Task & Motion Planning

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Örebro University, Sweden
MRPC Lab

Outline

- Problem definition(s)
- What makes it difficult?
- 3 approaches to TAMP
- Future directions

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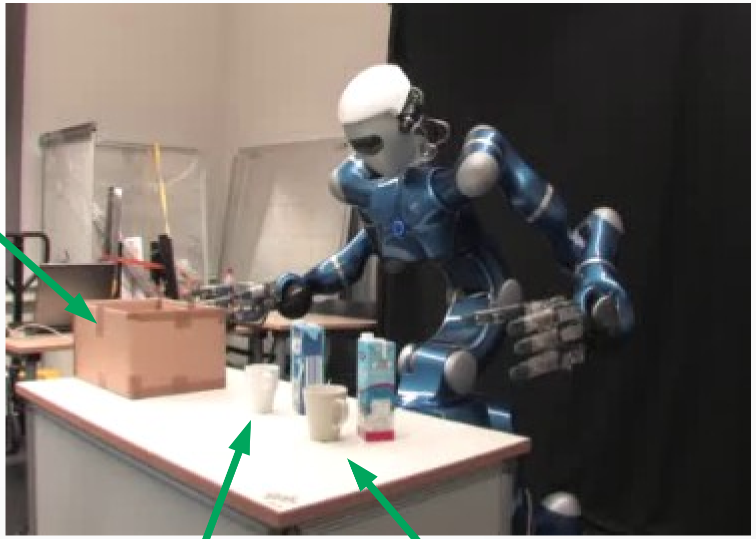
in (box1, cup1)
in (box1, cup2)

box1



cup1

cup2

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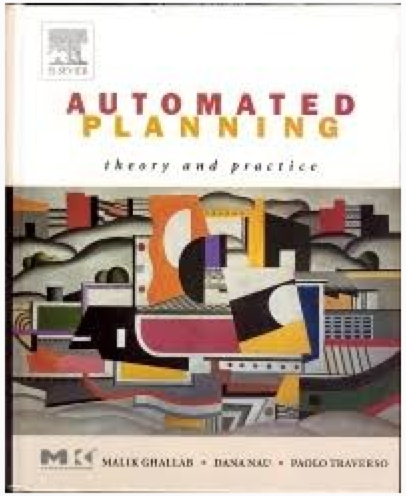
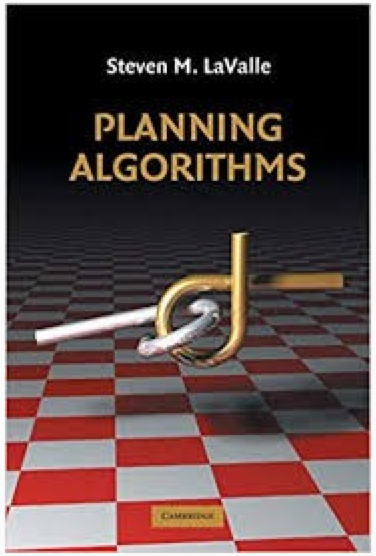


Task Planning



Motion Planning

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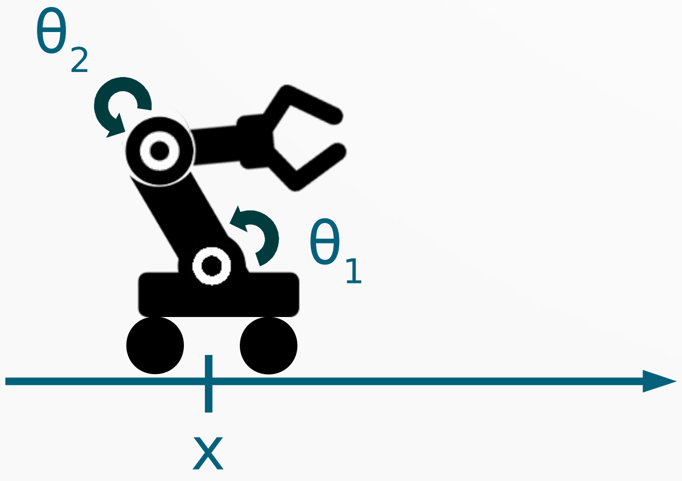

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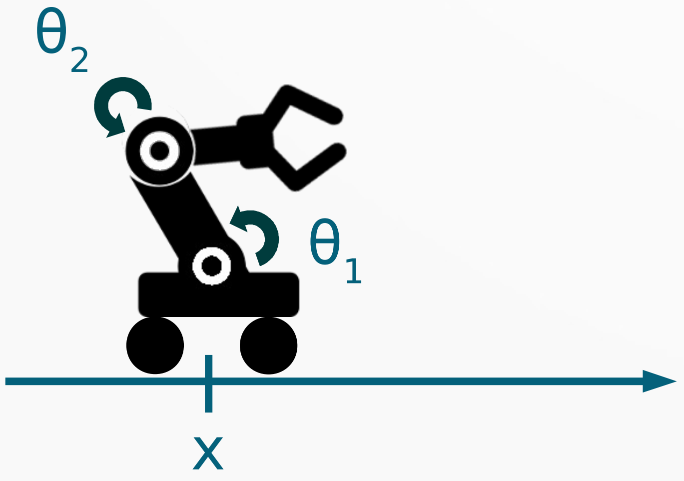

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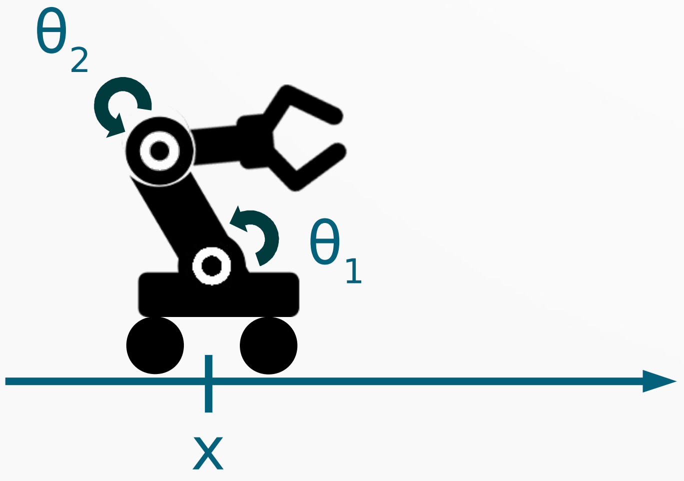

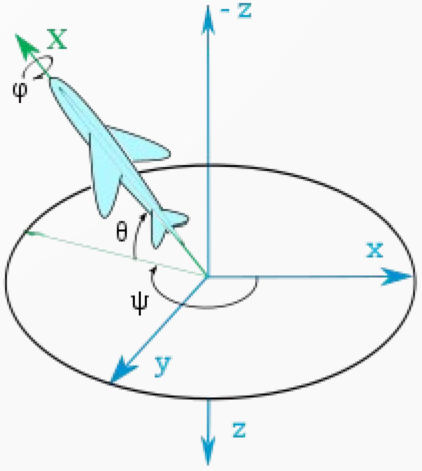

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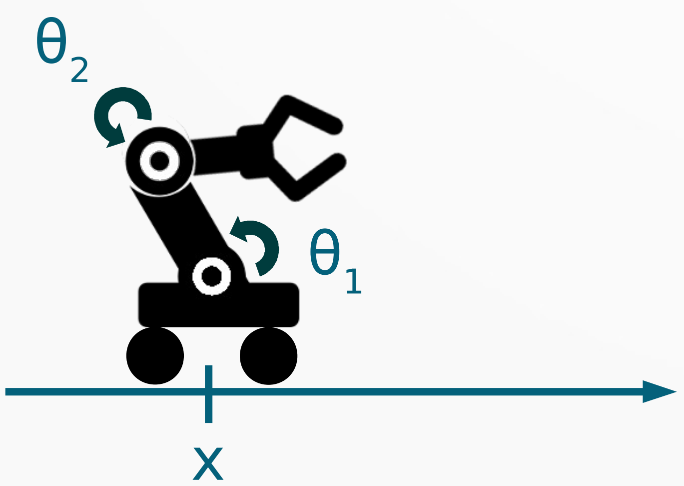

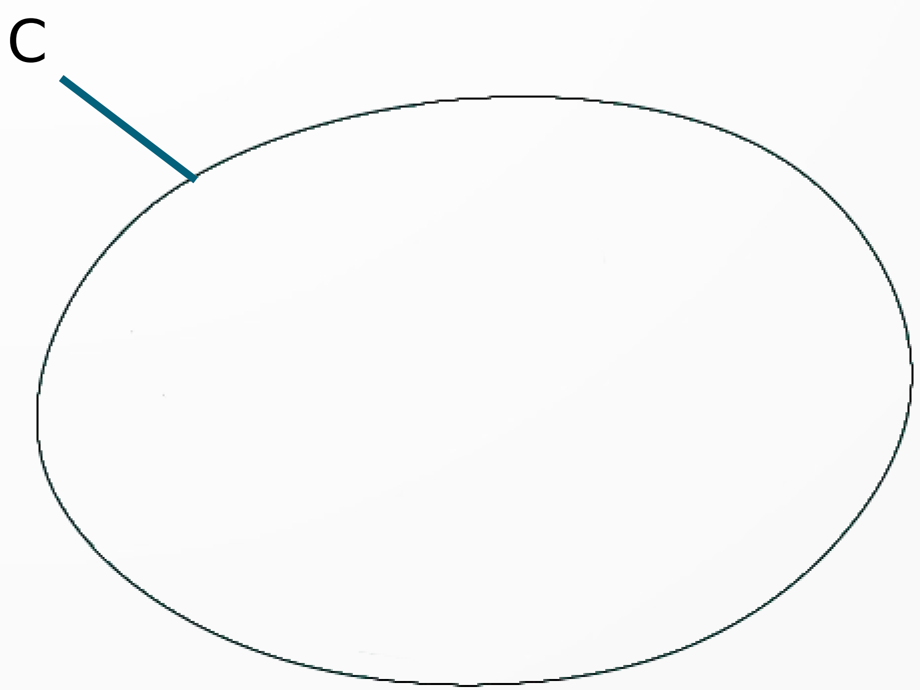

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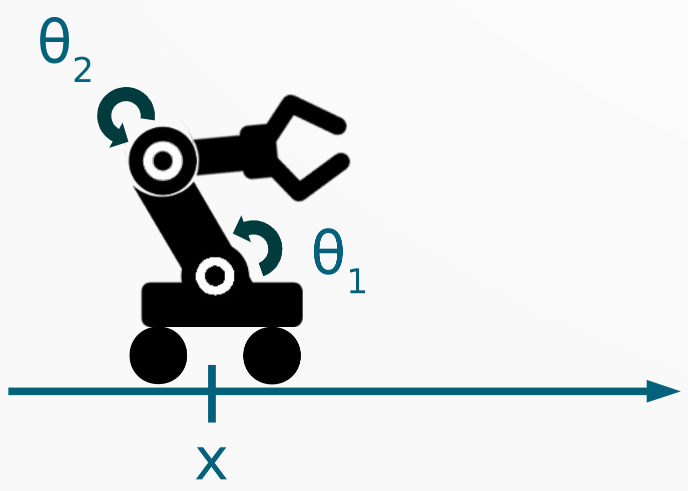

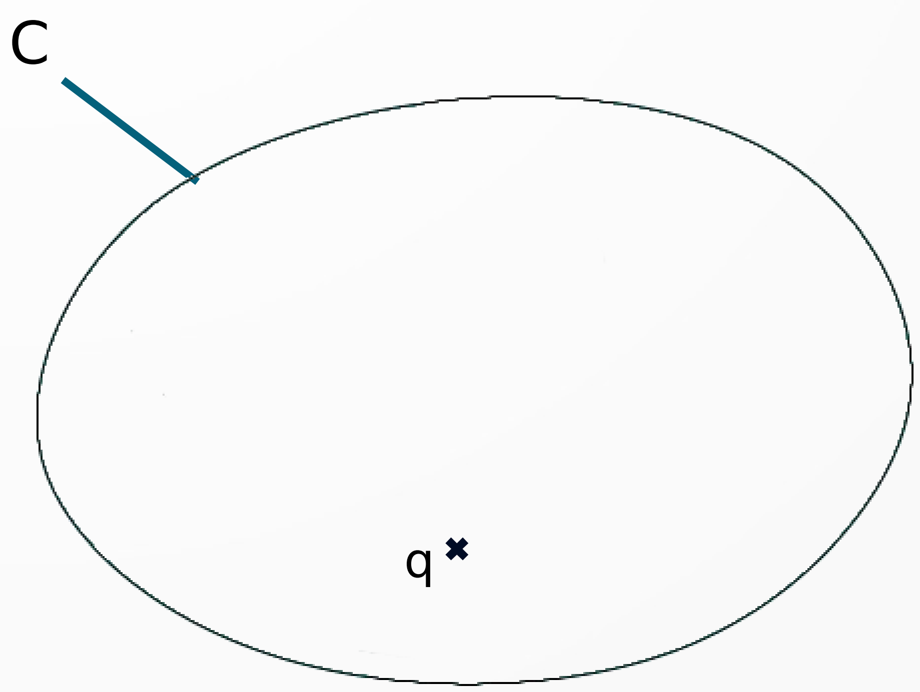

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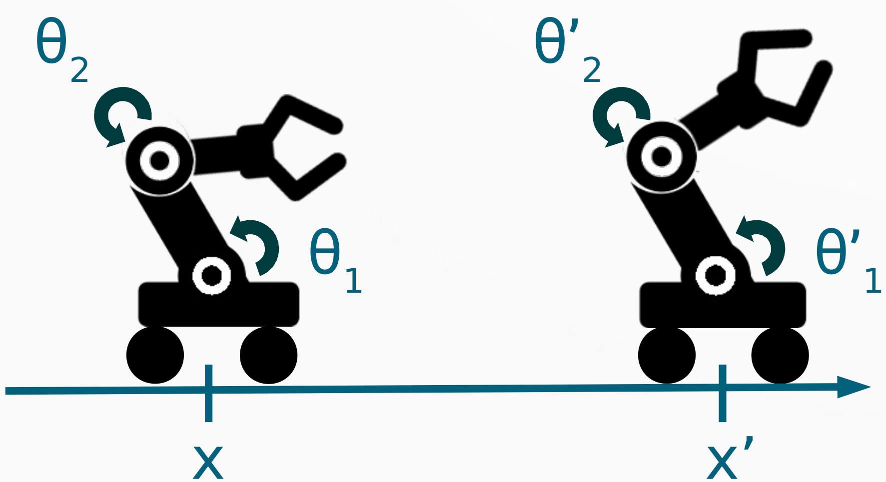

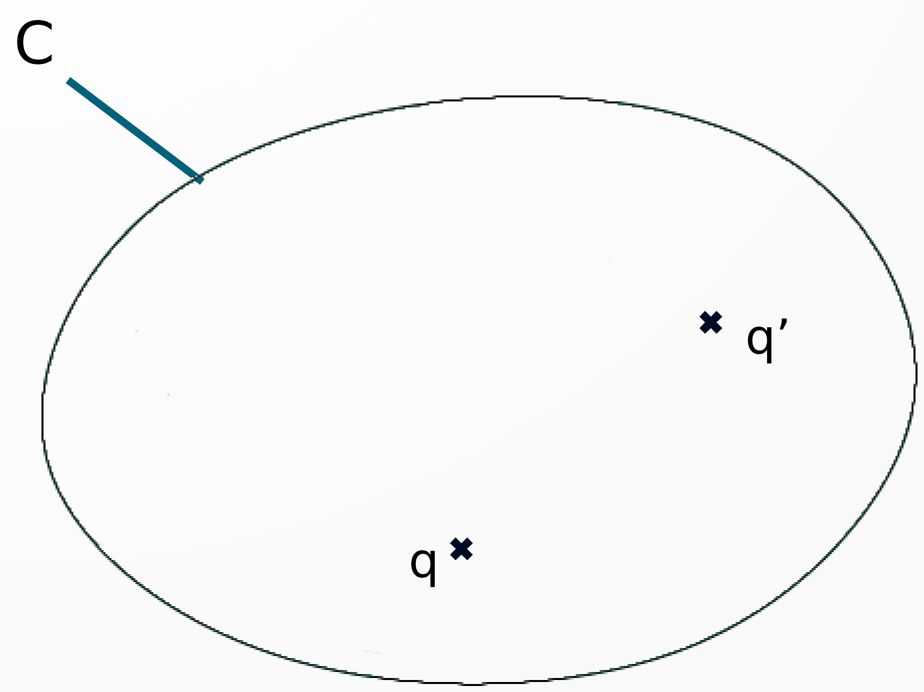

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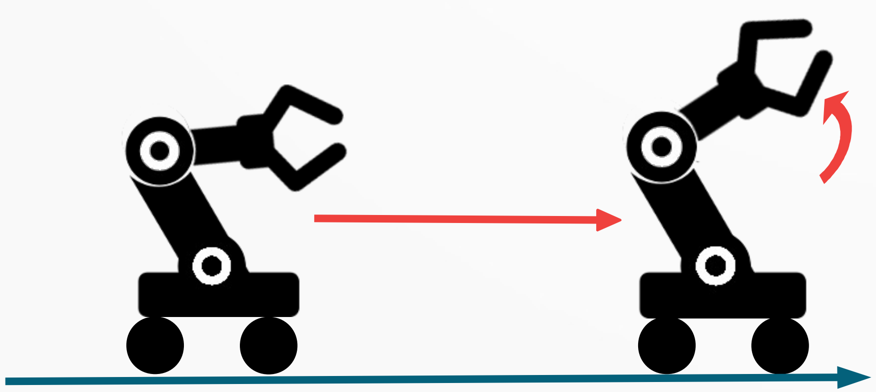

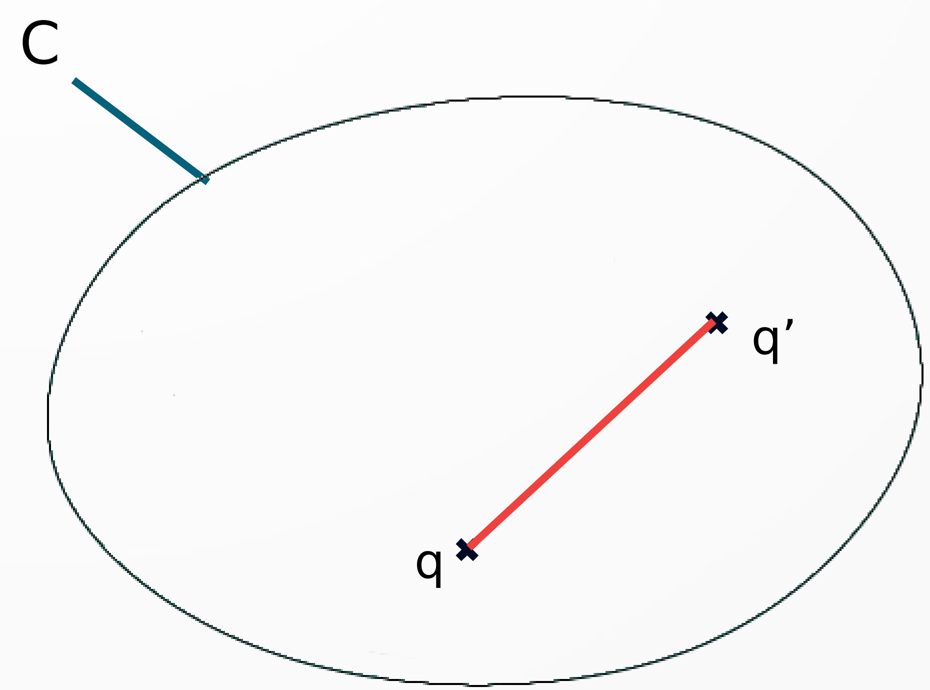

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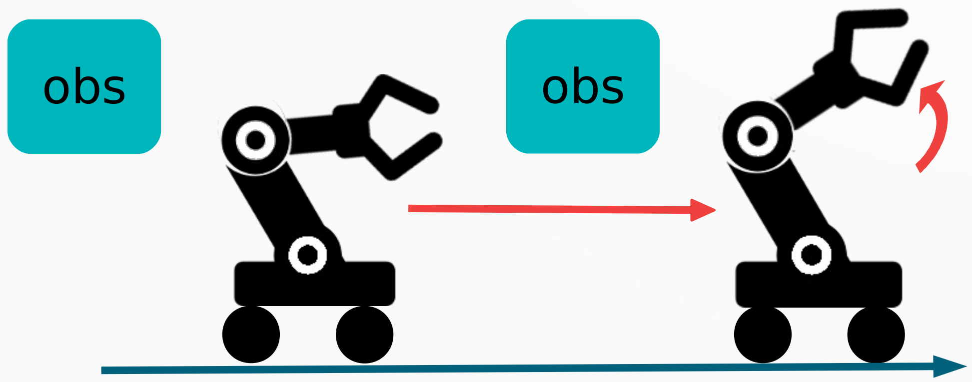

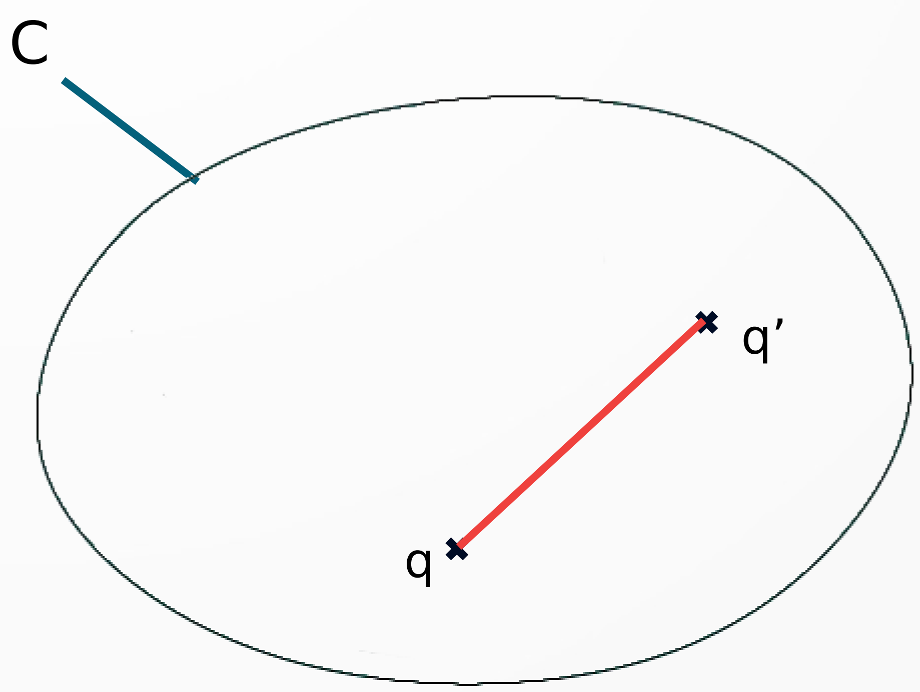

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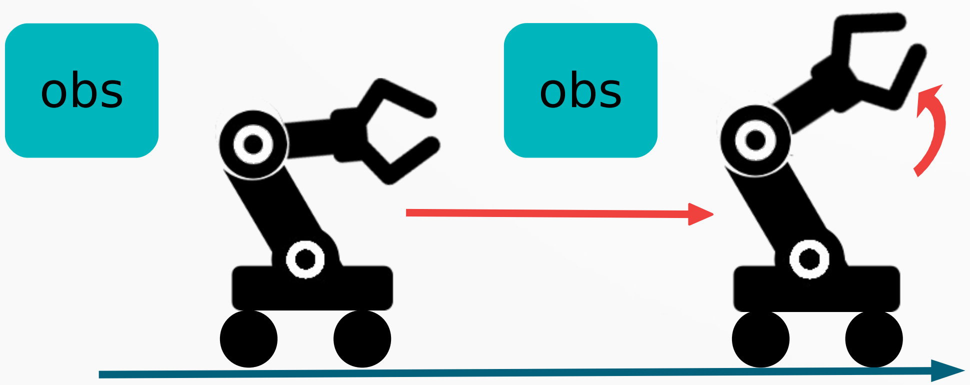

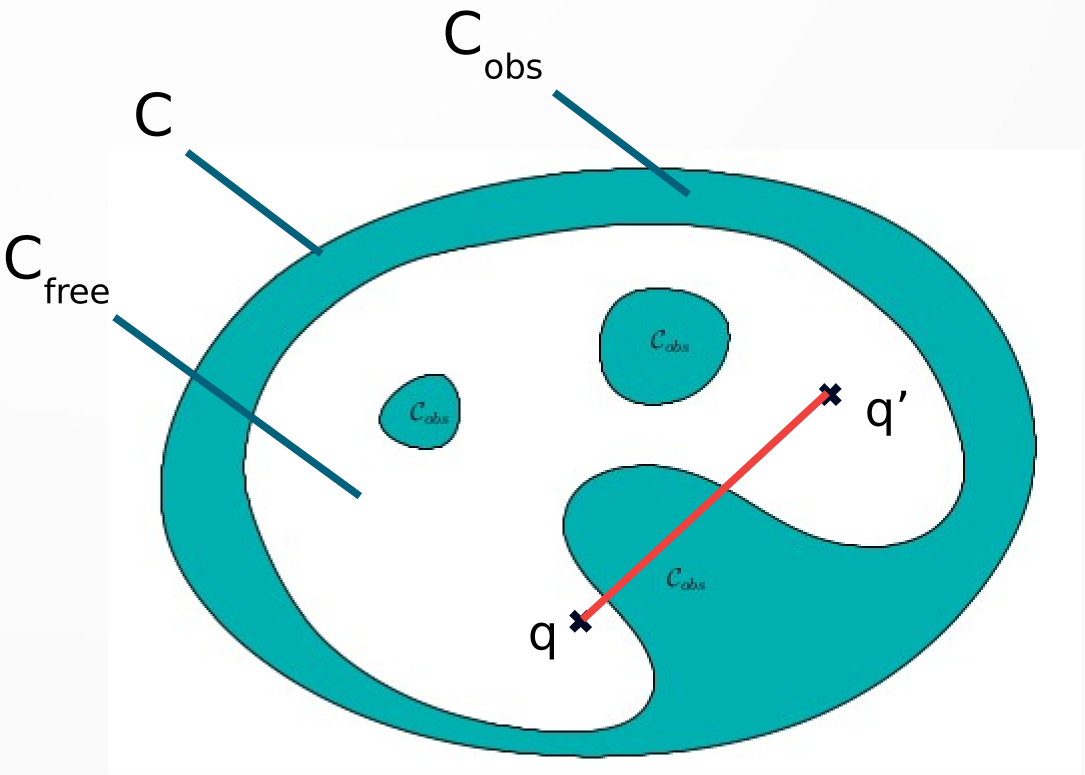

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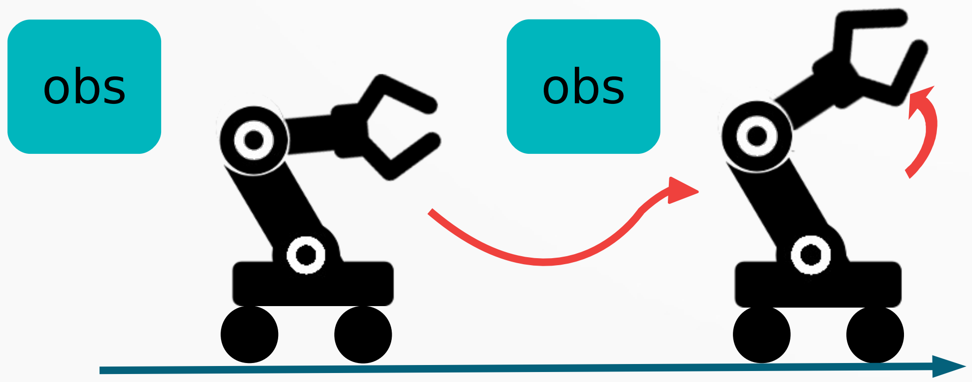

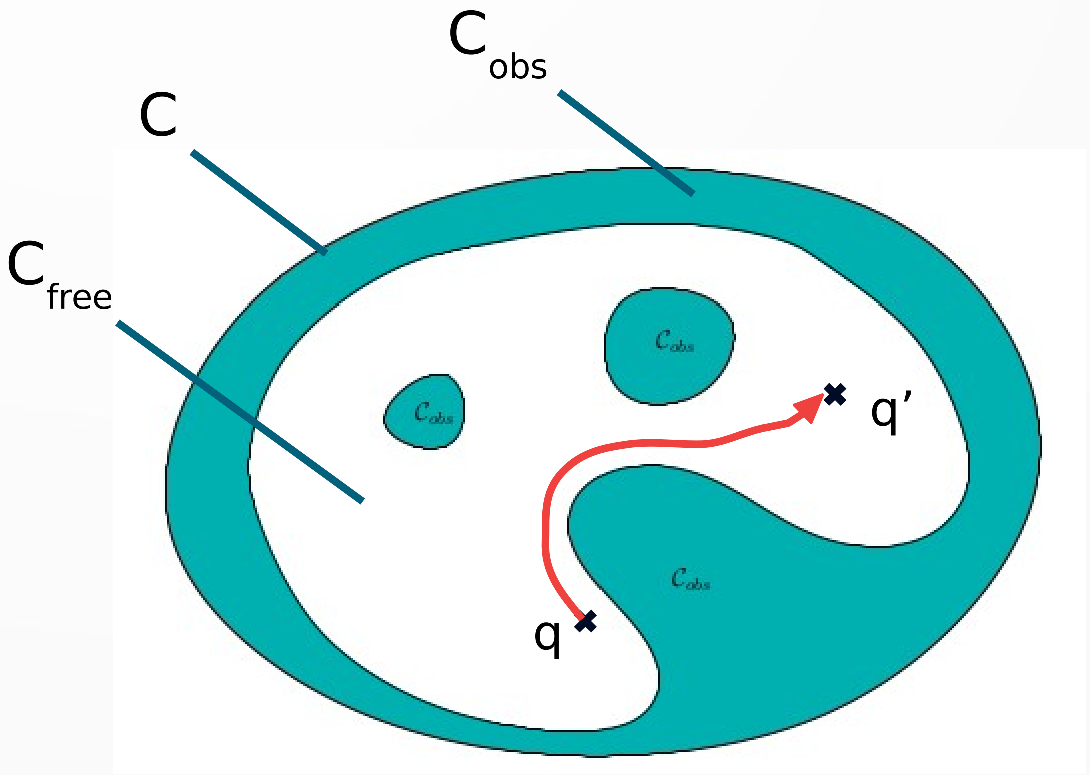

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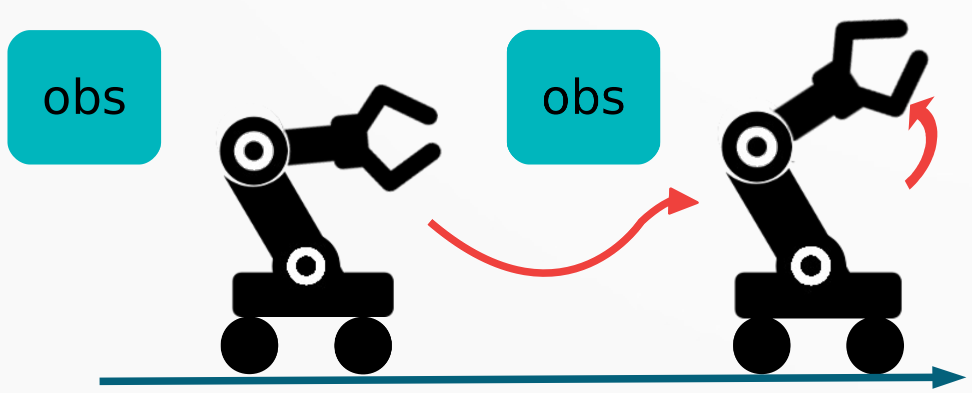

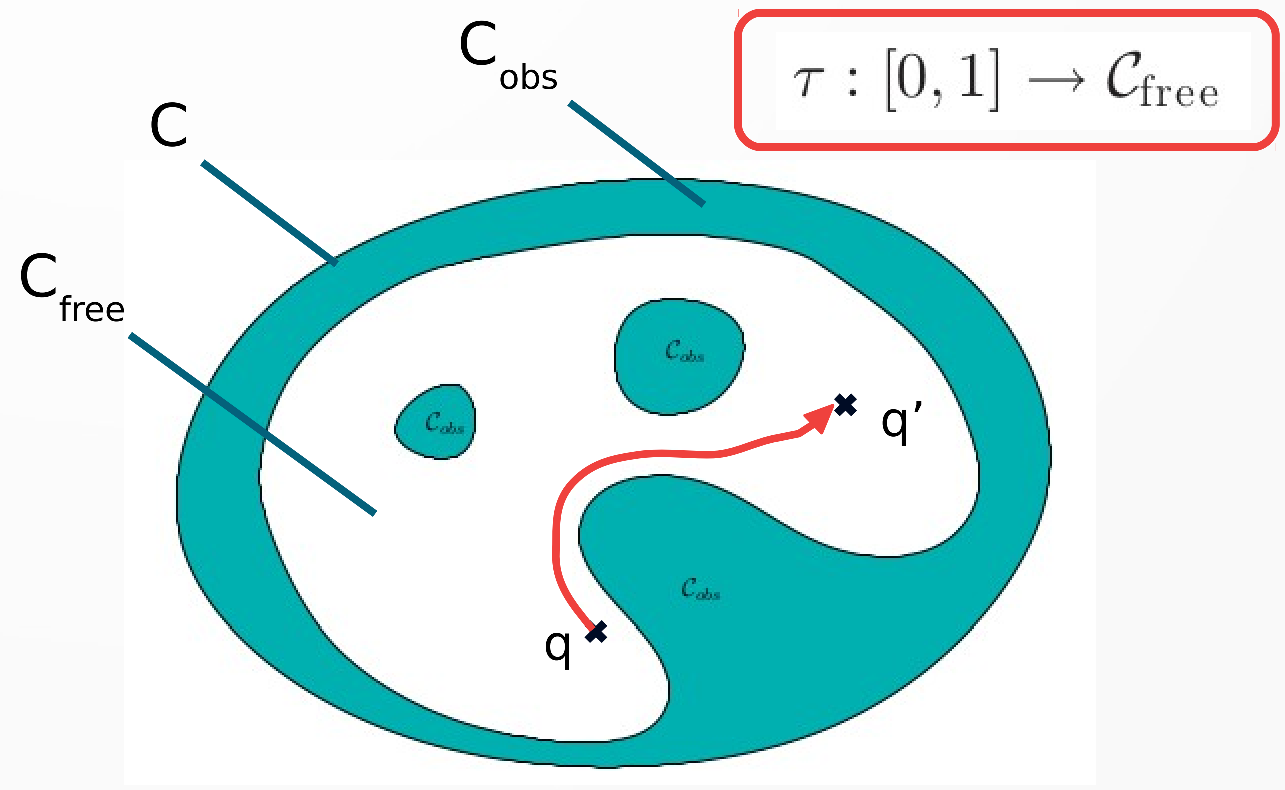

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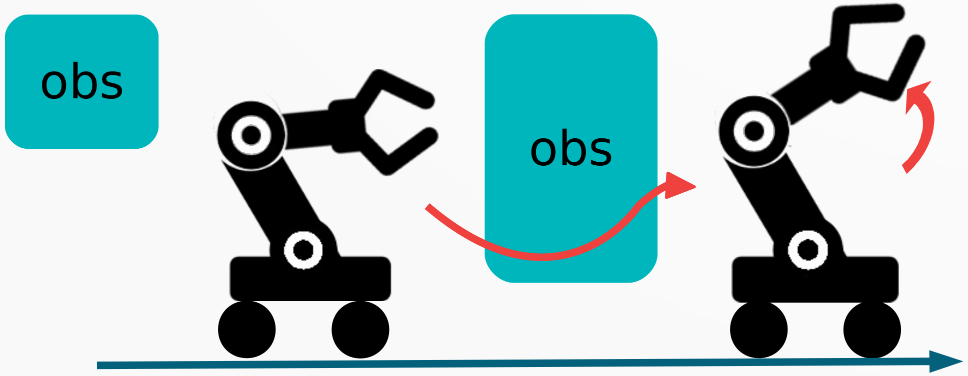

