Task and Motion Planning

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11/06/2018

6.881 - Intelligent Robot Manipulation

http://manipulation.csail.mit.edu/

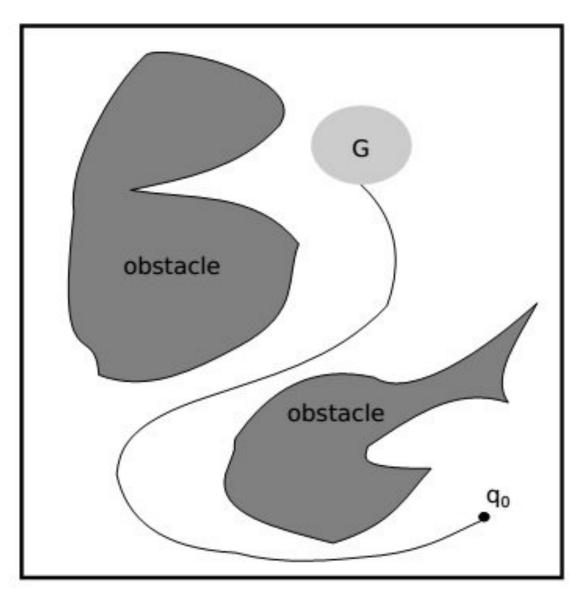
https://github.com/caelan/pddlstream

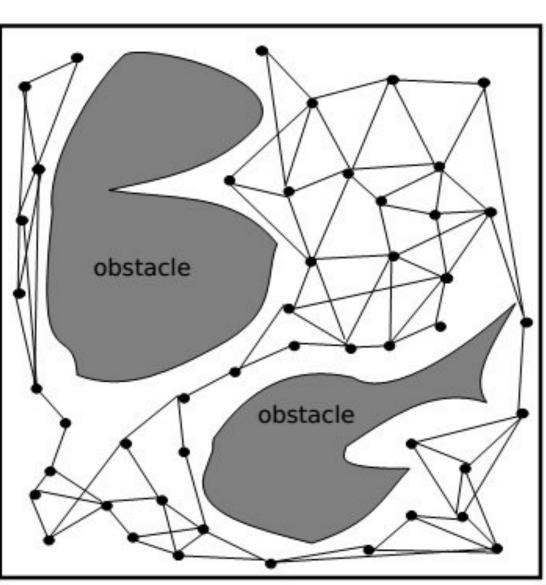
(Probable) Roadmap

- 1. Review motion planning & Al planning
- 2. Introduce task and motion planning
- 3. Survey existing approaches
- 4. Dive deep into our formalism PDDLStream
- 5. Present several PDDLStream algorithms
- 6. Describe extensions

Motion Planning (10/30/2018)

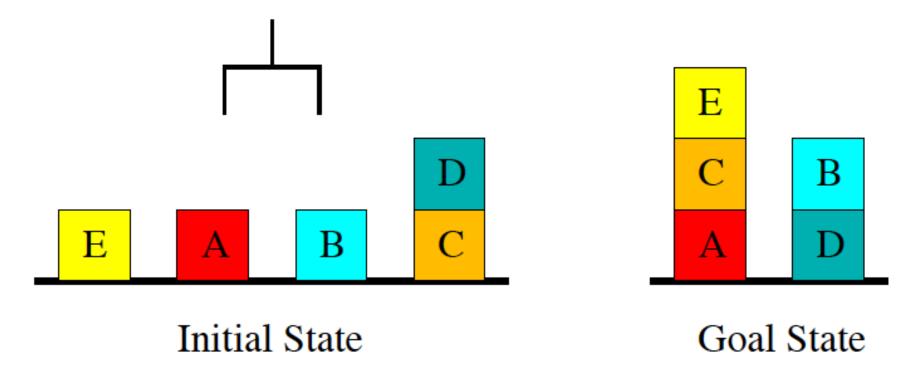
- Plan in a continuous configuration space
- Sampling-based motion planning
 - 1. Sample robot configurations (randomly)
 - 2. Connect nearby configurations if collision-free path
 - 3. Search for a path within resulting graph
- PRM
- RRT
- RRT*





Al (Task) Planning (11/01/2018)

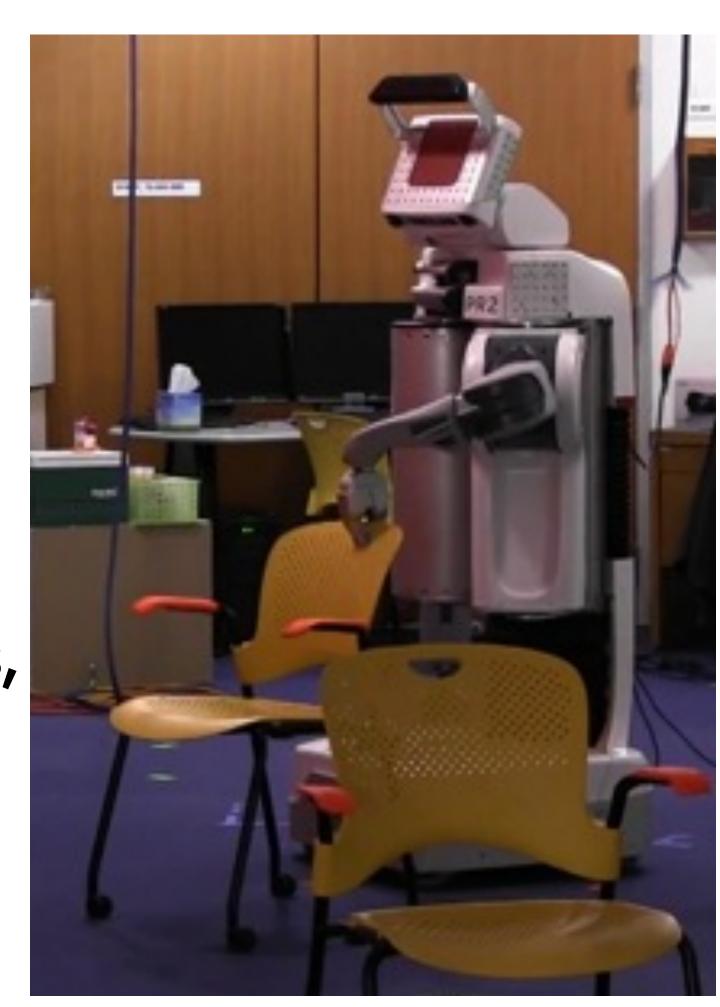
- Plan in a large discrete space with many variables
- Logical descriptions STRIPS/PDDL
 - Logical propositions = boolean variables
 - Parameterized actions
 - Preconditions & effects
- Heuristic search algorithms
 - Delete-relaxation (h_{FF})



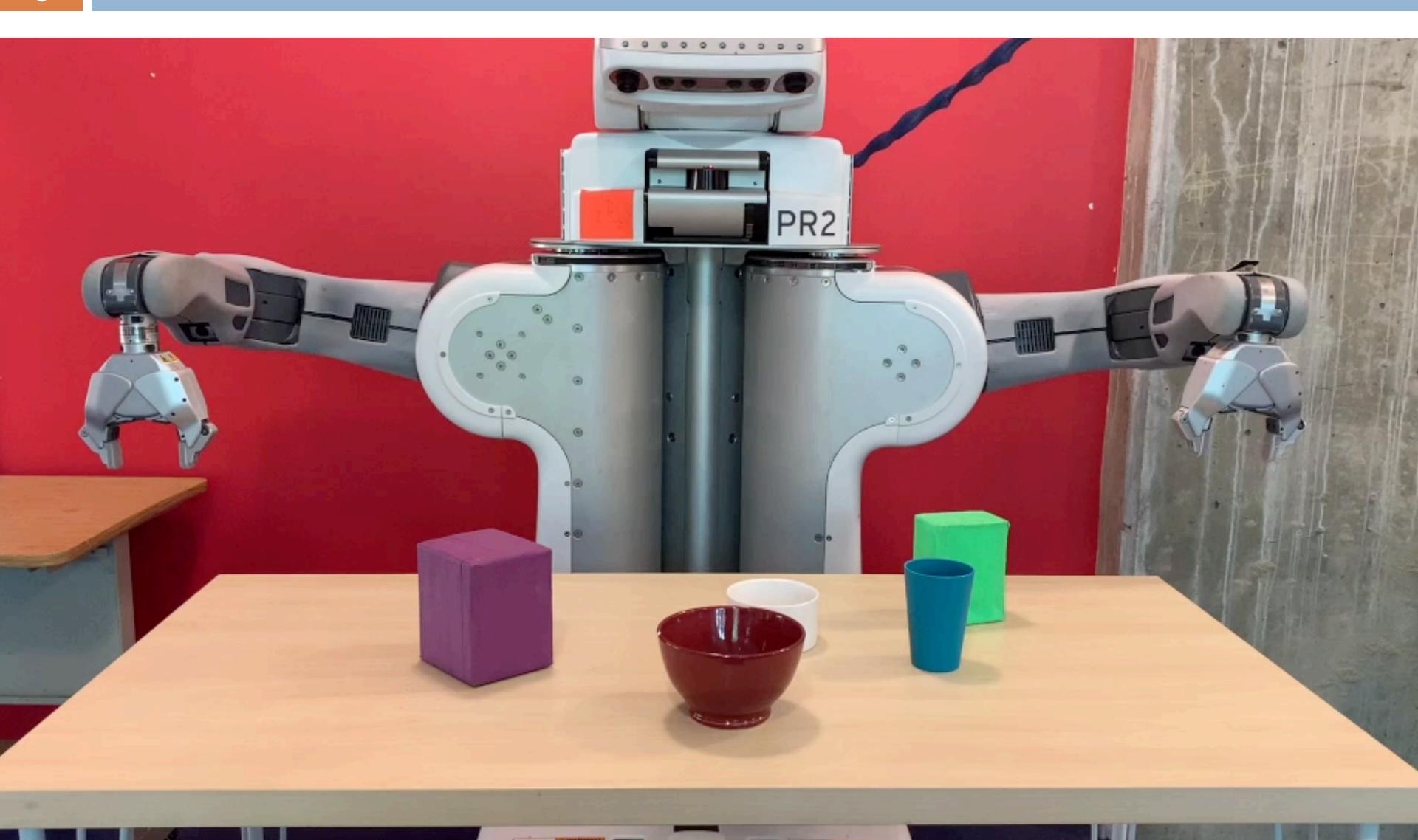
```
(define (domain blocksworld)
(:predicates (clear ?x) (holding ?x) (on ?x ?y)
            (on-table ?x) (arm-empty))
(:action stack
:parameters (?x ?y)
 :precondition (and (clear ?y) (holding ?x))
:effect (and (arm-empty) (on ?x ?y)
             (not (clear ?y)) (not (holding ?x)))
(define (problem bw-abcde)
(:domain blocksworld)
(:objects a b c d e)
(:init (on-table a) (clear a)
      (on-table b) (clear b)
      (on-table e) (clear e)
      (on-table c) (on d c) (clear d)
      (arm-empty))
(:goal (and (on e c) (on c a) (on b d))))
```

Task and Motion Planning (TAMP)

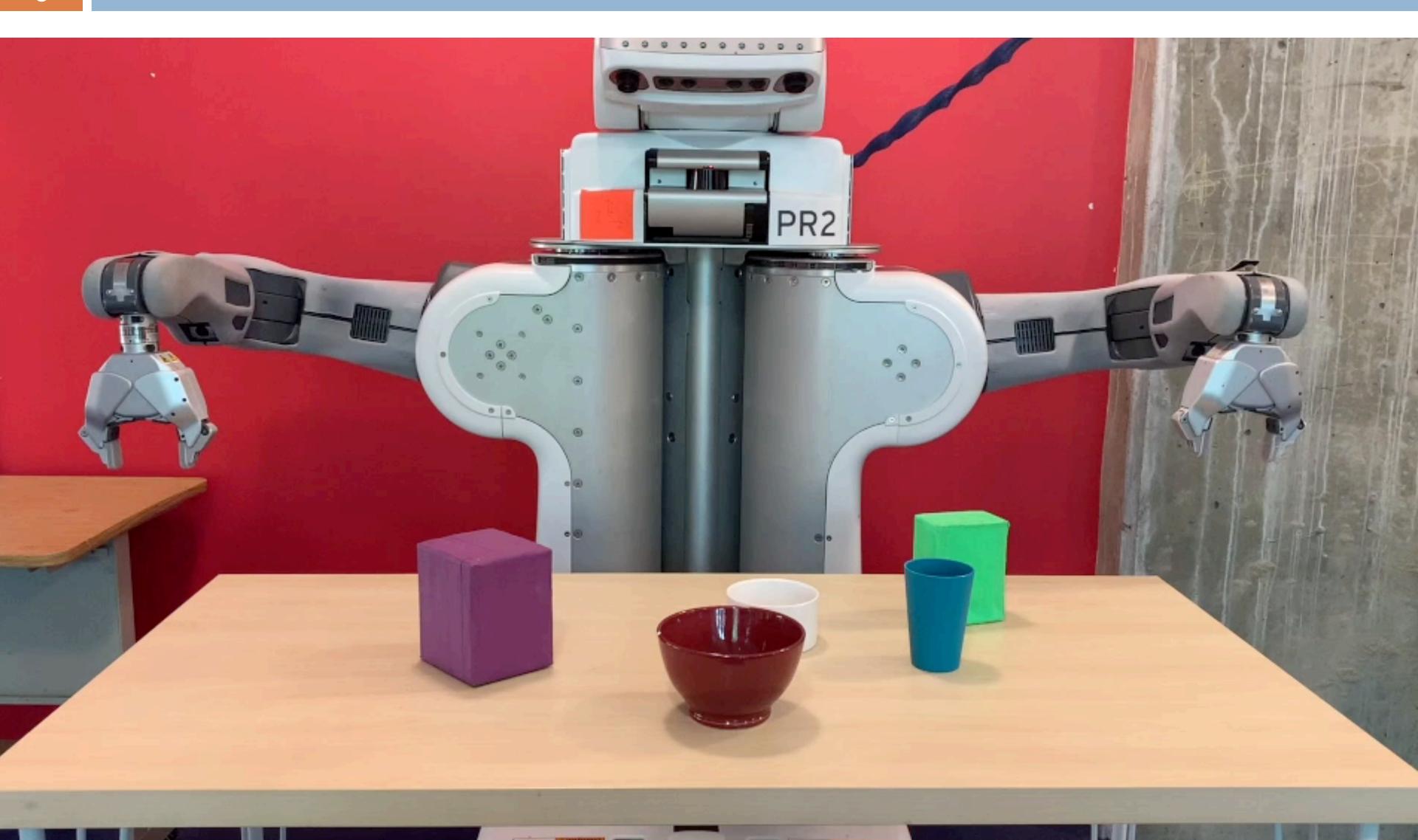
- Plan in a hybrid space with many variables
 - Discrete and continuous
 variables & actions
- Multi-step manipulation
 - Variables robot configuration, object poses, door joint positions, is-on, is-in-hand, is-holdingwater, is-cooked, ...
 - Actions move, pick, place, push, pull, pour, cook, ...



