



BACKWARD-FORWARD SEARCH FOR MANIPULATION PLANNING

Caelan Garrett, Tomás Lozano-Pérez, and Leslie Kaelbling
MIT CSAIL - IROS 2015

Hybrid Planning

- **Mixed discrete/continuous state & actions**

Hybrid Planning

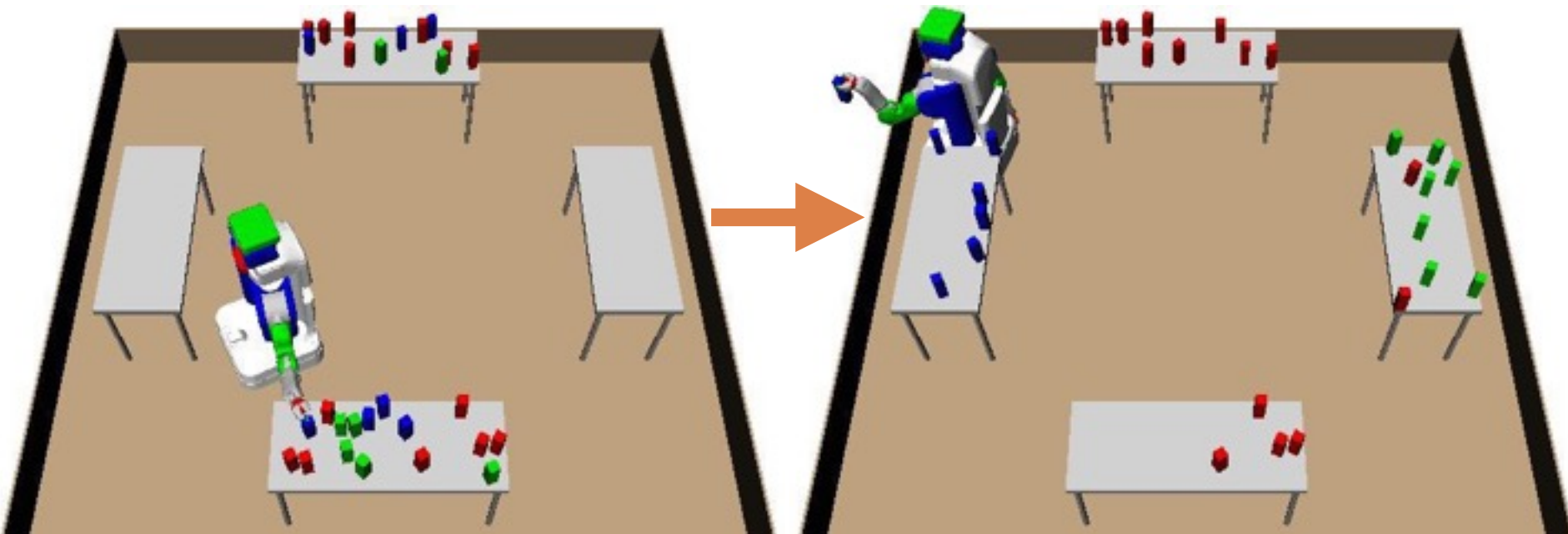
- **Mixed discrete/continuous state & actions**
- e.x. robotic planning
 - Continuous - robot configuration, object poses, grasp transforms, ...
 - Discrete - holding object label, object cleaned/cooked, ...

Hybrid Planning

- **Mixed discrete/continuous state & actions**
- e.x. robotic planning
 - Continuous - robot configuration, object poses, grasp transforms, ...
 - Discrete - holding object label, object cleaned/cooked, ...
- **Hybrid Backward-Forward (HBF) algorithm**
 - Probabilistically complete
 - Efficient empirical performance

High-Dimensional Manipulation

Separate **blue blocks** and **green blocks**

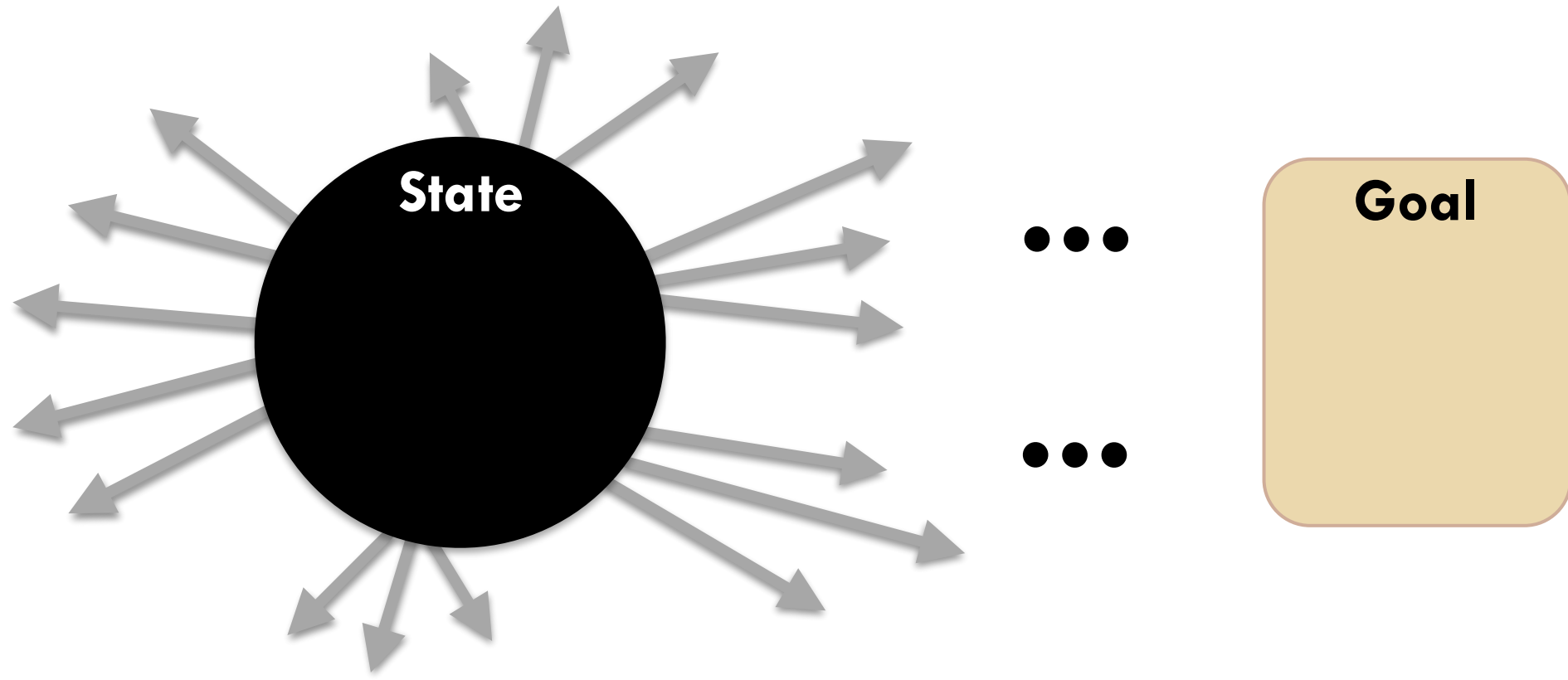


Early state

Late state

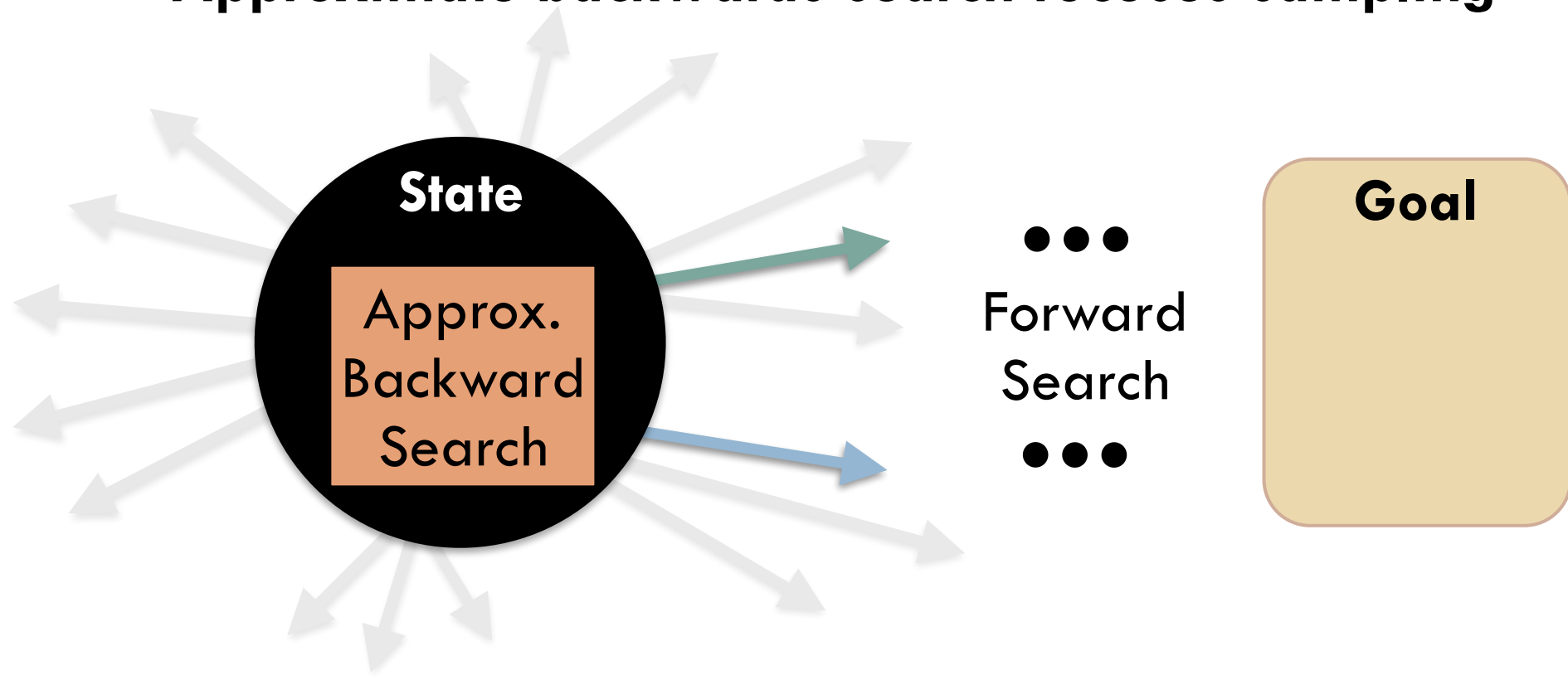
Infinite Branching Factor and Long Horizon

- Pure forward or backward search overwhelmed
- Unguided action sampling ineffective



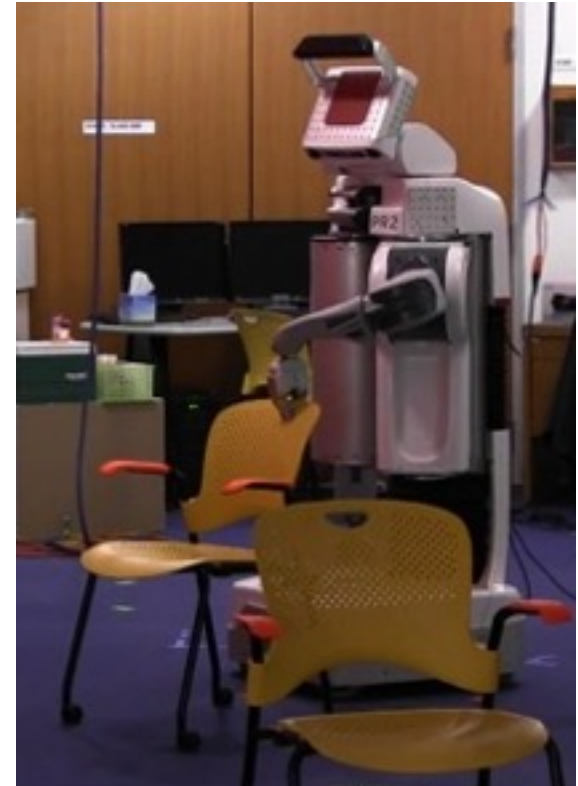
Infinite Branching Factor and Long Horizon

- Pure forward or backward search overwhelmed
- Unguided action sampling ineffective
- **Approximate backwards search focuses sampling**



Action Template Representation

Place(config, obj, transform)



Action Template Representation

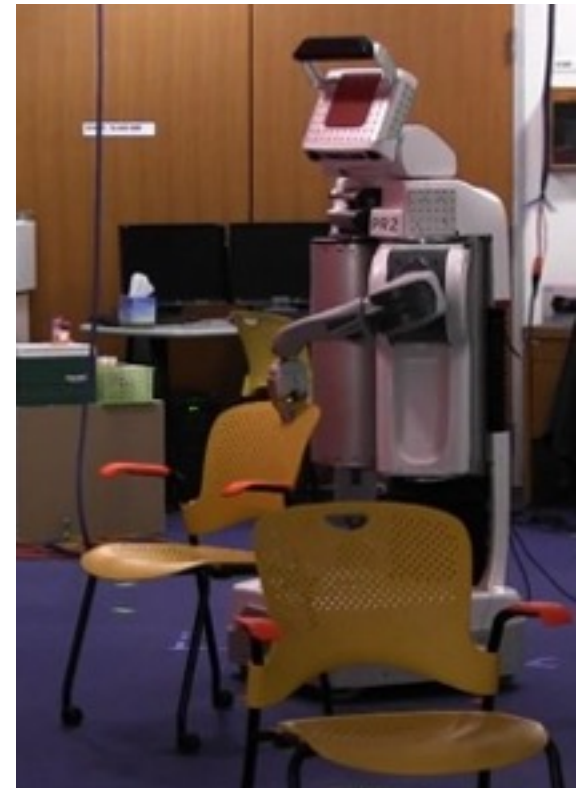
Place(*config*, *obj*, *transform*)

constraints

robot = *config*

holding = *obj*

grasp = *transform*



Action Template Representation

Place(*config*, *obj*, *transform*)

constraints

robot = *config*

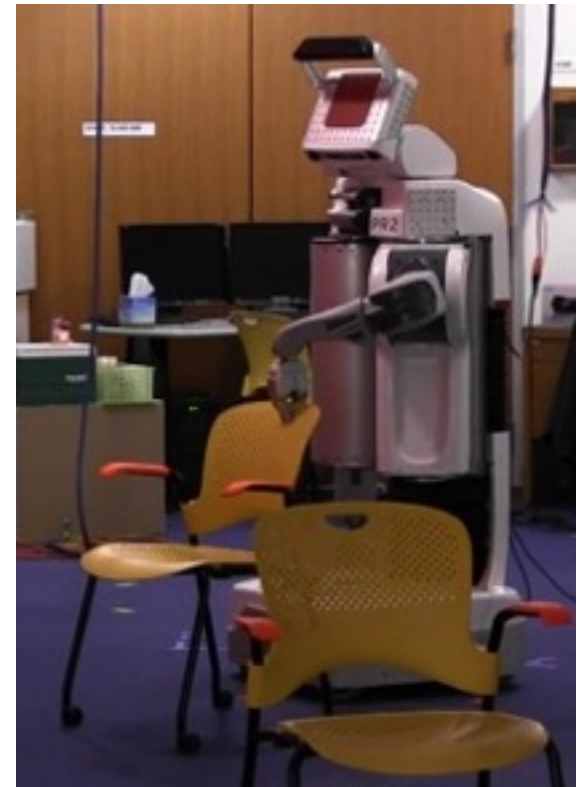
holding = *obj*

grasp = *transform*

effects

holding = **None**

obj = **Pose**(*config*, *obj*, *transform*)



