16-350
Planning Techniques for Robotics

Case Study:
Planning for Autonomous Driving

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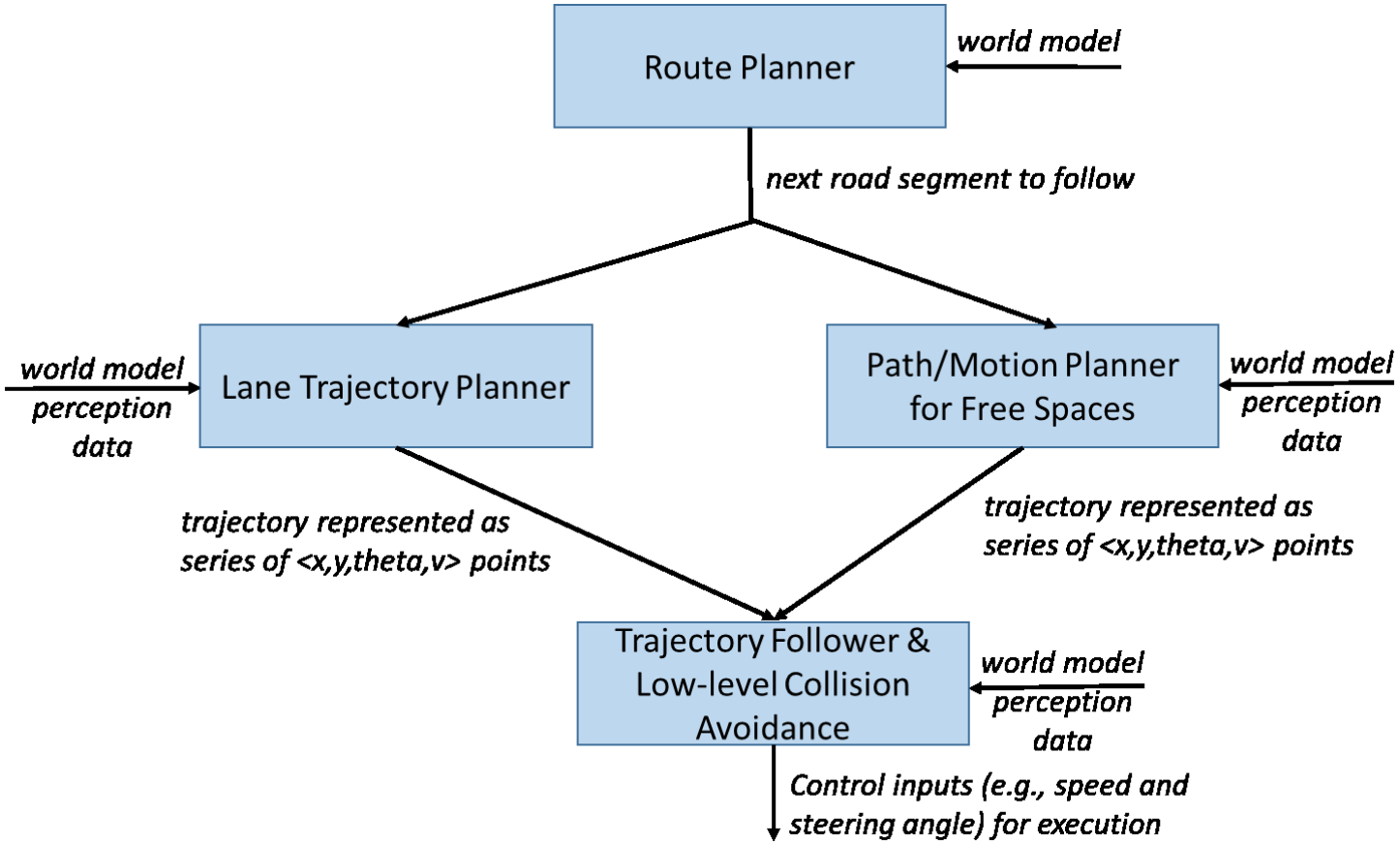
Robotics Institute

Carnegie Mellon University

Typical Planning Architecture for Autonomous Vehicle



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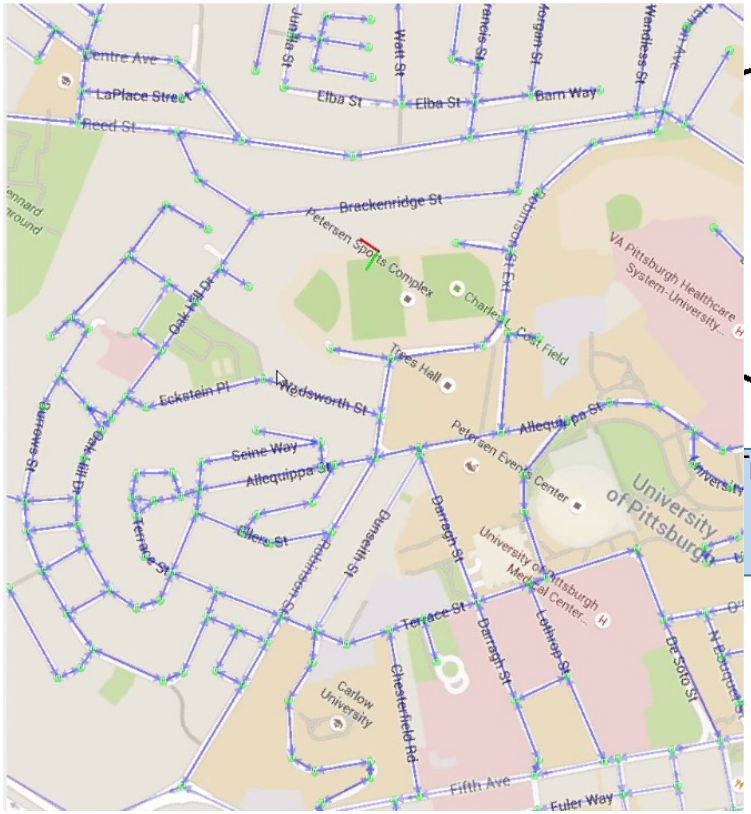