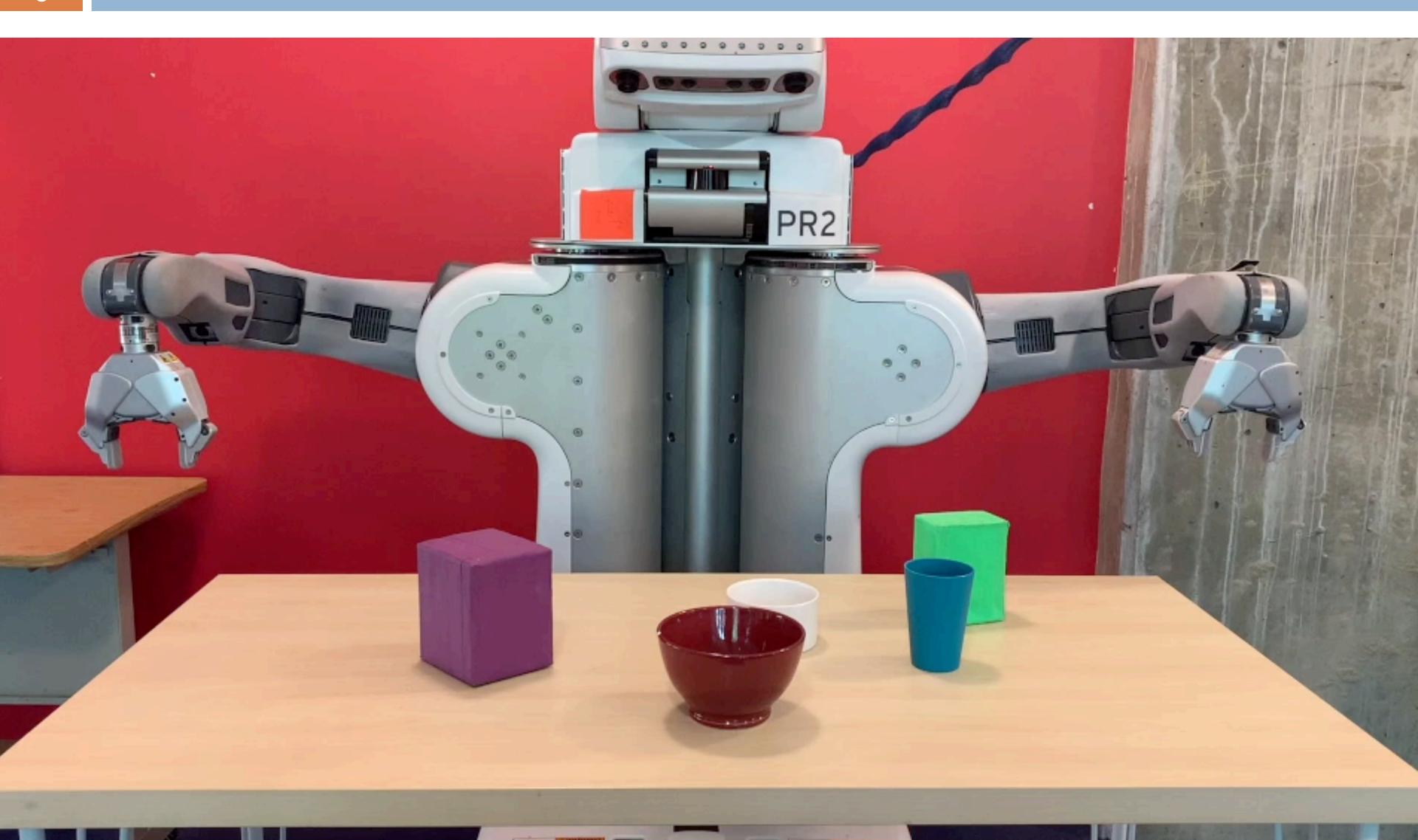
PR2 Tabletop Manipulation



PR2 Tabletop Manipulation

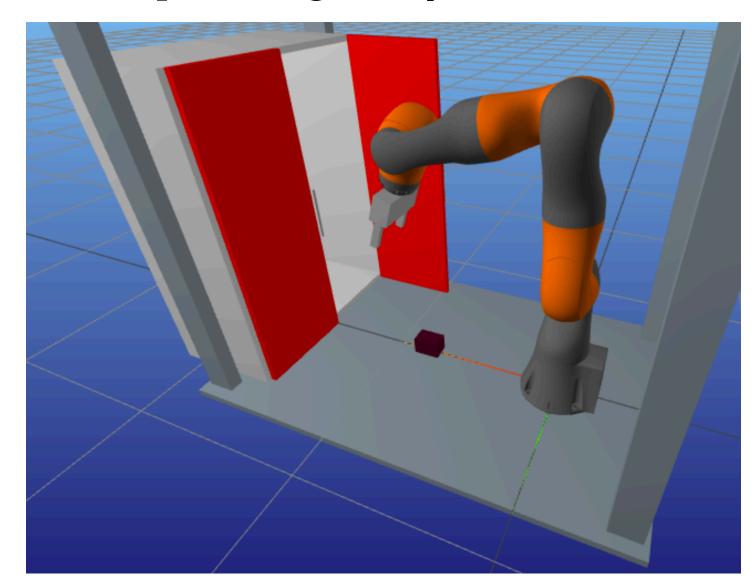


PR2 Tabletop Manipulation

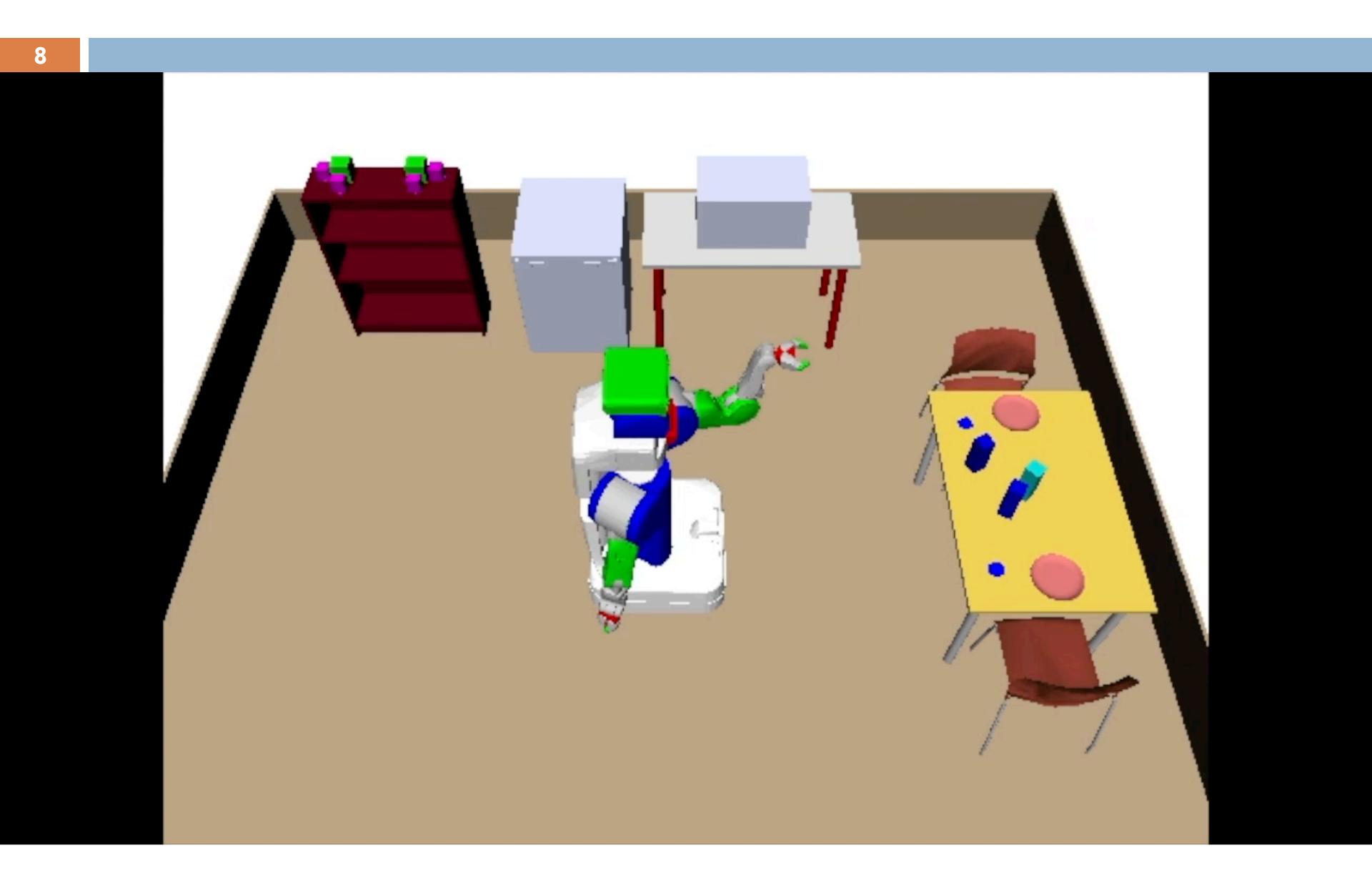


TAMP Challenges

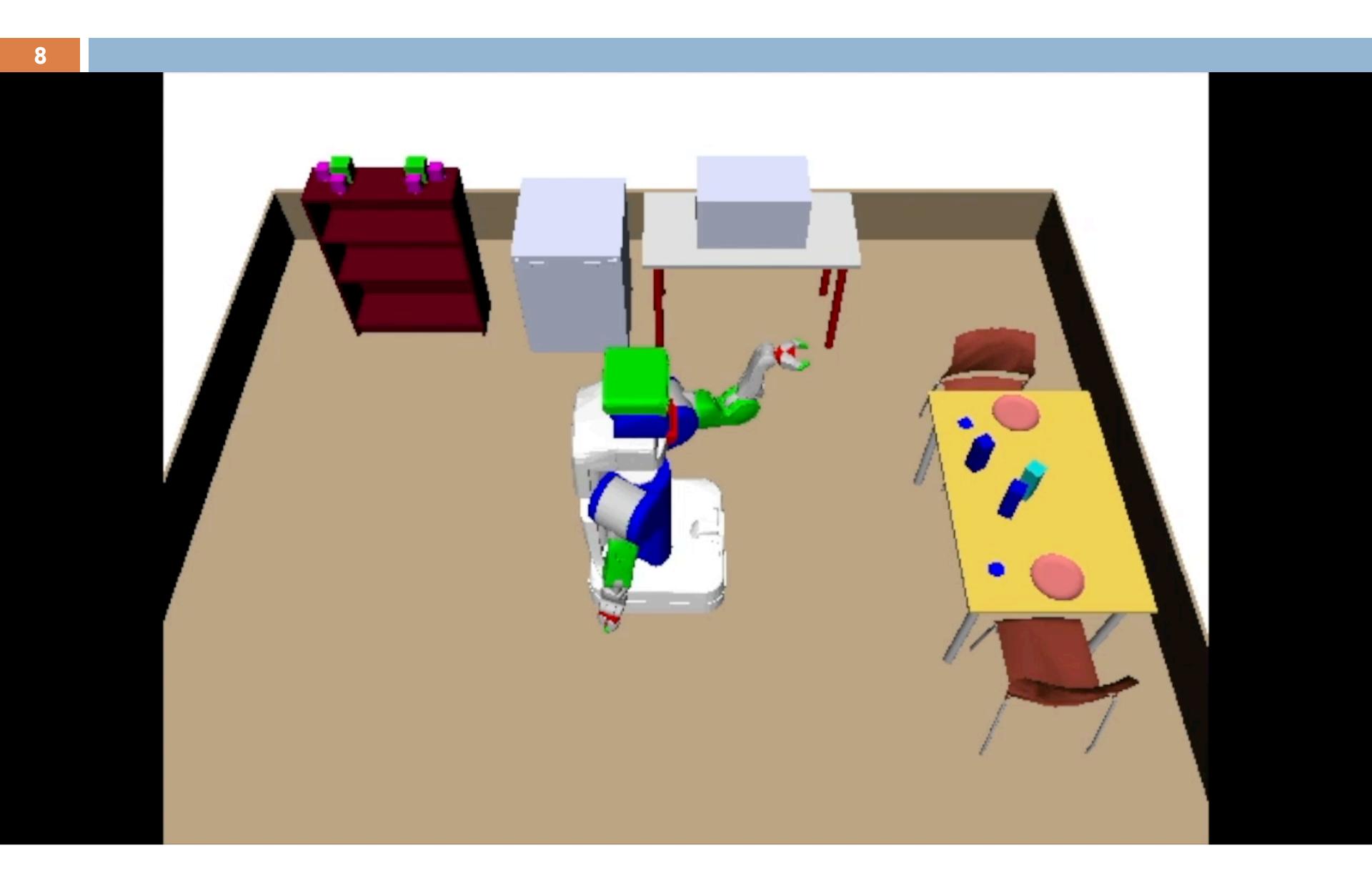
- Automated robotic planning
 - Robot only endowed with a model of the world
 - In contrast to preprogramming or prediscretizing
- Inherits challenges of both motion & Al planning
 - Continuous and combinatorially large spaces
- Continuous constraints limit high-level strategies
 - Kinematic reachability
 - Joint limits & collisions
- Long horizons



PR2 Mobile Manipulation



PR2 Mobile Manipulation



Survey of Approaches

Major Research Questions

- What is a TAMP problem?
- How do describe TAMP problems both in terms of:
 - Theoretical representation?
 - Operable forms consumable by an algorithm?
- How do we design algorithms that:
 - are general-purpose?
 - are empirically efficient?
 - have theoretical guarantees?
 - completeness & optimality
 - produce low-cost solutions?