Action Template Representation

MoveHolding(config1, config2, objA, transform)

constraints

robot = config1

holding = objA

grasp = transform

objB ∈ CollisionFreePoses(config1, config2, objA, transform, objB) for objB ≠ objA

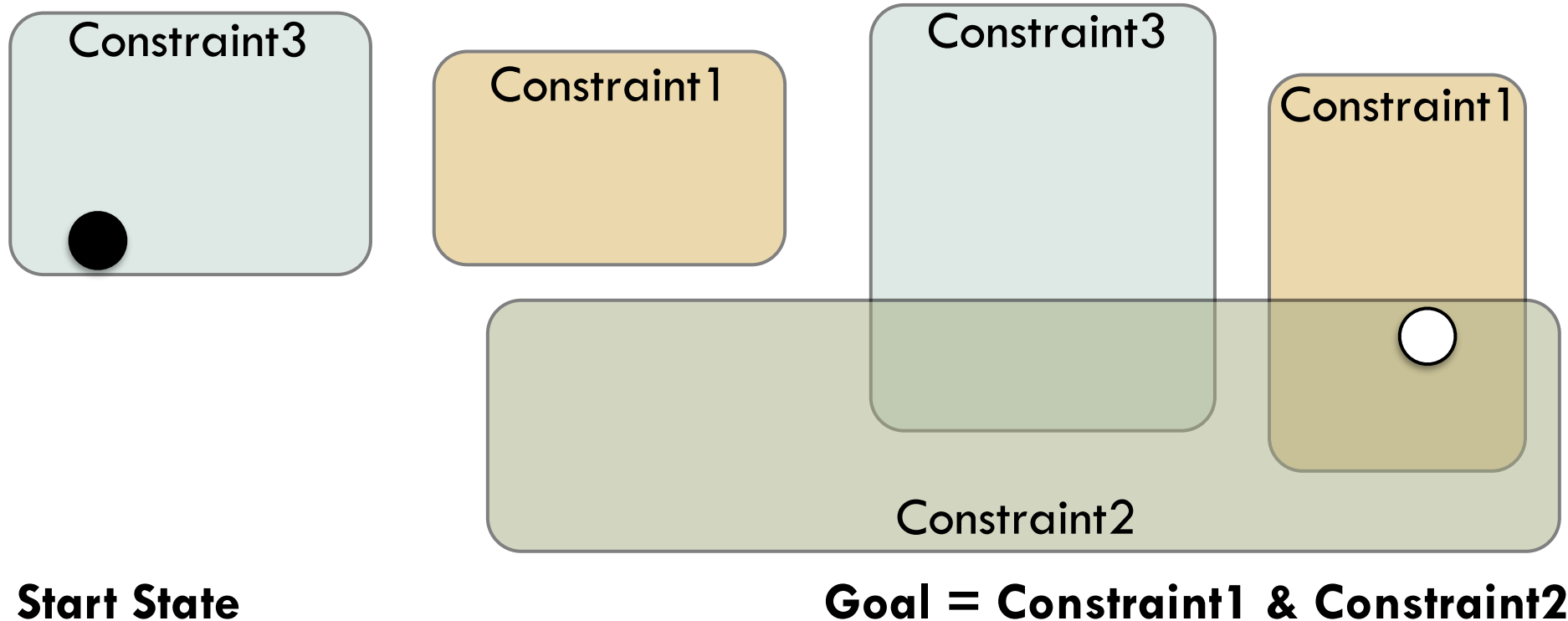
effects

robot = config2

objA = Pose(config2, objA, transform)

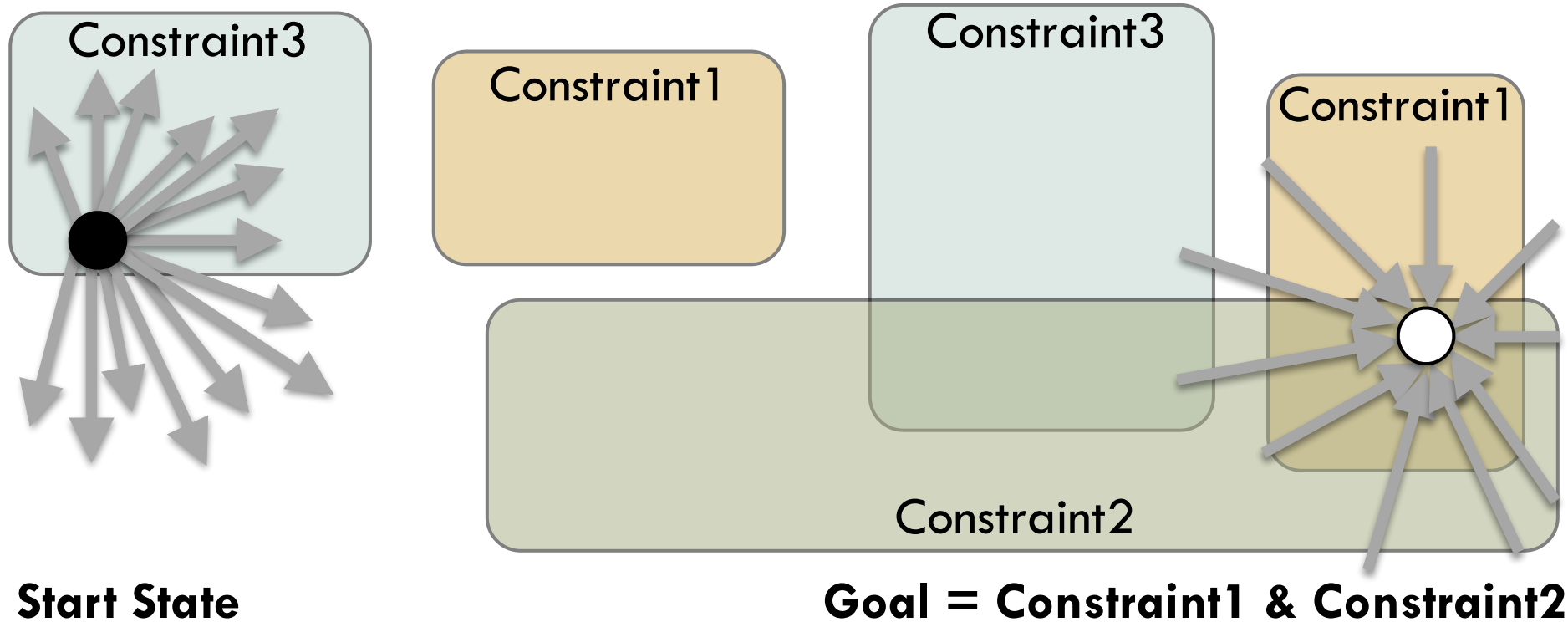
Example Hybrid Planning Problem

- Constraints define regions of state-space
- Goal is to reach a state in the **intersection of Constraint1 and Constraint2**



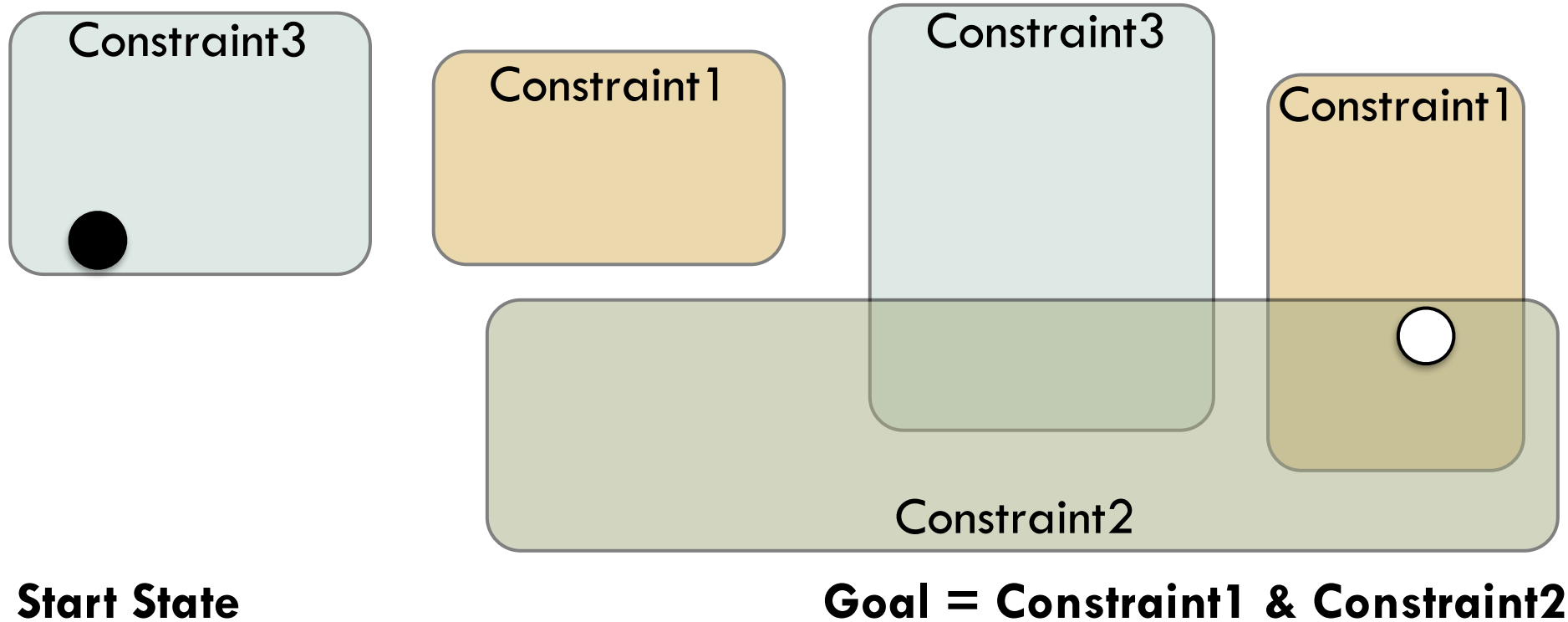
Unguided Search is Ineffective

- Pure forward or backward search **overwhelmed** by infinite branching factor and long horizon



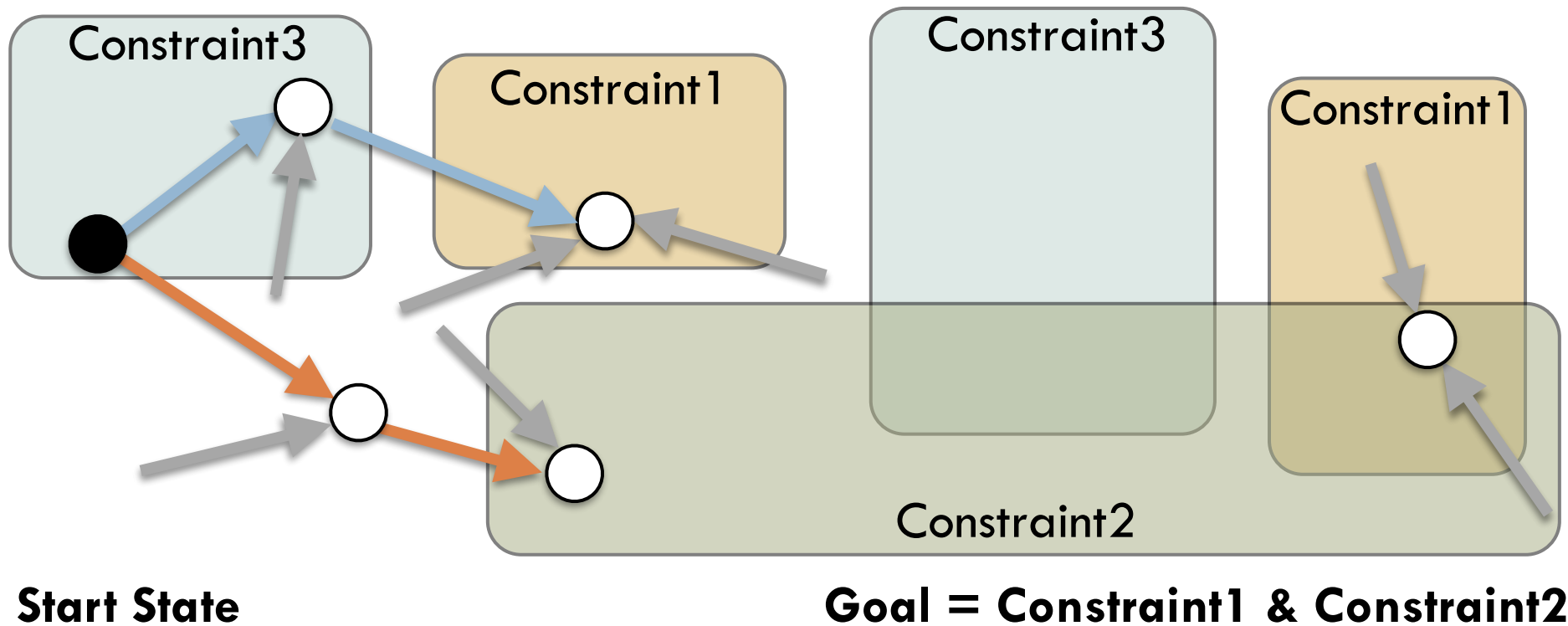
Hybrid Backward-Forward (HBF)