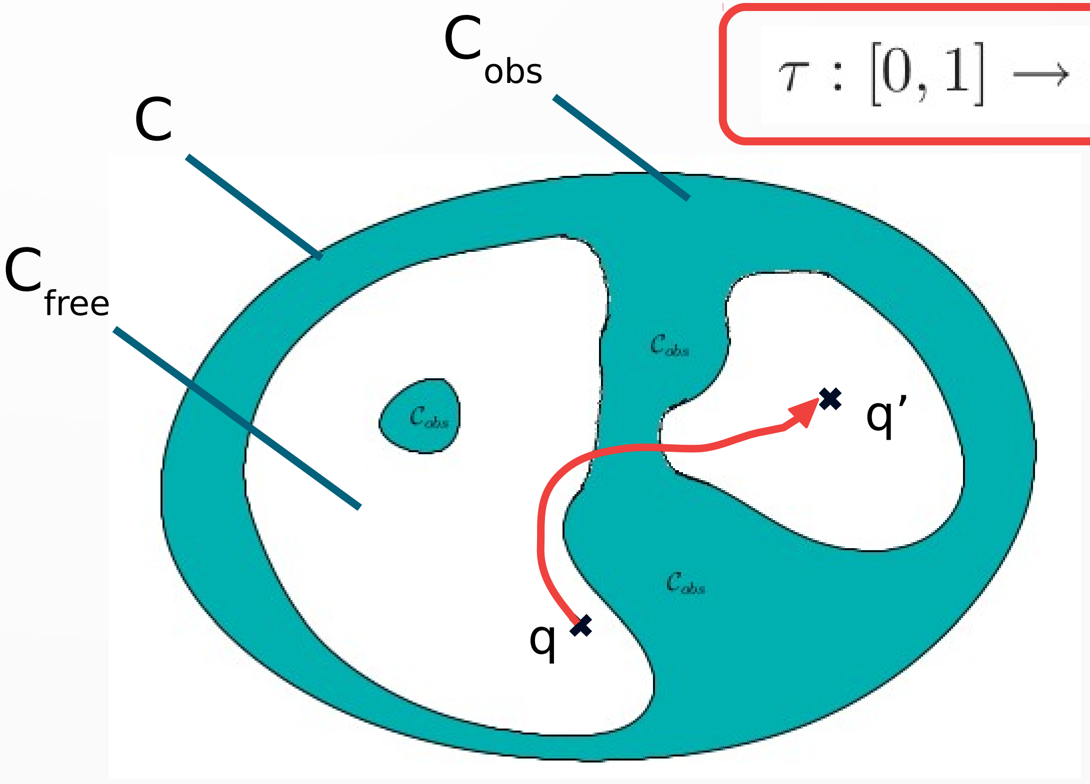

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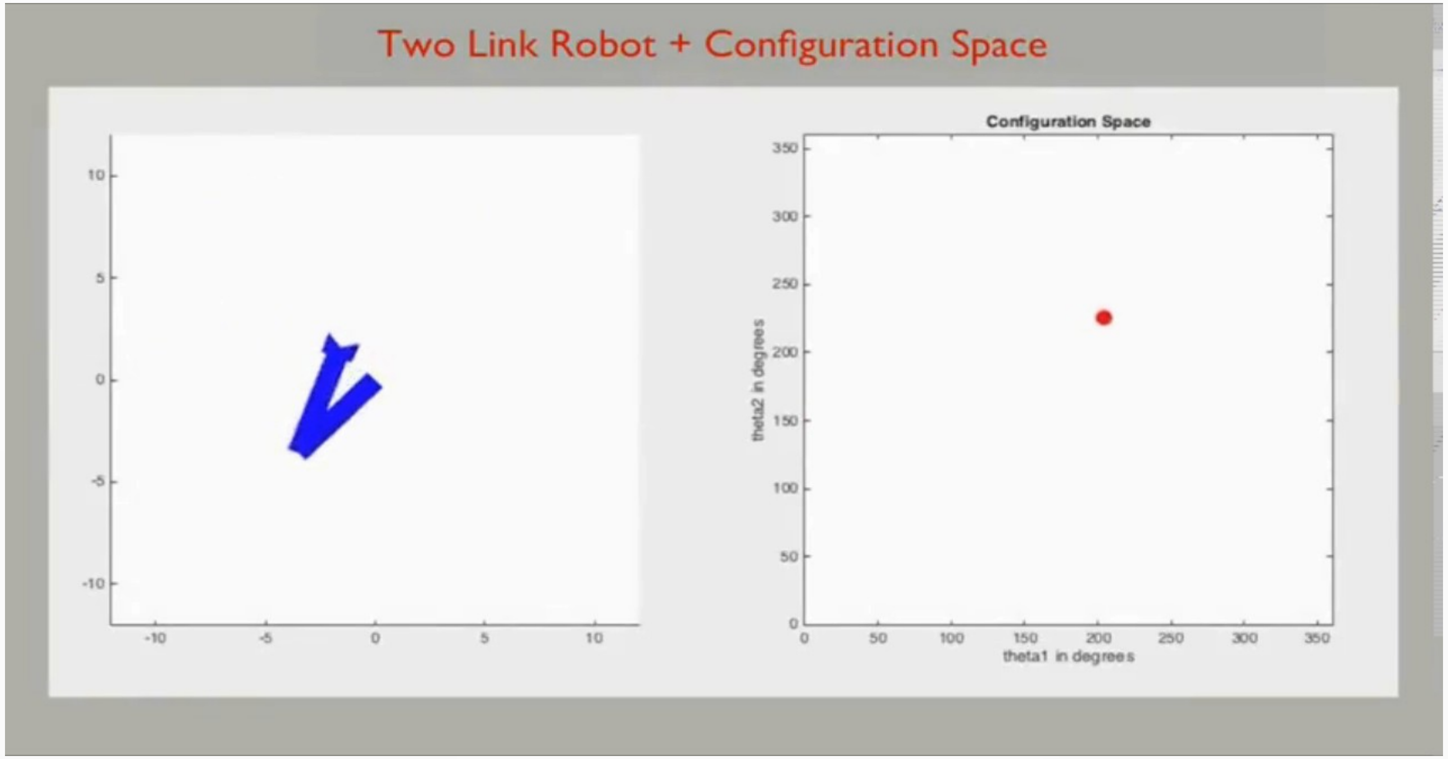

Courtesy Bob Trenwith

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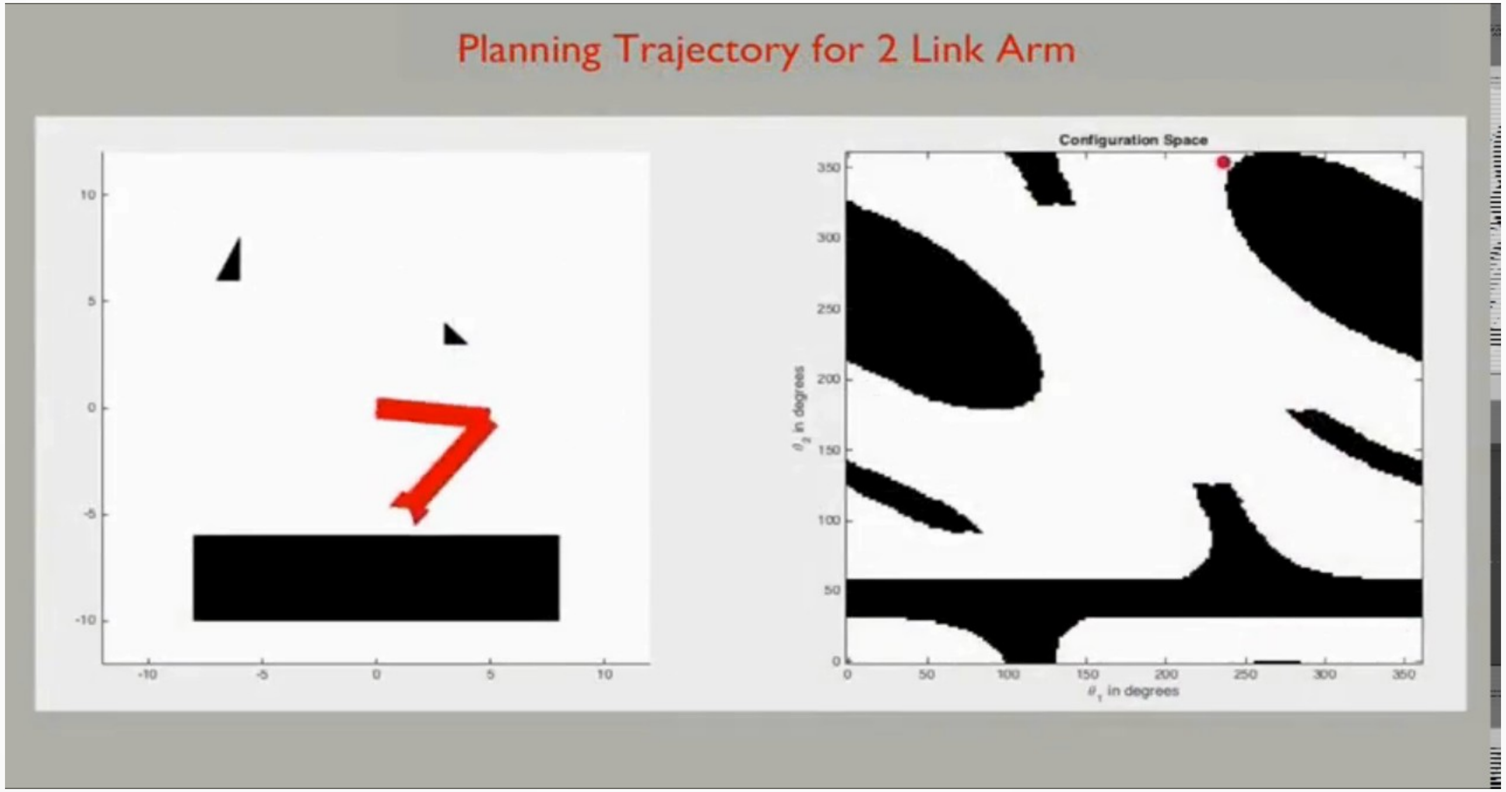

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Algorithms for Motion planning:

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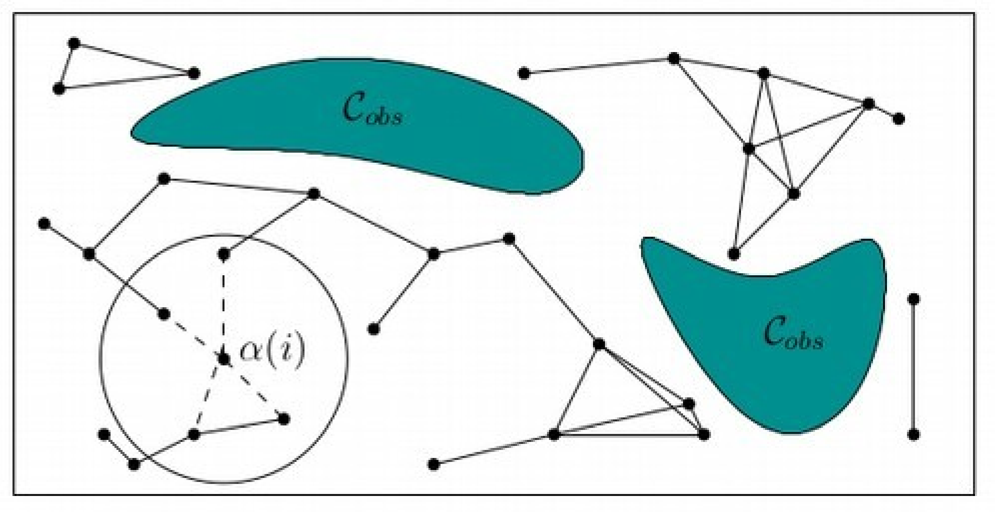
Algorithms for Motion planning:

- PRM (Probabilistic Roadmaps)

L. E. Kavraki, P. Svestka, J.-C. Latombe, and M. H. Overmars. *Probabilistic roadmaps for path planning in high-dimensional configuration spaces*. IEEE Transactions on Robotics & Automation, 12(4):566–580, June 1996.



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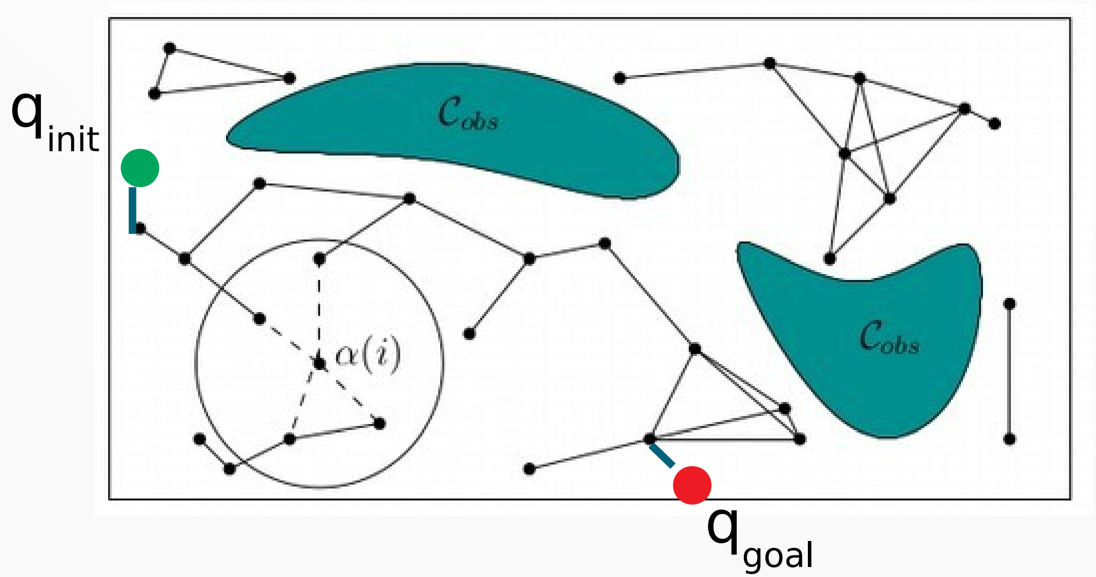

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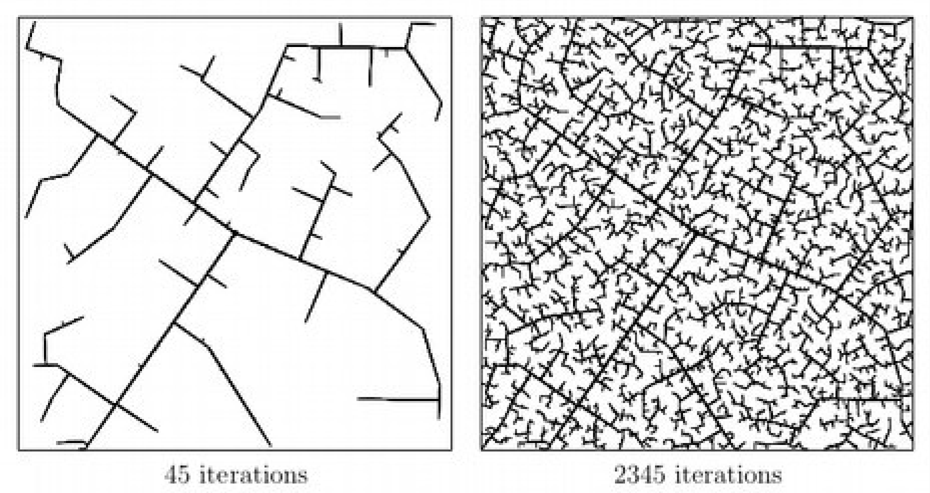

Problem definition(s)

Algorithms for Motion planning:

probabilistically complete

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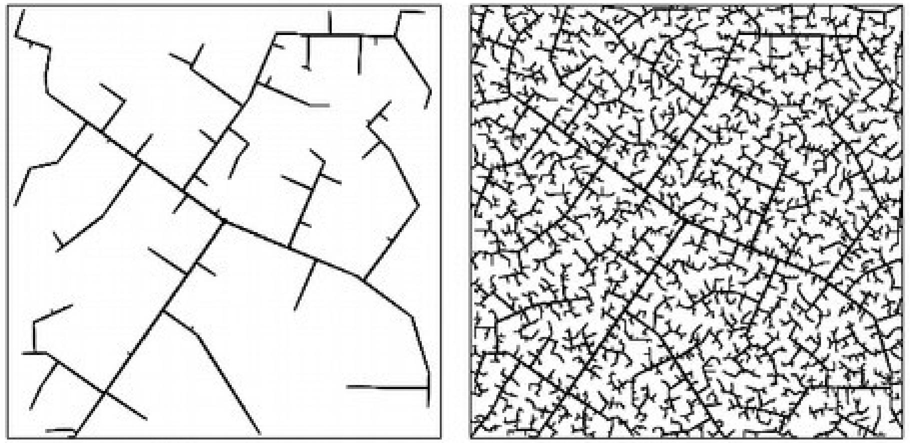

45 iterations 2345 iterations

Problem definition(s)

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Motion Planning

Given free configuration space $\mathcal{C}_{\text{free}}$,
initial configuration $q_I \in \mathcal{C}_{\text{free}}$, and
goal configurations $G \subseteq \mathcal{C}_{\text{free}}$,
a motion plan is defined as

$$\tau : [0,1] \rightarrow \mathcal{C}_{\text{free}}$$

$\tau(0) = q_I$ and $\tau(1) \in G$.

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Task Planning

$\Sigma = (S, A, \gamma, s_0, S_g)$ where,

- S is a finite set of states
- A is a finite set of actions
- $\gamma : S \times A \rightarrow S$ is a deterministic state-transition function, $\gamma(s, a) = s'$.
- $s_0 \in S$ is the start state
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TAMP

$\phi : S \to 2^C$ which maps states to configurations;
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TAMP

Space of grasps and placements

$\phi : S \to 2^C$ which maps states to configurations;
$\xi : A \to 2^C$ which maps actions to motion plans.

SSSP [edit]

The surfaces supporting stable placements are specified by 6 values (*xmin, xmax, ymin, ymax, zmin, zmax*) representing a rectangular region **in the reference frame of the object**.

```
<sssp>
   <xmin>-0.25<xmax><xmin>0.25<xmax>
   <ymin>-0.25<ymax><ymin>0.25<ymax>
   <zmin>0.5<zmax><zmin>0.5<zmax>
</sssp>
```

Alternatively, SSSP can be represented by polygonal regions. Then, the tag **<pssp>** (polygon supporting stable placements) is used and a polygonal region is specified as a list of 3D coordinates **in the reference frame of the object**, assumed to lie in a plane:

```
<pssp>
   <point><x>-0.15</x><y>0.33</y><z>0.5</z></point>
   <point><x>-0.22</x><y>0.25</y><z>0.5</z></point>
   <point><x>0.25</x><y>0.12</y><z>0.5</z></point>
   ...
</pssp>
```

Remarks:

- In stacking problems, the SSSP is defined by a single point centred on top of the object (i.e., *xmin=xmax, ymin=ymax*) therefore objects will be aligned on top of each other (e.g., *disc2* and *disc3* in the example below).
- The number of SSSP per object is currently limited to one. This assumes that if an object is rotated about the x or y axis, it is no longer possible to place something on it. This assumption is sufficient for the current set of benchmark problems, but it may be relaxed later, i.e., by allowing lists of SSOP.

SOP [edit]

The stable object poses are defined similarly to continuous grasps: a template rotation and a rotation axis (both expressed **in the world frame of reference**, plus the *distance* parameter, which is the distance between the centre of the object and the SSSP.

```
<sop>
   <template>1.0 0.0 0.0 0.0 1.0 0.0 0.0 0.0 1.0</template>
   <axis>0.0 0.0 1.0</axis>
   <distance>0.08</distance>
</sop>
```

MP

Space of grasps and placements

states to configurations;
actions to motion plans.

- $s_0 \in S$ is the start state
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TAMP

$\phi : S \to 2^C$ which maps states to configurations;
$\xi : A \to 2^C$ which maps actions to motion plans.

find a sequence of actions $\langle a_0, a_1, \ldots, a_{n-1} \rangle$ following a sequence of task states $\langle s_0, s_1, \ldots, s_n \rangle$ such that

$$s_n \in S_g \text{ and}$$

$$s_{i+1} = \gamma(s_i, a_i)$$

and to find a sequence of motion plans $\langle \tau_0, \tau_1, \ldots, \tau_{n-1} \rangle$ such that $\forall i = 0 \ldots n-1$:

$$\tau_i(0) \in \phi(s_i) \text{ and } \tau_i(1) \in \phi(s_{i+1})$$

$$\tau_i \in \xi(a_i), \text{ and}$$

$$\tau_i(1) = \tau_{i+1}(0)$$

Problem definition(s)

Initial state

On(B, Table)
On(A, Table)
On(C, A)

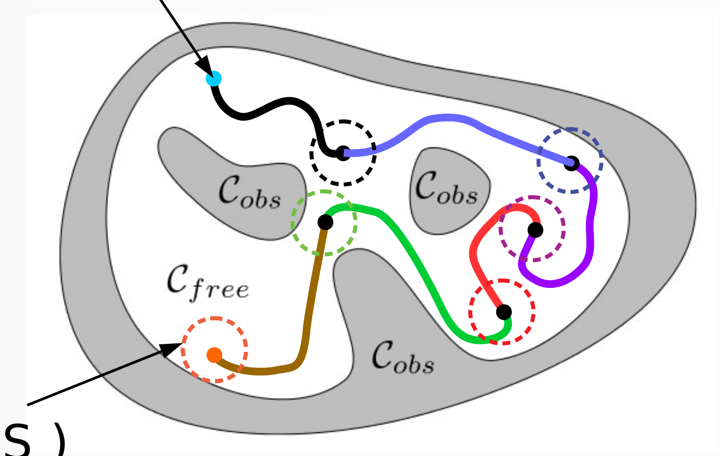
q_{init}

Goal state

On(C, Table)
On(B, C)
On(A, B)

Plan

Pick(C)
Place(C, Table)
Pick(B)
Place(B, C)
Pick(A)
Place(A, B)



$\Phi(S_g)$

TAMP

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$$\tau_i \in \xi(a_i), \text{ and}$$

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On(B, Table)
On(A, Table)
On(C, A)

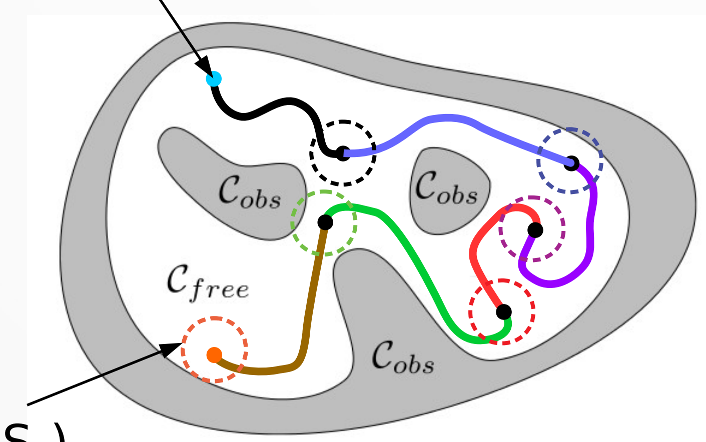
q_{init}

Goal state

On(C, Table)
On(B, C)
On(A, B)

Plan

Pick(C)
Place(C, Table)
Pick(B)
Place(B, C)
Pick(A)
Place(A, B)



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$$s_n \in S_g \text{ and}$$

$$s_{i+1} = \gamma(s_i, a_i)$$

and to find a sequence of motion plans $\langle \tau_0, \tau_1, \ldots, \tau_{n-1} \rangle$ such that $\forall i = 0 \ldots n-1$:

$$\tau_i(0) \in \phi(s_i) \text{ and } \tau_i(1) \in \phi(s_{i+1})$$

$$\tau_i \in \xi(a_i), \text{ and}$$

$$\tau_i(1) = \tau_{i+1}(0)$$

- Fully observable
- Deterministic

Problem definition(s)

TAMP's siblings:

- **Manipulation Planning**

  Siméon T, Laumond J-P, Cortés J, Sahbani A. *Manipulation Planning with Probabilistic Roadmaps*. The International Journal of Robotics Research. 2004;23(7-8):729-746.

- **NAMO** (Navigation Among Movable Obstacles)

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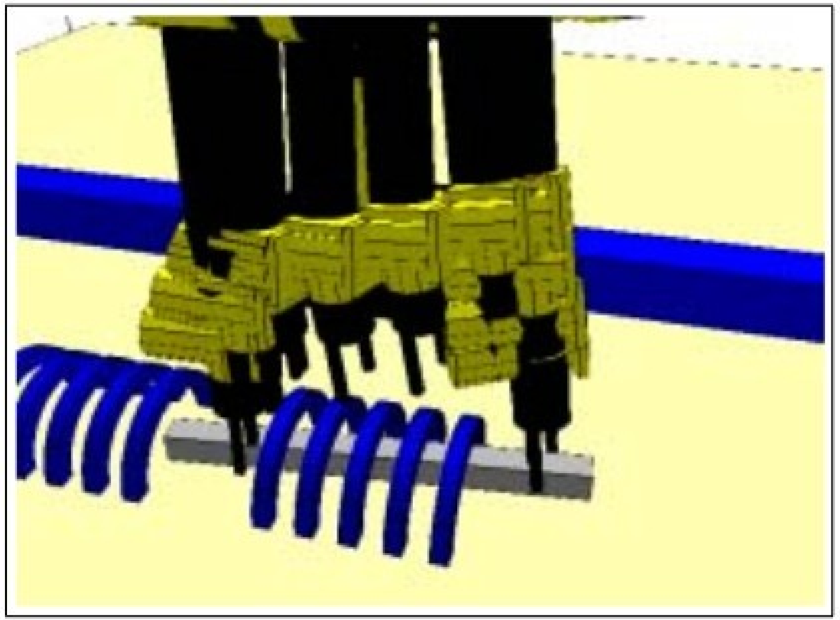

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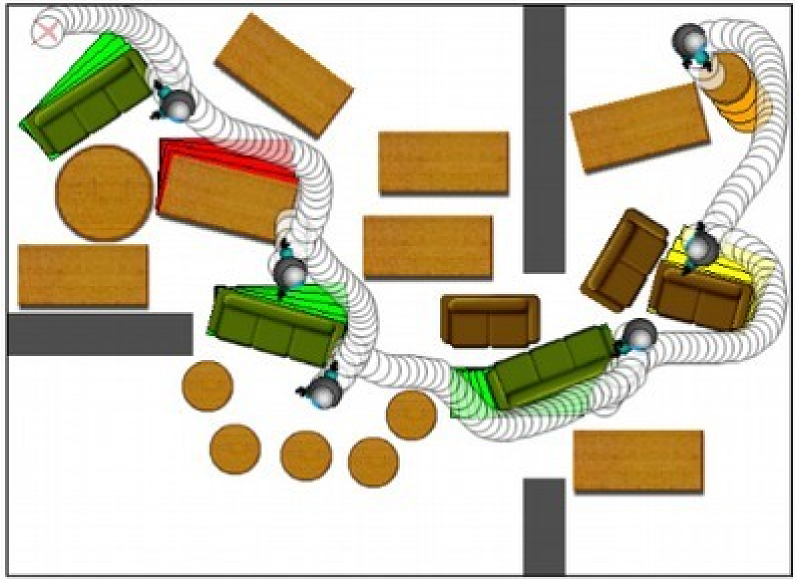

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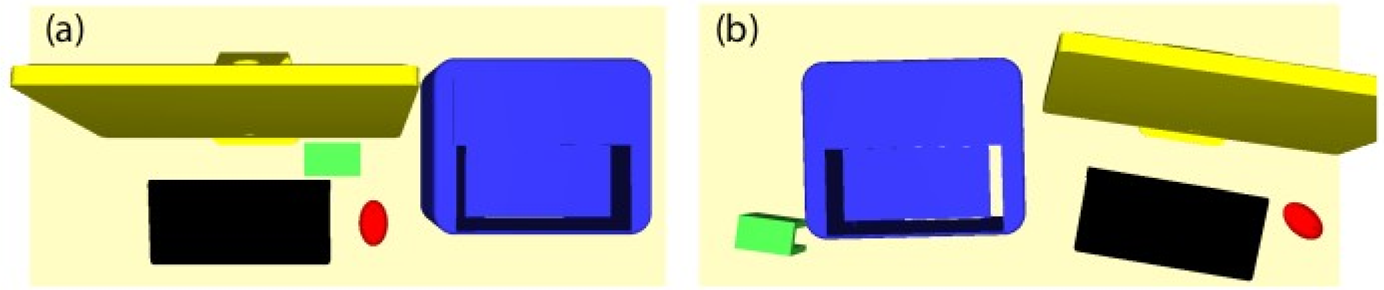

Figure 4. (a) Initial configuration, (b) Tentative final placement

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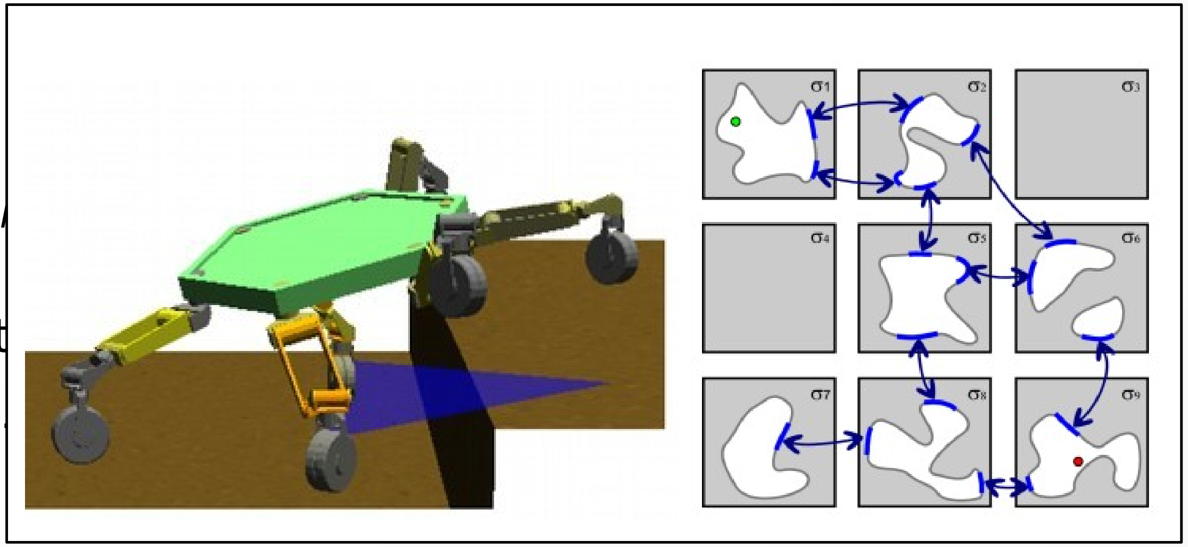

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Outline

- Problem definition(s)
- What makes it difficult?
- 3 approaches to TAMP
- Future directions

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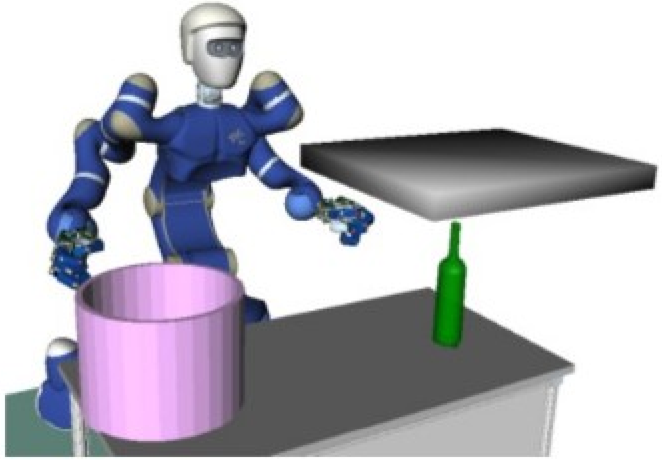

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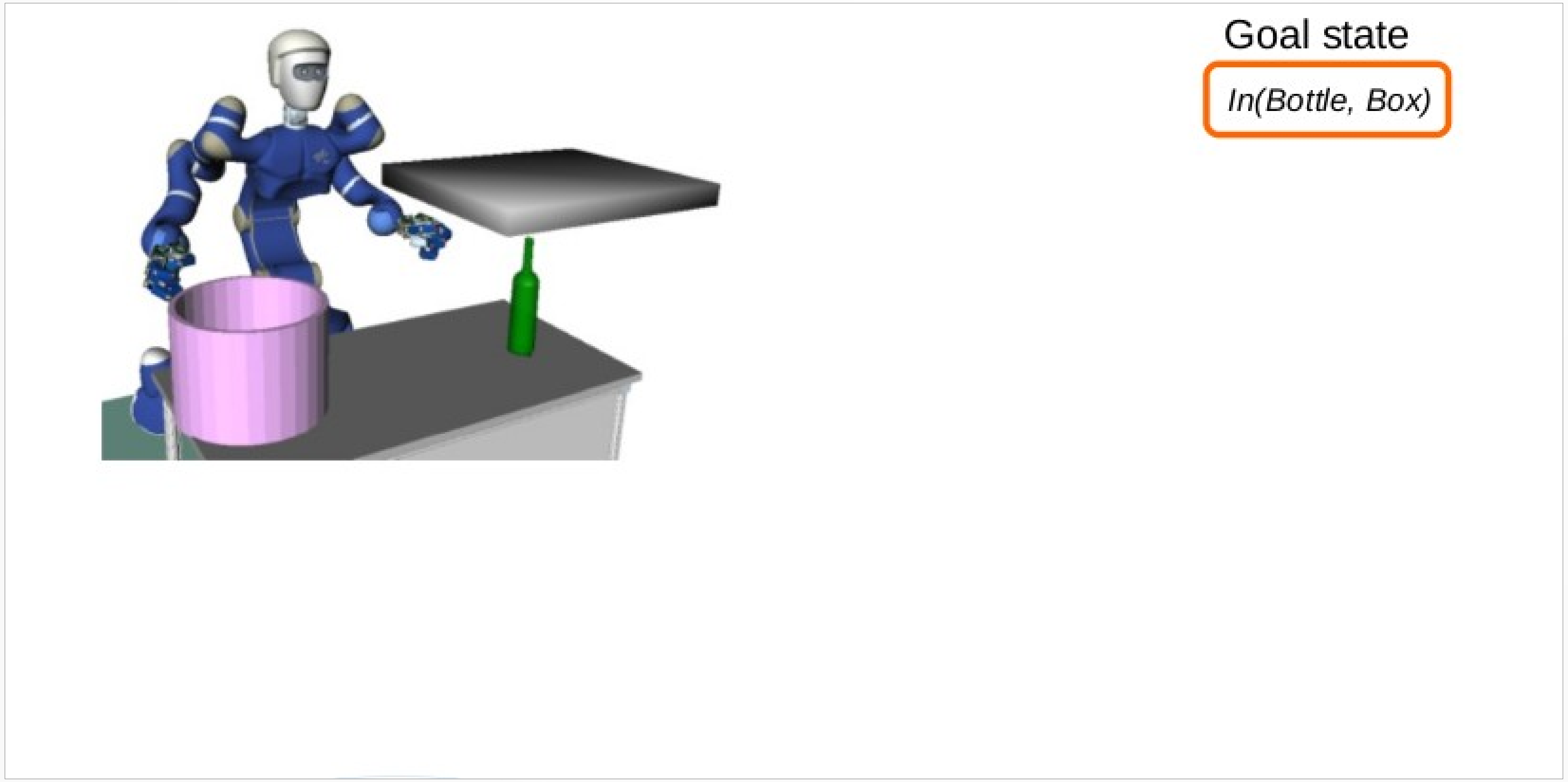

Naive approach: Task Planning first, Motion Planning then.