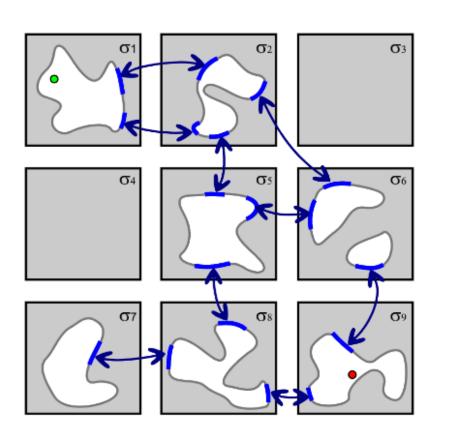
Taxonomy of Existing Approaches

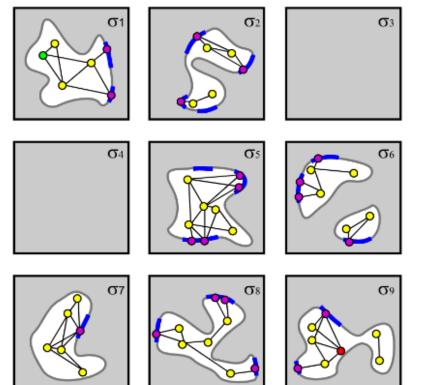
- TAMP is interdisciplinary intersection of Al and robotic planning
 - Most approaches stem from one community
- Extending motion planning
 - Multi-modal motion planning
 - Optimization and constraint satisfaction
- Extending Al planning
 - Semantic attachments
 - Task and motion interface

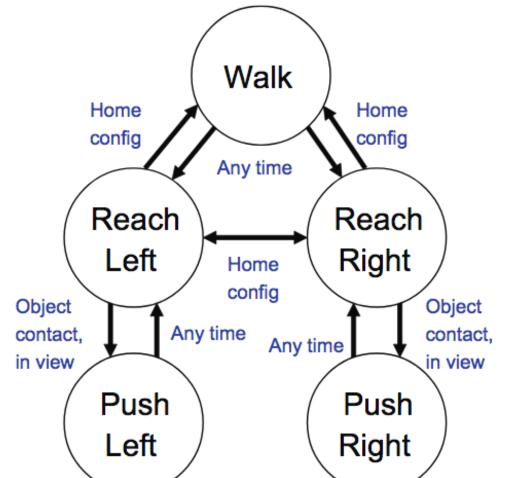
Multi-Modal Motion Planning

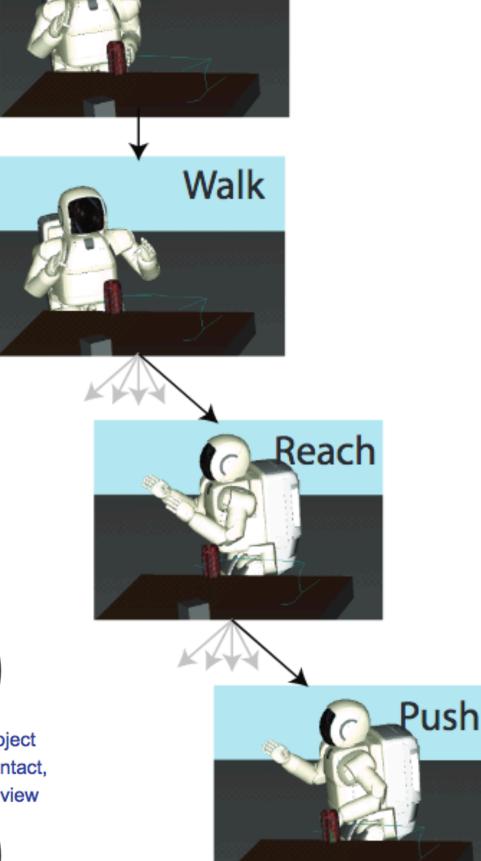
- Sequence of motion planning problems through adjacent modes (motion constraints)
 - [Alami & Siméon, Hauser & Latombe, Barry, Vega-Brown & Roy]

Example modes - hand empty,
 holding, pushing, ...





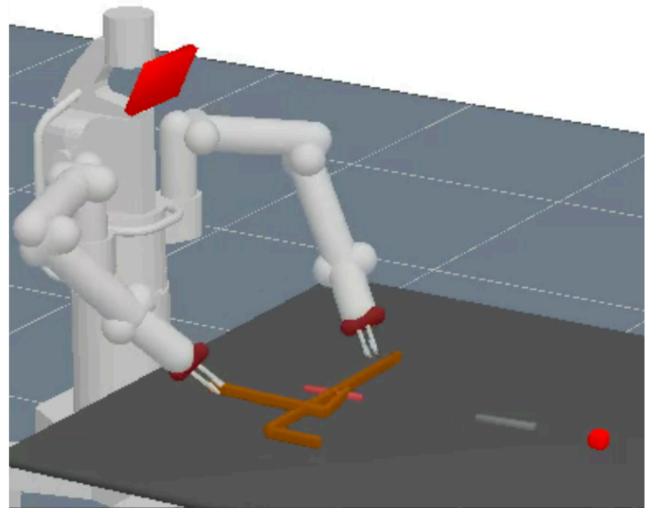




Reach

Mathematical Programming

- Discrete search over sequences of mode switches
- Solve for values of continuous variables
 - Discretized constraint satisfaction problem (CSP)
 [Lozano-Perez, Kaelbling]
 - Nonlinear constrained optimization [Toussaint]
- Optimization-based motion planning (11/08/18)



$$\min_{x,a_{1:K},s_{1:K}} \int_{0}^{T} f_{\text{path}}(\bar{x}(t)) dt + f_{\text{goal}}(x(T))$$
s.t.
$$x(0) = x_{0}, h_{\text{goal}}(x(T)) = 0, g_{\text{goal}}(x(T)) \leq 0,$$

$$\forall t \in [0,T]: h_{\text{path}}(\bar{x}(t), s_{k(t)}) = 0,$$

$$g_{\text{path}}(\bar{x}(t), s_{k(t)}) \leq 0$$

$$\forall k \in \{1, ..., K\}: h_{\text{switch}}(\hat{x}(t_{k}), a_{k}) = 0,$$

$$g_{\text{switch}}(\hat{x}(t_{k}), a_{k}) \leq 0,$$

$$s_{k} \in \text{succ}(s_{k-1}, a_{k}).$$
(2)

Semantic Attachments

- Some preconditions & effects are defined using a programming language (e.g. C++, *.so library)
 - [Dornhege et al., Gregory et al.]
- Example can the robot reach a placement?
- Evaluate attachments value during forward search

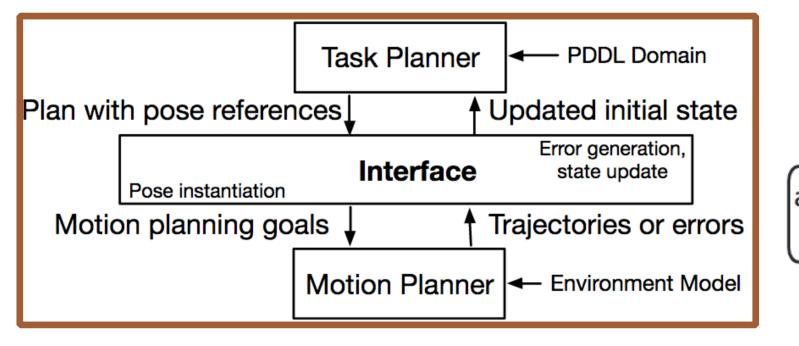
```
(:modules
  (putDown ?o - movable ?p - base ?g - grasp
        (q0) (q1) (q2) (q3) (q4) (q5) (q6)
        (x ?o) (y ?o) (z ?o)
        (yaw ?o) (pitch ?o) (roll ?o)
        effect putDown@libTrajectory.so))
(:action put-down
    :params (?o - movable ?p - base ?g - grasp)
    :condition (... ([checkPutDown ?o ?p ?g]))
    :effect (and (on ?o ?p) (handempty)
        (not (holding ?o ?g)) ( putDown ?o ?p ?g])
```

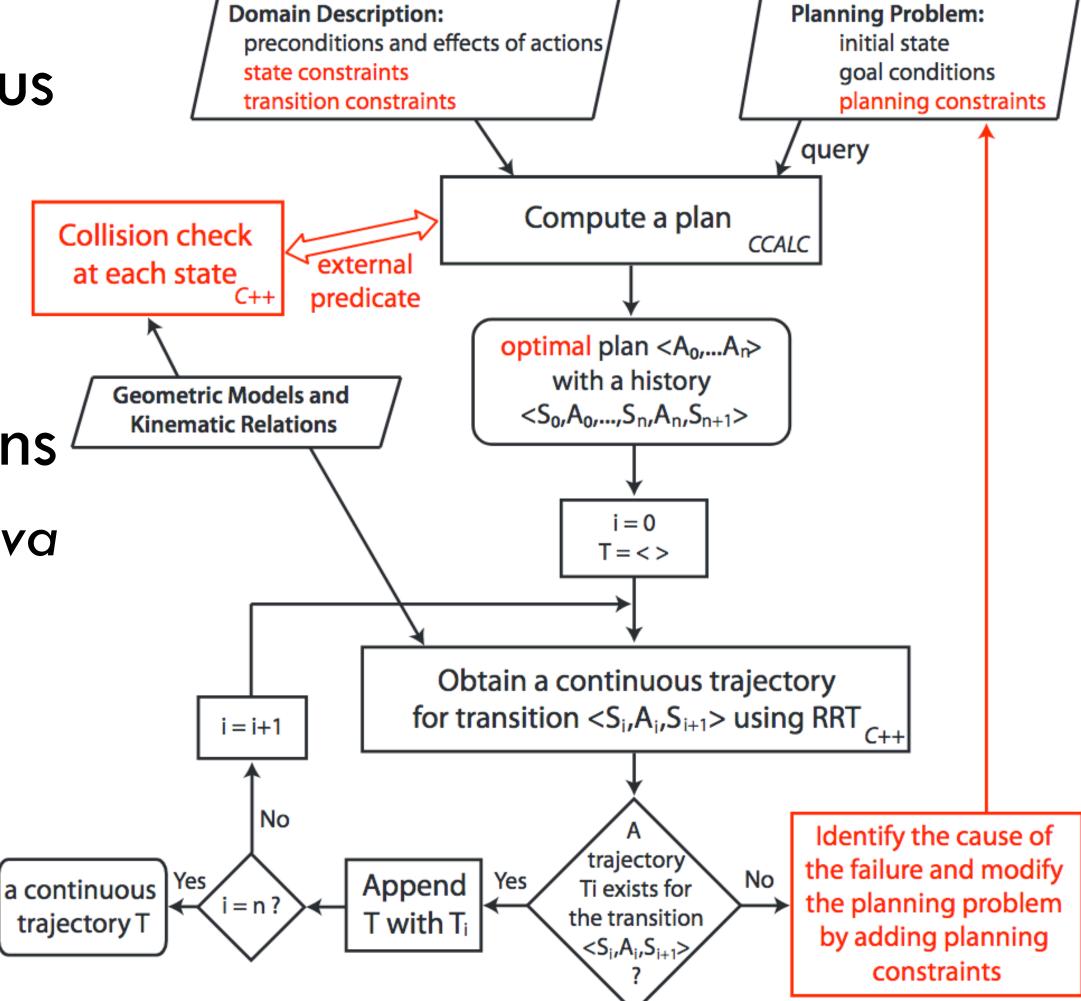
Task & Motion Interface

Maintain separate
 discrete & continuous
 descriptions

Design interface to communicate
 between descriptions

[Erdem et al., Srivastava et al., Dantam et al.]





Drawbacks

- Multi-modal motion planning brute-force search through a high-dimensional space
- Optimization and constraint satisfaction substantial backtracking when infeasible subproblems
- Semantic attachments restricted to problems with finitely many actions
- Task & motion interface lack of modularity

 Overall, no general-purpose, flexible framework for planning in a variety of TAMP problems

PDDLStream

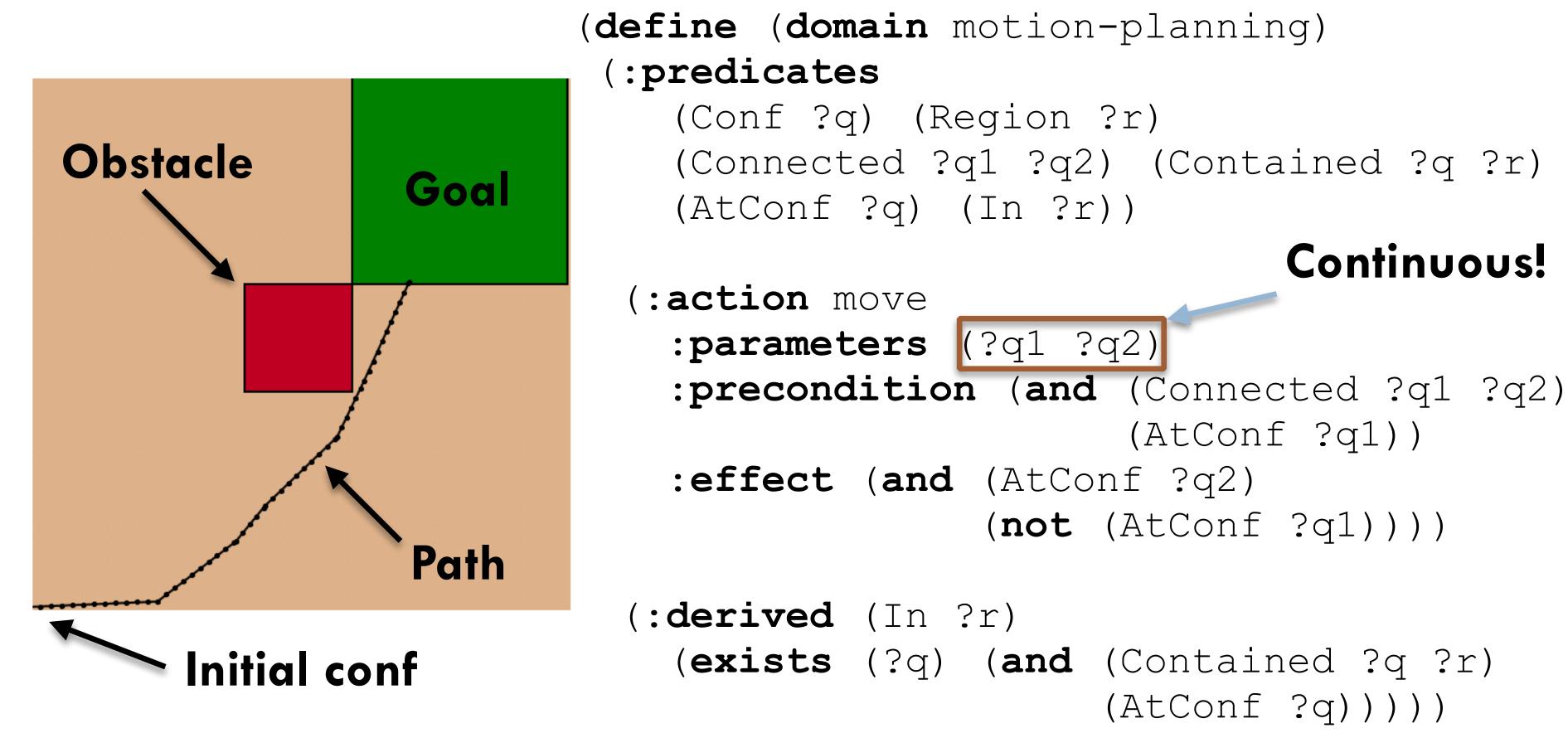
[Garrett, Lozano-Perez, Kaelbling]

