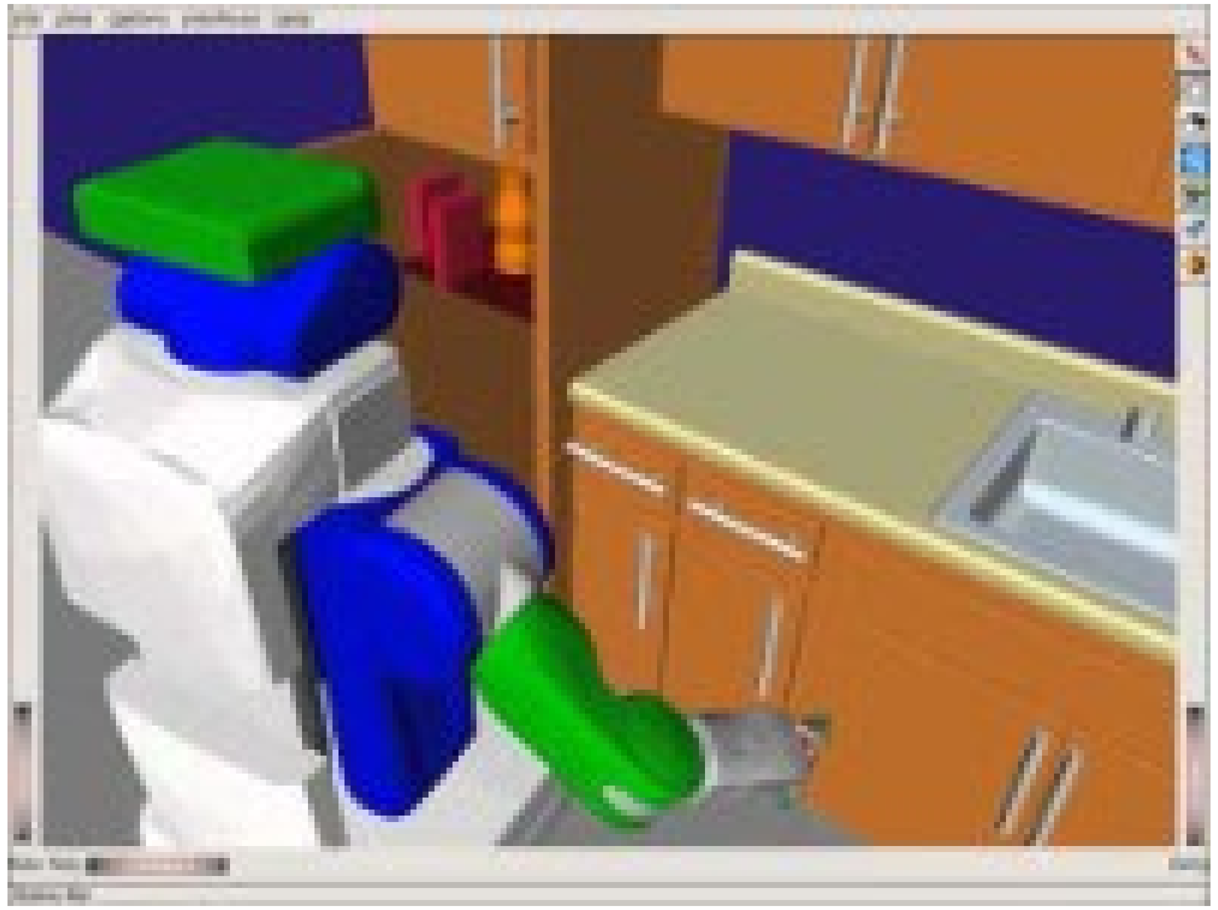


Red – Retrieved Path
Green - Repaired Path
Blue - Planning from Scratch Path

Lightning Framework - Results



Histogram of PFS time minus RR time (seconds).
Denser on the right is better.

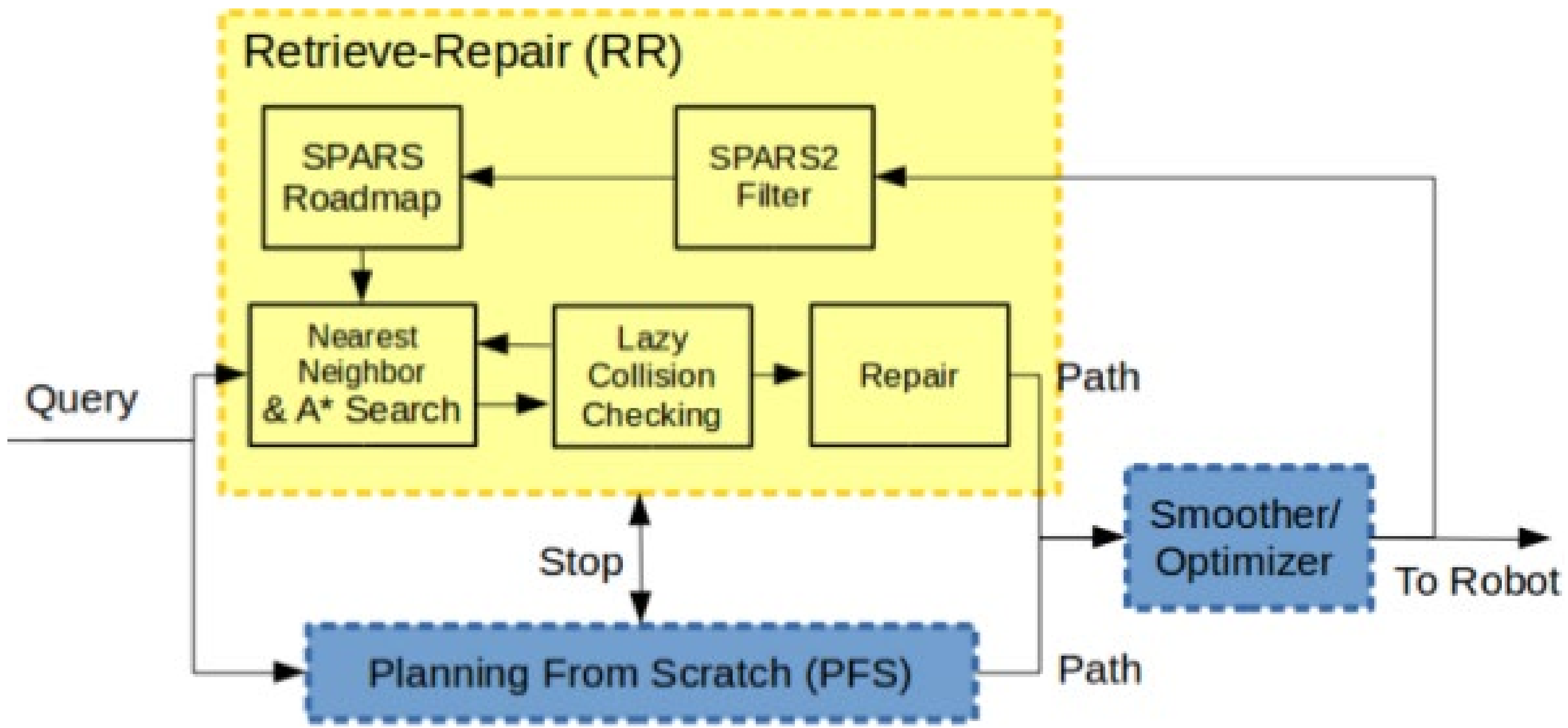


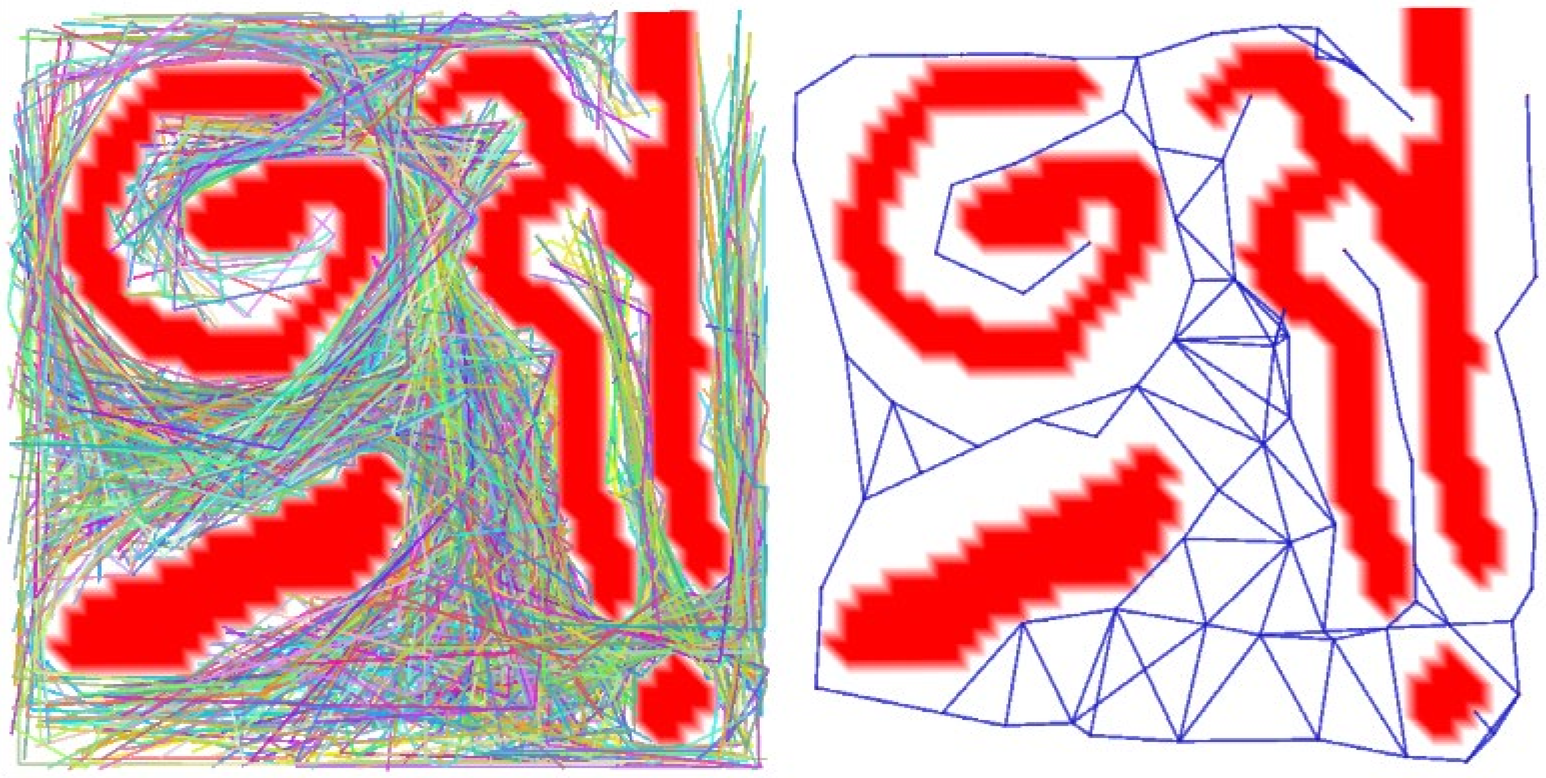
Retrieving an object
from a kitchen counter

Disadvantage: No memory bounds as experiences are added

Thunder Framework [2]

Key Idea: Store the paths in a SPARS2 roadmap



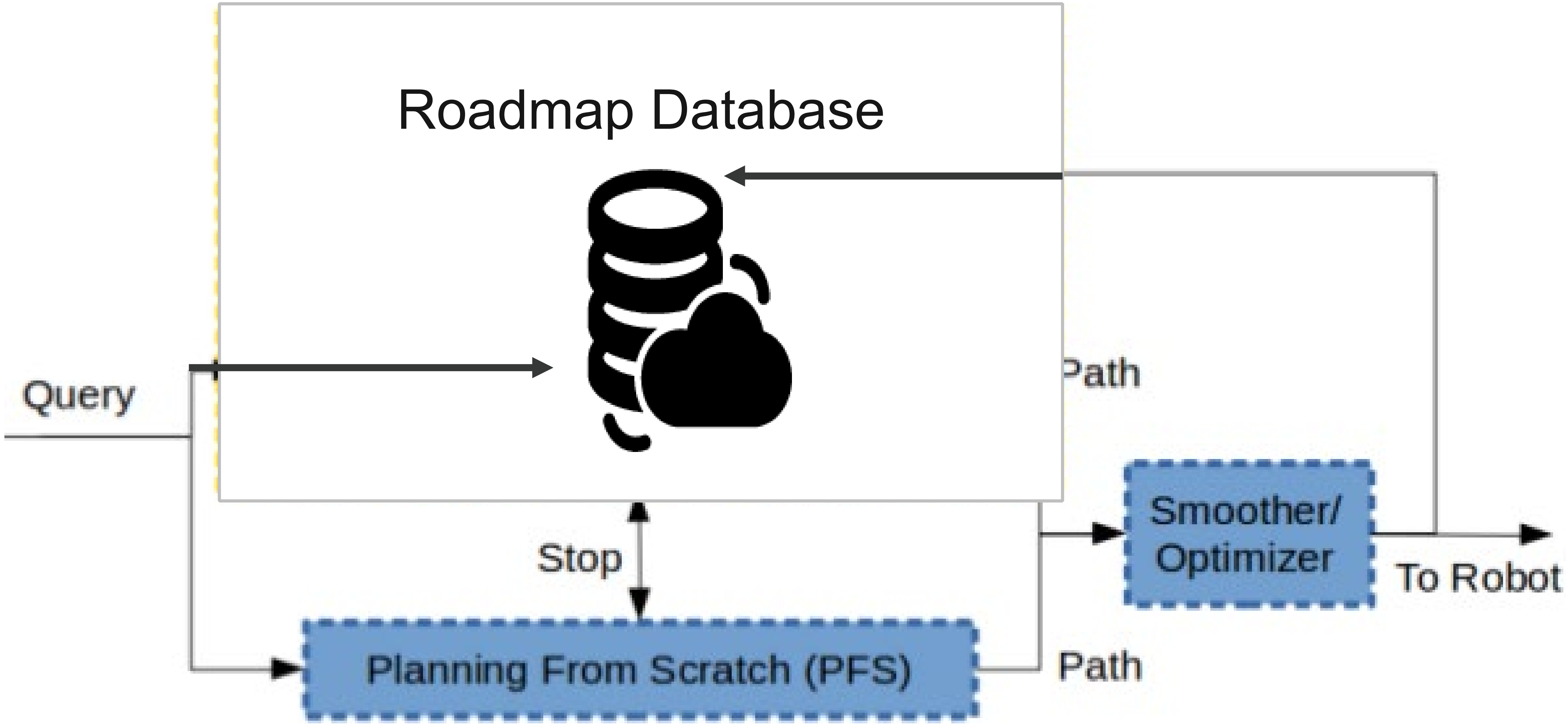


Library of Paths (Lightning)

SPARS2 Roadmap (Thunder)

[2] Coleman, David, et al. "Experience-based planning with sparse roadmap spanners." *International Conference on Robotics and Automation (ICRA)*. IEEE, 2015.

Paper 1: Thunder Framework (Retrieve-Repair)



Coleman, David, et al. "Experience-based planning with sparse roadmap spanners." *International Conference on Robotics and Automation (ICRA)*. IEEE, 2015.

