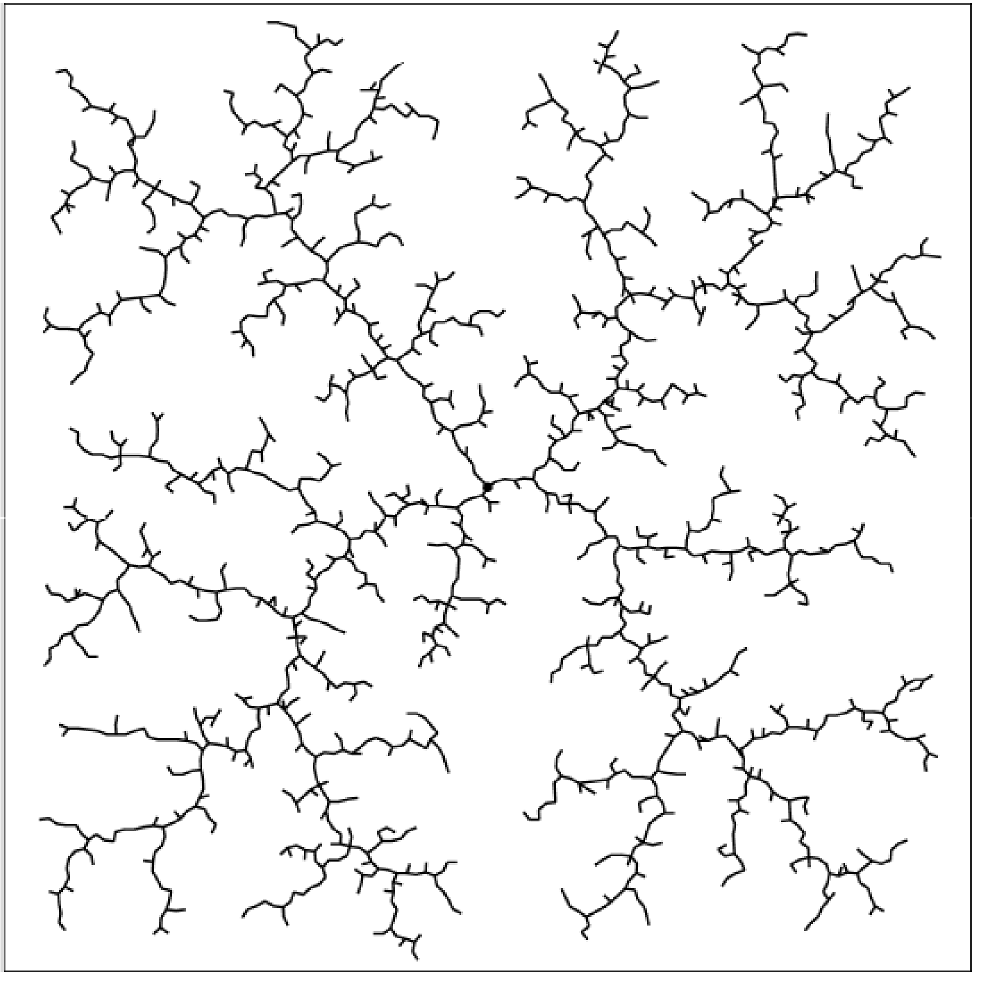
Rapidly-Exploring Random Trees (RRTs)



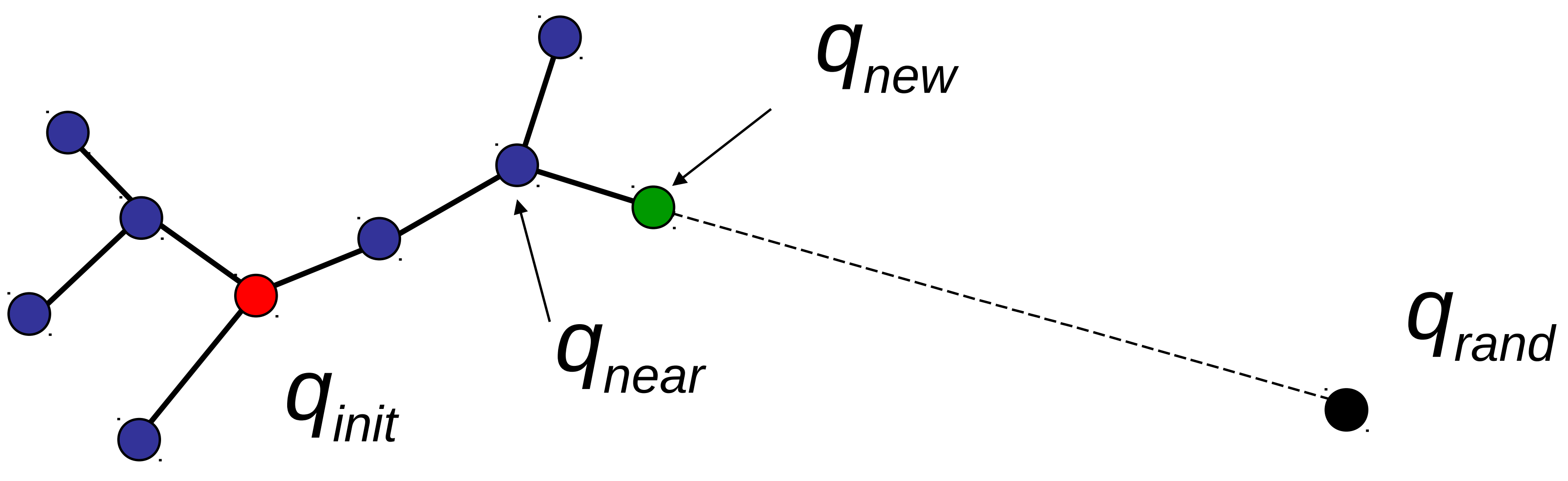
Robert Platt

Northeastern University

These slides contain material aggregated/developed by Howie Choset and others

Basic RRT Algorithm (no goal)

function RRT (q_{init}):
 T=q_{init}
 for i = 1 to K do:
  q_{rand} = RANDOM_CONFIG();
  T.EXTEND(q_{rand})



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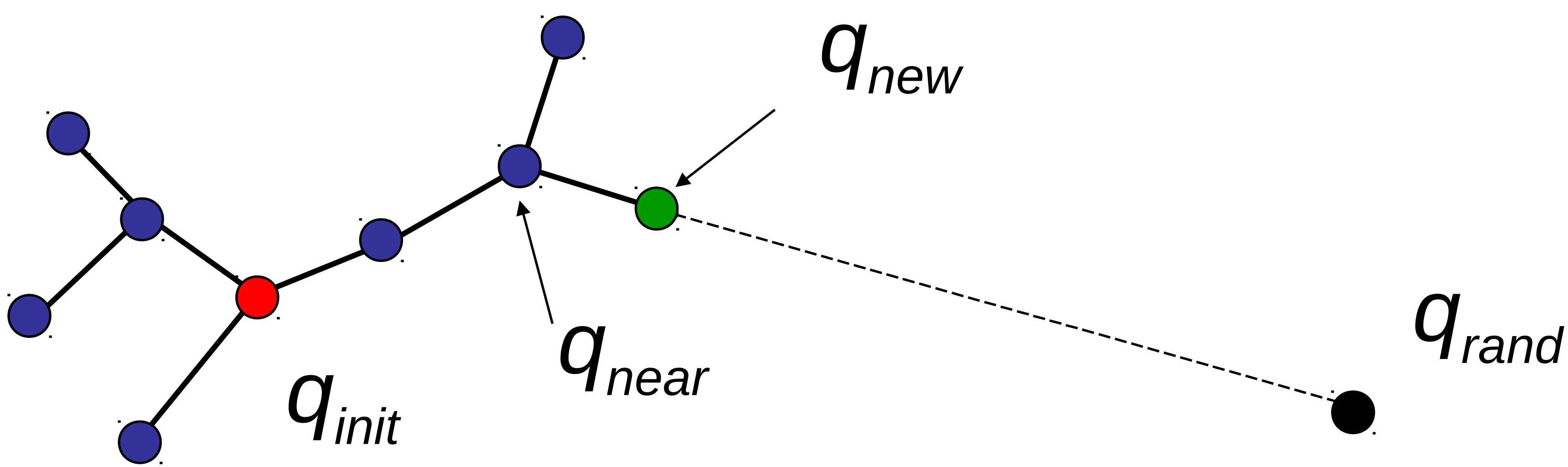


Basic RRT Algorithm (no goal)

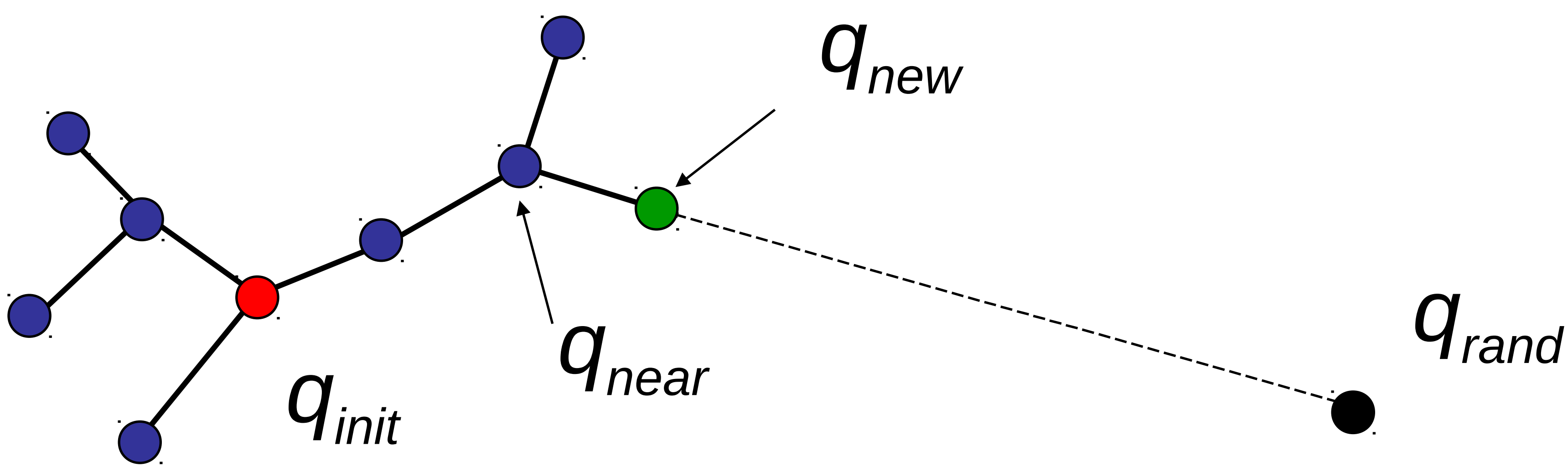
function RRT (q_{init}):
  $T = q_{init}$
  for i = 1 to K do:
    q_{rand} = RANDOM_CONFIG();
    T.EXTEND(q_{rand})

STEP_LENGTH: How far to sample

1. Sample just at end point
2. Sample all along
3. Small Step

Extend returns

1. Trapped, cant make it
2. Extended, steps toward node
3. Reached, connects to node



Basic RRT Algorithm

function RRT ($q_{init,}$ q_{goal}):

T=q_{init}

for i = 1 to K do:

if rand01() < 0.1:

q_{rand} =q_{goal}

else

q_{rand} = RANDOM_CONFIG();

T.EXTEND(q_{rand})

STEP_LENGTH: How far to sample

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Extend returns

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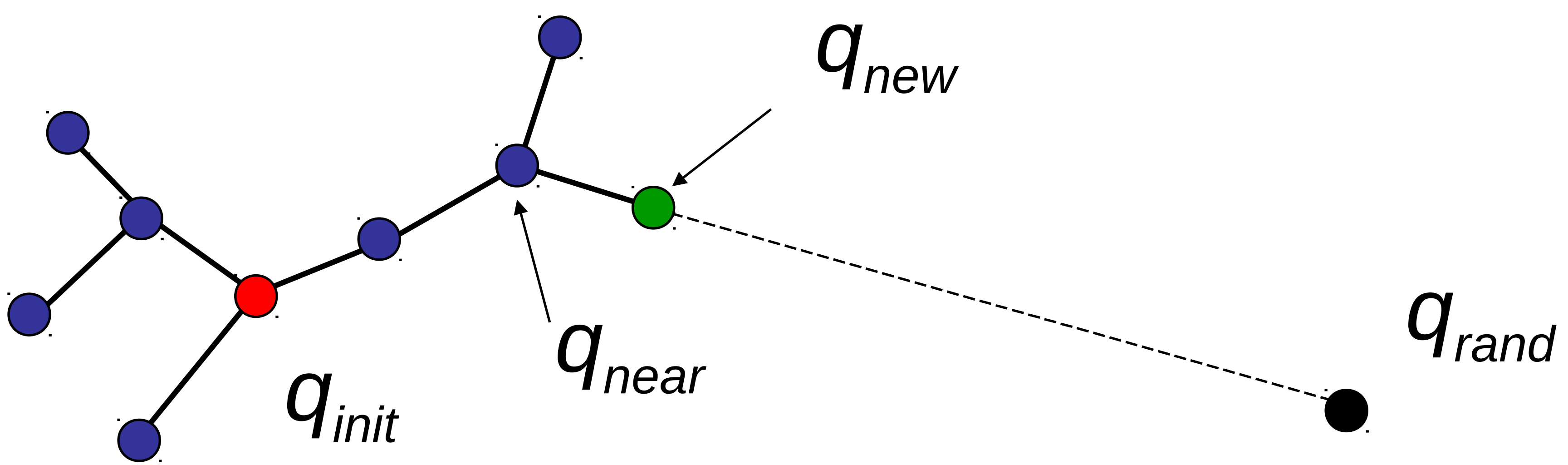
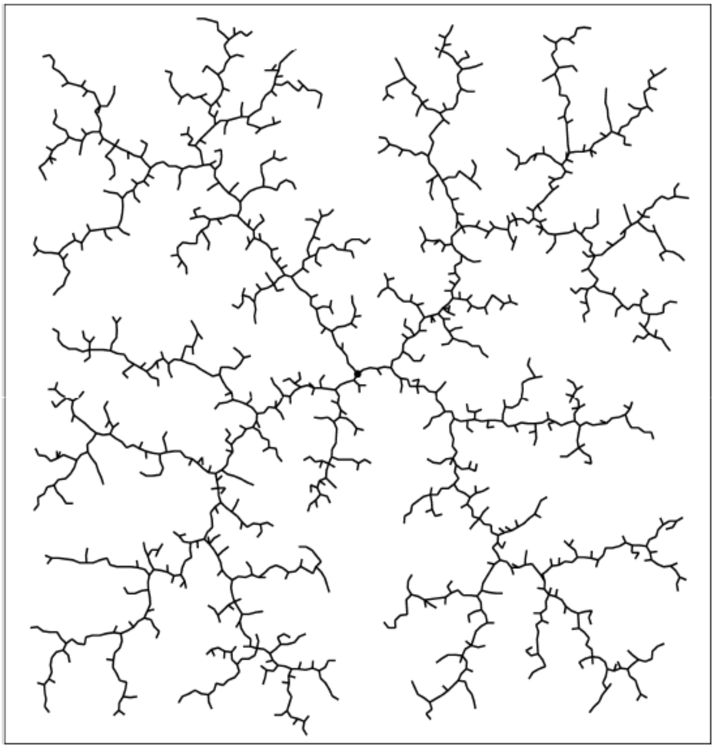
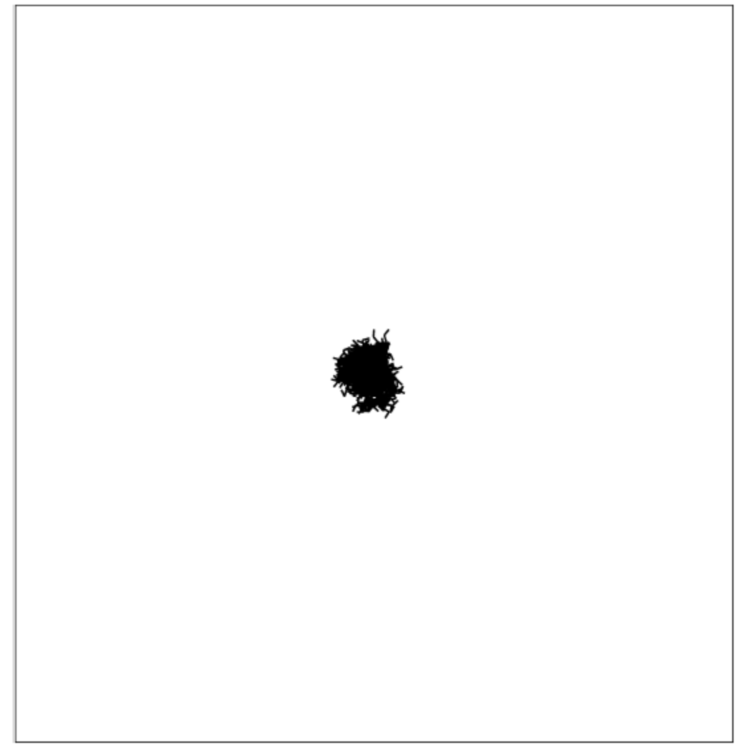