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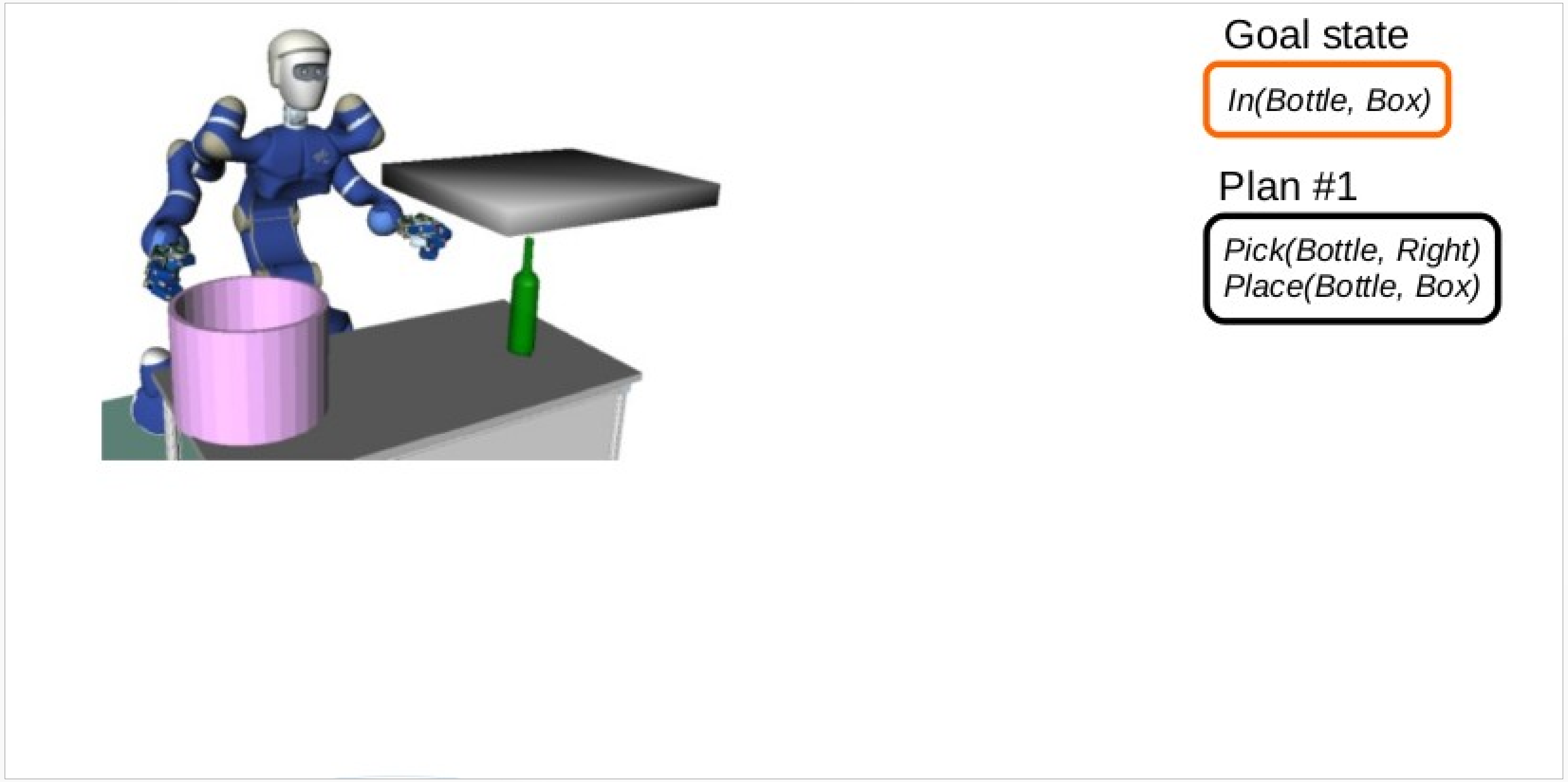

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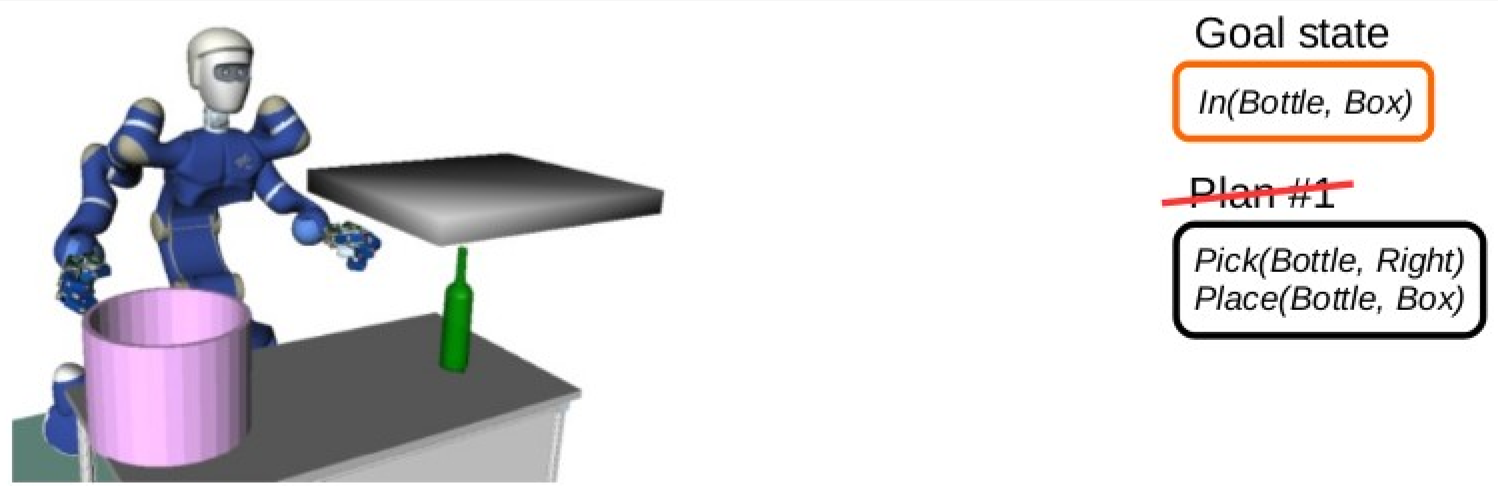

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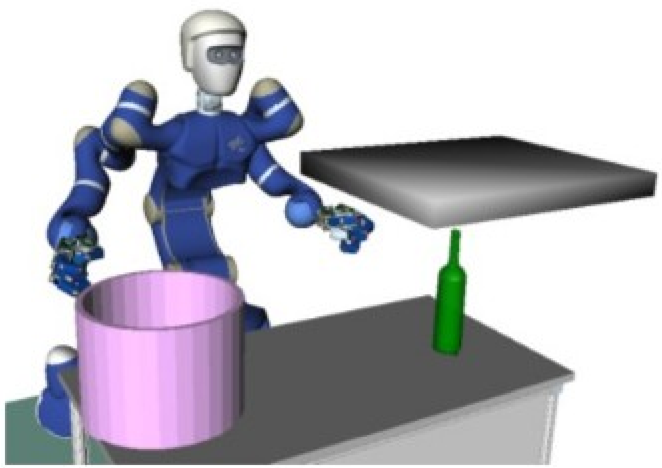

Goal state

In(Bottle, Box)

~~Plan #1~~

Plan #2

Pick(Bottle, Left)
Place(Bottle, Box)

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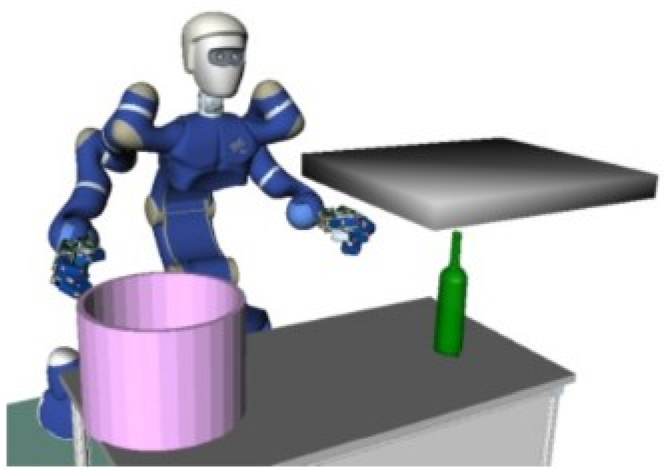

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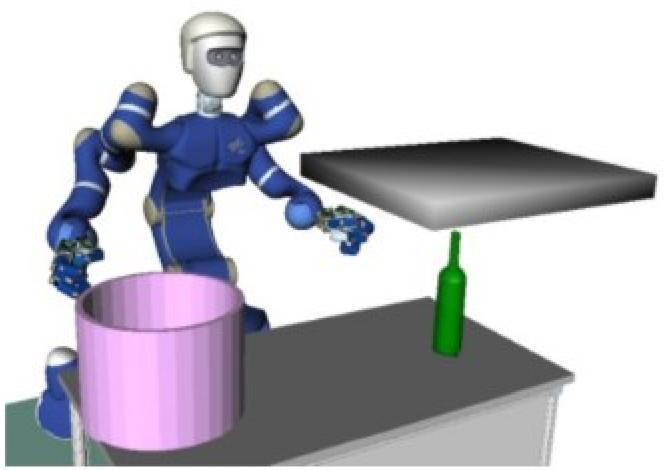

Goal state

In(Bottle, Box)

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Plan #3

Pick(Bottle, Left)
Place(Bottle, Table)
Pick(Bottle, Right)
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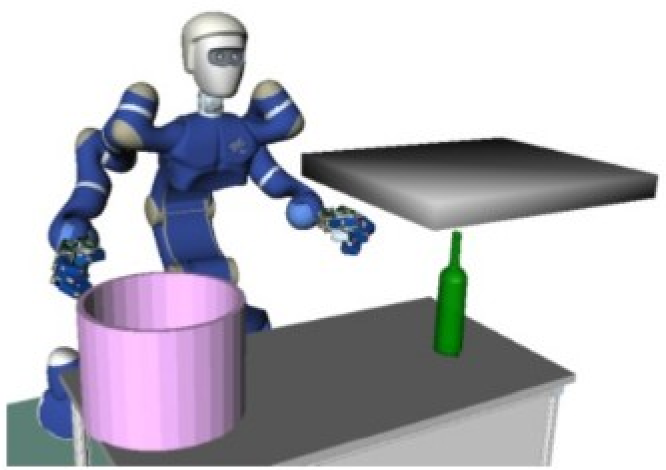

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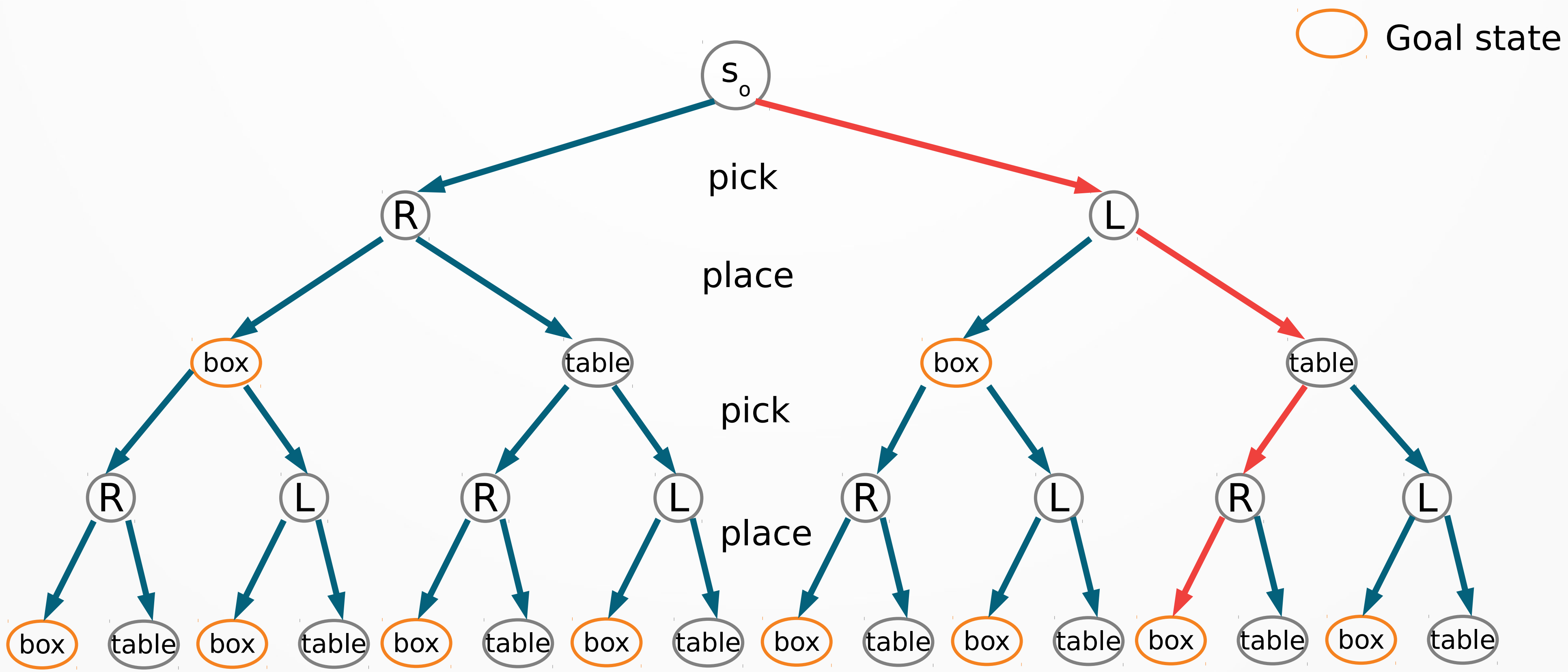

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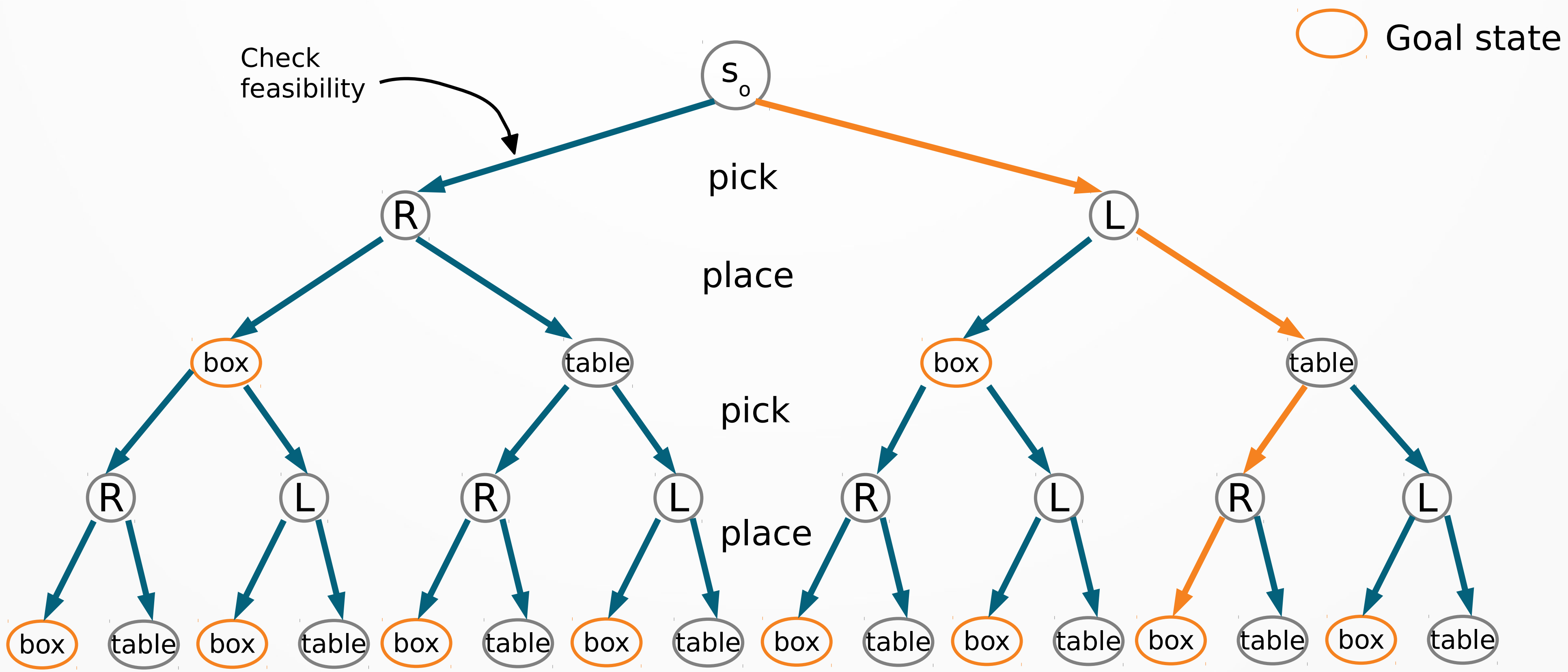

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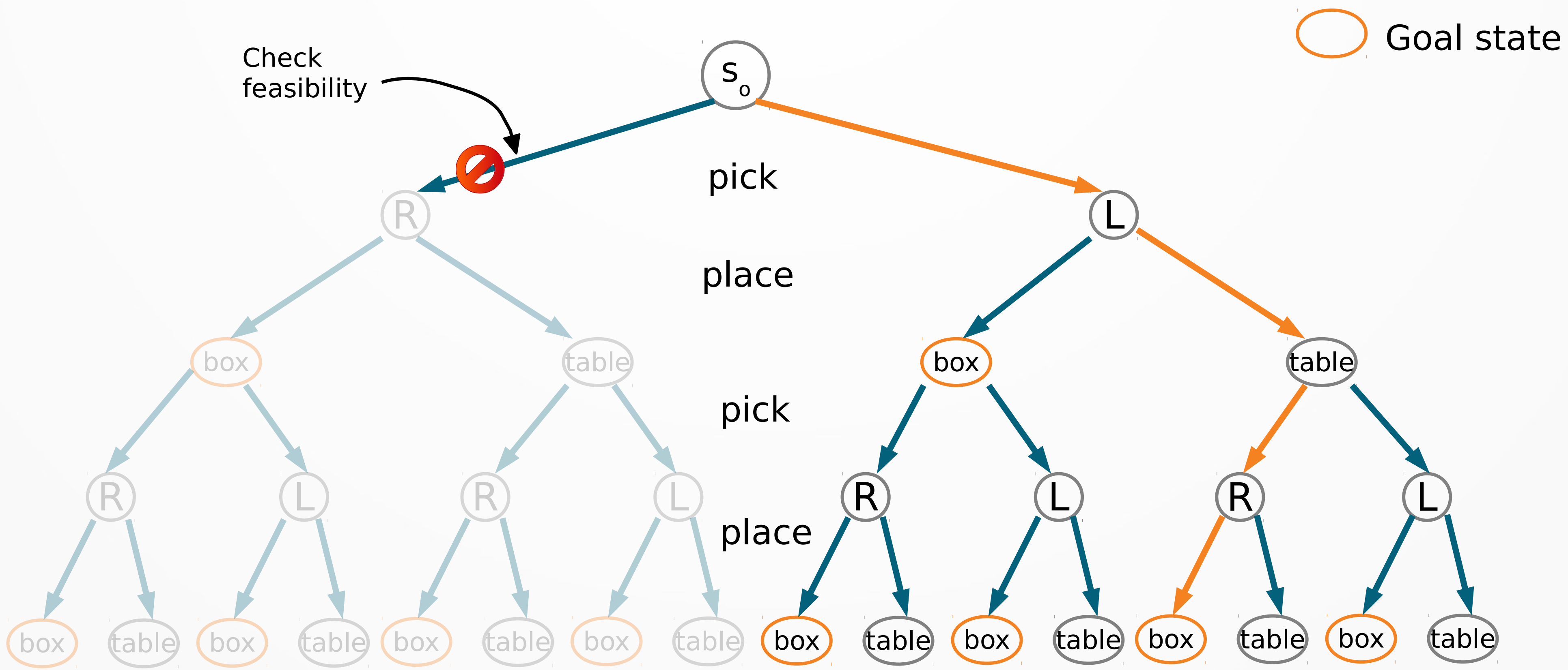

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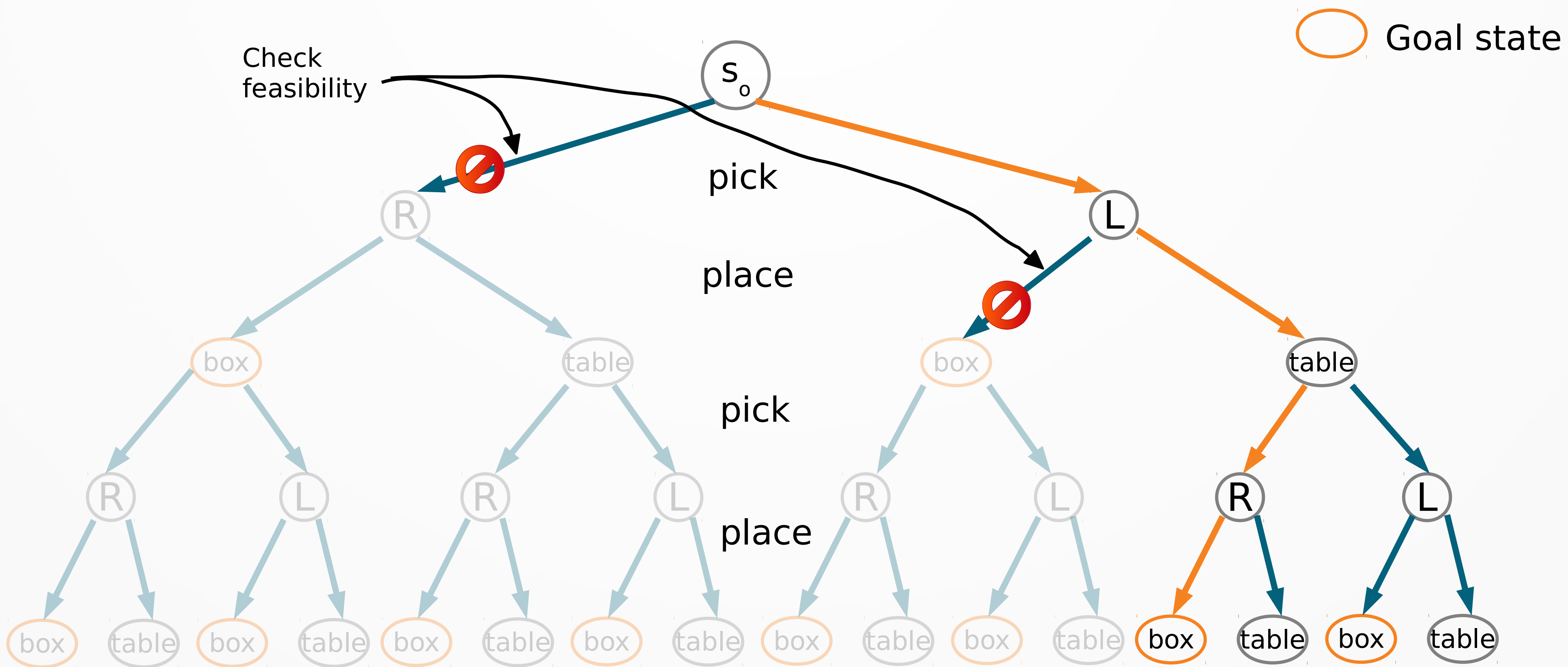

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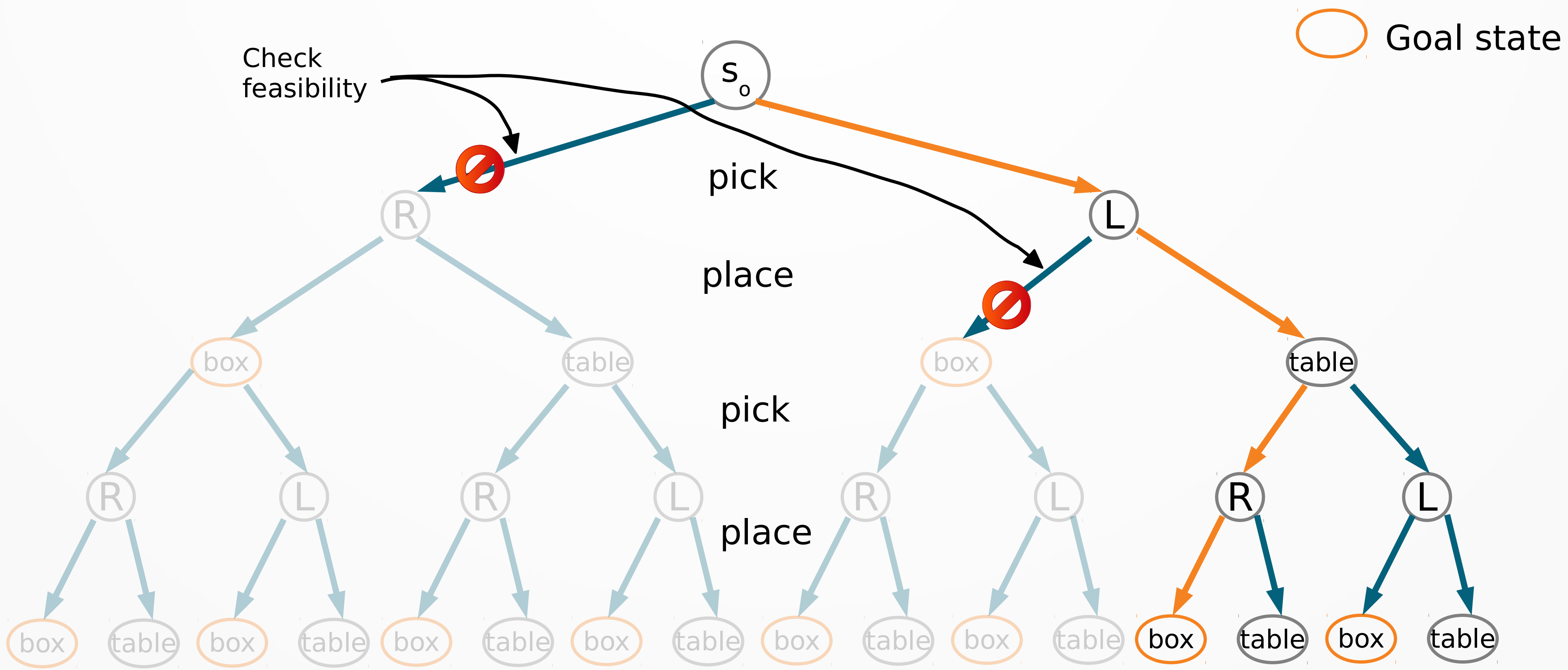

→ **Interleaving** symbolic and geometric search enables efficient pruning!

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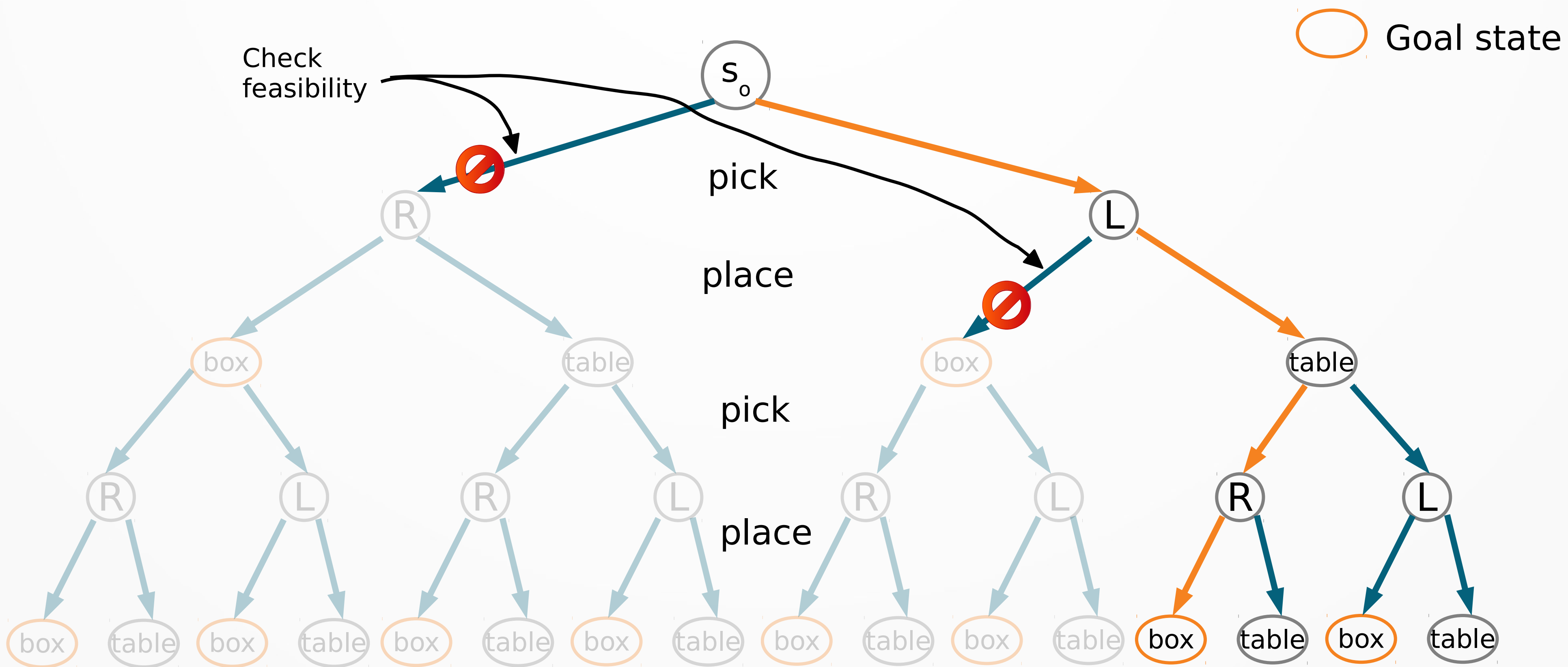

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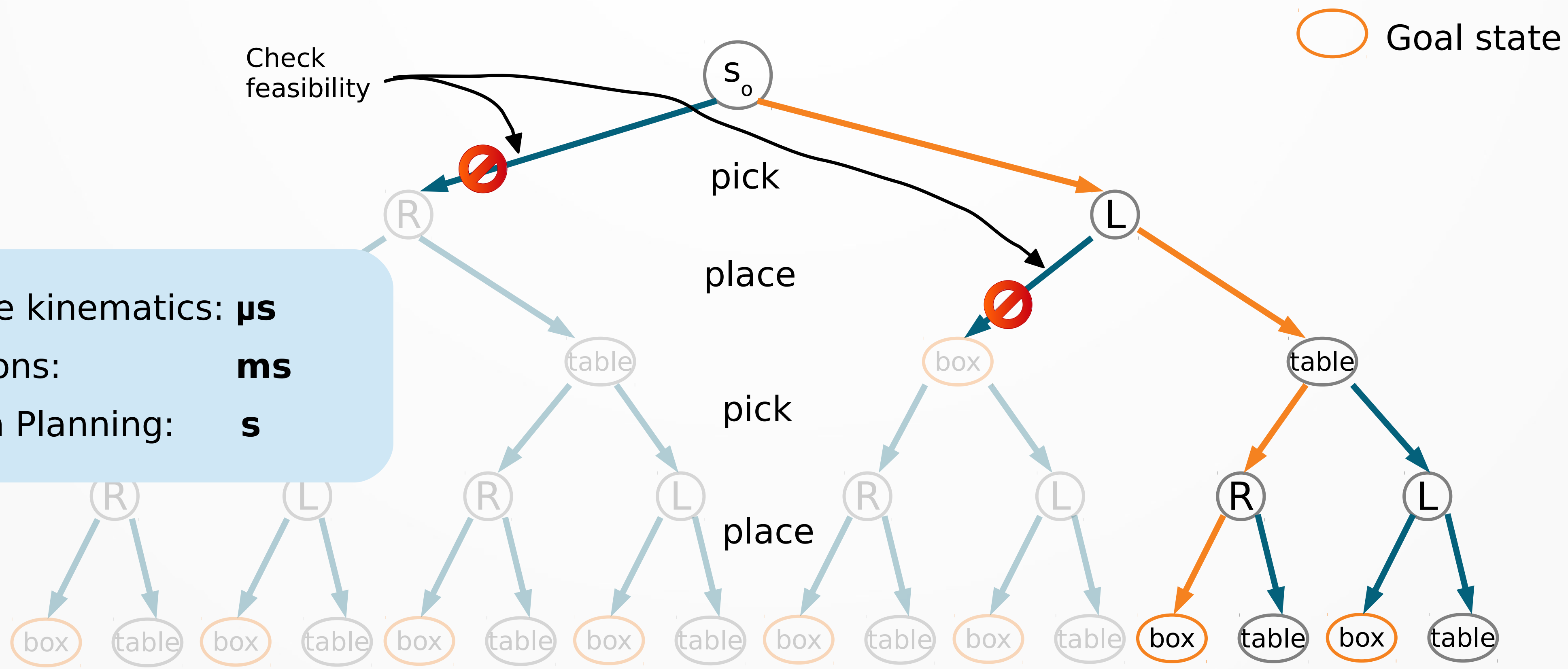

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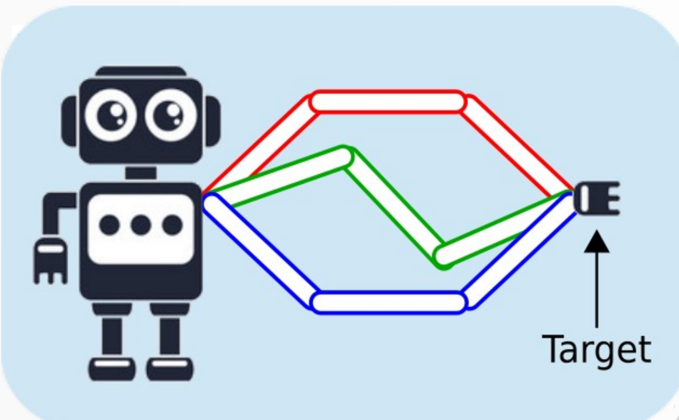

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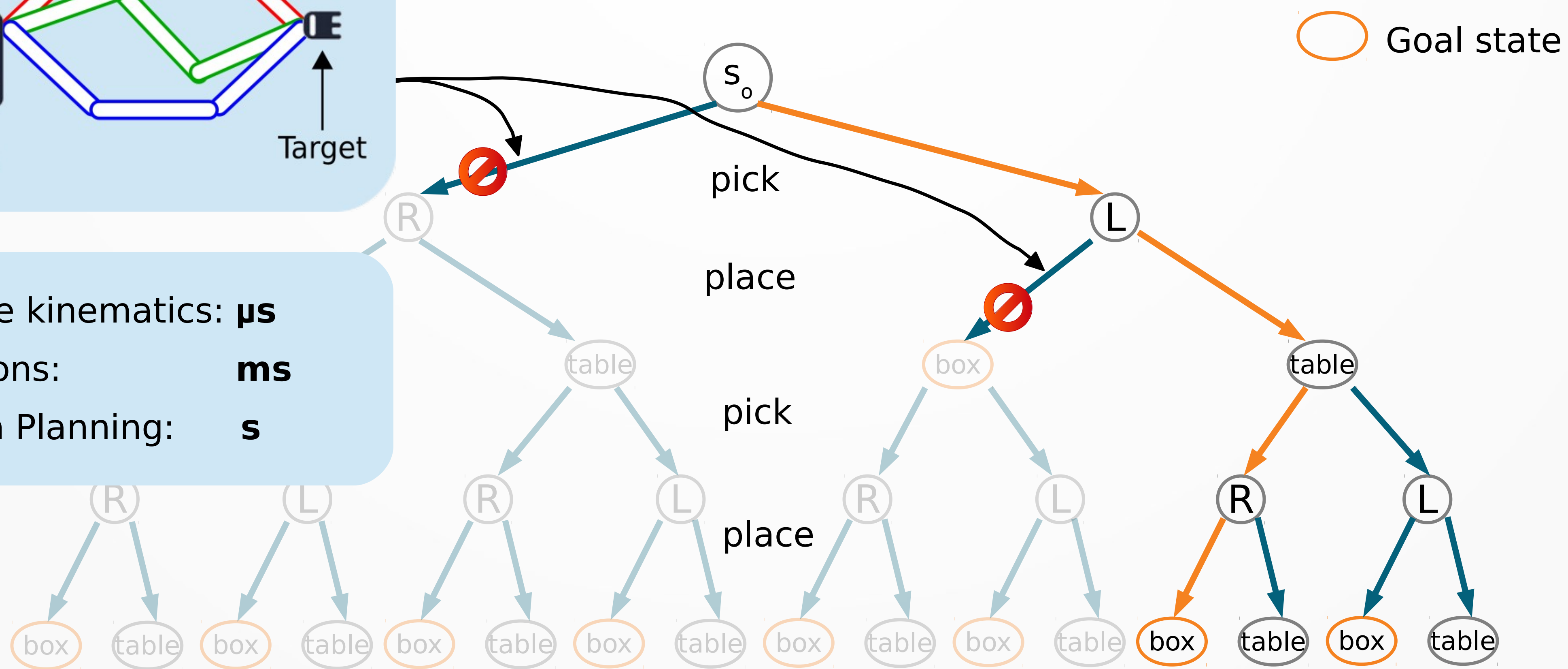

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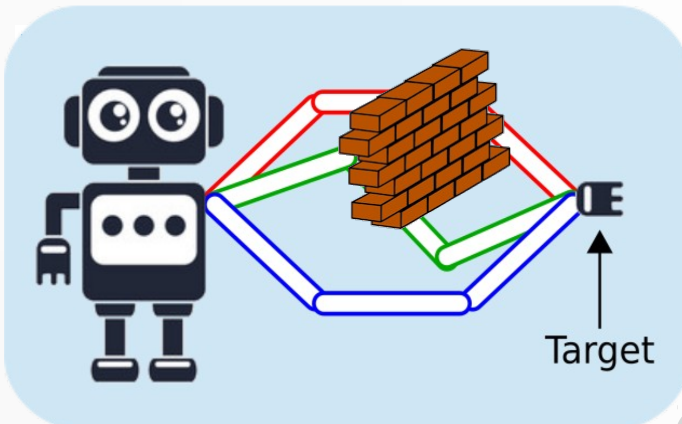

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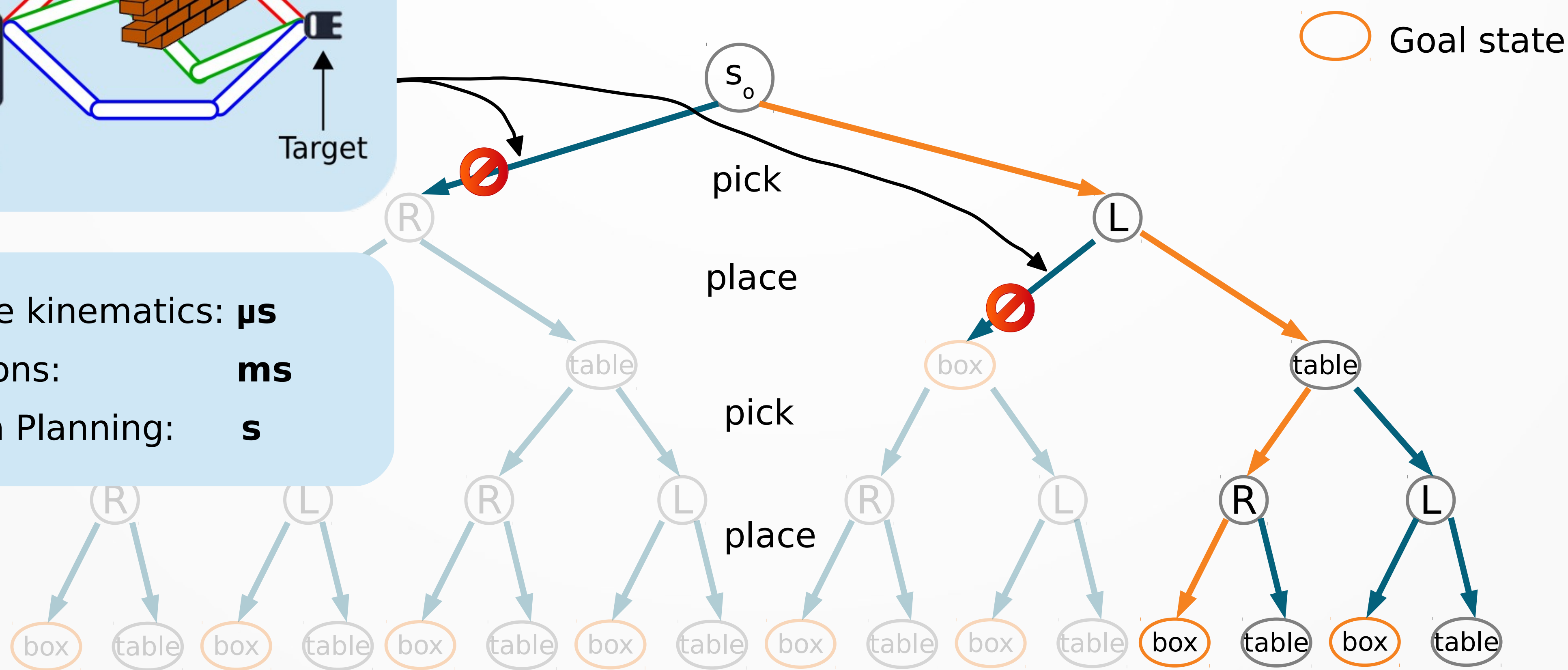