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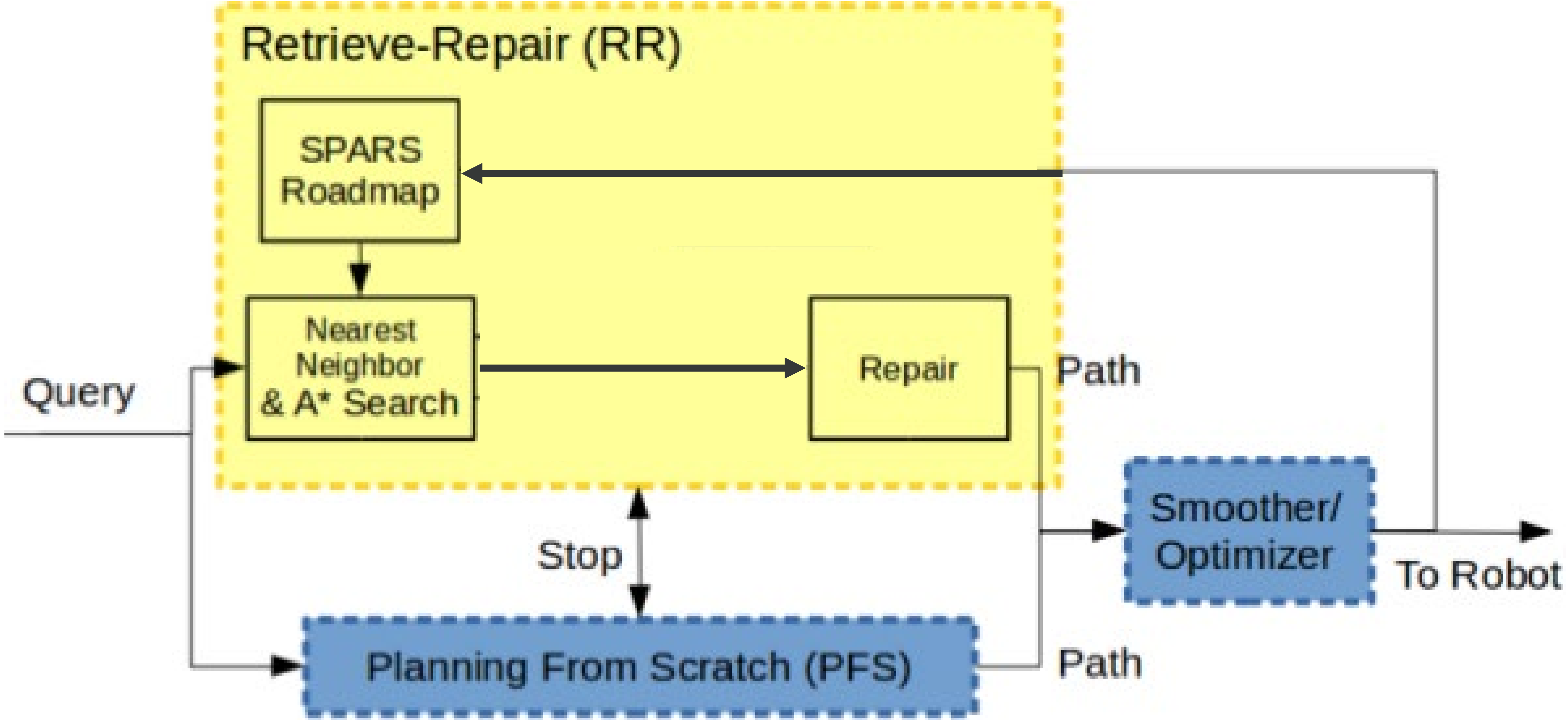
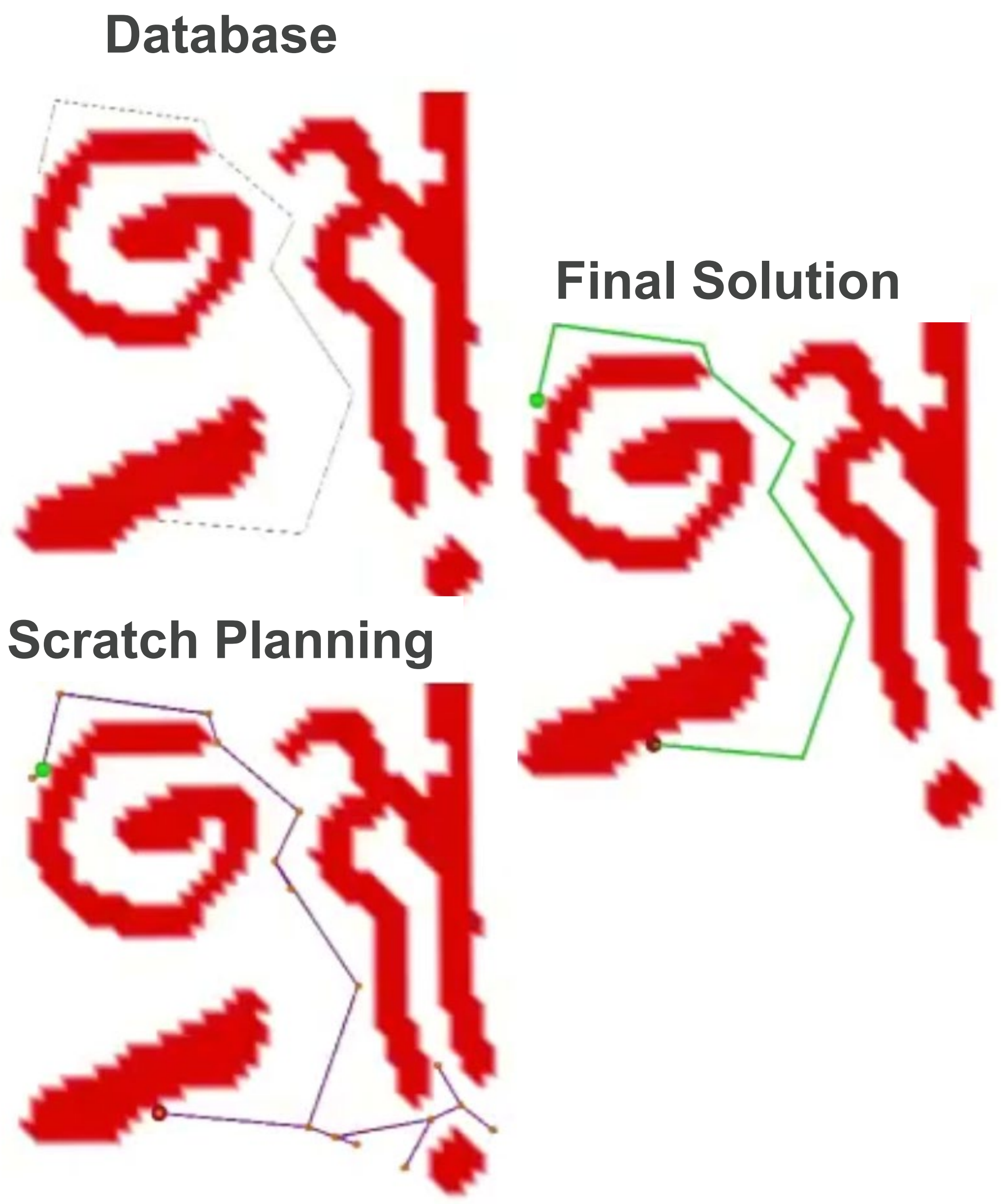


Coleman, David, et al. "Experience-based planning with sparse roadmap spanners." *International Conference on Robotics and Automation (ICRA)*. IEEE, 2015.

Thunder Iteration 1 (Empty Database)

Search Query

Scratch Planning

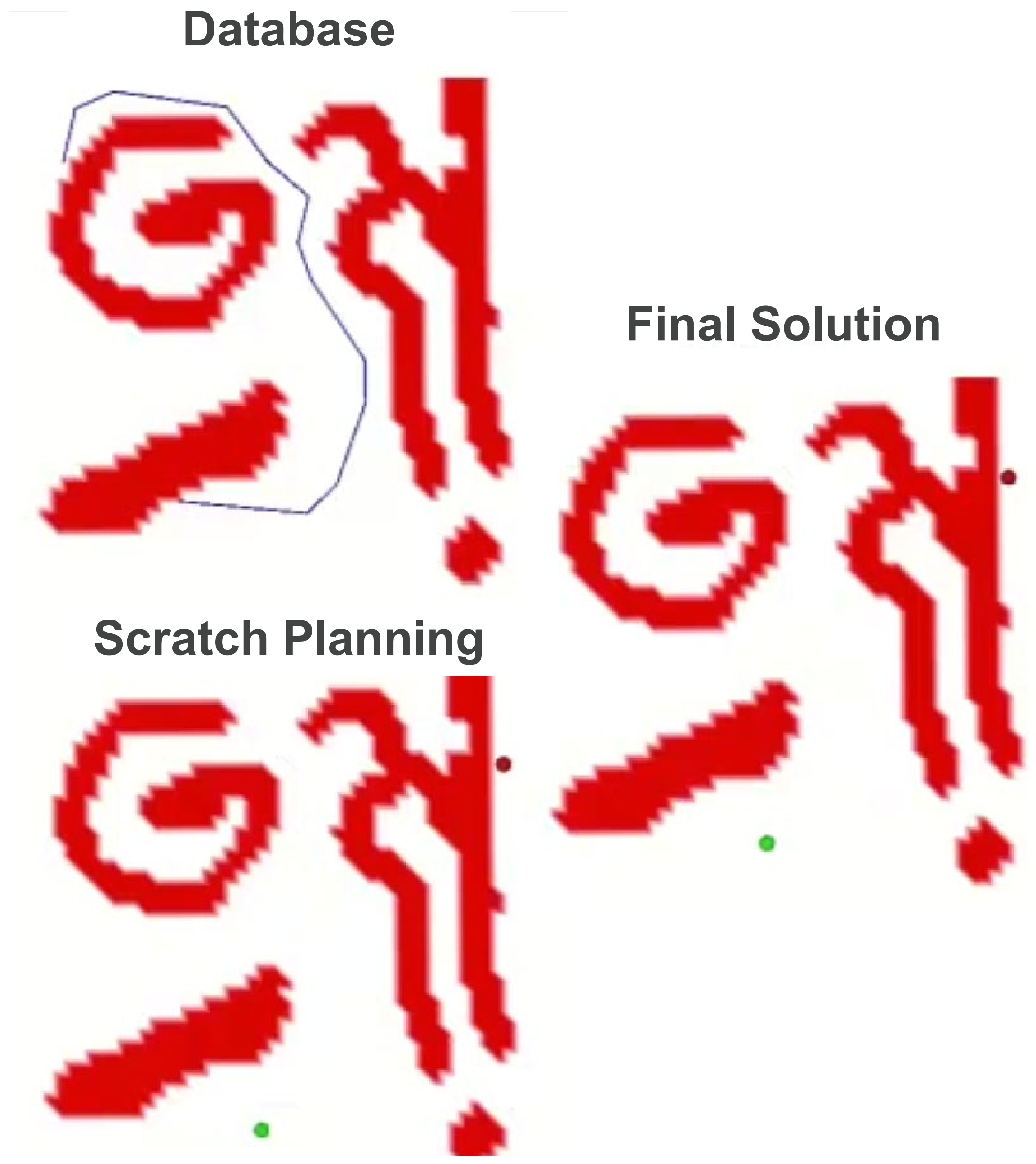


Adding to the Database

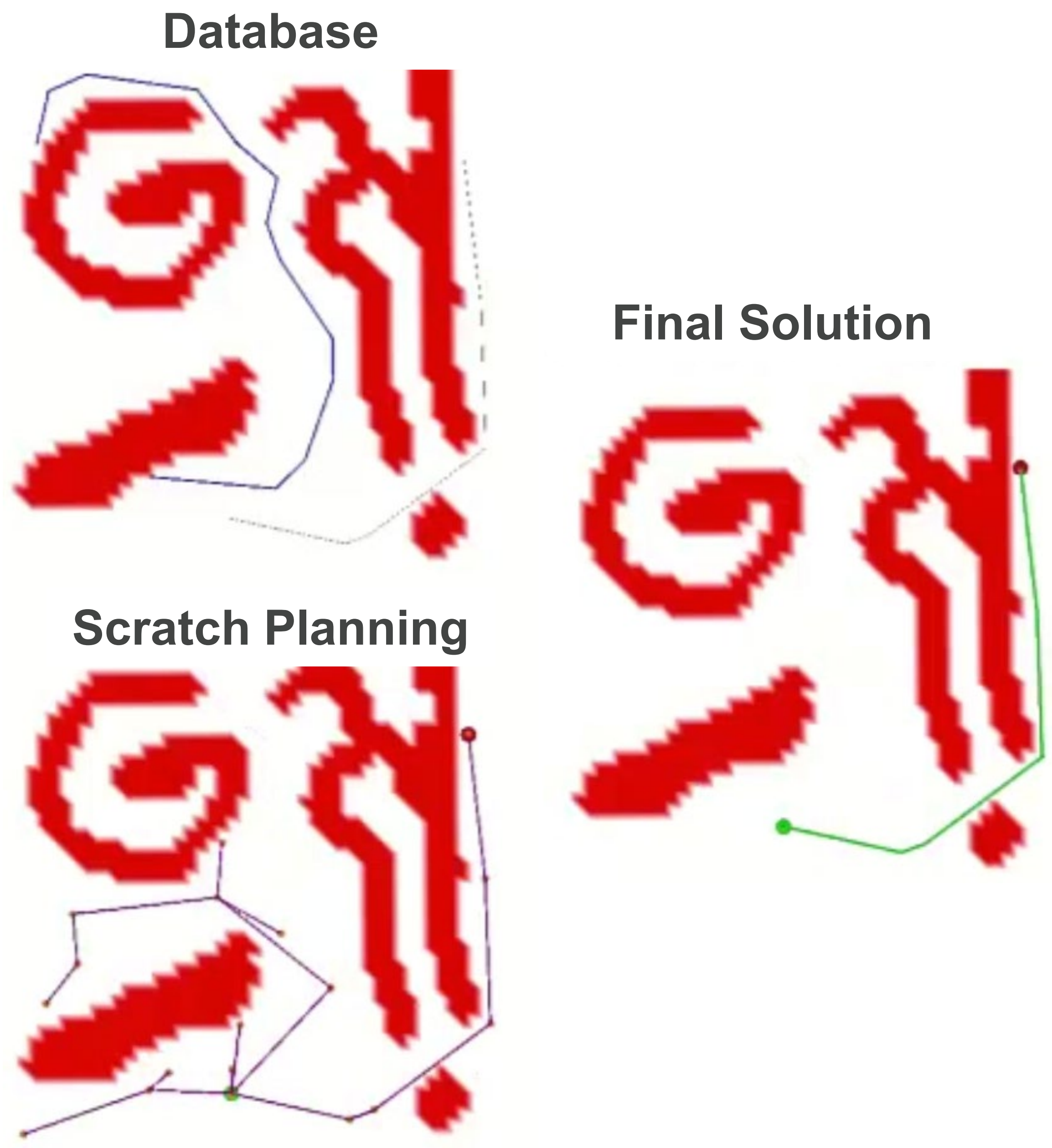
Coleman, David, et al. "Experience-based planning with sparse roadmap spanners." *International Conference on Robotics and Automation (ICRA)*. IEEE, 2015.

Thunder Iteration 2 (No relevant path is found)