RRT versus a naïve random tree

RRT

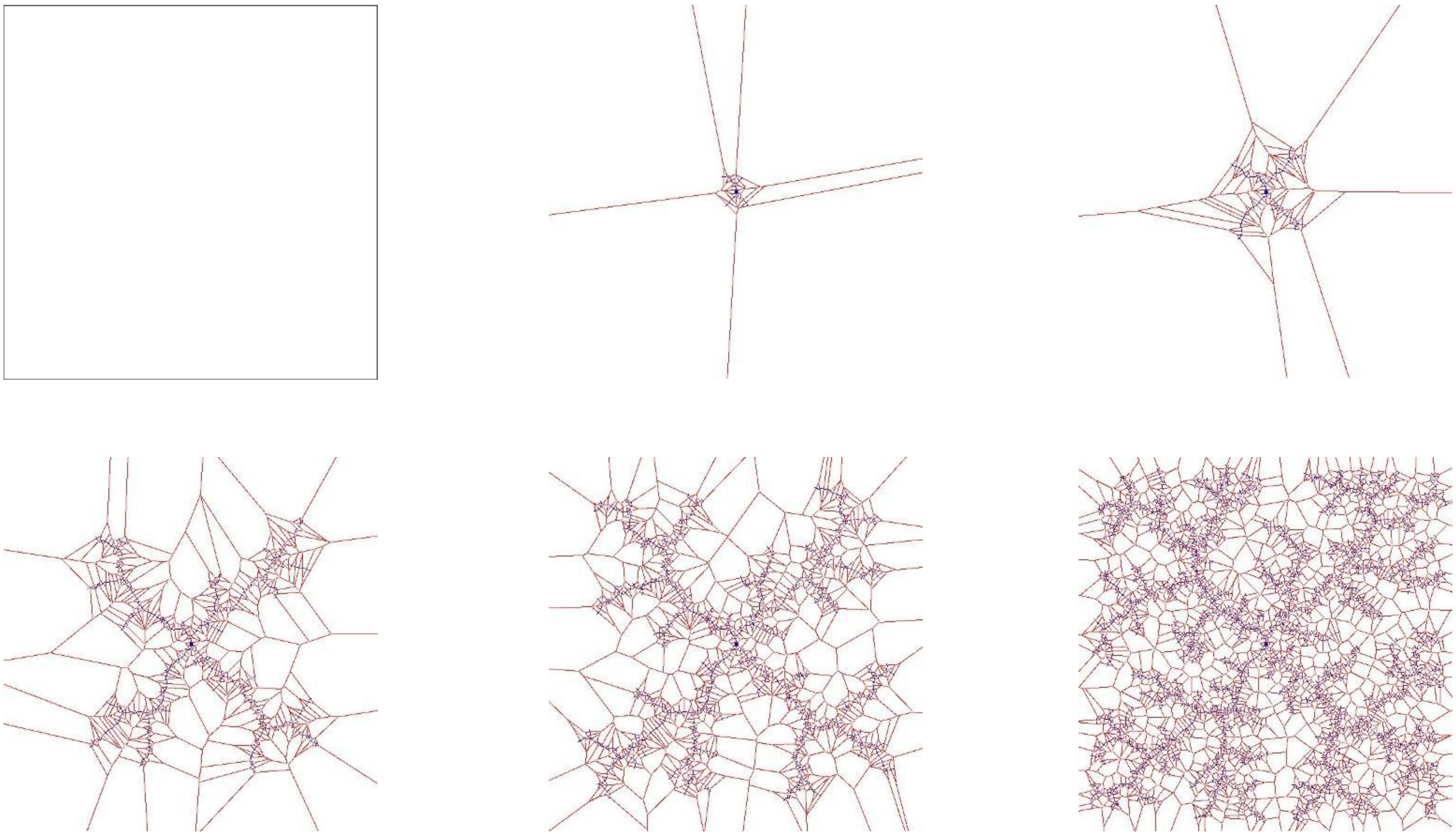


Naïve random tree



<u>Growing the naïve random tree</u>:
1. pick a node at random
2. sample a new node near it
3. grow tree from random node to new node

RRTs and
Bias toward large Voronoi regions



http://msl.cs.uiuc.edu/rrt/gallery.html

Biases

- Bias toward larger spaces
- Bias toward goal
  - When generating a random sample, with some probability pick the goal instead of a random node when expanding
  - This introduces another parameter
  - 5-10% is probably the right choice

RRT probabilistic completeness

Theorem (LaValle and Kuffner, 2001):

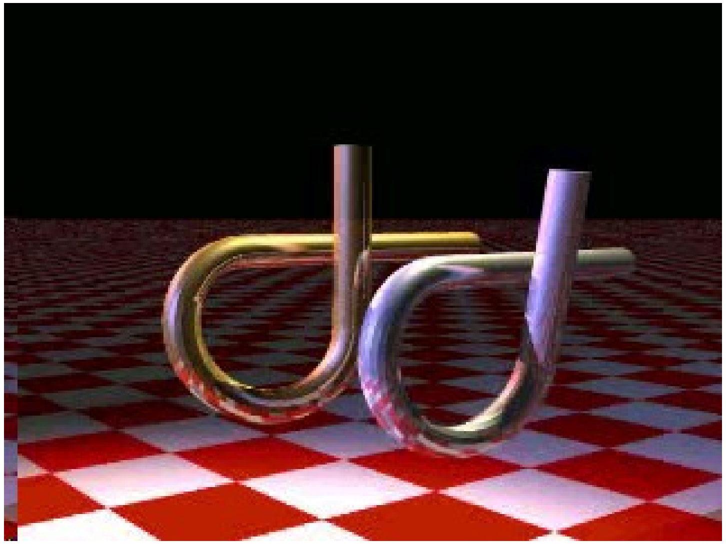
If a path planning problem is feasible, then there exist constants n_0 and a>0, such that:

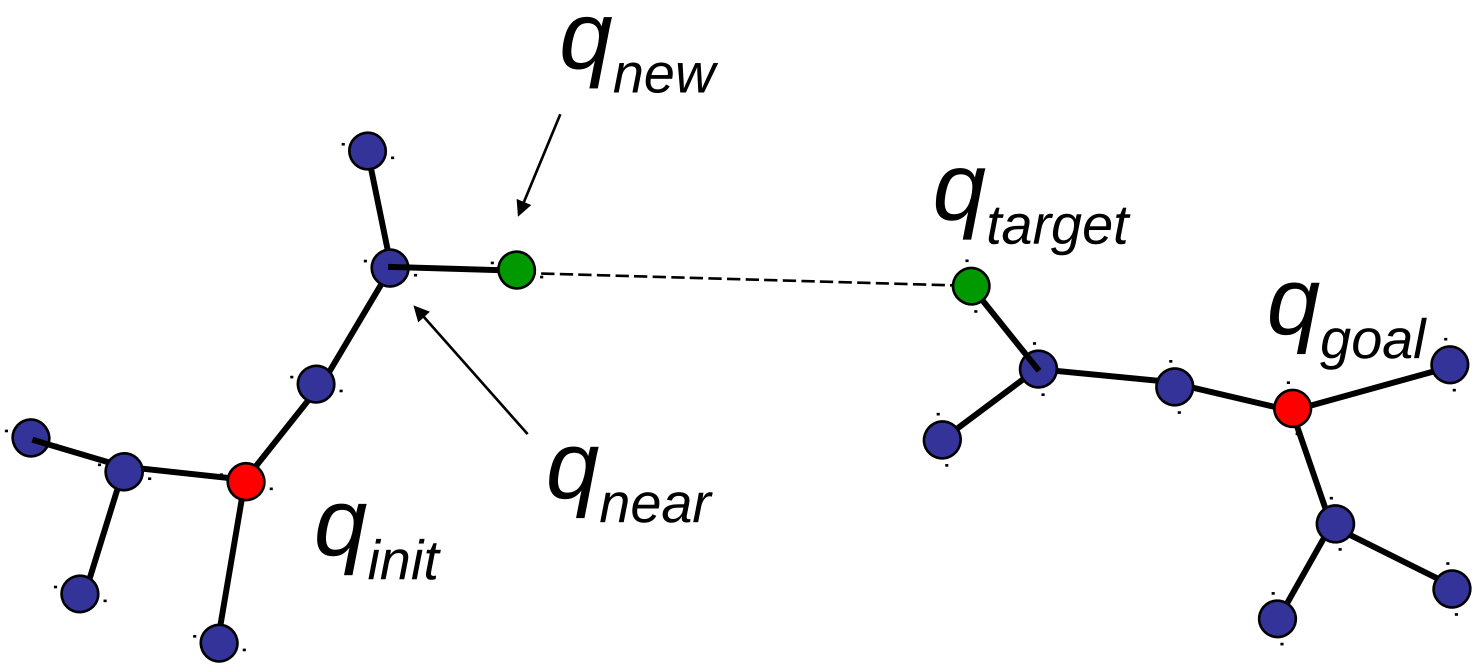
$$P(\text{a path is found}) \geq 1 - e^{-an}$$

where *n*>n_0 is the number of samples

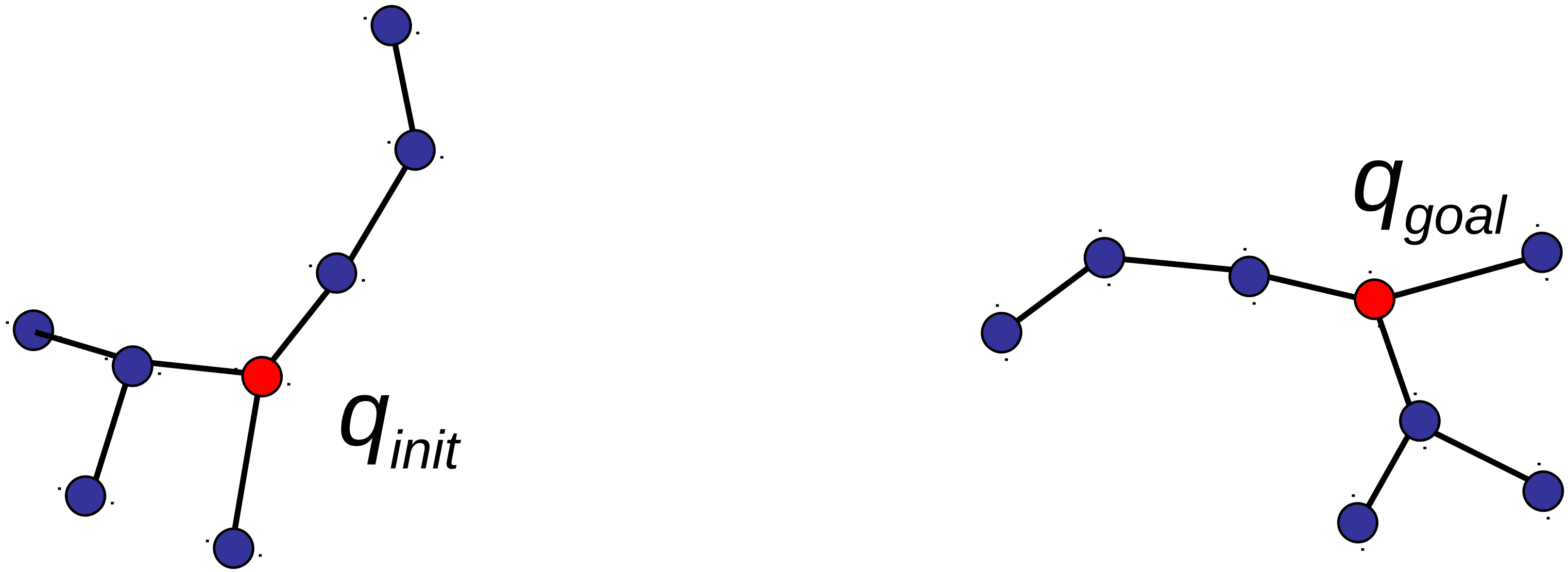
Notice that this is exactly the same theorem as given for PRMs...