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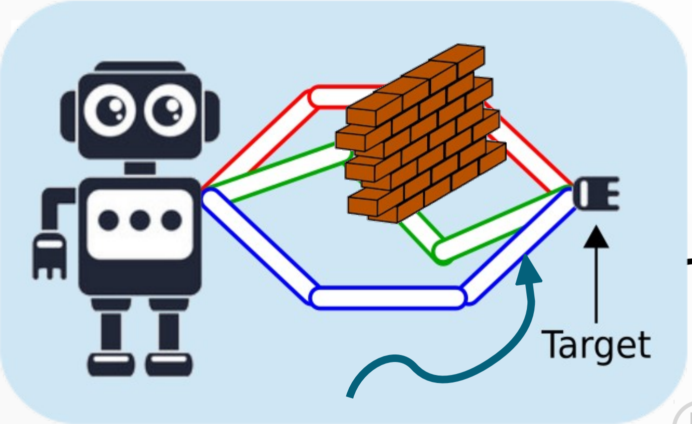

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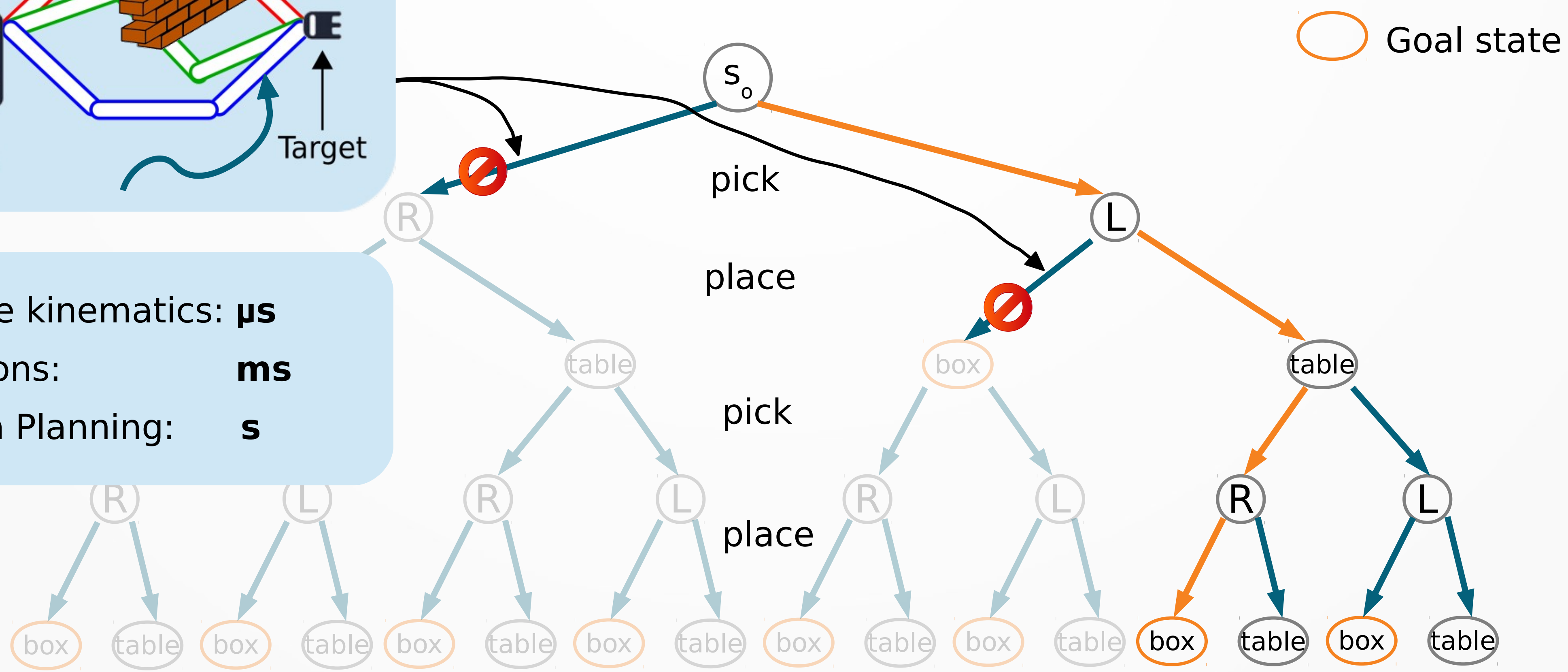

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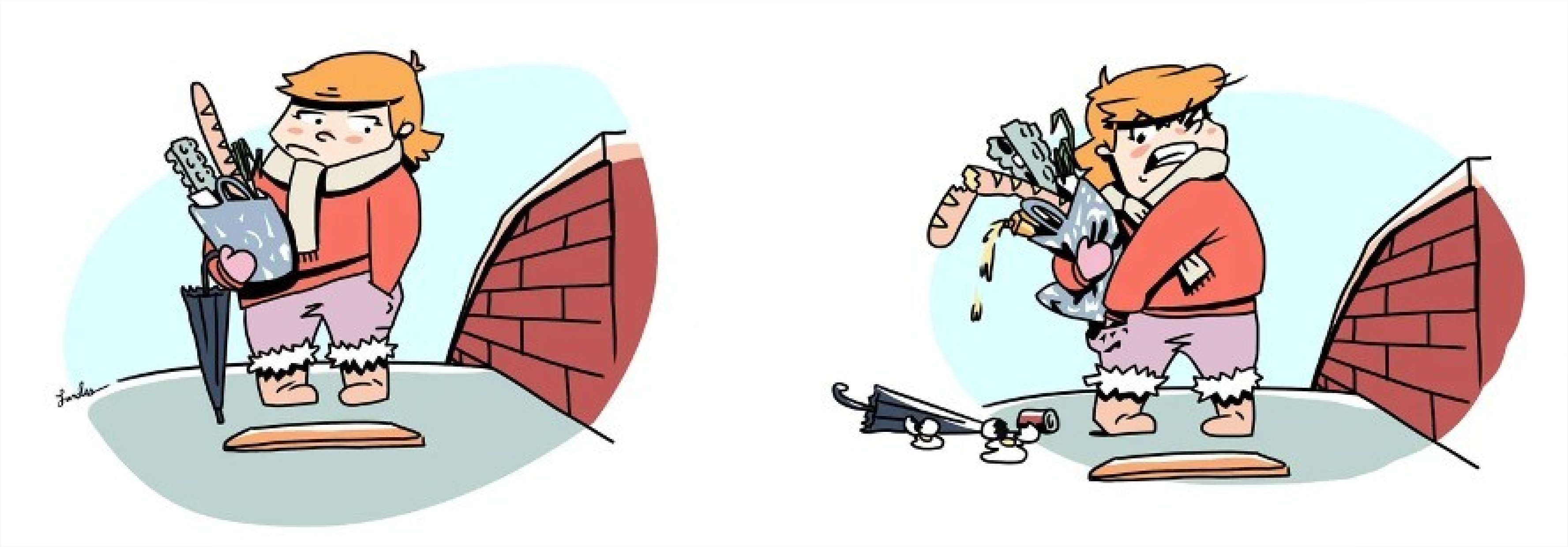

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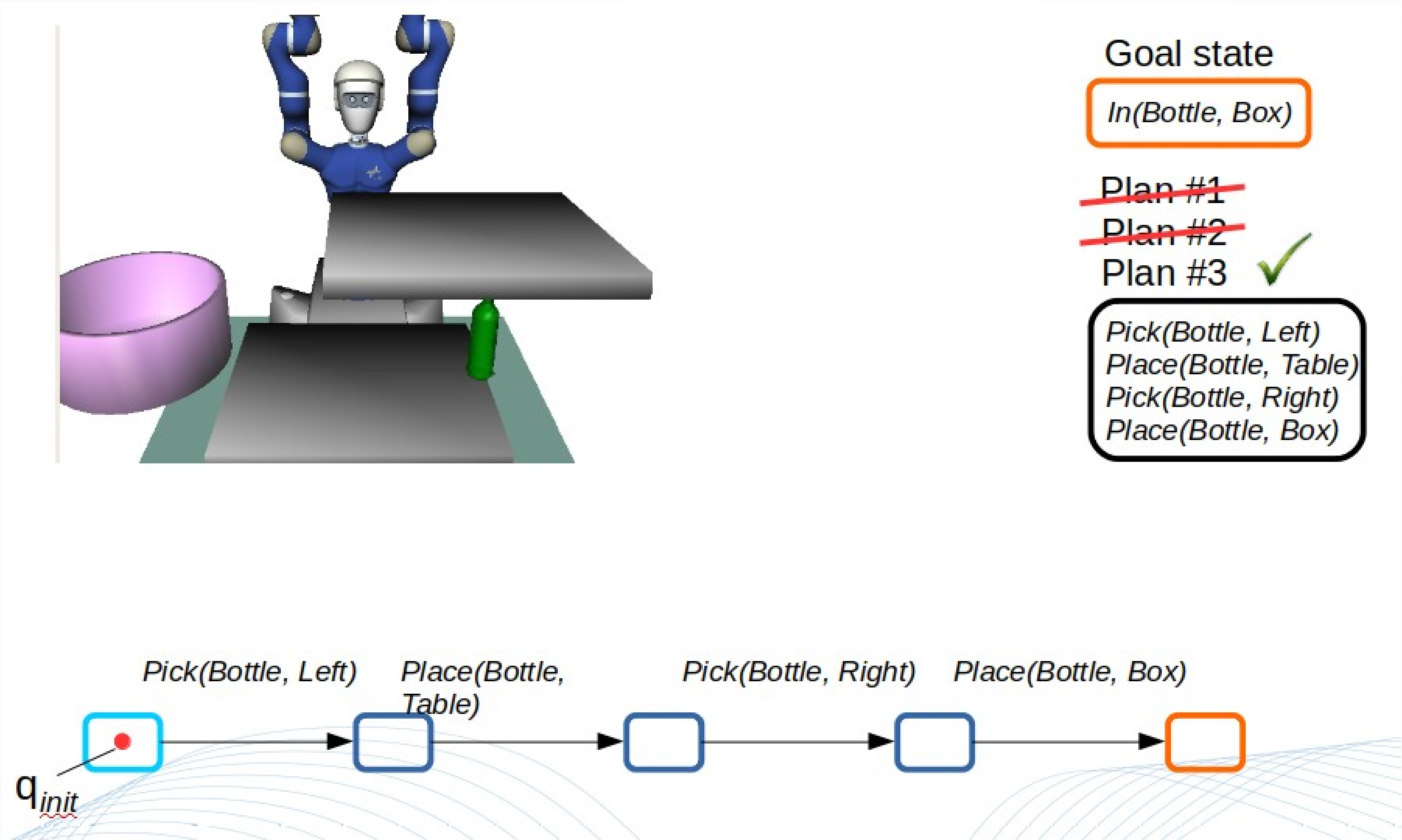

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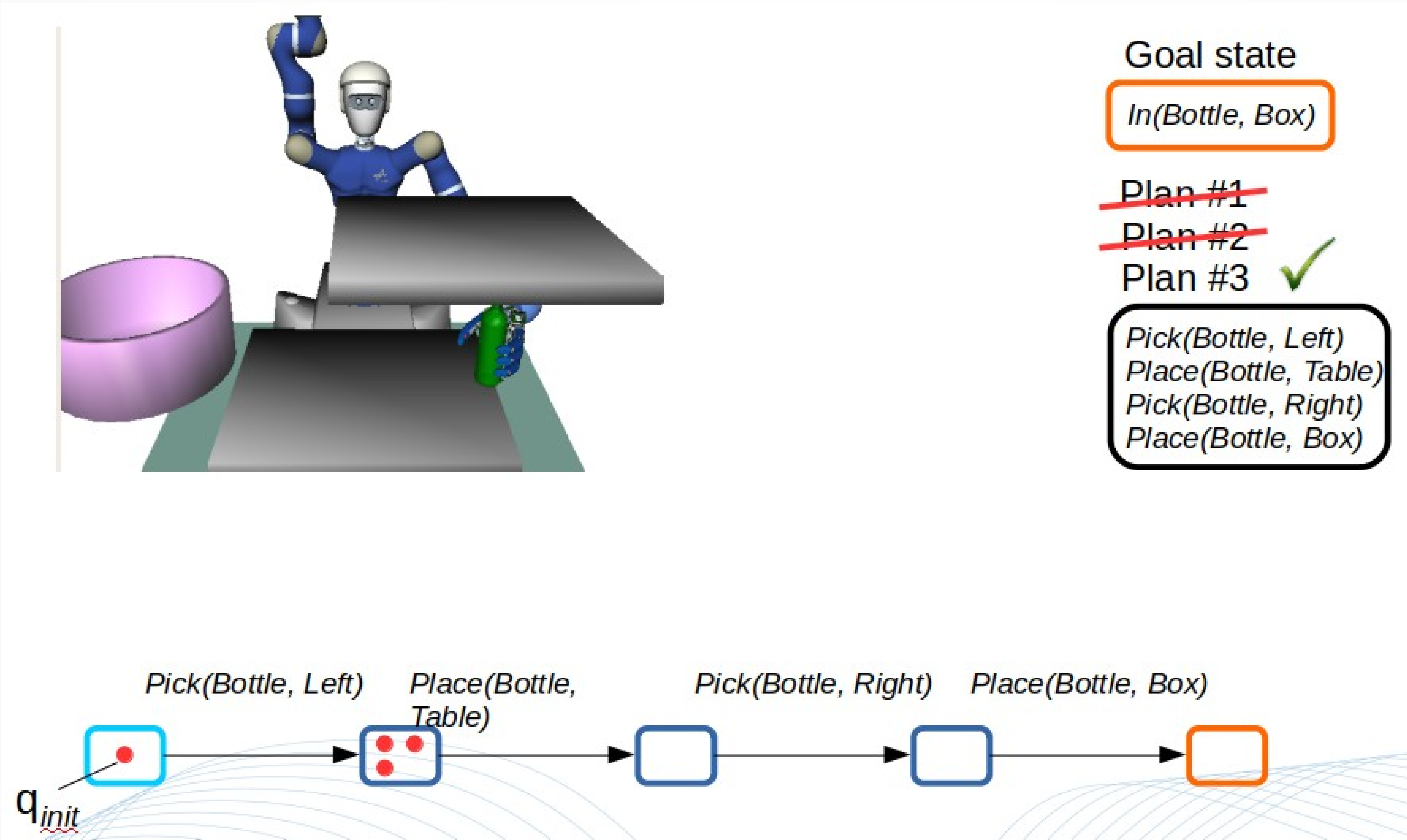

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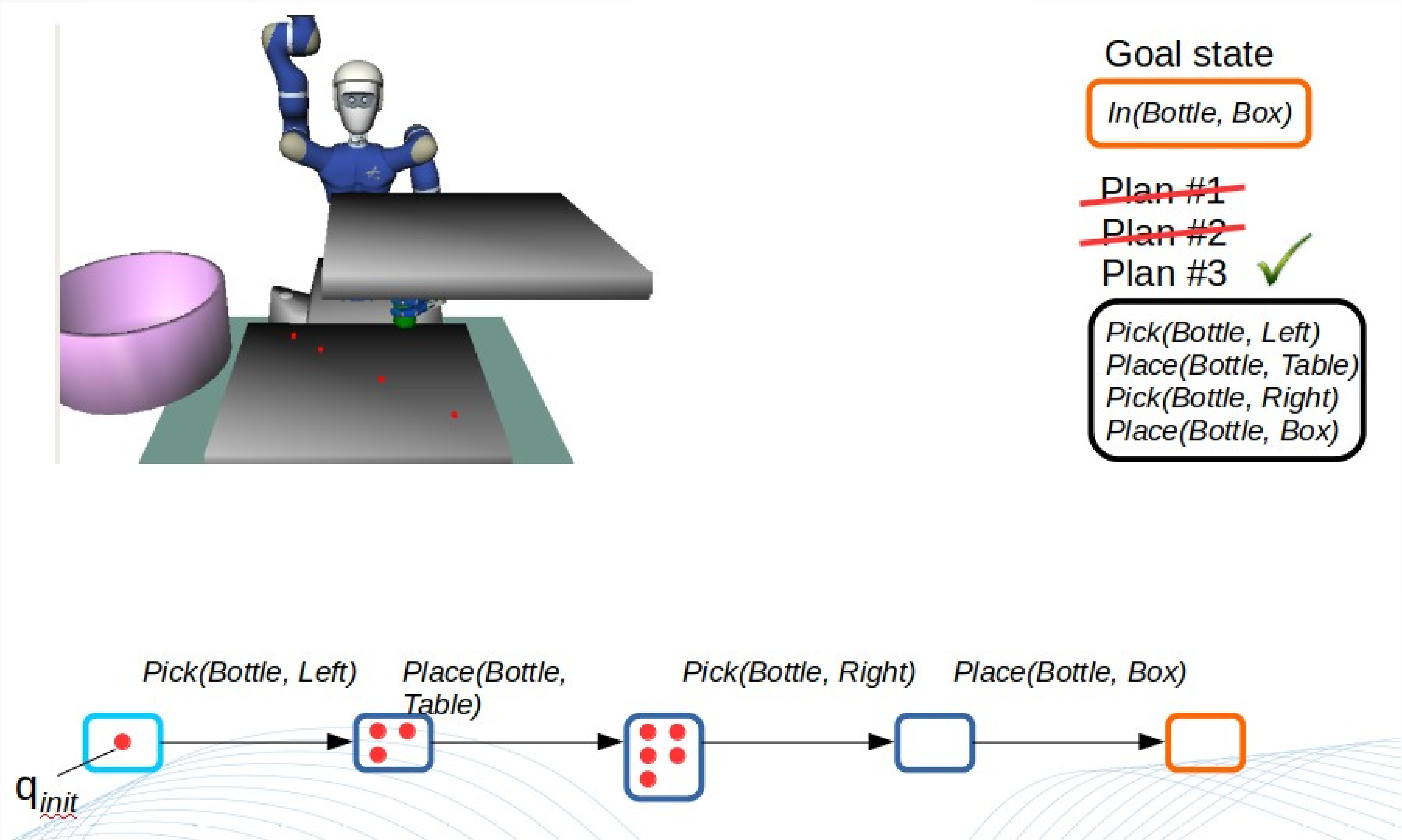

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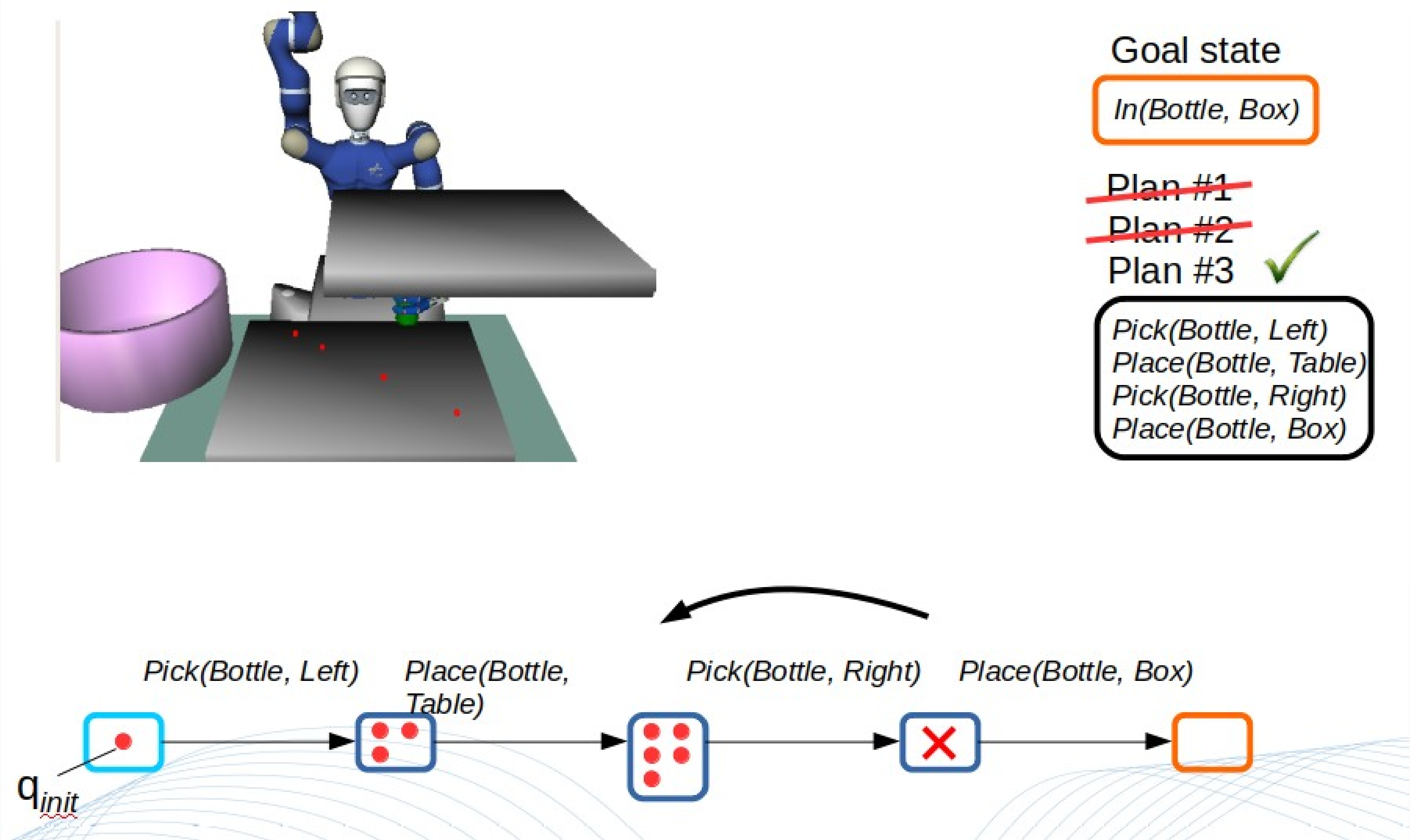

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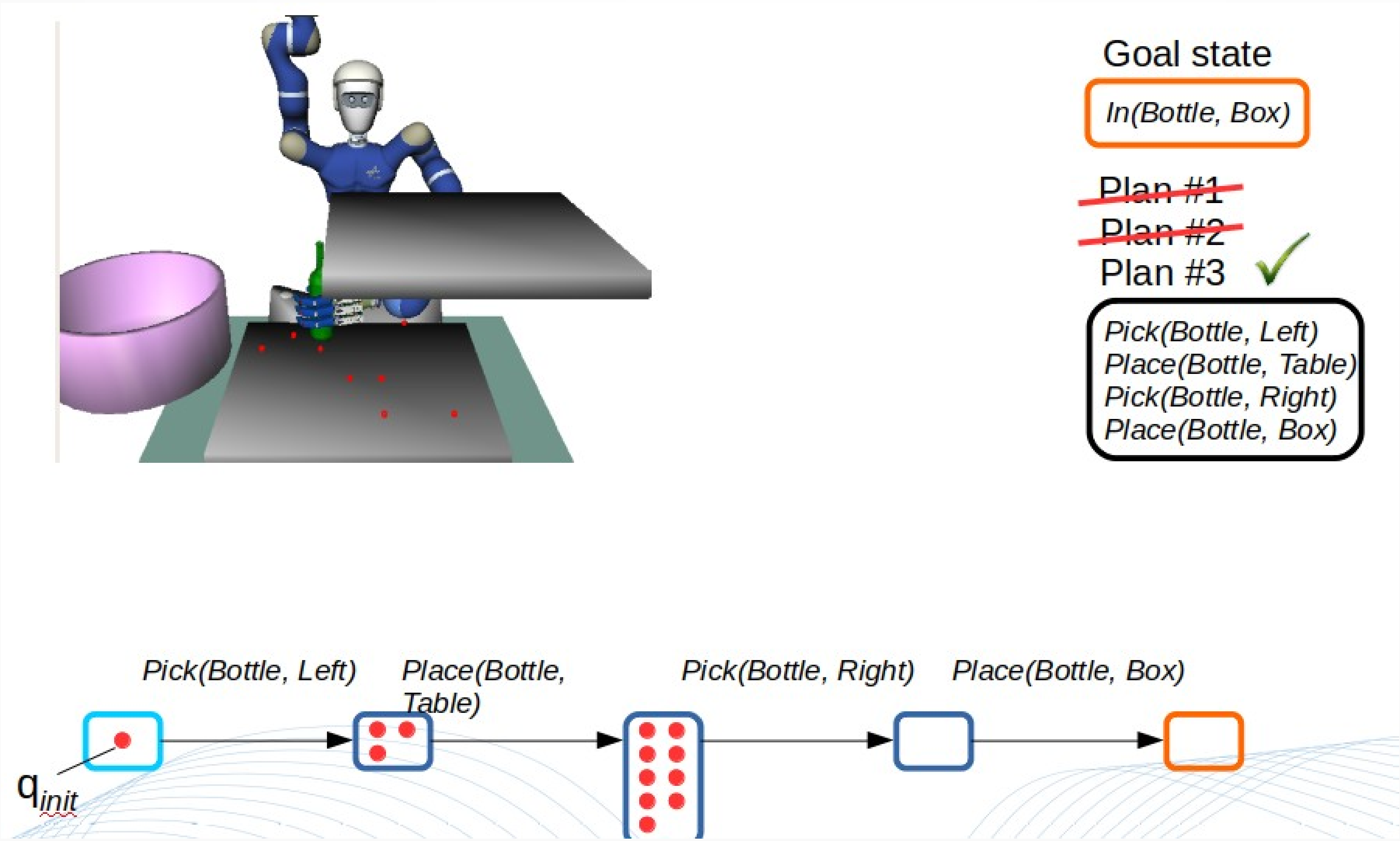

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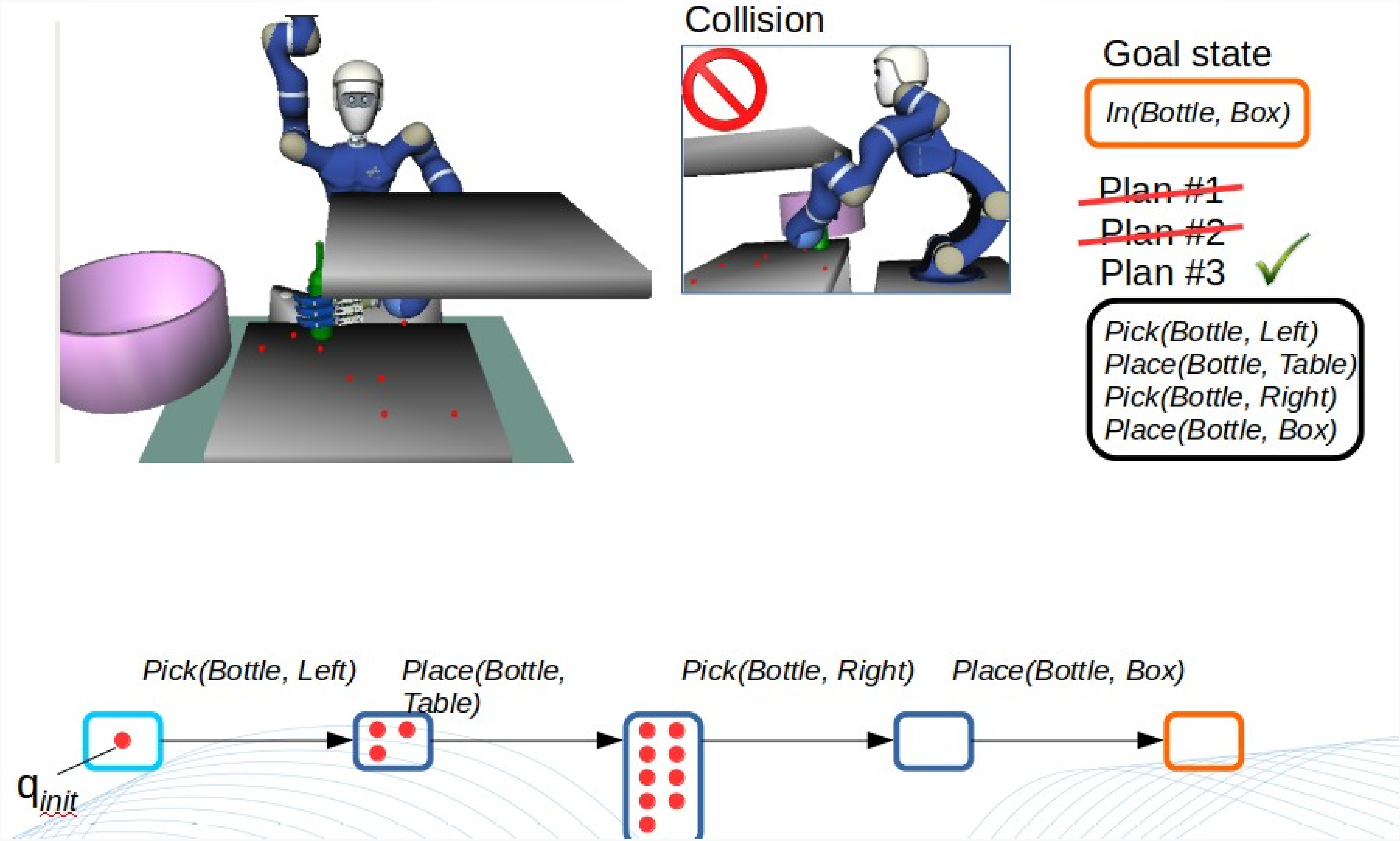

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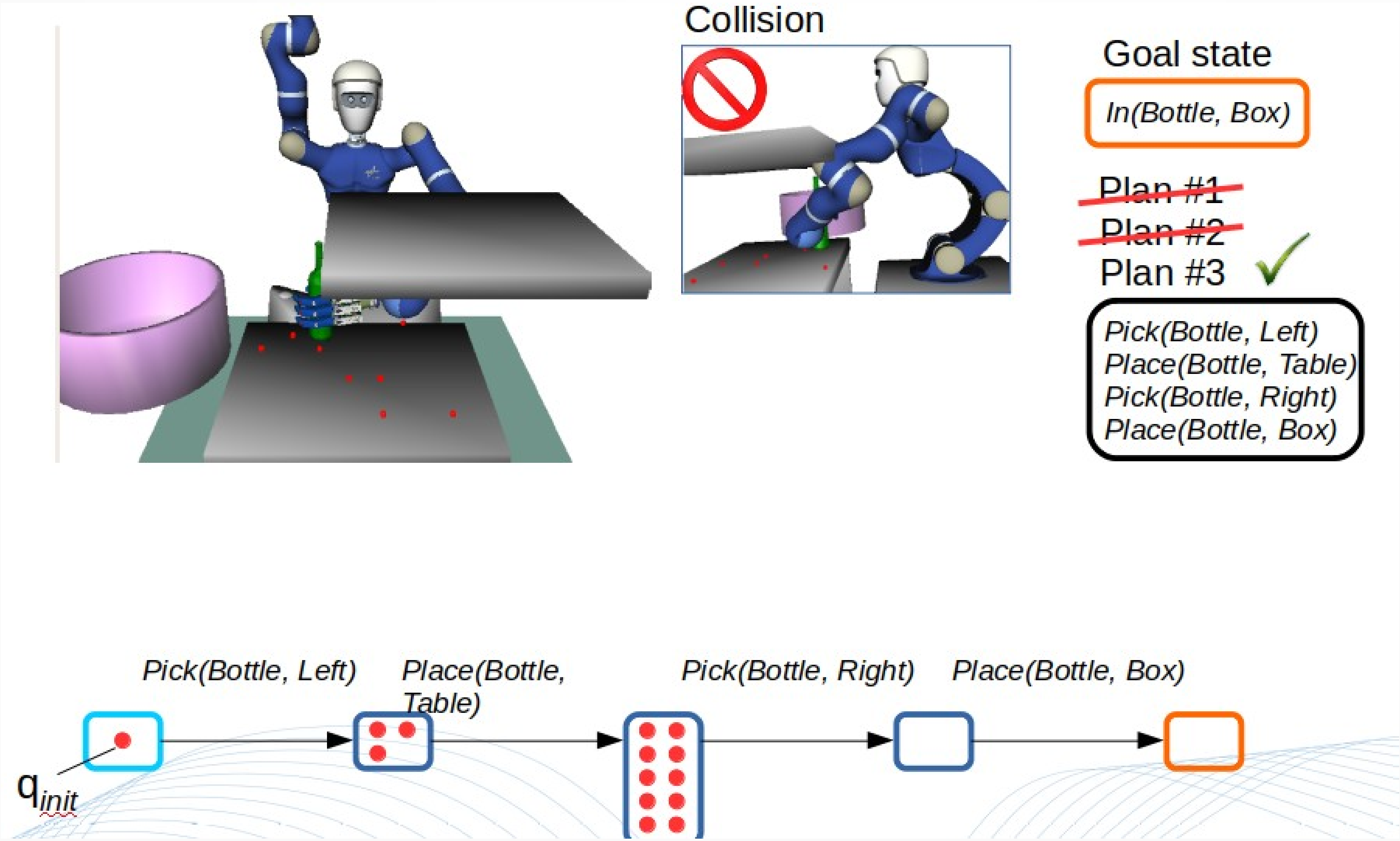

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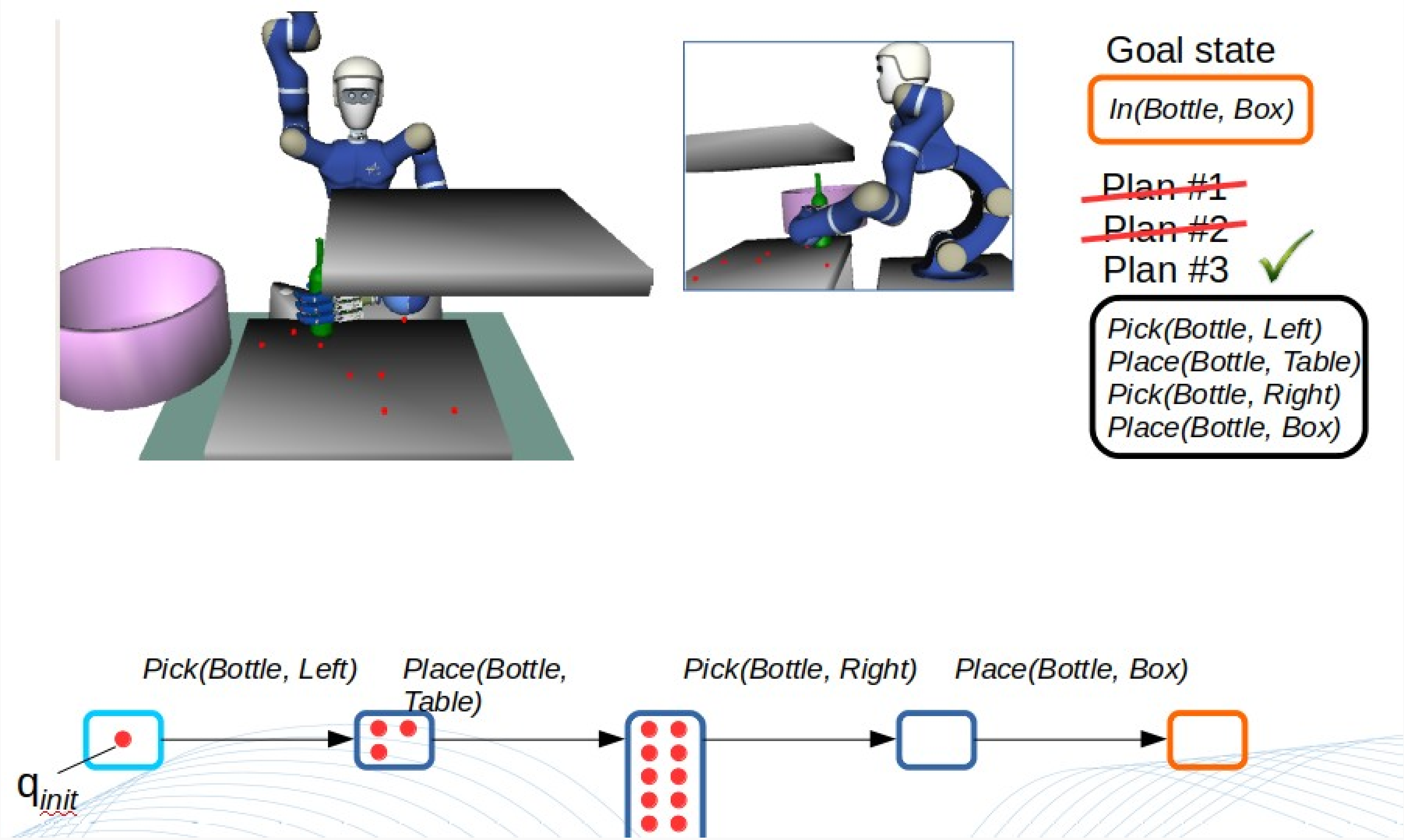