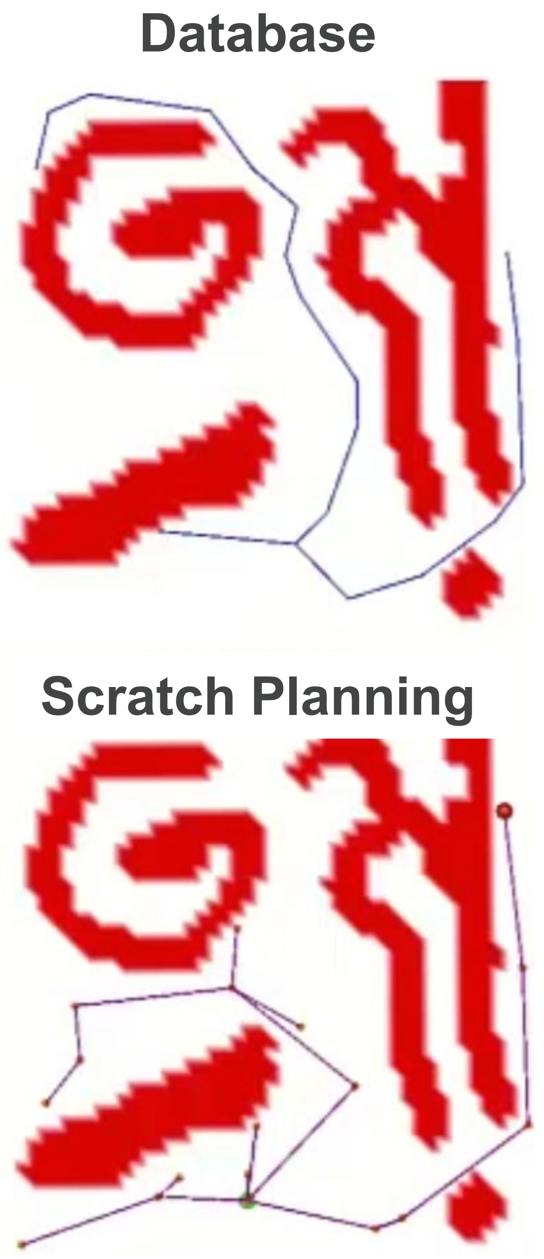
Search Query



Scratch Planning



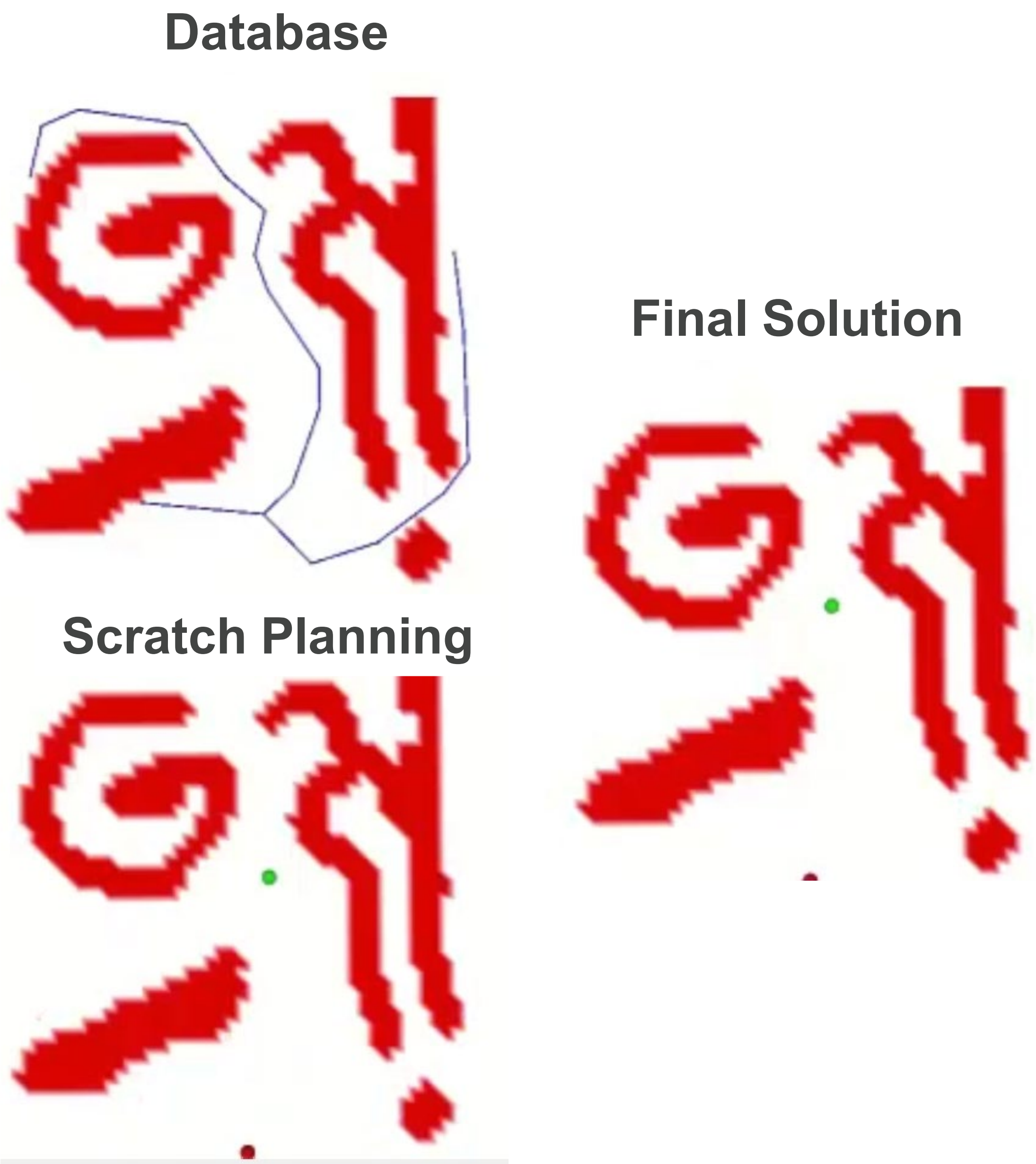
Adding to the Database



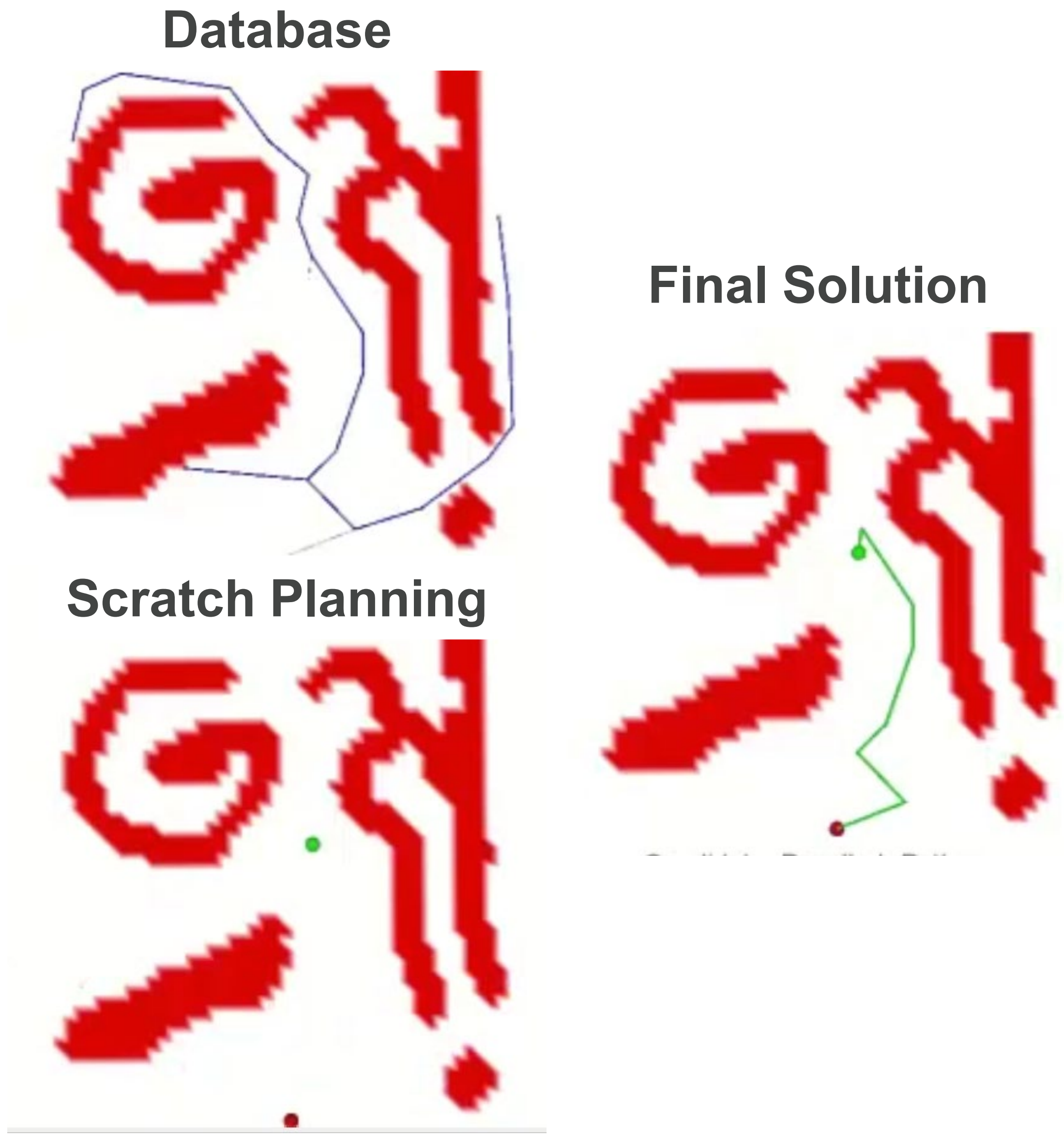
Coleman, David, et al. "Experience-based planning with sparse roadmap spanners." *International Conference on Robotics and Automation (ICRA)*. IEEE, 2015.

Thunder Iteration 3 (path found in DB)

Search Query



Retrieving Path



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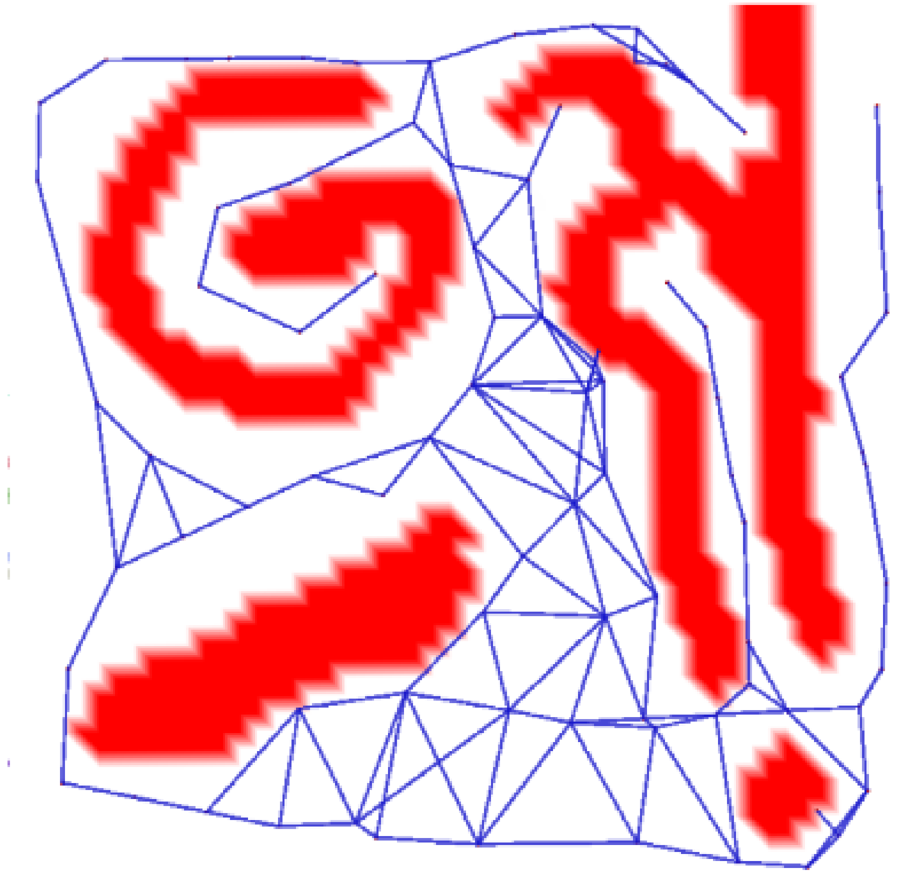
Thunder after N iterations – Compare to Lightning

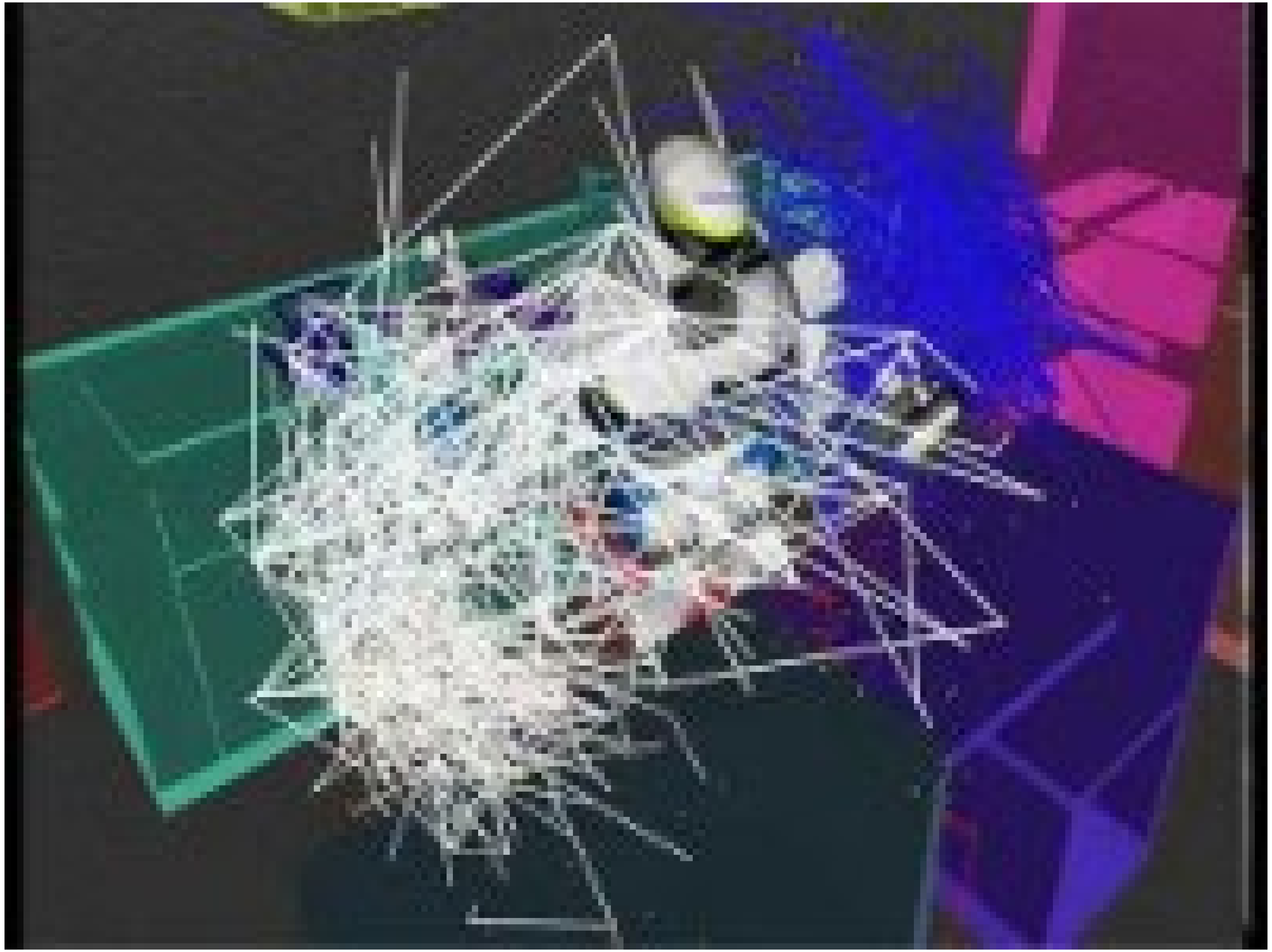


THUNDER – N Iterations

Lightning – N Iterations
(Competing Method)

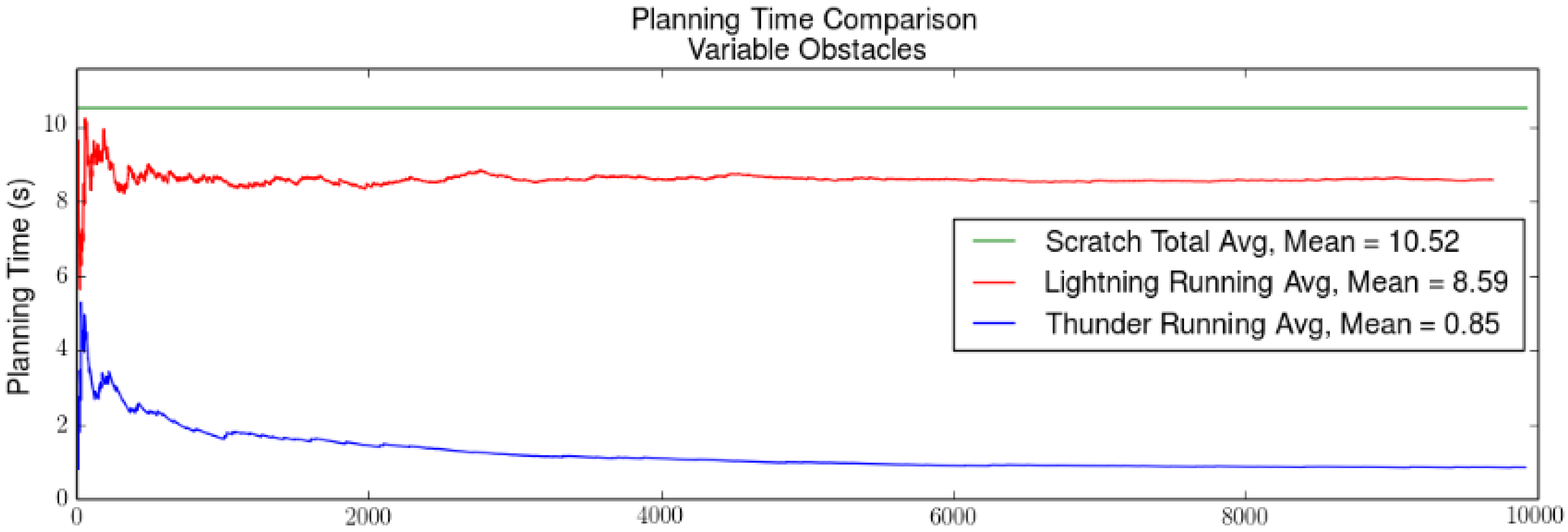
Coleman, David, et al. "Experience-based planning with sparse roadmap spanners." *International Conference on Robotics and Automation (ICRA)*. IEEE, 2015.

Thunder Framework - Results



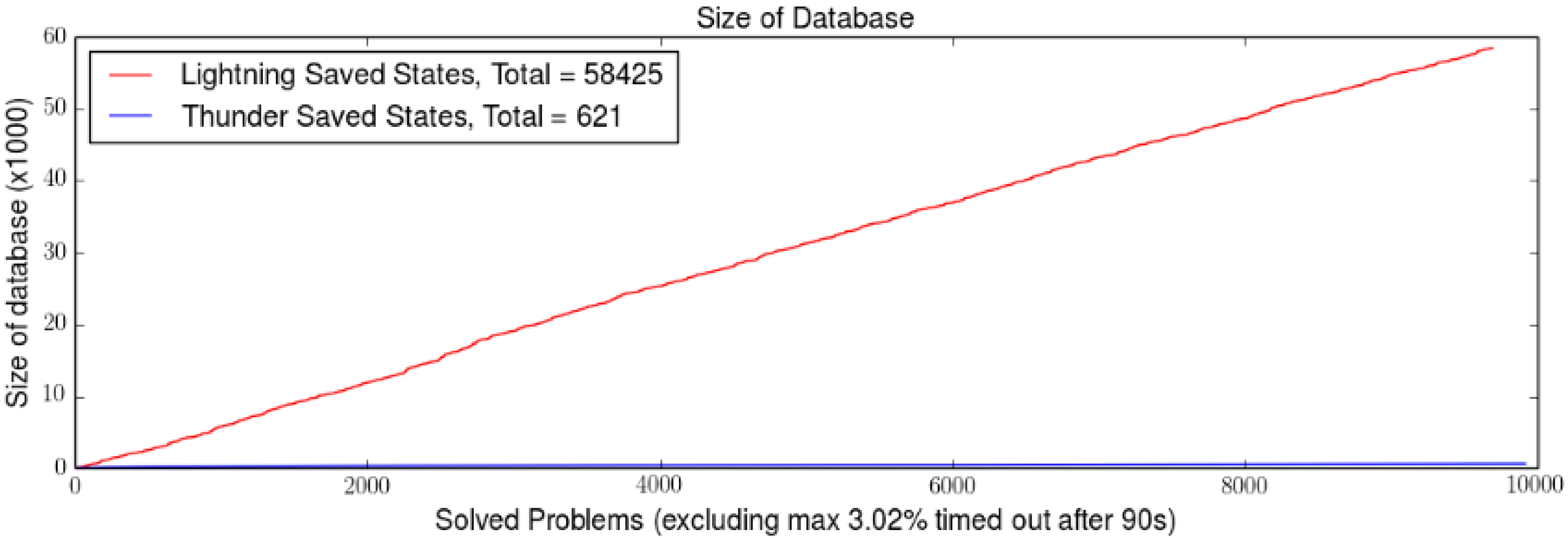
30-DoF HRP2 Humanoid balancing problems

Thunder Framework – Time Results



Significant **time improvement** is achieved

Thunder Framework Memory Results



Memory is **bounded** and does not grow with more experiences

Retrieve and Repair Overview

Advantages:

- **Incremental learning**, fits lifelong learning paradigm
- **Simple** to implement and train
- Significant **efficiency** Improvement (orders of magnitude)

Where would the retrieve and repair approaches not work well ?

For robots with many degrees of Freedom

For tasks that have many different start and goal locations

For problems where the workspace obstacles vary a lot

None of the above

Where would the retrieve and repair approaches not work well ?