RRT-Connect

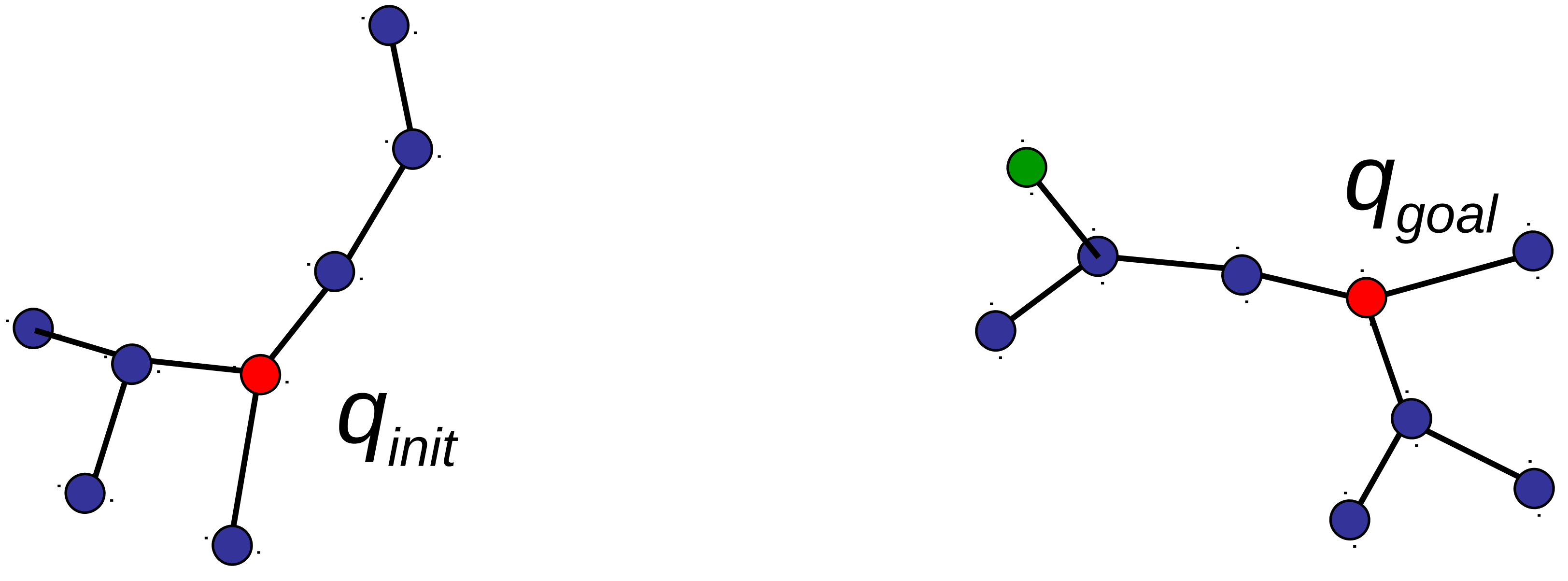




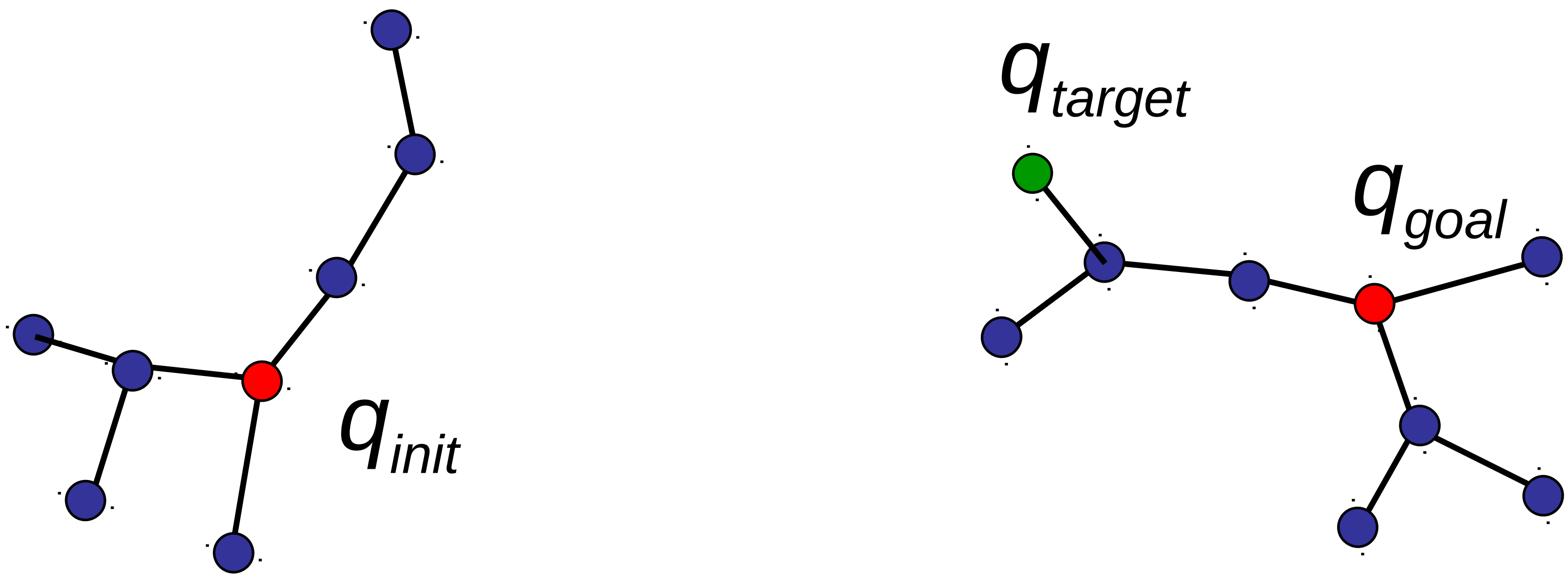
A single RRT-Connect iteration...



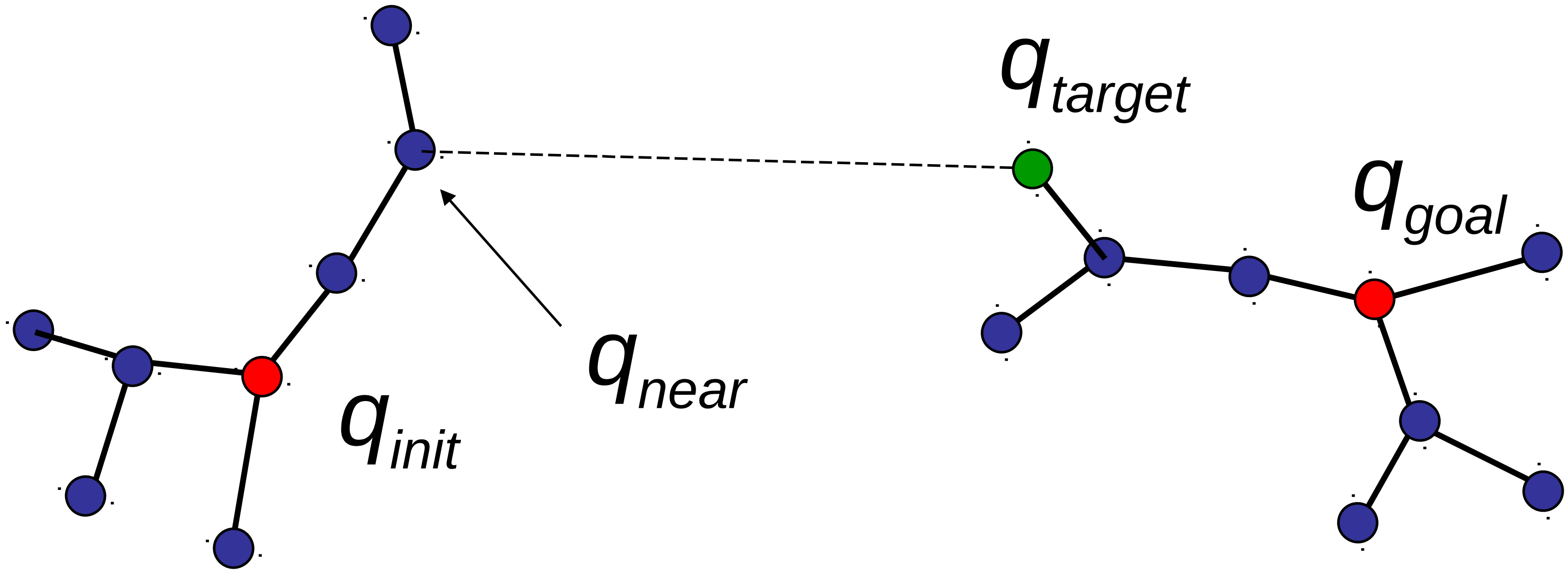
1) One tree grown using random target



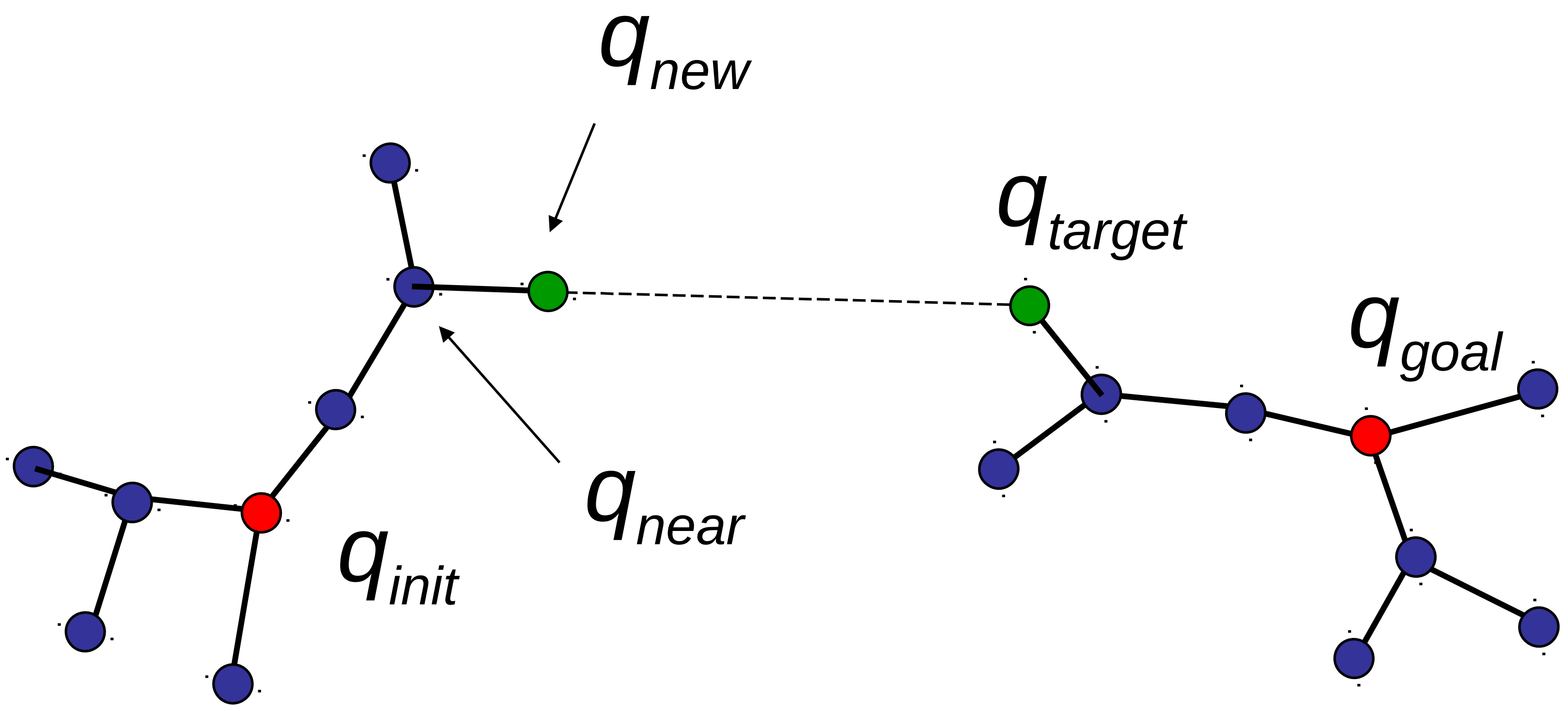
2) New node becomes target for other tree