State and Action Representation

- Requirements
 - Lifted actions are parameterized
 - Objects instantiate predicates & actions
 - Can encode an infinite set of action instances
 - Factored state is a collection of variables that can change independently
- Extend Planning Domain Description Language (PDDL)
 - Primarily just for standardization purposes
 - Other possible representations:
 - STRIPS, factored transition system, Prolog, ...

PDDLStream Motion Planning

- Model motion planning for a point robot using PDDL
- Goal: point robot within the green goal region



Motion Planning Initial & Goal

Static predicates - value is constant over time

```
(Conf ?q) (Region ?r) (Connected ?q1 ?q2) (Contained ?q ?r)
```

- Fluent predicates value may change over time due to action effects. Intuitively, comprise state variables (AtConf ?q)
- Derived predicates value is a logical formula

```
(:derived (In ?r)
(exists (?q) (and (Contained ?q ?r) (AtConf ?q)))))
```

- Initial state: [(Conf, [0 0]), (AtConf, [0 0]), (Region, green), (Region, env)]
- Goal formula: (In green)

Representing Infinitely Many Objects

- How do encode & use an infinite set of configurations?
 - How do we do this in a domain-independent fashion?

- Motion planning does this by abstracting out the following procedures as meta-parameters
 - Configuration sampler

sample Conf [q, q', q", ...]

Extension function

Conf q₁
extend Edge [e]
Conf q₂

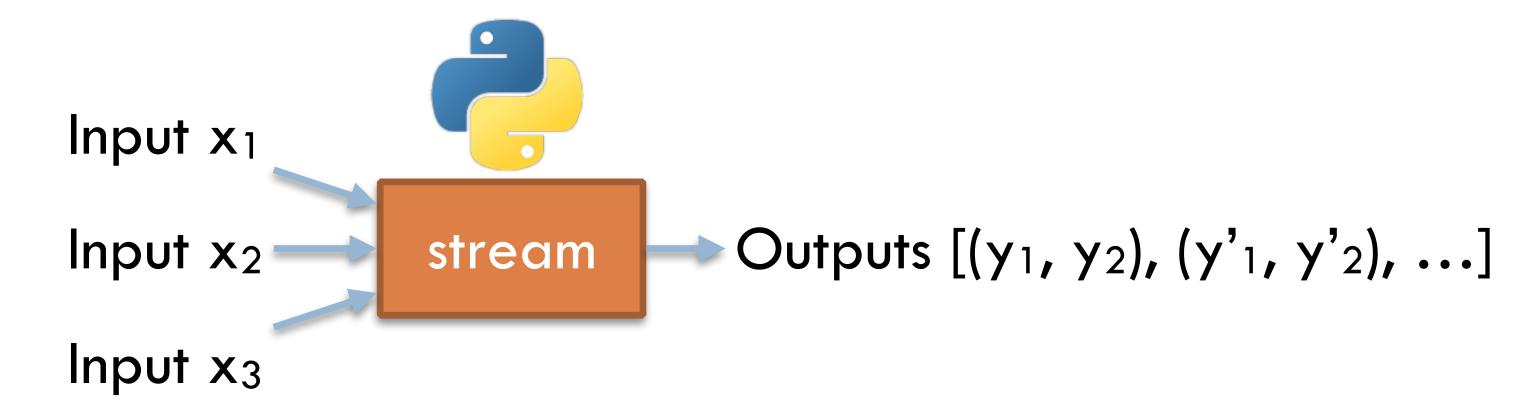
Edge e check True/False

Collision checker

Stream: a function to a generator

- Requirements
 - Programmatic implementation
 - Supports infinite sequences
 - Compositional

- def stream(x1, x2, x3):
 i = 0
 while True:
 y1 = i*(x1 + x2)
 y2 = i*(x2 + x3)
 yield (y1, y2)
 i += 1
- Stream function from an input object tuple (x₁, x₂, x₃) to a (potentially infinite) sequence of output object tuples [(y₁, y₂), (y'₁, y'₂), ...]



Stream Certified Facts

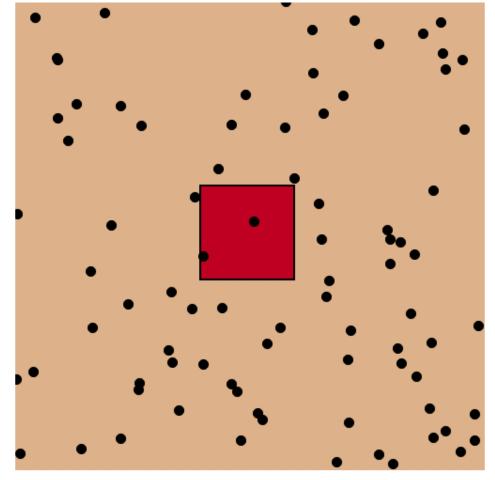
- Objects alone aren't helpful: what do they represent?
 - Communicate semantics using predicates!

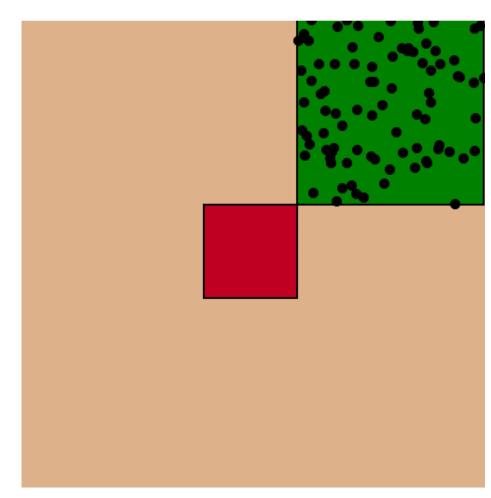
- Augment stream specification with:
 - Certified facts static facts that all outputs satisfy with their corresponding inputs
 - e.g. poses sampled from a region are within it
 - Domain facts static facts declaring legal inputs
 - e.g. only configurations can be connected

Motion Planning Streams

- Samples an axis-aligned region uniformly at random
- Generates arbitrarily many confs

```
(:stream sample-region
    :inputs (?r)
    :domain (Region ?r)
    :outputs (?q)
    :certified (and (Conf ?q)
                     (Contained ?q ?r)))
 def sample_region(r):
     (lower, upper) = REGIONS[r]
     while True:
         q = np.random.uniform(lower, upper)
         yield (q,)
            sample-region
                           Conf [(q), (q'), ...]
Region r
```



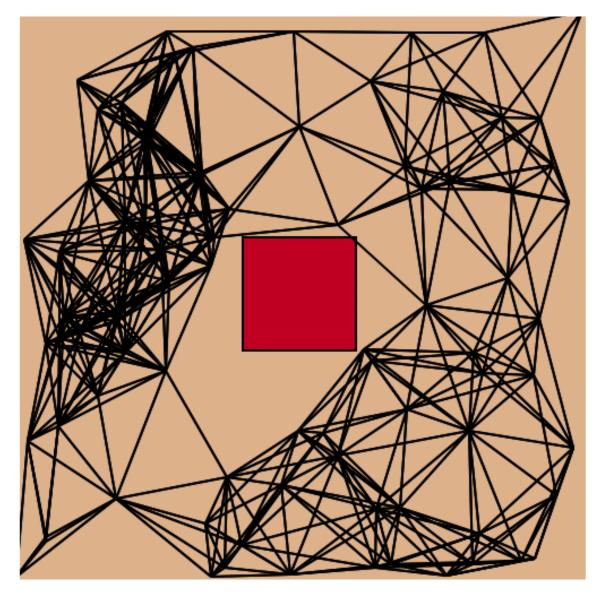


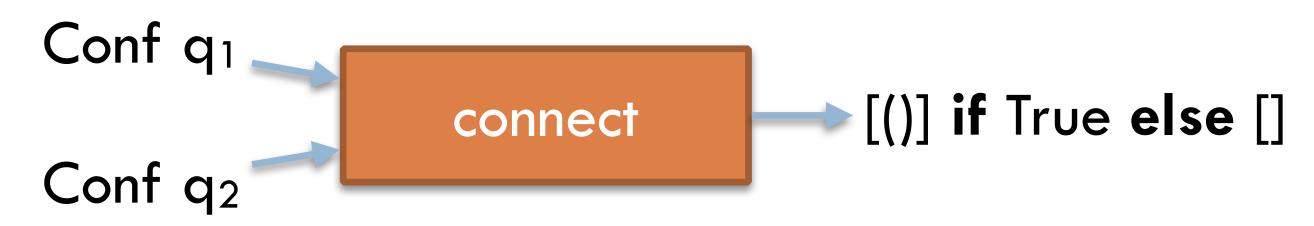
Motion Planning Streams

- Test stream: a stream without outputs
- If returns the empty tuple, its certified facts are true

```
(:stream connect
    :inputs (?q1 ?q2)
    :domain (and (Conf ?q1) (Conf ?q2))
    :outputs ()
    :certified (Connected ?q1 ?q2)))

def connect(q1, q2):
    if (np.linalg.norm(q2 - q1) < MAX_DIST) \
        and not segment_collision(q1, q2):
        yield tuple()</pre>
```