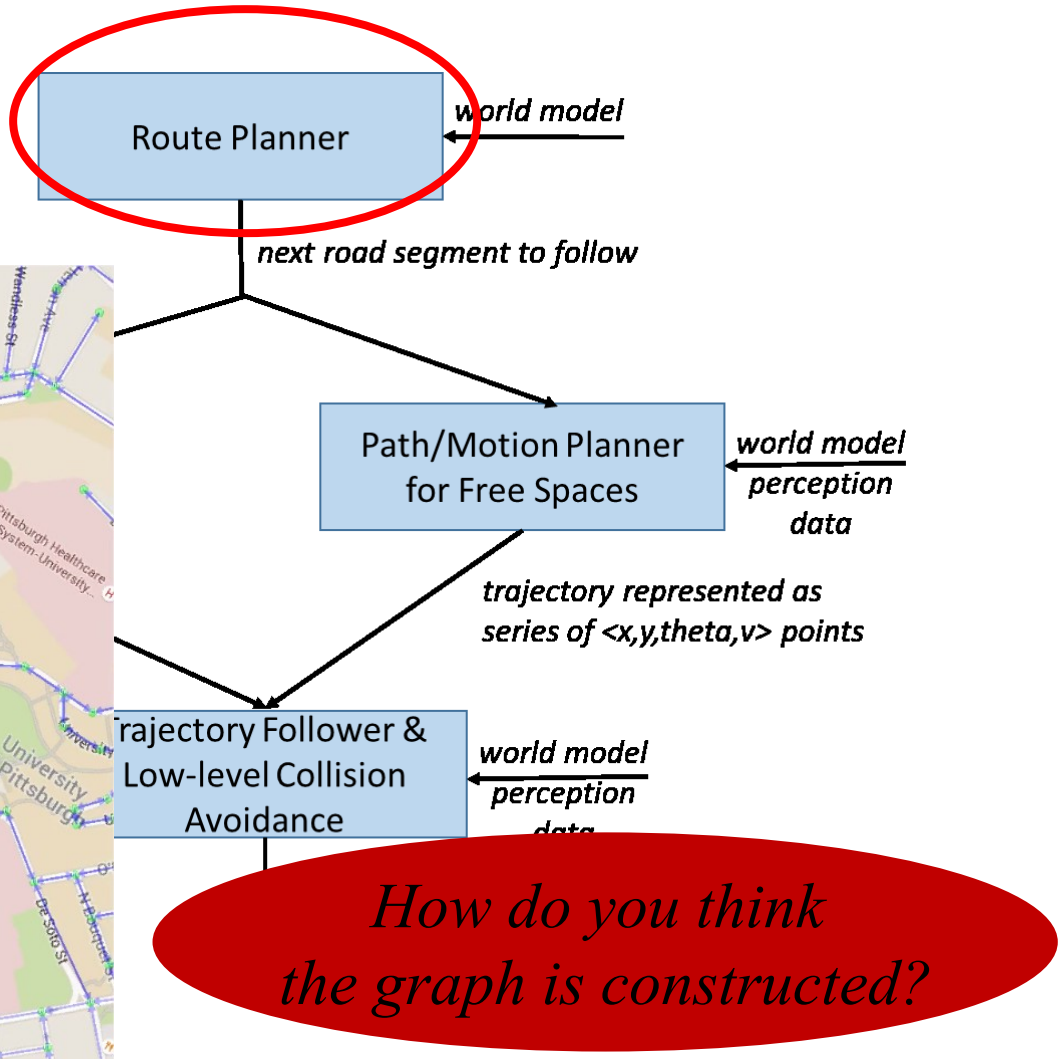

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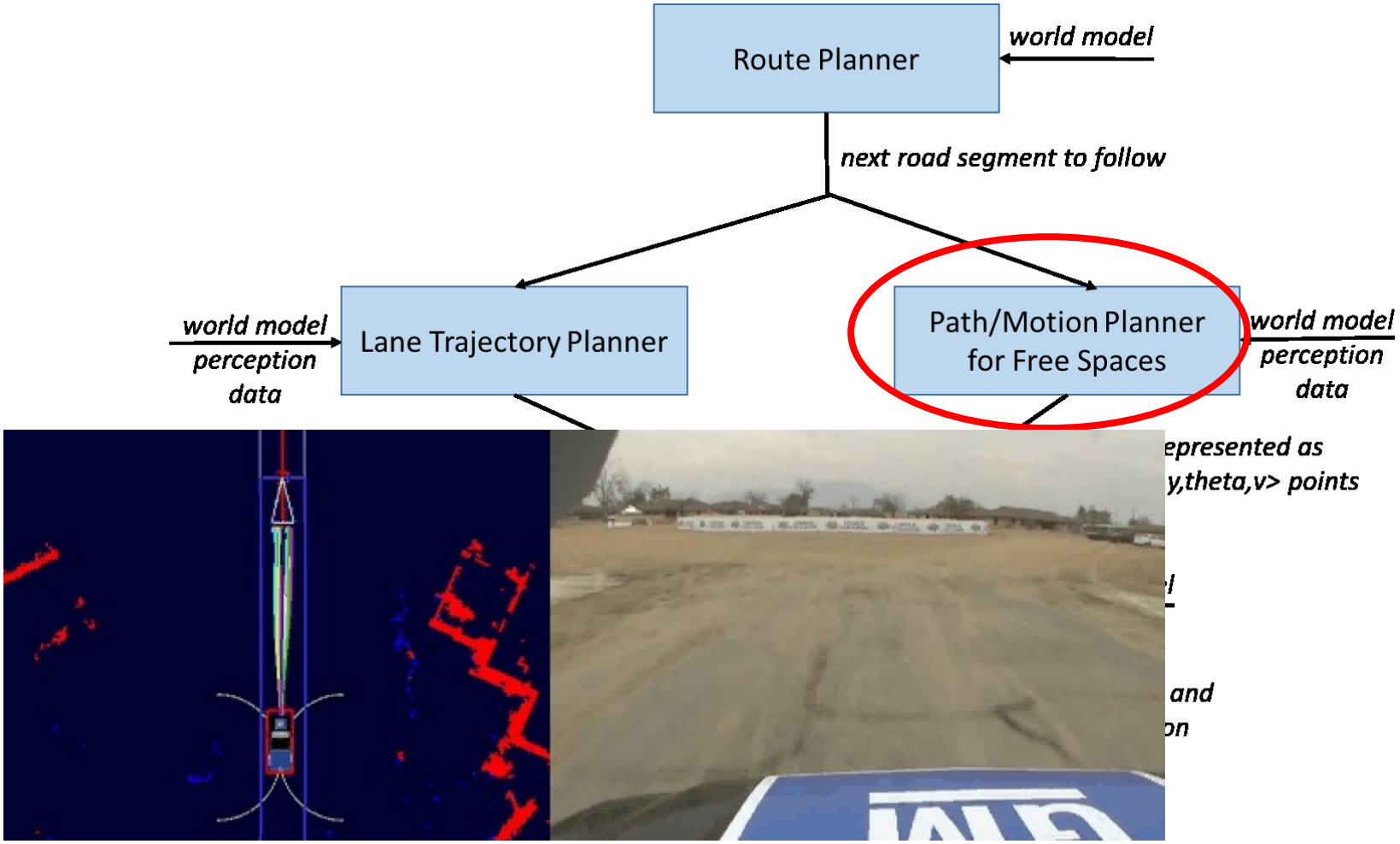
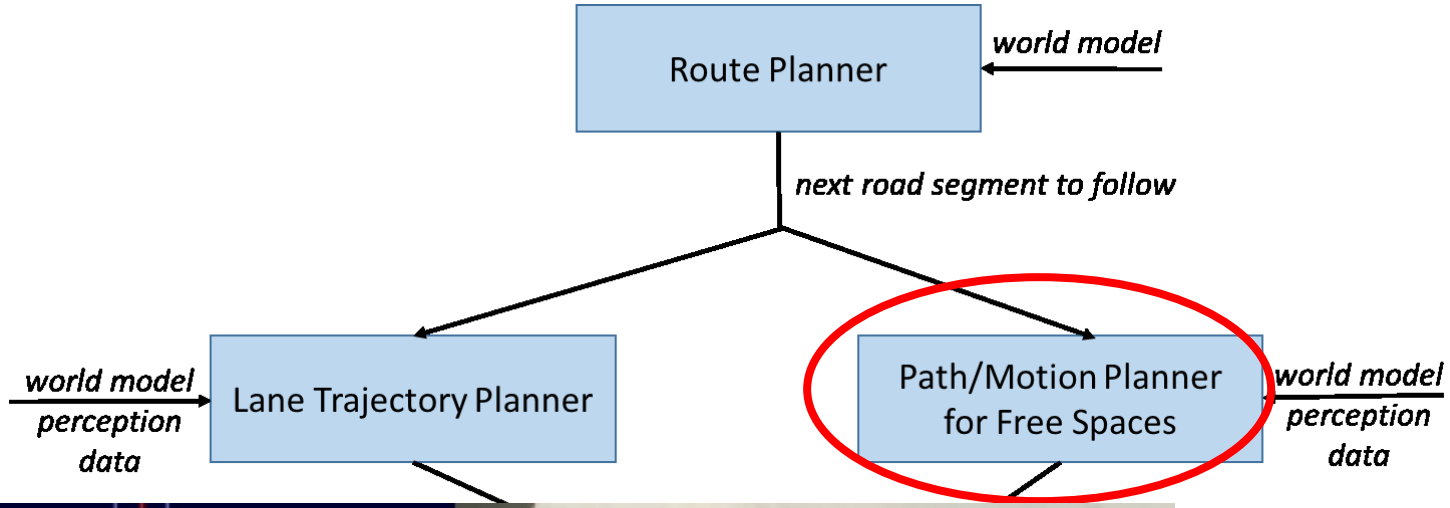
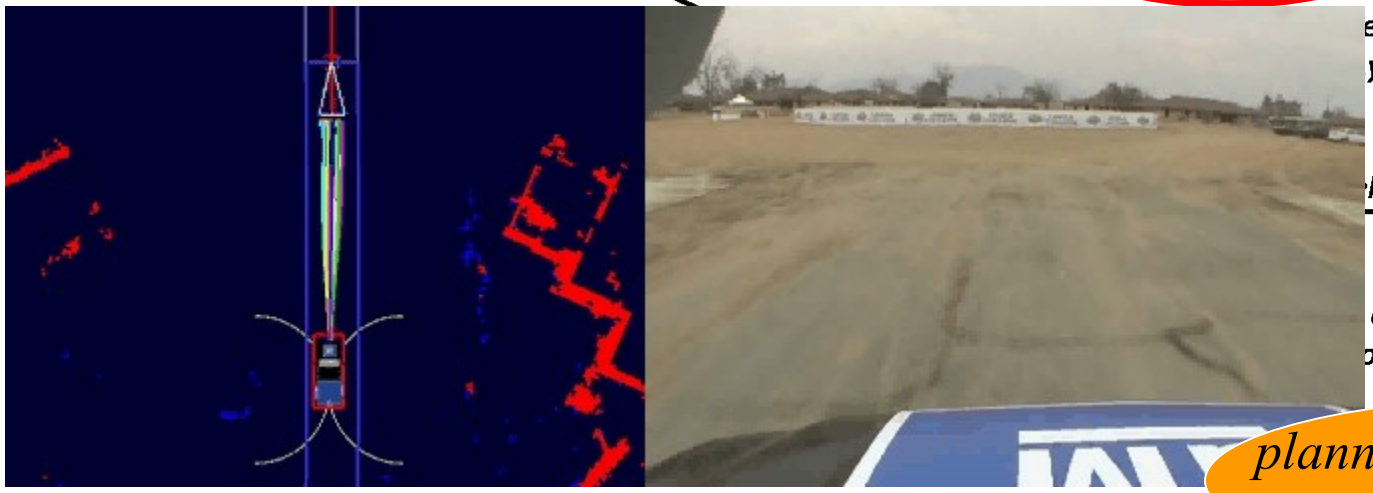


Tartanracing, CMU

Typical Planning Architecture for Autonomous Vehicle

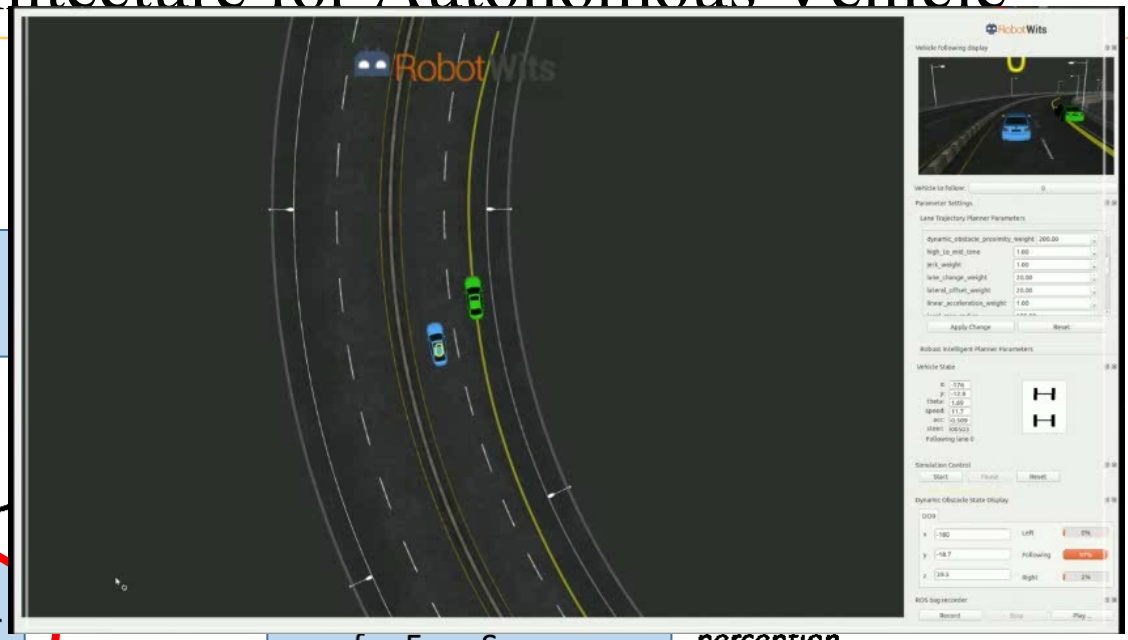




Tartanracing, CMU

planning states defined by:
x, y, Θ, v

Typical Planning Architecture for Autonomous Vehicle



world model
perception
data

Lane Trajectory Planner

for Free Spaces

perception
data

trajectory represented as
series of <x,y,theta,v> points

trajectory represented as
series of <x,y,theta,v> points

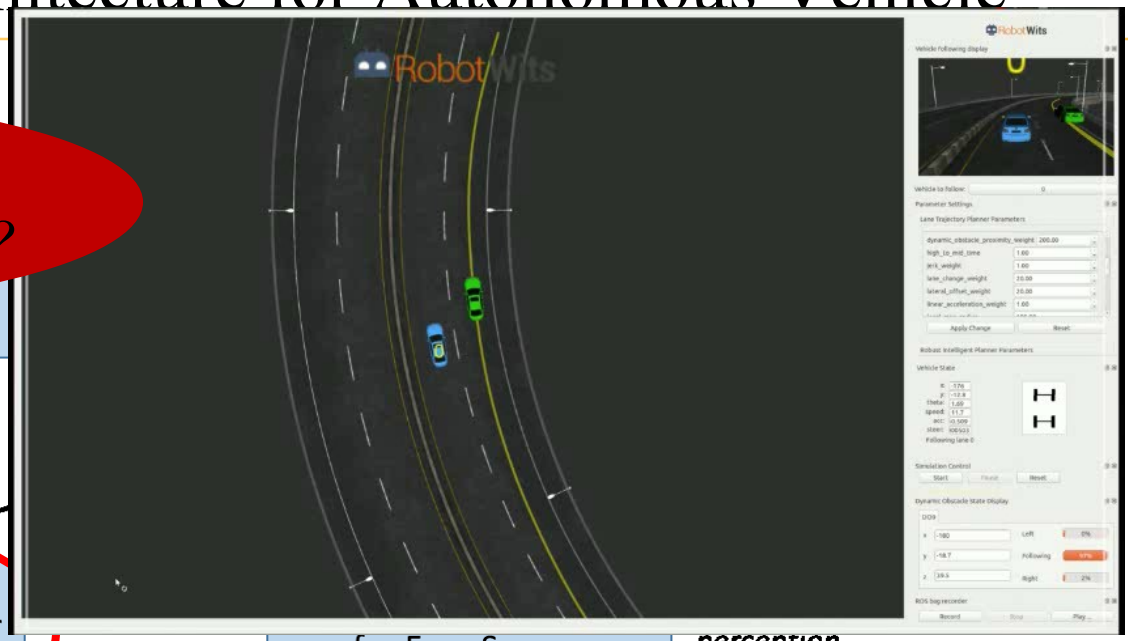
Trajectory Follower &
Low-level Collision
Avoidance

world model
perception
data

Control inputs (e.g., speed and
steering angle) for execution

Typical Planning Architecture for Autonomous Vehicle

How do you think the graph is constructed?



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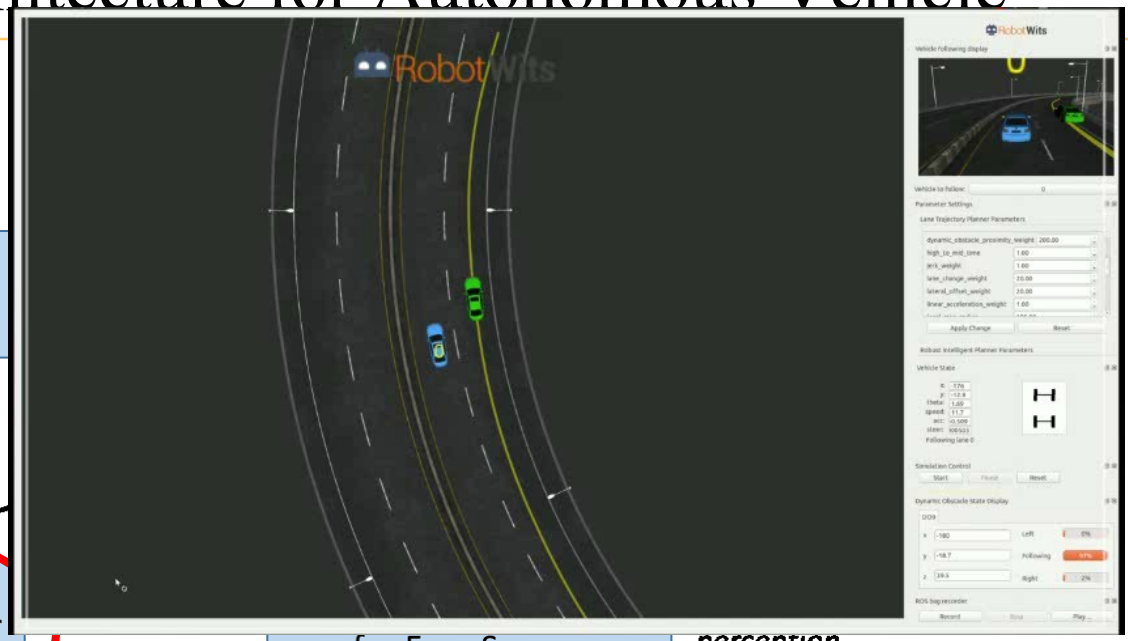
Typical Planning Architecture for Autonomous Vehicle