For robots with many degrees of Freedom

0%

For tasks that have many different start and goal locations

0%

For problems where the workspace obstacles vary a lot

0%

None of the above

0%

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0%

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0%

None of the above

0%

Retrieve and Repair Overview

Advantages:

- **Incremental learning**, fits lifelong learning paradigm
- **Simple** to implement and train
- Significant **efficiency** Improvement

Disadvantages:

- Applies primarily to problems with many invariants:

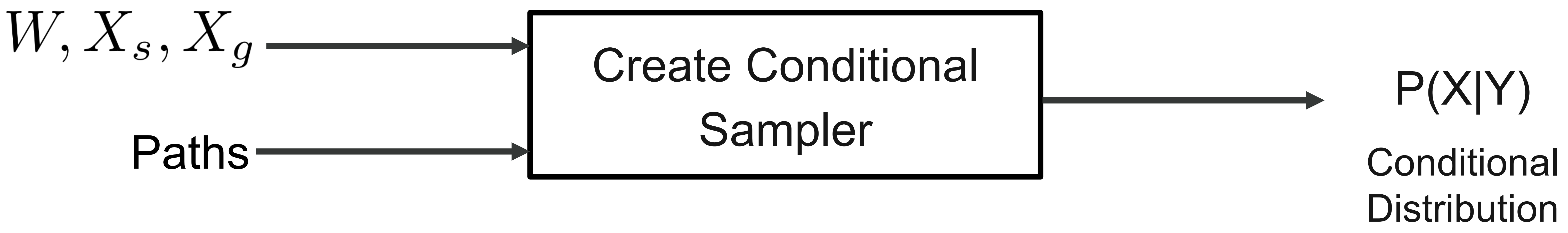
  - High number of self-collisions
  - Many static obstacles
  - Task invariants, e.g. always picking

Learning Archetypes (Methodologies)

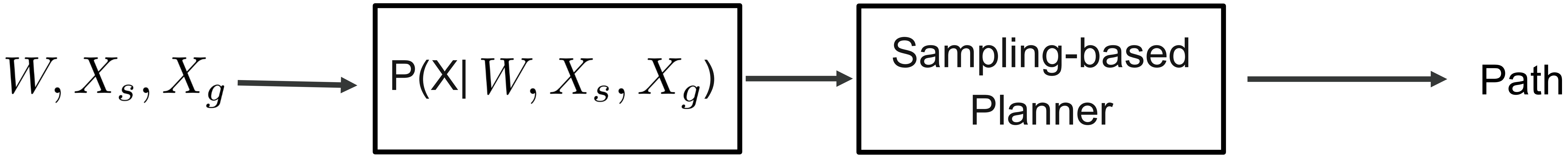
Learning Archetypes	Corresponding Papers
1. Retrieve and Repair	Lightning[1], **Thunder [2],** Sim-Obstacles[3], ERT[4], Traj-Pred[5]
2. Biased Samplers	**Rep-Sampling[6]**,**Rep-Roadmaps[7],** AWS[8], SPARK2D[9], CVAE[10], FLAME[11], FIRE[12]

2. Biased Samplers Archetype

Training/Learning Phase



Testing/Inference



Biasing the Sampling Distribution

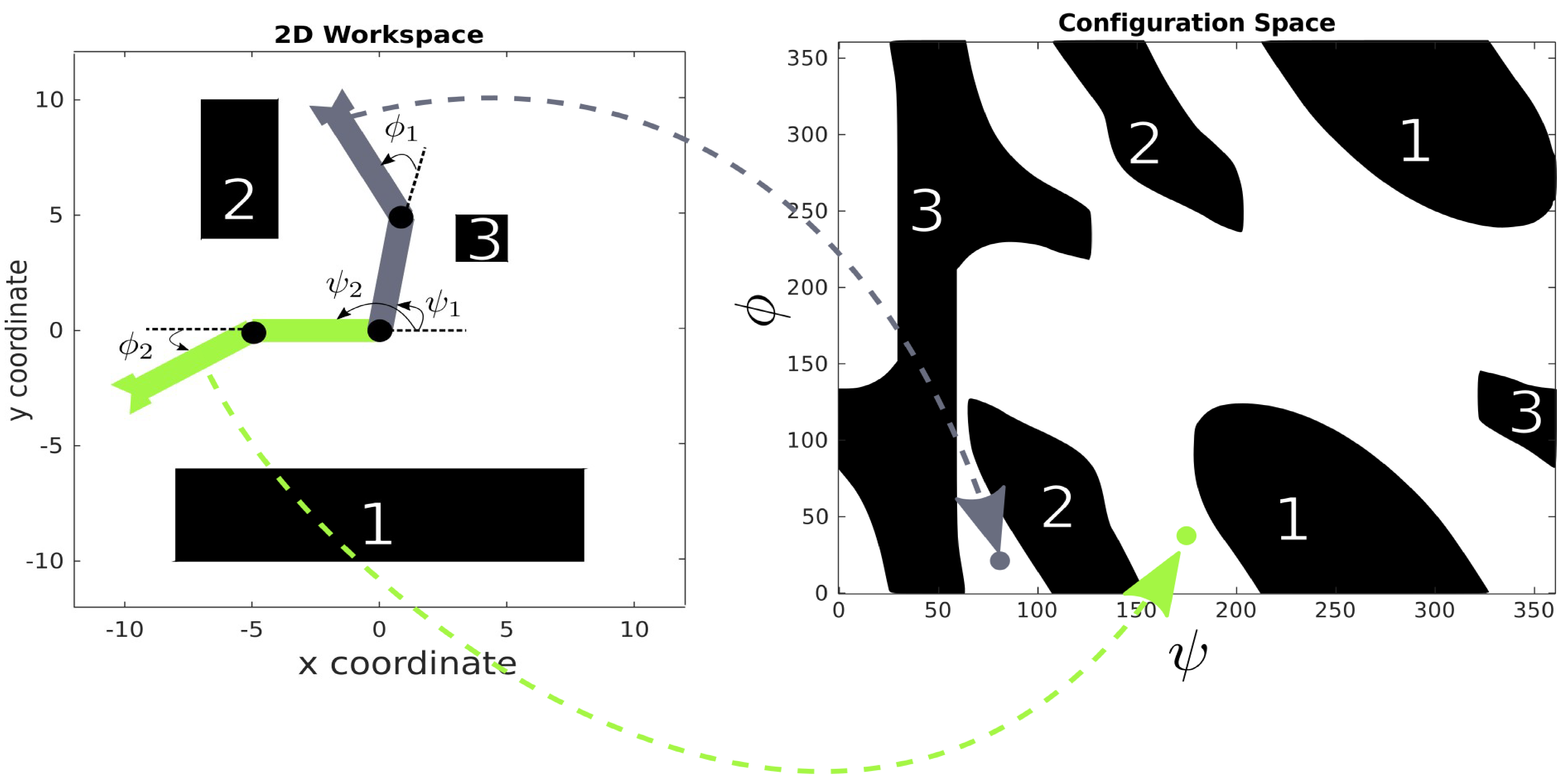
Algorithm 1: General Sampling Based Planner

Input : Number of iterations N
Output : Graph structure G

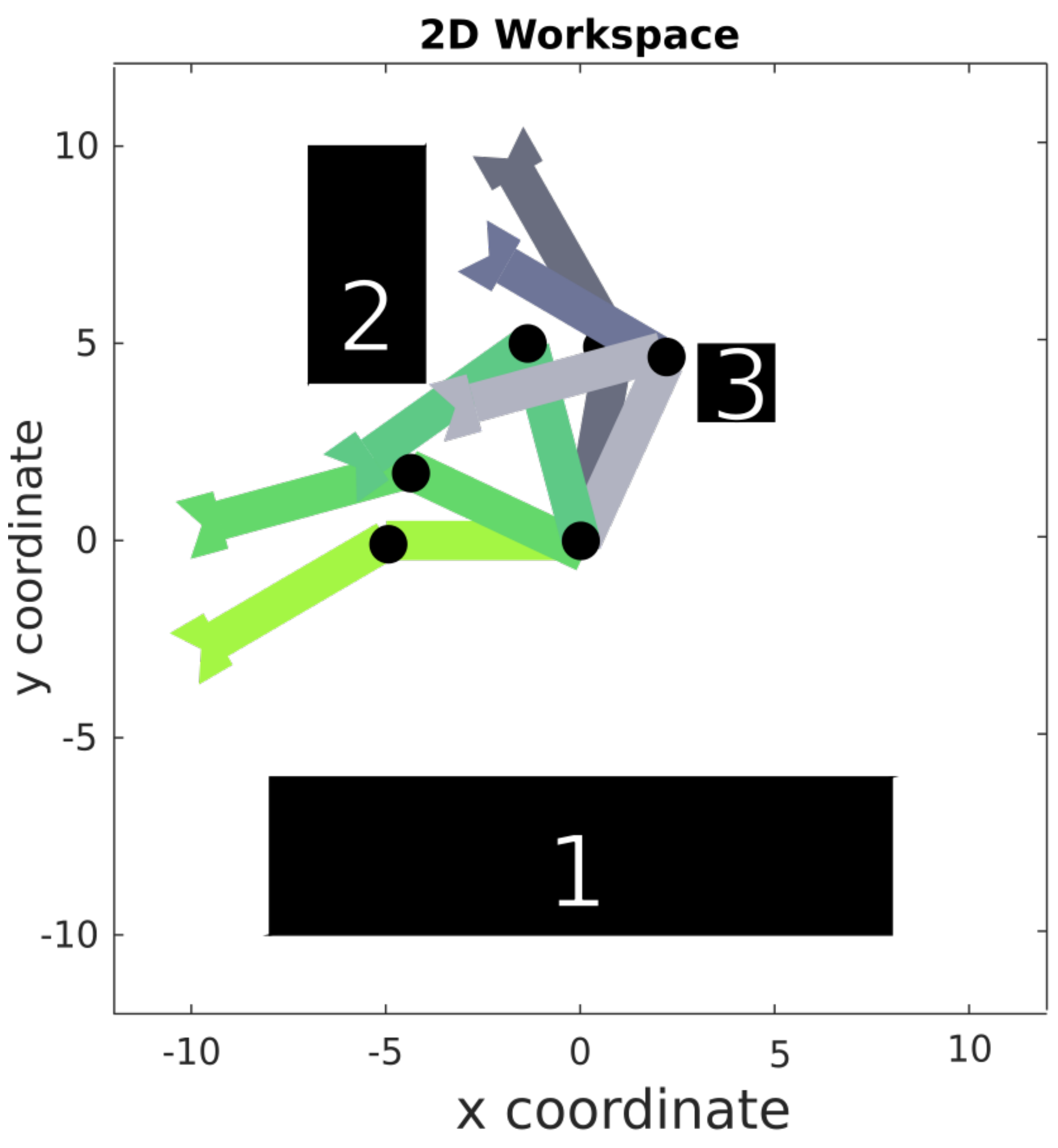
```
while i ≤ N  or  solutionFound() do
    x ∼ Uniform()
    update(G, x)
end
return G
```

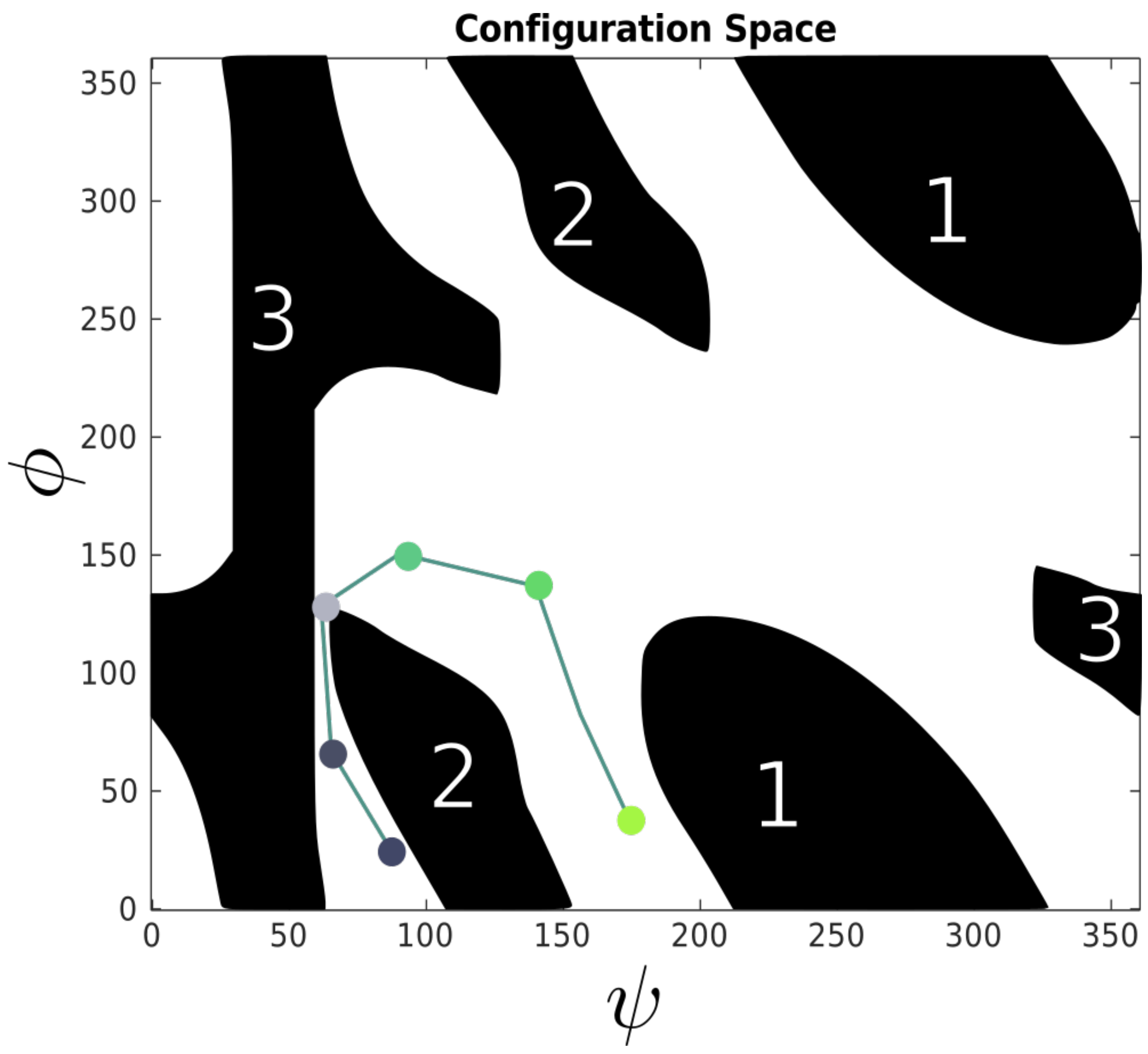
- Theoretical Insights supporting biased sampling
- Any sampling-based planner can be used