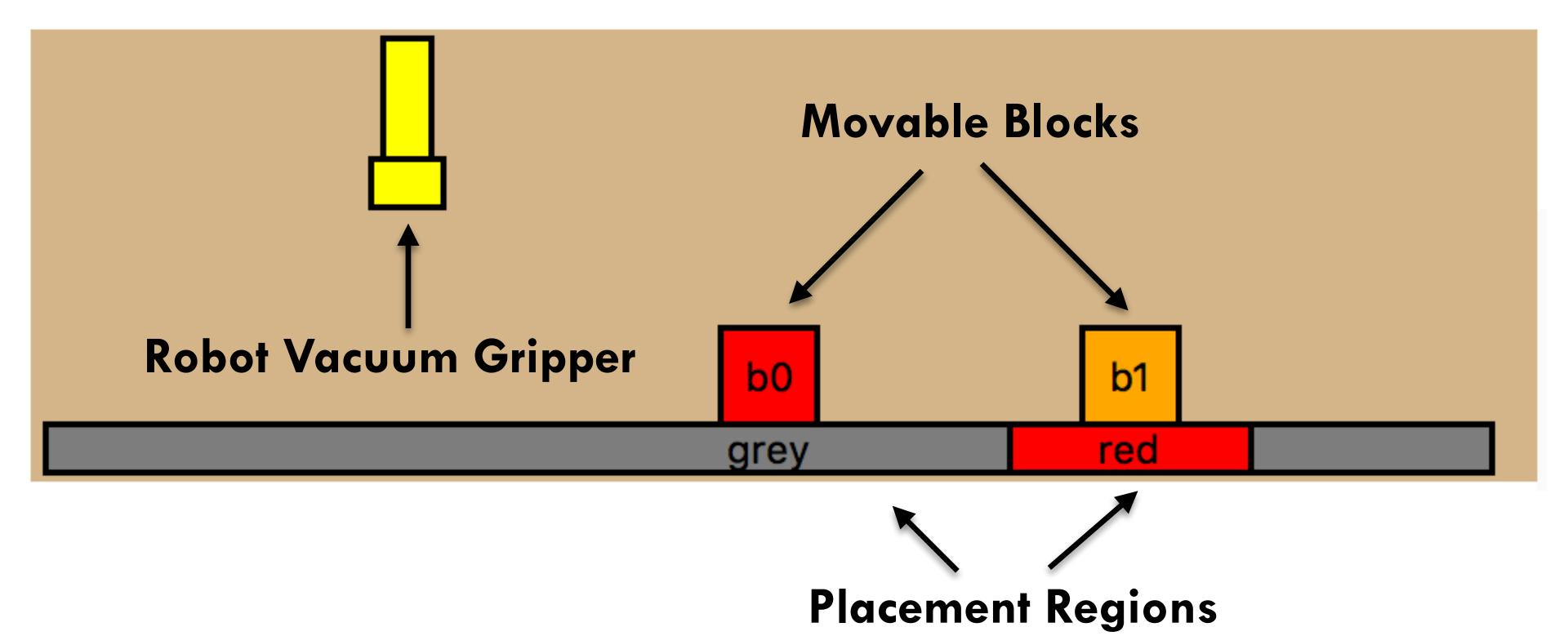


PDDLStream = PDDL + Streams

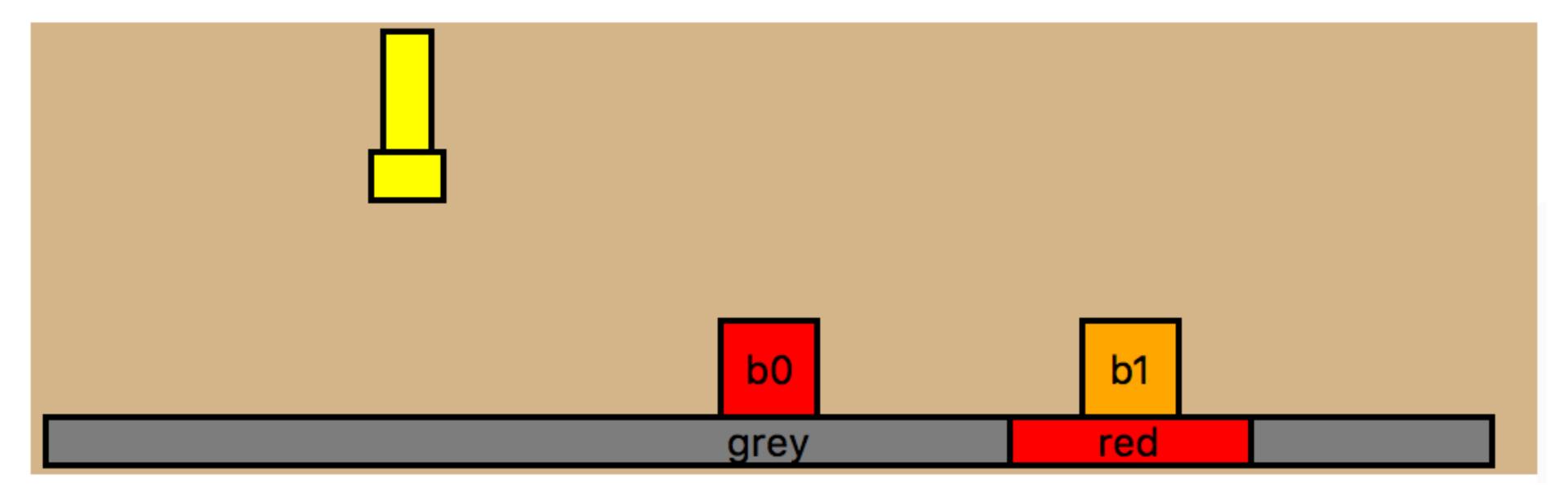
- Extension of PDDL to support the specification of blackbox procedures as streams
 - [Garrett, Lozano-Perez, Kaelbling]
- The true initial state is the set of all static facts that can be certified by streams (may be infinitely large)
- Static facts restrict domain of action parameters

2D Pick-and-Place Example

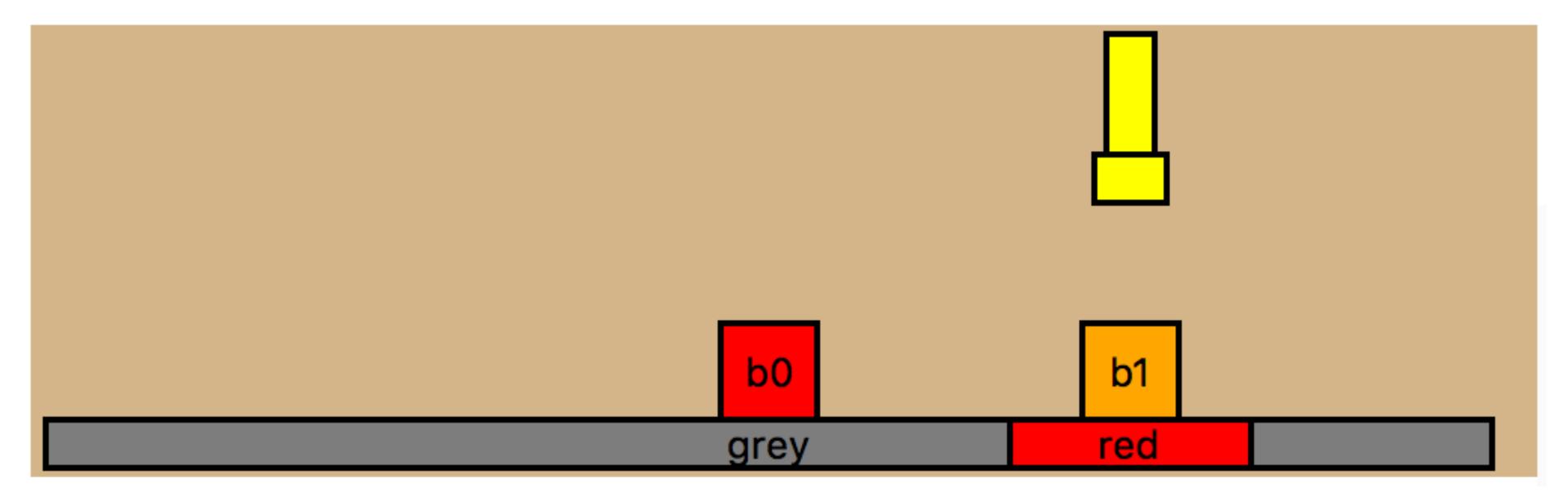
- Goal: block b0 within the red region
- Robot and block poses are continuous (x, y) pairs
- Block b1 obstructs the placement of b0



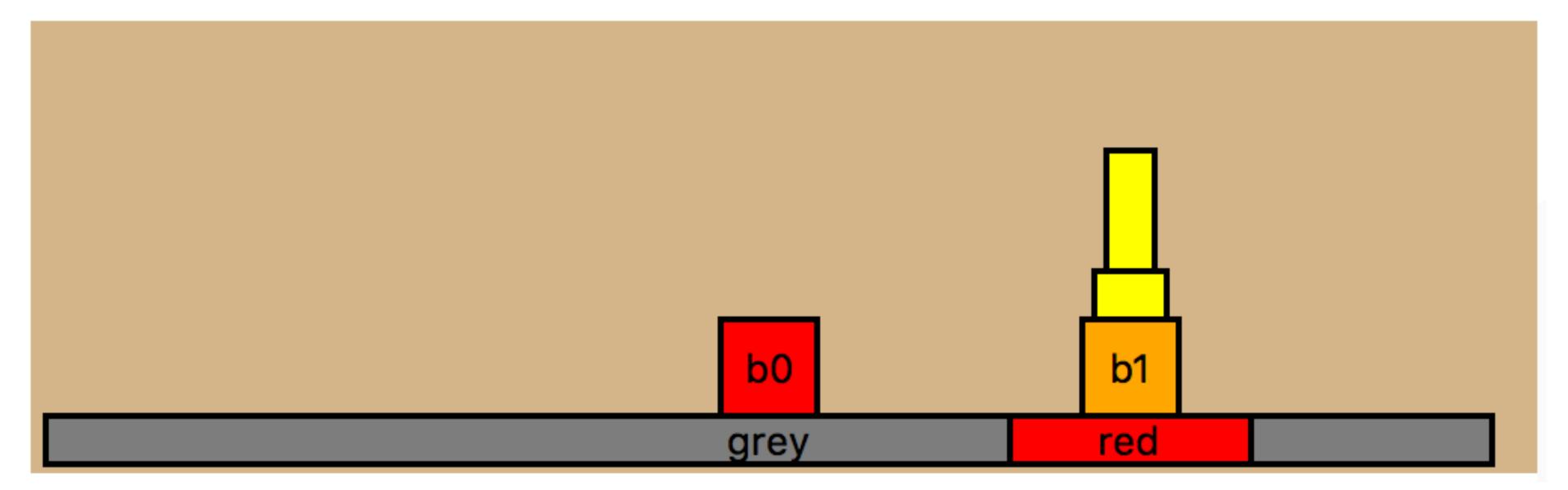
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



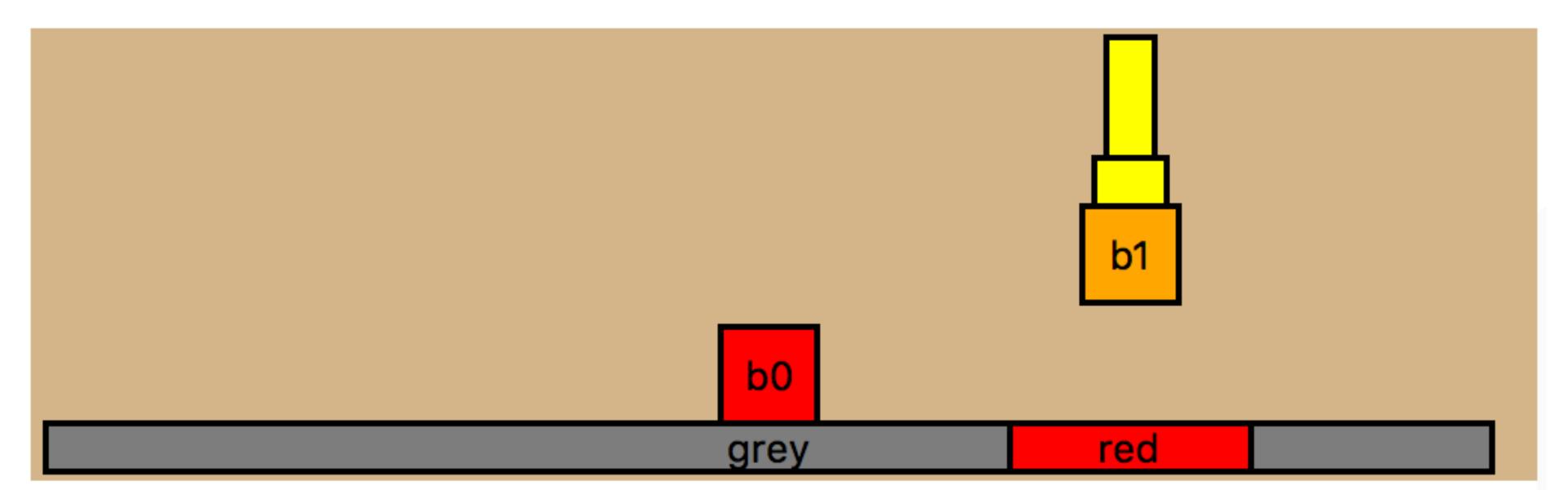
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



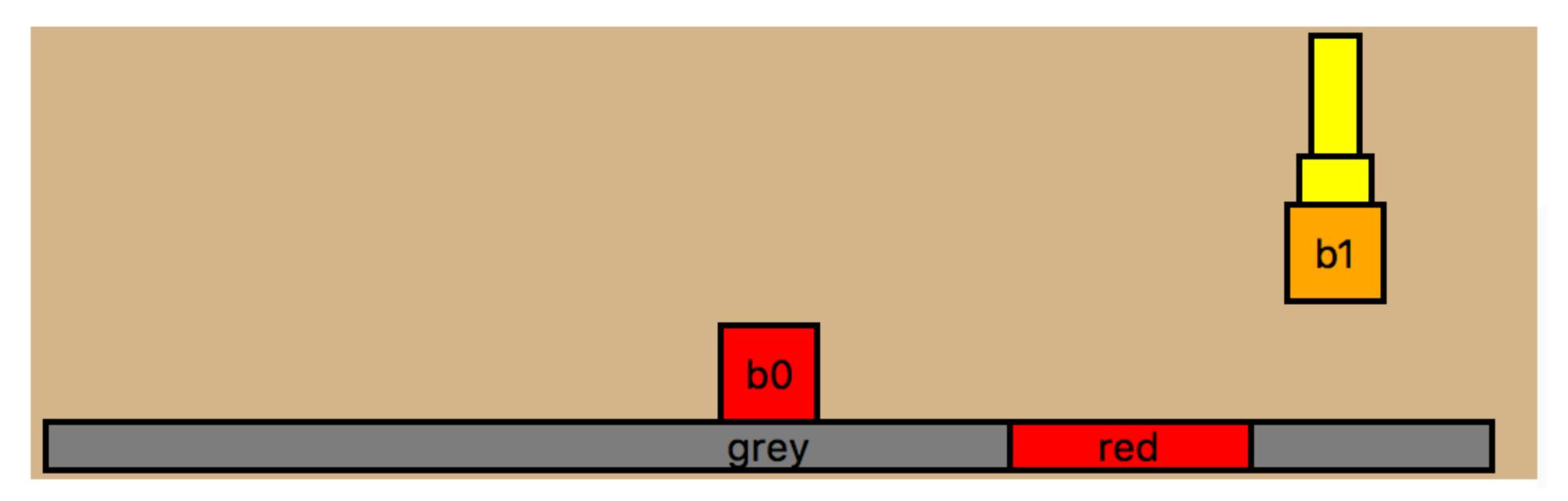
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



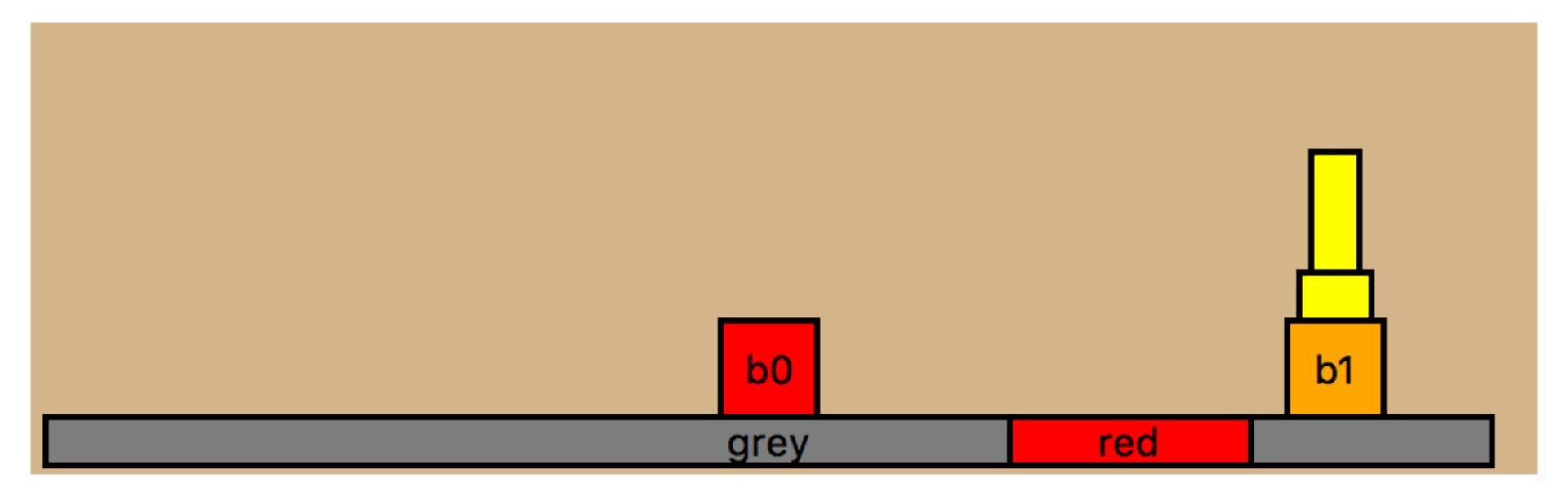
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