- Backwards approximation - **constraint independence**



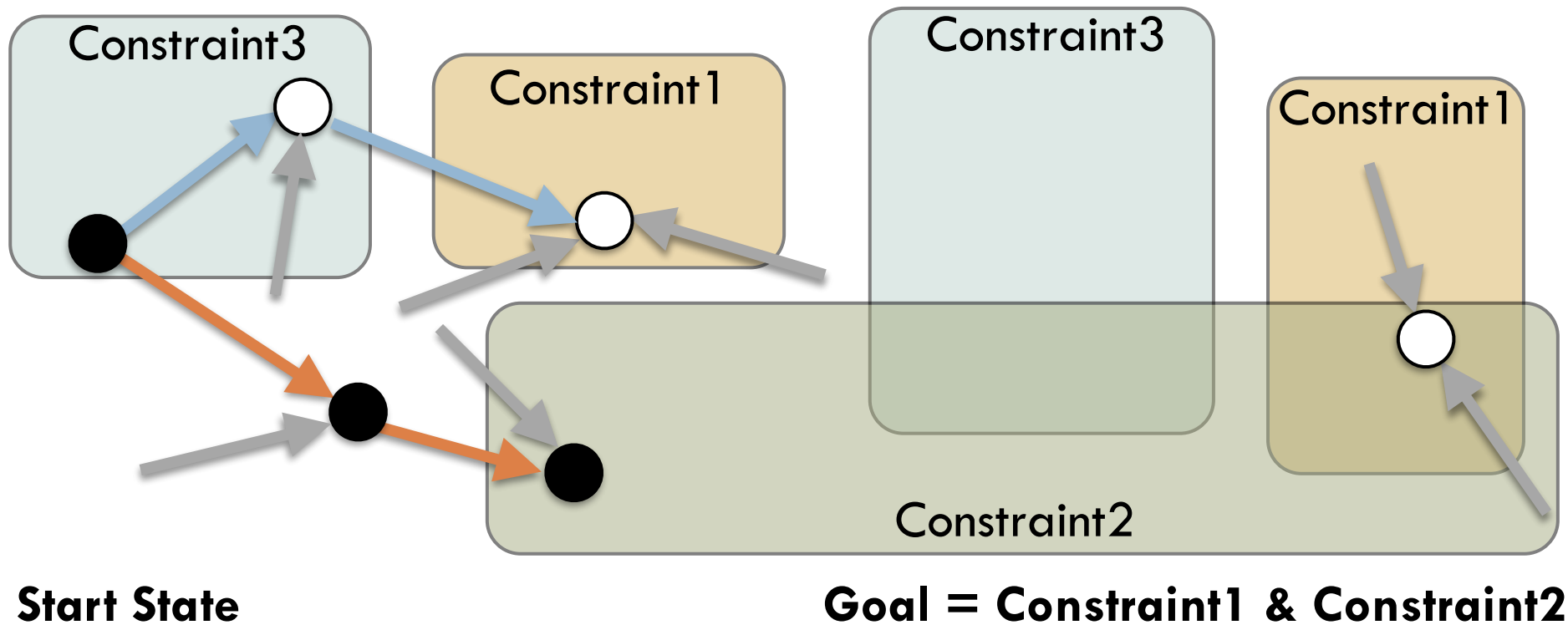
Hybrid Backward-Forward (HBF)

- Backwards approximation - **constraint independence**
- Long problem becomes **many short problems**



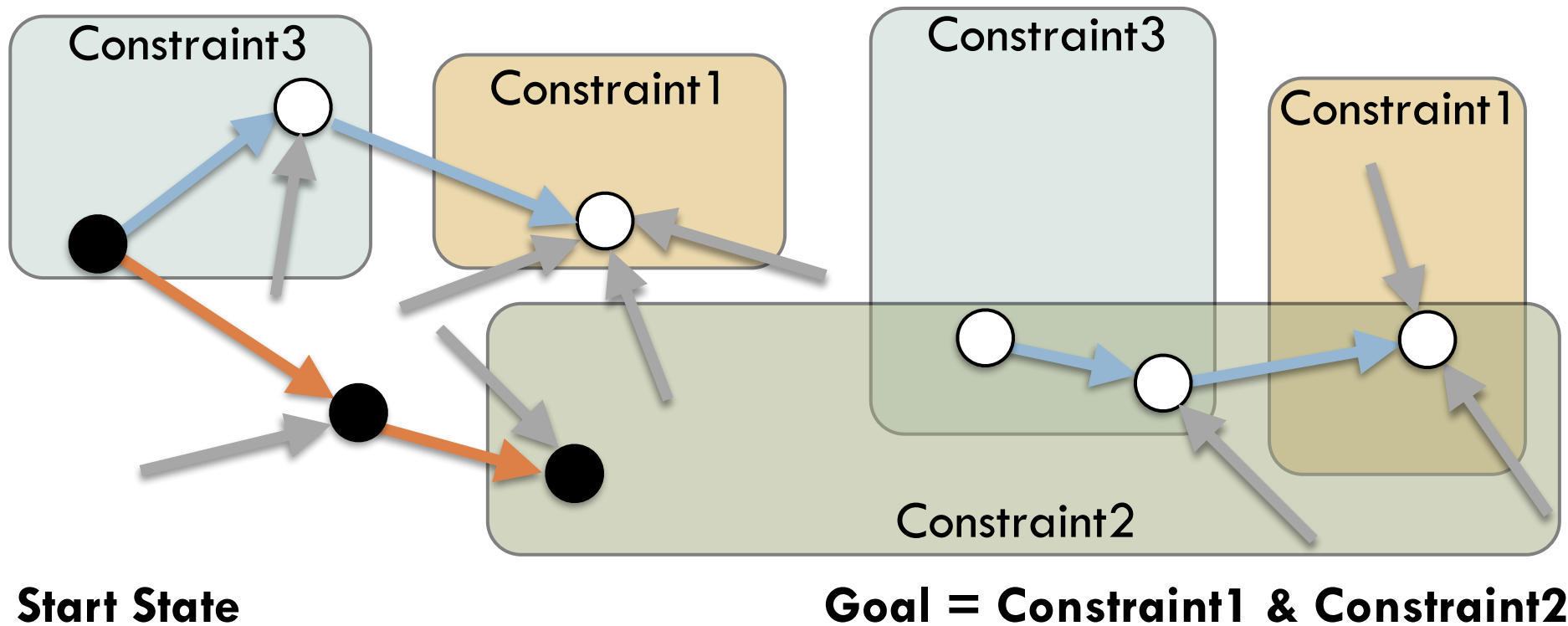
Hybrid Backward-Forward (HBF)

- Backwards approximation - **constraint independence**
- Long problem becomes **many short problems**



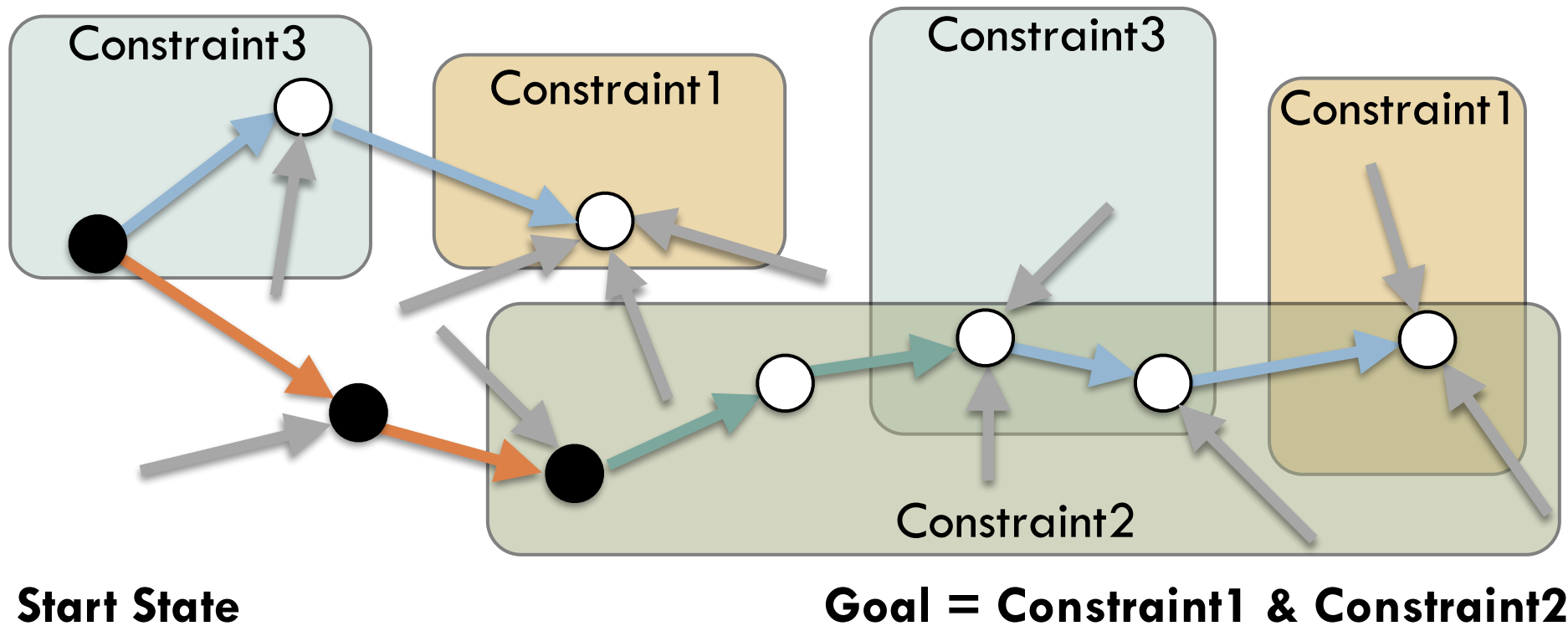
Hybrid Backward-Forward (HBF)

- Backwards approximation - **constraint independence**
- Long problem becomes **many short problems**
- Forward search **resolves** approximation errors



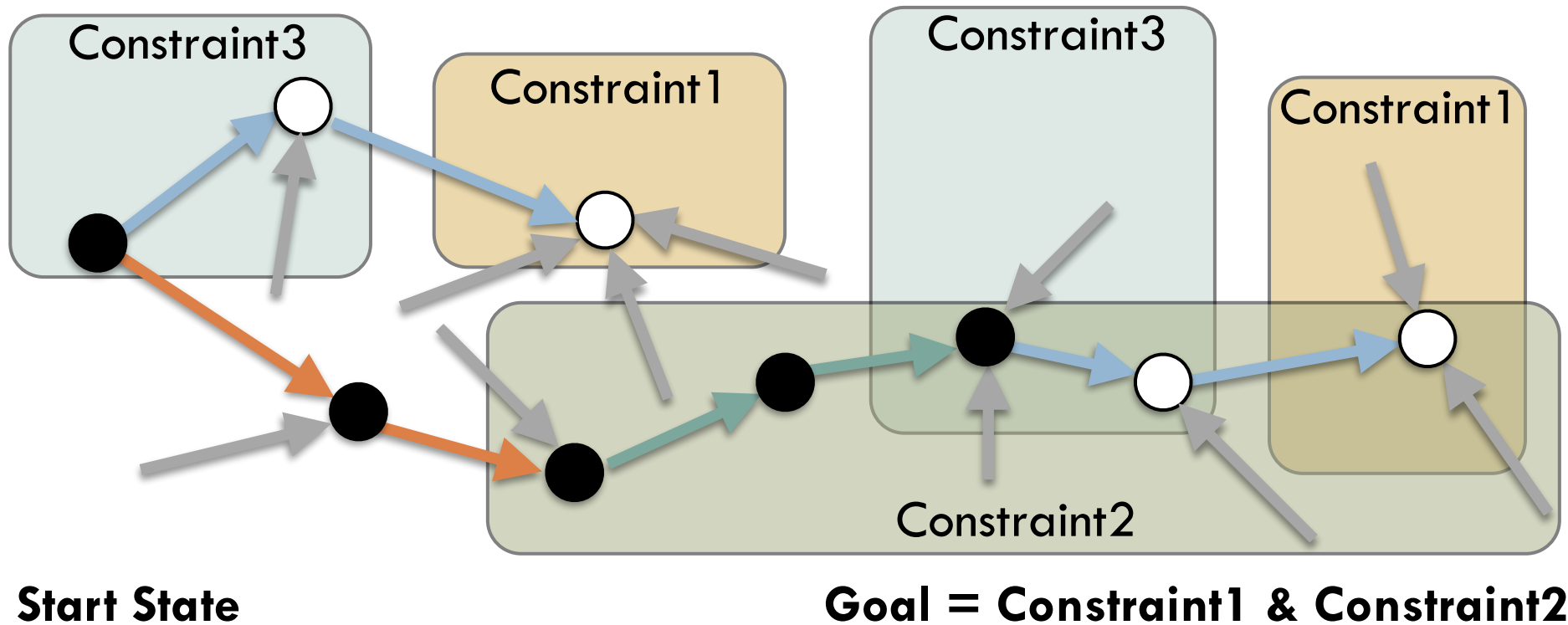
Hybrid Backward-Forward (HBF)

- Backwards approximation - **constraint independence**
- Long problem becomes **many short problems**
- Forward search **resolves** approximation errors