world model
perception
data

Lane Trajectory Planner

perception

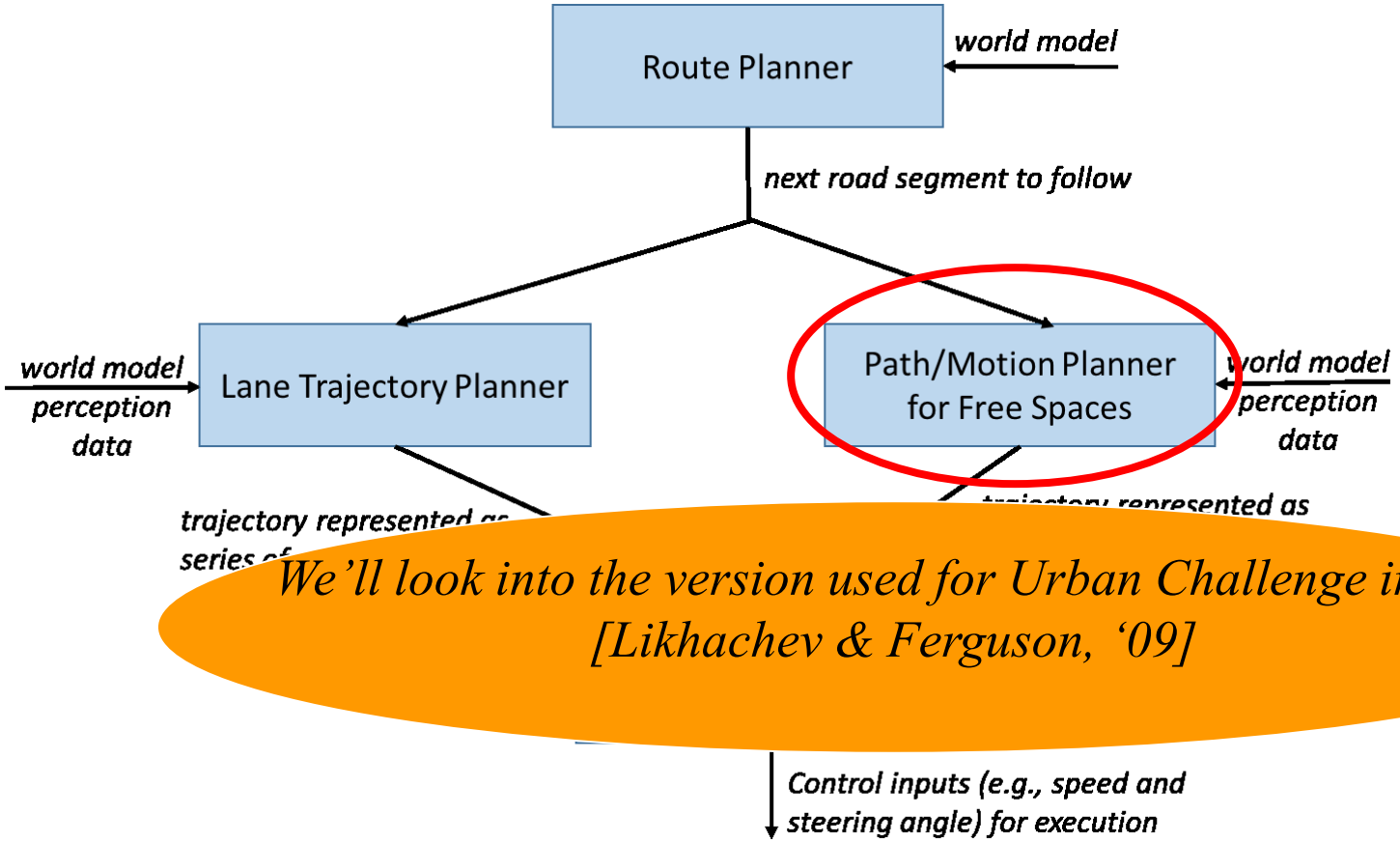
planning states defined by:
discretization along a lane (=x) and perpendicular to it (=y),
lane ID, v, time

Low-level Collision Avoidance

world model
perception
data

Control inputs (e.g., speed and steering angle) for execution

Typical Planning Architecture for Autonomous Vehicle



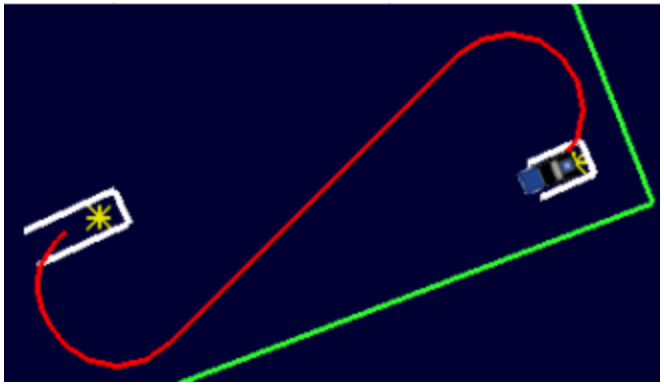
Motivation

- Planning **long complex maneuvers** for the Urban Challenge vehicle from CMU (Tartanracing team)

- Planner suitable for
  - autonomous parking in very large (200m by 200m) cluttered parking lots
  - navigating in off-road conditions
  - navigating cluttered intersections/driveways

Desired Properties

- Generate a path that can be tracked well (at up to 5m/sec):



  - path is a 4-dimensional trajectory:

$$(x,\ y,\ \theta,\ v)$$

orientation *speed*

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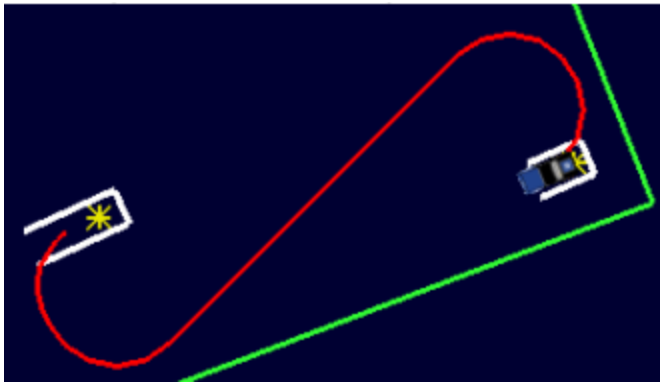


  - path is a 4-dimensional trajectory:

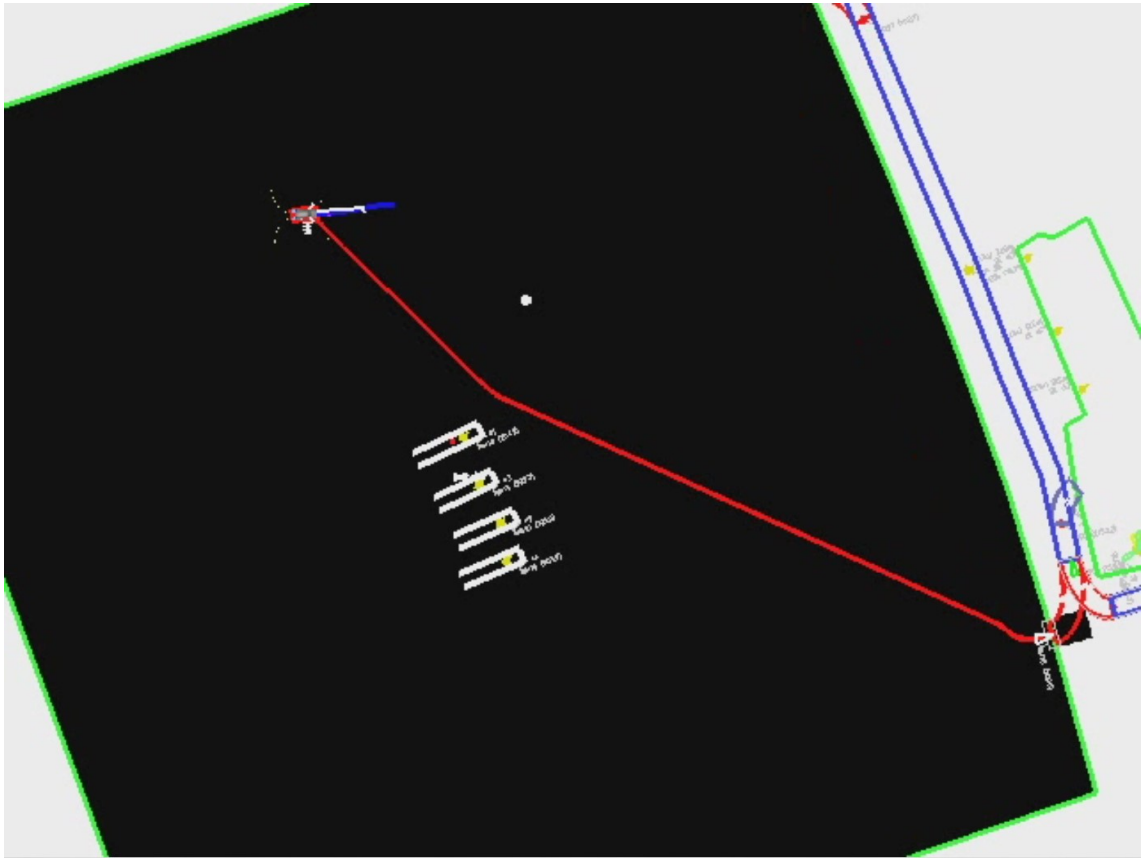
$$(x,\ y,\ \theta,\ v)$$

orientation *speed*

Orientation of the wheels is not included. When will that be a problem?

Desired Properties

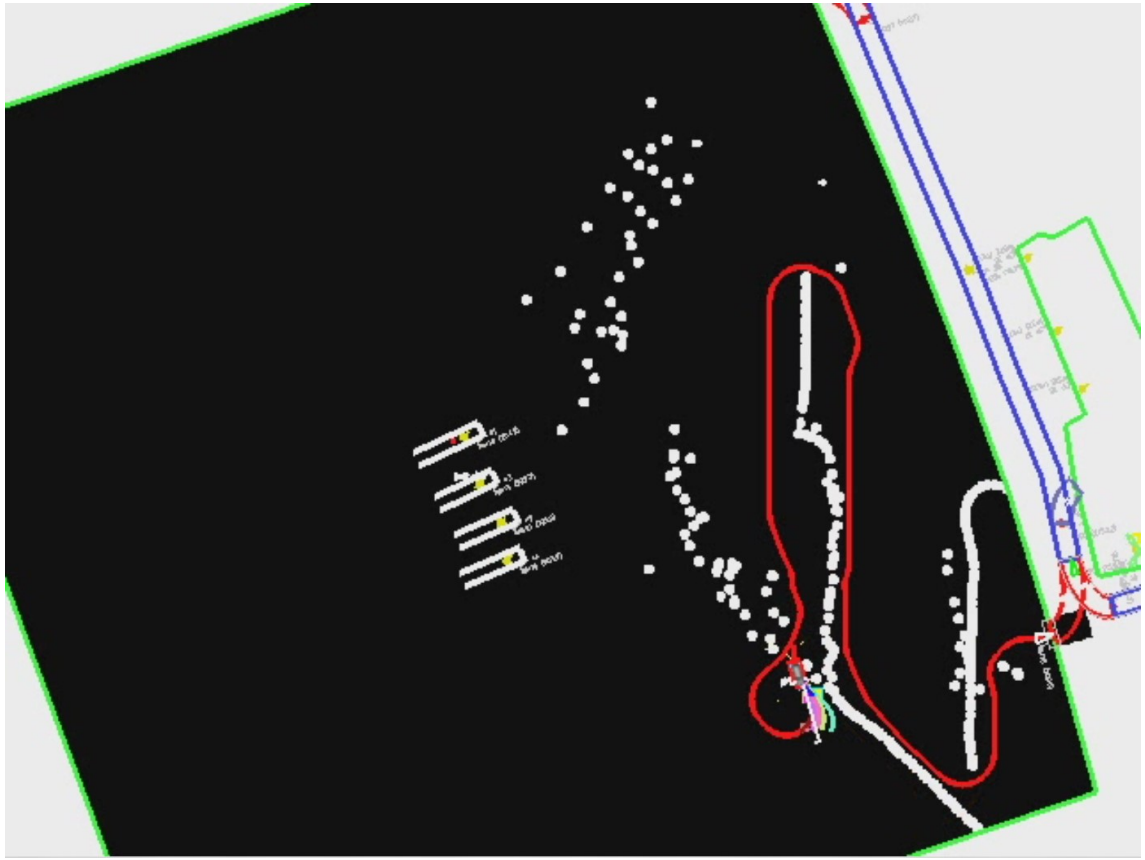
- Fast (2D-like) planning in trivial environments:



200 by 200m parking lot

Desired Properties

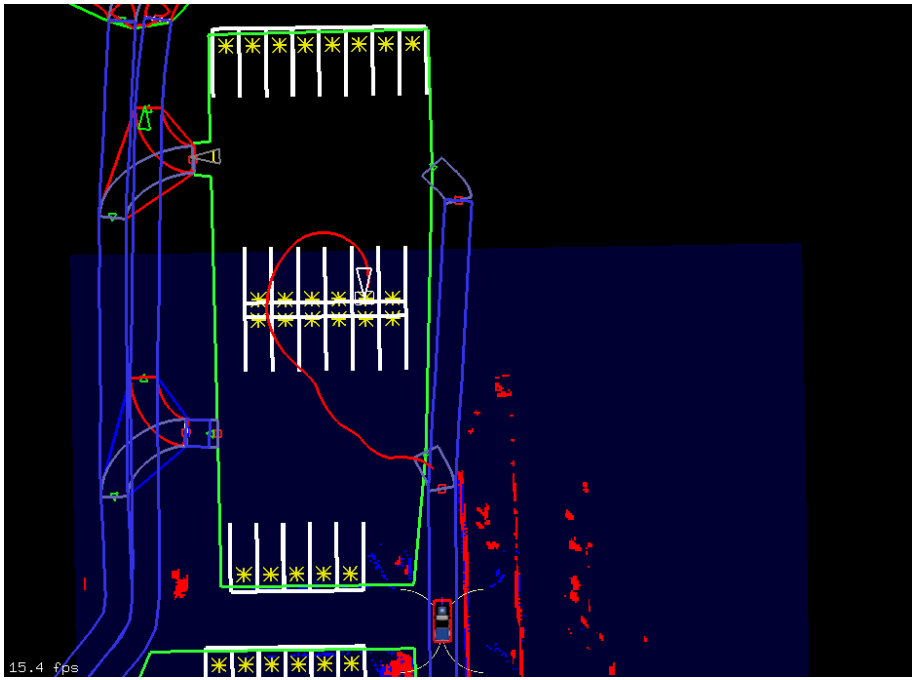
- But can also handle large non-trivial environments:



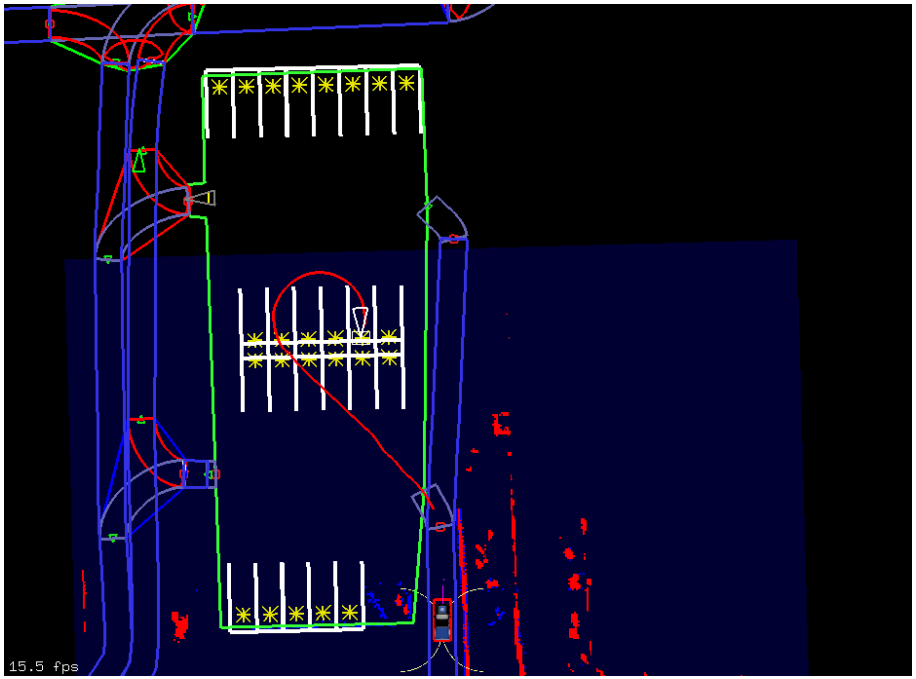
200 by 200m parking lot

Desired Properties

- Anytime property: finds the best path it can within X secs and then improves the path while following it



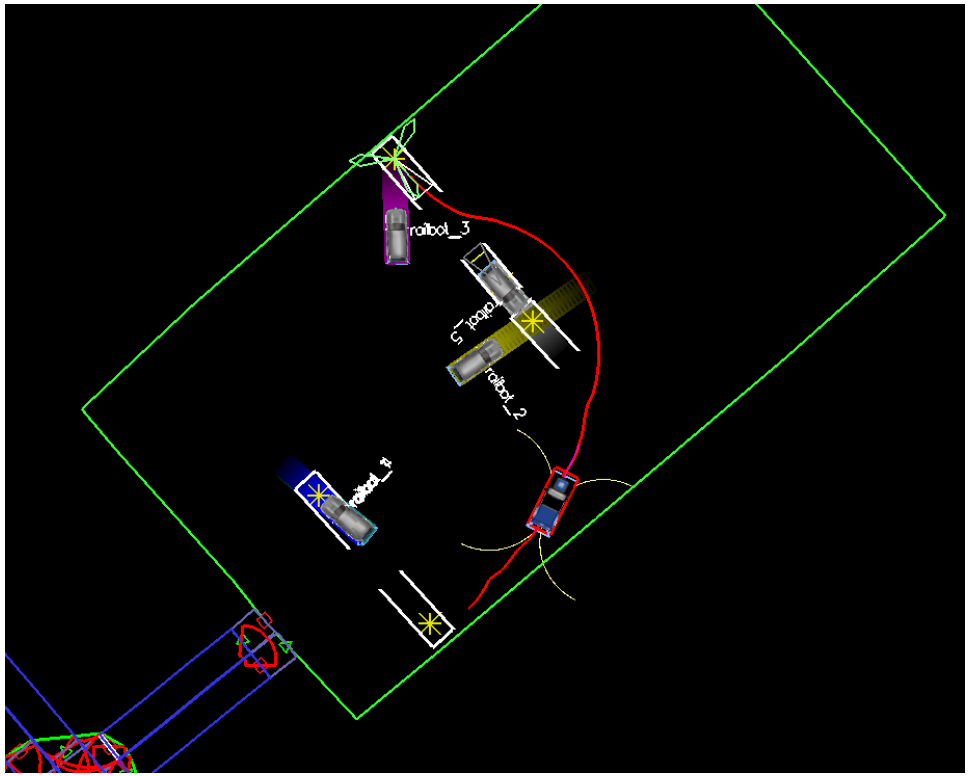
initial path



converged (to optimal) path

Desired Properties

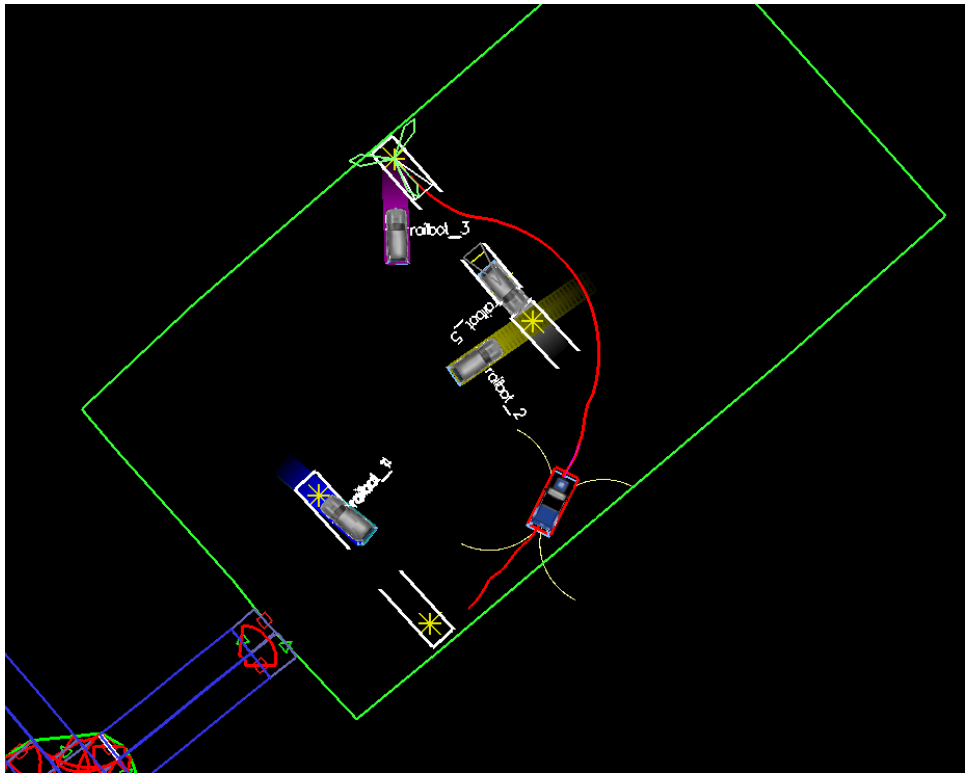
- Fast replanning, especially since we need to avoid other vehicles



planning a path that avoids other vehicles

Desired Properties

- Fast replanning, especially since we need to avoid other vehicles



...her vehicles

Time is not part of the state-space.
When will that be a problem?

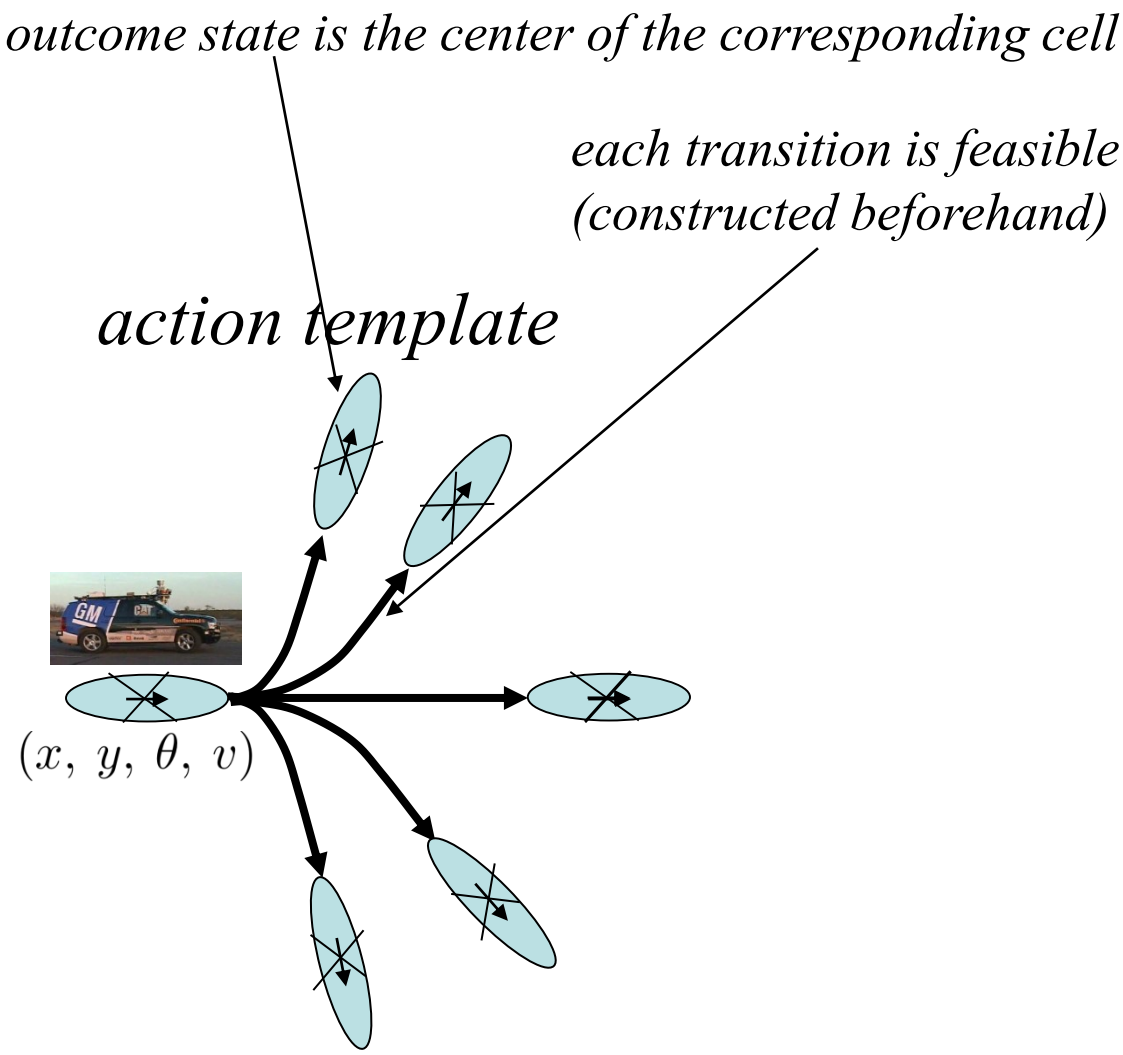
The Approach

- Define an **Implicit** graph
  - multi-resolution version of a lattice graph

- Search the graph for a least-cost path
  - Anytime D* (ARA* + D* Lite)

Building the Graph

- Lattice-based graph:



Building the Graph

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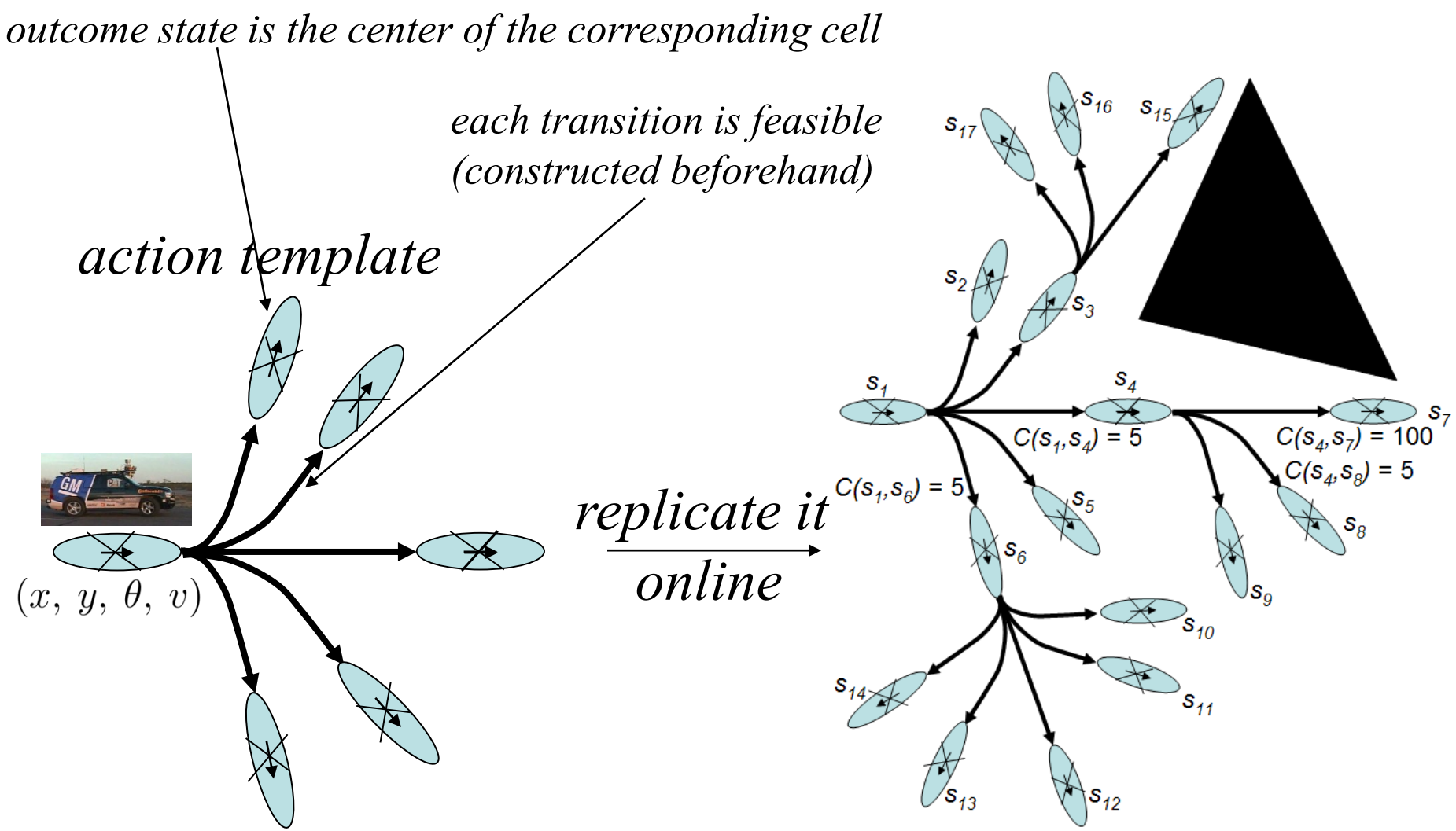

Building the Graph

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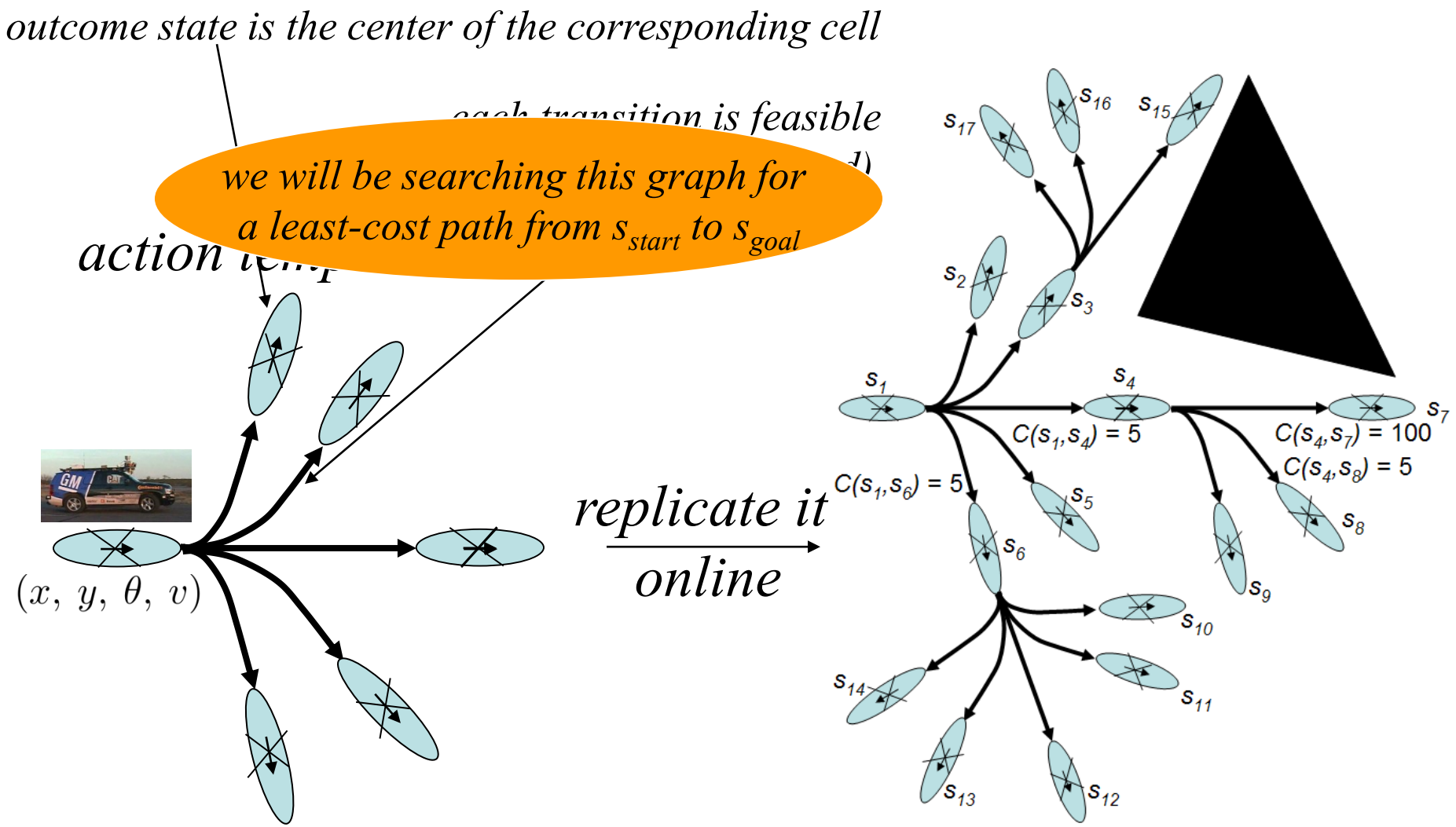
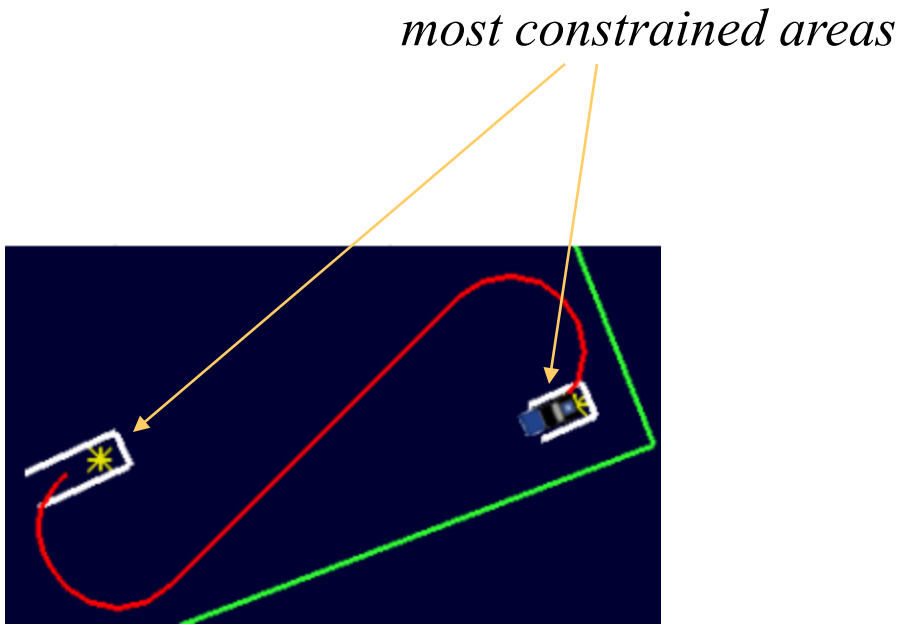


Building the Graph

- Multi-resolution lattice:
  - high density in the most constrained areas (e.g., around start/goal)
  - low density in areas with higher freedom for motions



Building the Graph

- The construction of multi-resolution lattice:
  - the action space of a low-resolution lattice is a strict subset of the action space of the high-resolution lattice

reduces the branching factor for the low-res. lattice

Building the Graph

- The construction of multi-resolution lattice:
  - the action space of a low-resolution lattice is a strict subset of the action space of the high-resolution lattice

reduces the branching factor for the low-res. lattice

  - the state-space of a low-resolution lattice is discretized to be a subset of the possible discretized values of the state variables in the high-resolution lattice

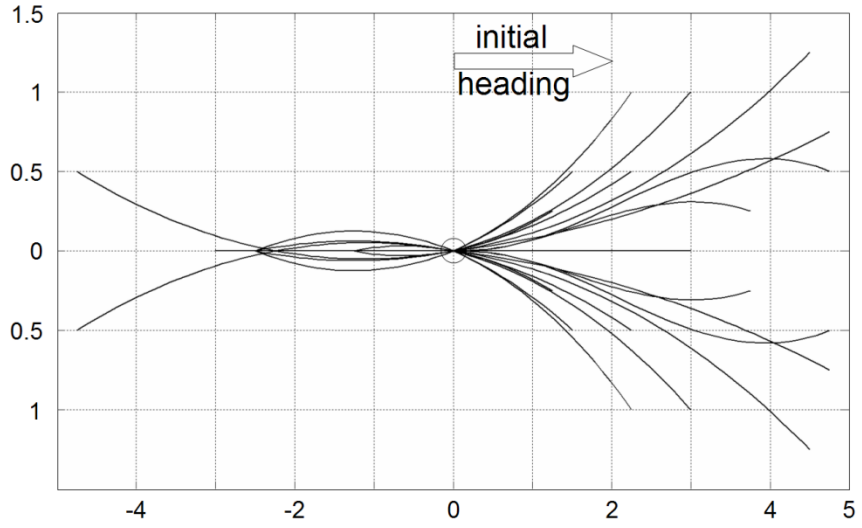
reduces the size of the state-space for the low-res. lattice

both allow for seamless transitions

Building the Graph

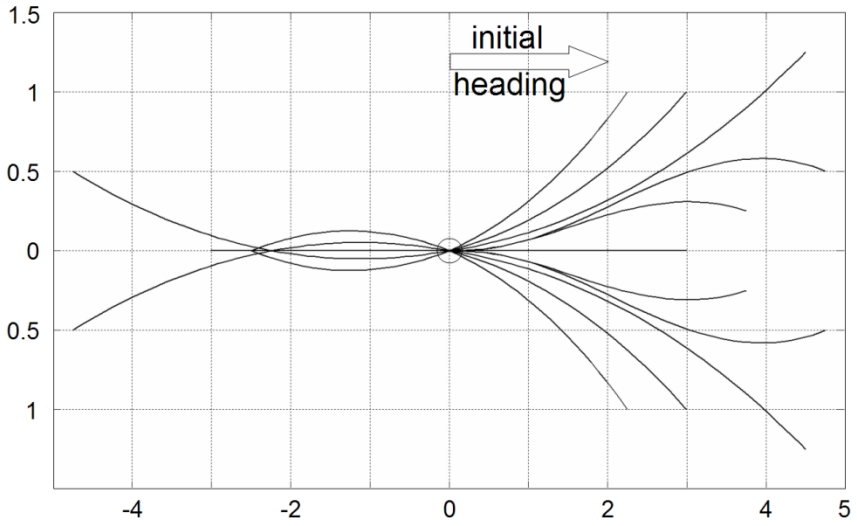
- Multi-resolution lattice used for Urban Challenge:

dense-resolution lattice



36 actions,
32 discrete values of heading
0.25m discretization for x,y

low-resolution lattice



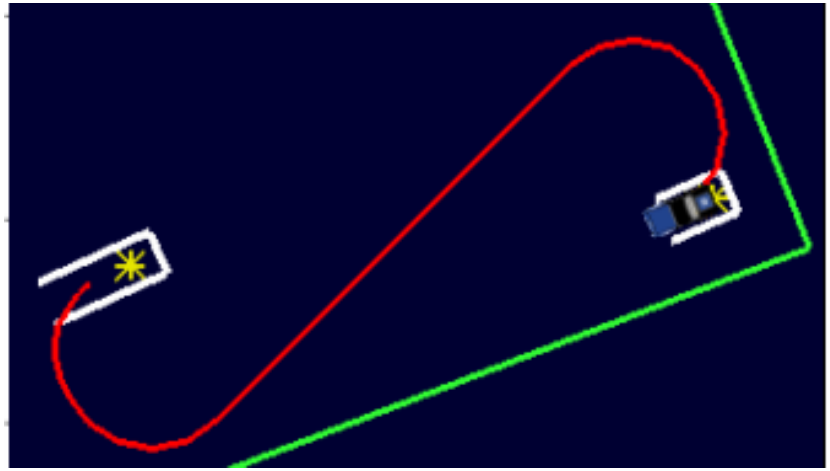
24 actions,
16 discrete values of heading
0.25m discretization for x,y