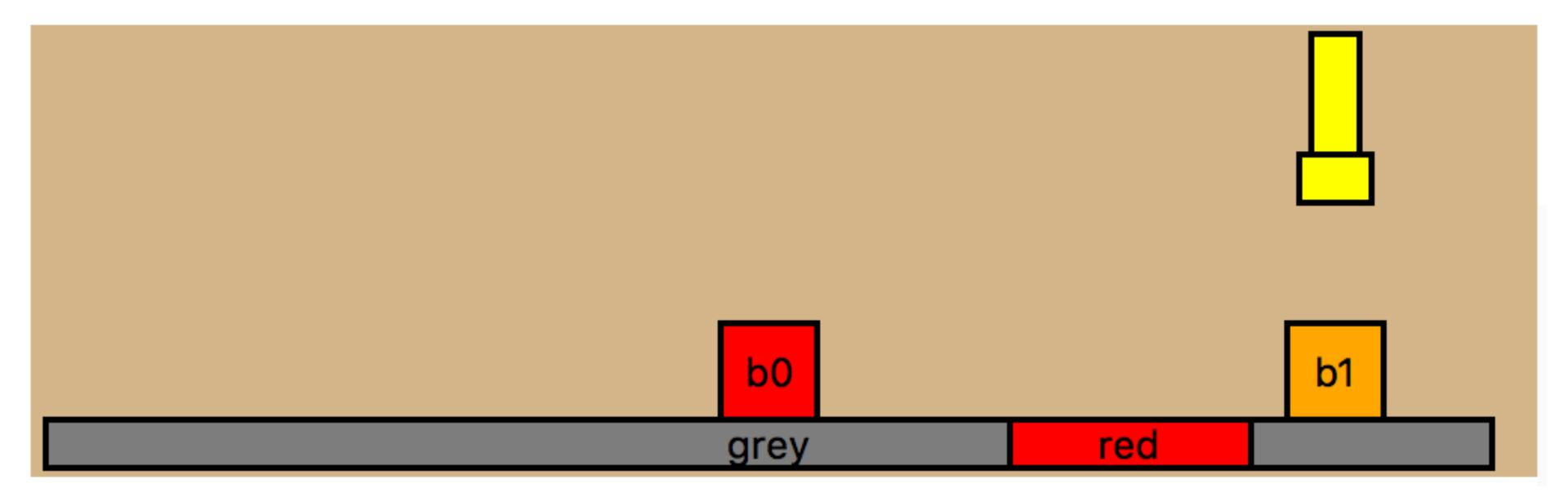
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



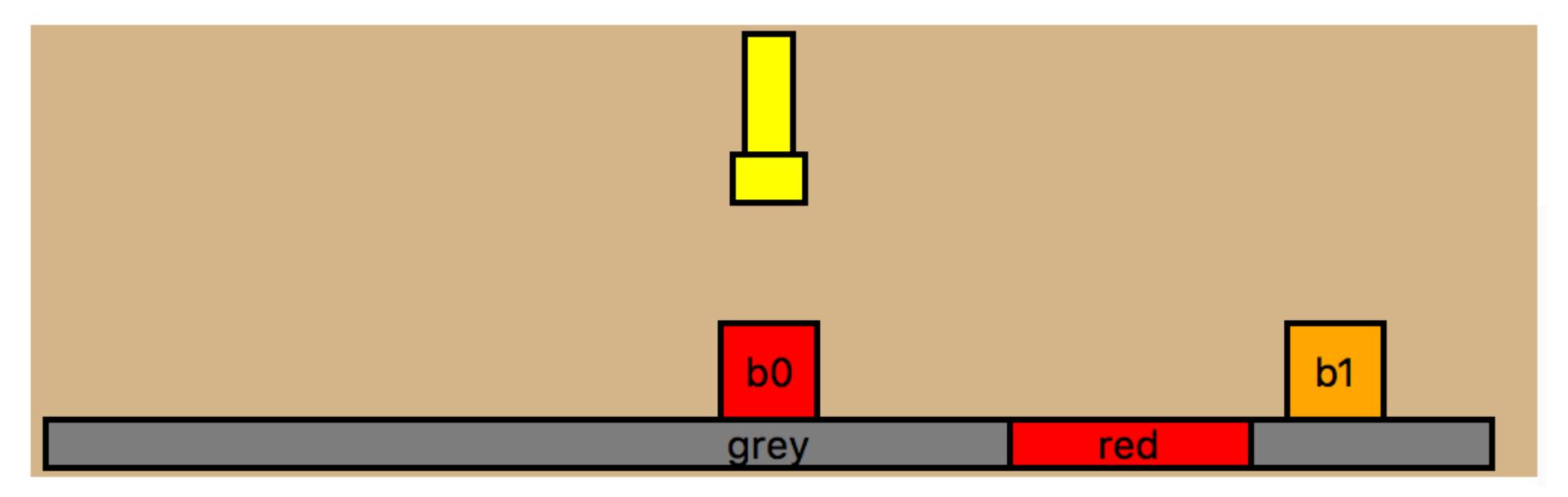
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



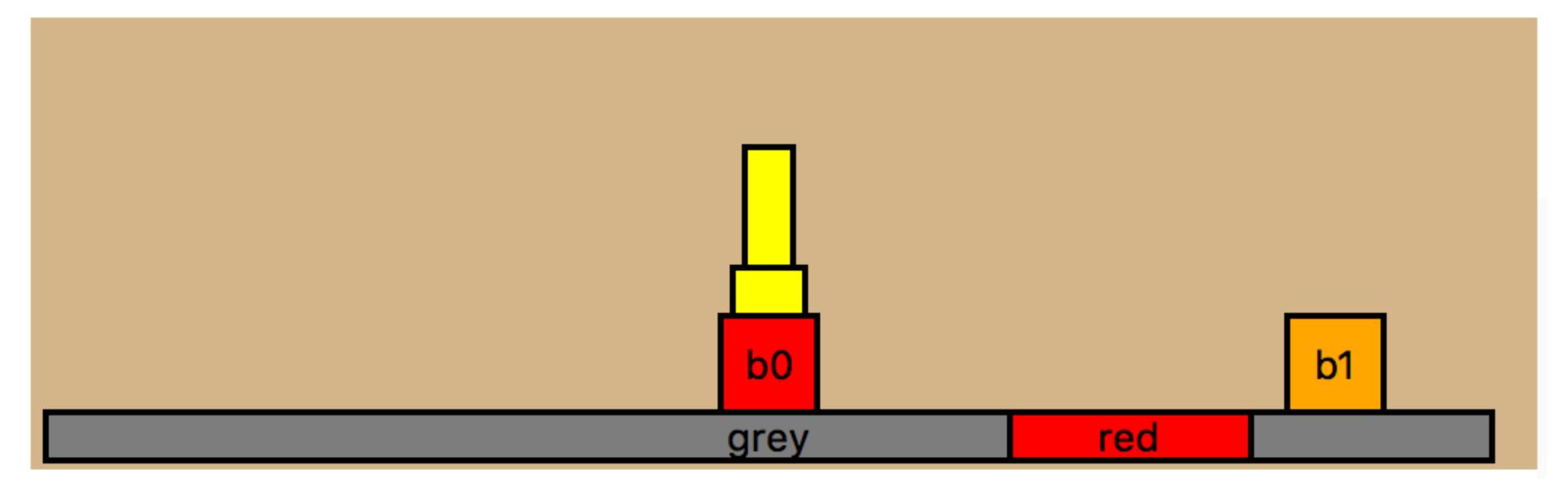
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



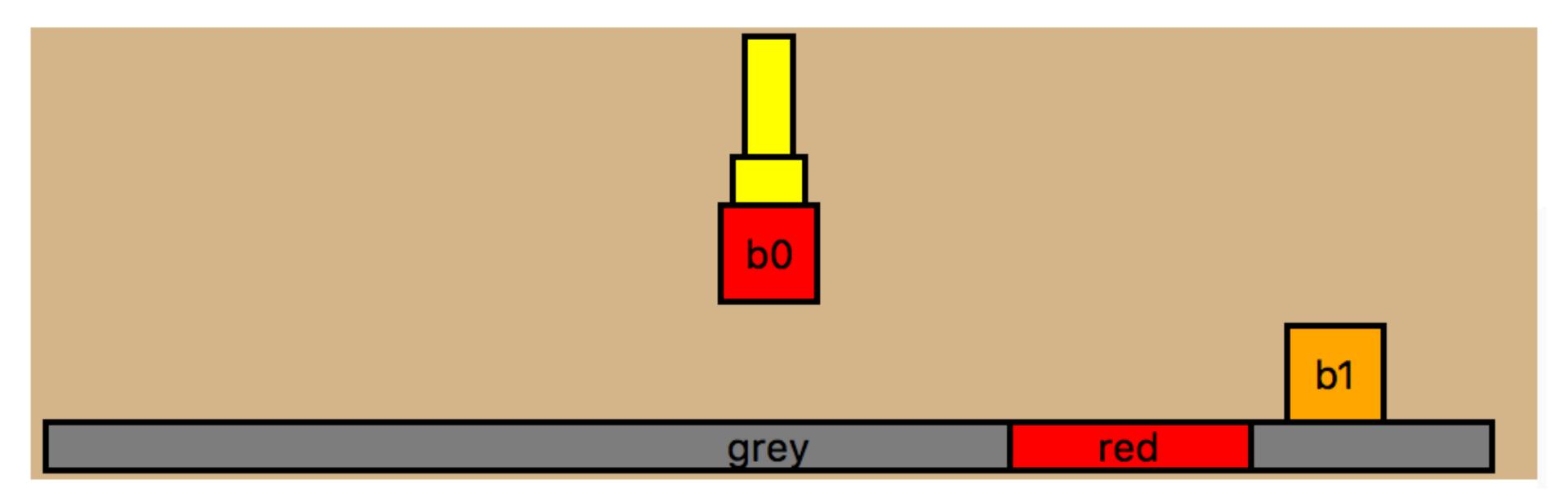
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



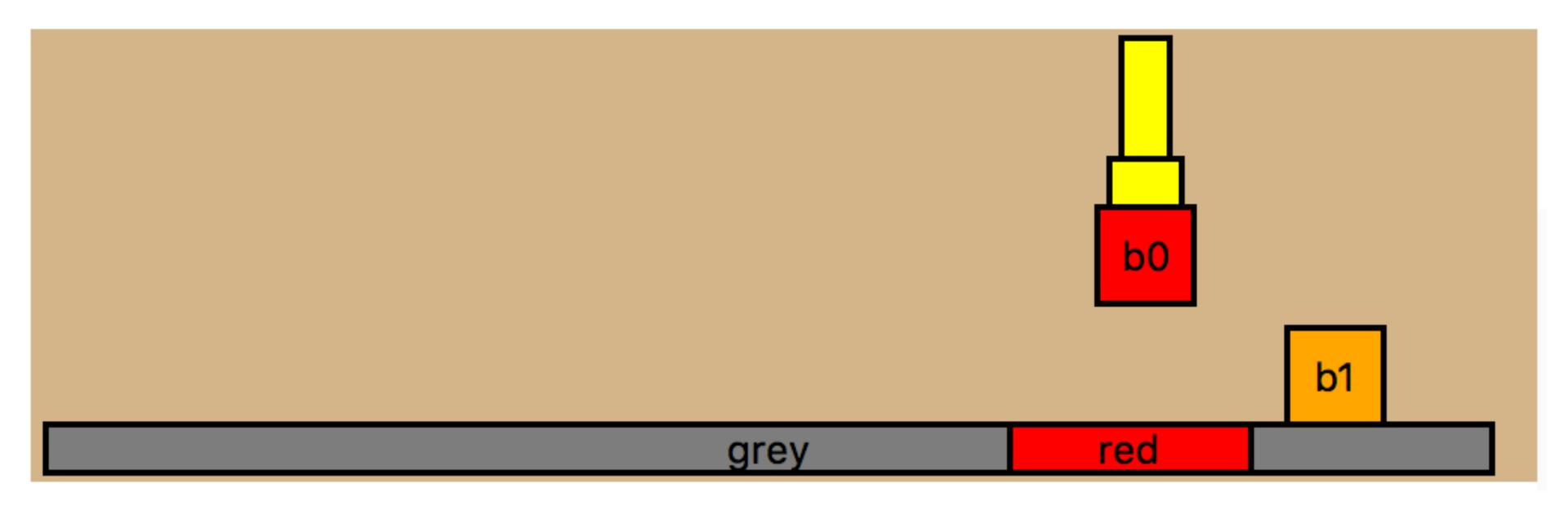
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