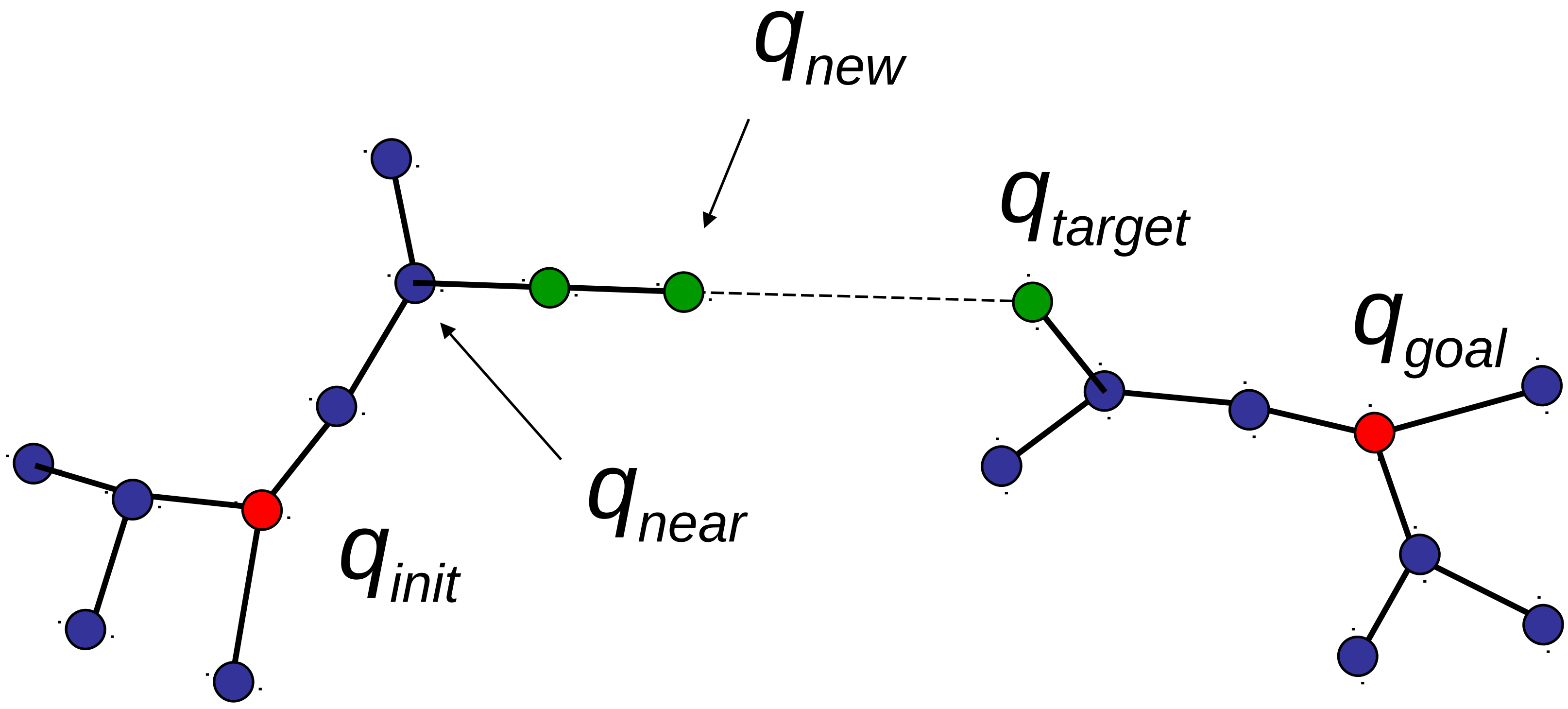
3) Calculate node “nearest” to target



4) Try to add new collision-free branch



5) If successful, keep extending branch



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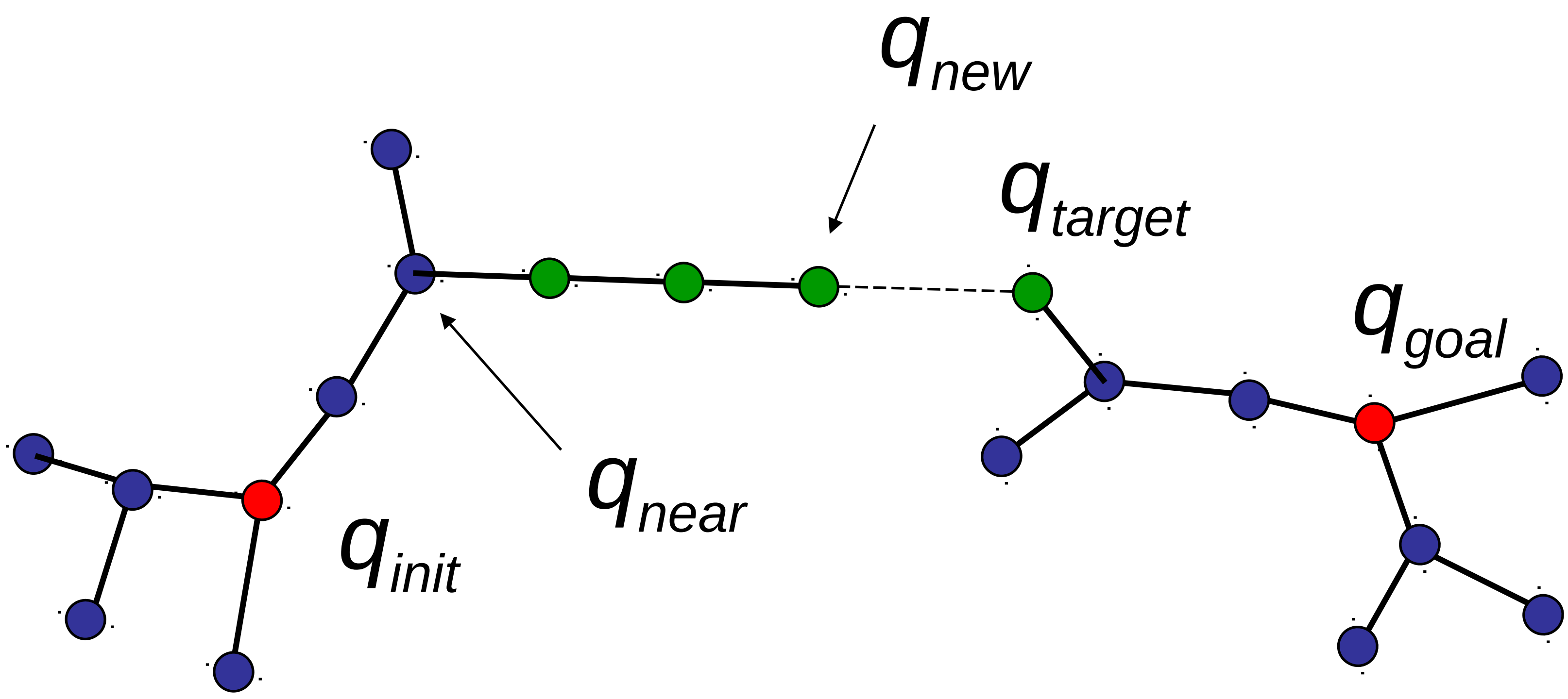

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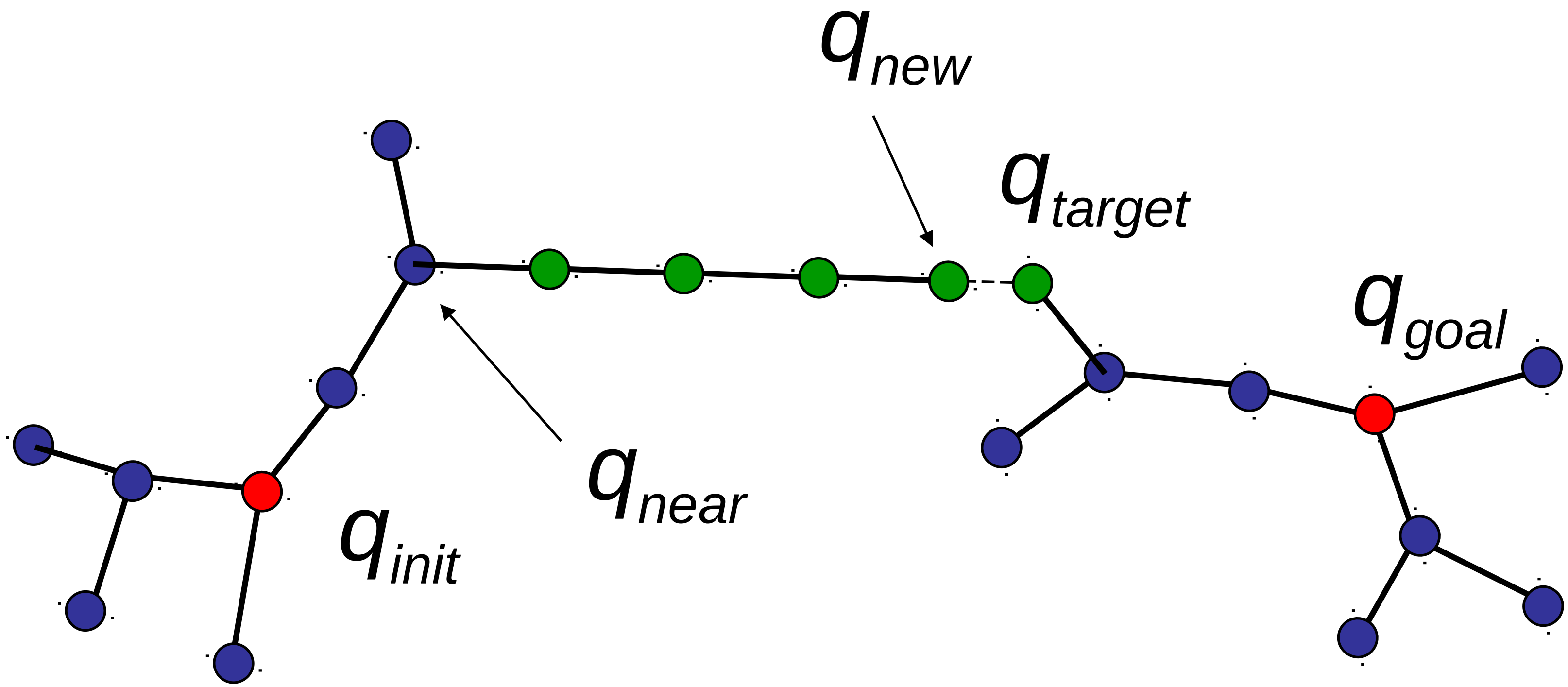
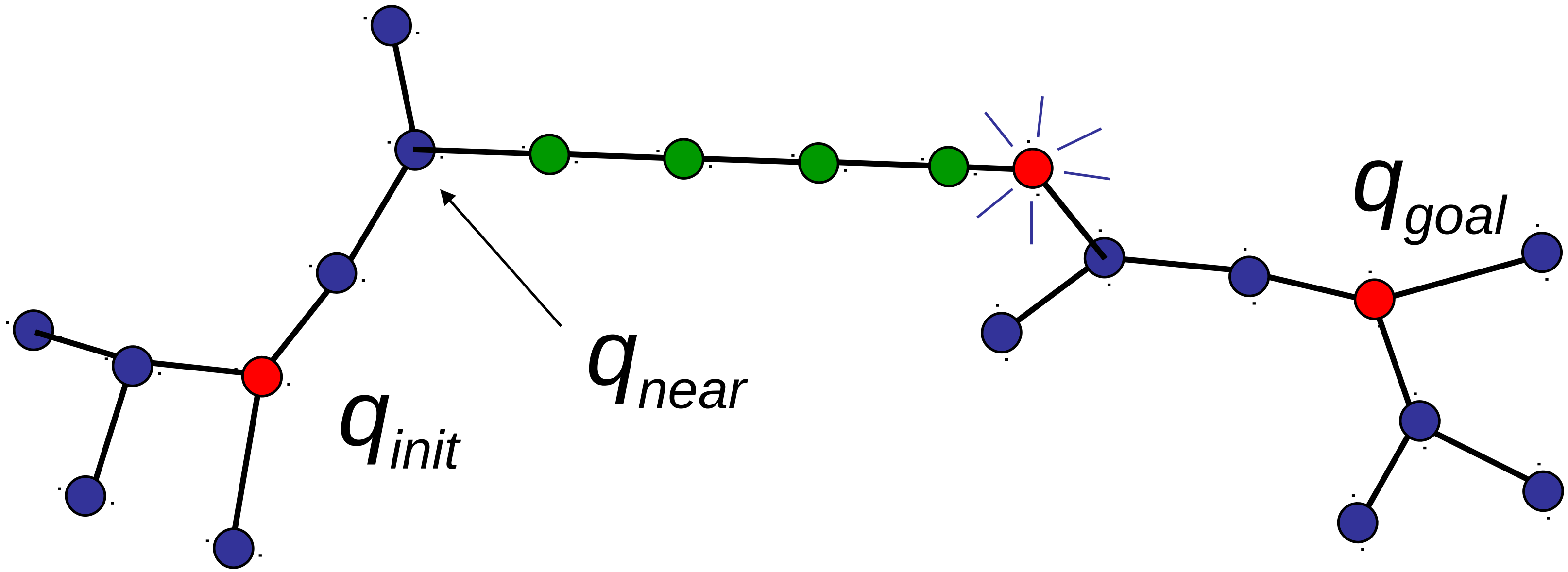
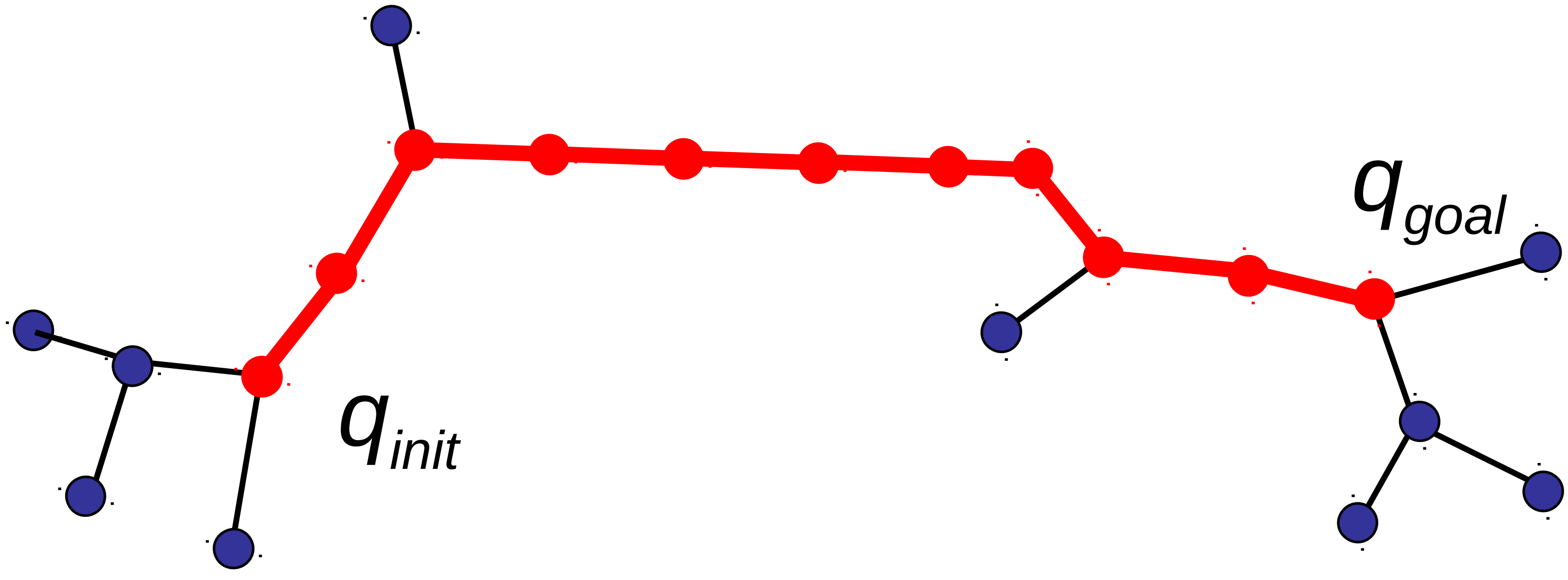