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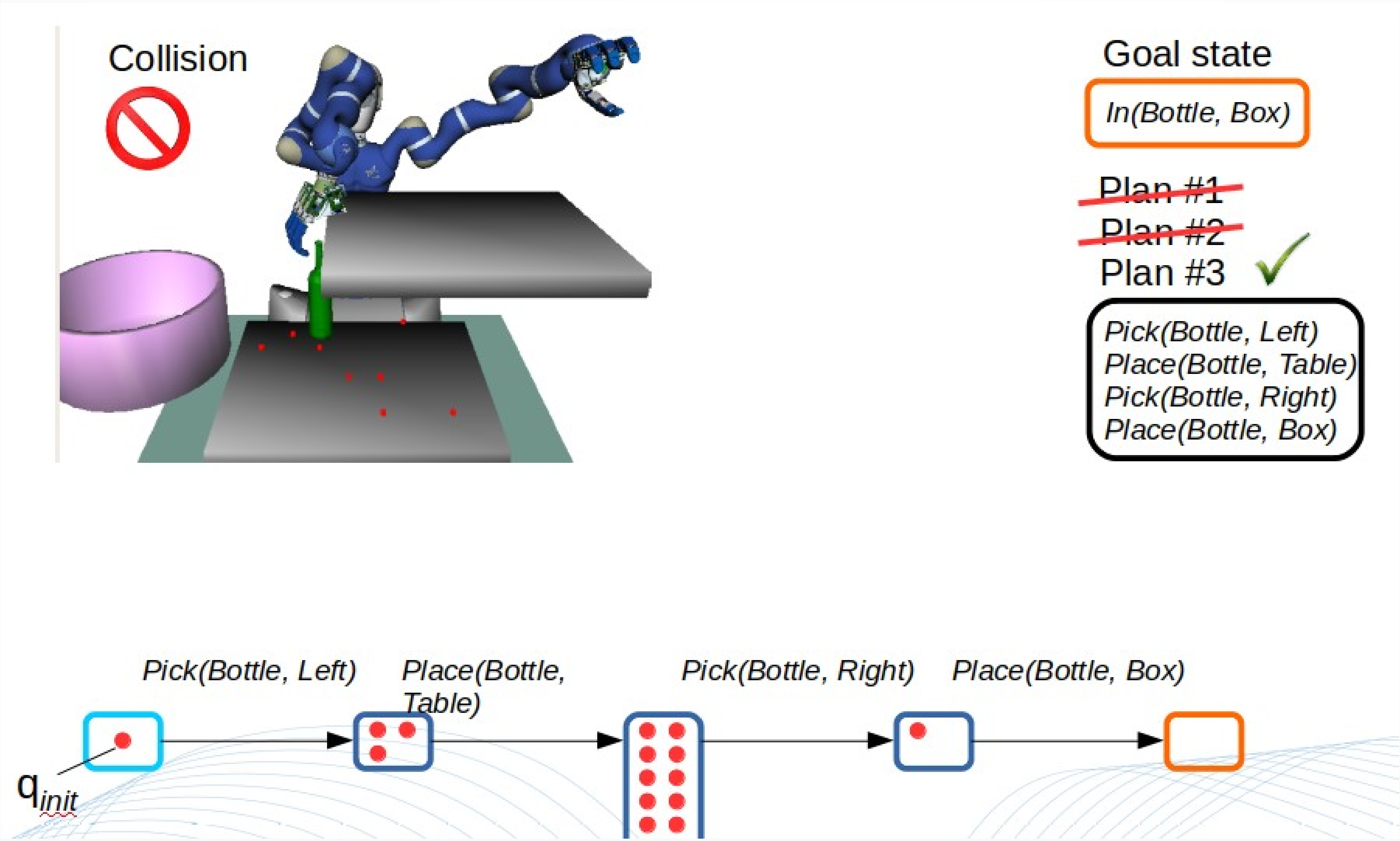

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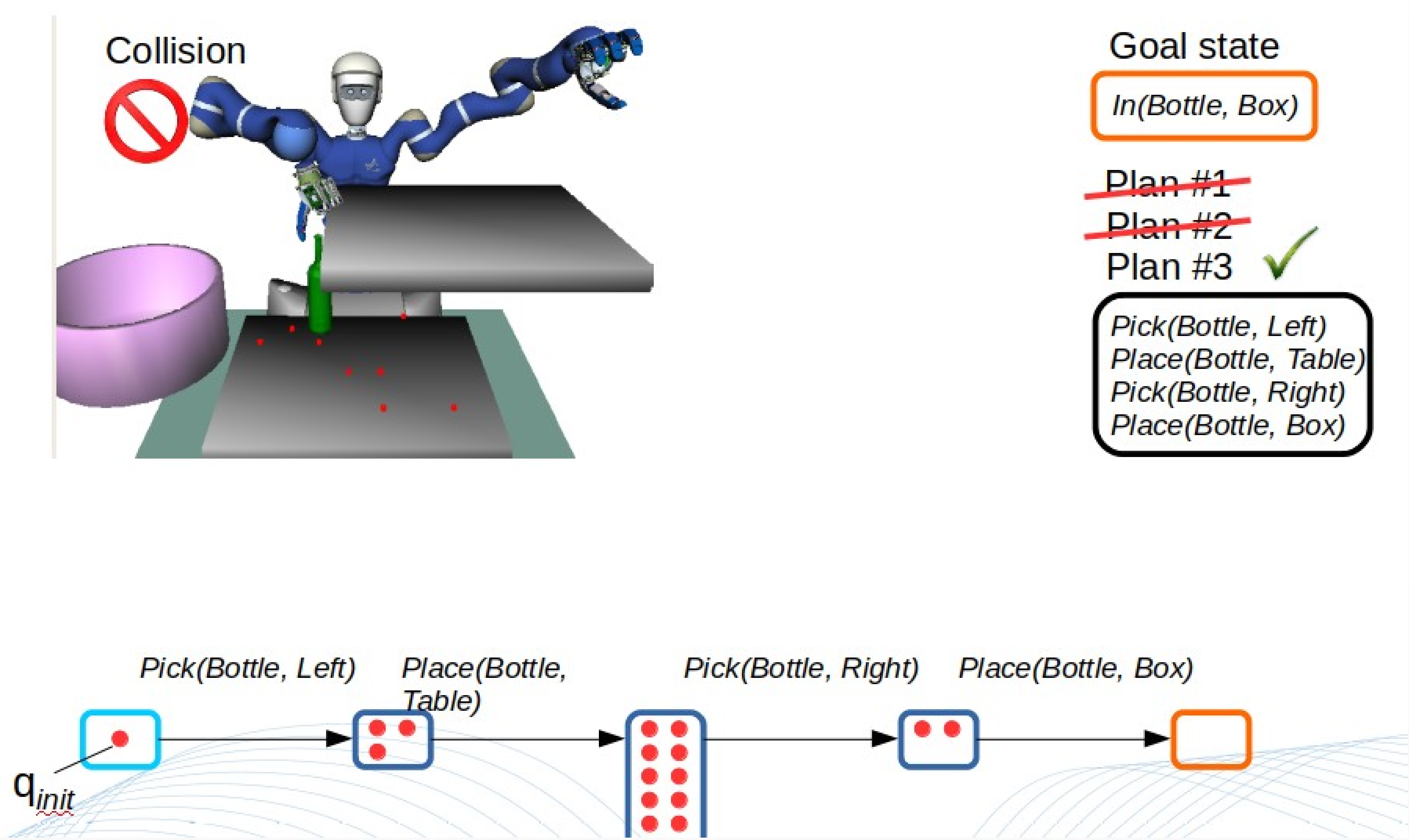

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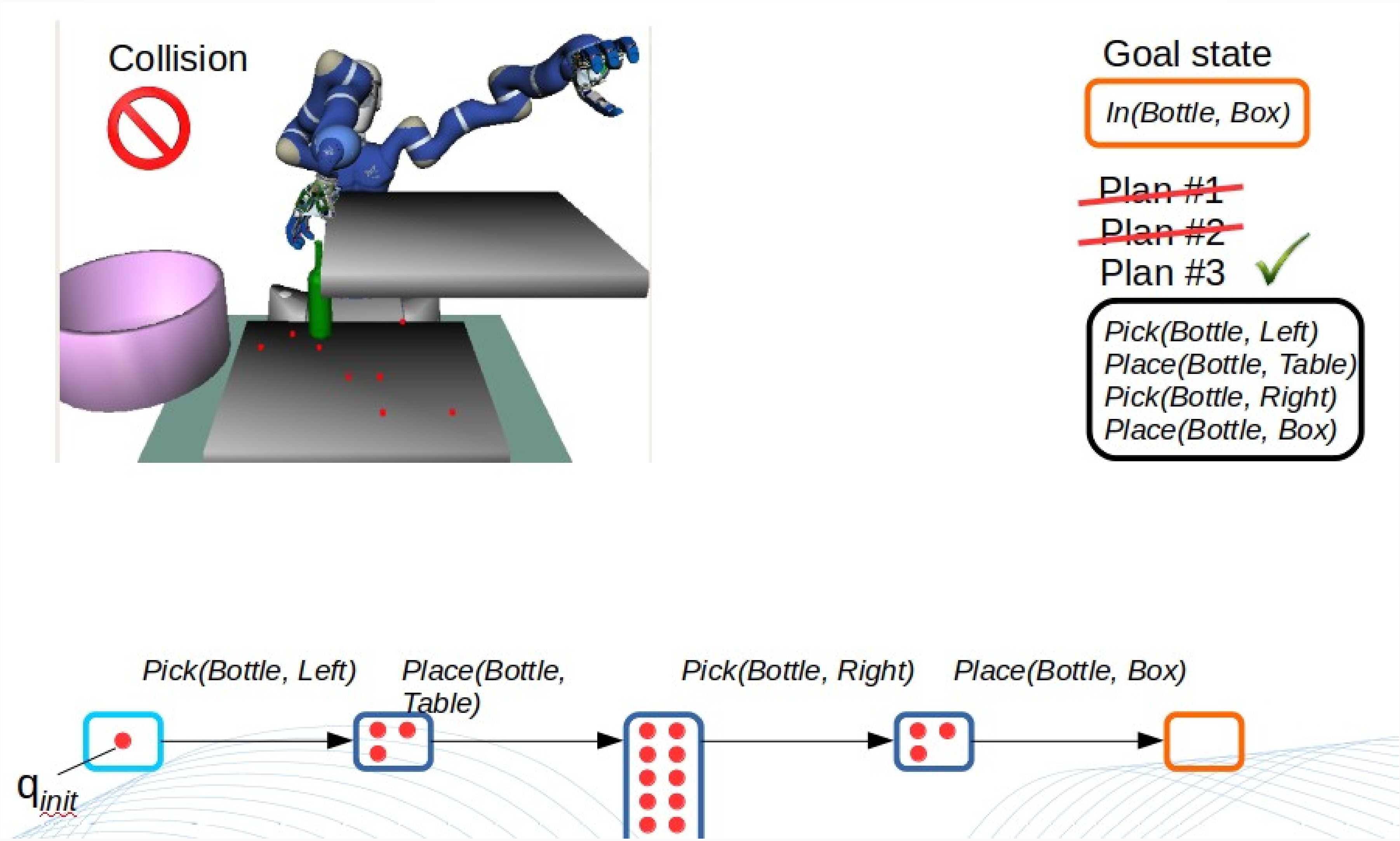

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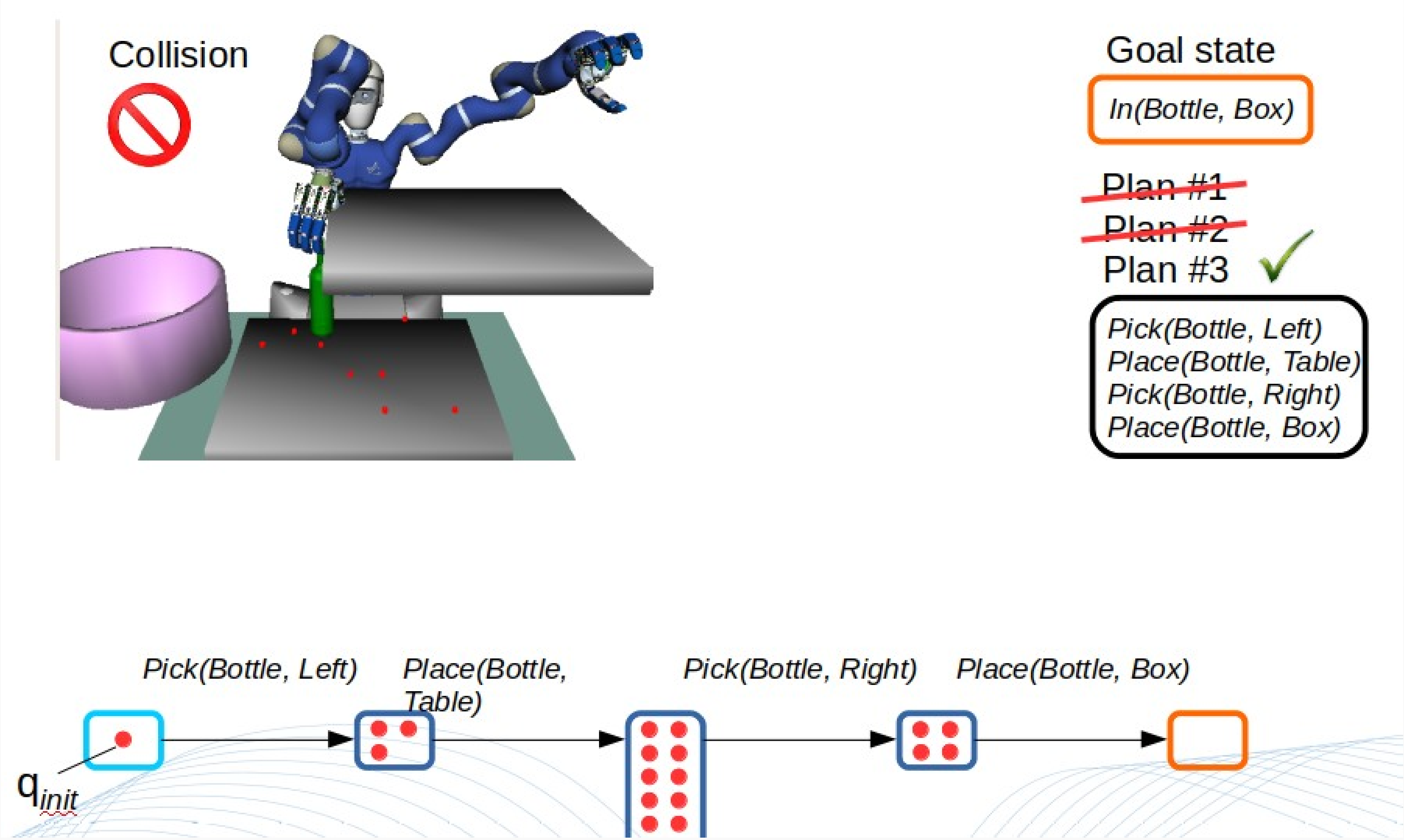

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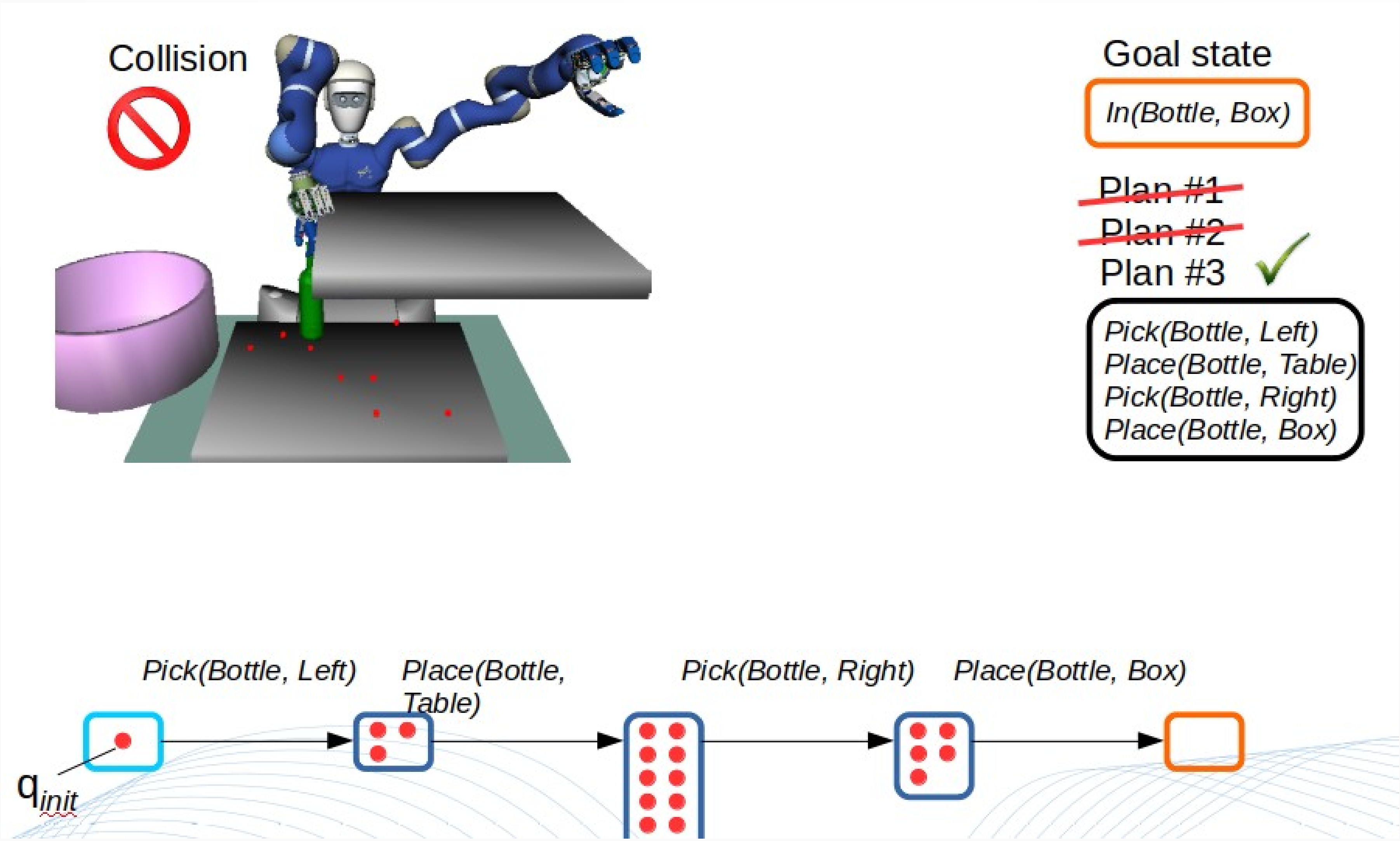

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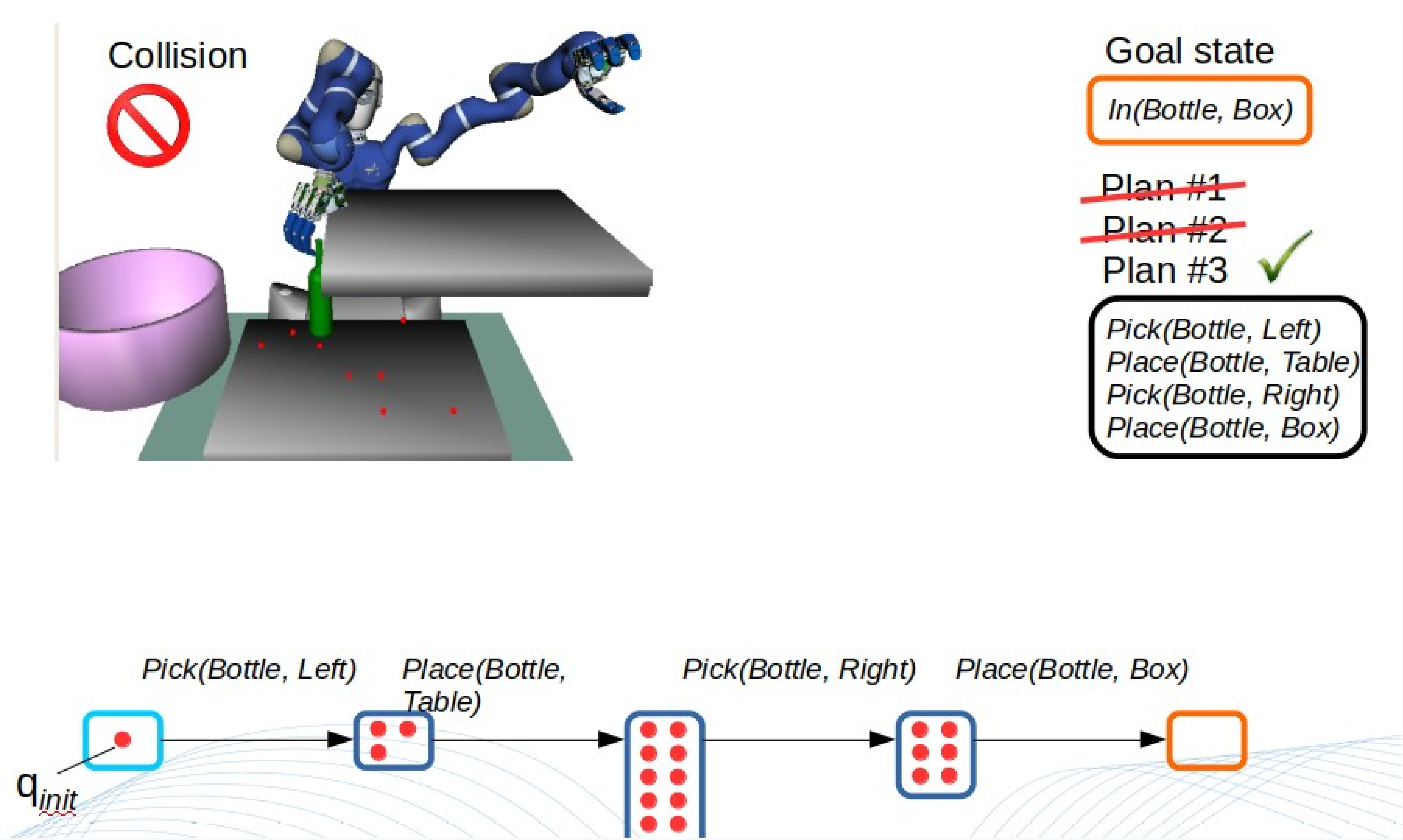

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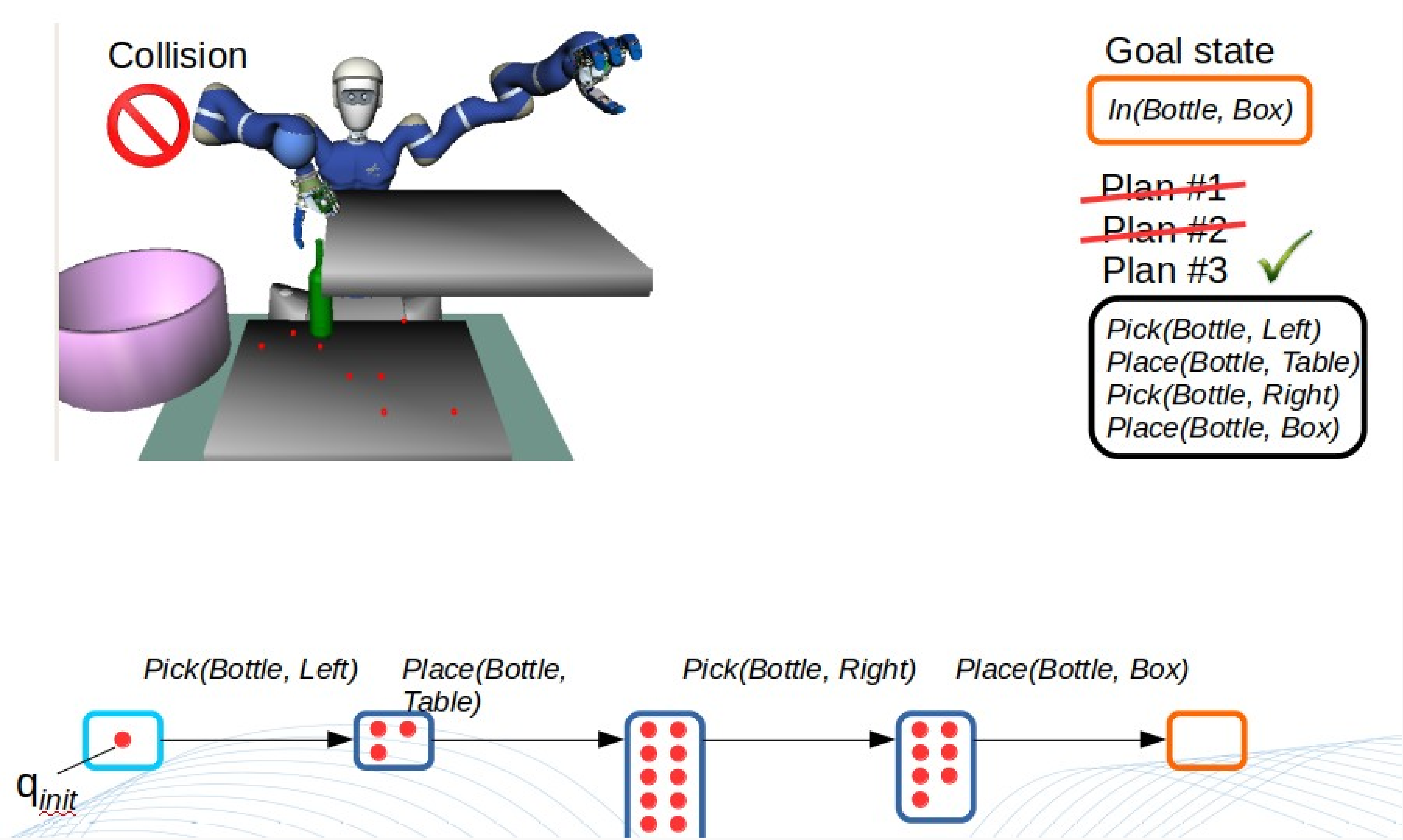

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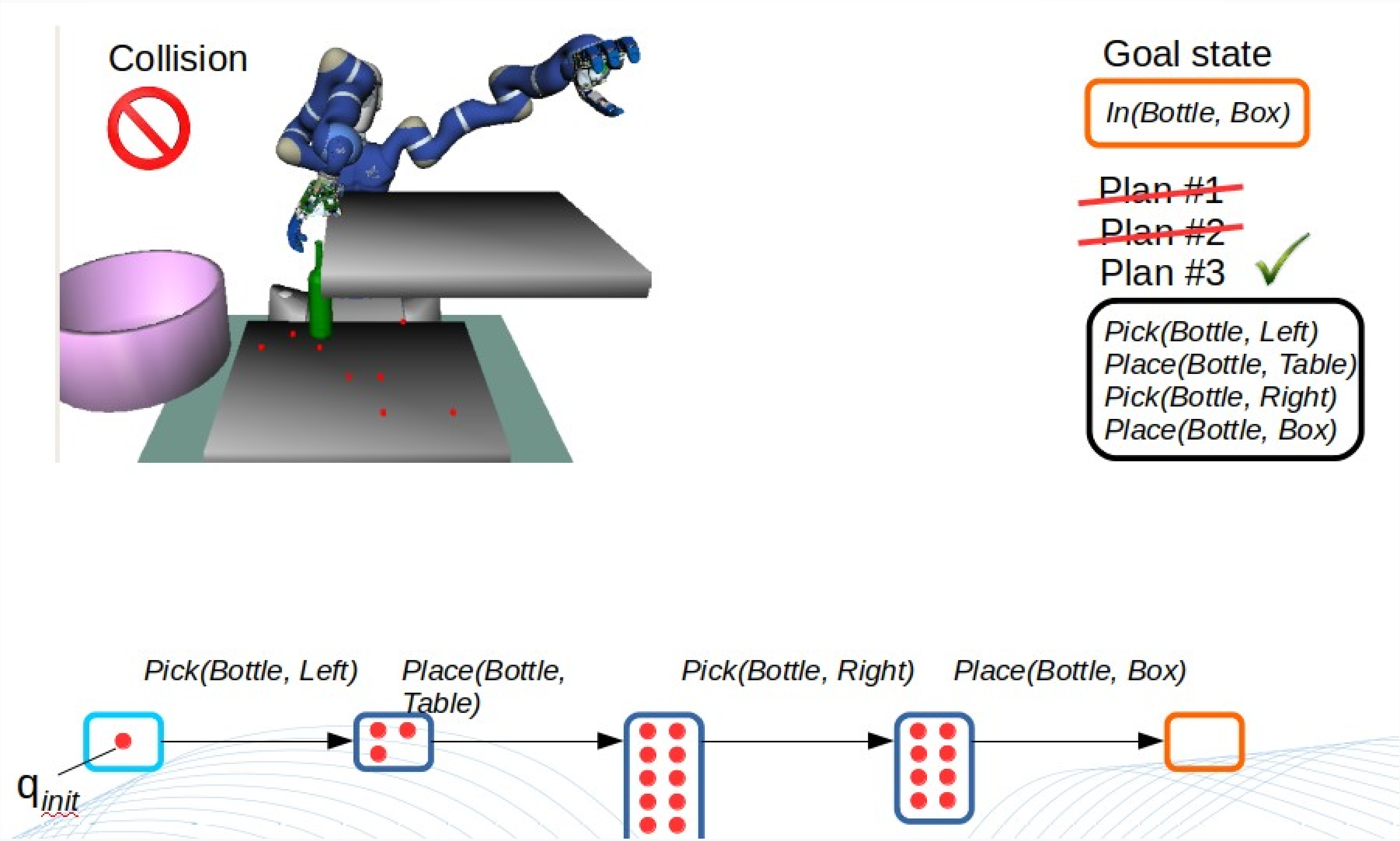

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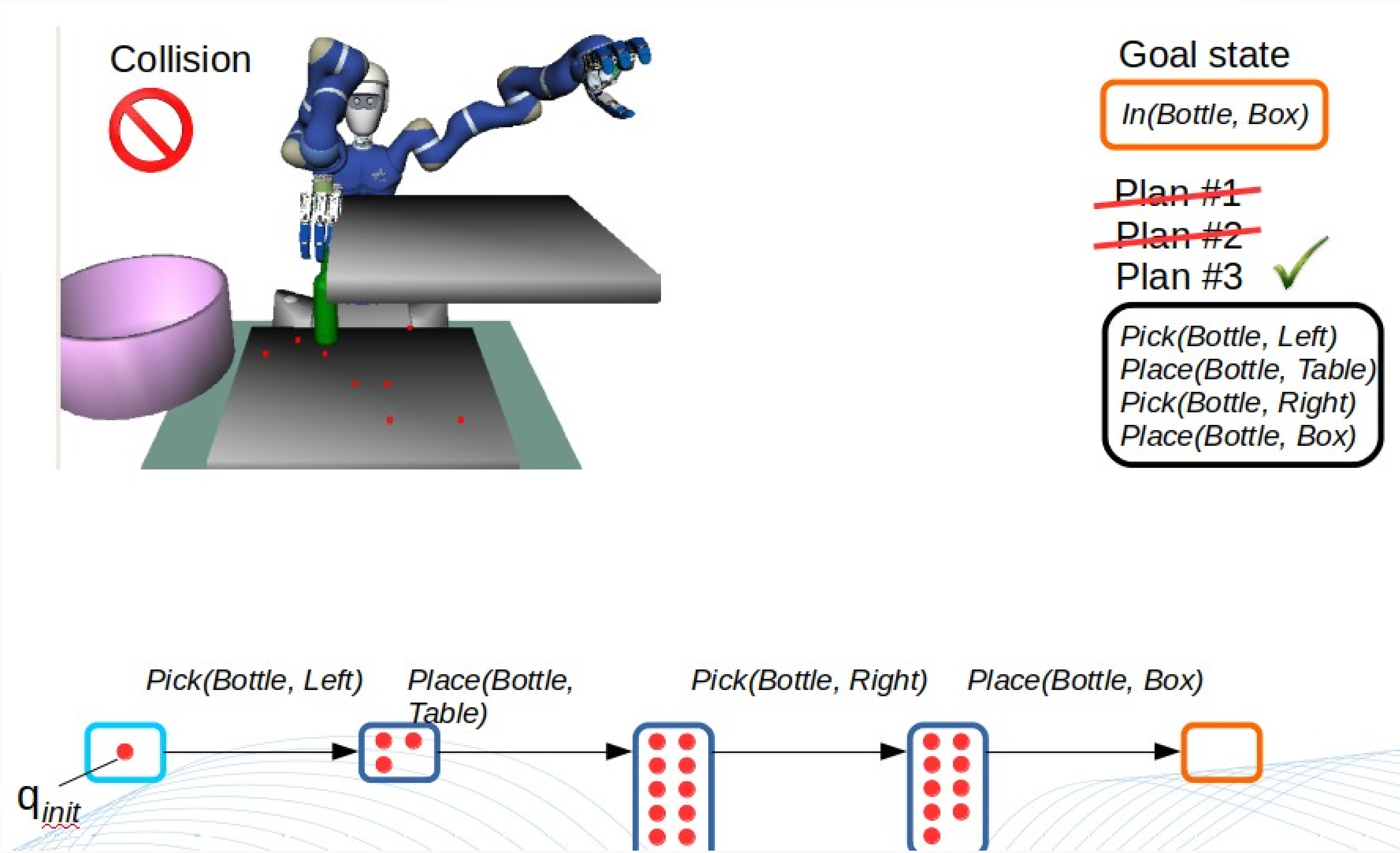

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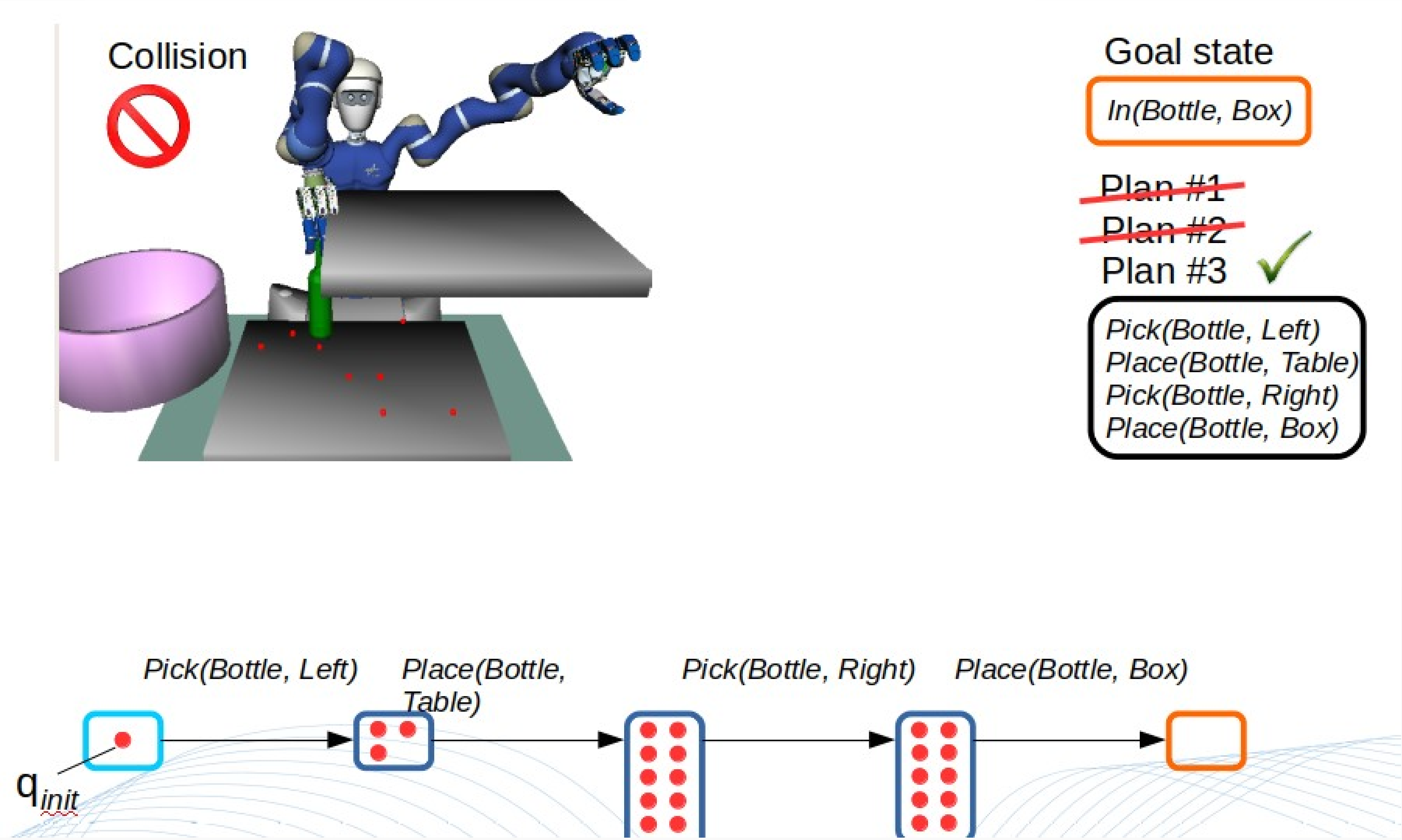