A 2D Manipulator Problem

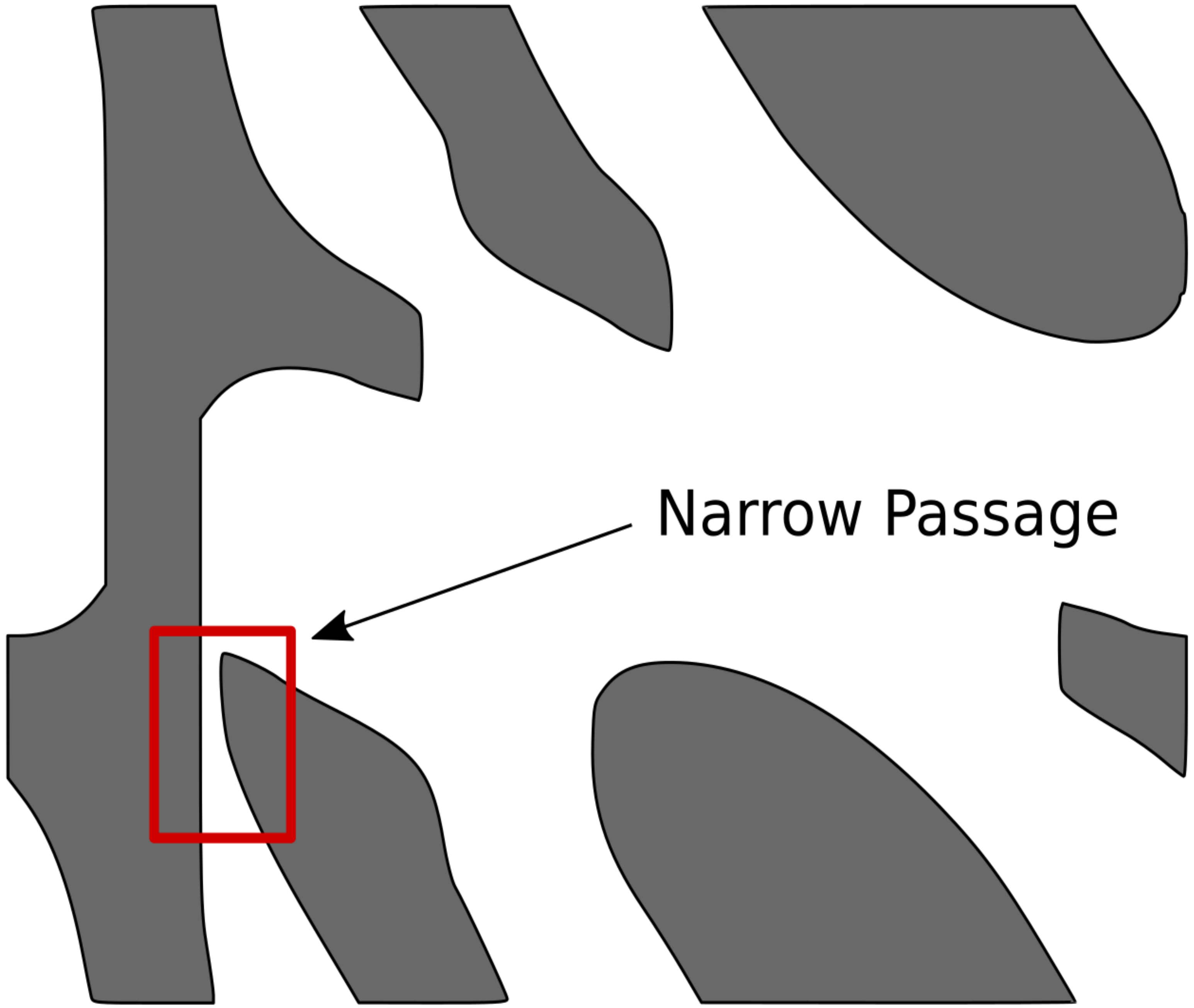


A 2D Manipulator Path/Solution

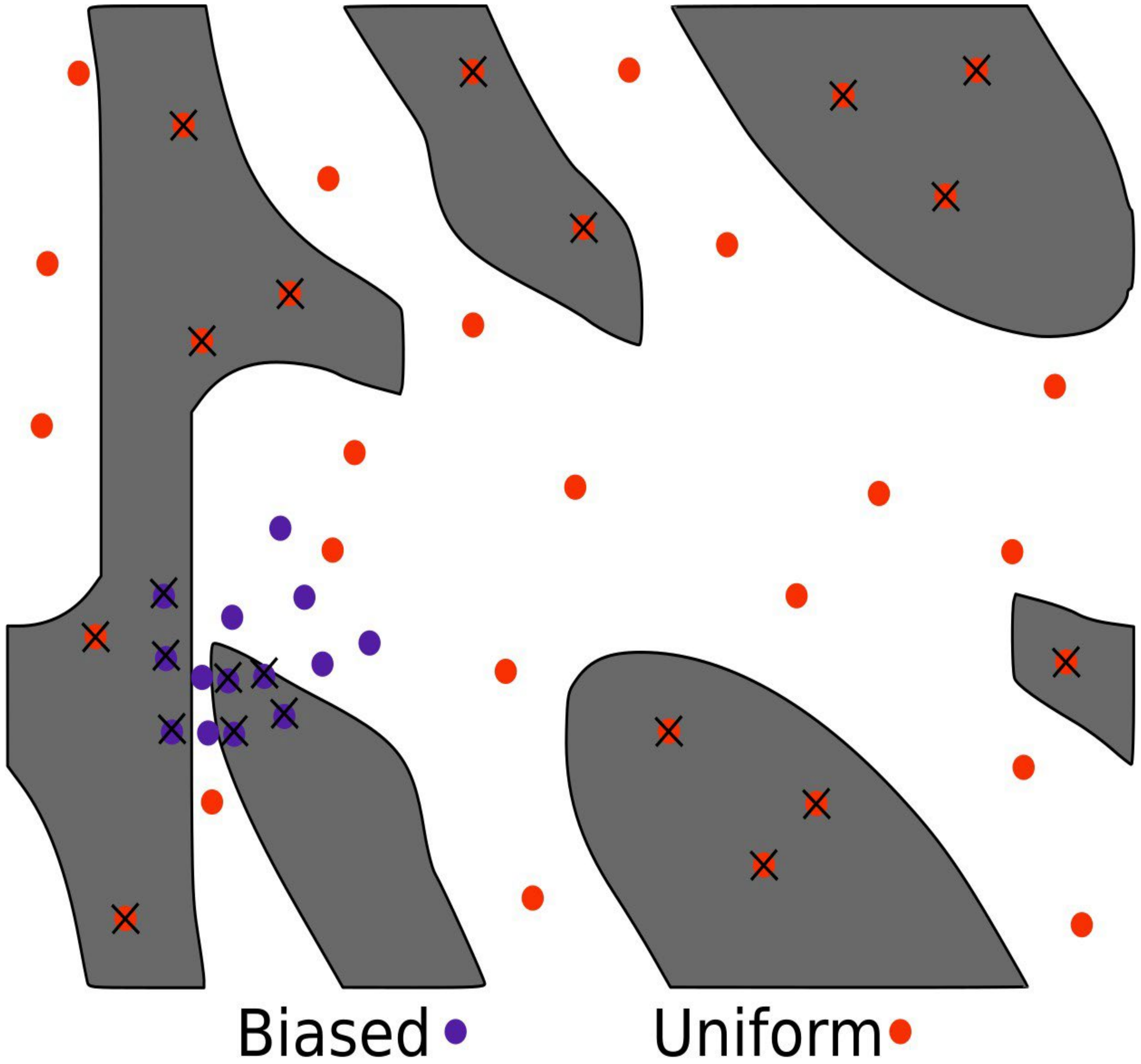




Biasing Sampling can increase performance



The narrow passage problem



Use prior knowledge to target these passages

Conditioned Biased Sampling Distributions

- P(x): Learning Only Invariants
- P(x| Start, Goal): Sampling conditioned on start and goal
- P(x| W): Sampling biased from workspace features
- P (x| Start, Goal, W): Sampling leveraging both workspace, start and goal information

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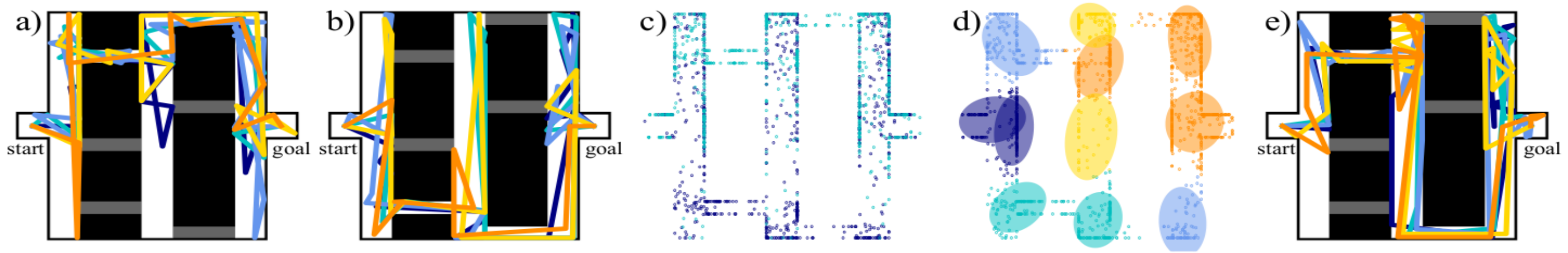
Paper 2: Repetition Sampling (Biased Sampler)

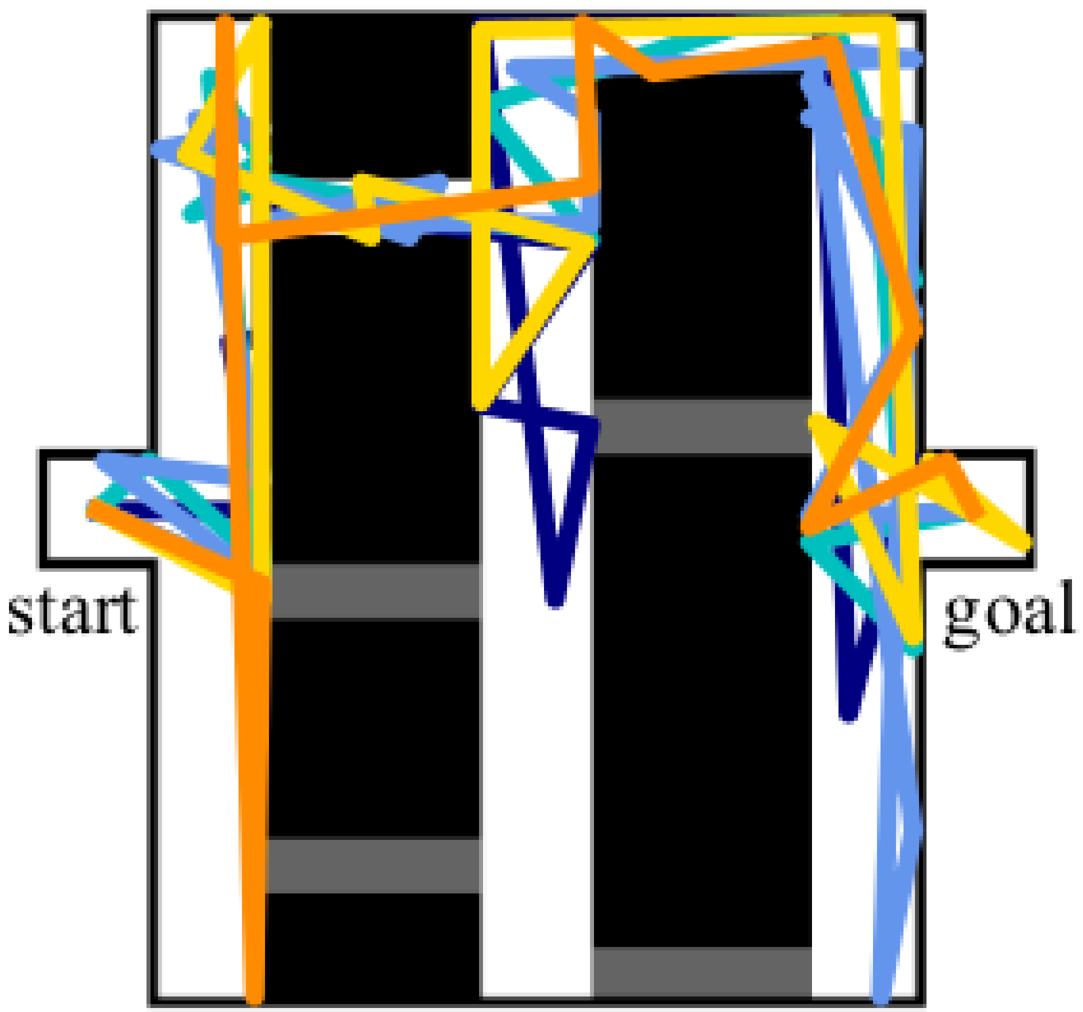
Main Idea:

- Learn a sampling distribution from past solution paths
- Use learned distribution to guide a sampling-based planner
- Only a static distribution is learned, **P(X)**

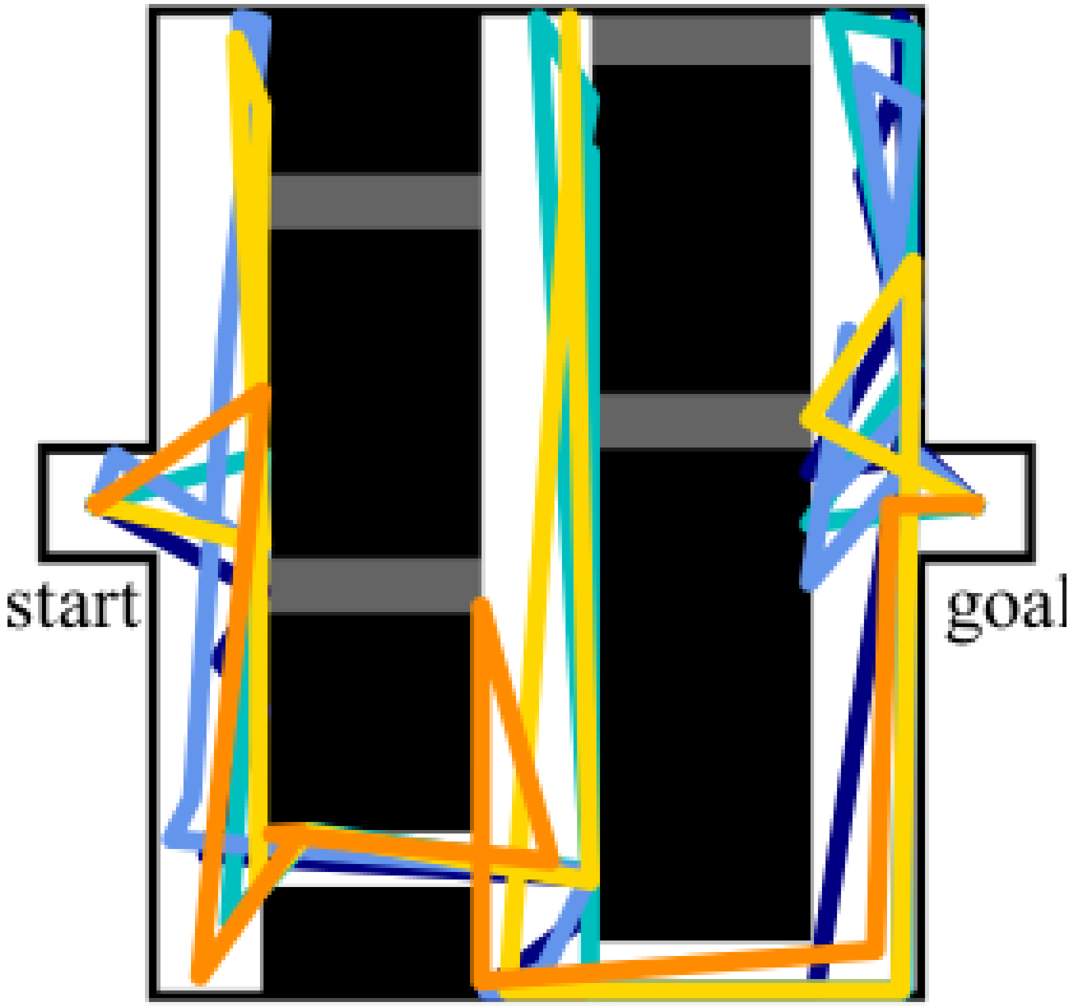


Lehner, Peter, and Alin Albu-Schäffer. "Repetition sampling for efficiently planning similar constrained manipulation tasks." *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2017.

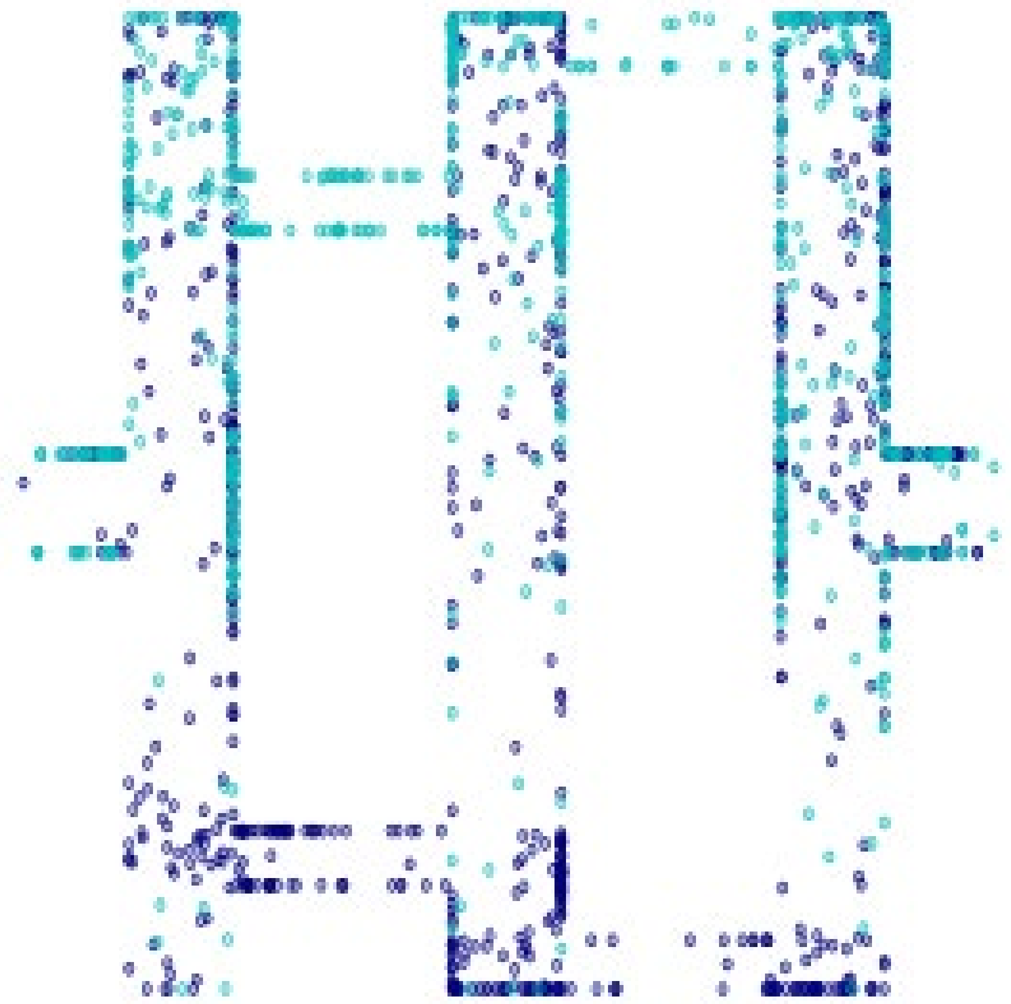
Repetition Sampling – Collecting Samples



Paths from problem1



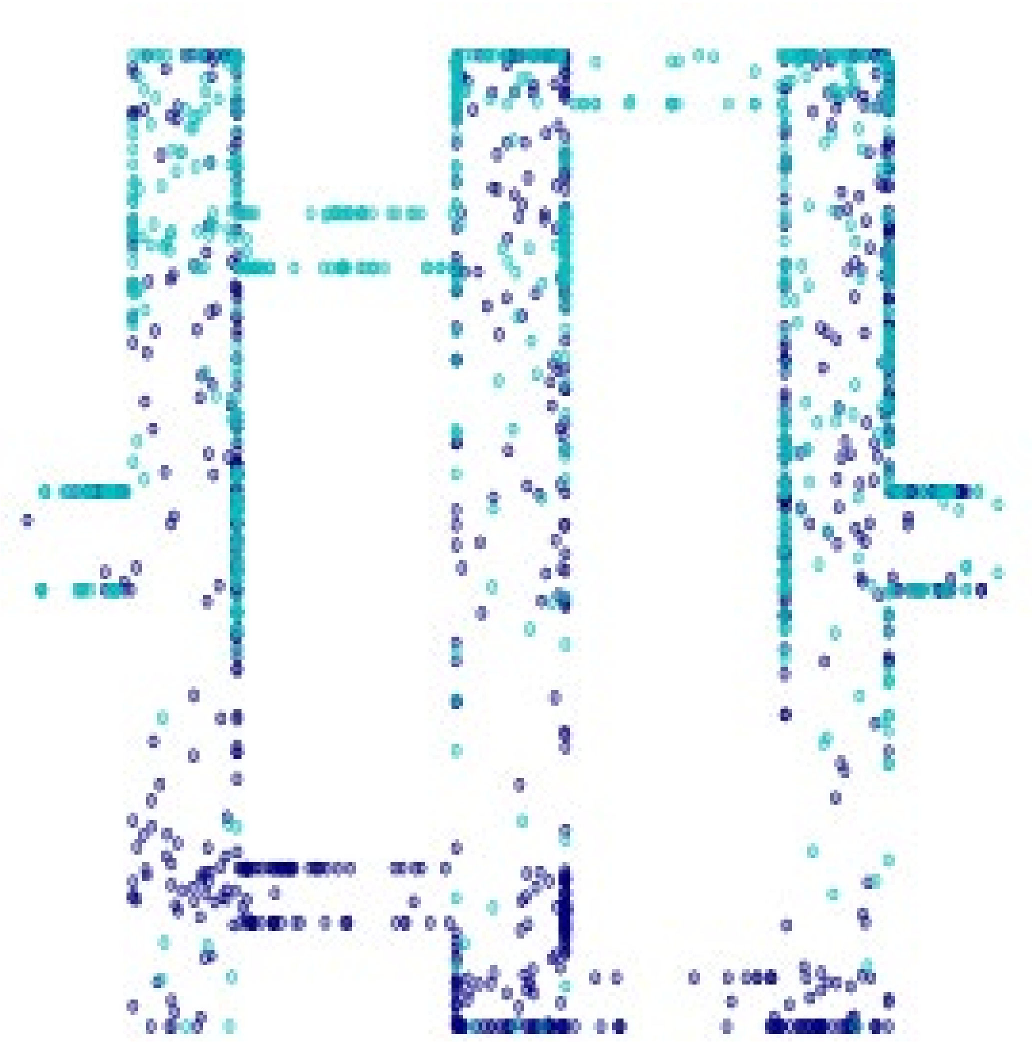
Paths from problem2



Collect waypoints as samples

Lehner, Peter, and Alin Albu-Schäffer. "Repetition sampling for efficiently planning similar constrained manipulation tasks." *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2017.