6) Path found if branch reaches target



7) Return path connecting start and goal



Basic RRT-Connect

function RRT_CONNECT ($q_{init,}\ q_{goal}$):

$T_a = q_{init}$; $T_b = q_{goal}$;

for i = 1 to K do

q_{rand} = RANDOM_CONFIG();

if (T_a.EXTEND(q_{rand}) = extended) then

if (T_b.EXTEND(q_{new}) = reached) then

Return PATH($T_{a,}\ T_b$);

SWAP($T_{a,}\ T_b$);

Basic RRT-Connect

function RRT_CONNECT ($q_{init,}$ q_{goal}):

$T_a = q_{init}$; $T_b = q_{goal}$;

for i = 1 to K do

q_{rand} = RANDOM_CONFIG();

if (T_a.EXTEND(q_{rand}) = extended) then

if (T_b.EXTEND(q_{new}) = reached) then

Return PATH($T_{a,}$ T_b);

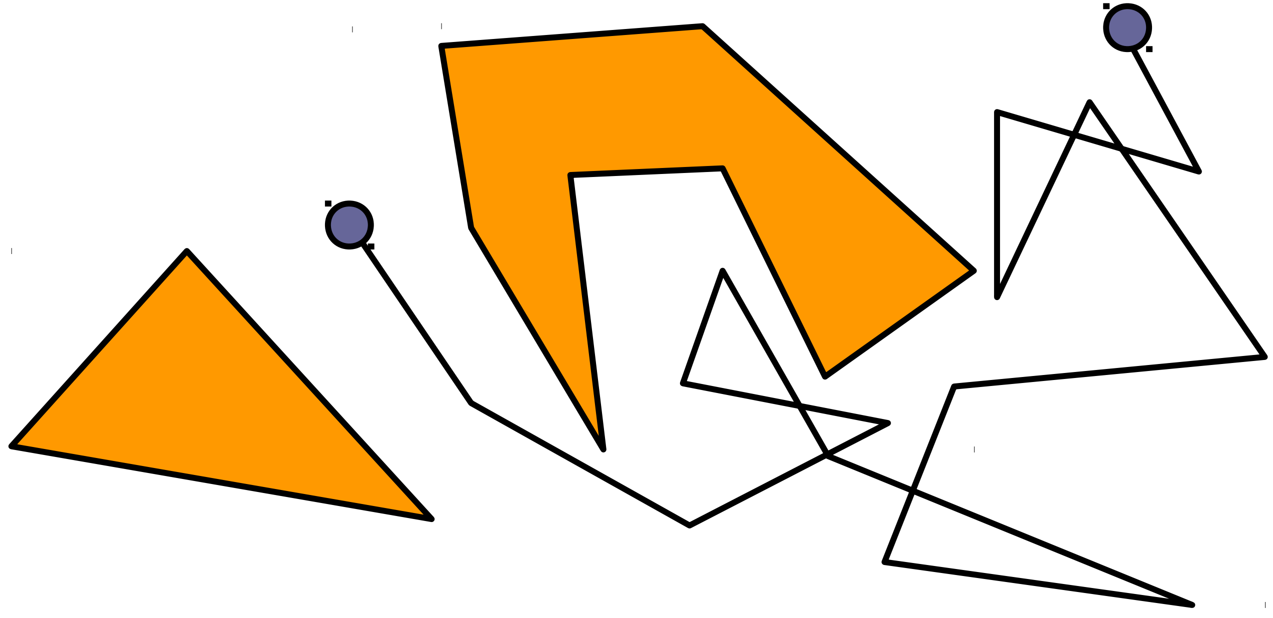
SWAP($T_{a,}$ T_b);

Successfully added a node to tree

Successfully connected T_b to q_new

Instead of switching, use T_a as smaller tree.

Smoothing the path



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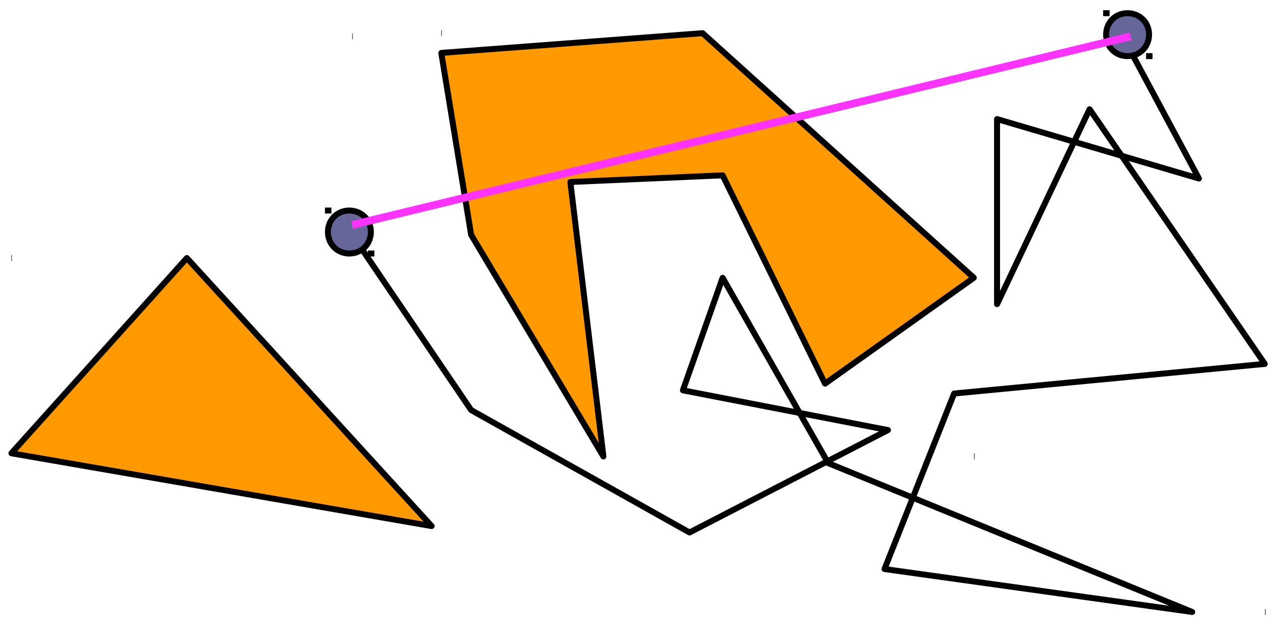

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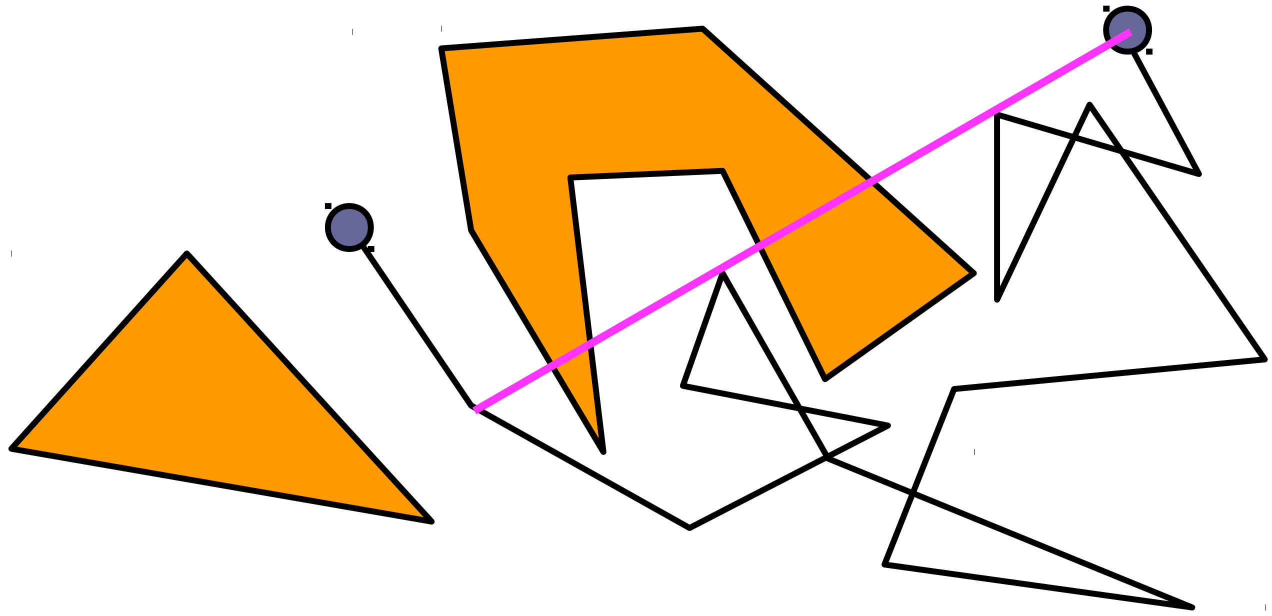

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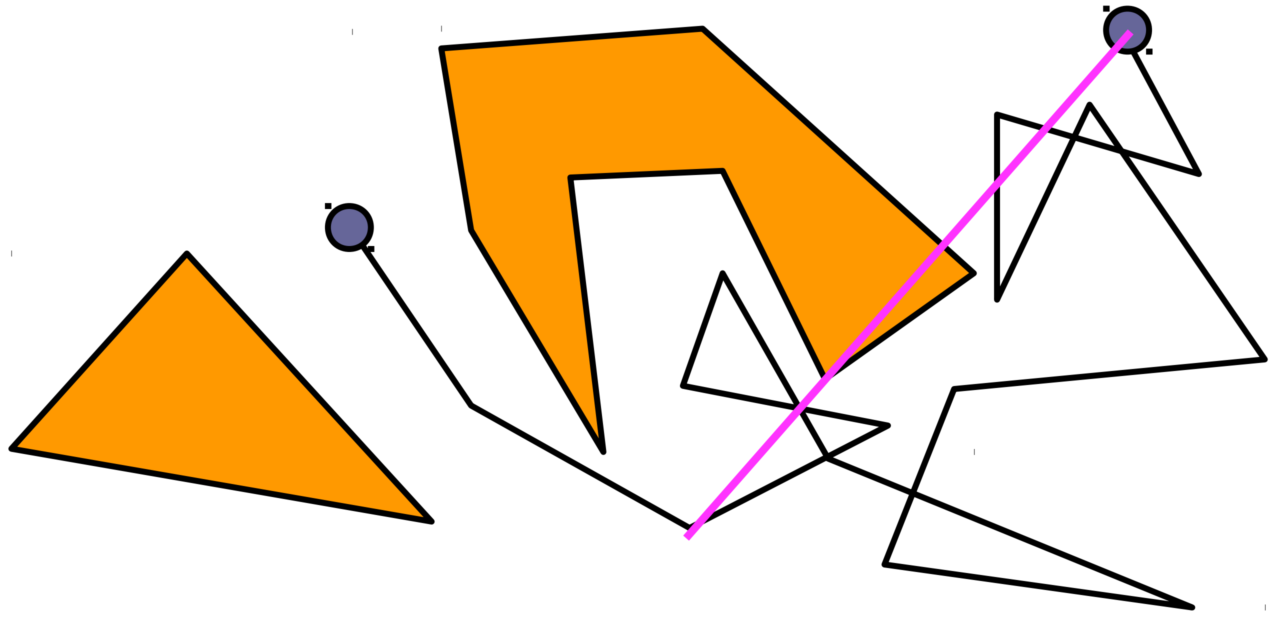

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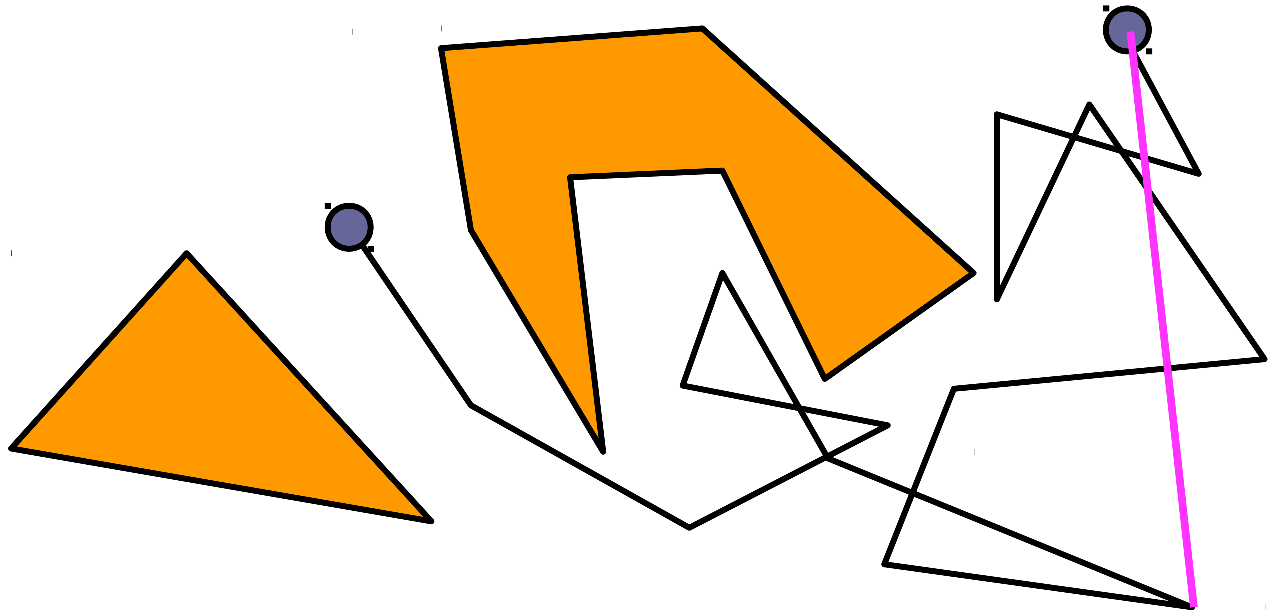