Building the Graph

- Properties of multi-resolution lattice:
  - ***utilization of low-resolution lattice:*** *every path that uses only the action space of the low-resolution lattice is guaranteed to be a valid path in the multi-resolution lattice*
  - ***validity of paths:*** *every path in the multi-resolution lattice is guaranteed to be a valid path in a lattice that uses only the action space of the high-resolution lattice*

Building the Graph

- Benefit of the multi-resolution lattice:



Lattice	States Expanded	Planning Time (s)
High-resolution	2,933	0.19
Multi-resolution	1,228	0.06

Searching the Graph

- Anytime D*:
  - anytime incremental version of A*
  - **anytime:** computes the best path it can within provided time and improves it while the robot starts execution.
  - **incremental:** it reuses its previous planning efforts and as a result, re-computes a solution much faster

Searching the Graph

- Anytime D*:

desired bound on the

computes a path reusing all of the previous search efforts

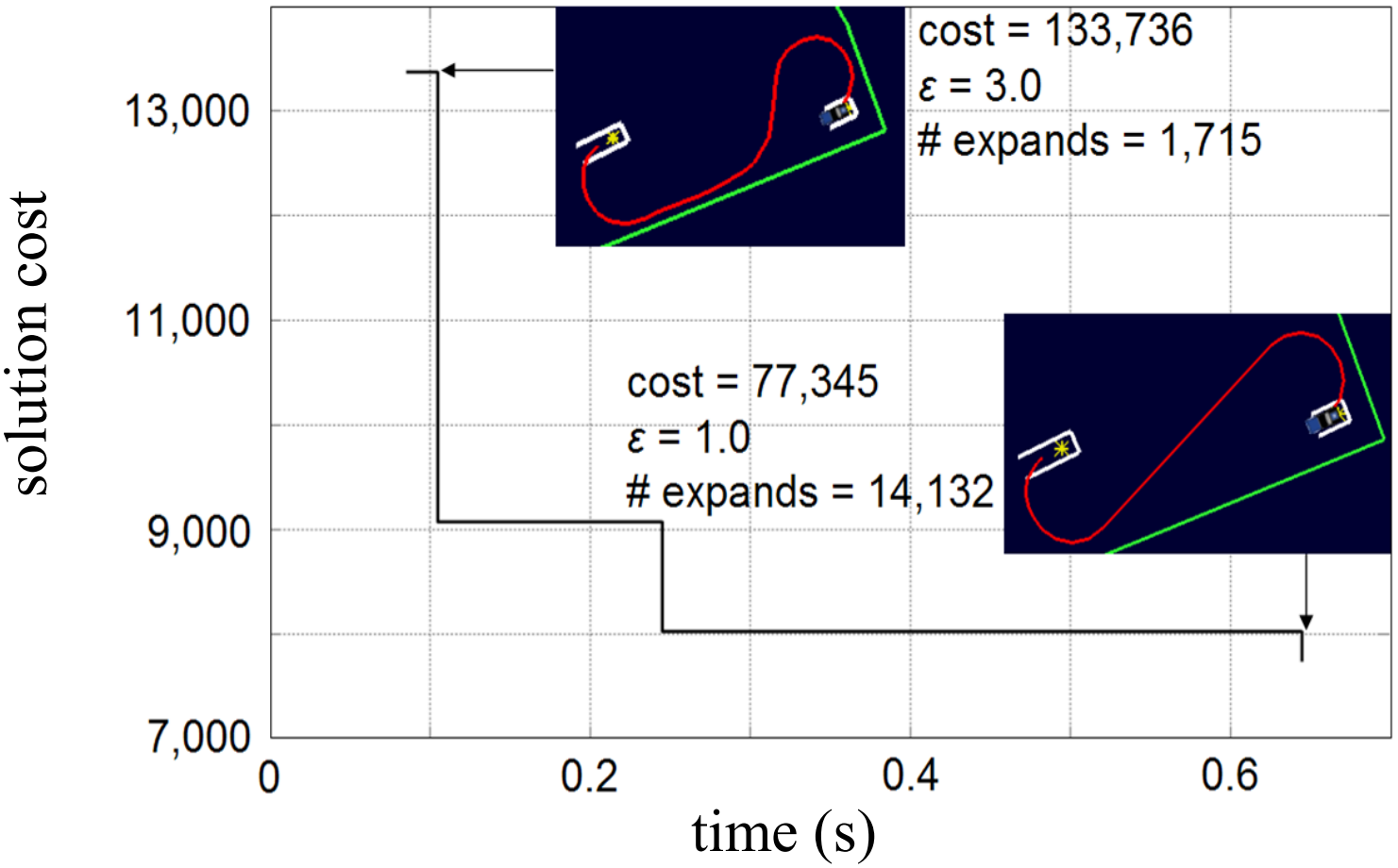
set ε to large value;
until goal is reached
    ComputePathwithReuse();
    publish ε-suboptimal path for execution;
    update the map based on new sensory information;
    update current state of the agent;
    if significant changes were observed
        increase ε or replan from scratch;
    else
        decrease ε;

guarantees that cost(path) $\leq \varepsilon$ cost(optimal path)

makes it improve the solution

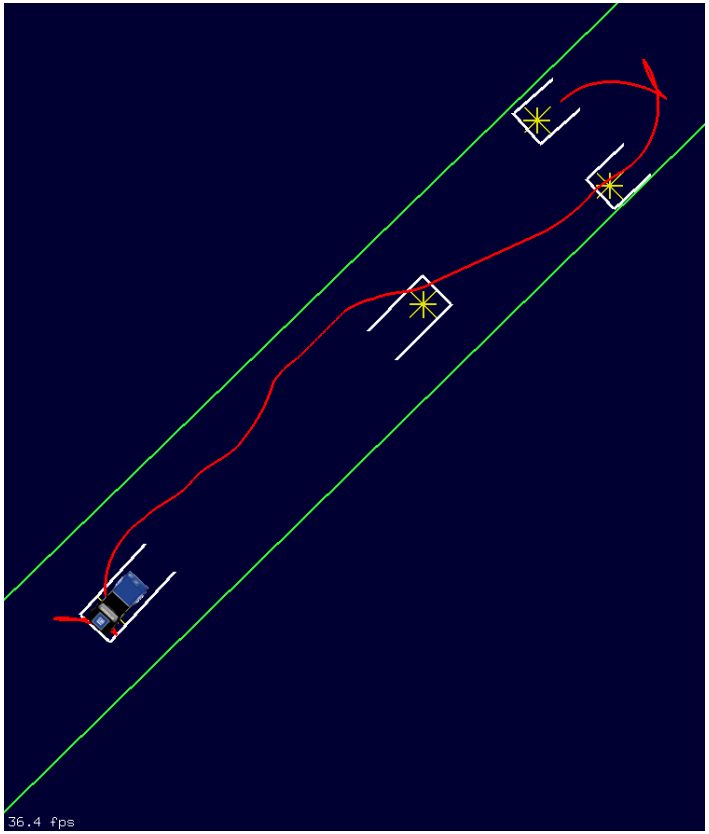
Searching the Graph

- Anytime behavior of Anytime D*:

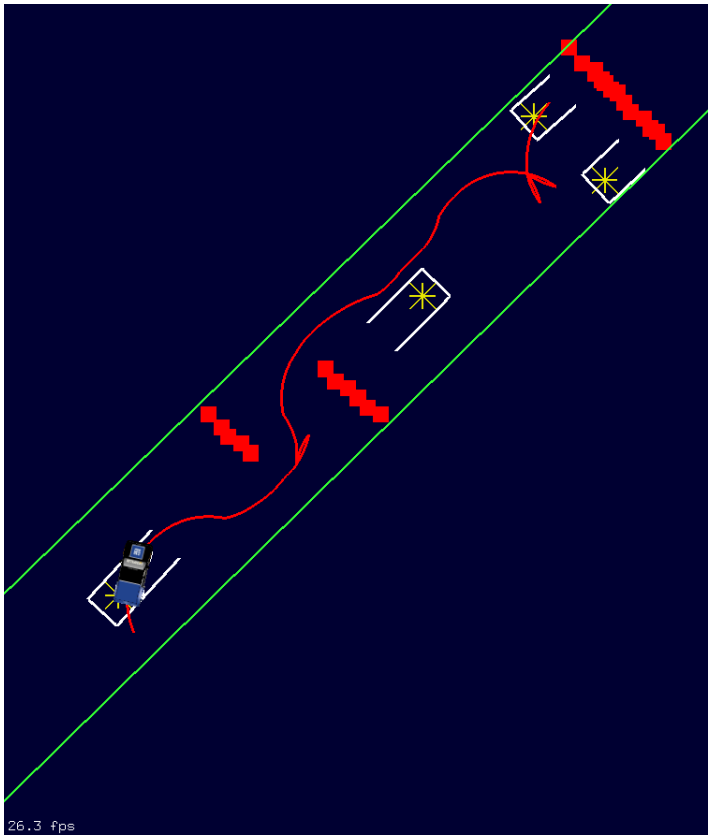


Searching the Graph

- Incremental behavior of Anytime D*:



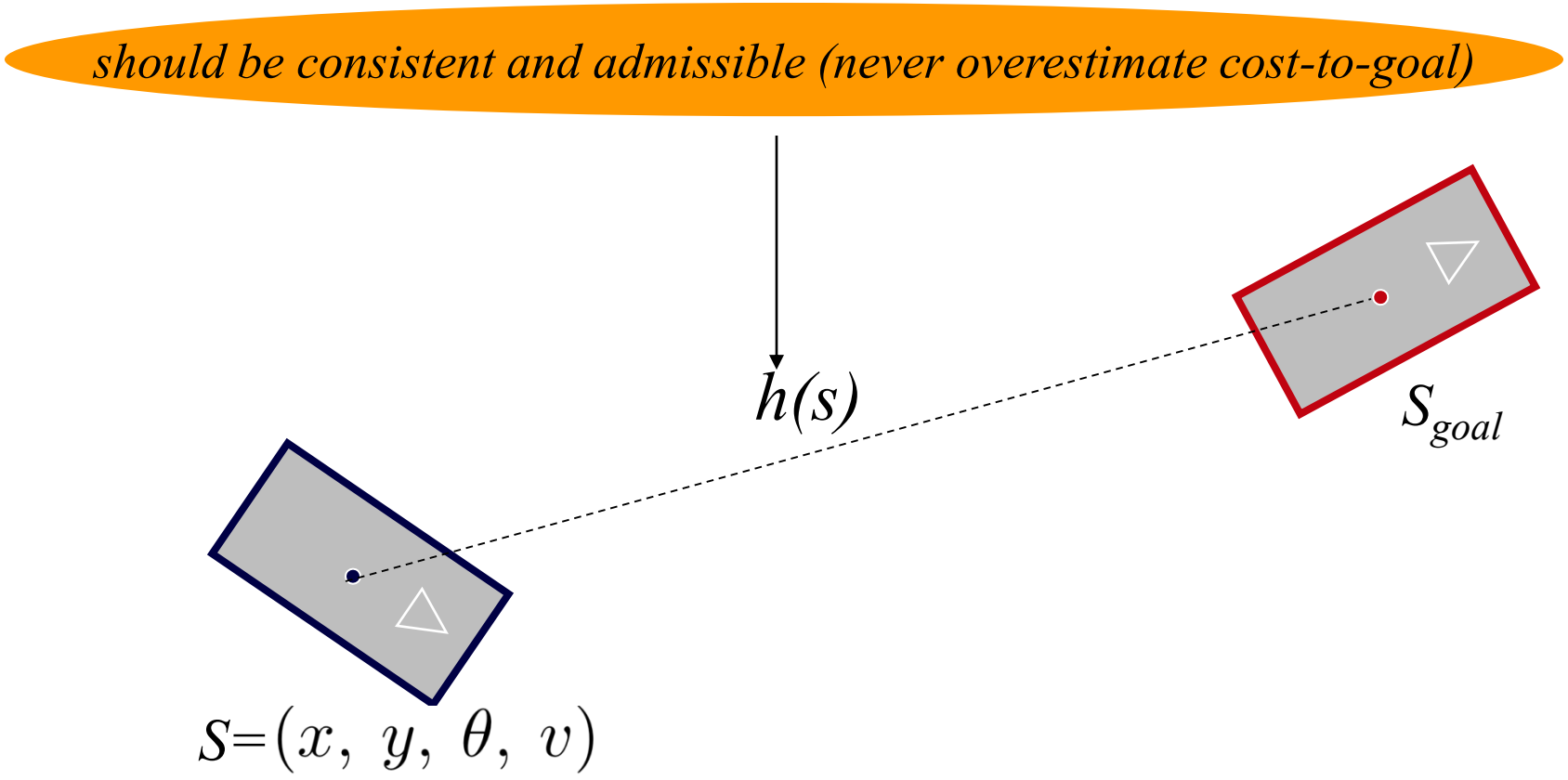
initial path



a path after re-planning

Searching the Graph

- Performance of Anytime D* depends strongly on heuristics *h(s)*: estimates of cost-to-goal