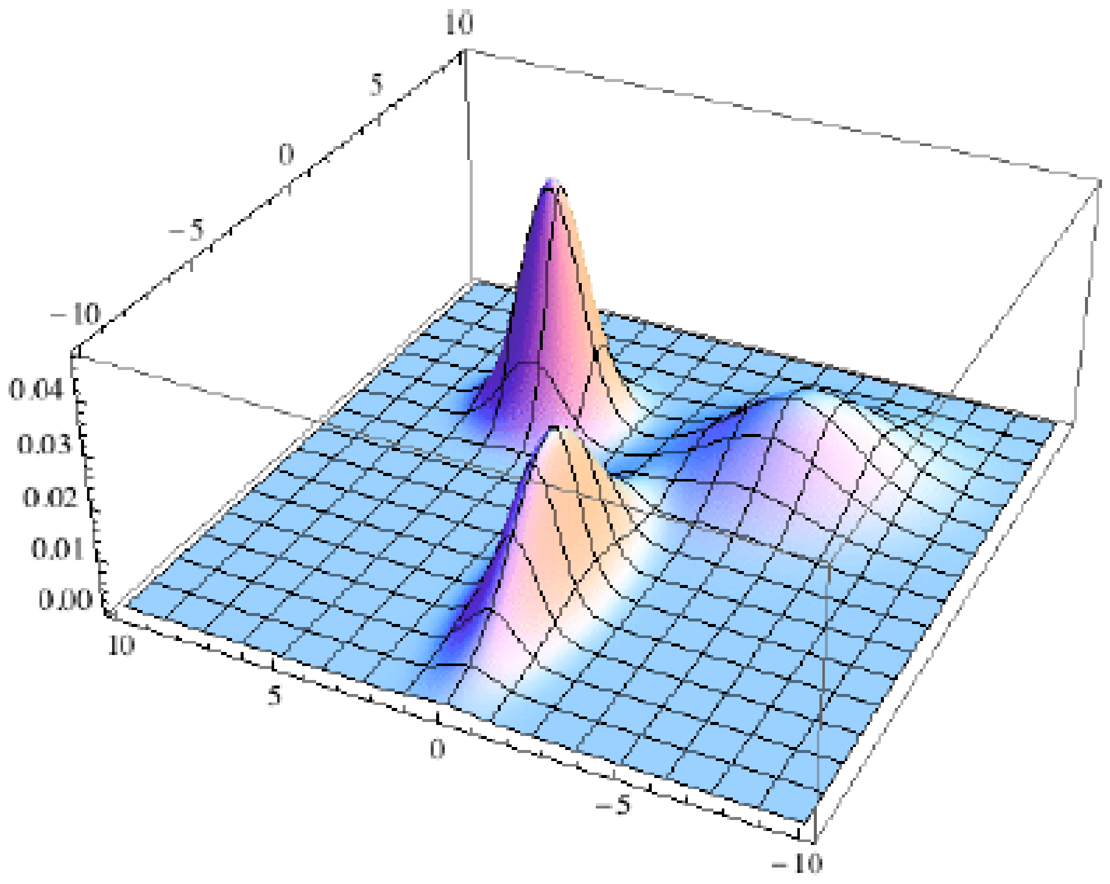
Repetition Sampling – Fitting a Distribution

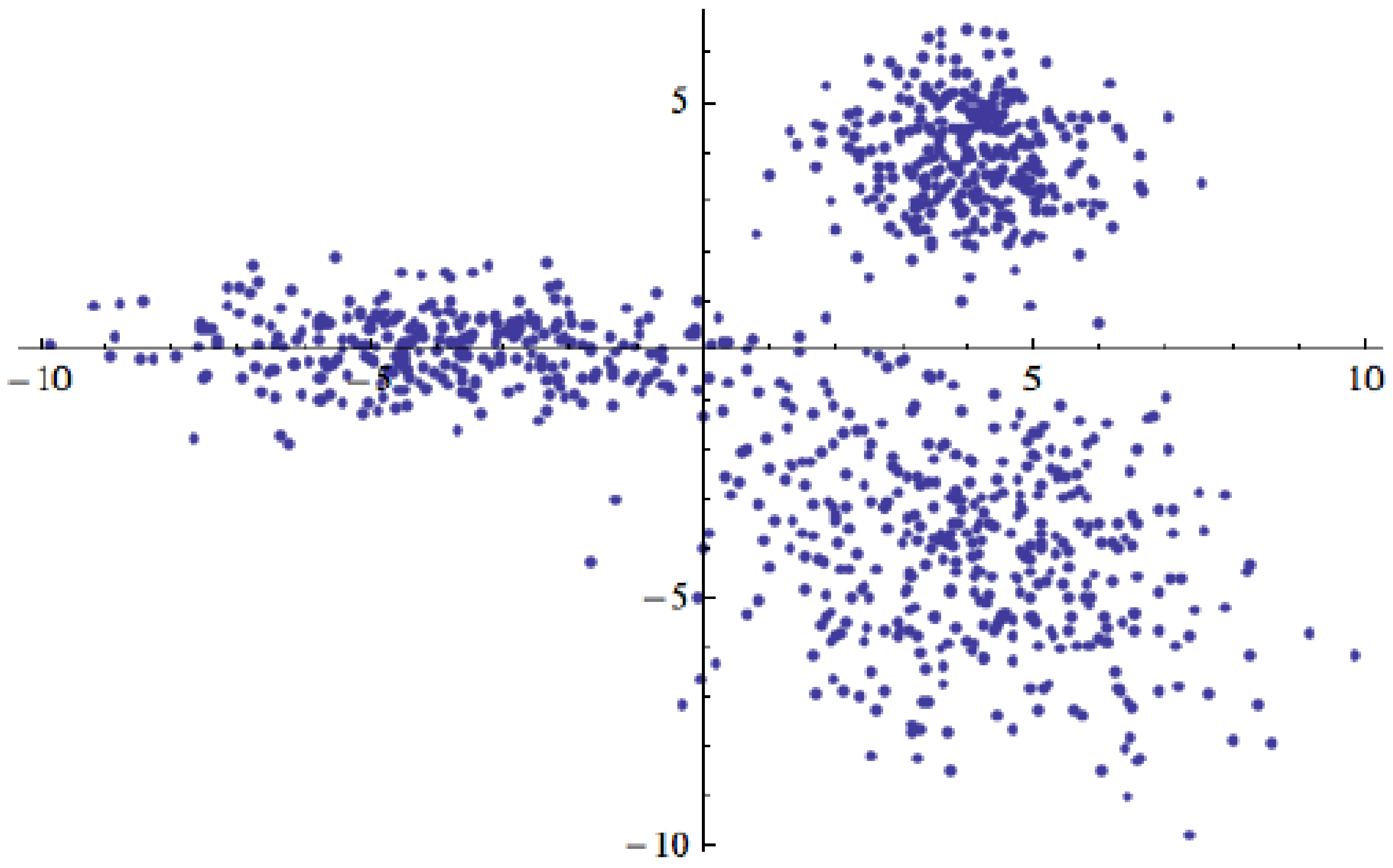


What distribution to use?

Lehner, Peter, and Alin Albu-Schäffer. "Repetition sampling for efficiently planning similar constrained manipulation tasks." *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2017.

Gaussian Mixture Models





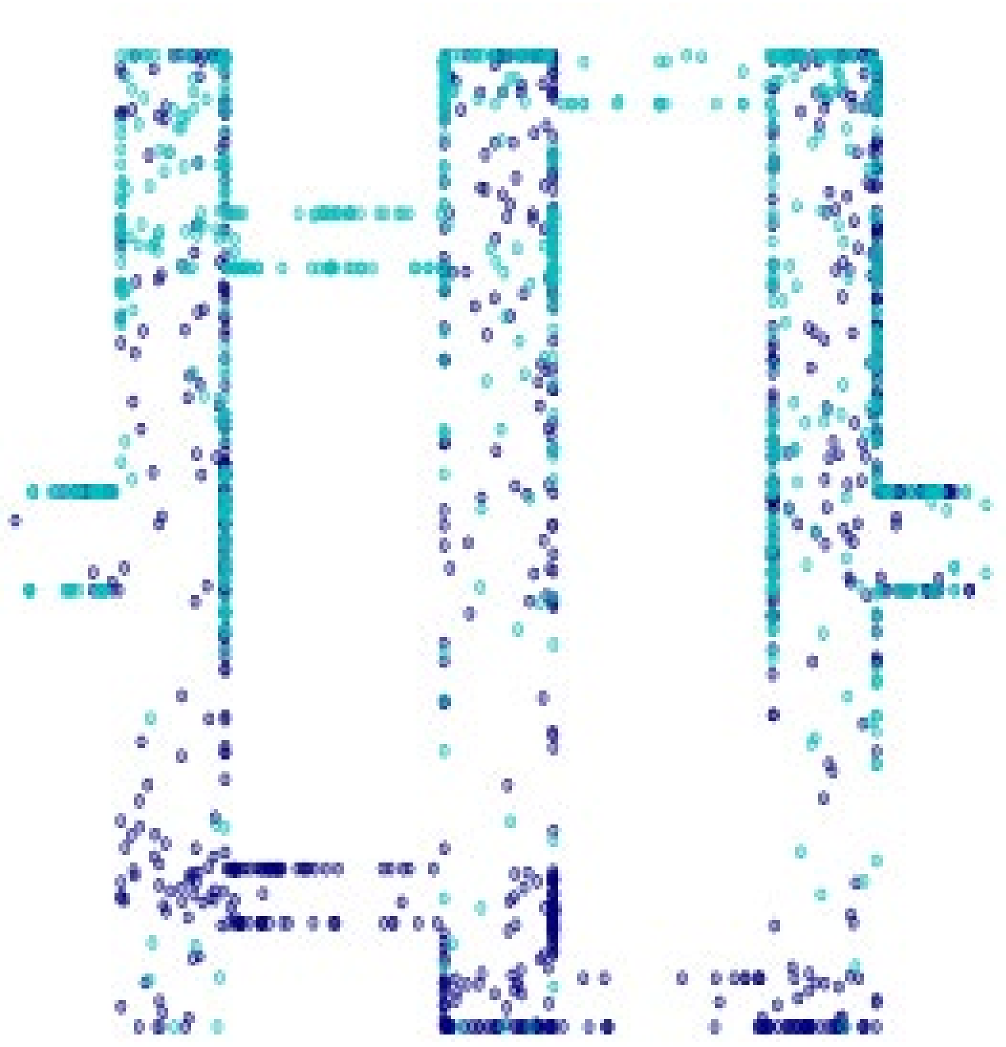
GMM: $\frac{1}{M_i}\sum_{j=1}^{M_i}\mathcal{N}(q_{ij},\Sigma_{ij})$

Samples from the model

Advantages: multimodal, easy to sample from, have been studied for decades

GMM Image from [link]

Repetition Sampling – Fitting a Distribution

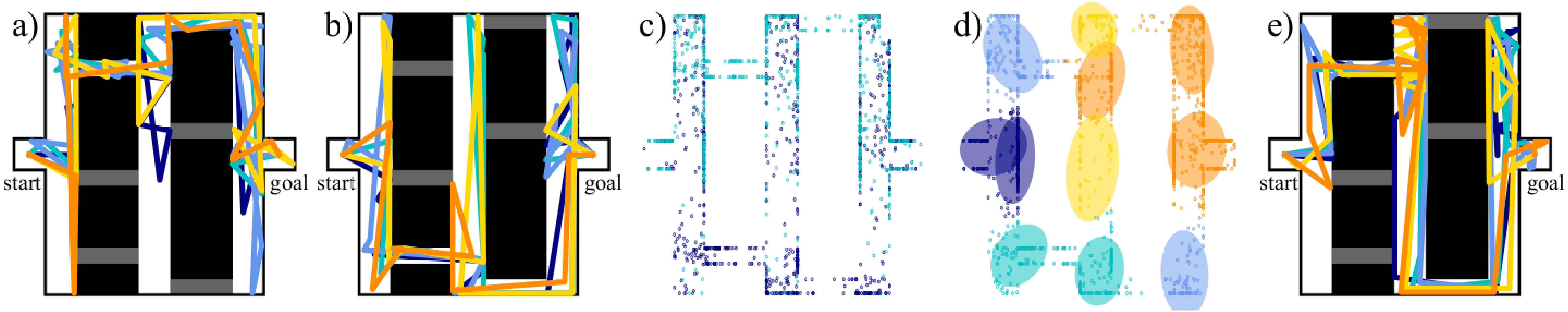


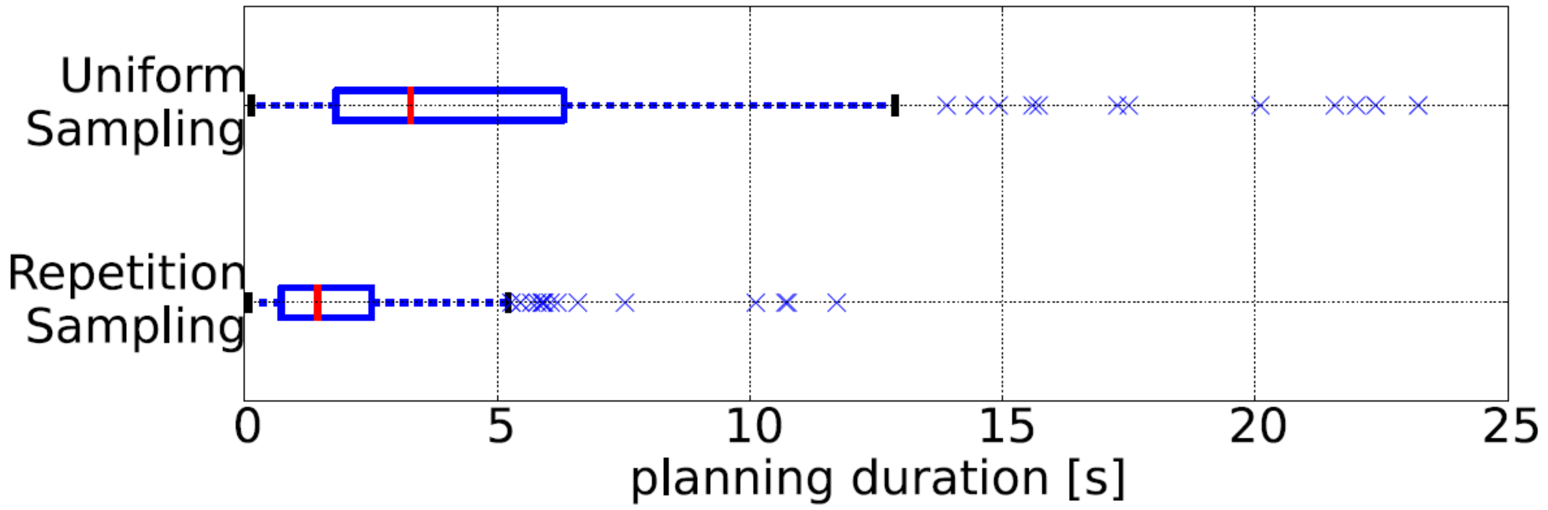
What distribution to use?

Fitting a Gaussian Mixture Model with the EM algorithm

Lehner, Peter, and Alin Albu-Schäffer. "Repetition sampling for efficiently planning similar constrained manipulation tasks." *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2017.