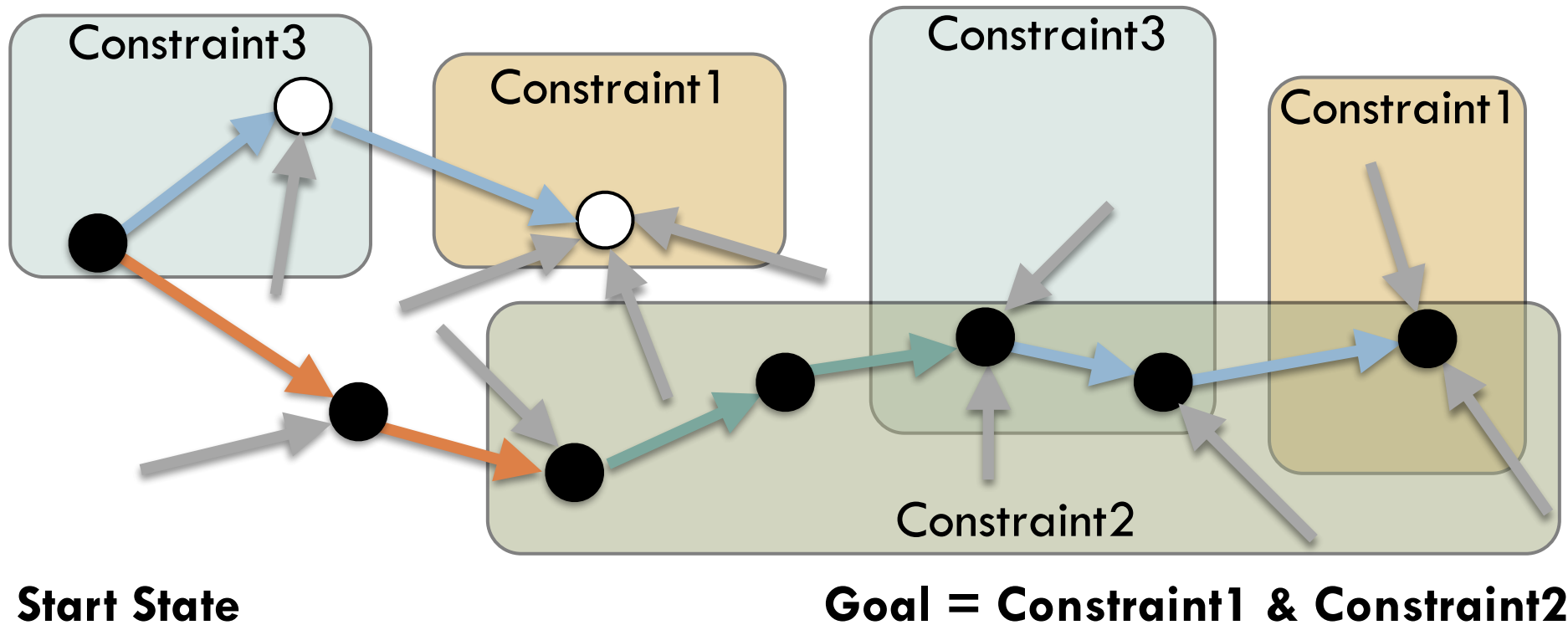
Hybrid Backward-Forward (HBF)

- Backwards approximation - **constraint independence**
- Long problem becomes **many short problems**
- Forward search **resolves** approximation errors



Hybrid Backward-Forward (HBF)

- Backwards approximation - **constraint independence**
- Long problem becomes **many short problems**
- Forward search **resolves** approximation errors



Backwards Search Algorithm

BackwardsSearch(*state, goal-constraints, action-templates*):

1. *Queue* initialized to *goal-constraints*

2. Repeat

3. Pop a *constraint* from the *queue*

4. Sample *actions* from each *action-template* that achieve the *constraint*

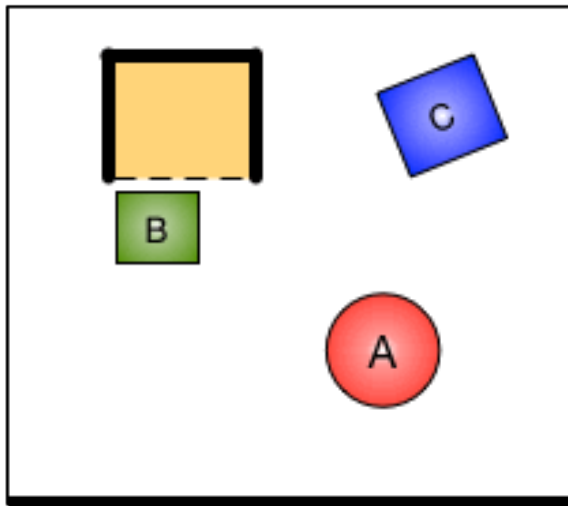
5. Yield *actions* applicable from *state* to forward search

6. Add the new *action constraints* not satisfied by *state* to the *queue*

Action Sampling

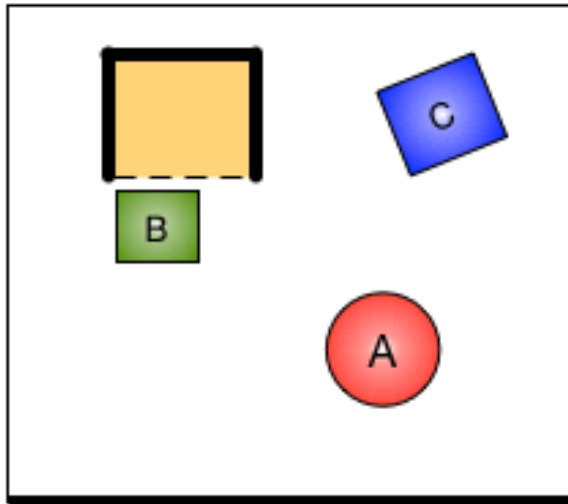
- Need to generate actions that satisfy a constraint
- For manipulation, we sample:
 - Configs/grasps/poses that **satisfy** the constraint
 - *Monte Carlo rejection sampling*
 - Other **relevant** configs/grasps/poses
 - *Current state, intersection of manifolds*
 - Actions that **connect** these values
 - *Blackbox motion planner (e.x. RRT)*
- Reuse previously sampled values/actions when possible

Push A into Yellow Cabinet



- Robot is a point
- Goal - object A in yellow cabinet
 - Need to move object B!
- **Trace backwards search**

Backwards Search - Iteration 1



- Search starts at the goal constraint

A in cabinet

holding = None

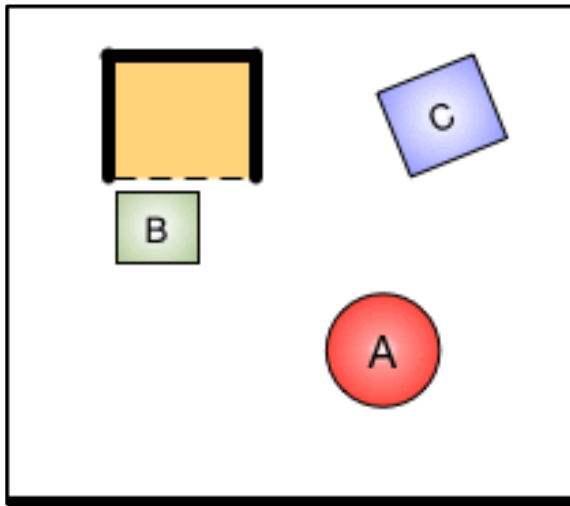
A = poseA0

B = poseB0

C = poseC0

robot = config0

Backwards Search - Iteration 1



- Pop constraint “A in cabinet” from the queue

A in cabinet

holding = None

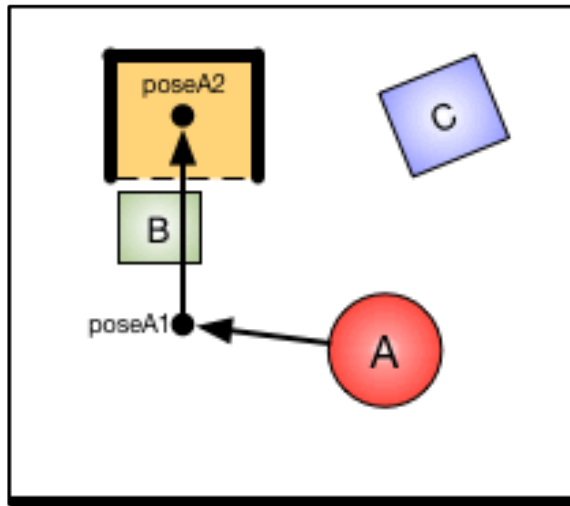
A = poseA0

B = poseB0

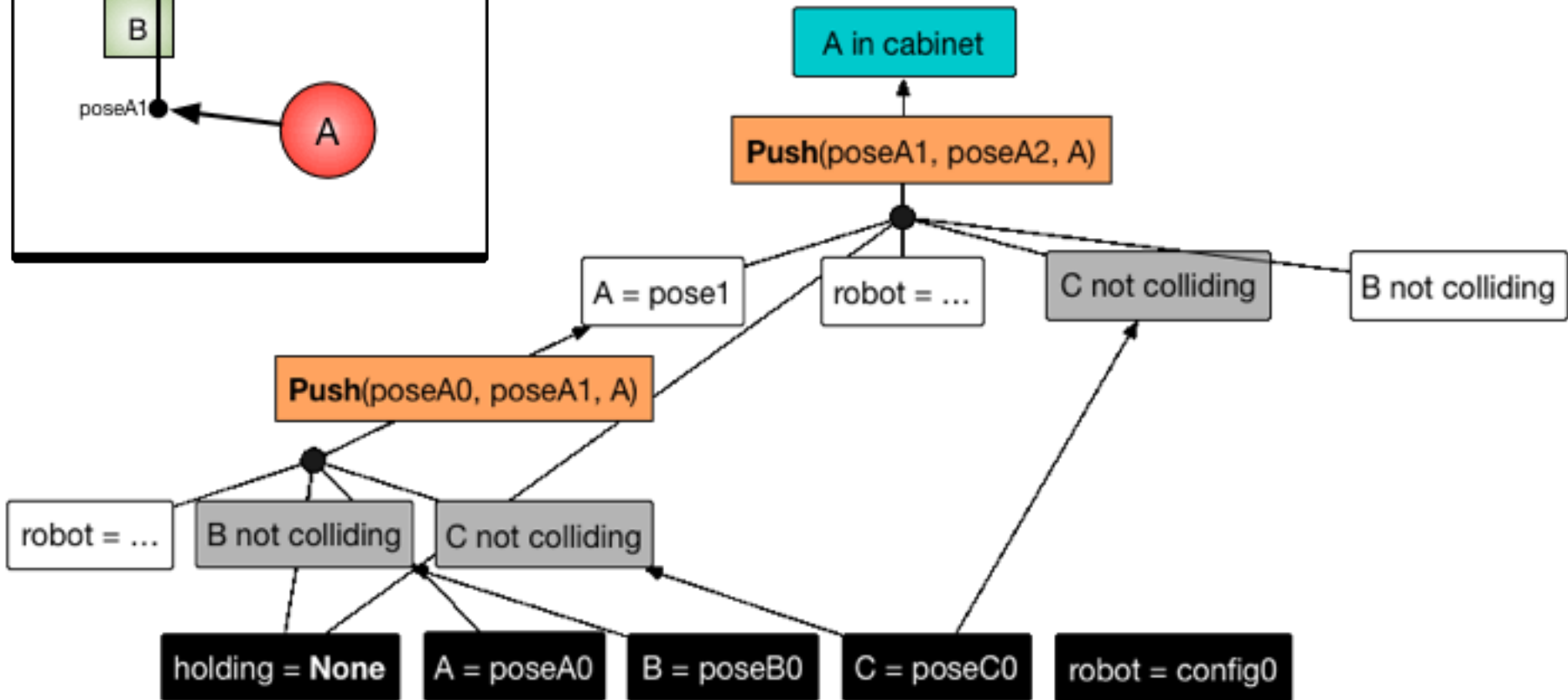
C = poseC0

robot = config0

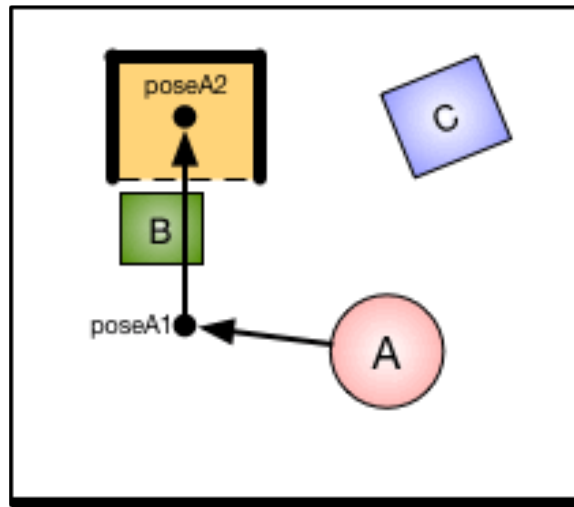
Backwards Search - Iteration 1



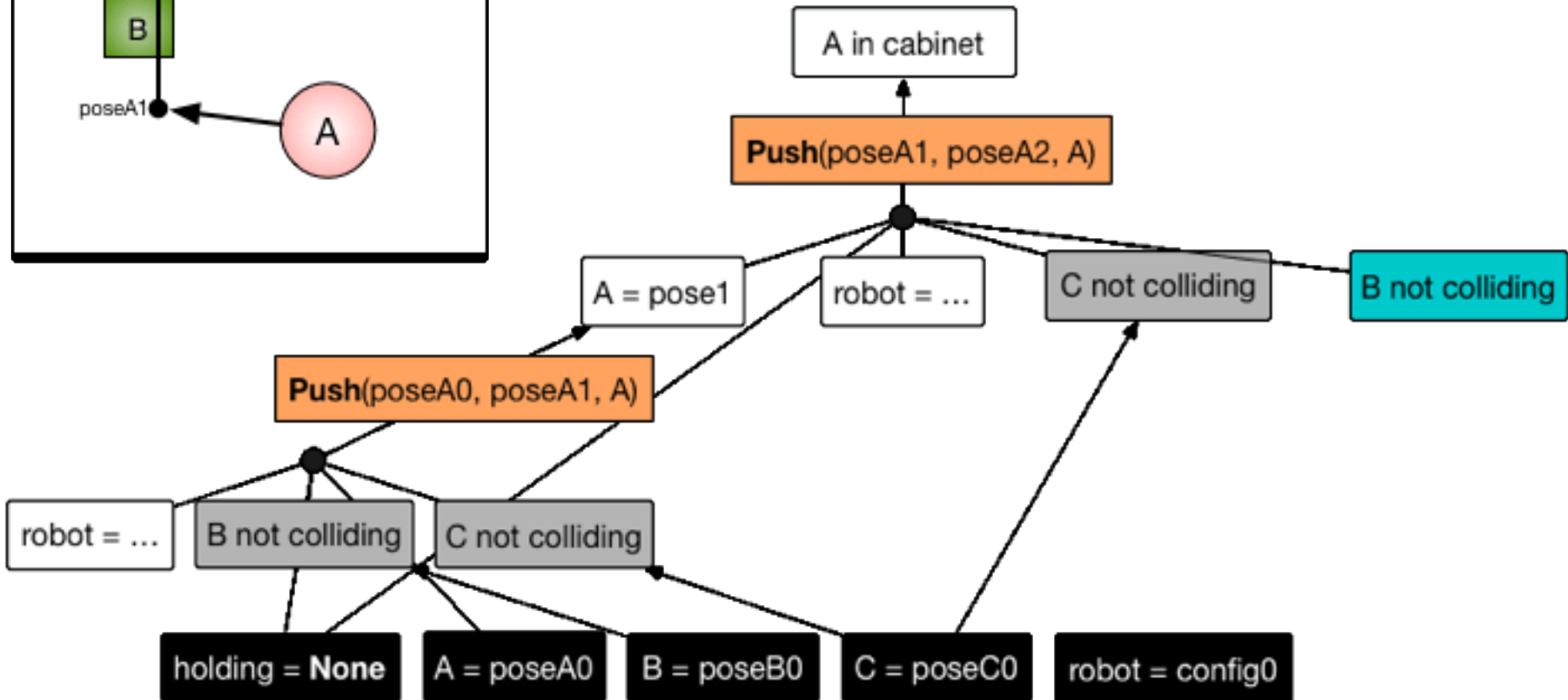
- Sample **Push** actions
- Add new constraints to queue