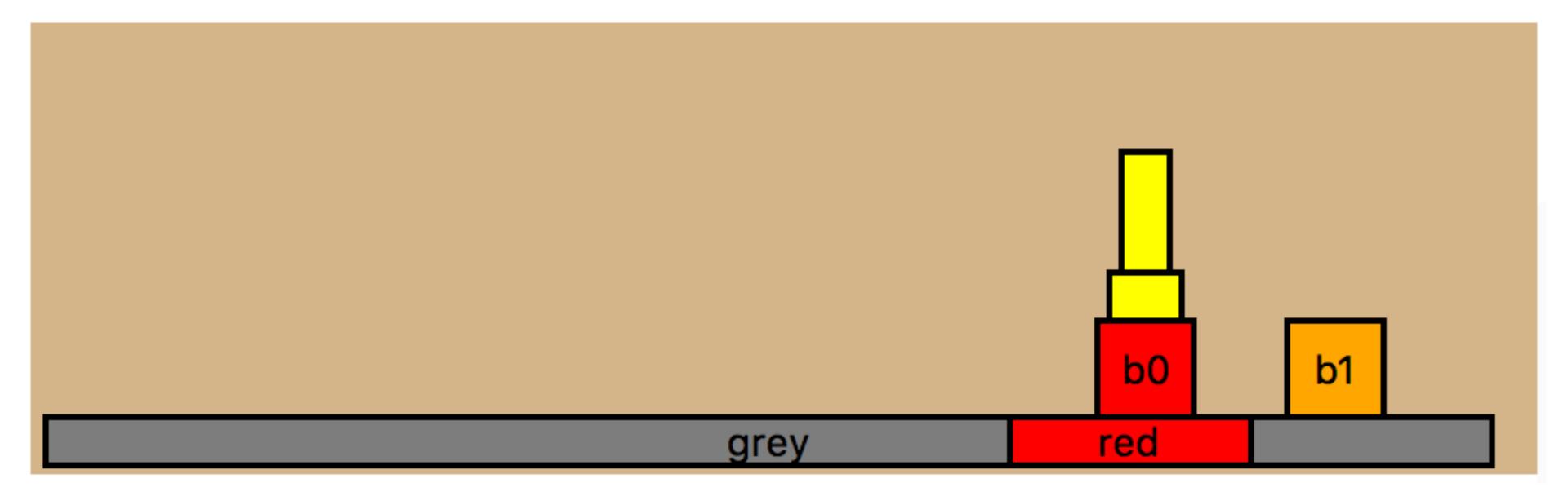
- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



- One (of many) possible solutions
 - move, pick b1, move, place b1,
 move, pick b0, move, place b0



2D Pick-and-Place Actions

 Typical STRIPS action description except that arguments are mostly continuous!

```
(:action move
 :parameters (?q1 ?t ?q2)
  :precondition (and (Motion ?q1 ?t ?q2) (AtConf ?q1))
 :effect (and (AtConf ?q2) (not (AtConf ?q1))))
(:action pick
 :parameters (?b ?p ?q)
 :precondition (and (Kin ?b ?q ?p)
                     (AtConf ?q) (AtPose ?b ?p) (HandEmpty))
 :effect (and (Holding ?b)
               (not (AtPose ?b ?p)) (not (HandEmpty))))
(:action place
  :parameters (?b ?p ?q)
  :precondition (and (Kin ?b ?q ?p) (AtConf ?q) (Holding ?b))
 :effect (and (AtPose ?b ?p) (HandEmpty) (not (Holding ?b))))
```

2D Pick-and-Place Initial & Goal

Static predicates

```
(Block ?b) (Region ?r) (Pose ?b ?p) (Conf ?q) (Traj ?t) (Contained ?b ?p ?r) (Kin ?b ?q ?p) (Motion ?q1 ?t ?q2) (CFree ?b1 ?p1 ?b2 ?p2)
```

Fluent predicates

```
(AtPose ?b ?p) (AtConf ?q) (Holding ?b) (HandEmpty)
```

Derived predicates

```
(:derived (In ?b ?r)
  (exists (?p) (and (Contained ?b ?p ?r) (AtPose ?b ?p))))
```

- Initial state: [(Conf, [-7.5 5.]), (AtConf, [-7.5 5.]), (HandEmpty), (Block, b0), (Block, b1), (Pose, b0, [0.0.]), (Pose, b1, [7.5 0.]), (AtPose, b0, [0.0.]), (AtPose, b1, [7.5 0.]), (Region, red), (Region, grey)]
- Goal formula: (In, b0, red)

```
(:stream sample-region
 :inputs (?b ?r)
 :domain (and (Block ?b) (Region ?r))
 :outputs (?p)
 :certified (and (Pose ?b ?p) (Contained ?b ?p ?r)))
       def sample region(b, r):
         x_{min}, x_{max} = REGIONS[r]
         w = BLOCKS[b] width
         while True:
             x = random_uniform(x_min + w/2, x_max - w/2)
             p = np.array([x, 0])
             yield (p,)
        Block b
                    sample-region
                                       Pose [(p), (p'), (p"), ...]
       Region r
```

Multiple streams can certify the same predicates

```
(:stream test-region
  :inputs (?b ?p ?r)
  :domain (and (Pose ?b ?p) (Region ?r))
  :outputs ()
  :certified (Contained ?b ?p ?r))
             def test_region(b, p, r):
                x, y = p
               w = BLOCKS[b].width
                x_min, x_max = REGIONS[r]
                if x_{min} \le (x - w/2) \le (x + w/2) \le x_{max}:
                  yield tuple()
          Block b
          Pose p
                                         [()] if True else []
                        test-region
         Region r
```

- Inverse kinematics to produce grasping configuration
 - Trivial in 2D, more interesting in general (7 DOF arm)

```
(:stream sample-ik
 :inputs (?b ?p)
 :domain (Pose ?b ?p)
 :outputs (?q)
 :certified (and (Conf ?q) (Kin ?b ?q ?p)))
                   def sample_ik(b, p):
                        q = p + GRASP
                        yield (q,)
            Block b
                                          Conf [(q)]
                          sample-ik
            Pose p
```

- "Sample" (via an RRT) multi-waypoint trajectories
- Include joint limits & fixed obstacle collisions, but not movable object collisions

```
(:stream sample-motion
   :inputs (?q1 ?q2)
   :domain (and (Conf ?q1) (Conf ?q2))
   :outputs (?t)
   :certified (and (Traj ?t) (Motion ?q1 ?t ?q2)))
                  def sample_motion(q1, q2):
                   t = rrt(q1, q2)
                   if t is not None:
                       yield (t,)
           Conf q
                                         Trajectory [(t)]
                       sample-motion
          Conf q2
```

2D Pick-and-Place Collisions

- Need to ensure place actions do not cause collisions
- Add parameters for the pose of each block bad!
- Use a derived predicate for whether currently unsafe
 - Decomposes collision checking into a logical AND

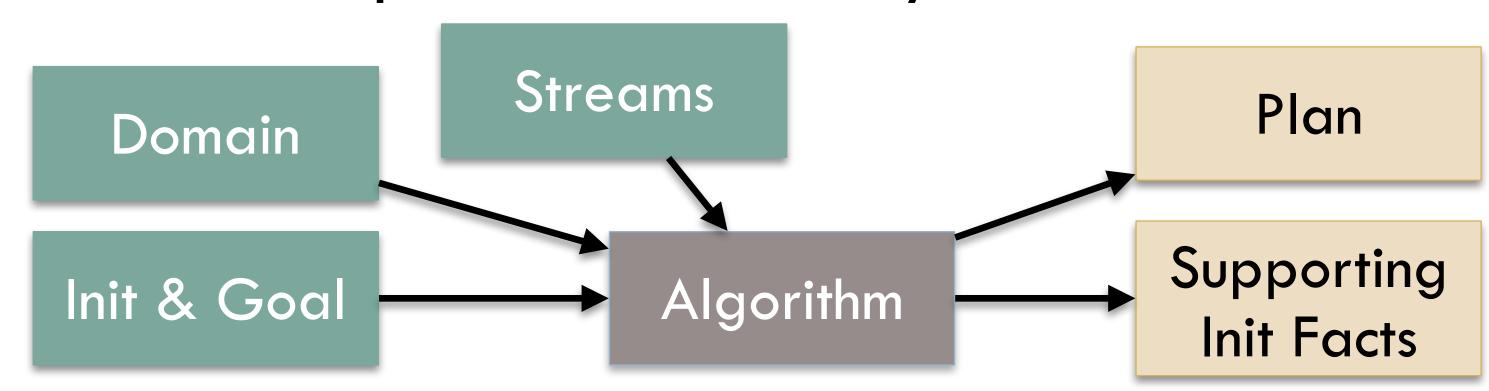
2D Pick-and-Place Collisions

```
(:stream test cfree
  :inputs (?b1 ?p1 ?b2 ?p2)
  :domain (and (Pose ?b1 ?p1) (Pose ?b2 ?p2))
  :outputs ()
  :certified (CFree ?b1 ?p1 ?b2 ?p2))
               def test_cfree(b1, p1, b2, p2):
                    x1, y1 = p1
                    x2, y2 = p2
                    w1 = BLOCKS[b1].width
                    w2 = BLOCKS[b2].width
                    if (w1 + w2)/2 \le abs(x2 - x1):
                         yield tuple()
          Block b<sub>1</sub>
           Pose p<sub>1</sub>
                                             [()] if True else []
                           test-cfree
          Block b<sub>2</sub>
          Pose p<sub>2</sub>
```

PDDLStream Algorithms

PDDLStream Specification

- Domain dynamics domain.pddl
 - Specifies actions and derived predicates
- Stream properties stream.pddl
 - Declares input/output arity as well as certified facts
- Problem and stream implementation problem.py
 - Initial state a set of facts & goal formula
 - Stream implementation in Python



Two PDDLStream Algorithms

- Each algorithm repeats:
 - 1. Search a finite PDDL problem for plan
 - 2. Modify the PDDL problem depending on the plan
- Search implemented using blackbox algorithms
 - Breadth-First Search (BFS)
 - Off-the-shelf Al planner FastDownard
 - Exploits factoring in its search heuristics (e.g. h_{FF})
 - http://www.fast-downward.org/

Incremental Algorithm

- Incrementally construct all possible initial facts
- Periodically check if admits a solution
- Alternation between sampling and searching is similar in spirit to a Probabilistic Roadmap (PRM)
- Repeat:
 - 1. Compose and evaluate a finite number of streams to unveil more facts in the initial state
 - 2. Search the current PDDL problem for plan
 - 3. Terminate when a plan is found

Incremental Example: Iteration 1

```
Stream evaluations:
1. s-motion:([-7.5 5.], [-7.5 5.])->[([[-7.5 5.], [-7.5 5.], [-7.5 5.], [-7.5 5.], [-7.5 5.])]
2. s-ik:(b0, [0.0.])->[([0.2.5])]
3. t-cfree:(b0, [0. 0.], b0, [0. 0.])->[] (failed to produce an output)
4. s-ik:(b1, [7.5 \ 0.\ ])->[([7.5 \ 2.5])]
5. t-cfree:(b1, [7.5 0.], b0, [0. 0.])->[()]
6. t-cfree:(b0, [0. 0.], b1, [7.5 0. ])->[()]
7. t-cfree:(b1, [7.5 \ 0.], b1, [7.5 \ 0.])->[] (failed to produce an output)
8. t-region:(b0, [0. 0.], grey)->[()]
9. t-region:(b1, [7.5 0.], grey)->[()]
10.t-region:(b0, [0. 0.], red)->[] (failed to produce an output)
11.s-region:(b0, red)->[([7.65 0. ])]
12.s-region:(b1, red)->[([8.15 0. ])]
13.s-region:(b0, grey)->[([2.88 0. ])]
14.s-region:(b1, grey)->[([1.26 0. ])]
```

grey

red

Incremental Example: Iteration 2

```
Stream evaluations
1. s-motion:([0. 2.5], [-7.5 5.])->[([[0. 2.5], [0. 5.], [-7.5 5.], [-7.5 5.])]
2. s-motion:([-7.5 5.], [0. 2.5])->[([[-7.5 5.], [-7.5 5.], [0. 5.], [0. 2.5]])]
3. s-motion:([0. 2.5], [0. 2.5])->[([[0. 2.5], [0. 5.], [0. 5.], [0. 2.5])]
4. s-motion:([7.5 2.5], [-7.5 5.])->[([[7.5 2.5], [7.5 5.], [-7.5 5.], [-7.5 5.])]
5. s-motion:([7.5 2.5], [0. 2.5])->[([[7.5 2.5], [7.5 5.], [0. 5.], [0. 2.5]])]
6. s-motion:([-7.5 5.], [7.5 2.5])->[([[-7.5 5.], [-7.5 5.], [7.5 5.], [7.5 2.5]])]
7. s-motion:([0. 2.5], [7.5 2.5])->[([[0. 2.5], [0. 5.], [7.5 5.], [7.5 2.5]])]
8. s-motion:([7.5 2.5], [7.5 2.5])->[([[7.5 2.5], [7.5 5.], [7.5 5.], [7.5 5.], [7.5 2.5]])]
9. s-ik:(b0, [7.65 0. ])->[([7.65 2.5 ])]
10.t-cfree:(b0, [7.65 0. ], b0, [0. 0.])->[()]
11.t-cfree:(b0, [7.65\ 0.\ ], b1, [7.5\ 0.\ ])->[] (failed to produce an output)
12.t-cfree:(b0, [0. 0.], b0, [7.65 0. ])->[()]
13.t-cfree:(b1, [7.5 0.], b0, [7.65 0.])->[] (failed to produce an output)
14.t-cfree:(b0, [7.65 0. ], b0, [7.65 0. ])->[] (failed to produce an output)
15.t-region:(b0, [7.65 \ 0.], grey)->[()]
16.t-region:(b0, [7.65 0. ], red)->[()]
17.s-region:(b0, red)->[([7.27 0. ])] (second generator output)
18.s-ik:(b1, [8.15 0. ])->[([8.15 2.5 ])]
54.s-region:(b1, grey)->[([10.97 0. ])] (second generator output)
```