Repetition Sampling - Results Toy Example

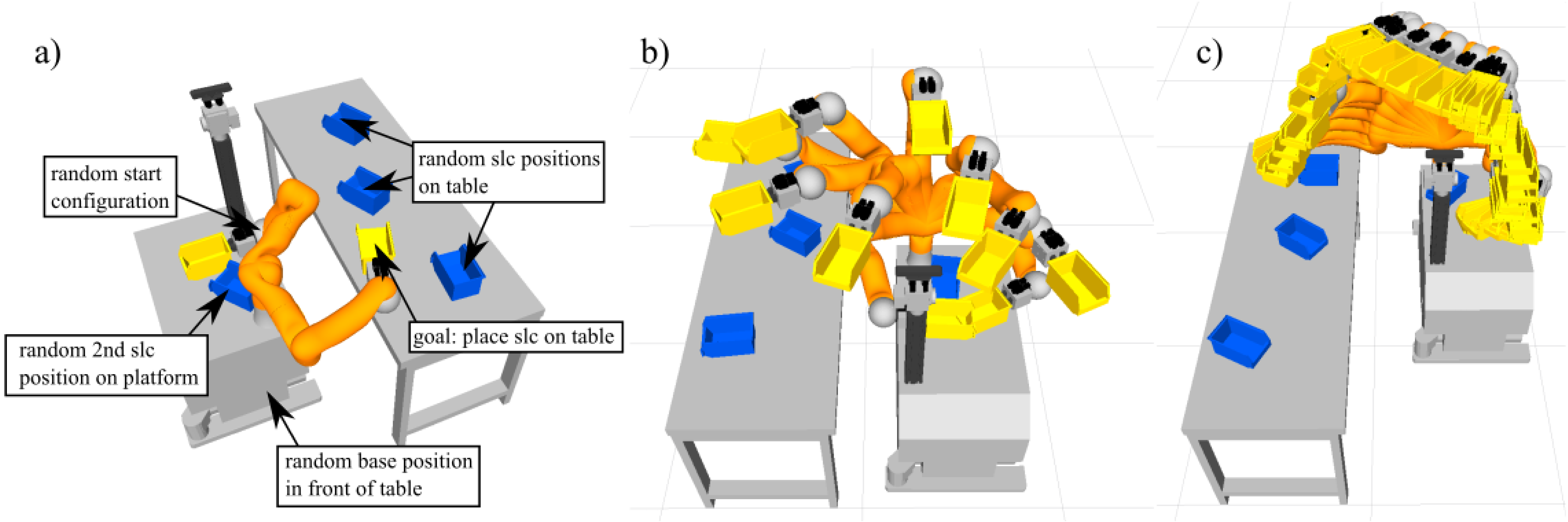


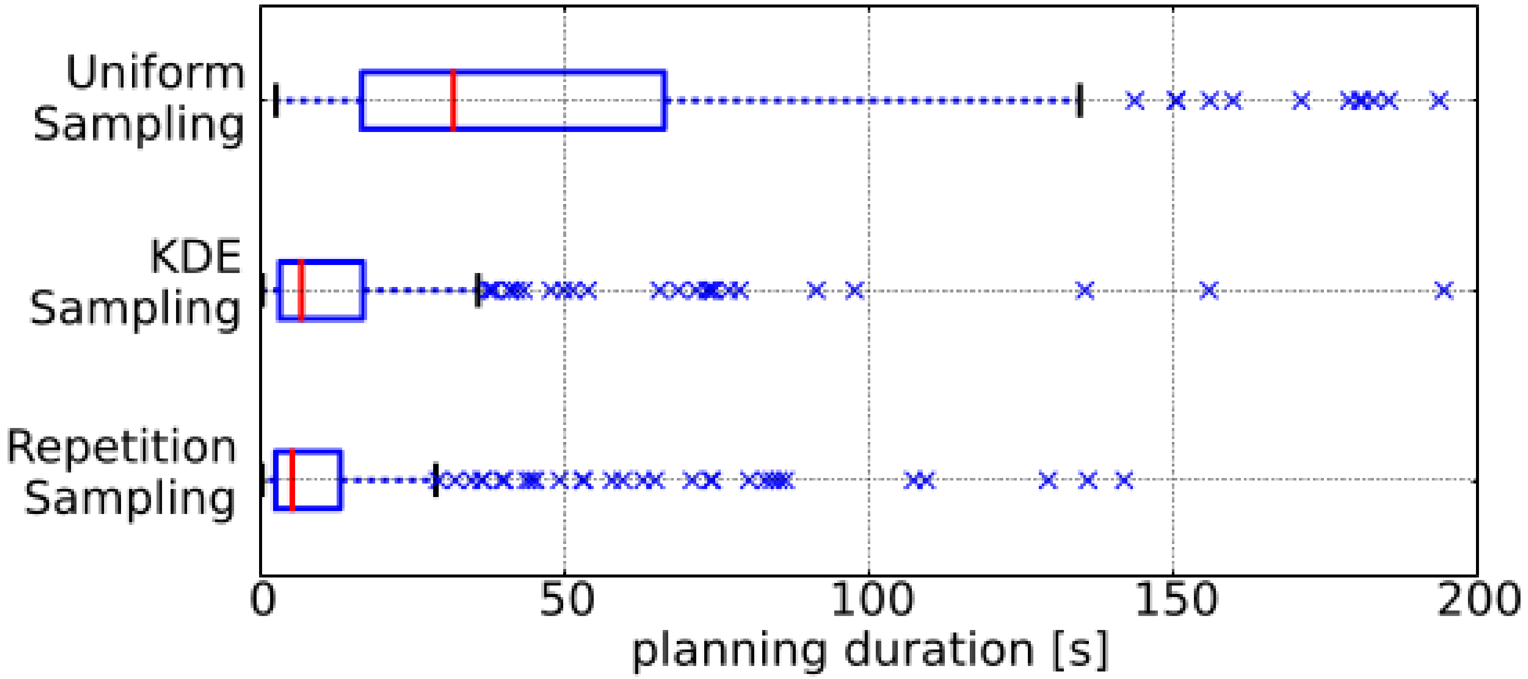


In this simple example Bi-RRT was improved 2-3 times on average

Lehner, Peter, and Alin Albu-Schäffer. "Repetition sampling for efficiently planning similar constrained manipulation tasks." *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2017.

Repetition Sampling - Results Real Robot





Applied in a constraint manipulation setting (tray must be up) and increased performance over uniform sampling and another sampling distribution (KDE)

Conditioned Biased Sampling Distributions

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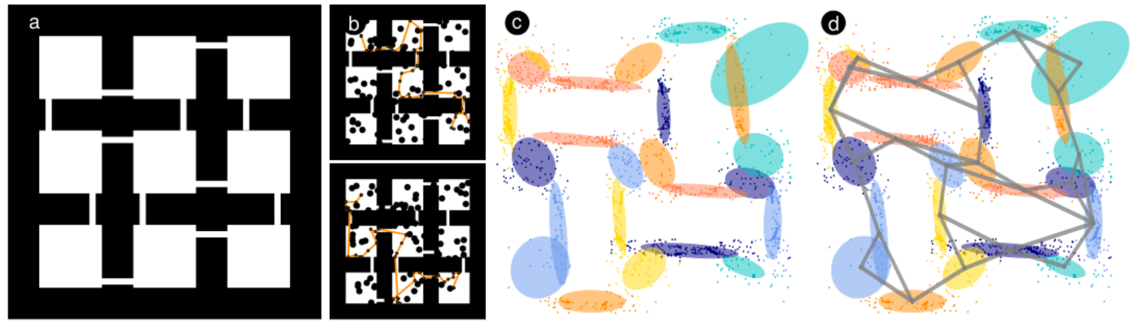
- **P(x| Start, Goal): Sampling conditioned on start and goal**
- P(x| W): Sampling biased from workspace features
- P (x| Start, Goal, W): Sampling leveraging both workspace, start and goal information

Paper 3: Repetition Roadmaps (Biased Sampler)

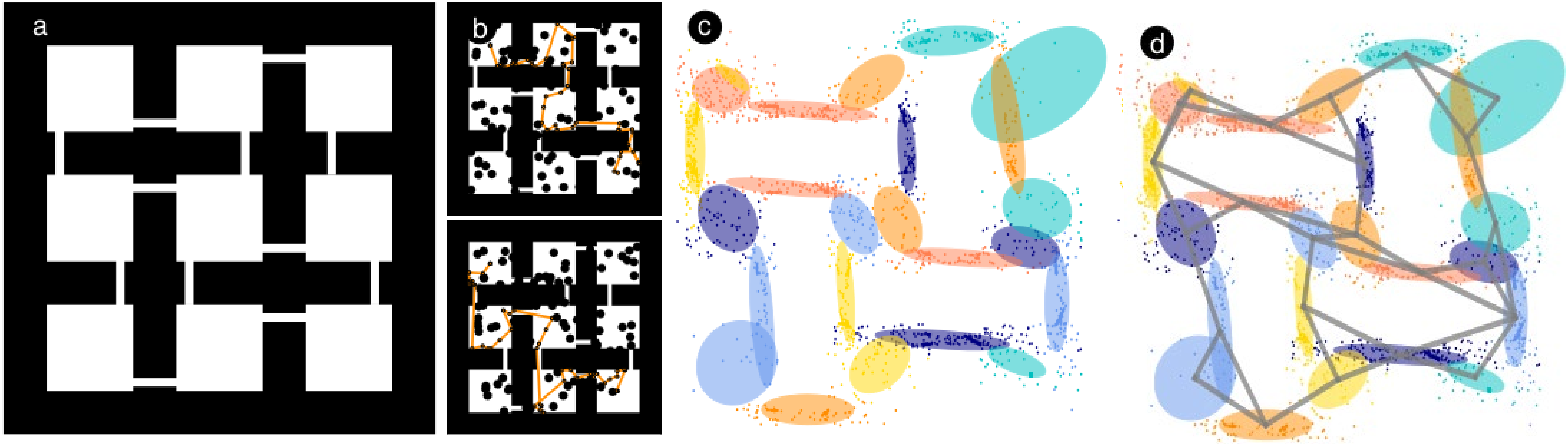
Main Idea:

- Create an Abstract Roadmap over the means of each Gaussian mixture
- Connect to Abstract Roadmap using start/goal and search for samplers
- The learned sampling distribution is conditioned with start, goal P(x| S,G)



Lehner, Peter, and Alin Albu-Schäffer. "The repetition roadmap for repetitive constrained motion planning." *IEEE Robotics and Automation Letters* 3.4 (2018): 3884-3891.

Repetition Roadmaps - Overview



Paths from different problems | Fit GMM | Create a Abstract Roadmap

Same as Repetition Sampling | New

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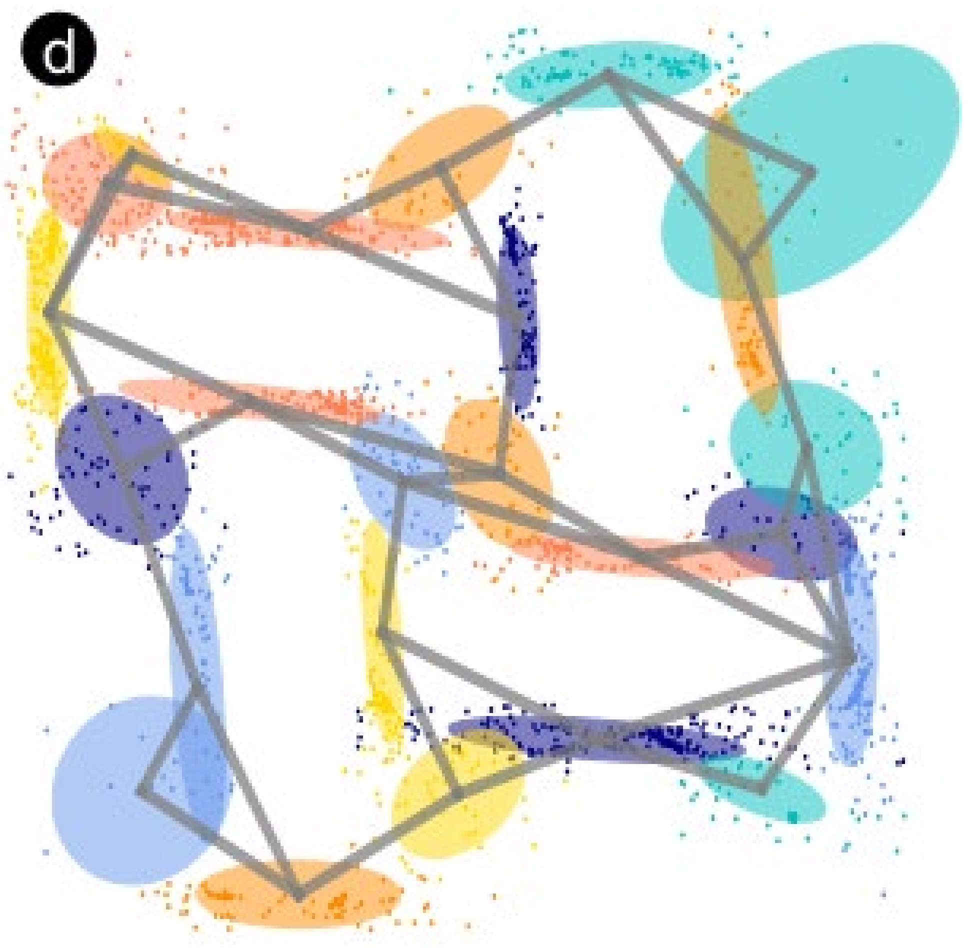
Repetition Roadmaps – Abstract Roadmap



Creating the Abstract Roadmap:

- Every Gaussian mean is a vertex
- For each two connected waypoints of past paths, that are assigned to different mixtures add an edge
- Cost of each edge is inv. proportional to number of same edges

Using the Abstract Roadmap:
Just search for the path with smallest cost

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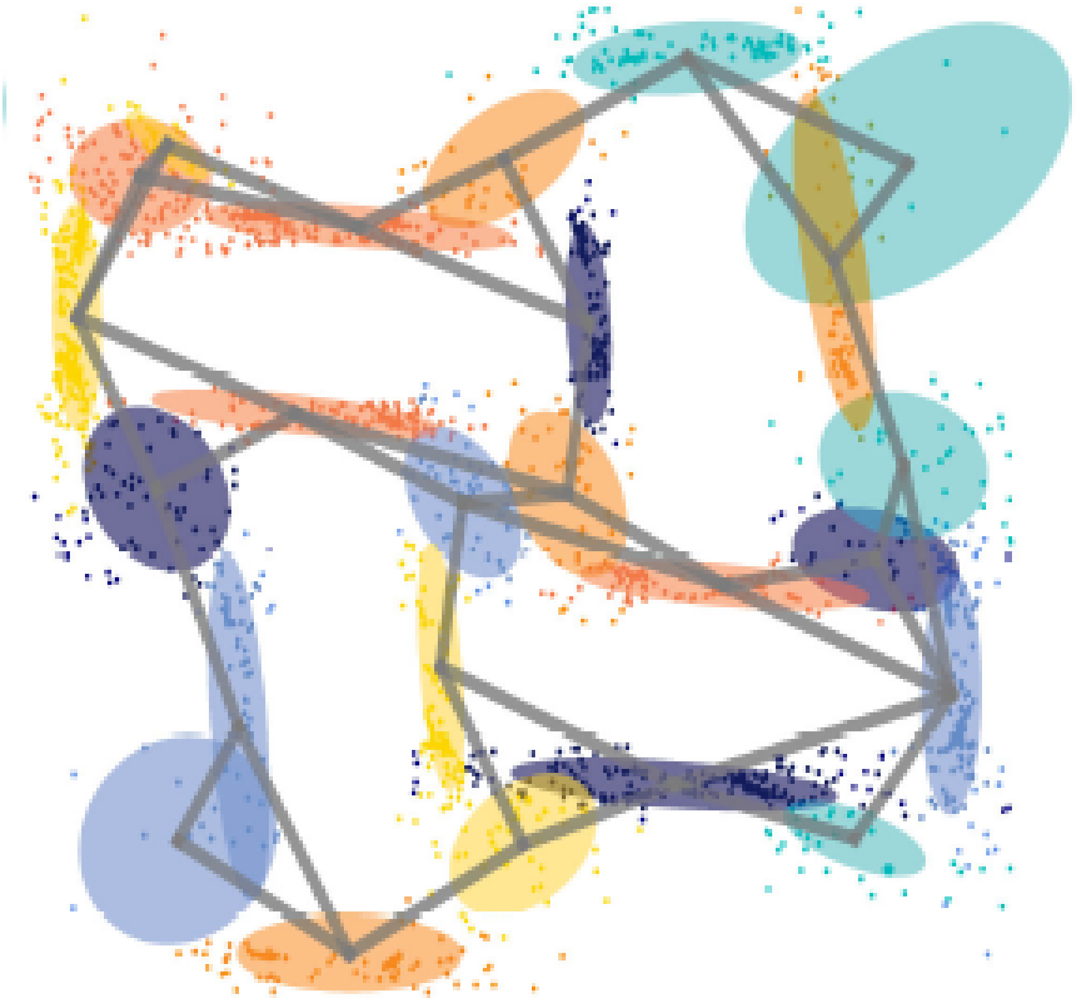
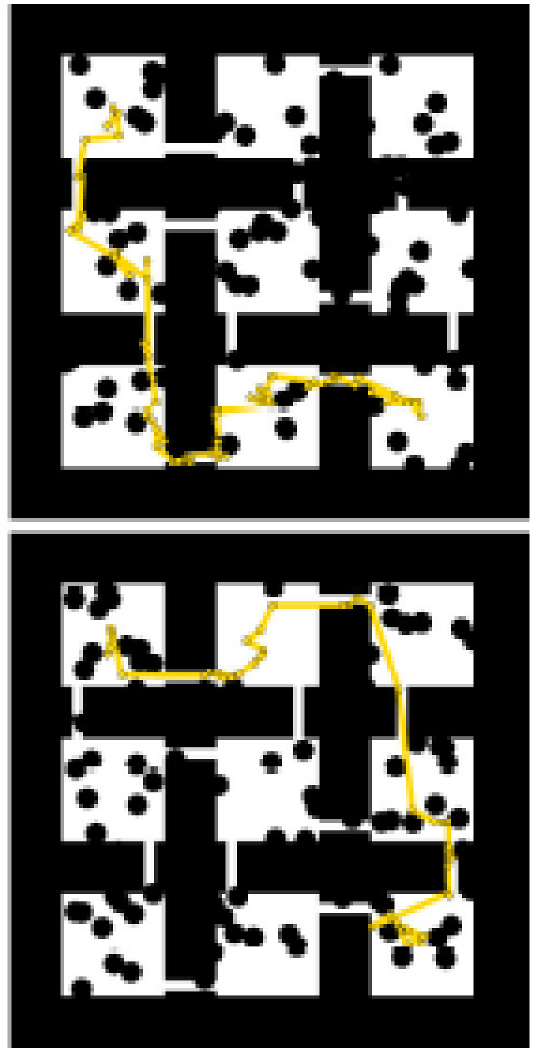
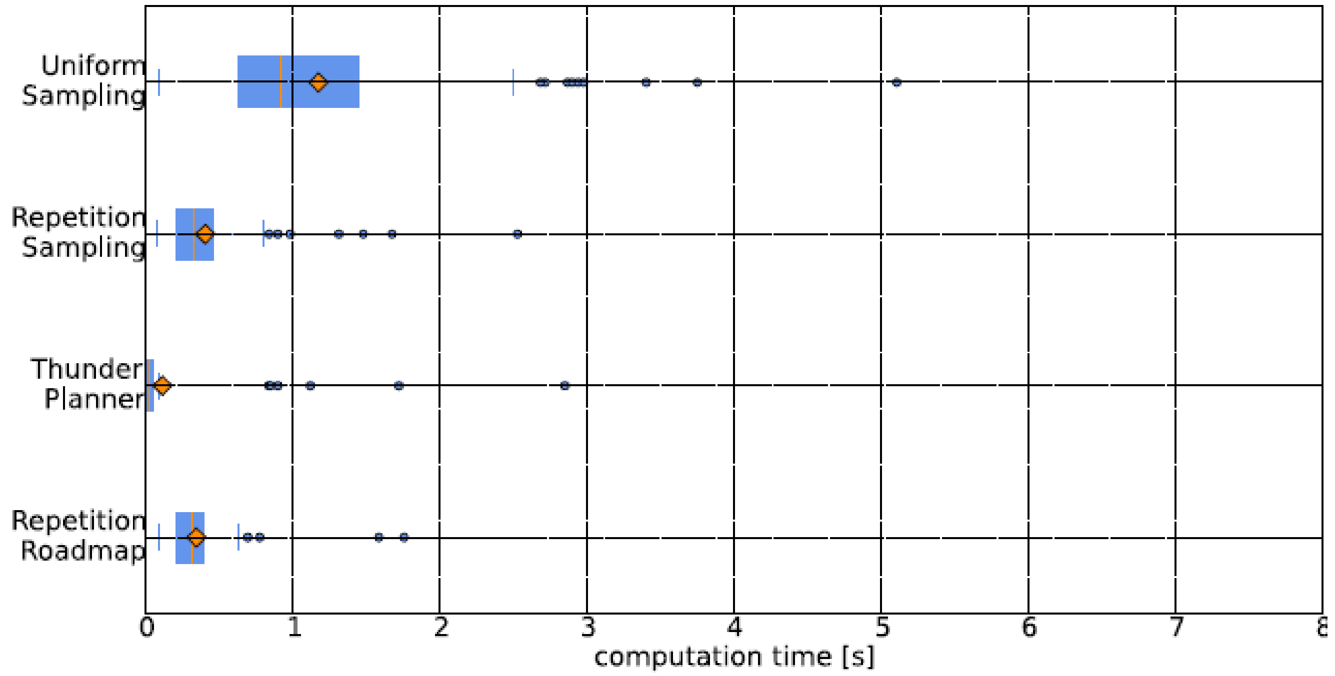
Repetition Roadmaps – Results Toy Example