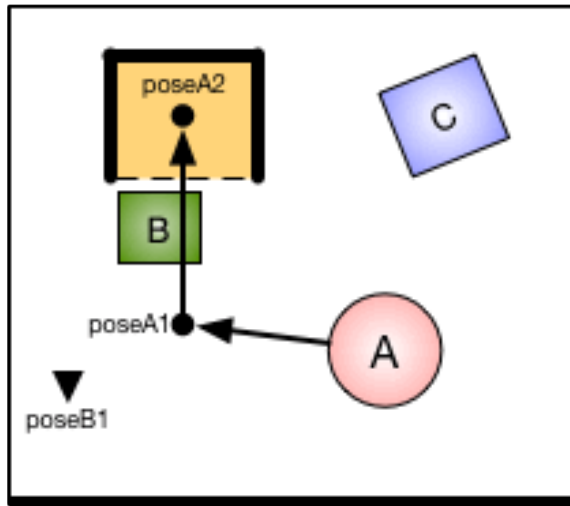
Backwards Search - Iteration 2



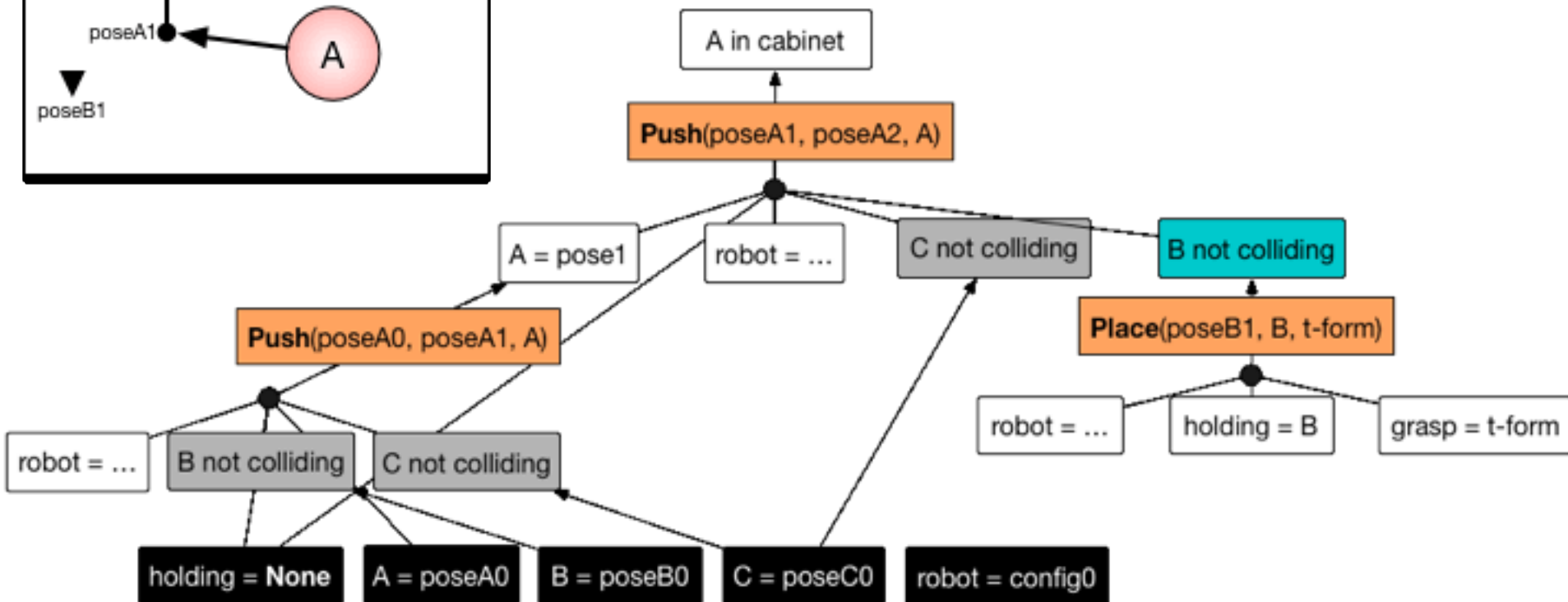
- Pop constraint “B not colliding” with the push from the queue



Backwards Search - Iteration 2

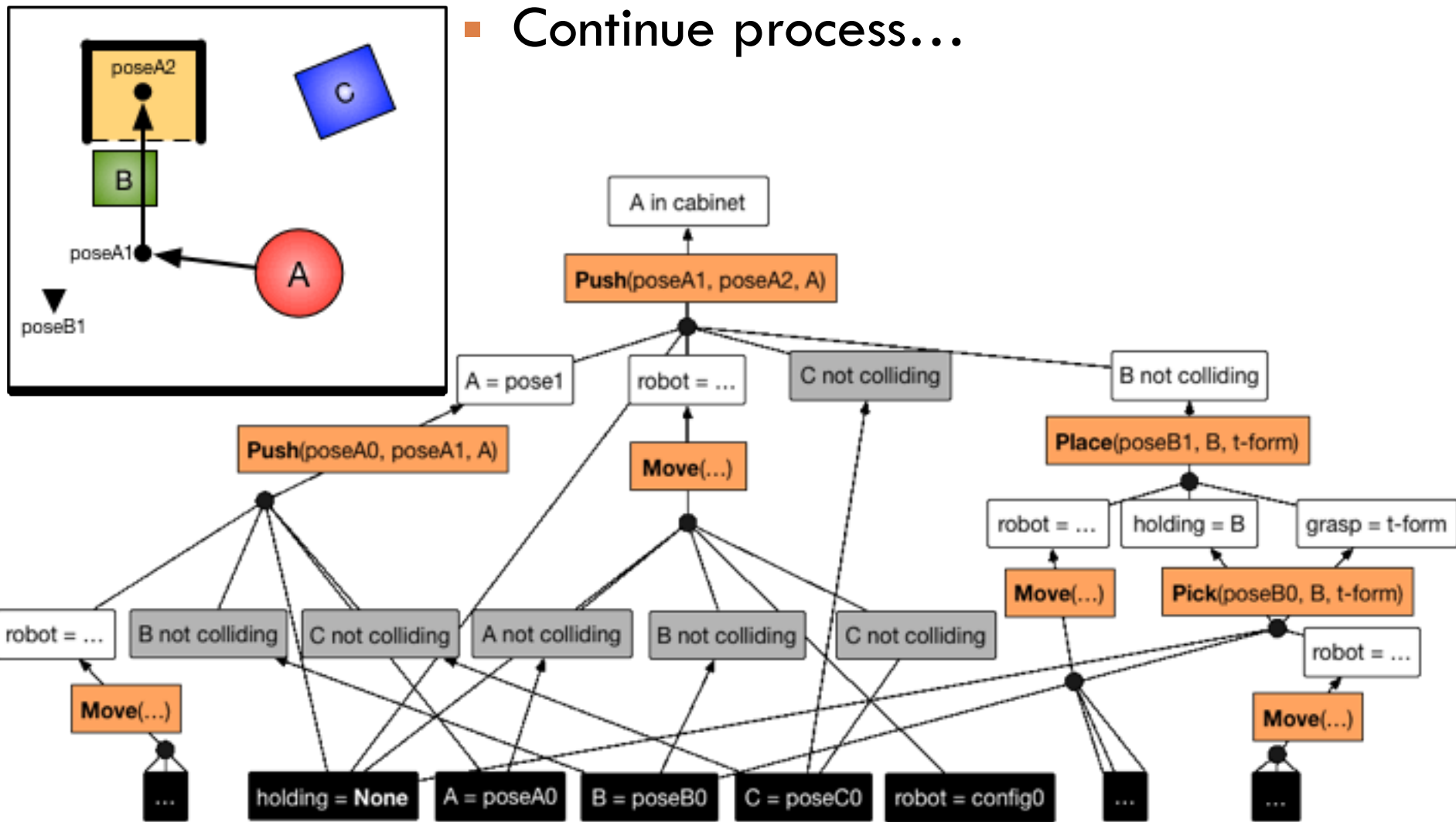


- Sample collision-free **Place** for B
- Add new constraints to the queue

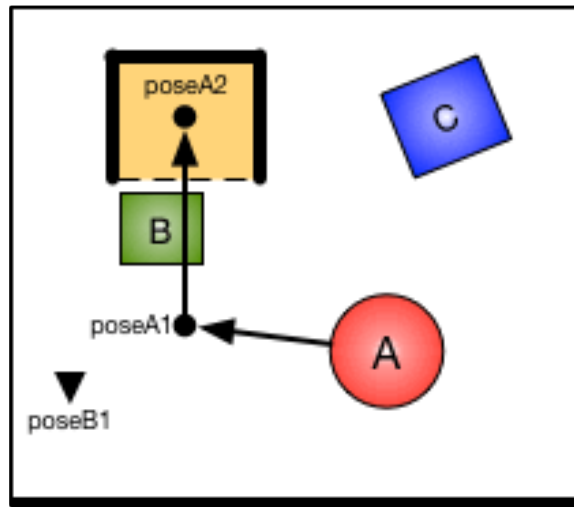


Backwards Search - Continued...

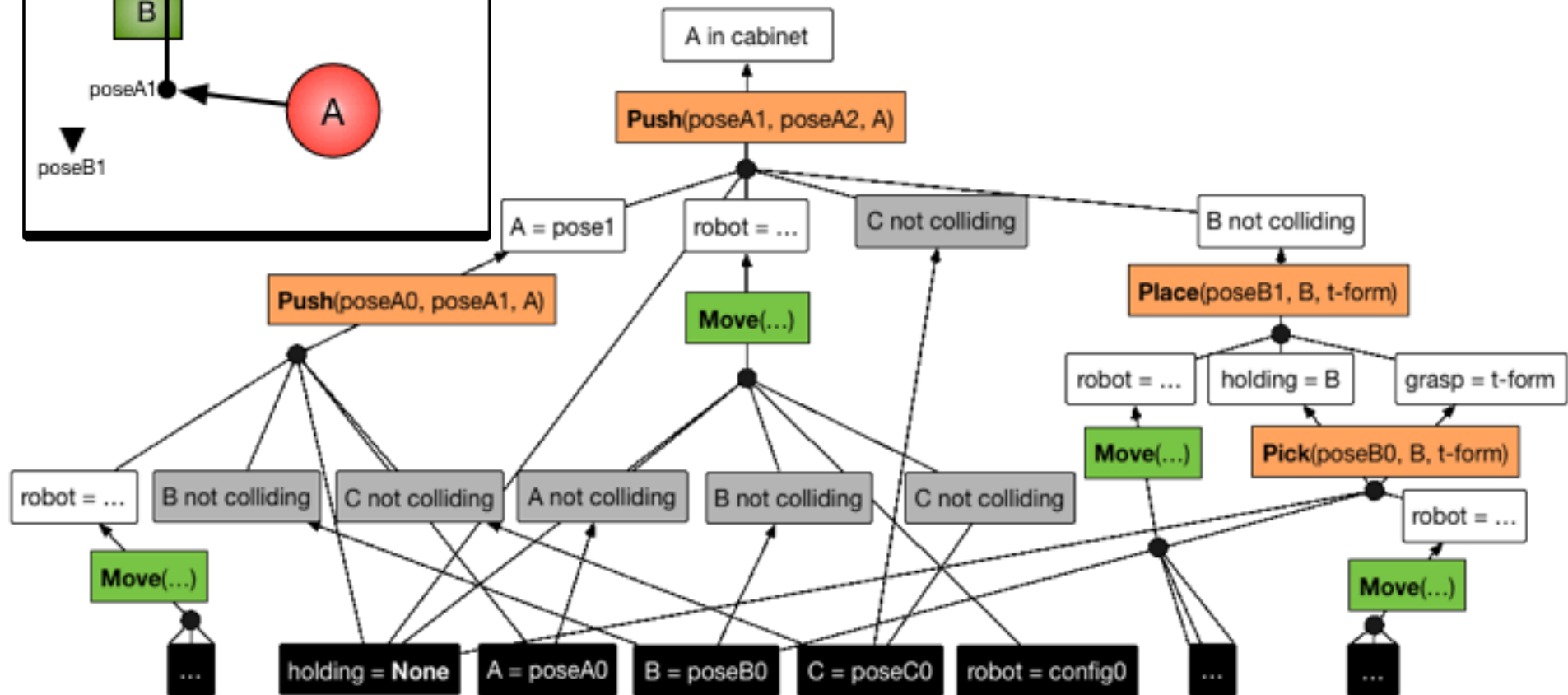
- Continue process...



Backwards Search - Continued...