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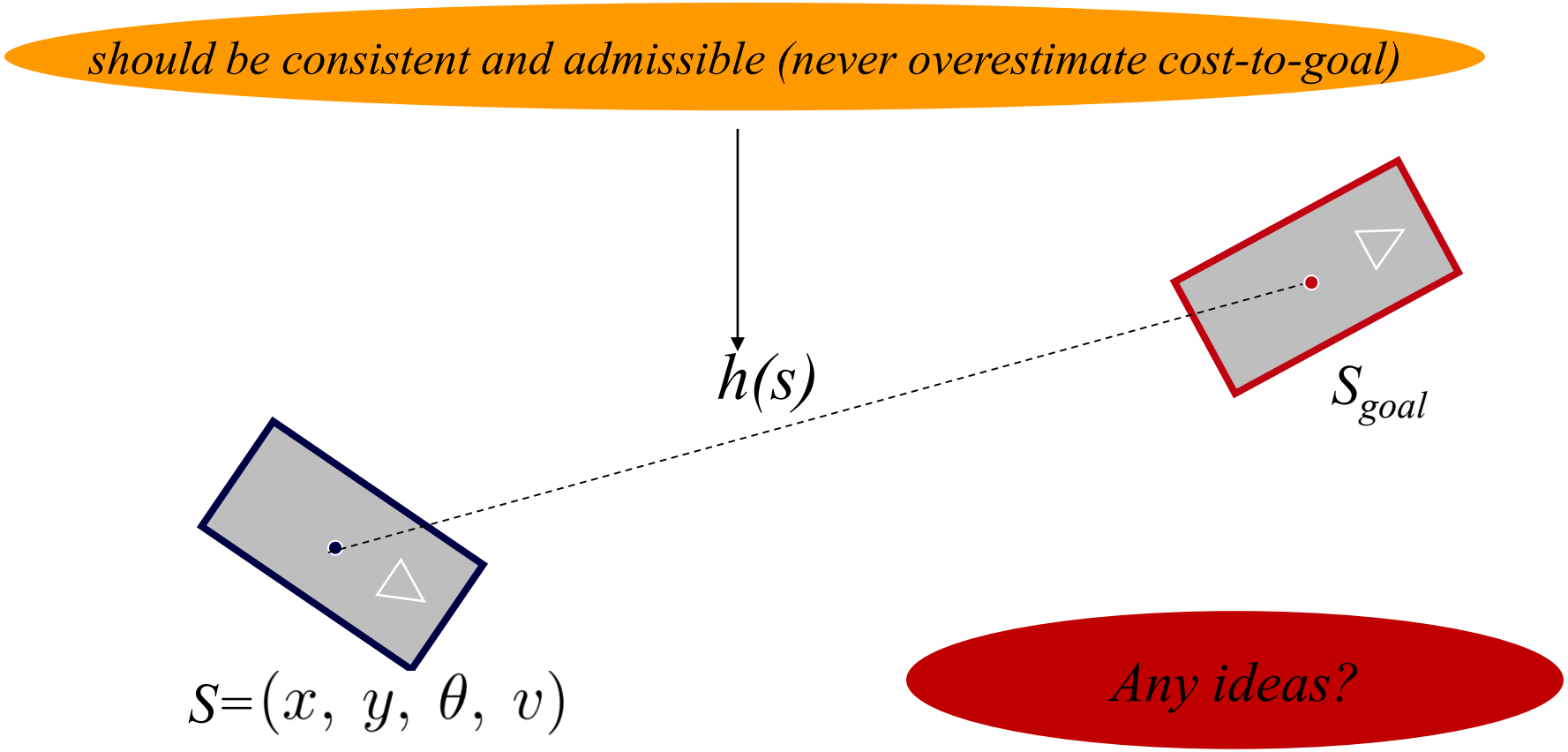
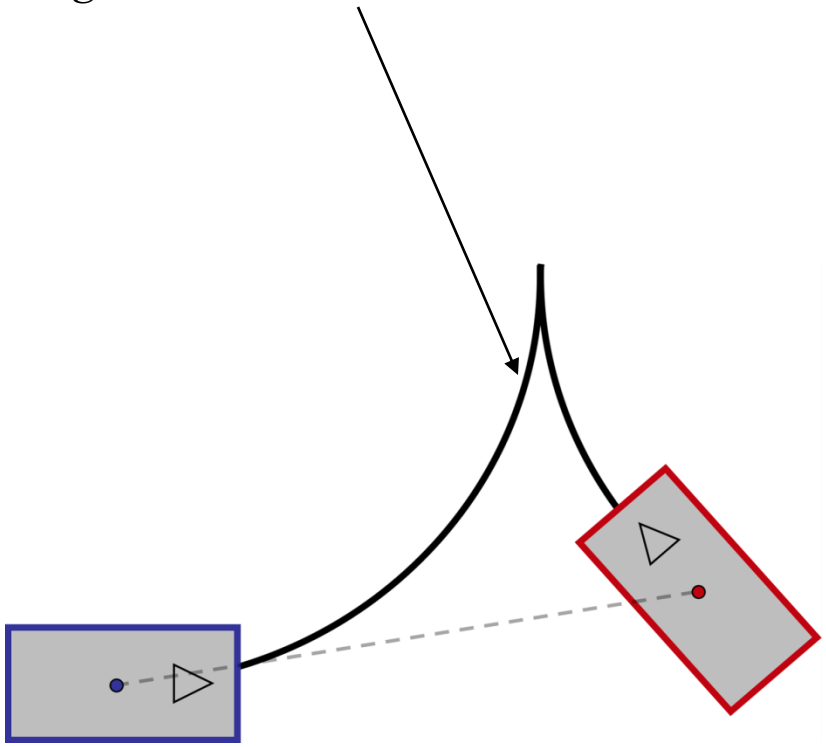


Searching the Graph

- In our planner: $h(s) = max(h_{mech}(s), h_{env}(s))$, where
  - $h_{mech}(s)$ – mechanism-constrained heuristic
  - $h_{env}(s)$ – environment-constrained heuristic

$h_{mech}(s)$ – considers only dynamics constraints and ignores environment



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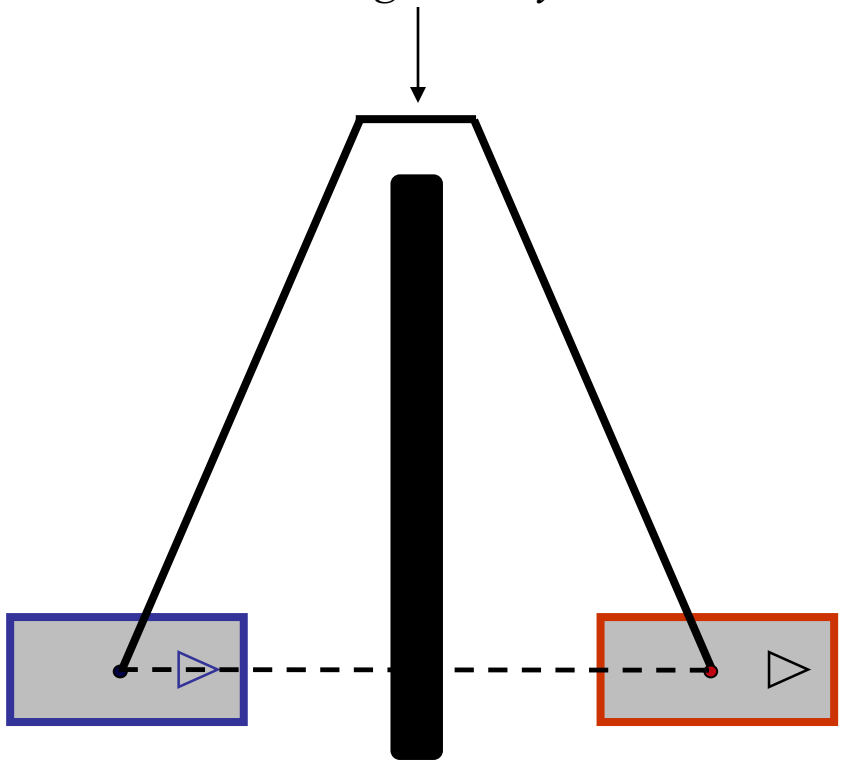

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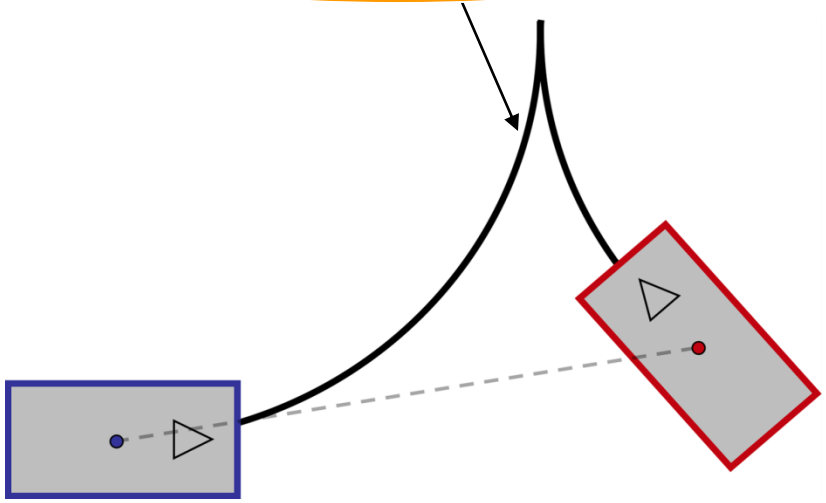
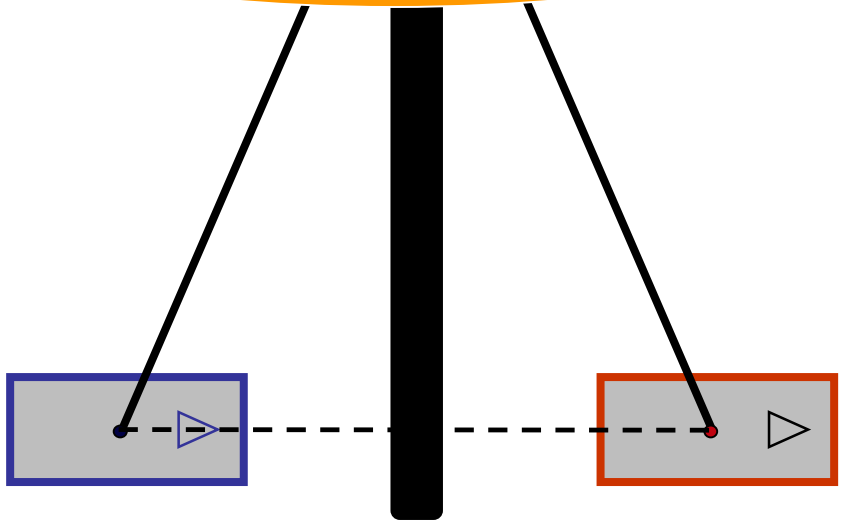
$h_{mech}(s)$ – considers only dynamics constraints and ignores environment

pre-computed as a table lookup for high-res. lattice



$h_{env}(s)$ – considers only environment constraints and ignores dynamics

computed online by running a 2D A with late termination*



Searching the Graph

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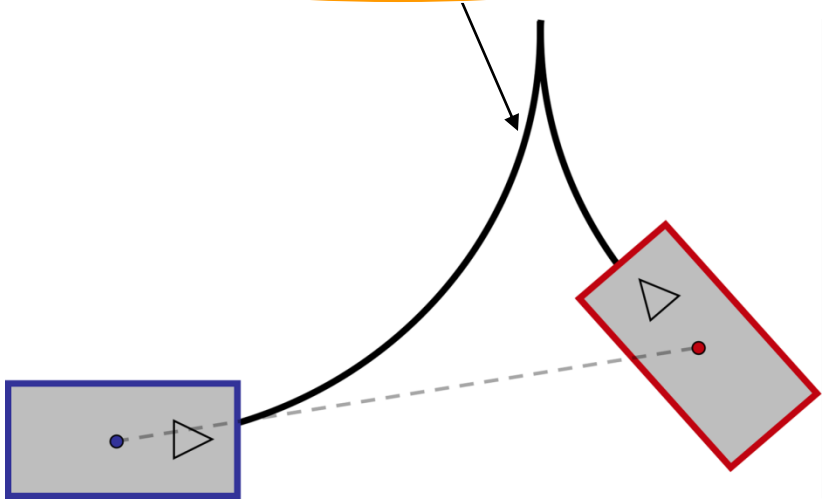