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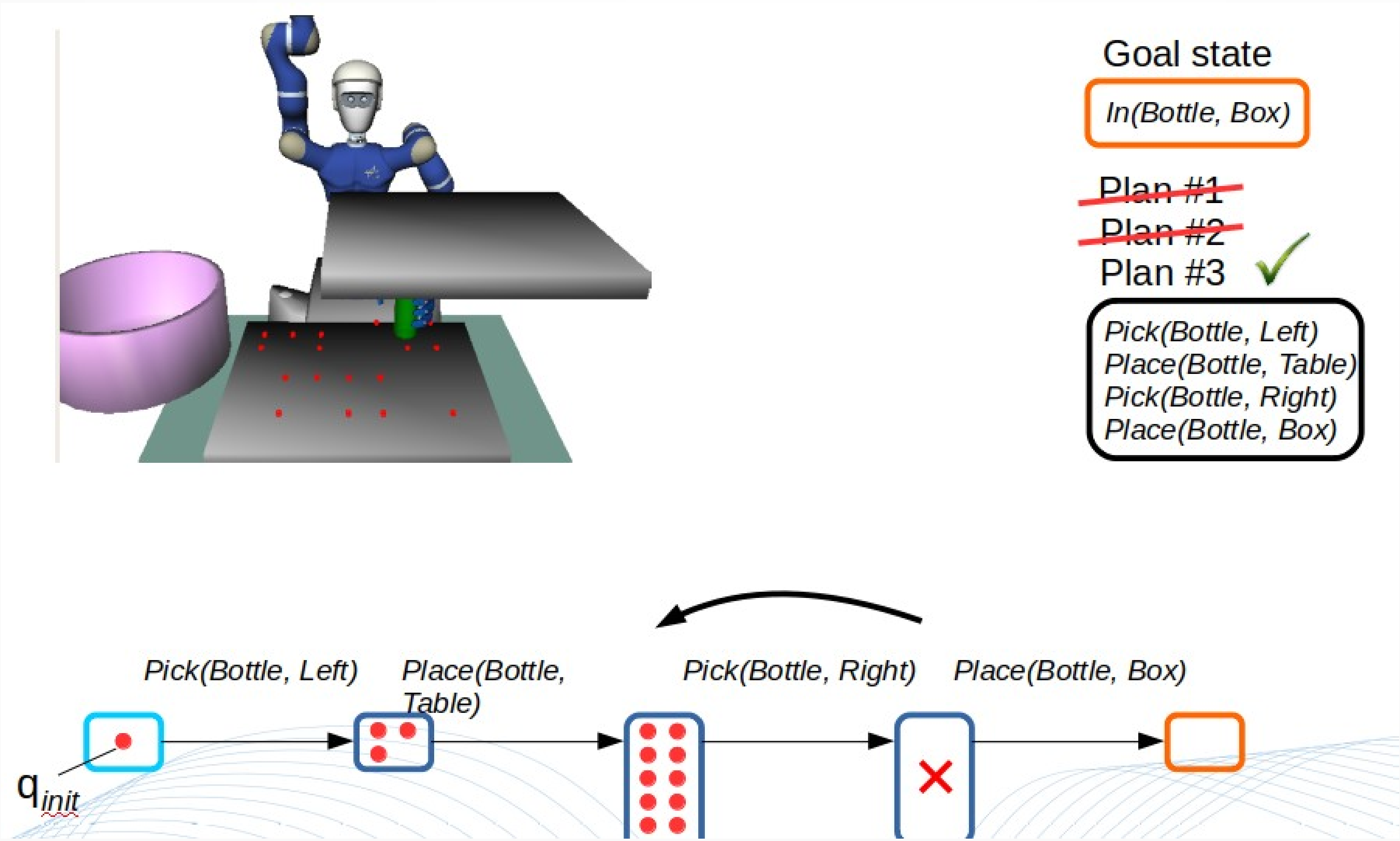

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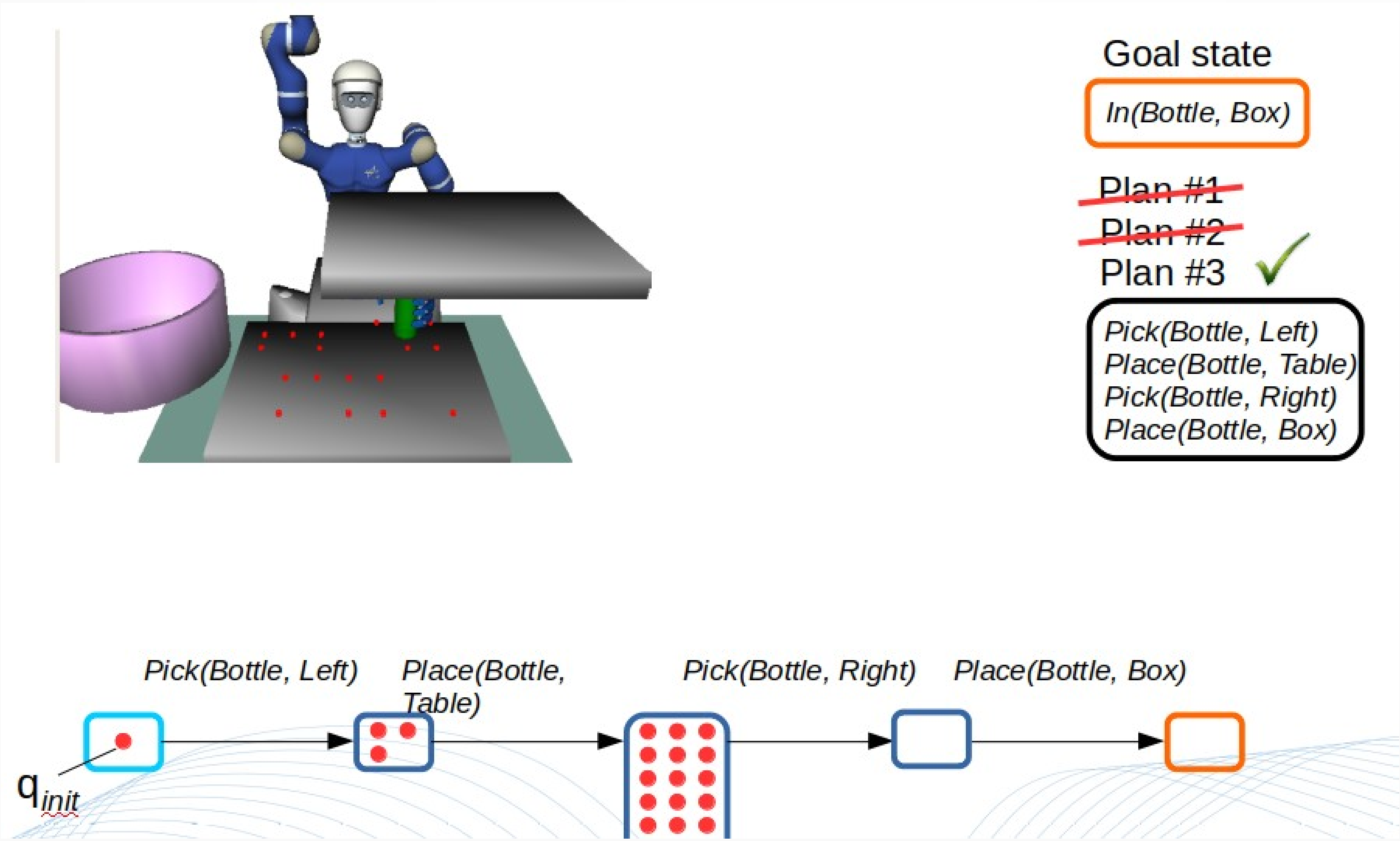

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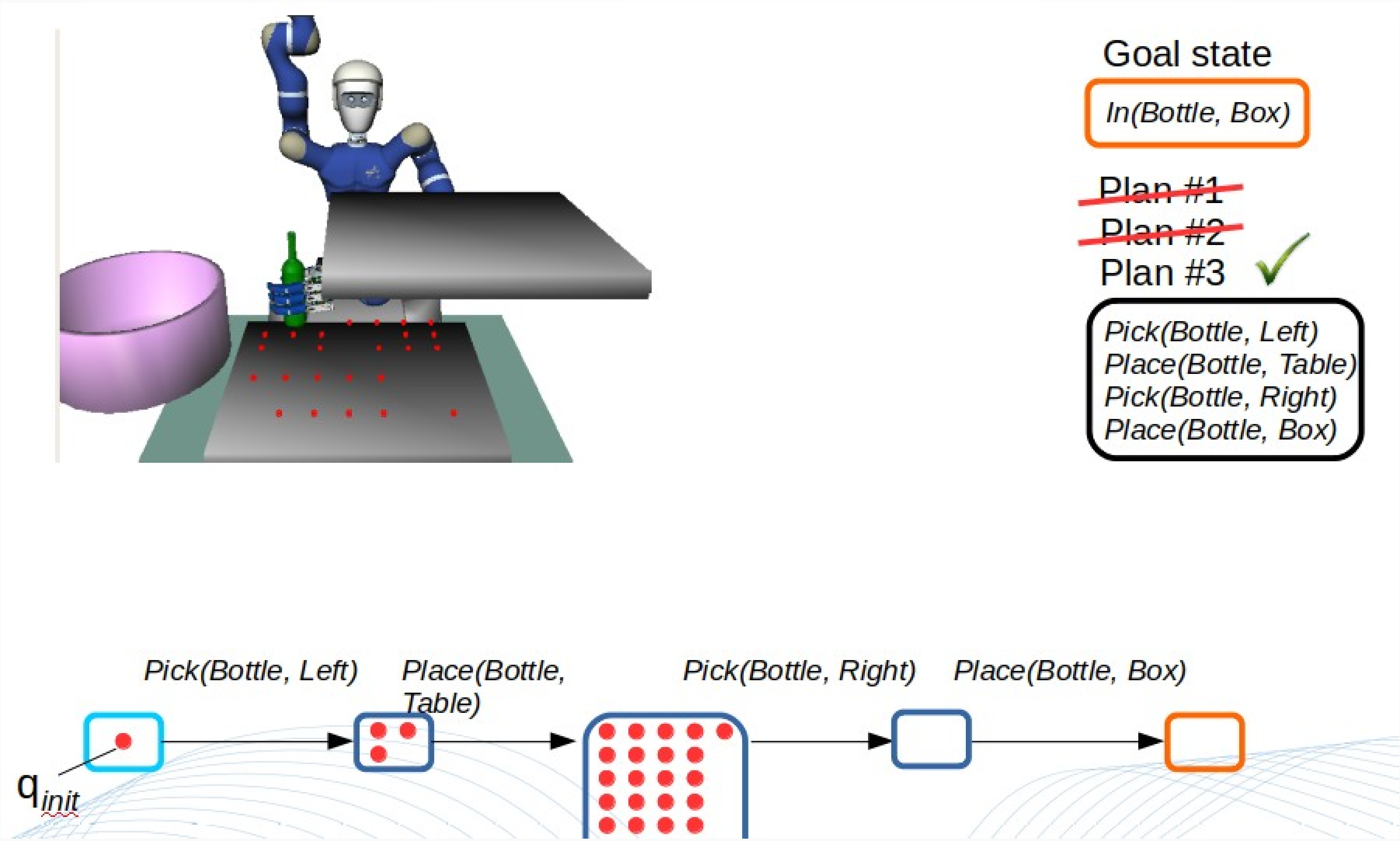

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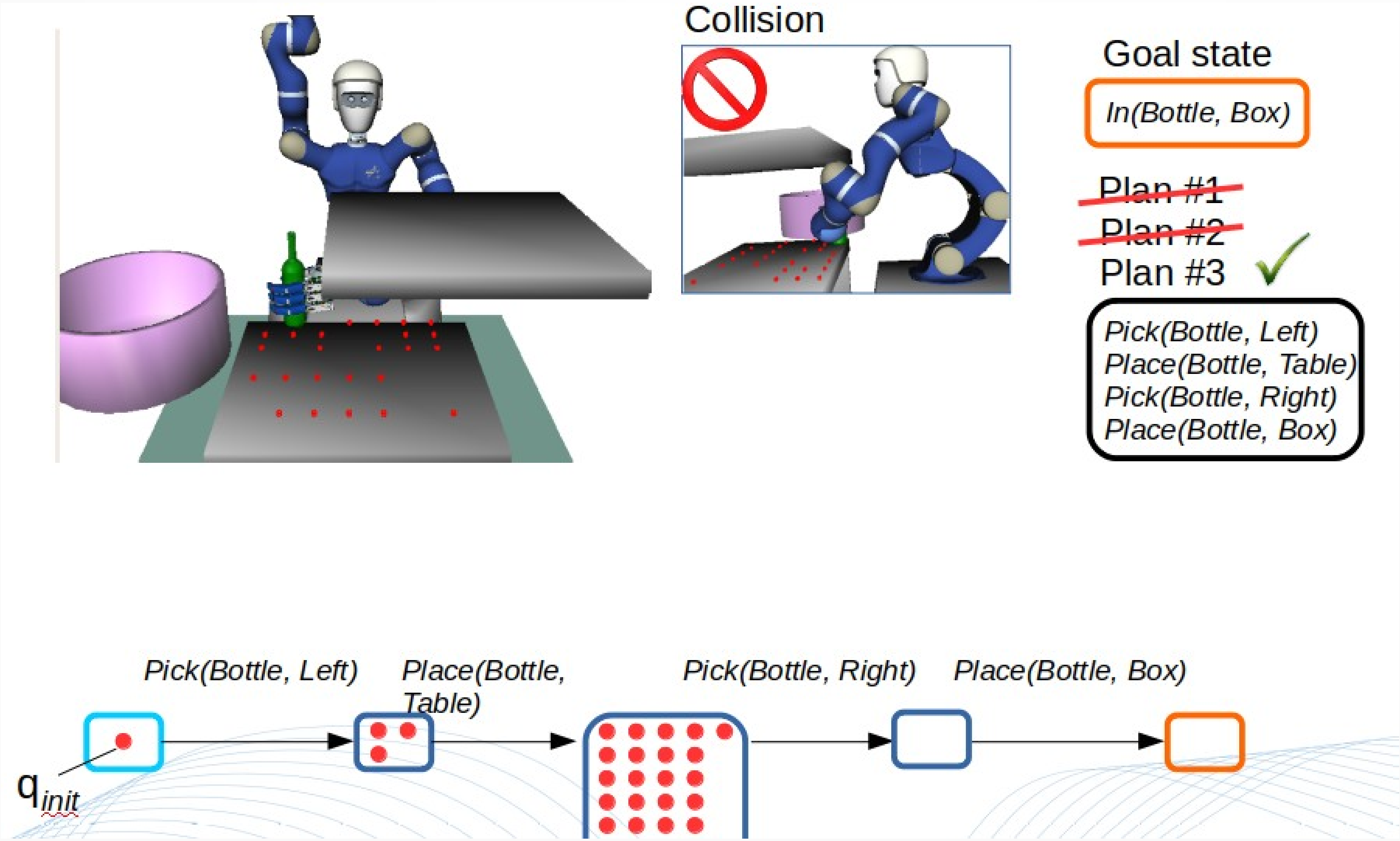

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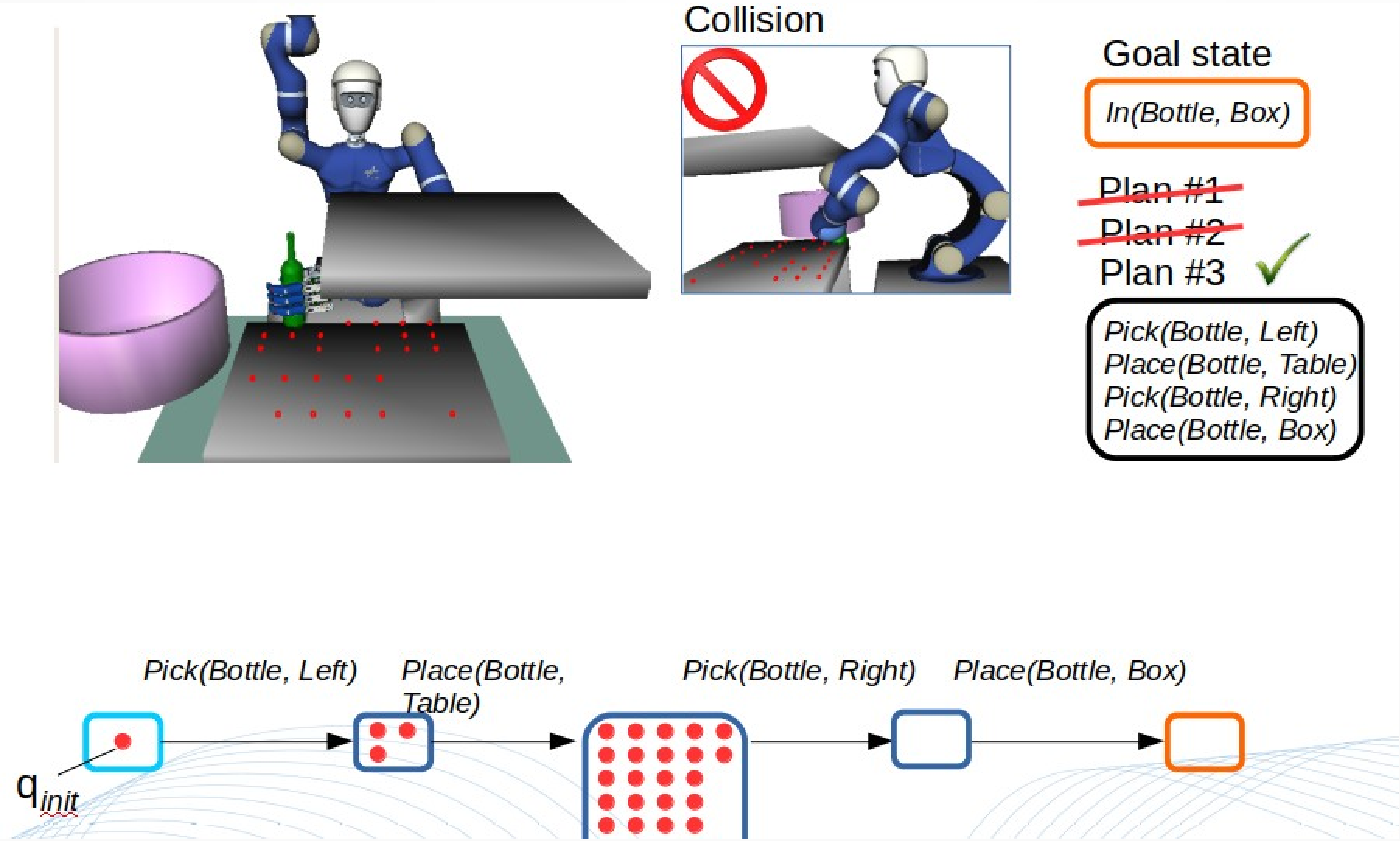

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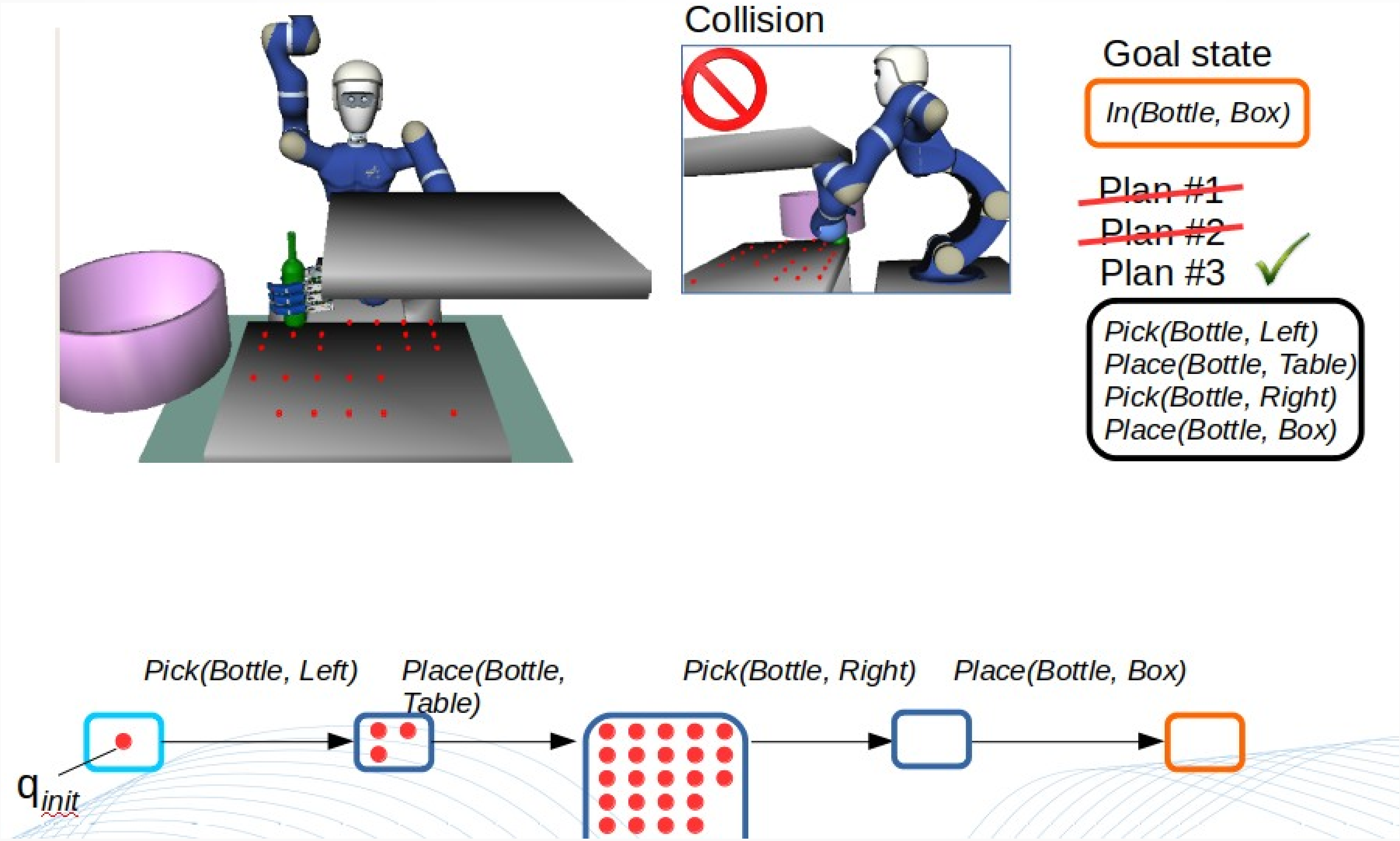

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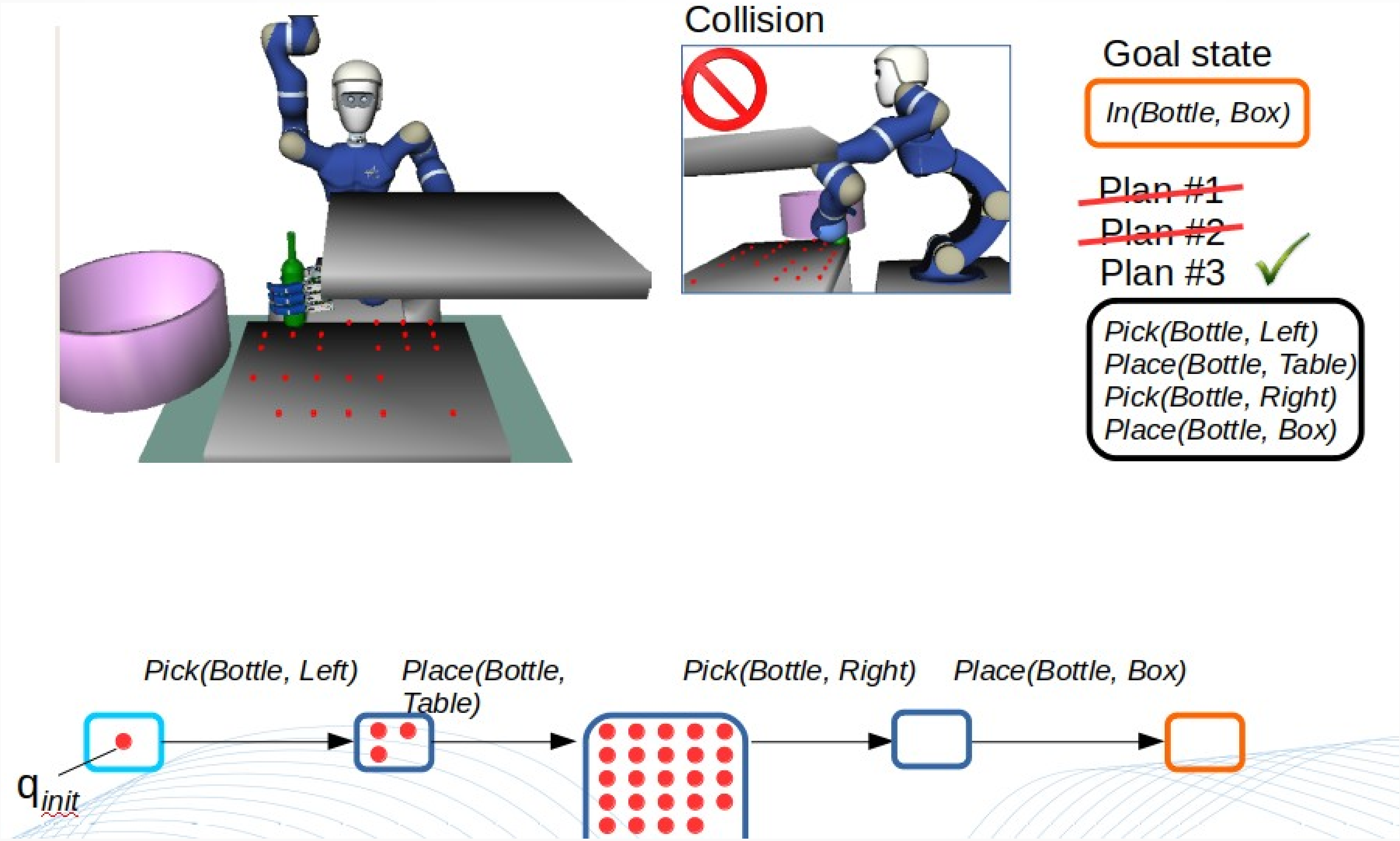

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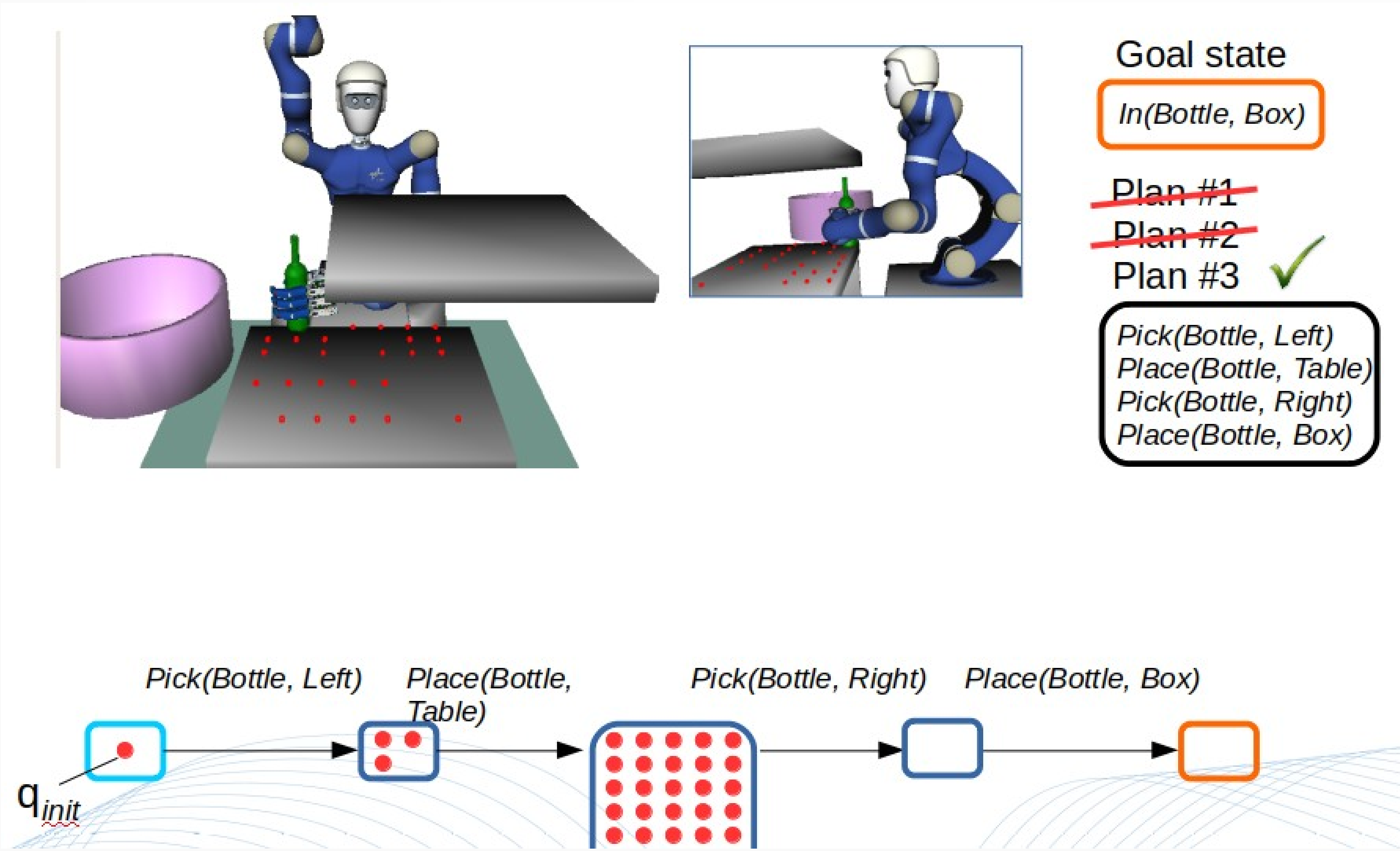

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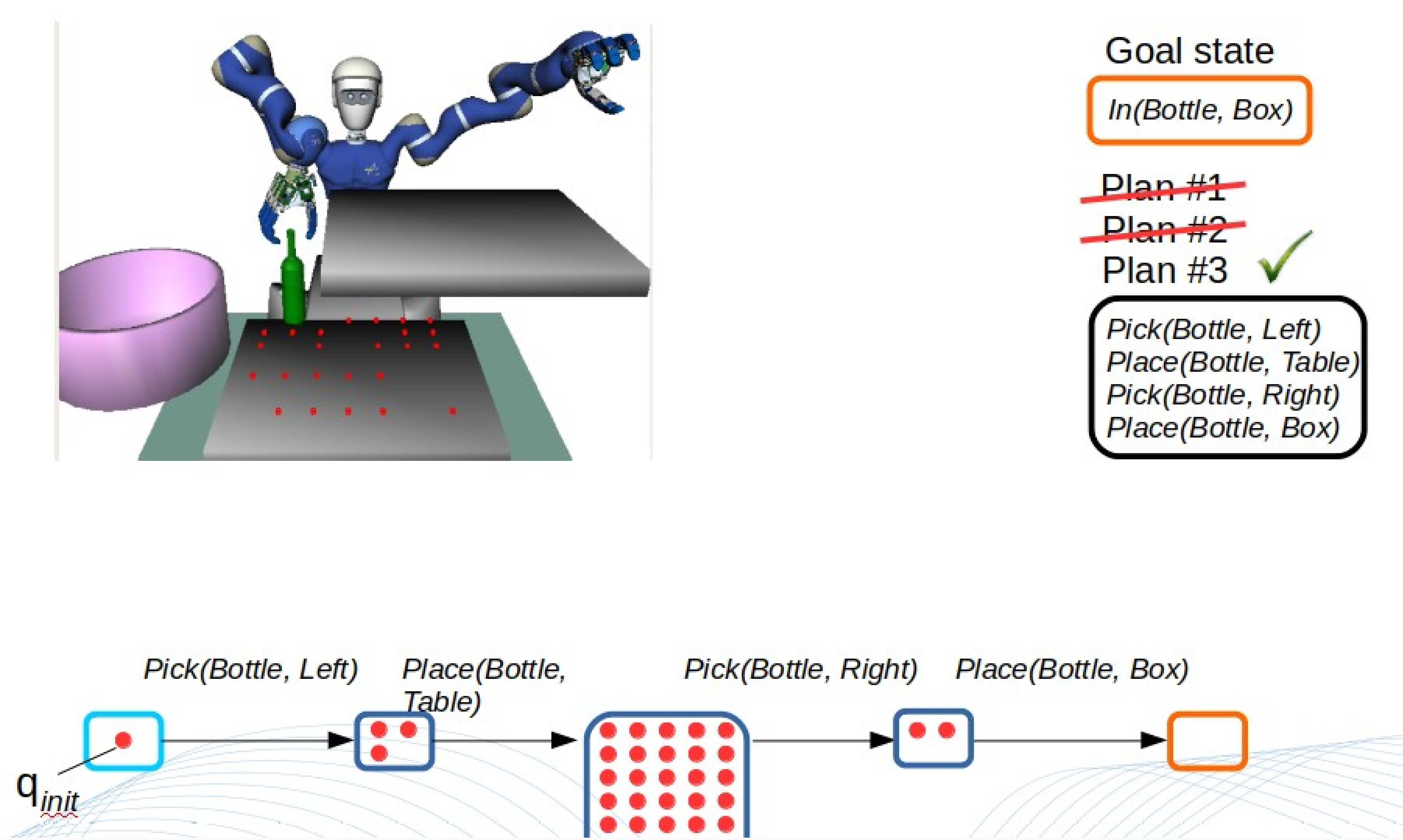

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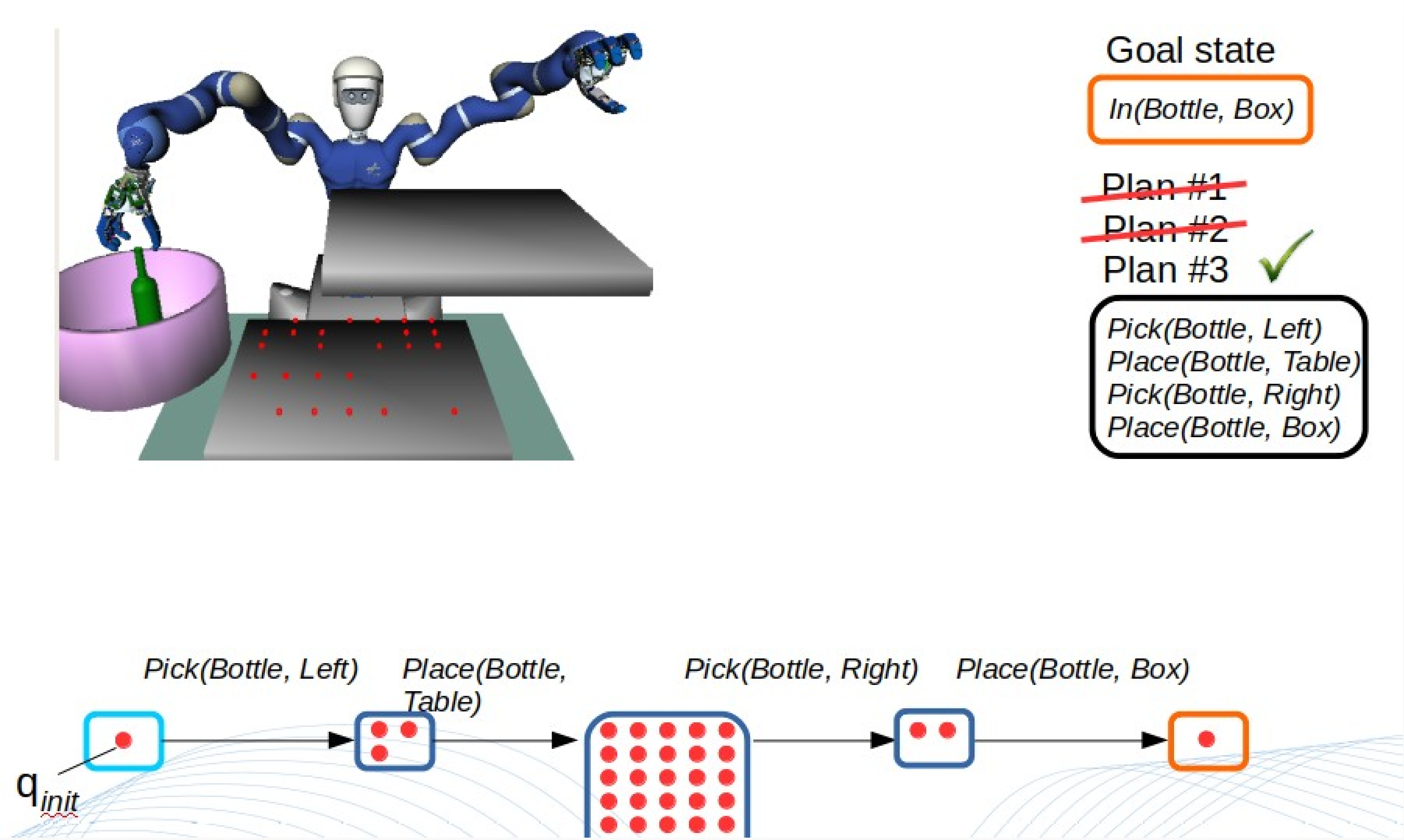

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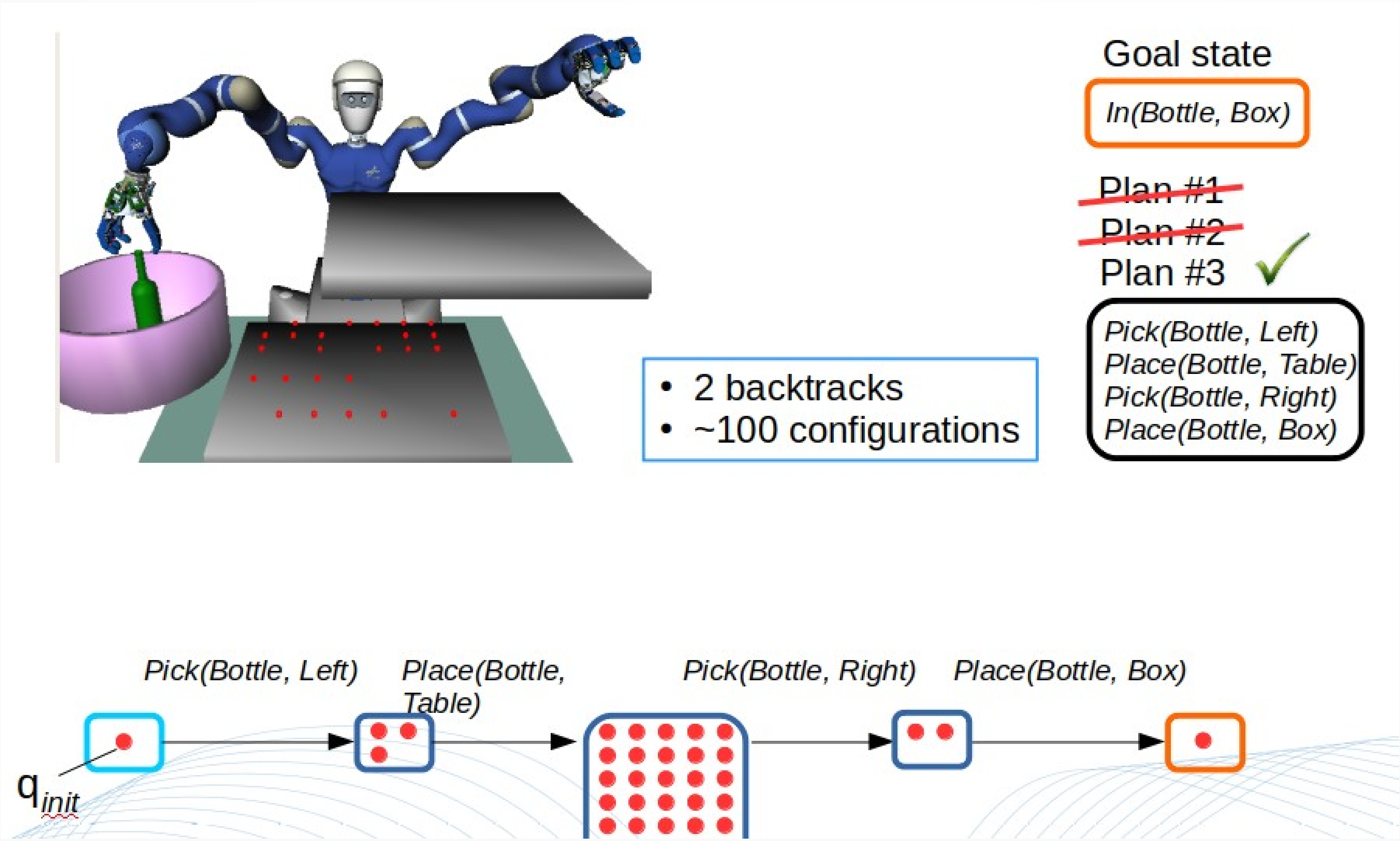

What makes it difficult?