- Move actions are forward search successors



Forward Search Algorithm

- Forward state-space heuristic search
 - Hill climbing, best-first search, ...
- Backward search focuses forward search by:
 - Identifying **successor actions**
 - Incidentally creating **approximate plans**
 - **Heuristic** is length of an approximate plan (idea from AI planning)

Probabilistic Completeness

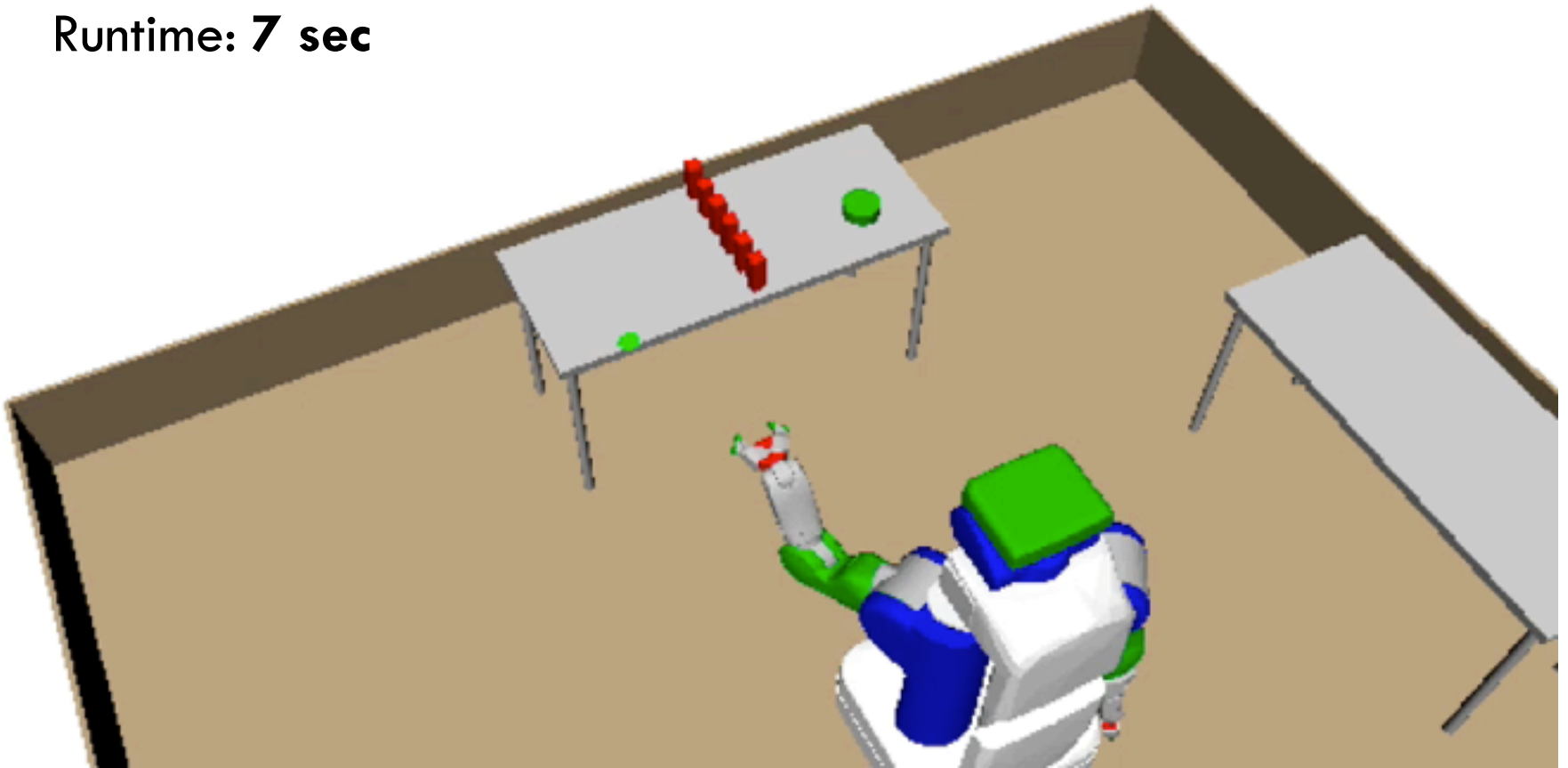
- **Definition** - A hybrid planning problem is **robustly feasible** if there exists sequence of action templates with a **family of solutions** such that for all state and pre-image pairs on a solution, the solution family actions that partially satisfy the state and achieve the pre-image have **nonzero measure**
- **Lemma** - the backwards search performed from any state in the solution family will generate a successor action in the solution family with a **probability of one** as $n \rightarrow \infty$
- **Theorem** - HBF will solve any robustly feasible hybrid planning problem with a **probability of one** as $n \rightarrow \infty$
 - *Proof* - inductively apply the lemma

Non-prehensile Actions

Push **green cylinder** to **green dot**

Success rate: **100%**

Runtime: **7 sec**



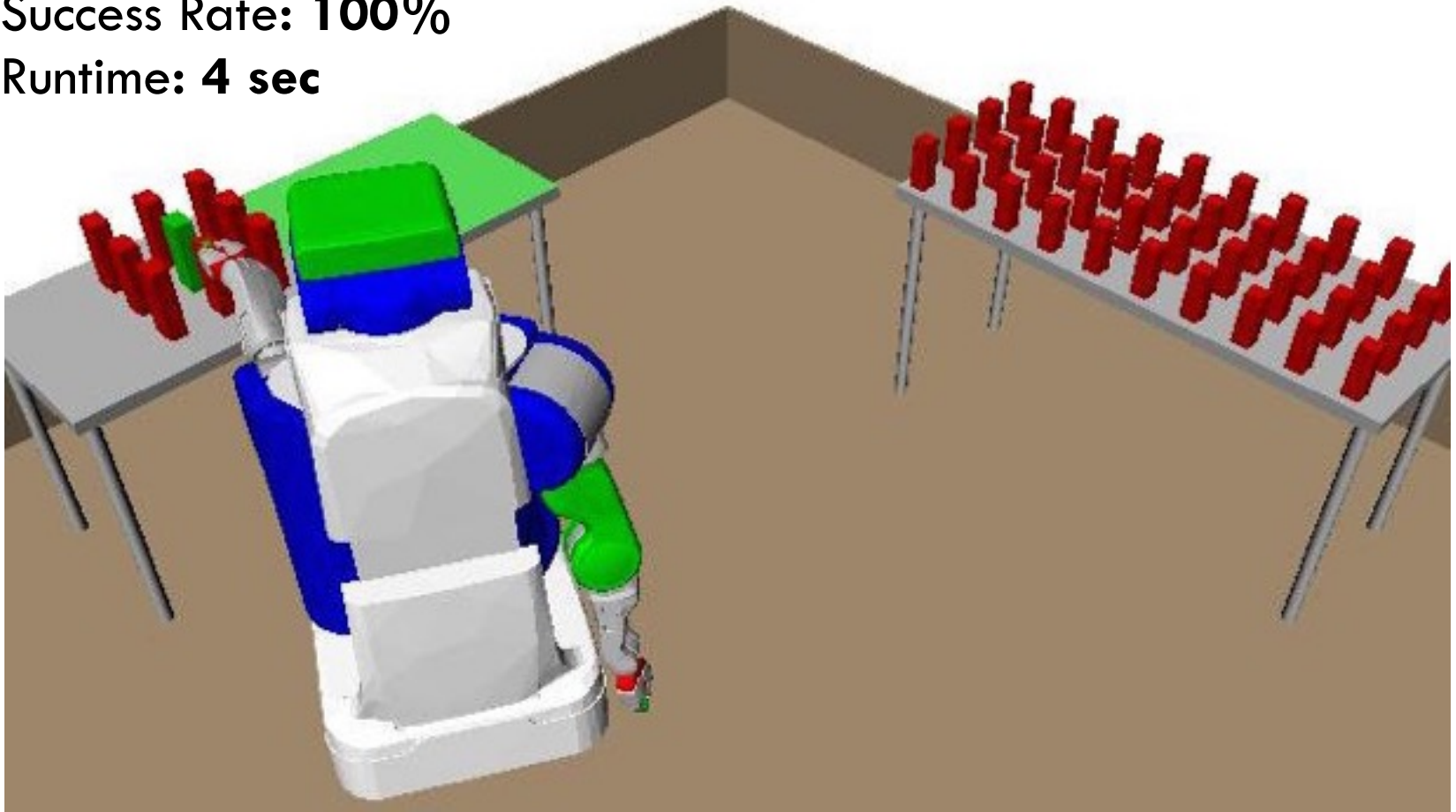
Python, 60 trials, 300 sec timeout, median runtime

High-Dimensional State-Space

Pick and place **green block**

Success Rate: **100%**

Runtime: **4 sec**



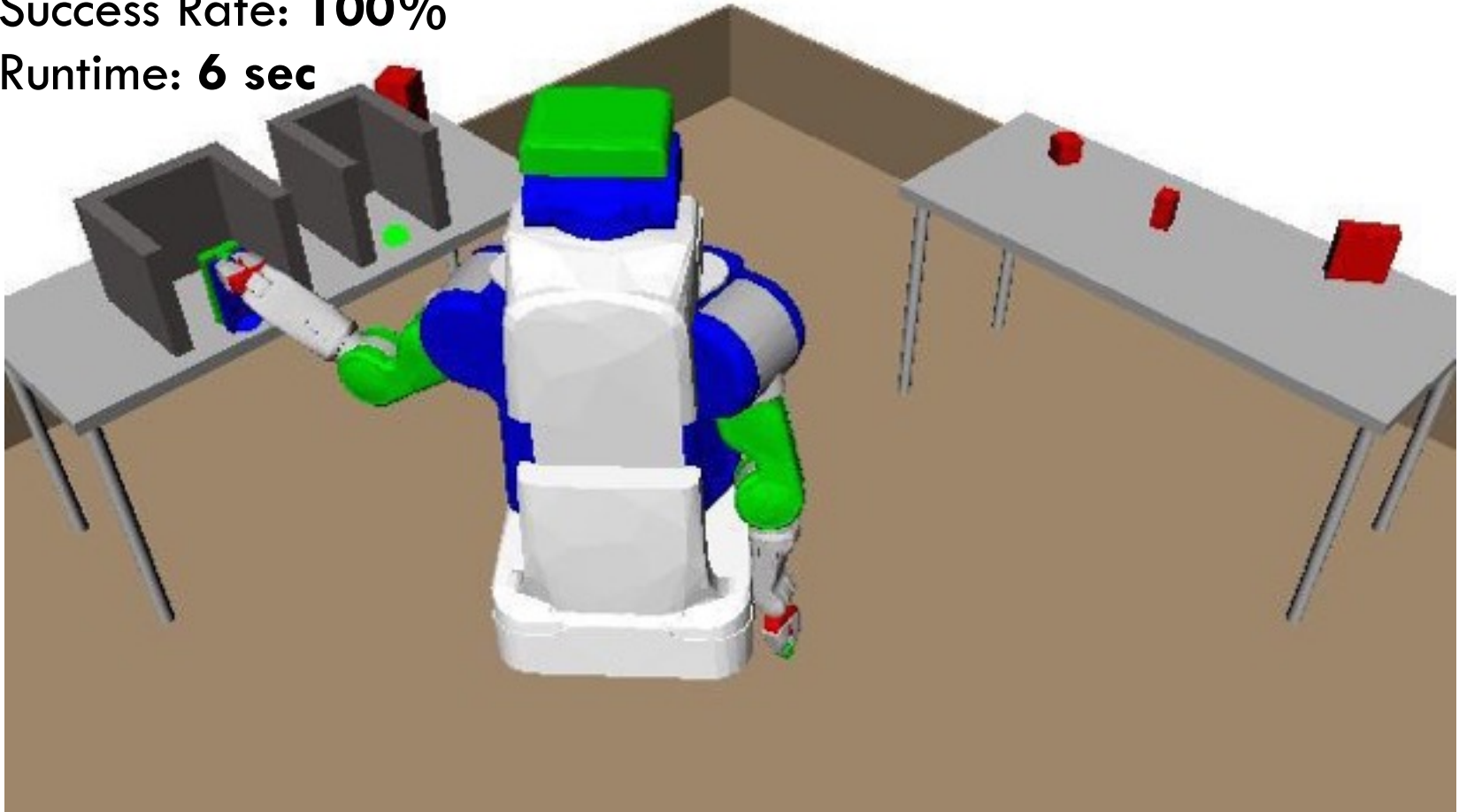
Python, 60 trials, 300 sec timeout, median runtime