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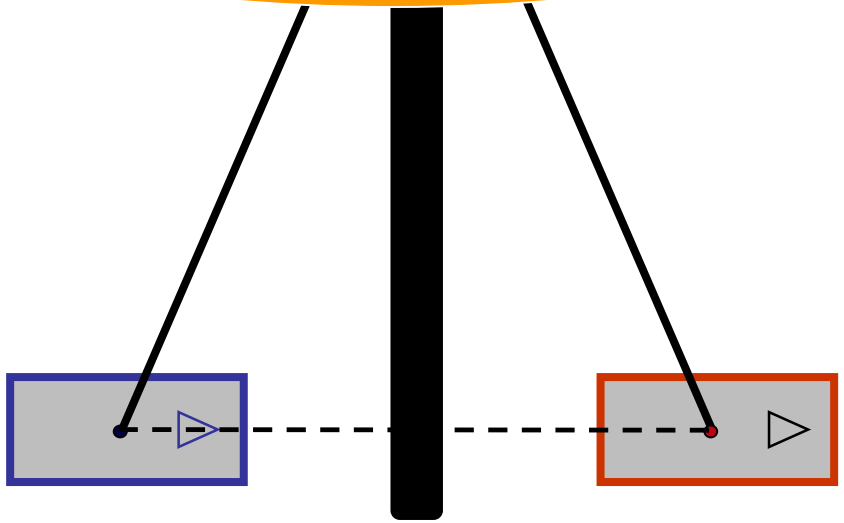


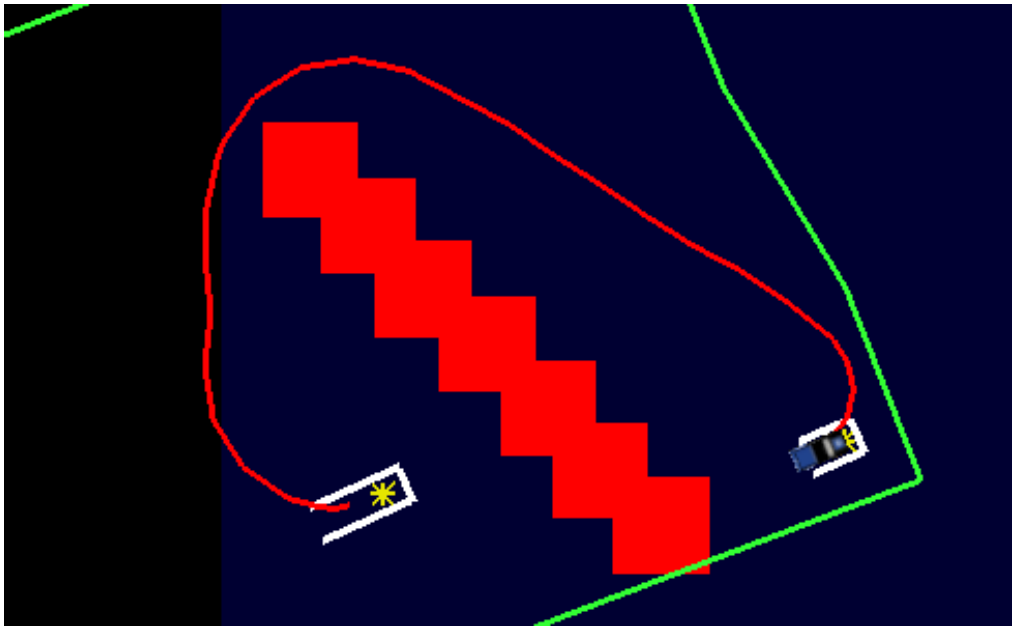
Searching the Graph

- In our planner: $h(s) = max(h_{mech}(s), h_{env}(s))$
- $h_{mech}(s)$ – admissible and consistent
- $h_{env}(s)$ – admissible and consistent
- $h(s)$ – admissible and consistent

Theorem. *The cost of a path returned by Anytime D* is no more than ε times the cost of a least-cost path from the vehicle configuration to the goal configuration using actions in the multi-resolution lattice, where ε is the current value by which Anytime D* inflates heuristics.*

Searching the Graph

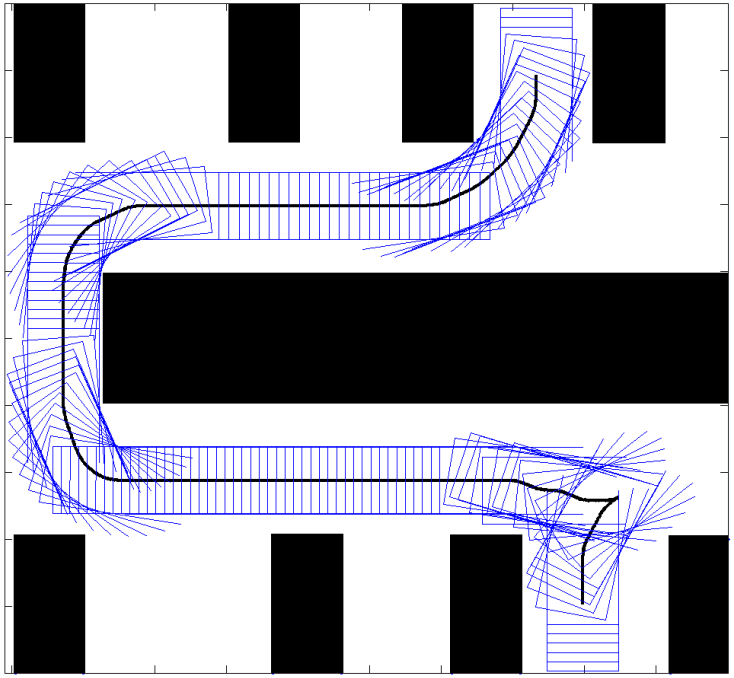
- Benefit of the combined heuristics:



Heuristic	States Expanded	Planning Time (s)
Environment-constrained only	26,108	1.30
Mechanism-constrained only	124,794	3.49
Combined	2,019	0.06

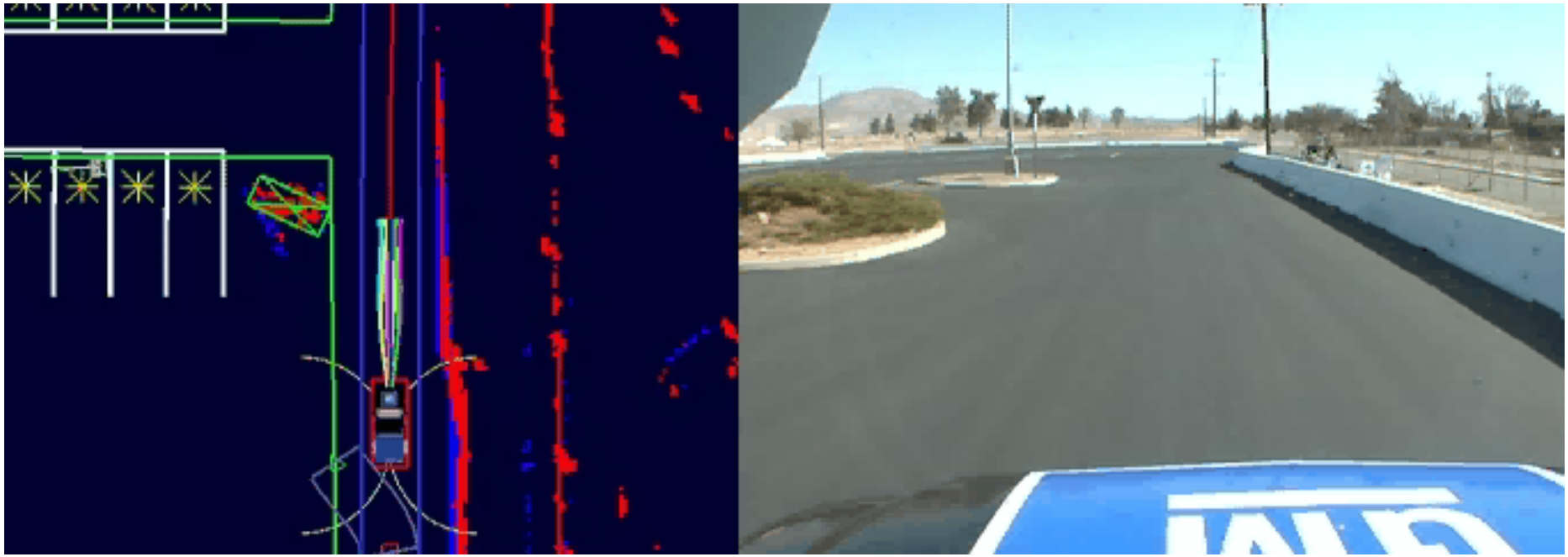
Optimizations

- Pre-compute as much as possible
  - convolution cells for each action for each initial heading



Results

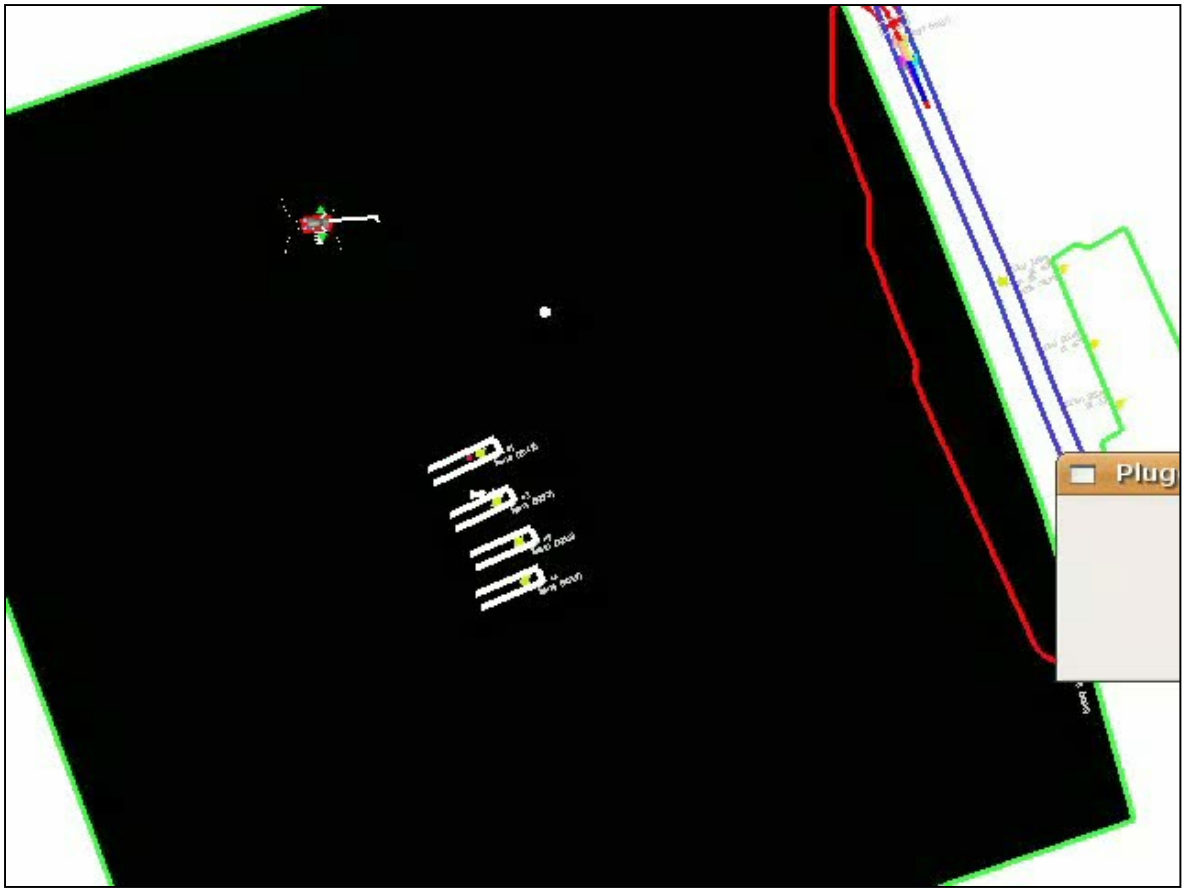
- Plan improvement



Tartanracing, CMU

Results

- Replanning in a large parking lot (200 by 200m)



Tartanracing, CMU

Summary

- Multiple levels of planning (high-level route planning to motion planning to local planning/path following)

- Multi-resolution lattice in Motion Planner is beneficial
  - seamless transitions in between resolutions
  - a simple but general enough for planning with other dimensions

- Anytime re-planner is critical
  - improves the solution as time allows and during execution
  - reuses previous search efforts for faster re-planning

- Design of proper heuristics is a key to efficiency