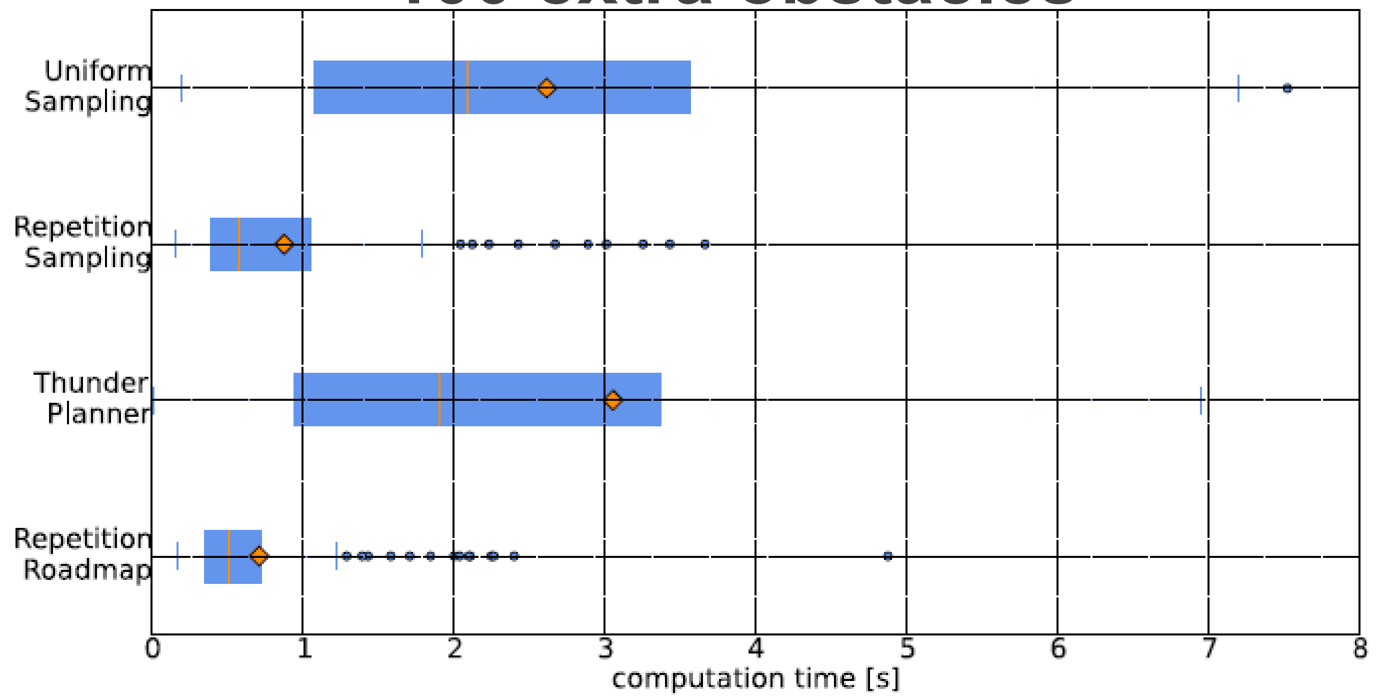




10 extra random obstacles

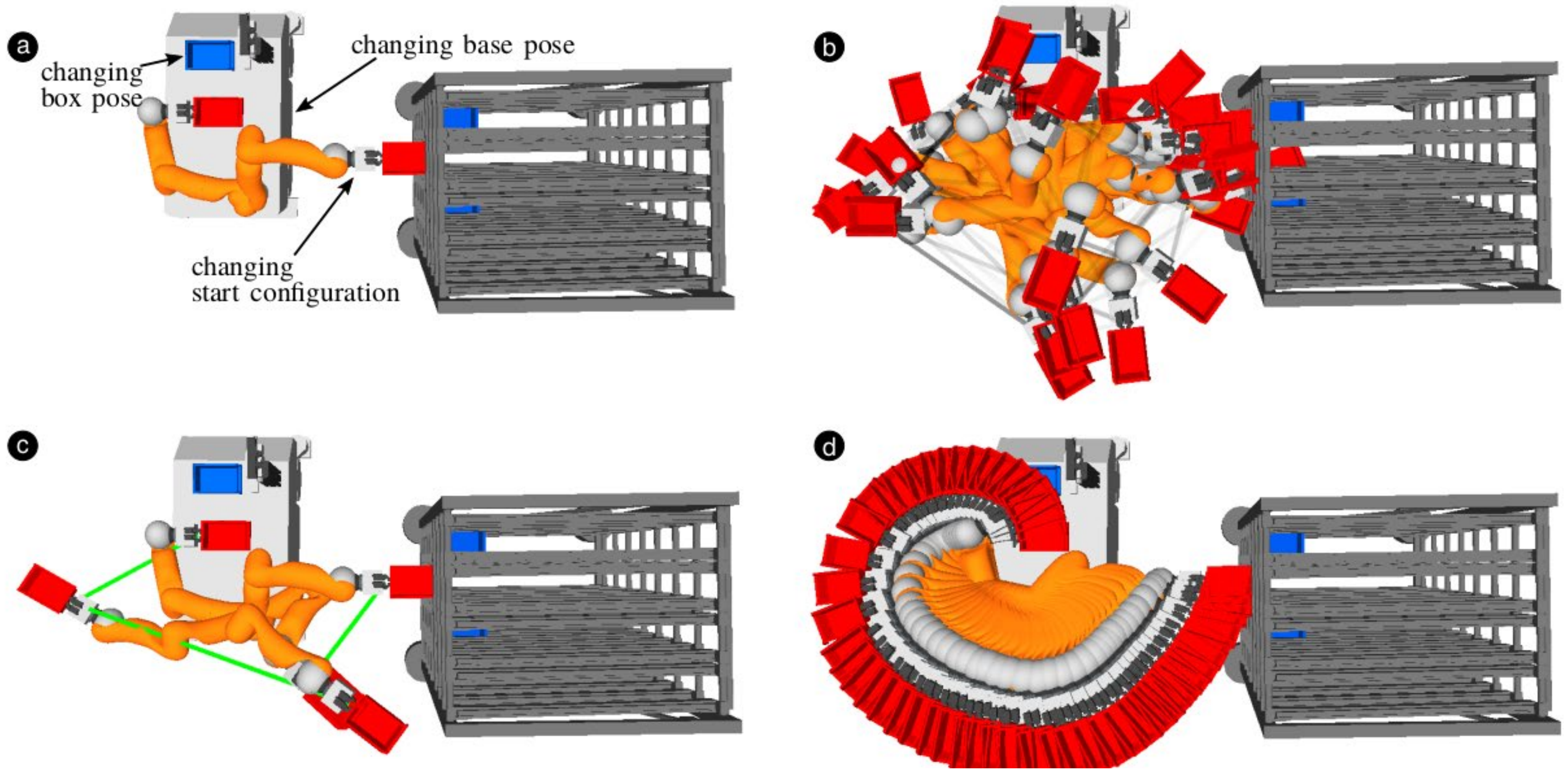


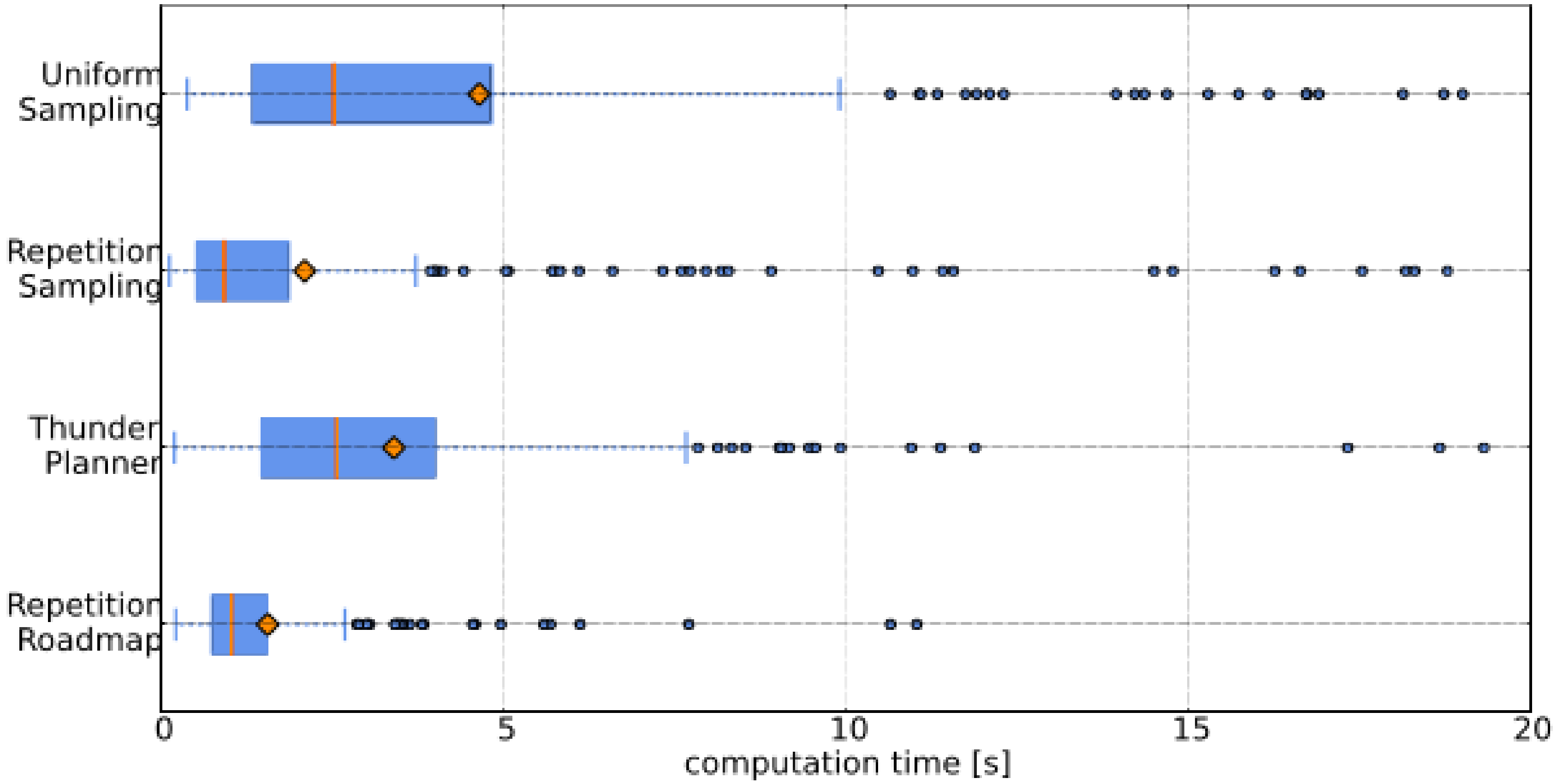
100 extra obstacles



Lehner, Peter, and Alin Albu-Schäffer. "The repetition roadmap for repetitive constrained motion planning." *IEEE Robotics and Automation Letters* 3.4 (2018): 3884-3891.

Repetition Roadmap – Results Real Robot





Applied in a similar constraint manipulation setting (tray must be up) and outperformed *Thunder* and *Repetition Sampling*

Conclusions

- This is an emerging field which could transform traditional motion planning (not yet)!
- A challenge for research is that no standard benchmarks exist.
- No method currently outperforms all other, and applications to real robots are limited.
- Other avenues exists, such as optimizing for clearance, or planning under uncertainty.

Lecture Overview

- Why Combine Learning and Motion Planning?
  – To improve planning efficiency in challenging problems

- Learning For Motion Planning Archetypes
  - Retrieve and Repair, Biased Sampling

- Discussed 4 Papers
  - Lightning (2012) Thunder (2015), Rep Sampling (2017), Rep (Roadmap) (2019)

References (Retrieve-and-Repair)

[1] Berenson, Dmitry, Pieter Abbeel, and Ken Goldberg. "A robot path planning framework that learns from experience."*International Conference on Robotics and Automation*. IEEE, 2012.

[2] Coleman, David, et al. "Experience-based planning with sparse roadmap spanners." *International Conference on Robotics and Automation (ICRA)*. IEEE, 2015.

[3] Pairet, Èric, et al. "Path Planning for Manipulation using Experience-driven Random Trees." *IEEE Robotics and Automation Letters* 6.2 (2021): 3295-3302.

[4] Lien, Jyh-Ming, and Yanyan Lu. "Planning motion in environments with similar obstacles." *Robotics: Science and systems*. 2009.

[5] Jetchev, Nikolay, and Marc Toussaint. "Fast motion planning from experience: trajectory prediction for speeding up movement generation." *Autonomous Robots* 34.1 (2013): 111-127.

References (Biased Samplers 1)

[6] Lehner, Peter, and Alin Albu-Schäffer. "Repetition sampling for efficiently planning similar constrained manipulation tasks." *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2017.

[7] Lehner, Peter, and Alin Albu-Schäffer. "The repetition roadmap for repetitive constrained motion planning." *IEEE Robotics and Automation Letters* 3.4 (2018): 3884-3891.

[8] Zucker, Matt, James Kuffner, and J. Andrew Bagnell. "Adaptive workspace biasing for sampling-based planners."*International Conference on Robotics and Automation*. IEEE, 2008.

[9] Chamzas, Constantinos, Anshumali Shrivastava, and Lydia E. Kavraki. "Using local experiences for global motion planning." *International Conference on Robotics and Automation (ICRA)*. IEEE, 2019.

References (Biased Samplers 2)

[10] Chamzas, Constantinos, et al. "Learning sampling distributions using local 3D workspace decompositions for motion planning in high dimensions."*International Conference on Robotics and Automation (ICRA)*. IEEE, 2021

[11] Ichter, Brian, James Harrison, and Marco Pavone. "Learning sampling distributions for robot motion planning."*International Conference on Robotics and Automation (ICRA)*. IEEE, 2018.

[12] Chamzas, Constantinos, et al. "Learning to retrieve Relevant Experiences for Motion Planning "*International Conference on Robotics and Automation (ICRA)*. IEEE, 2021