Regrasping and Non-monotonicity

Move **blue block**, regrasp **green block**, and replace **blue block**

Success Rate: **100%**

Runtime: **6 sec**



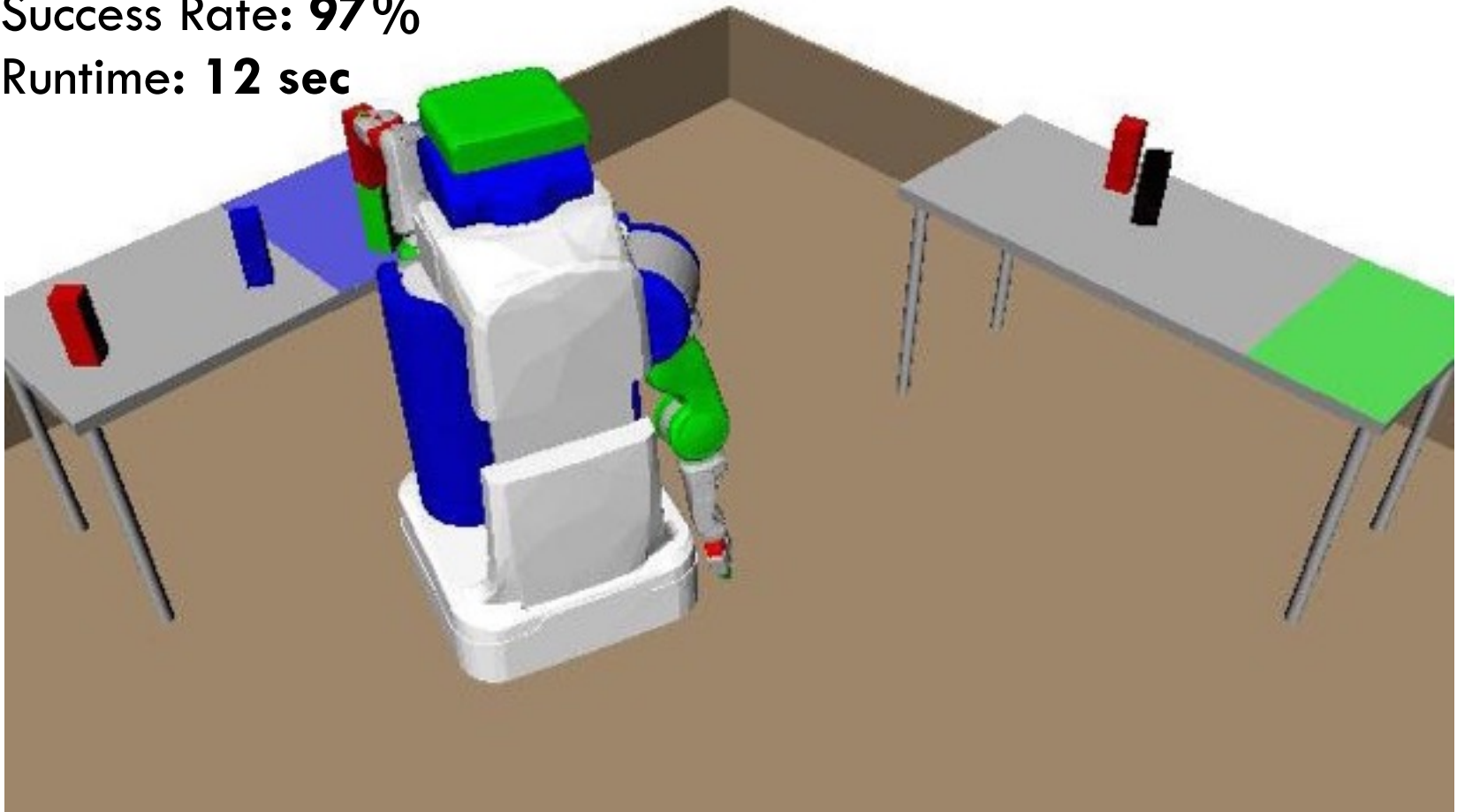
Python, 60 trials, 300 sec timeout, median runtime

Dynamic Unstacking and Stacking

Unstack **red block** and stack **black block** on **blue block**

Success Rate: **97%**

Runtime: **12 sec**

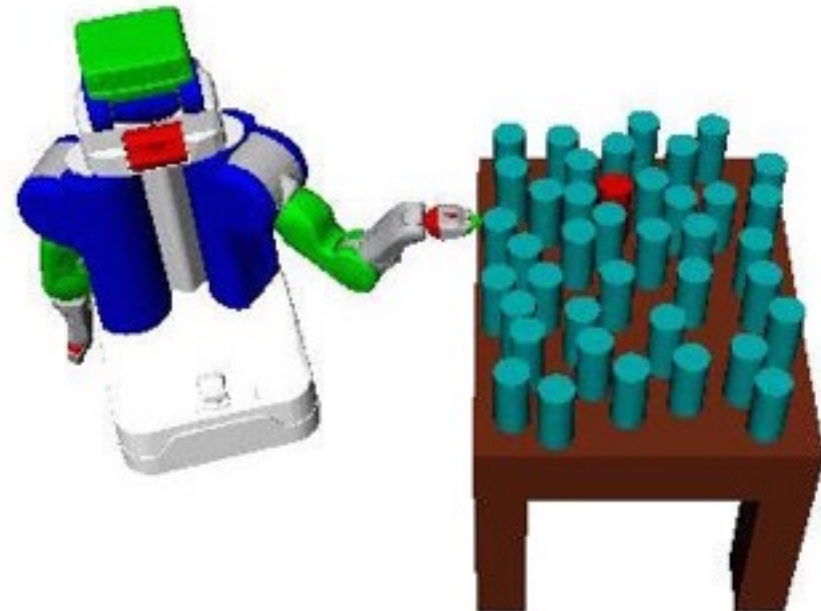


Python, 60 trials, 300 sec timeout, median runtime

Comparison with Srivastava et al.

Grasp **red cylinder** on crowded table
Single goal but must move many objects

	<i>Success Rate</i>	<i>Runtime</i>
<i>Srivastava et al.</i>	63%	68 sec
<i>HBF</i>	<u>98%</u>	<u>23 sec</u>



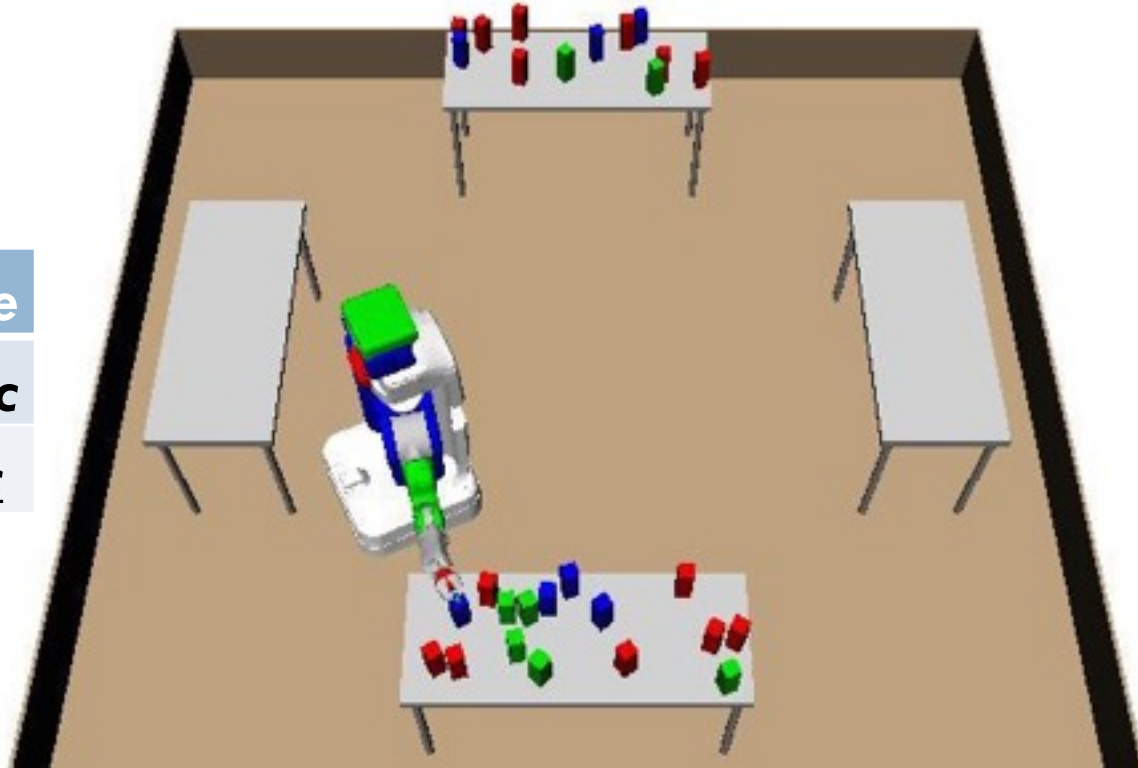
Python, 60 trials, 300 sec timeout, median runtime

Comparison with FFRob

Separate **blue blocks** and **green blocks**

Many goals and must order achieving the goals

	<i>Success Rate</i>	<i>Runtime</i>
<i>FFRob</i>	84%	157 sec
<i>HBF</i>	<u>100%</u>	<u>82 sec</u>



Python, 60 trials, 300 sec timeout, median runtime

Takeaways

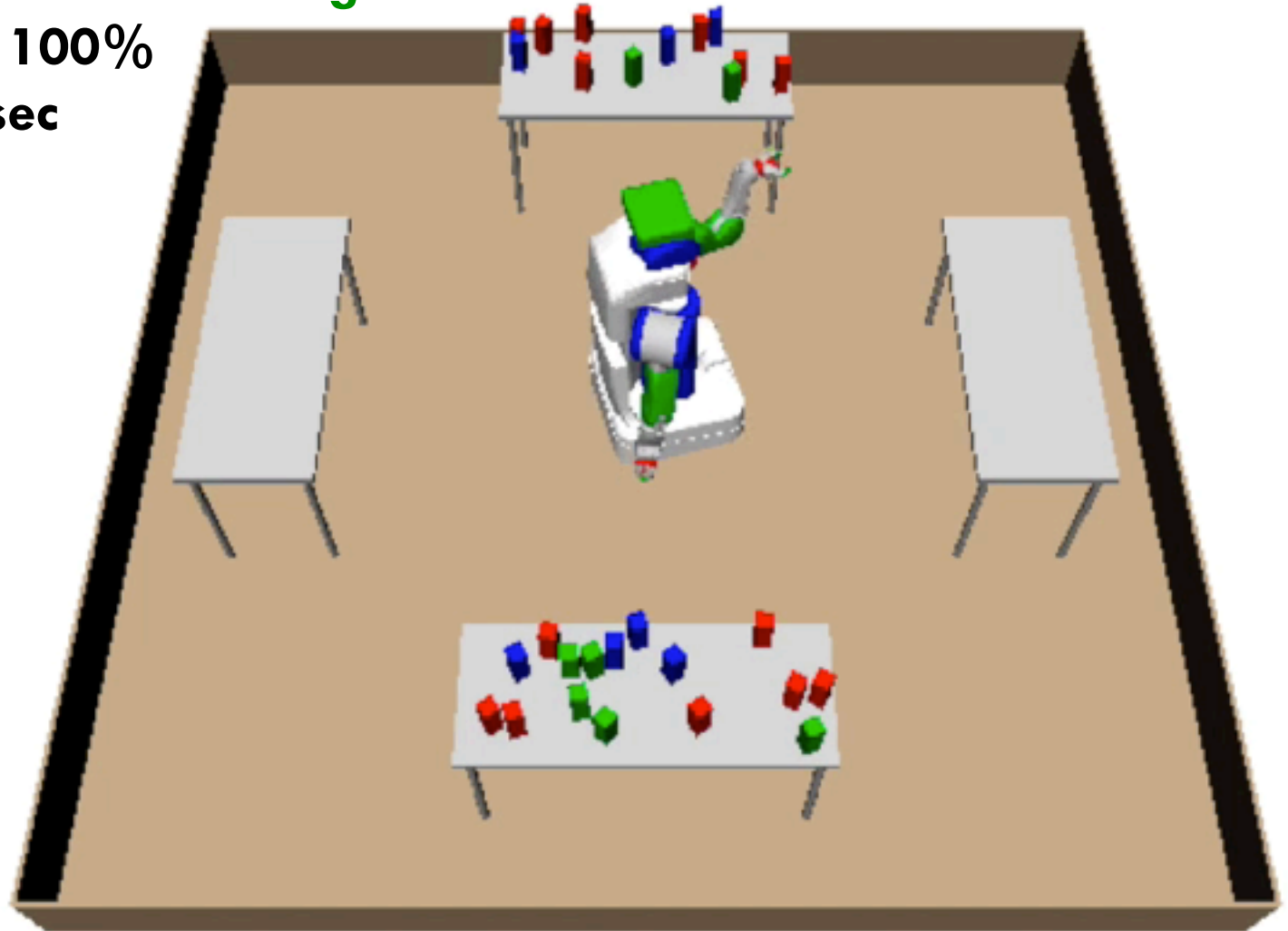
- General purpose hybrid planning algorithm (**HBF**)
 - **Approximate backward search**
 - Focuses successor actions to reduce branching factor
 - Gives heuristic cost
 - **Forwards search**
 - Resolves backwards approximations
- **Probabilistically complete**
- **Application** - efficiently solves manipulation problems

Any Questions?

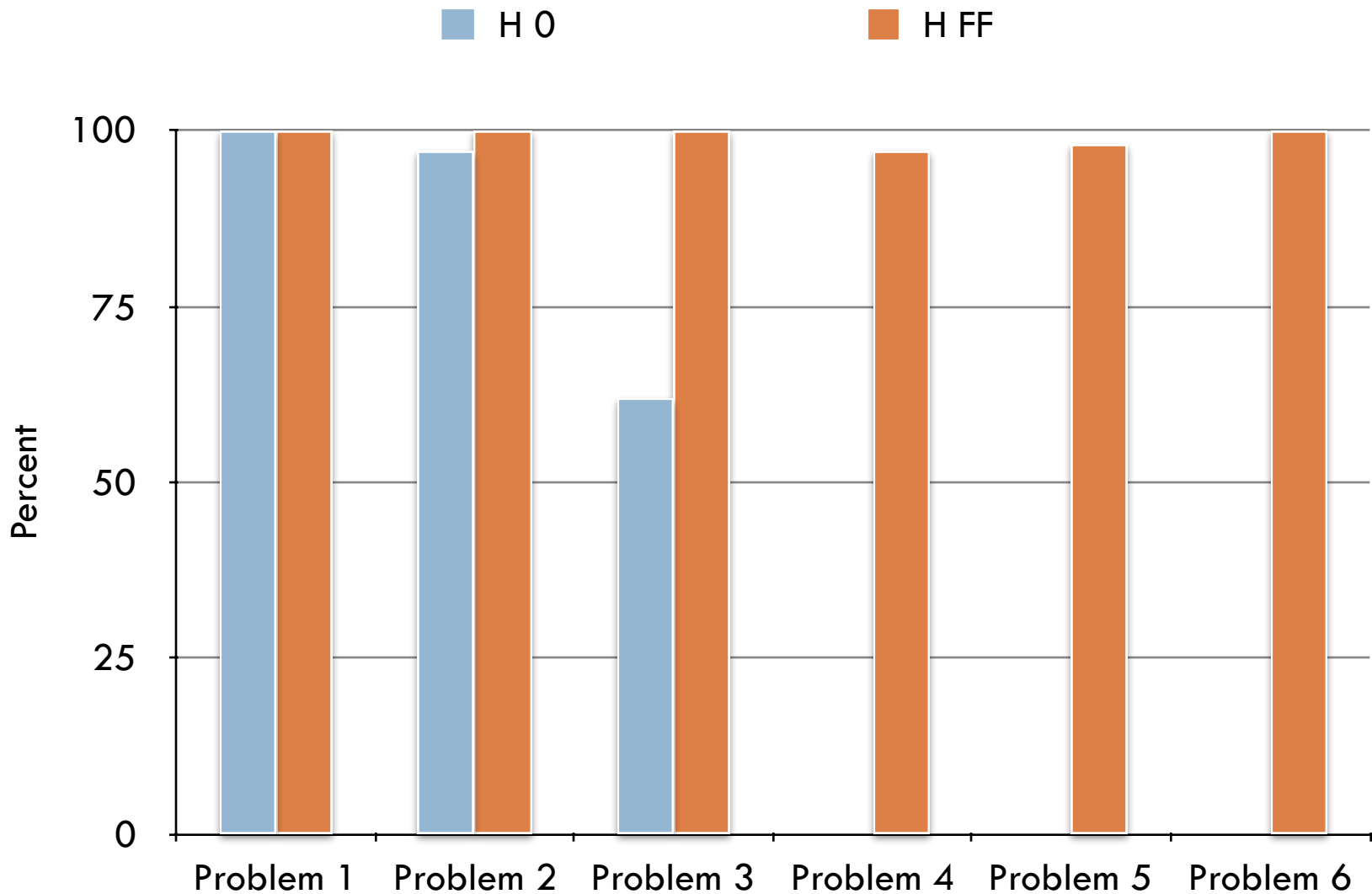
Separate **blue blocks** and **green blocks**