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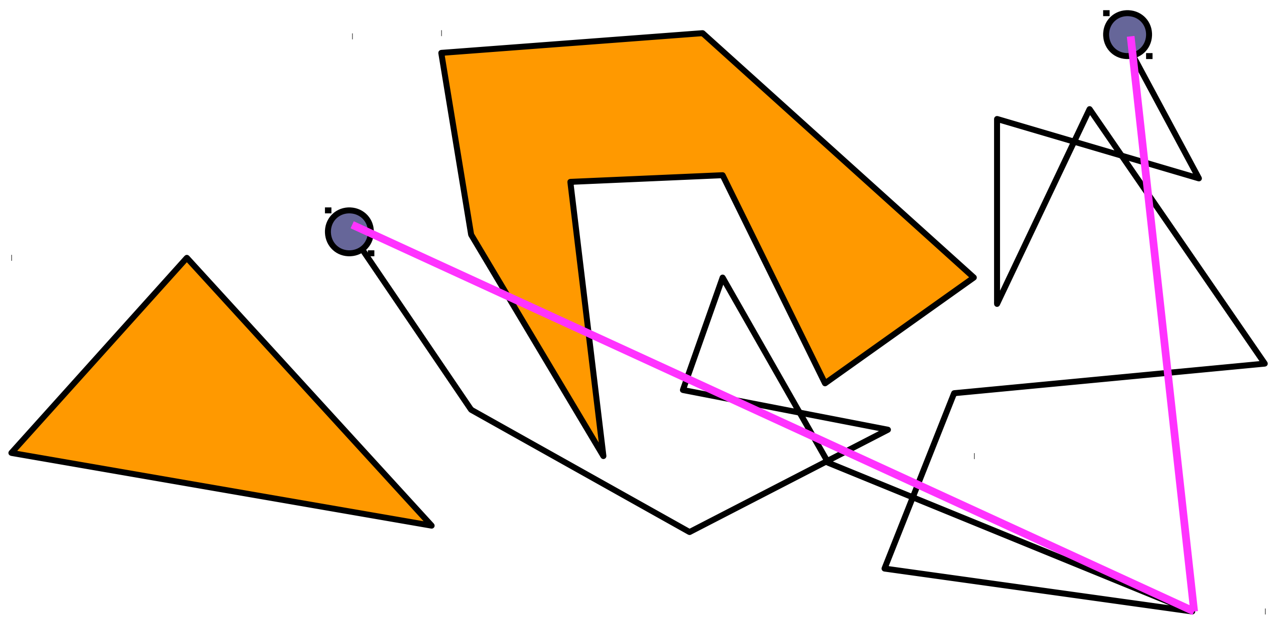

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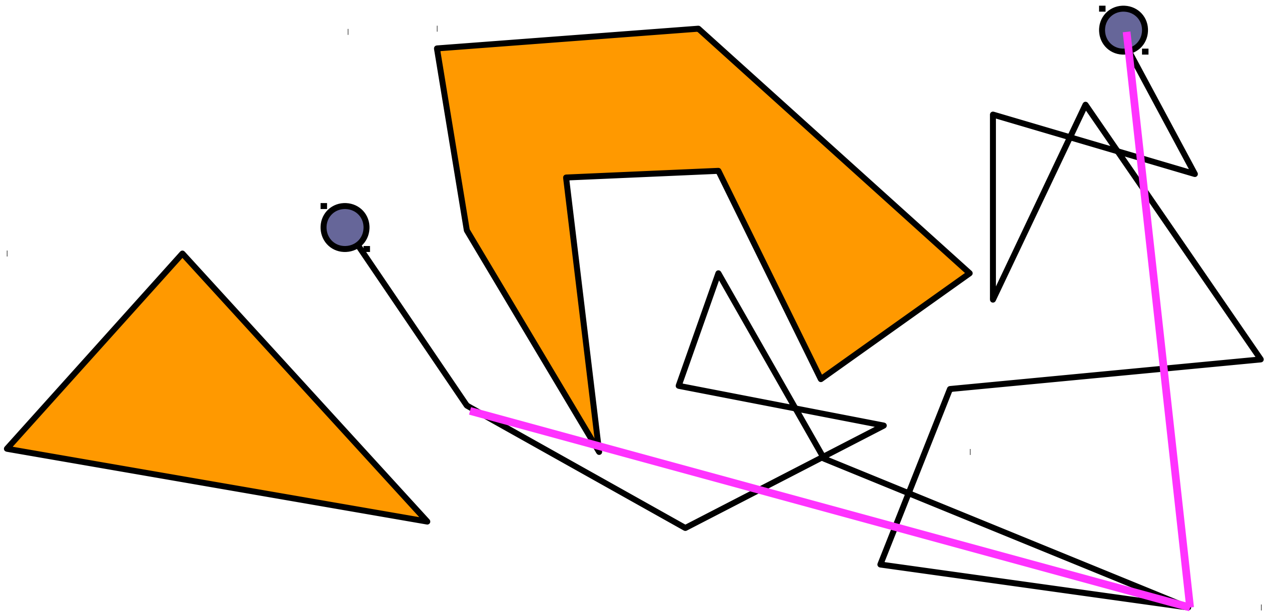

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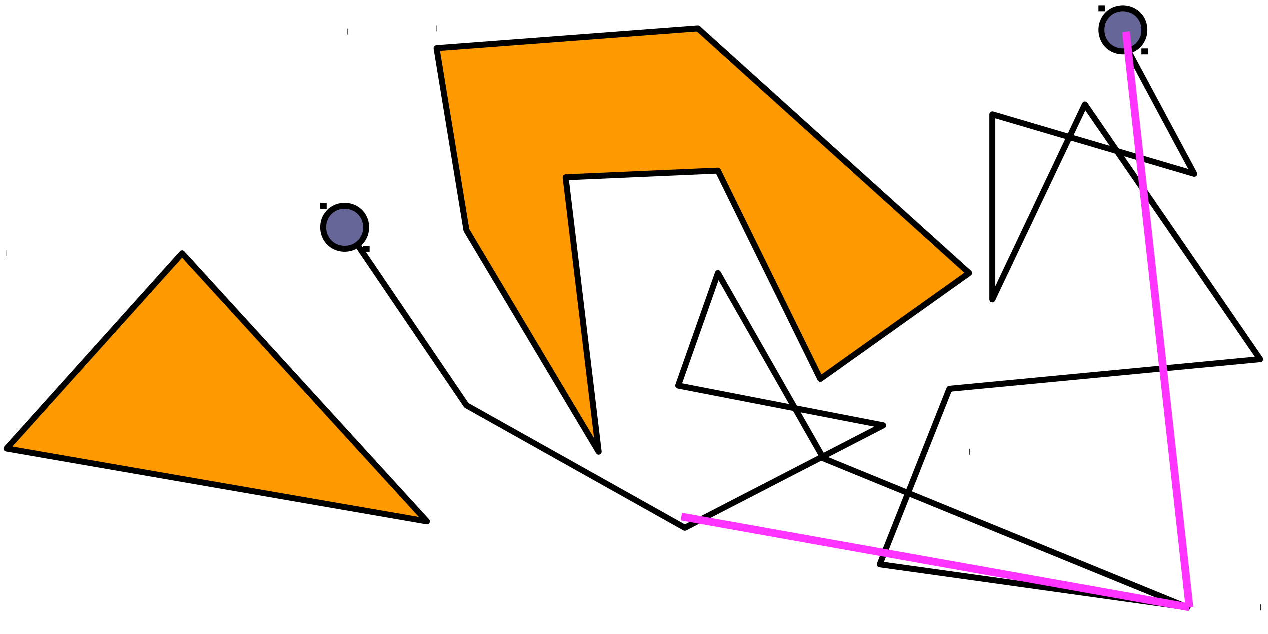

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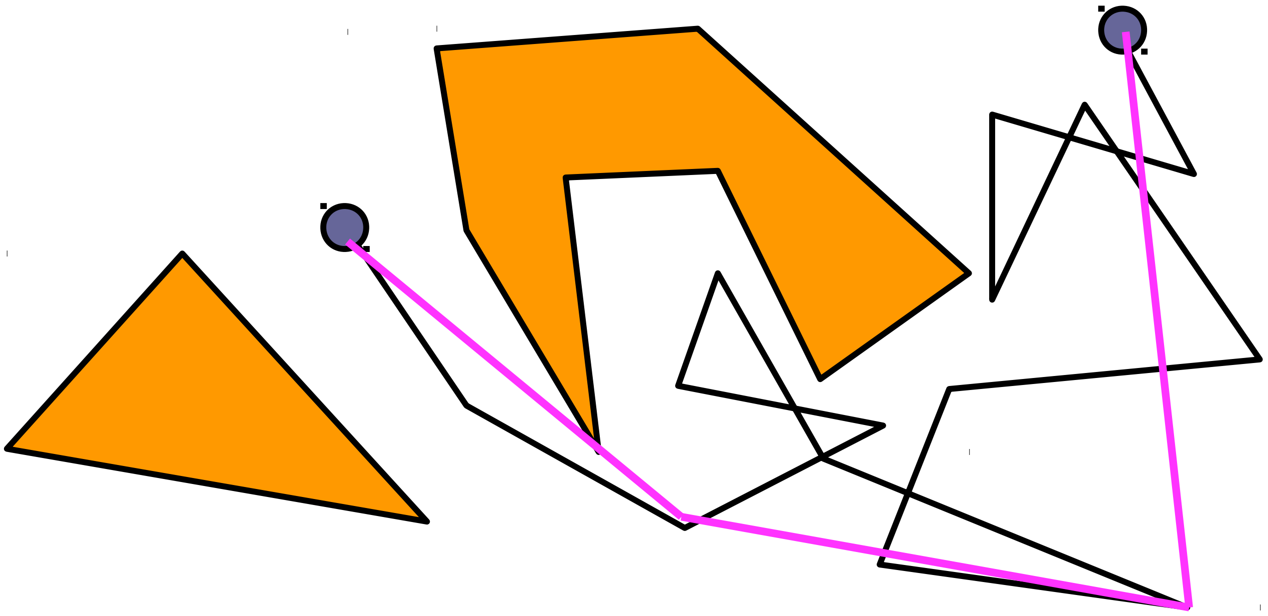

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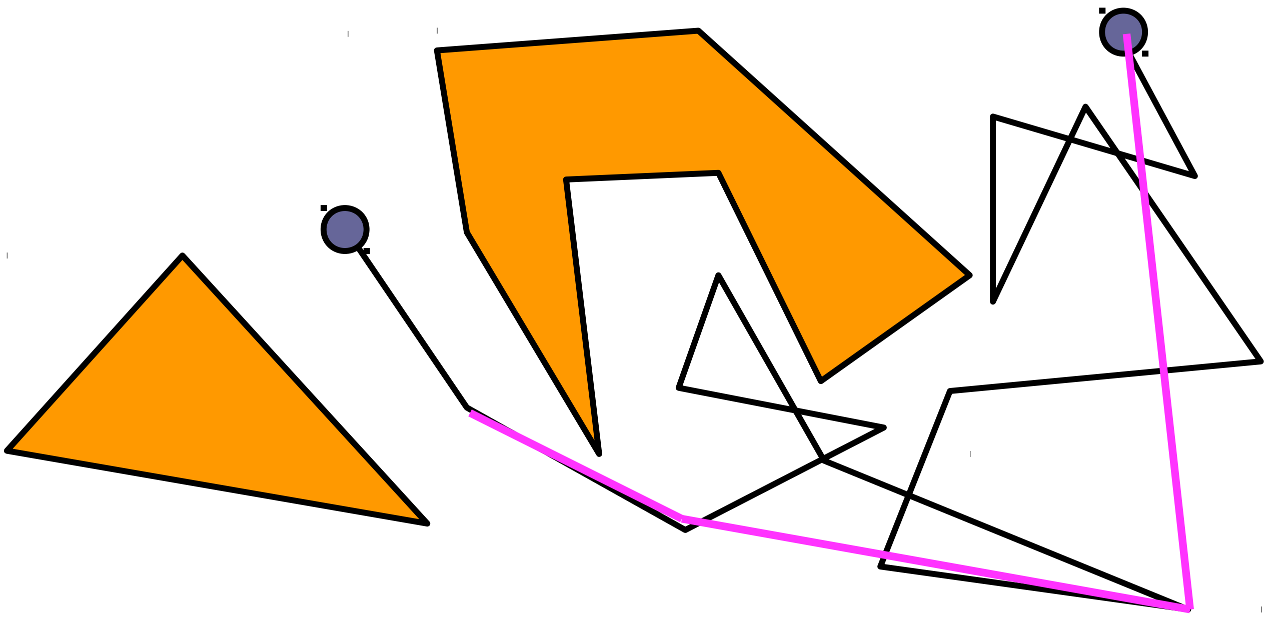

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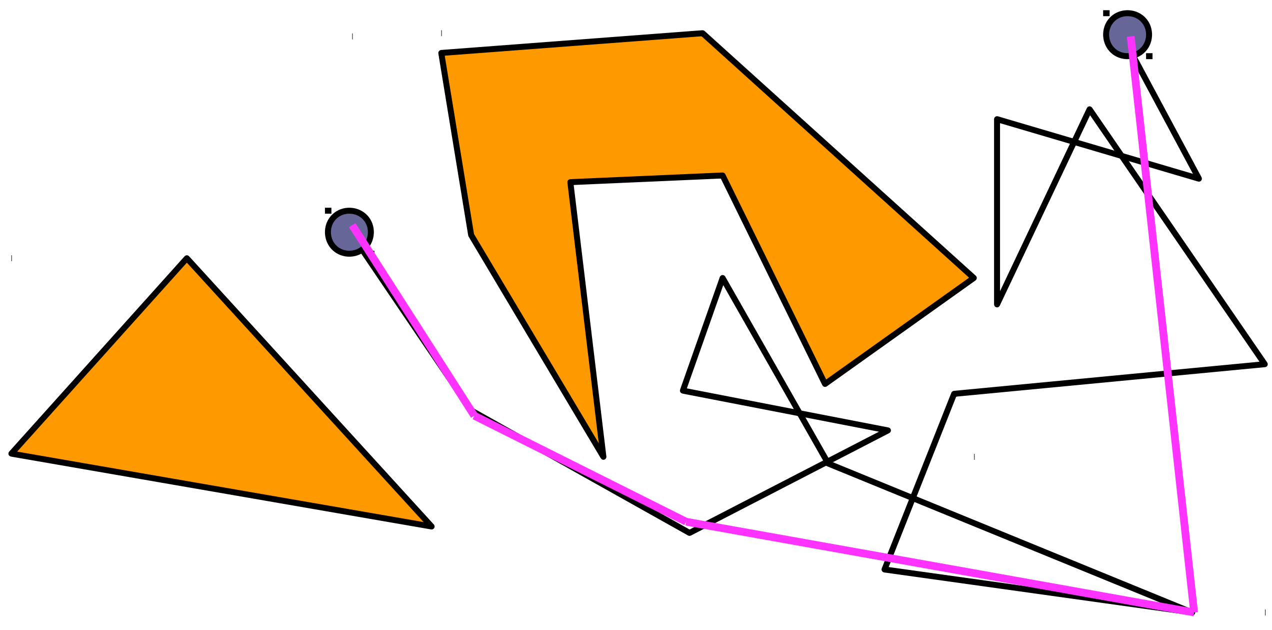