- Coupling between S and C
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- Large search space, different metrics

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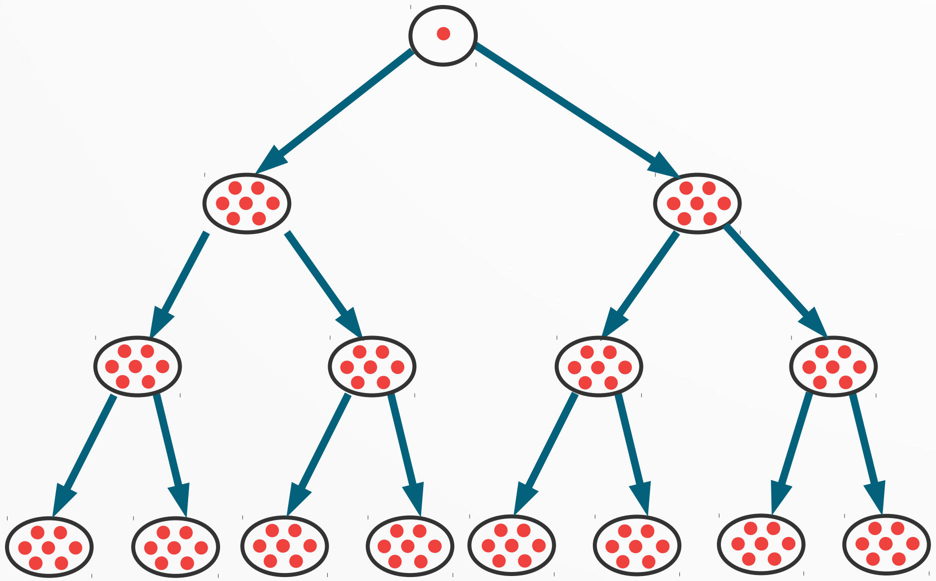

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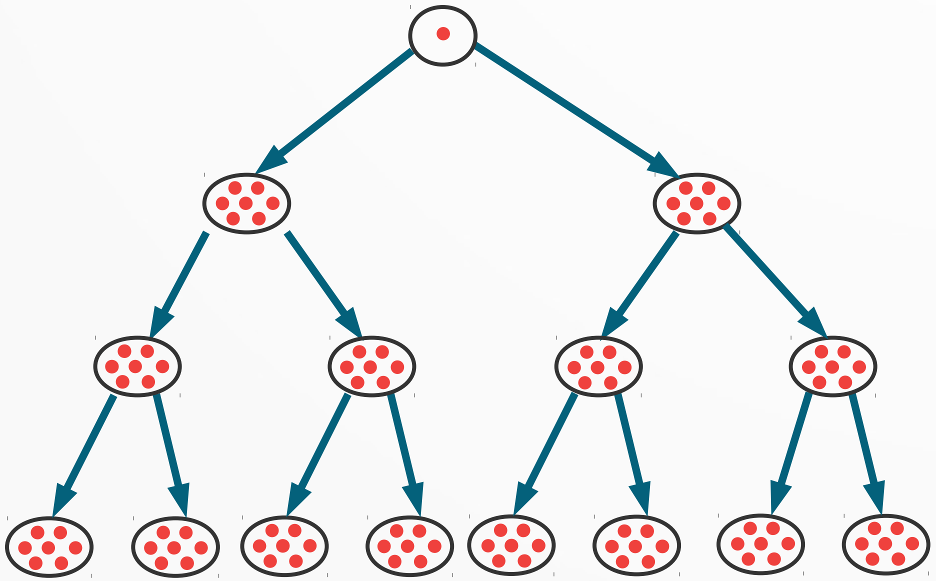

- 2 equal symbolic states may have very different geometric configurations
- 2 different symbolic states may have very similar geometric configurations

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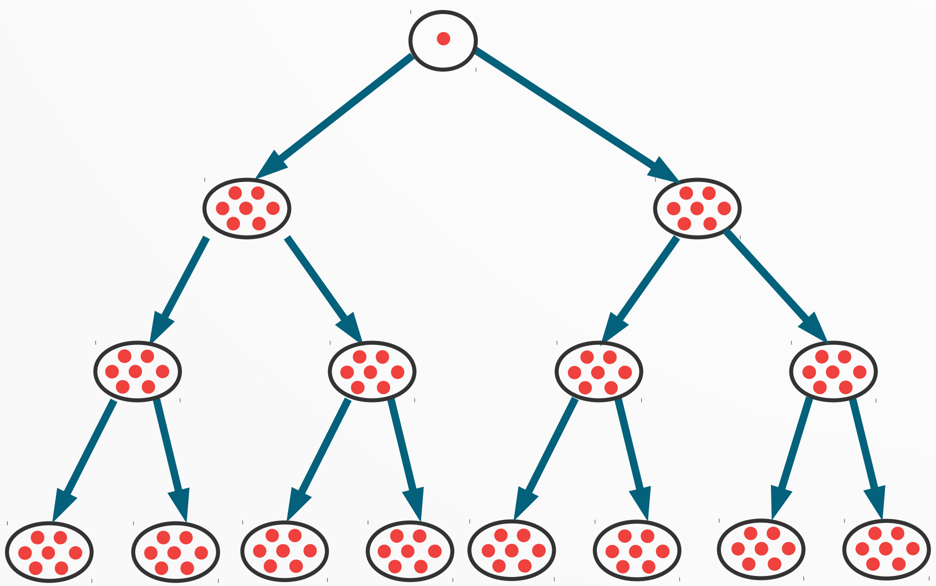

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→ no easy "distance to goal" heuristics

Outline

- Problem definition(s)
- What makes it difficult?
- 3 approaches to TAMP
- Future directions

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3 approaches to TAMP

- AsyMov
- FFRob
- ASP + failure explanation

3 approaches to TAMP

- AsyMov

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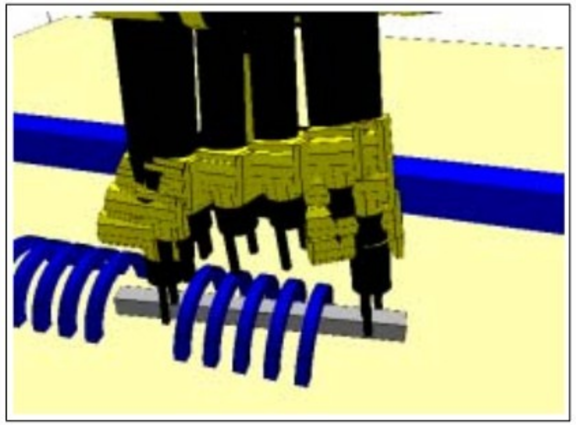
Grasp
Planning

- *A Geometrical Approach to Planning Manipulation Tasks. The Case of Discrete Placements and Grasps*
R. Alami, T. Siméon, and J.-P. Laumond. in International Symposium on Robotics Research, 1989.

3 approaches to TAMP

AsyMov

Grasp Planning → Manipulation Planning



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3 approaches to TAMP

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Grasp Planning → Manipulation Planning → TAMP

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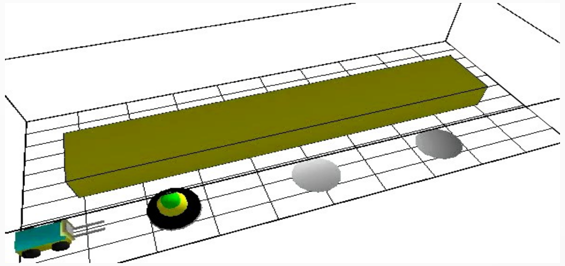
- *A Hybrid Approach to Intricate Motion, Manipulation and Task Planning*. S. Cambon, R. Alami, and F. Gravot, International Journal of Robotics Research, 2009.



3 approaches to TAMP

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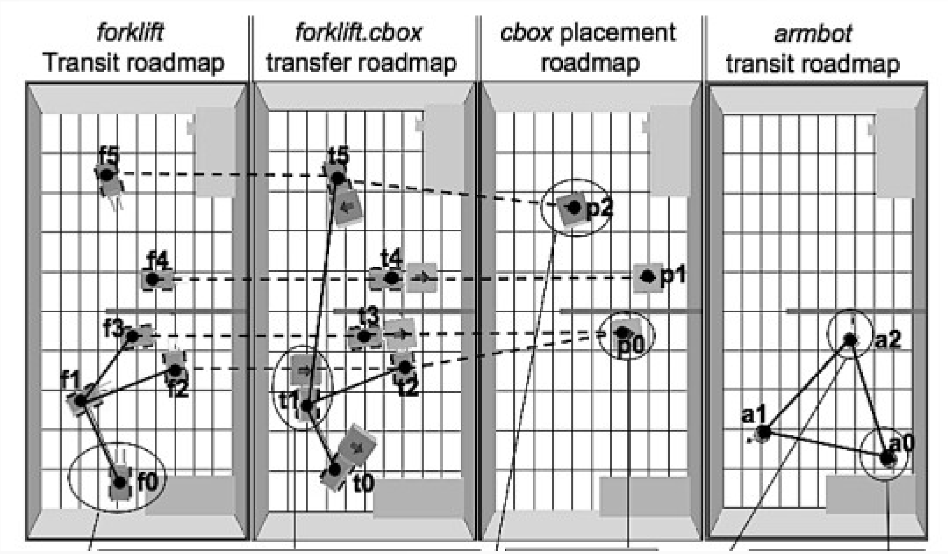

Roadmaps (manipulation planning)

3 approaches to TAMP

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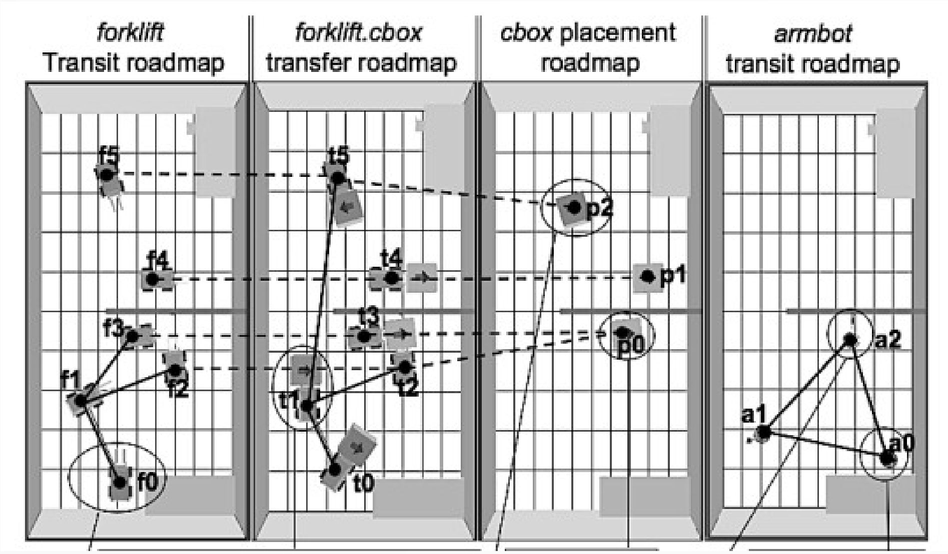

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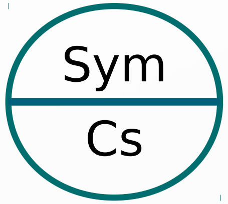

3 approaches to TAMP

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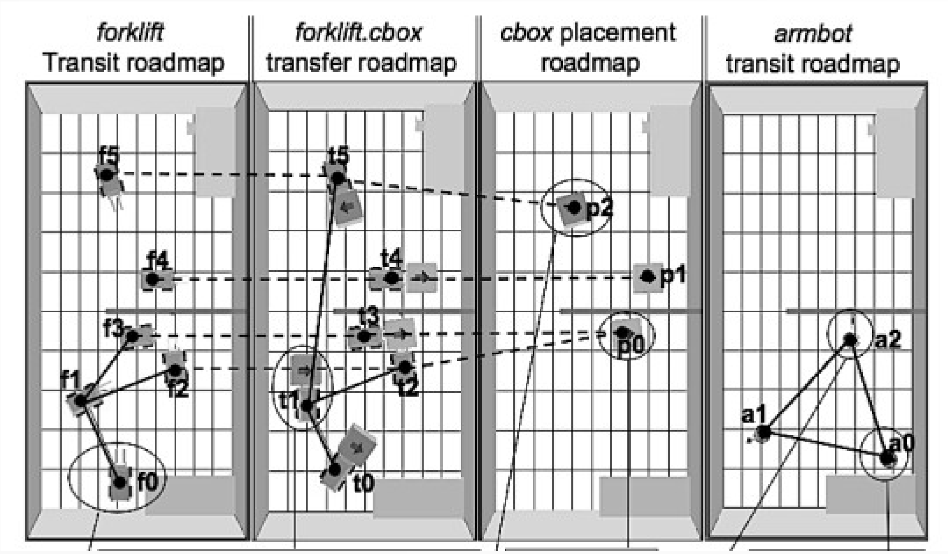

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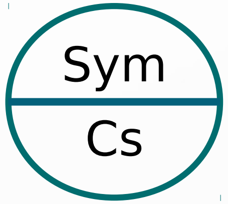

Cost:

Accumulated cost (h)
+ Heuristic cost
+ Cost of the number of failures

3 approaches to TAMP

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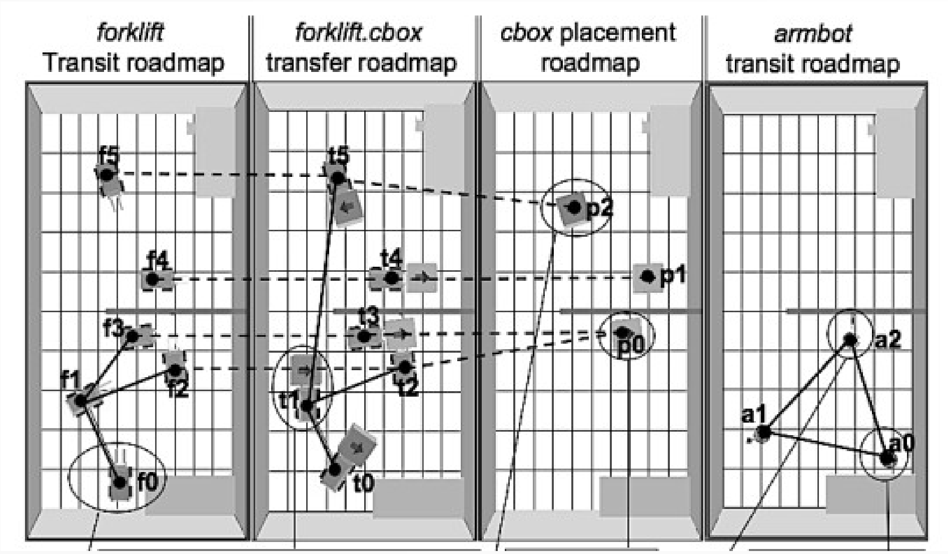

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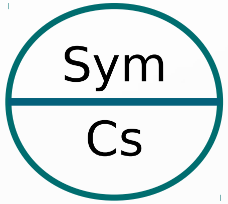

Cost =

Accumulated cost (h)
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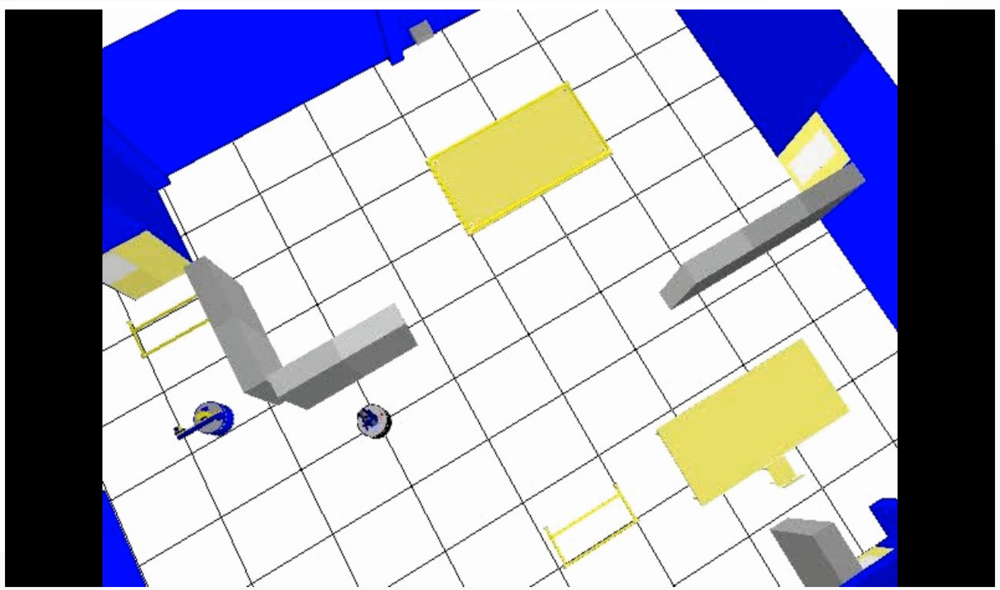
Length of the symbolic plan from current state to goal state (computed with FF planner)

Trying to geometrically validate the state

3 approaches to TAMP

- AsyMov



A*

Sym

Cs

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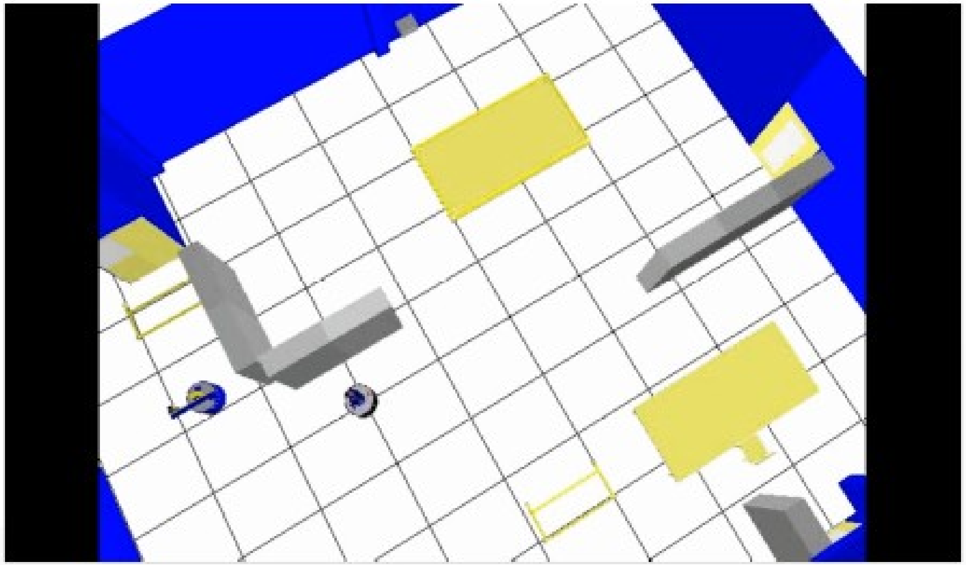
3 approaches to TAMP

Erion Plaku and Gregory D. Hager, *Sampling-based motion and symbolic action planning with geometric and differential constraints*, in ICRA, 2010, p. 5002--5008

AsyMov



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$\textsc{Pick}(C_1, O, G, P, C_2)$:

pre: $\mathit{HandEmpty}$, $\mathit{Pose}(O, P)$, $\mathit{Robotconf}(C_1)$, $\mathit{CanGrasp}(O, P, G, C_2)$, $\mathit{Reachable}(C_1, C_2)$
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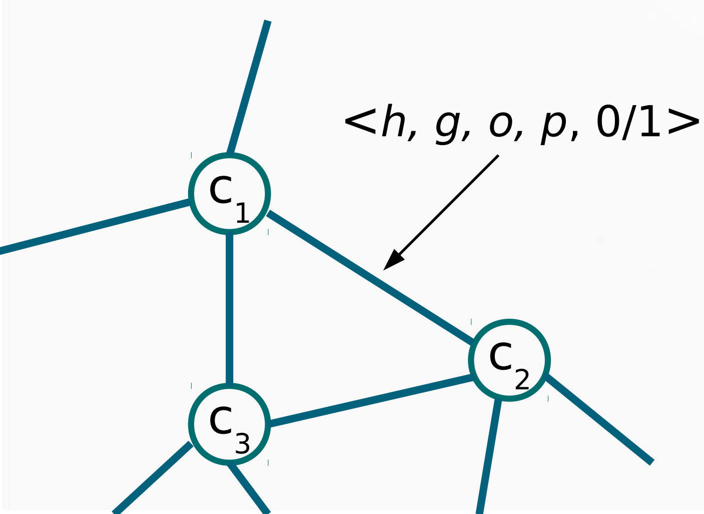
CRG: Conditional Reachability Graph



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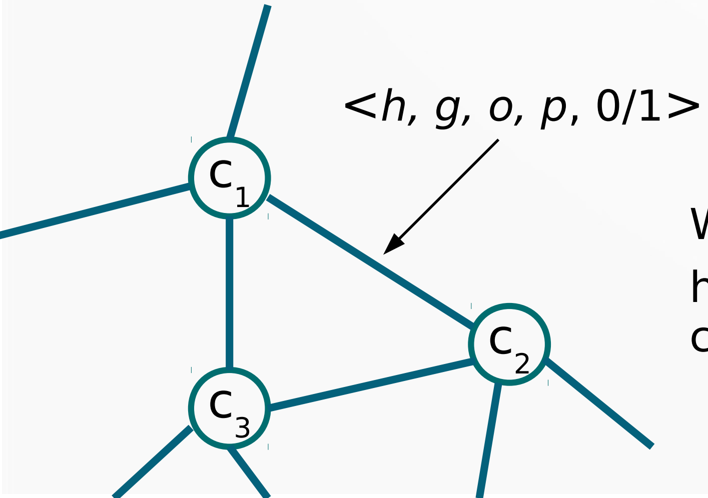

When, moving from c_1 to c_2,
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3 approaches to TAMP

FFRob

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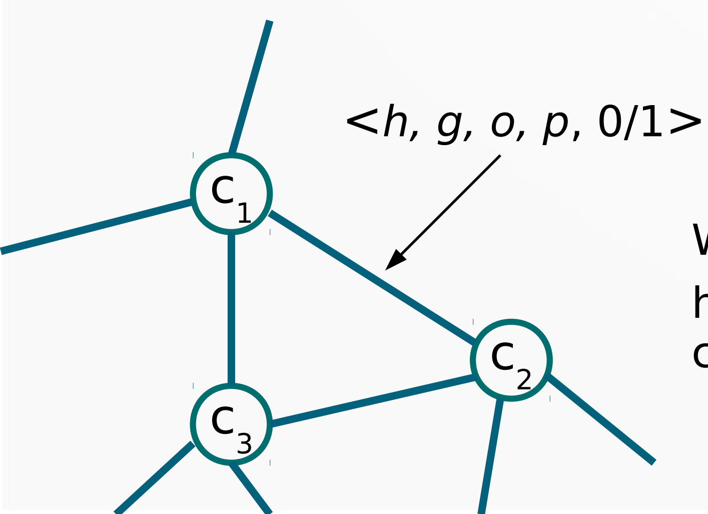

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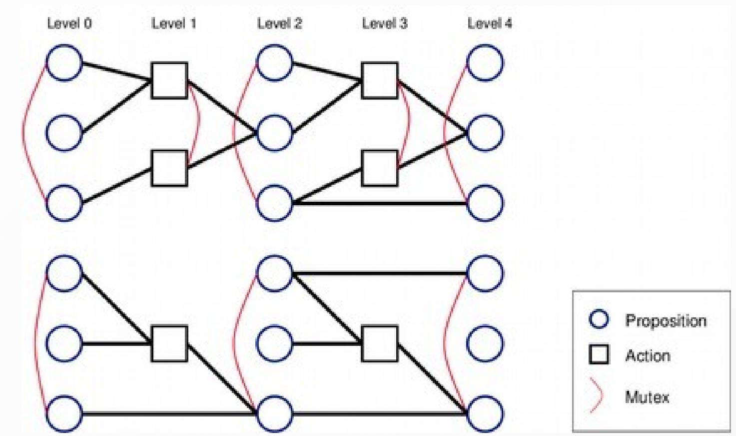
Modified FF heuristic



H_{FF} = #actions to achieve the goal, ignoring deletions

3 approaches to TAMP

FFRob

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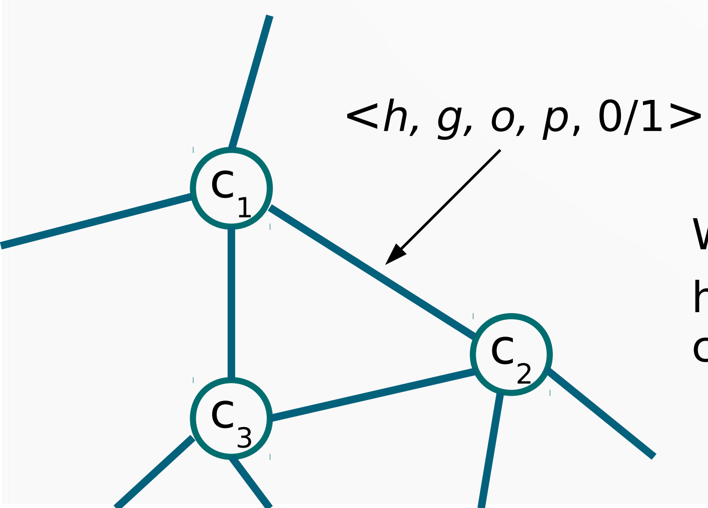

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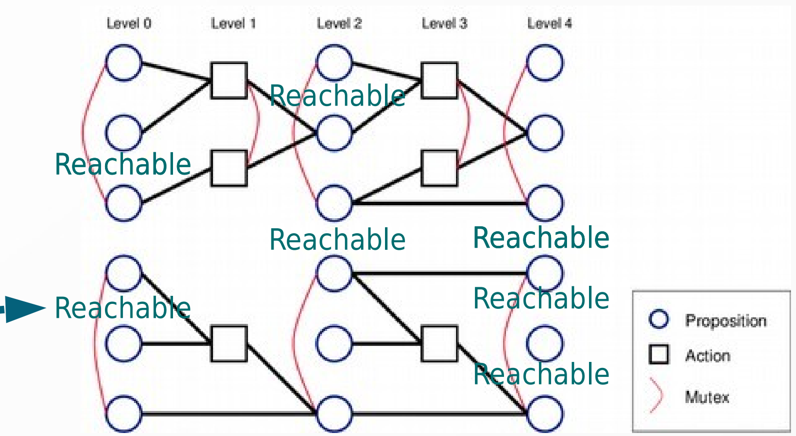

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3 approaches to TAMP

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Caelan R. Garrett, Tomas Lozano-Perez, Leslie P. Kaelbling. *FFRob: An Efficient Heuristic for Task and Motion Planning*, International Workshop on the Algorithmic Foundations of Robotics (WAFR), 2014.

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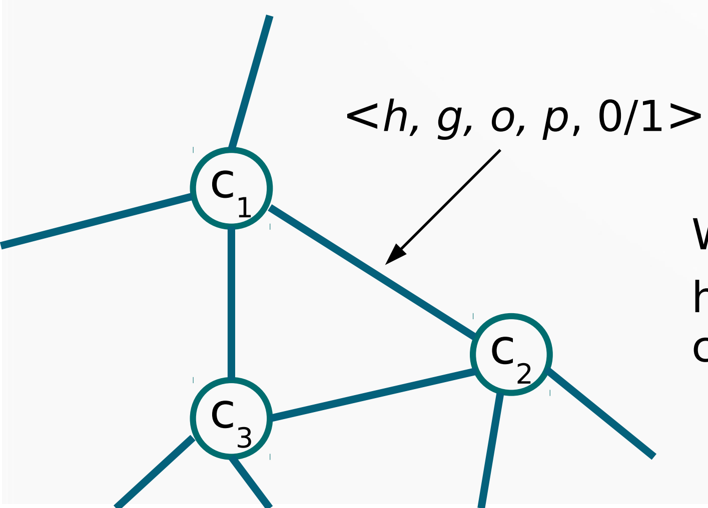

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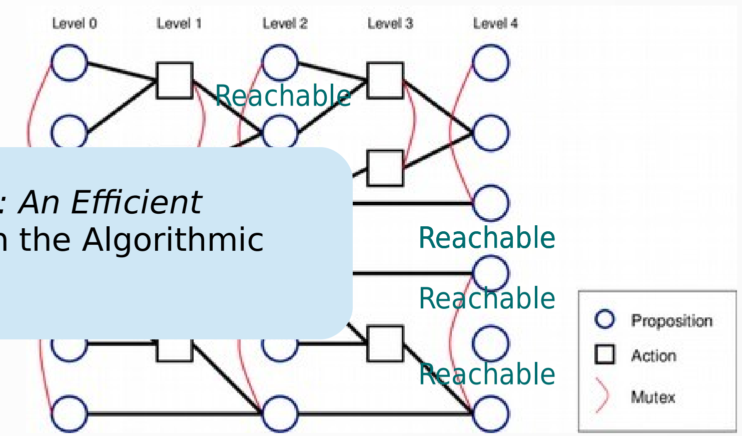

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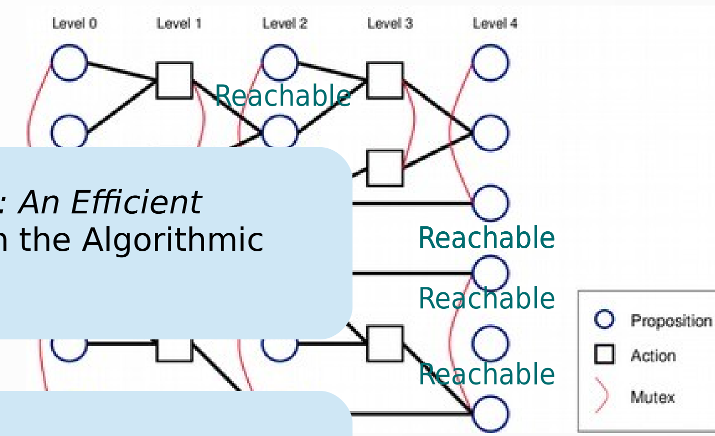

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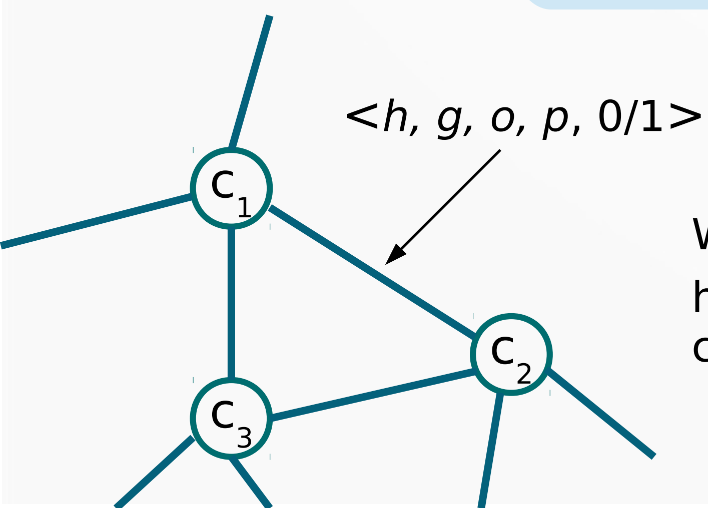
CRG: Conditi...

Akbari, A., Lagriffoul, F. & Rosell, J. *Combined heuristic task and motion planning for bi-manual robots*. Autonomous Robot 43, 1575–1590 (2019).