Success rate: **100%**

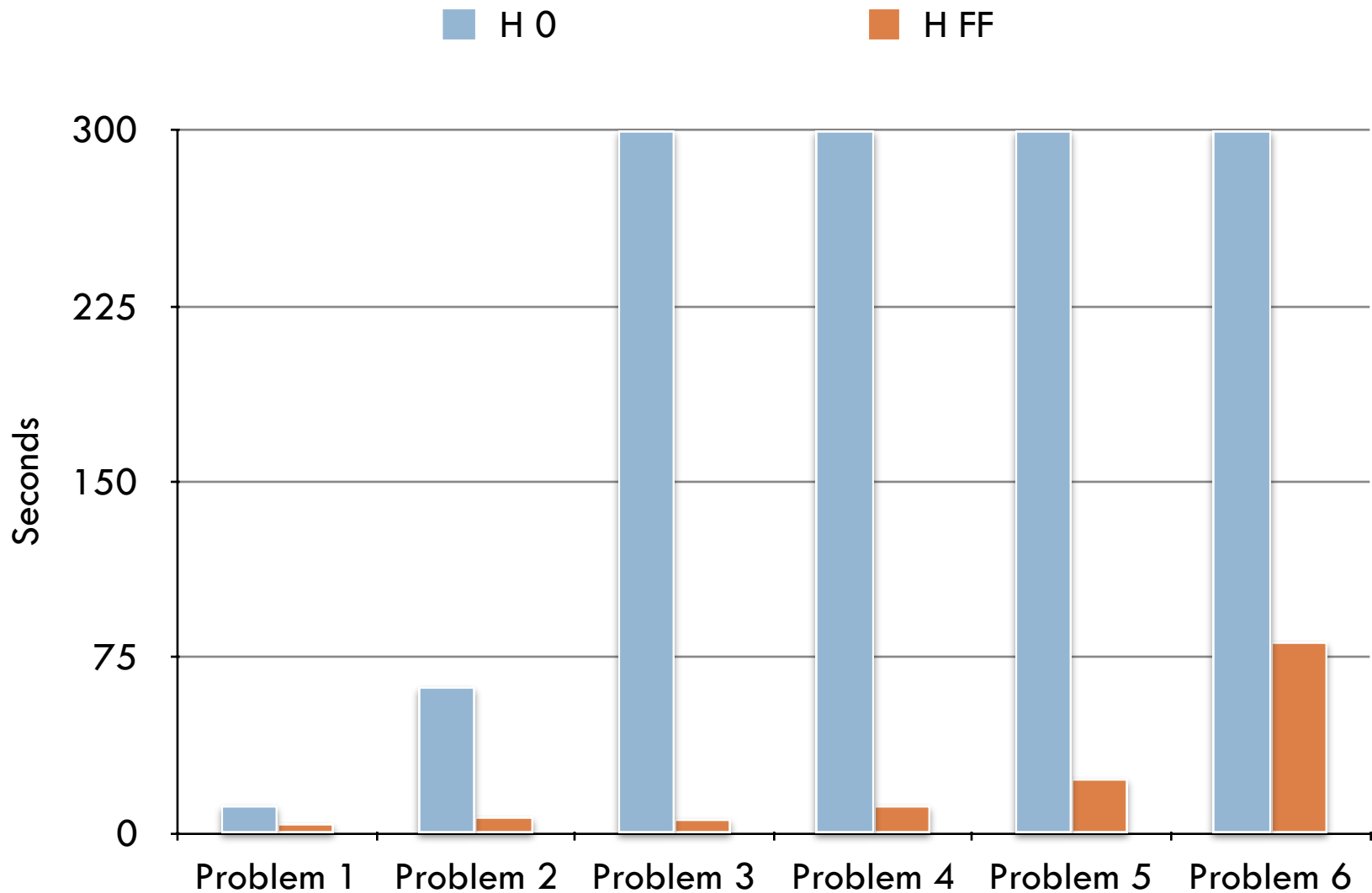
Runtime: **82 sec**



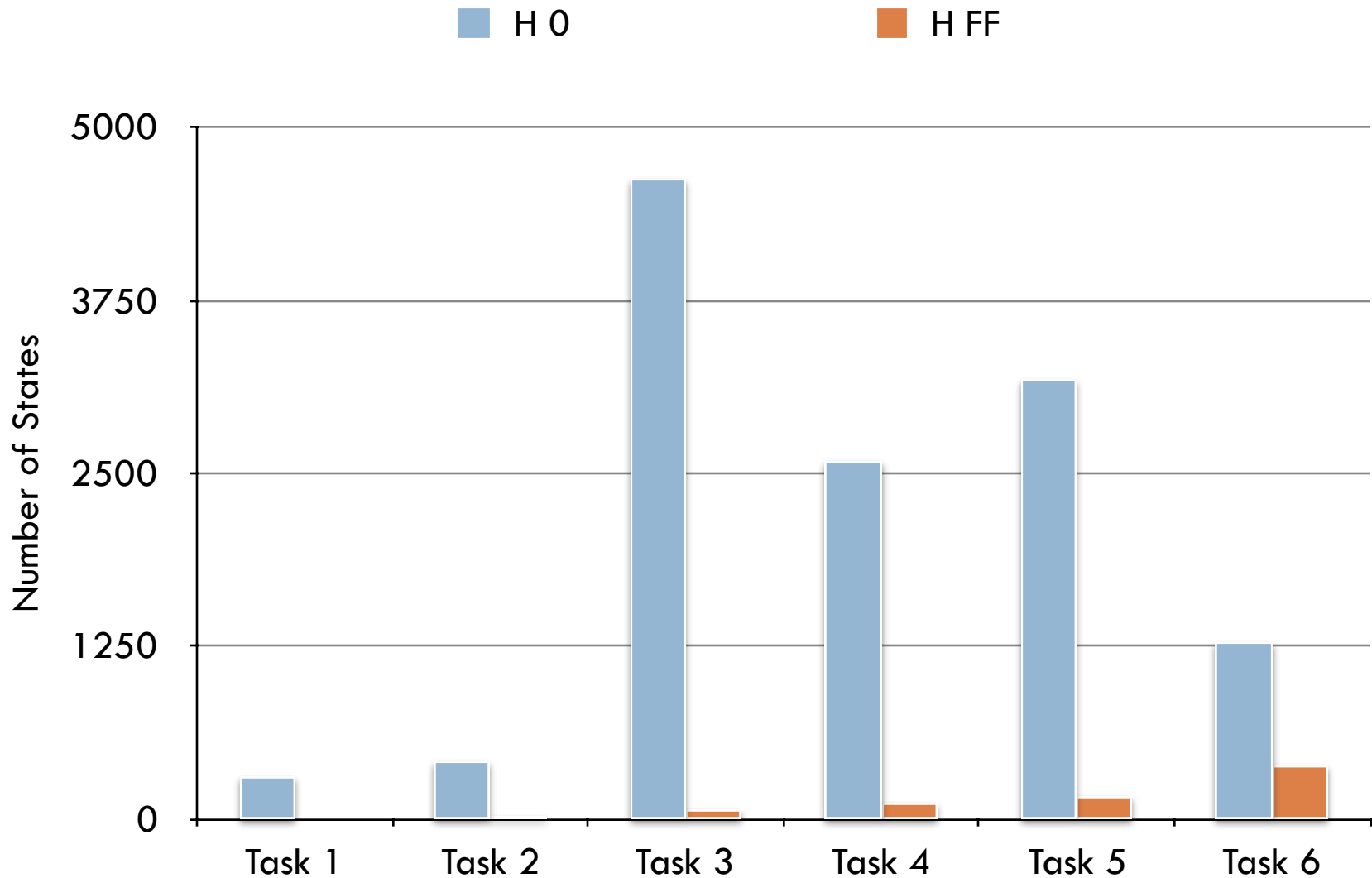
Success Rate (60 Trials)



Median Runtime (300s Timeout)



Median States Visited

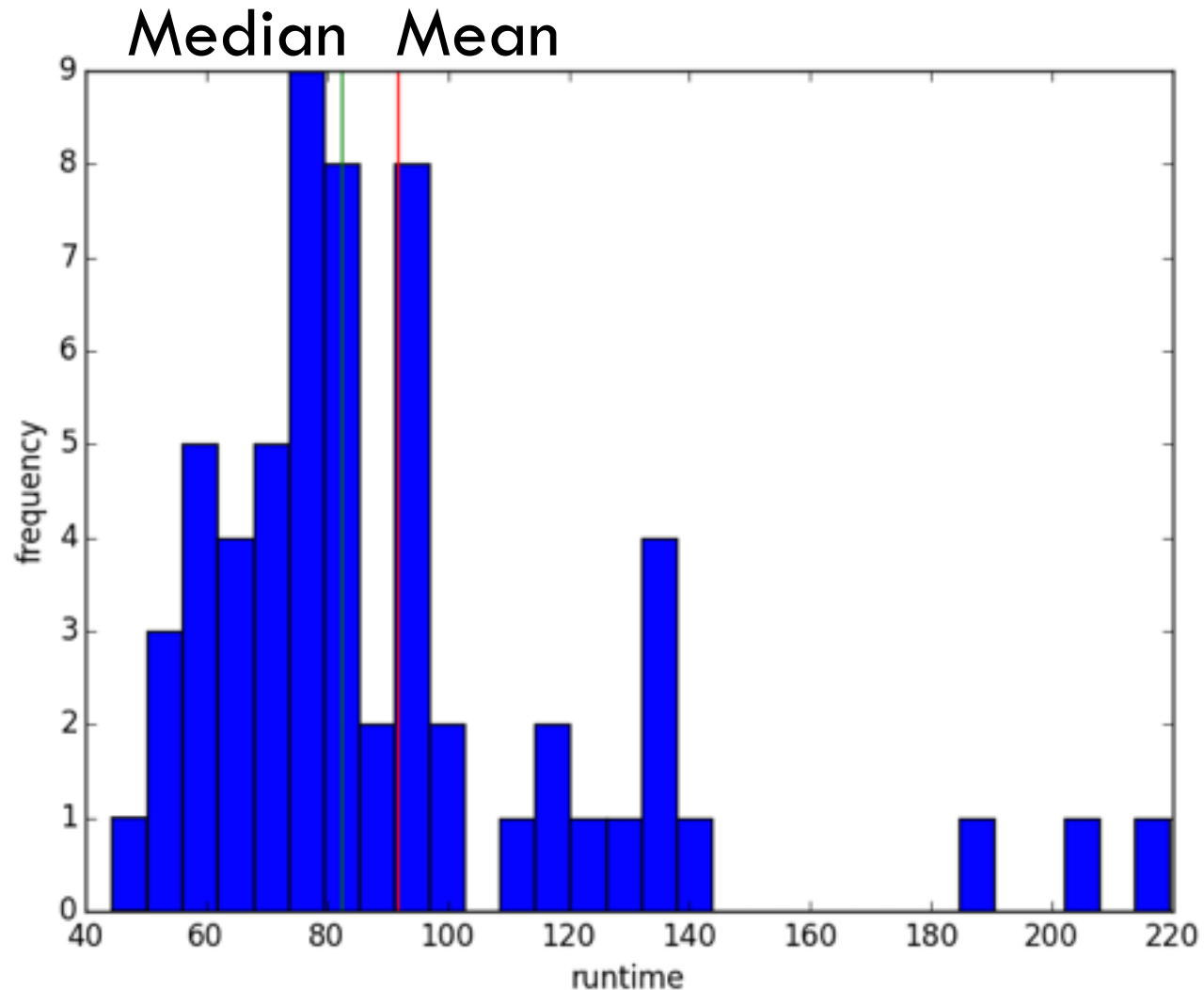


Full Experimental Results

P	H_0				H_{FF}			
	%	runtime	length	visited	%	runtime	length	visited
1	100	12 (7)	8 (0)	156 (140)	100	4 (1)	12 (2)	6 (2)
2	97	62 (26)	16 (0)	208 (37)	100	7 (1)	16 (0)	10 (1)
3	62	238 (62)	16 (0)	2315 (712)	100	6 (1)	16 (0)	37 (2)
4	0	300 (0)	- (-)	1293 (93)	97	12 (4)	24 (4)	56 (24)
5	0	300 (0)	- (-)	1591 (381)	98	23 (9)	24 (4)	85 (37)
6	0	300 (0)	- (-)	637 (40)	100	82 (13)	72 (4)	191 (37)

- 6 problems
- 60 trials per algorithm and problem
- Timeout of 300 seconds
- Median statistics (MAD in parentheses)
- Python implementation uses OpenRAVE

Problem 6 H_{FF} Runtime Histogram



Prior Work

- **Manipulation Planning**

- Lozano-Pérez - explicit configuration space
- Siméon et al. - manipulation graph
- Hauser - multi-modal motion planning
- Barry et al. - multi-modal biRRT

- **Task and Motion Planning**

- Lagriffoul, Saffiotti, Dornhege & Nebel, Cambon et al., ...
- Srivastava et al. - planner-independent interface
- Garrett et al. - FFRob

- **Discrete Planning**

- Bonet & Geffner - HSP
- Hoffmann & Nebel - FF