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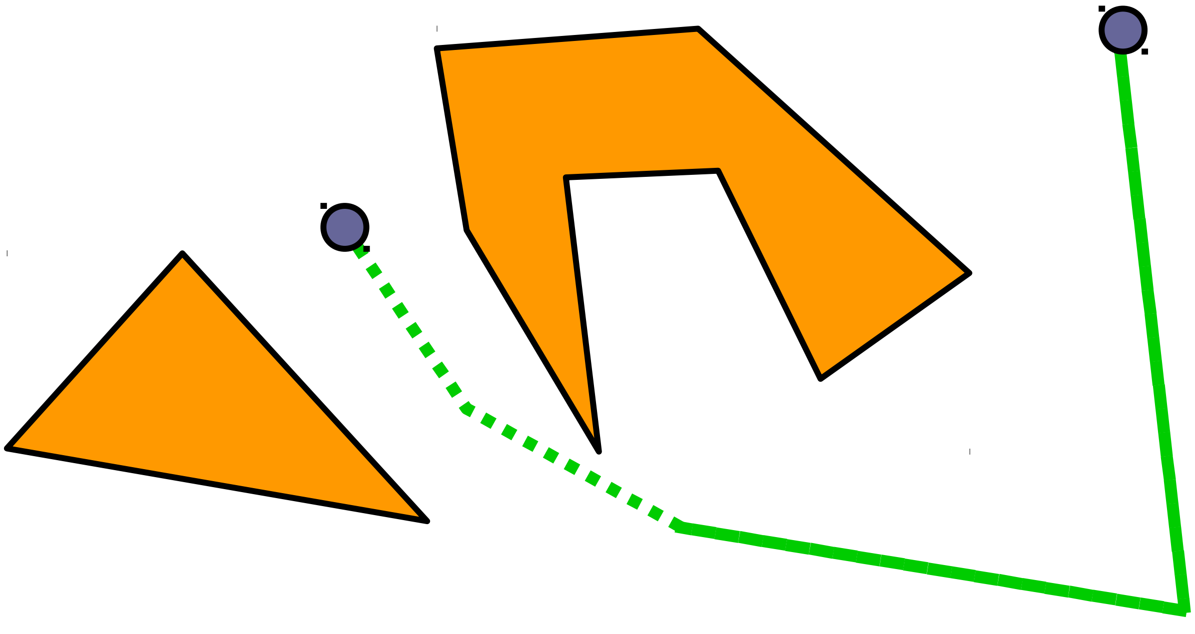

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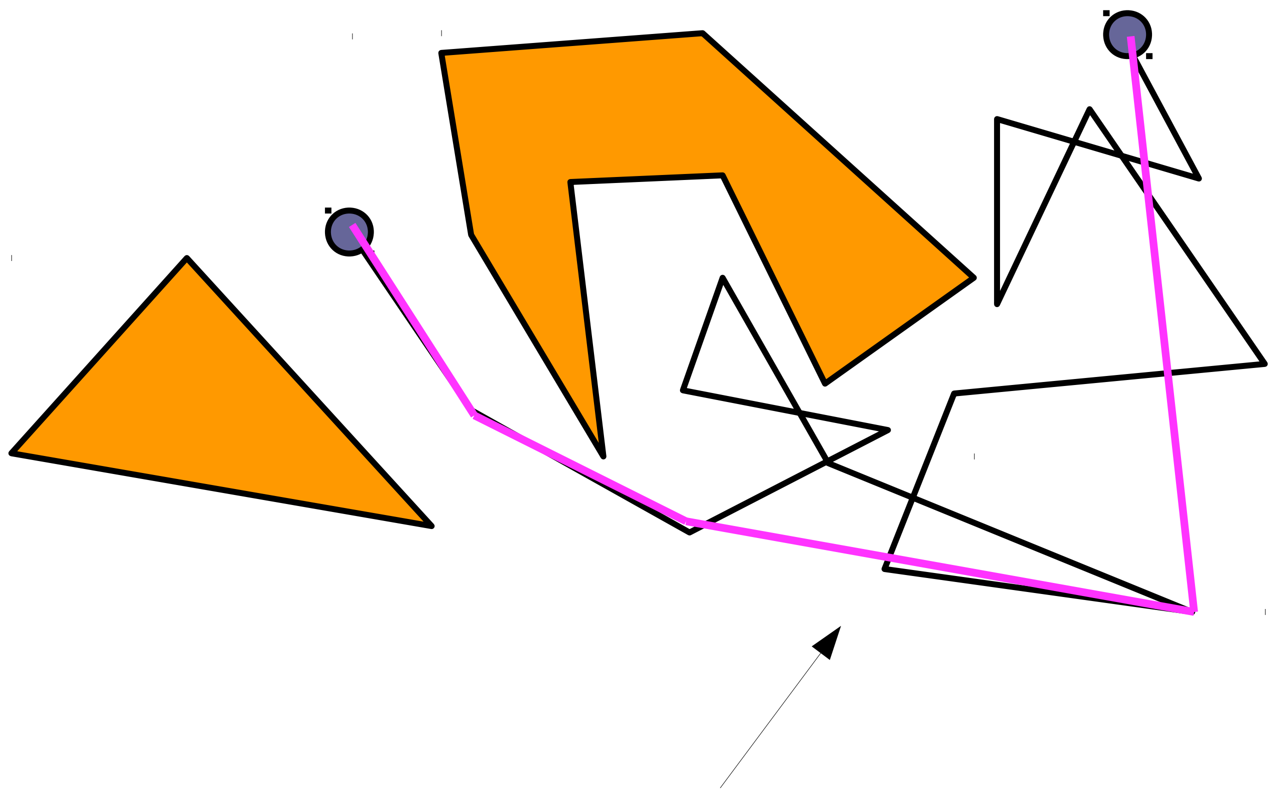
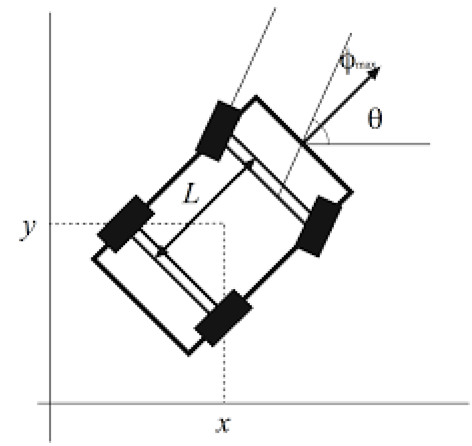


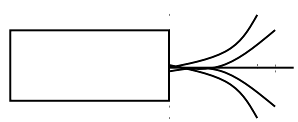
Notice that it wasn't the shortest path...
– we're just smoothing, not optimizing

Kinodynamic planning with RRTs

So far, we have assumed that the system has no dynamics
– the system can instantaneously move in any direction in c-space
– but what if that's not true?



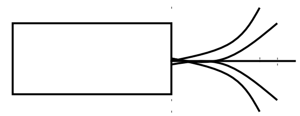
Consider the Dubins car:
– c-space: x-y position and velocity, angle
– control forward velocity and steering angle
– plan a path through c-space with the
corresponding control signals



$$x_{t+1} = f(x_t, u_t)$$

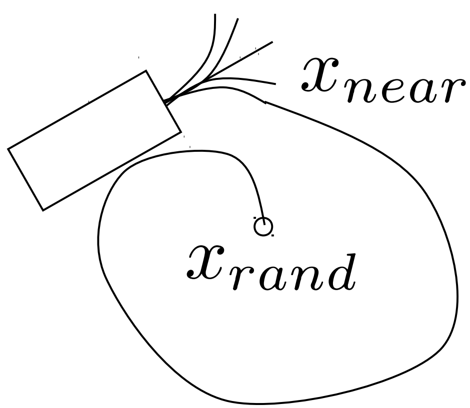
<u>where:</u>
x_t – state (x/y position and velocity, steering angle)
u_t – control signal (forward velocity, steering angle)

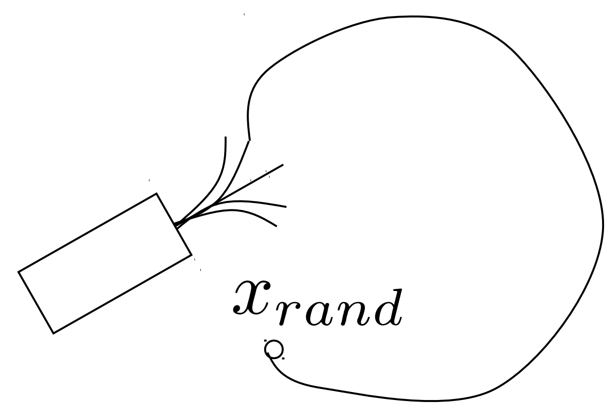
Kinodynamic planning with RRTs



$$x_{t+1} = f(x_t, u_t)$$

$$u^* = \arg\min_u (d(x_{rand}, f(x_{near}, u)))$$





But, what if x_{near} isn't the right node to expand ???

So, what do they do?

- Use nearest neighbor anyway

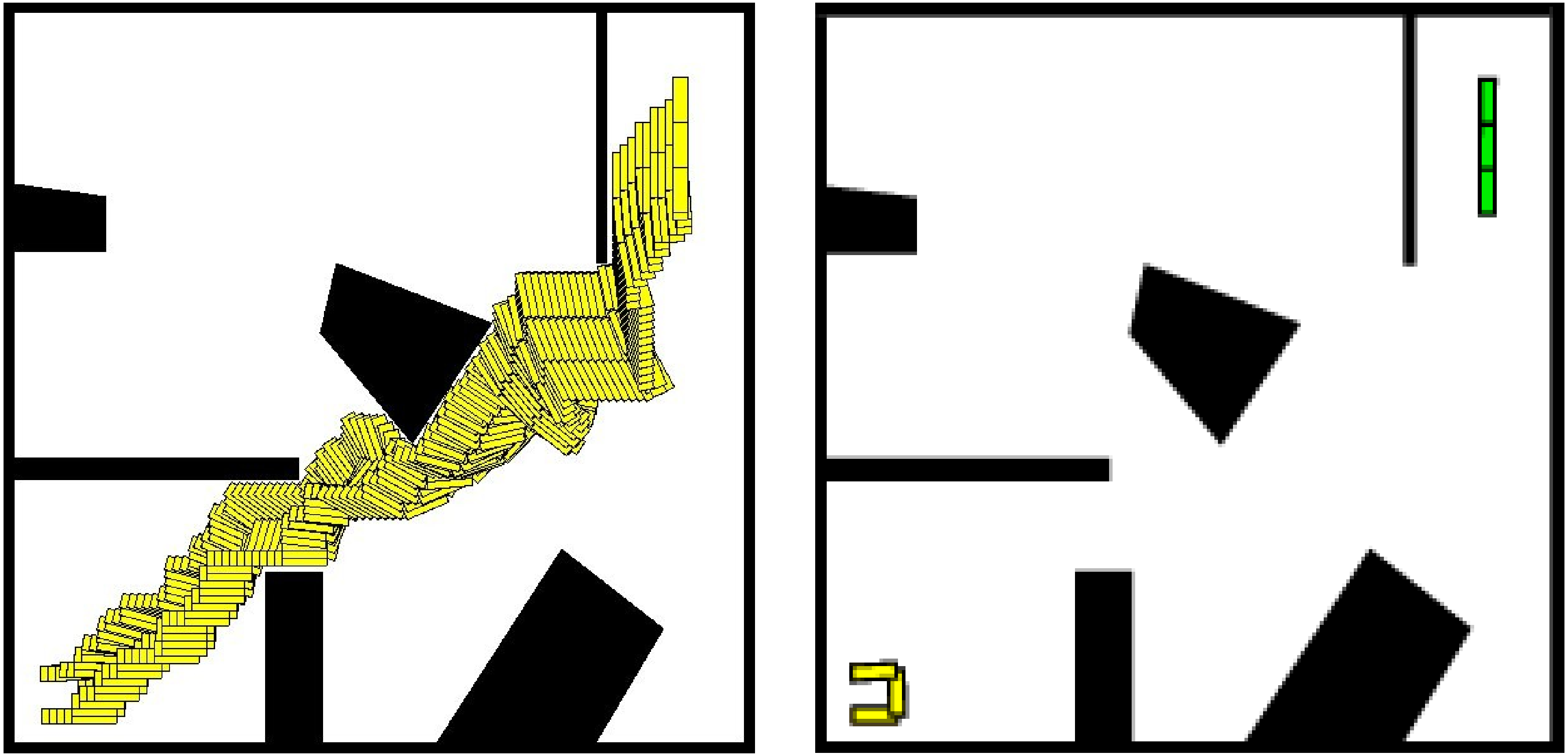
- As long as heuristic is not bad, it helps

  (you have already given up completeness and optimality, so what the heck?)