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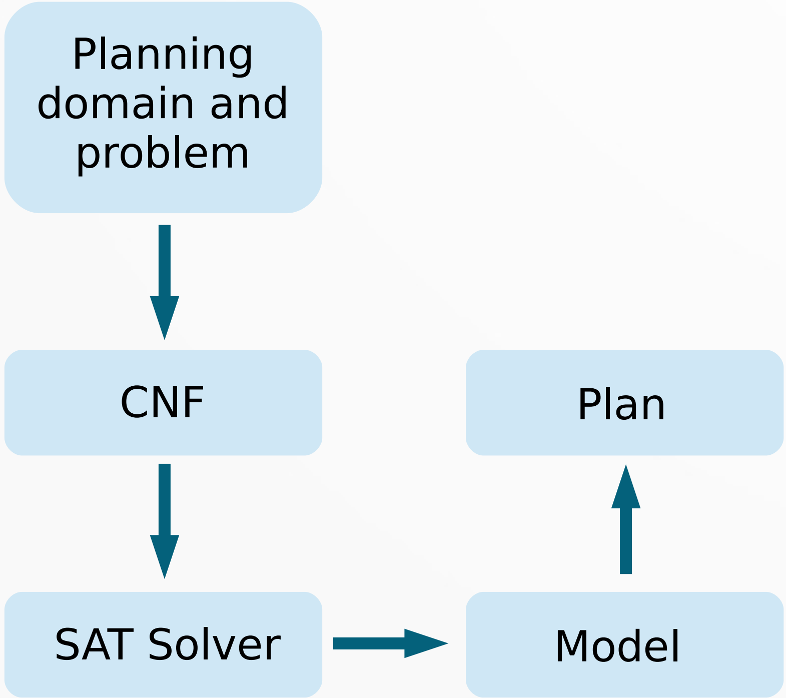
SAT Planning:



3 approaches to TAMP

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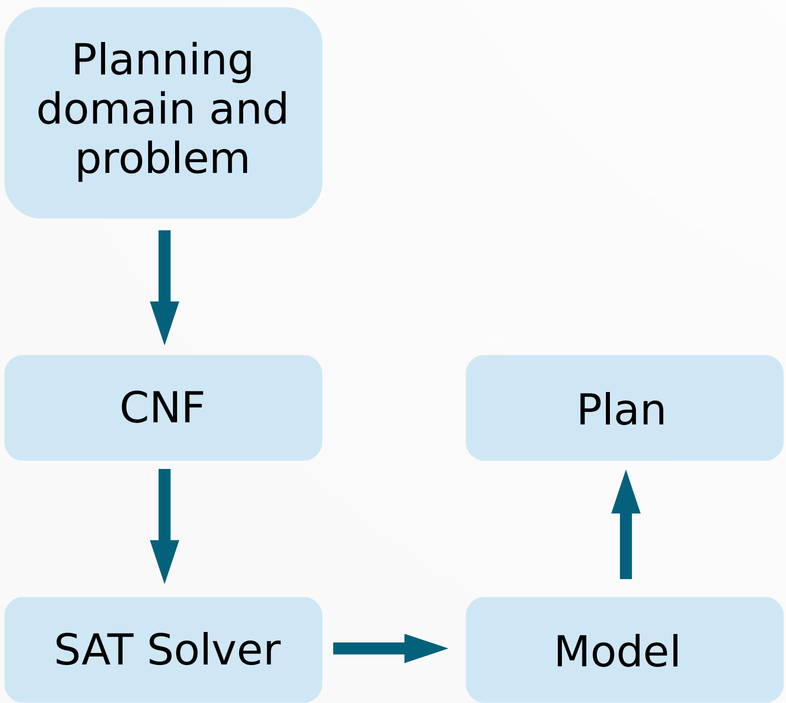

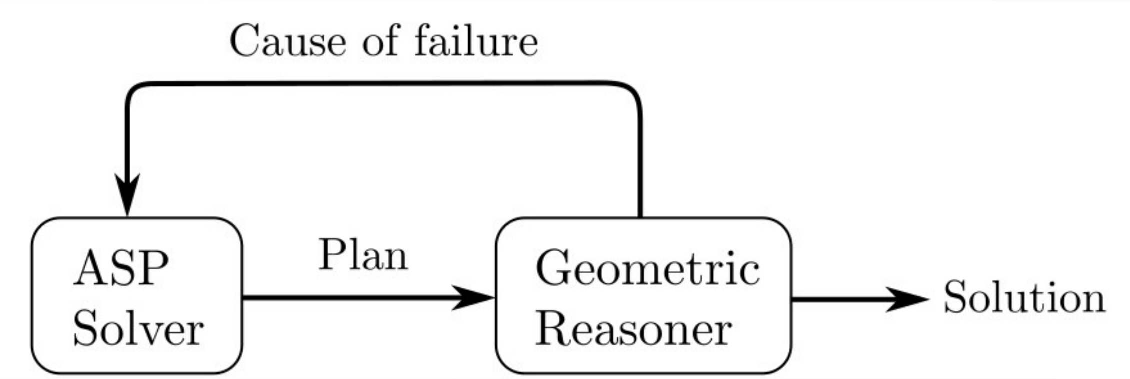

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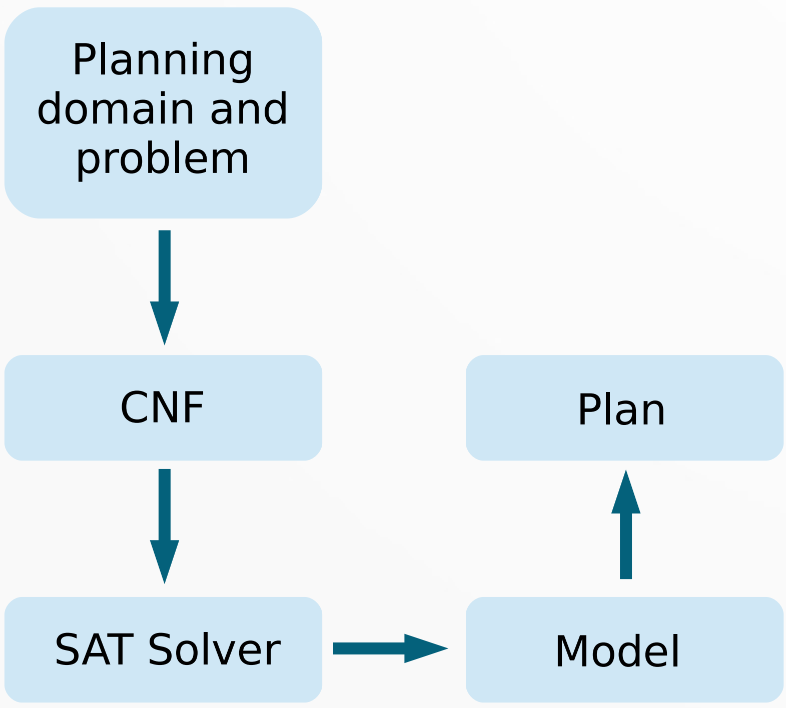

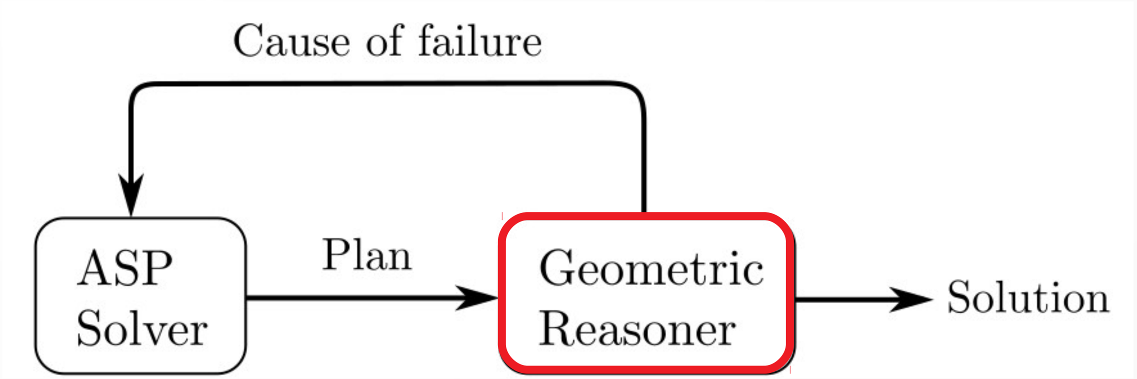

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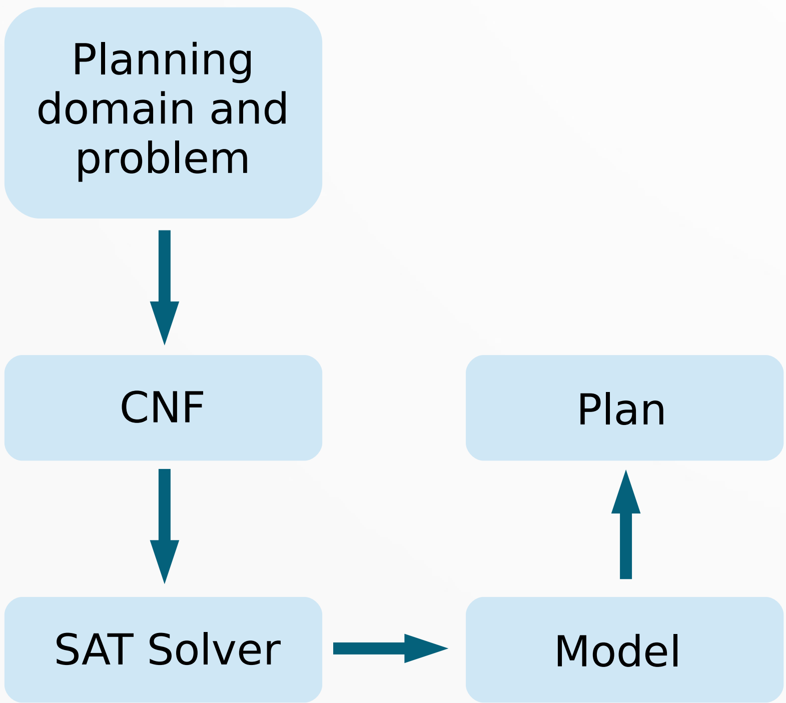

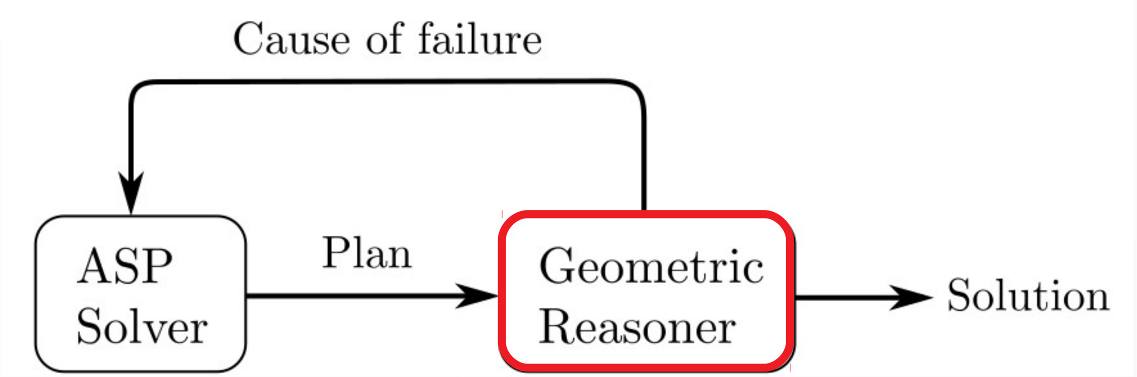

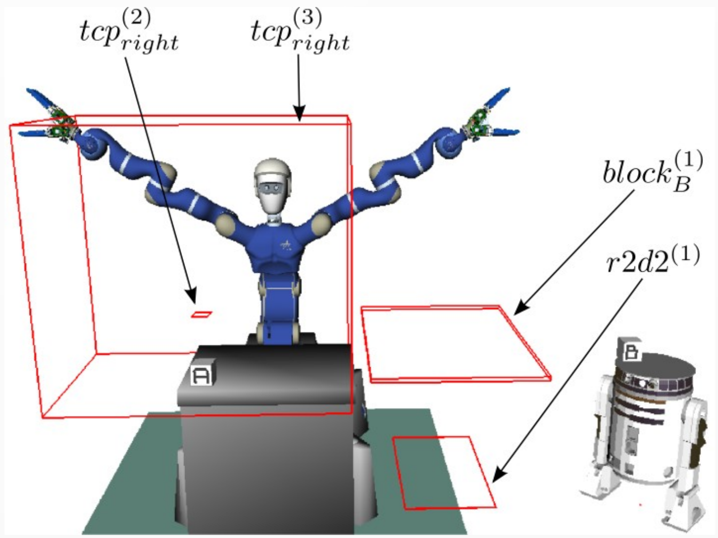

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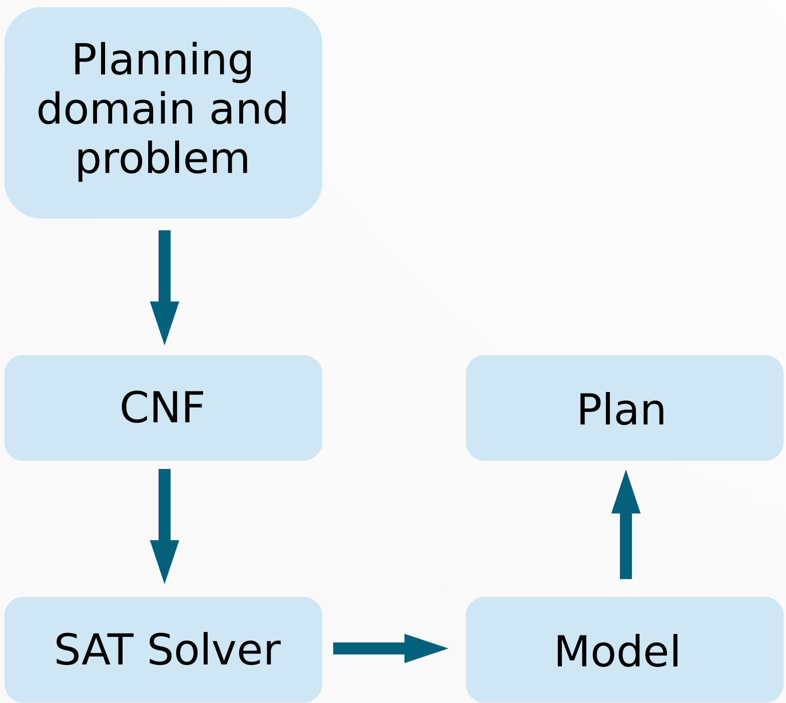
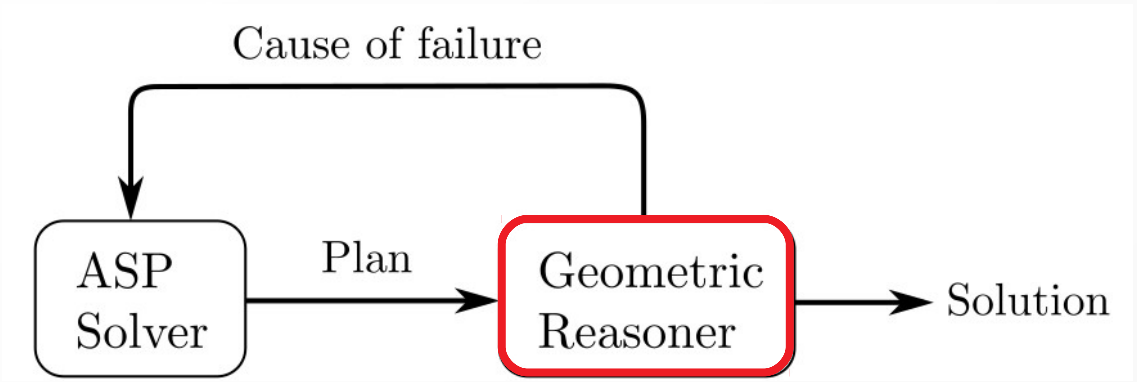
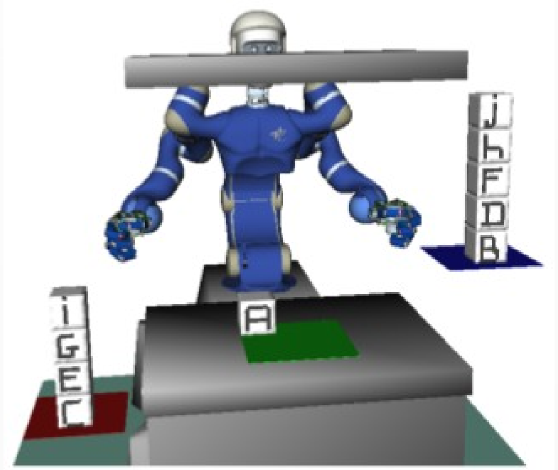




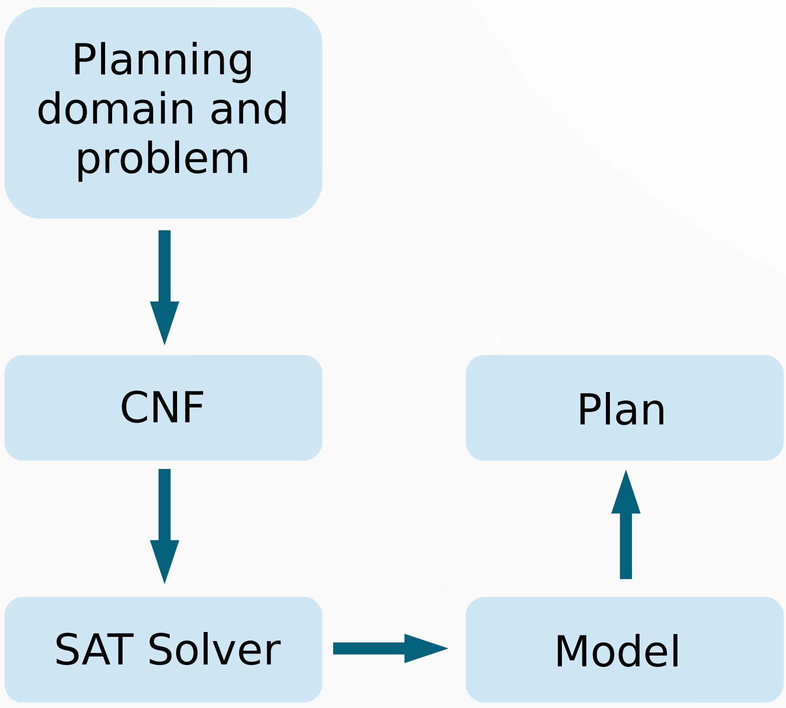


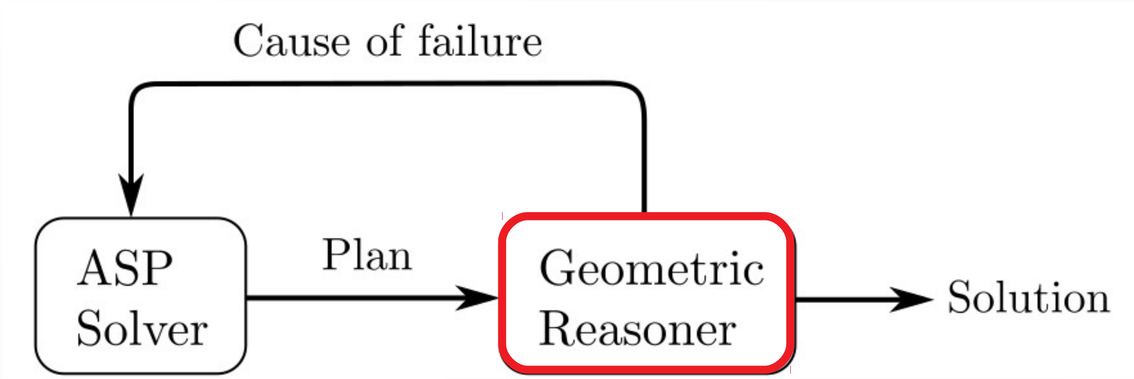
Blocks world 3D

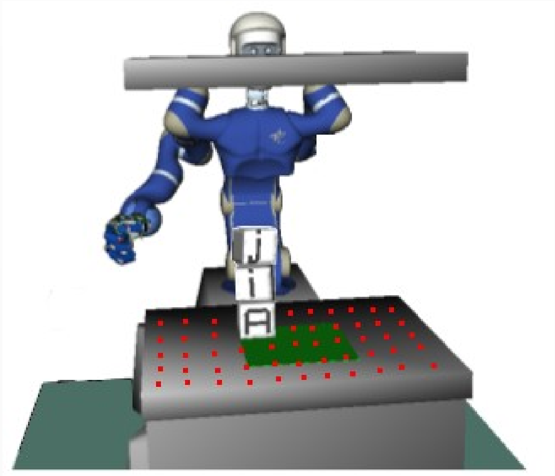
3 approaches to TAMP

- ASP + failure explanation

SAT Planning:







Blocks world 3D

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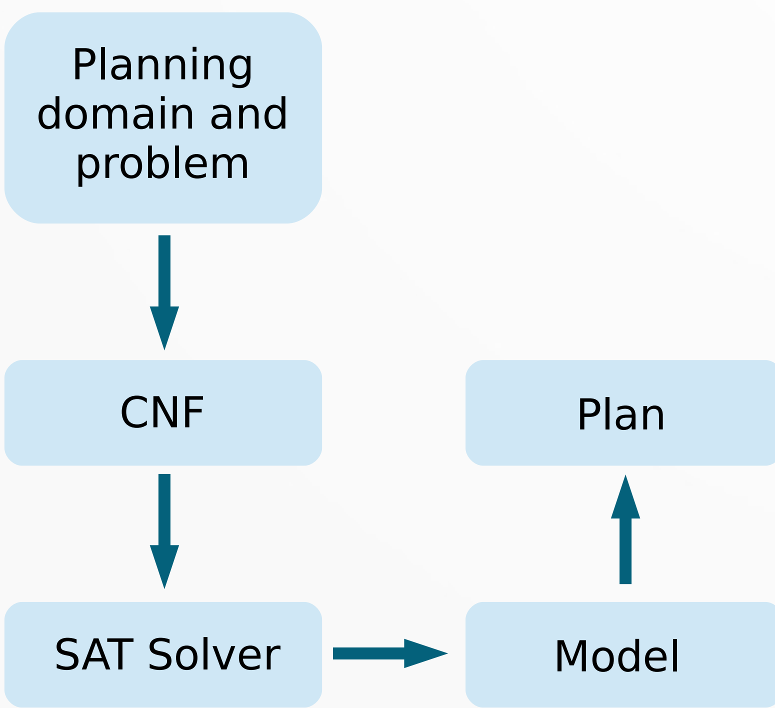
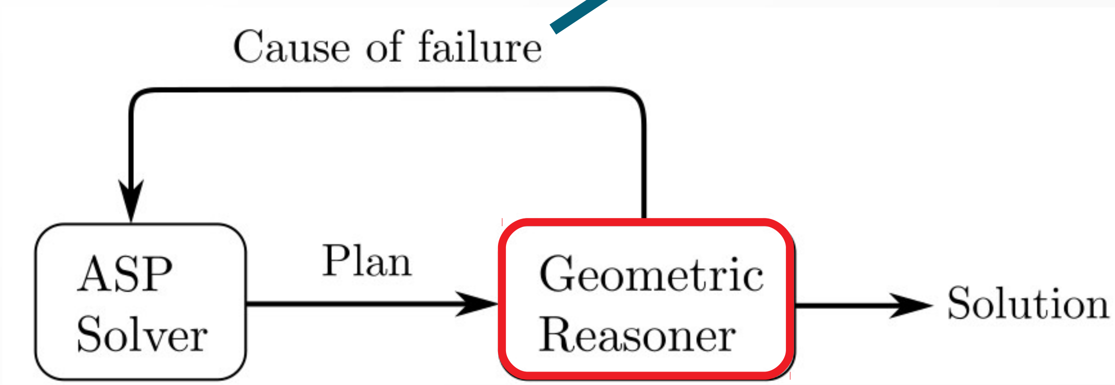
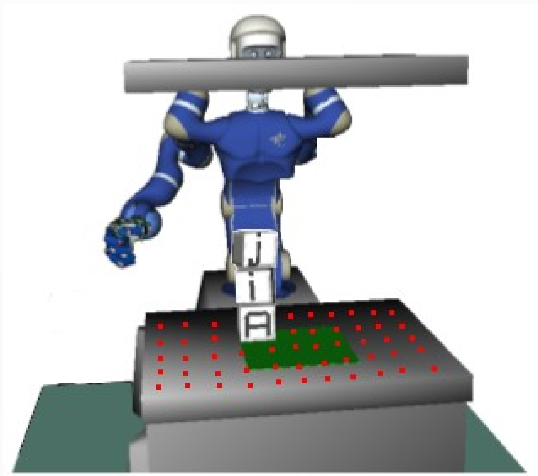


NOT (on (J, I)
AND on (I, A)
AND on (A, table))





Blocks world 3D

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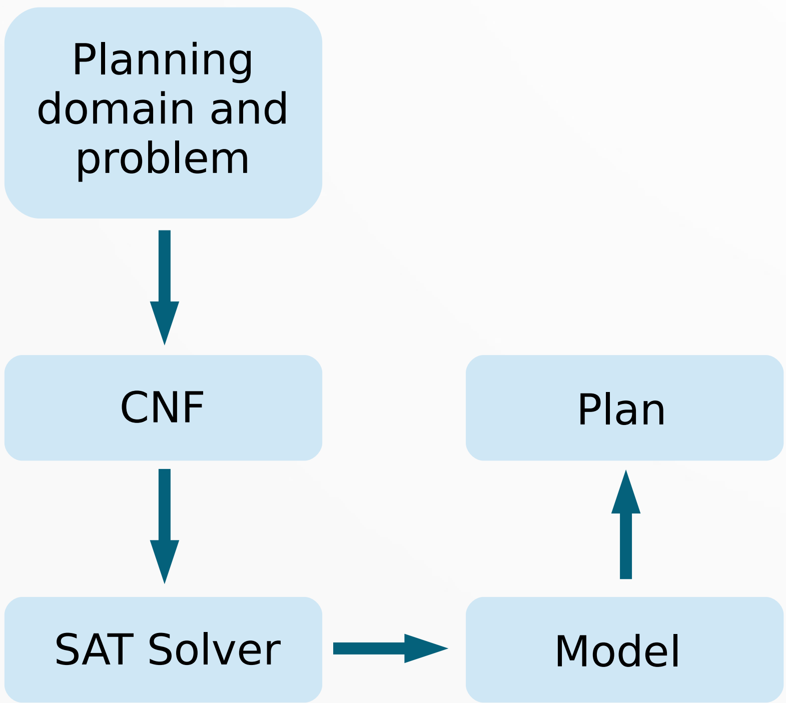
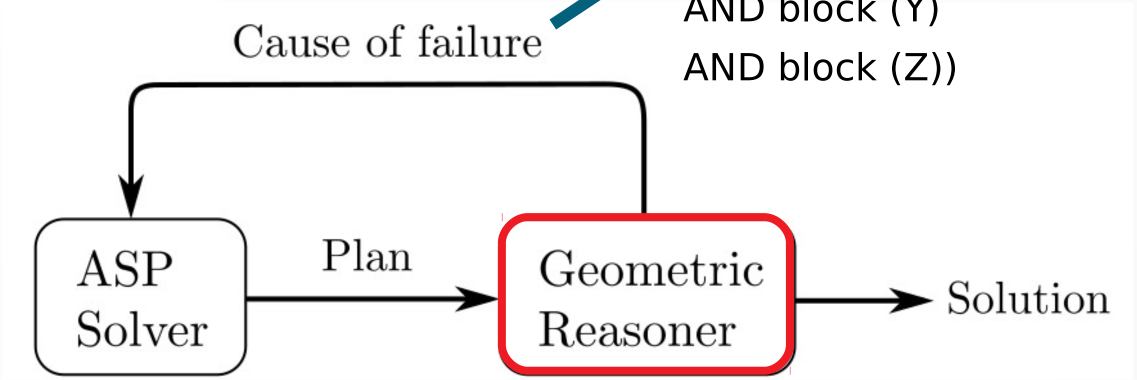
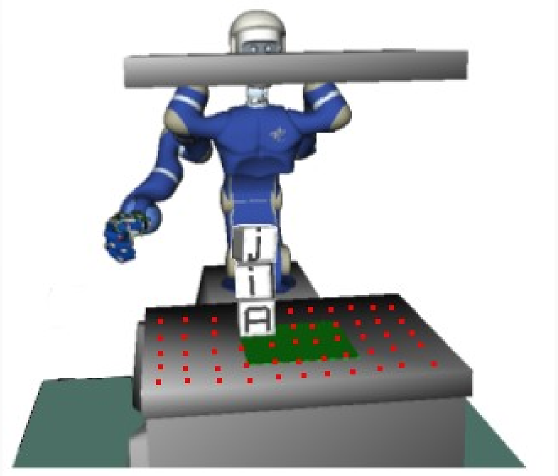


NOT (on (X, Y)
AND on (Y, Z)
AND on (Z, table)
AND block (X)
AND block (Y)
AND block (Z))





Blocks world 3D

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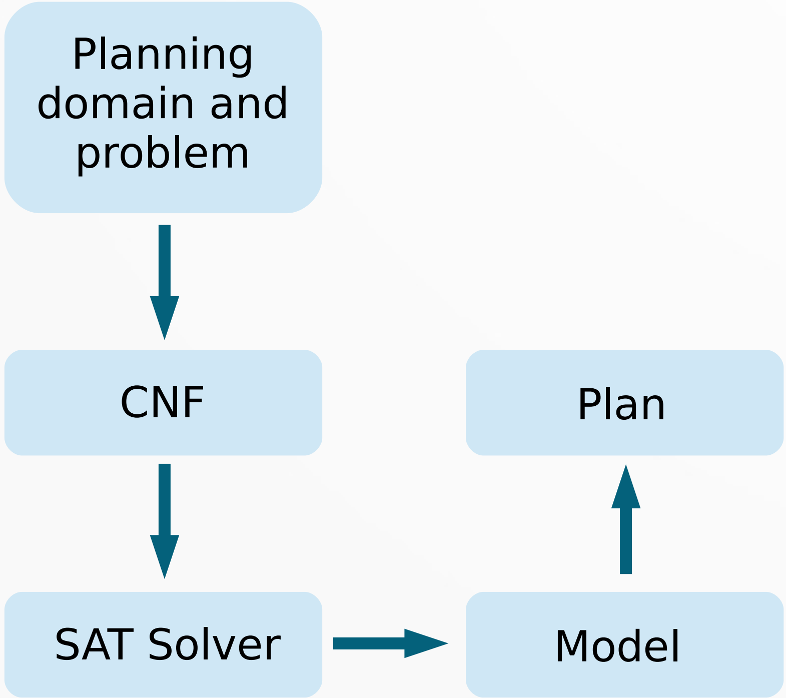

NOT (on (X, Y)
AND on (Y, Z)
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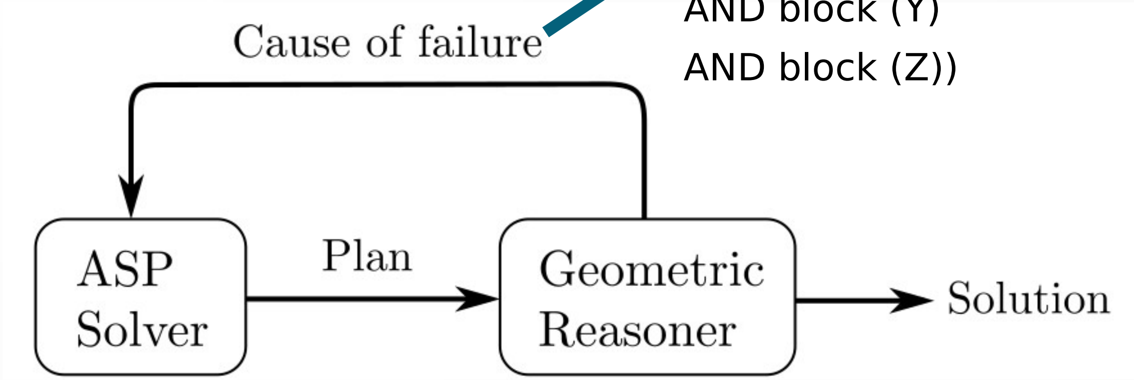
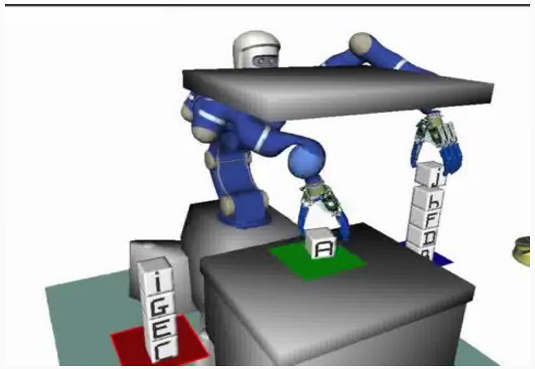




Blocks world 3D

3 approaches to TAMP

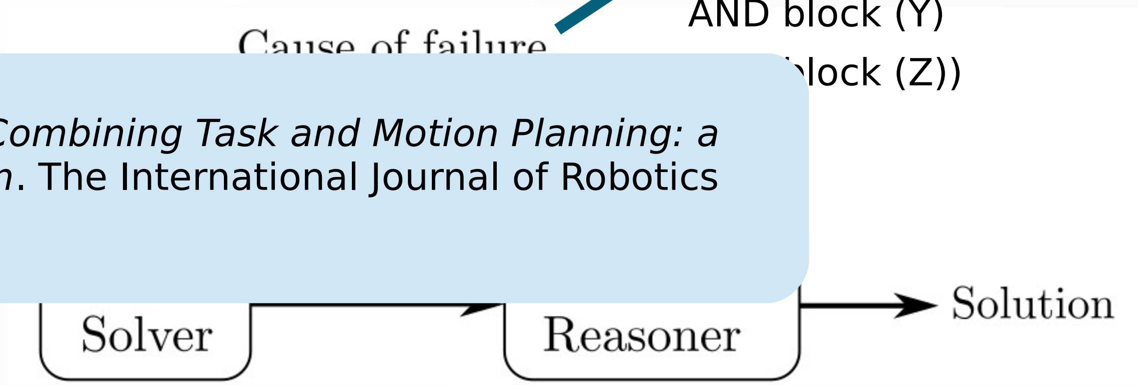
ASP + failure explanation

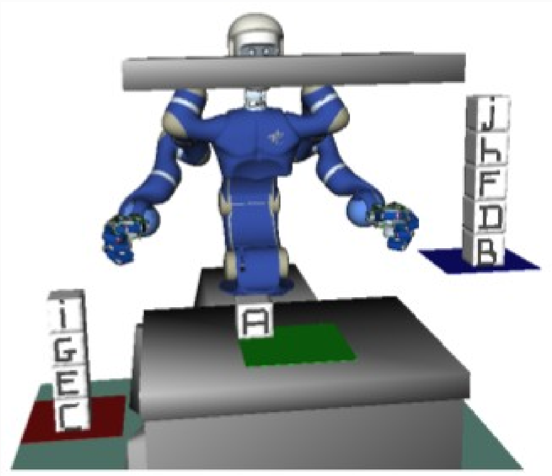
NOT (on (X, Y)
AND on (Y, Z)
AND on (Z, table)
AND block (X)
AND block (Y)
lock (Z))

SAT Planning:

Planning domain and problem → CNF → SAT Solver → Model → Plan

F. Lagriffoul, B. Andres, *Combining Task and Motion Planning: a culprit detection problem*. The International Journal of Robotics Research, 2016.





Blocks world 3D

3 approaches to TAMP

- AsyMov
- FFRob
- ASP + failure explanation

3 approaches to TAMP

- AsyMov — Roadmaps + task planner as heuristic
- FFRob — Task planner + CRG as heuristic
- ASP + failure explanation — Geometric reasoner pruning the search space of the task planner

Outline

Outline

- Problem definition(s)
- What makes it difficult?
- 3 approaches to TAMP
- Future directions

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- Problem definition(s)
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Future directions

- Learning

A. M. Wells, N. T. Dantam, A. Shrivastava, and L. E. Kavraki, *Learning Feasibility for Task and Motion Planning in Tabletop Environments,* IEEE Robotics and Automation Letters, vol. 4, no. 2, pp. 1255–1262, Apr. 2019.

Kim B, Wang Z, Kaelbling LP, Lozano-Pérez T. *Learning to guide task and motion planning using score-space representation*. The International Journal of Robotics Research. 2019;38(7):793-812.

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- Theory

  William Vega-Brown, Nicholas Roy, *Task and Motion Planning Is PSPACE-Complete*. AAAI 2020: 10385-10392.

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- You guys!

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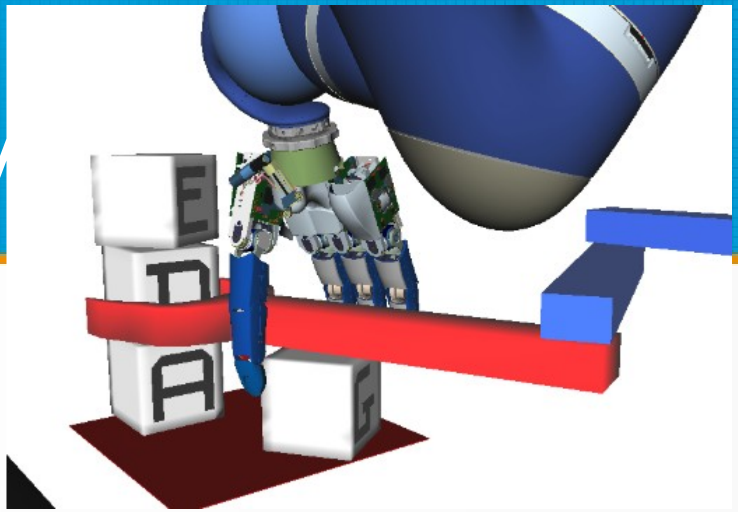
- Hauser K. The minimum constraint removal problem with three robotics applications. The International Journal of Robotics Research. 2014;33(1):5-17.

- WIKI: http://tampbenchmark.aass.oru.se/

3 approaches to TAM



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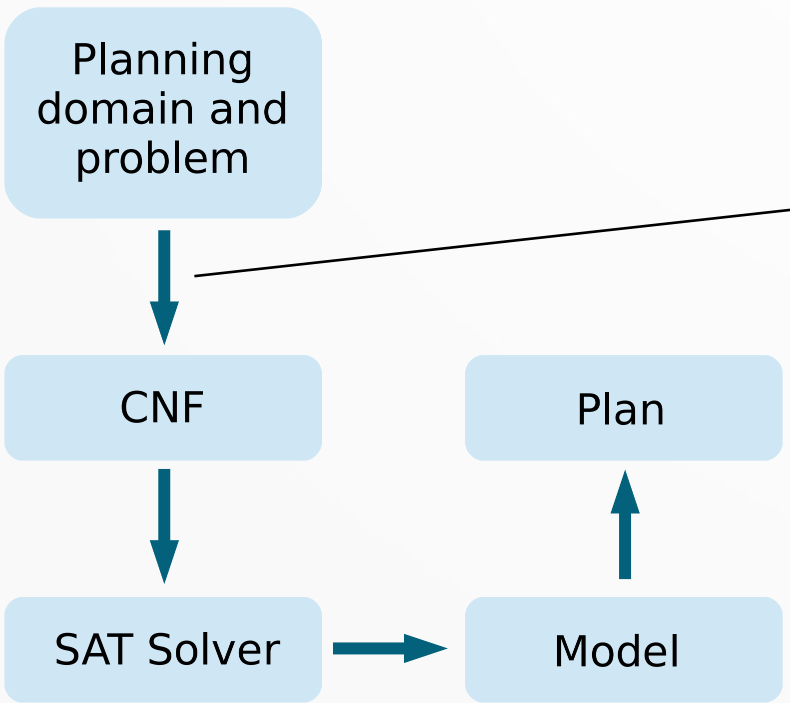
SAT Planning:



Formula describing the initial state:

$$\bigwedge\{l_0 \mid l \in s_0\} \wedge \bigwedge\{\neg l_0 \mid l \in L - s_0\}$$

Formula describing the goal state:

$$\bigwedge\{l_n \mid l \in g^+\} \wedge \bigwedge\{\neg l_n \mid l \in g^-\}$$

Formulas describing the preconditions and effects of actions:

For every action a in A, formulas describing what changes a would make if it were the i'th step of the plan:

- $a_i \Rightarrow \bigwedge\{p_i \mid p \in \text{Precond}(a)\} \wedge \bigwedge\{e_{i+1} \mid e \in \text{Effects}(a)\}$

Formulas describing *Complete exclusion*:

- For all actions a and b, formulas saying they cannot occur at the same time
  $\neg a_i \vee \neg b_i$
- this guarantees there can be only one action at a time