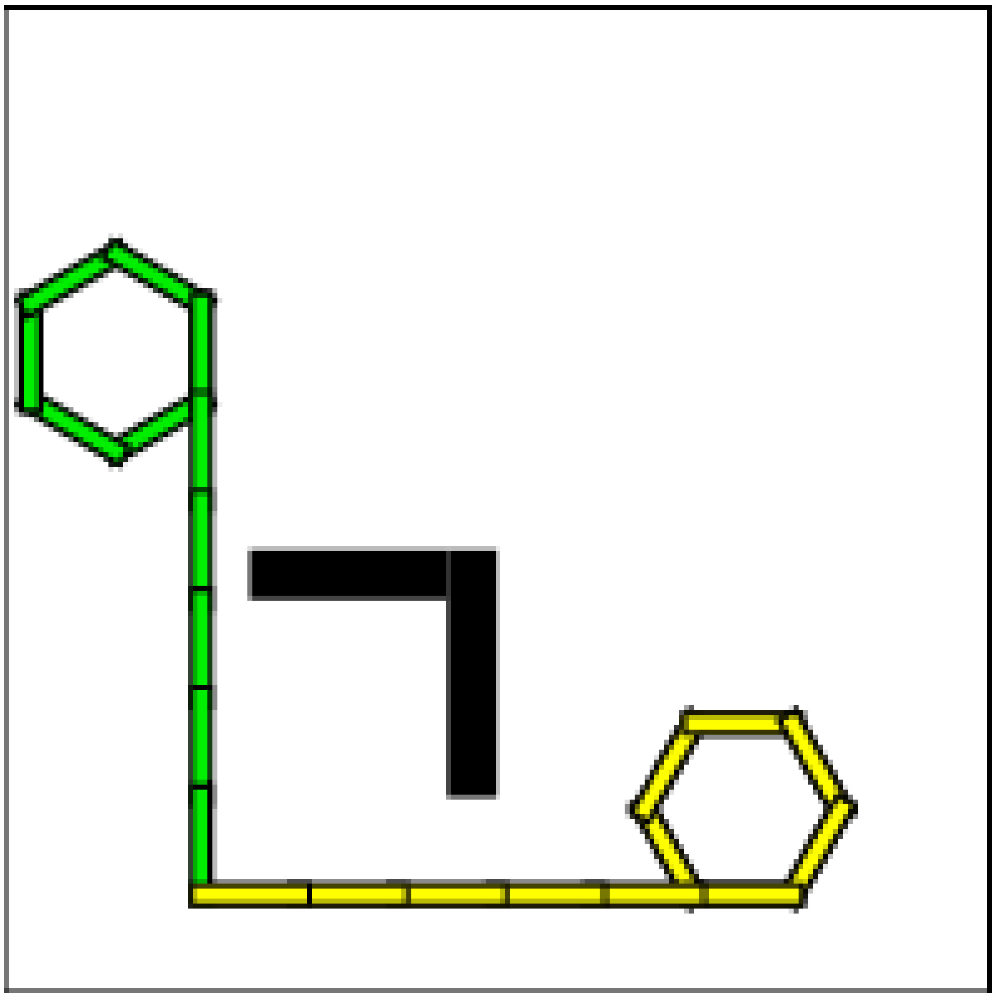
- Nearest neighbor calculations begin to dominate the collision avoidance

- Remember K-D trees

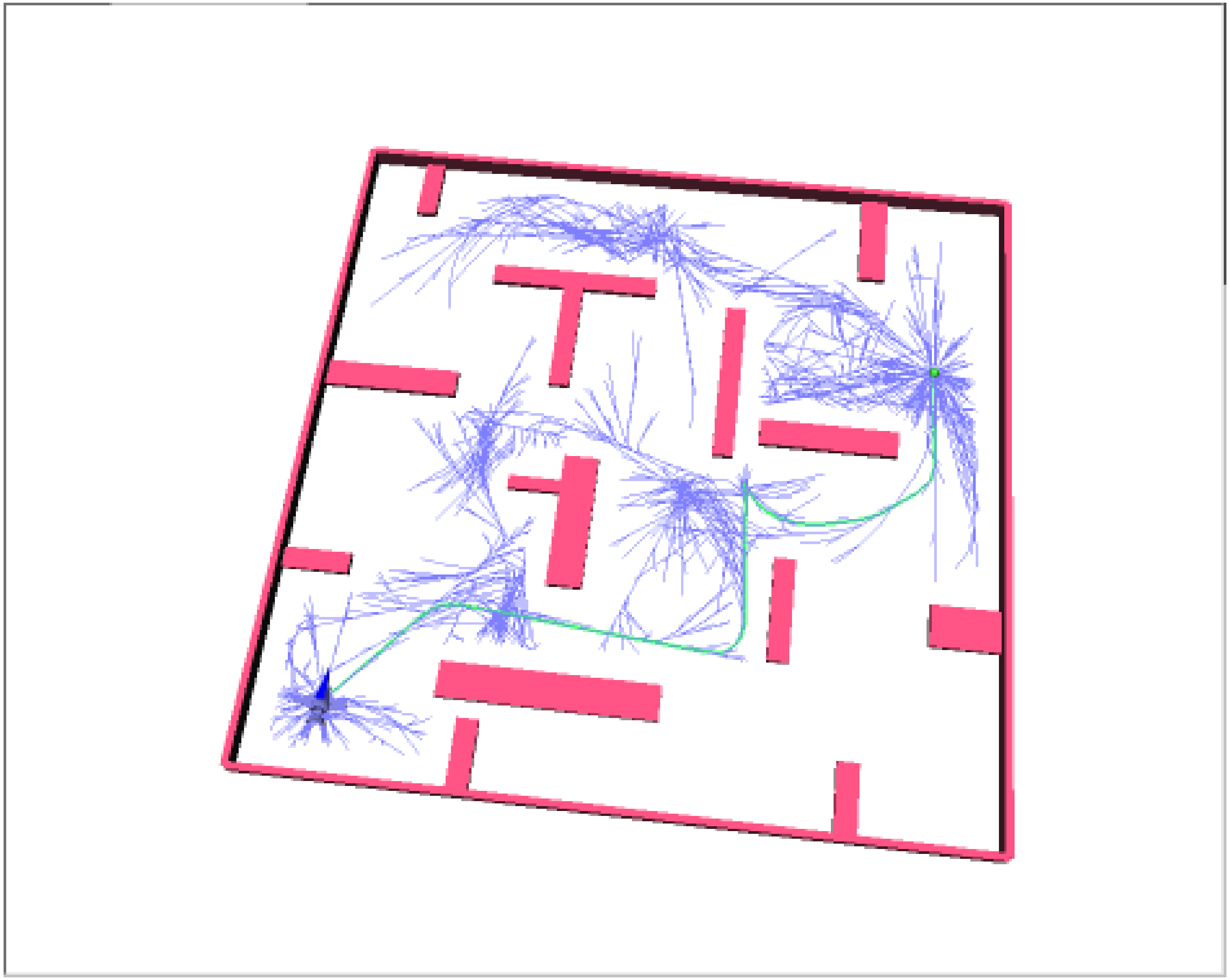
Articulated Robot



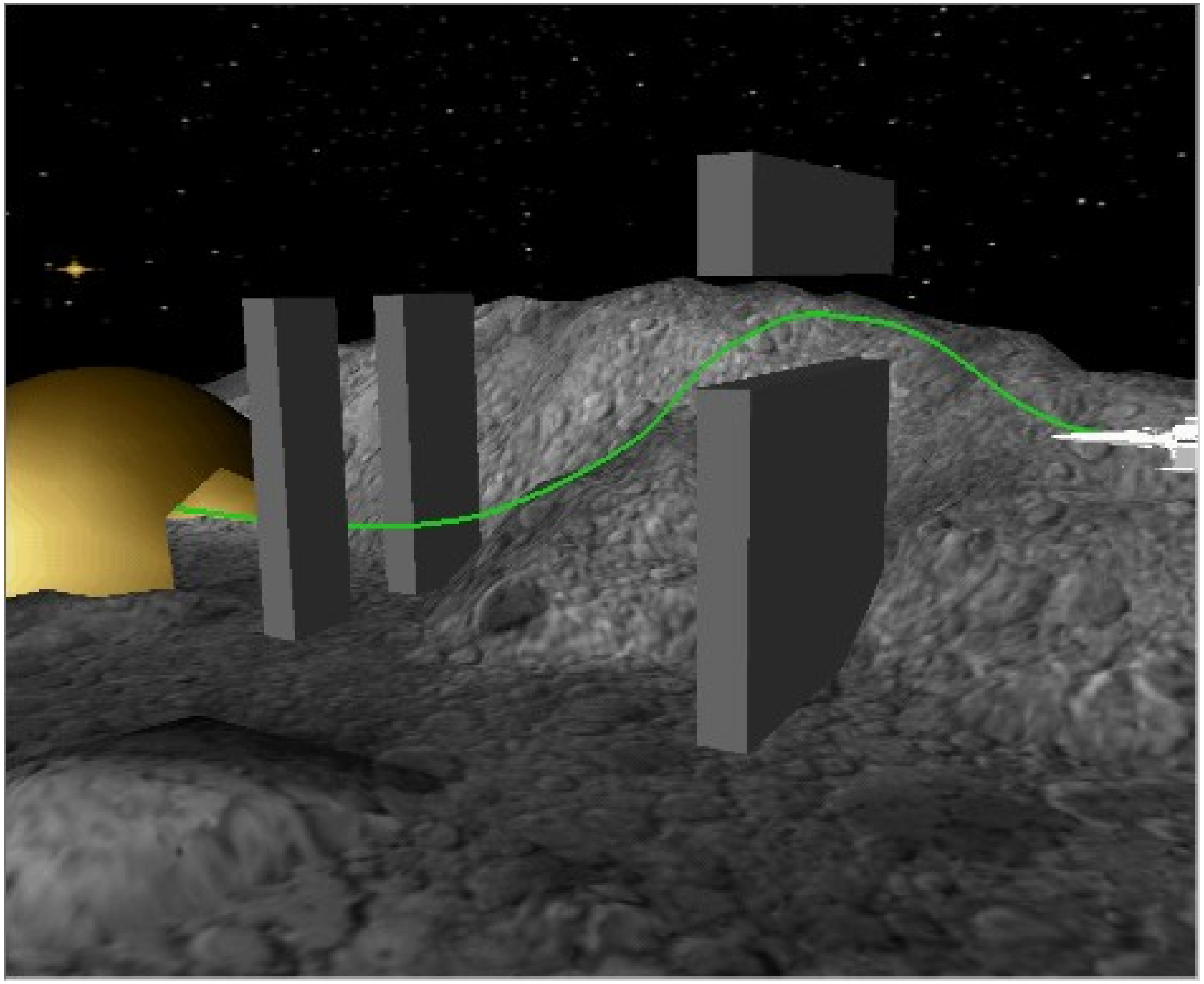
Highly Articulated Robot



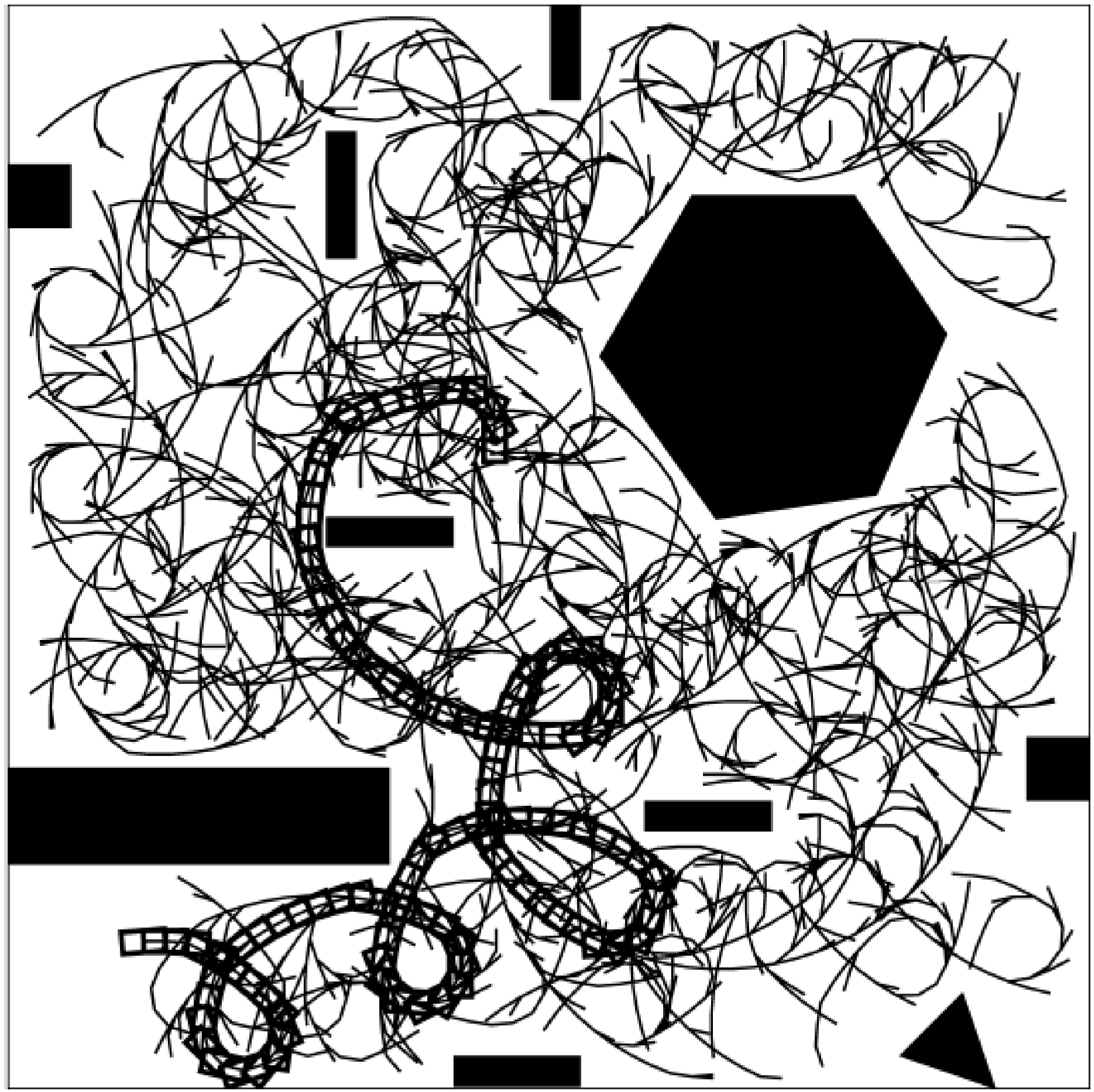
Hovercraft with 2 Thusters



Out of This World Demo



Left-turn only forward car



Applications of RRTs

- Robotics Applications
  - mobile robotics
  - manipulation
  - humanoids
- Other Applications
  - biology (drug design)
  - manufacturing and virtual prototyping (assembly analysis)
  - verification and validation
  - computer animation and real-time graphics
  - aerospace
- RRT extensions
  - discrete planning (STRIPS and Rubik's cube)
  - real-time RRTs
  - anytime RRTs
  - dynamic domain RRTs
  - deterministic RRTs
  - parallel RRTs
  - hybrid RRTs