Iteration 3 - 118 stream evaluations

Incremental Example: Iterations 3-4

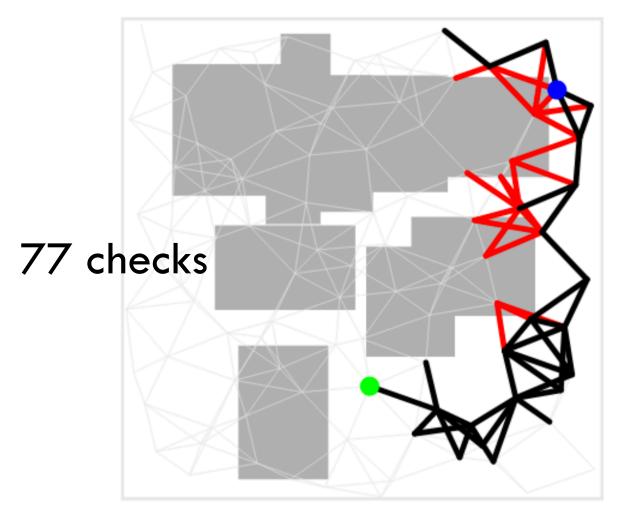
```
Plan:
1) move [-7.5 5.] [[-7.5 5.], [-7.5 5.], [7.5 5.], [7.5 2.5]] [7.5 2.5]
2) pick b1 [7.5 0.] [7.5 2.5]
3) move [7.5 2.5] [[7.5 2.5], [7.5 5.], [10.97 5.], [10.97 2.5]] [10.97 2.5]
4) place b1 [10.97 0.] [10.97 2.5]
5) move [10.97 2.5] [[10.97 2.5], [10.97 5.], [0. 5.], [0. 2.5]] [0. 2.5]
6) pick b0 [0. 0.] [0. 2.5]
7) move [0. 2.5] [[0. 2.5], [0. 5.], [7.65 5.], [7.65 2.5]] [7.65 2.5]
8) place b0 [7.65 0.] [7.65 2.5]
```

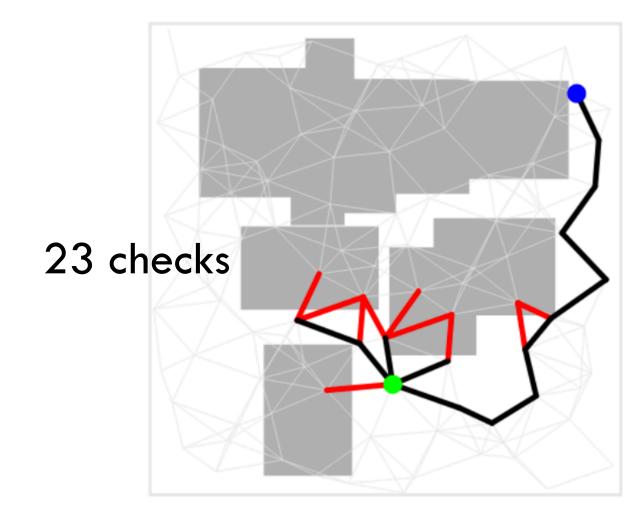
- Drawback many unnecessary samples produced
 - Computationally expensive to generate
 - Induce large discrete planning problems
- Motivates designing more intelligent algorithms

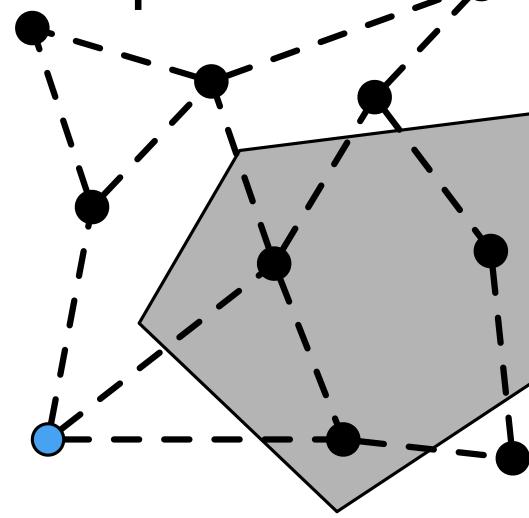
Lazy Probabilistic Roadmap (PRM)

- Motivated by expensive collision checks
 - [Bohlin & Kavraki, Dellin & Srinivasa]
- Defers collision checking until a path is found
- 1. Find a path using the unchecked and safe edges
- 2. Check collisions for edges only along the path

3. If collision, goto 1. Otherwise, return the path.



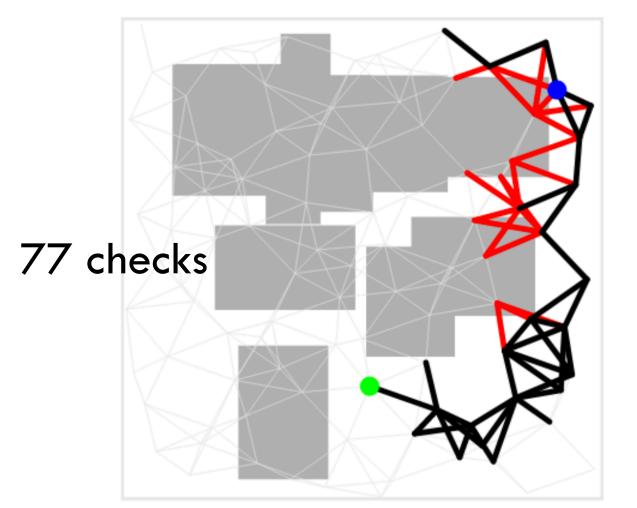


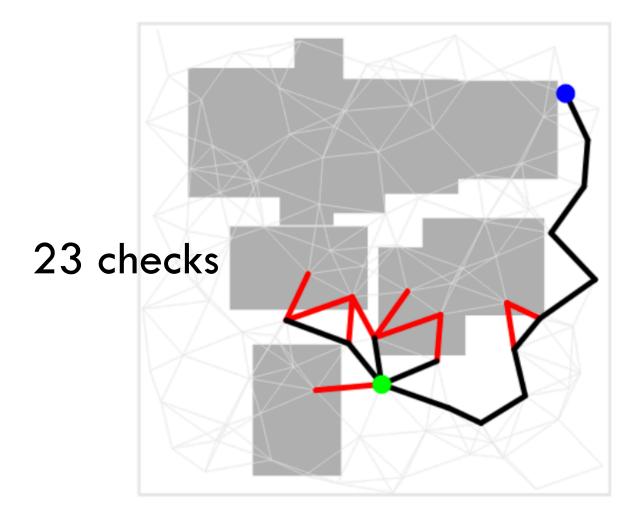


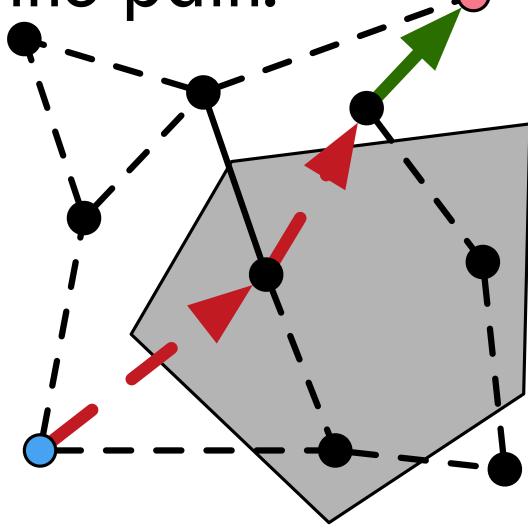
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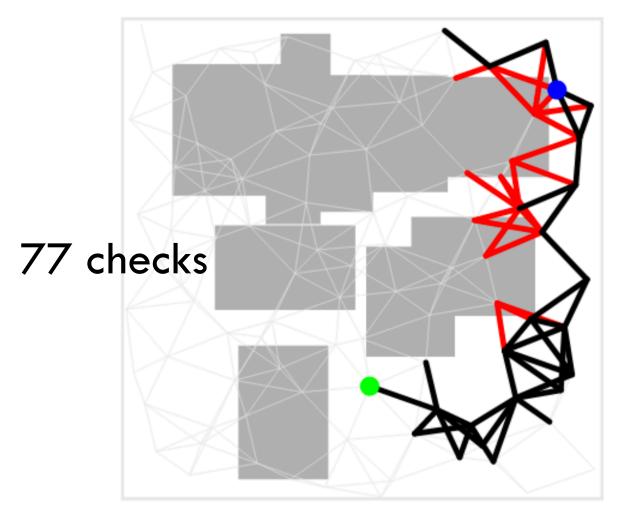


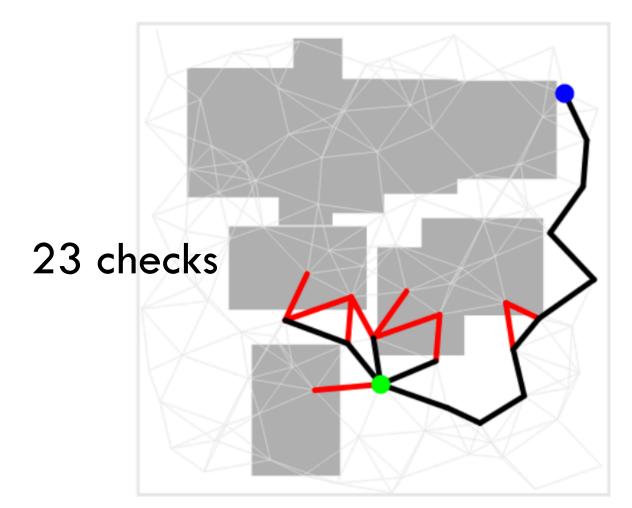


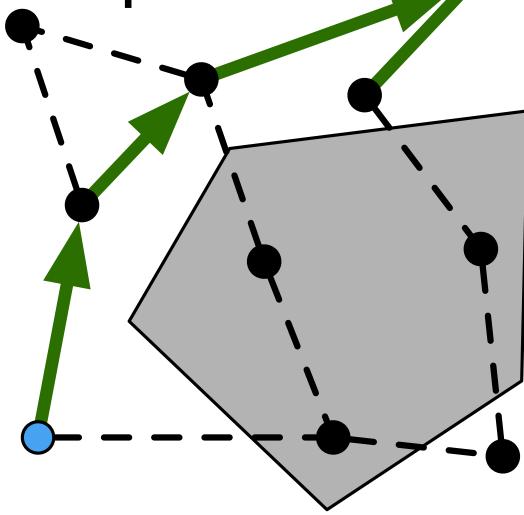
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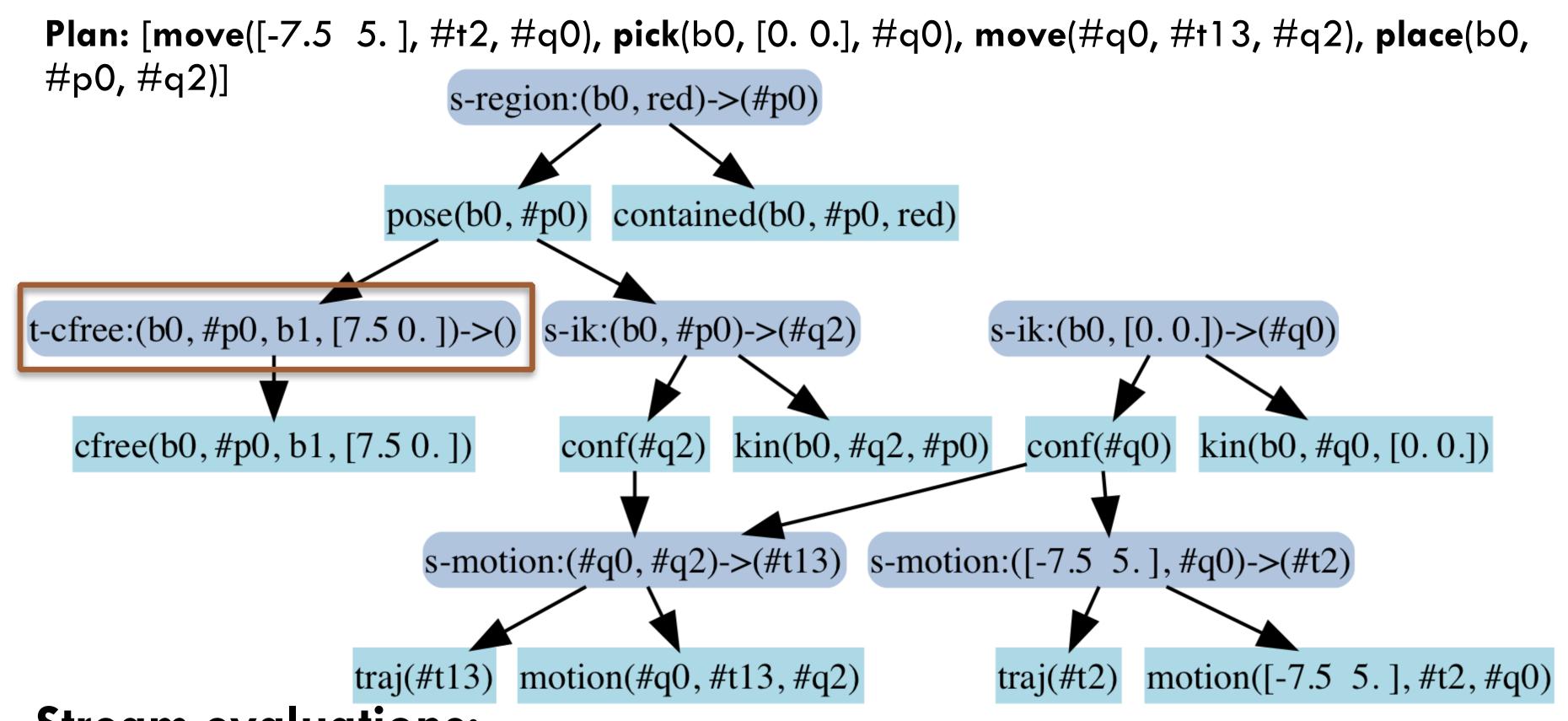
Optimistic Stream Outputs

- Many TAMP streams are exceptionally expensive
 - Inverse kinematics, motion planning, ...
- Generalize lazy collision checking idea to streams
- Inductively create unique placeholder output objects for each stream instance (has # as its prefix)
- Optimistic evaluations:
- 1. [s-region:(b0, red)->(#p0), ...
- 2. [s-ik:(b0, [0. 0.])->($\underline{\#q0}$), s-ik:(b0, $\underline{\#p0}$)->($\underline{\#q2}$), t-cfree: (b0, $\underline{\#p0}$, b1, [7.5 0.])->() ...
- 3. [s-motion:([-7.5 5.], #q0)->(#t2), s-motion:(#q0, #q2)->(#t13), ...]

Focused Algorithm

- Plan using optimistic stream outputs before evaluating stream instances
- Recover set of possibly helpful stream instances from identified plans
- Repeat:
 - 1. Construct current optimistic objects & facts
 - 2. Search with real & optimistic objects
 - 3. If only real objects used, return plan
 - 4. Evaluate stream instances supporting plan
 - 5. Disable evaluated stream instances

Focused Example: Iteration 1

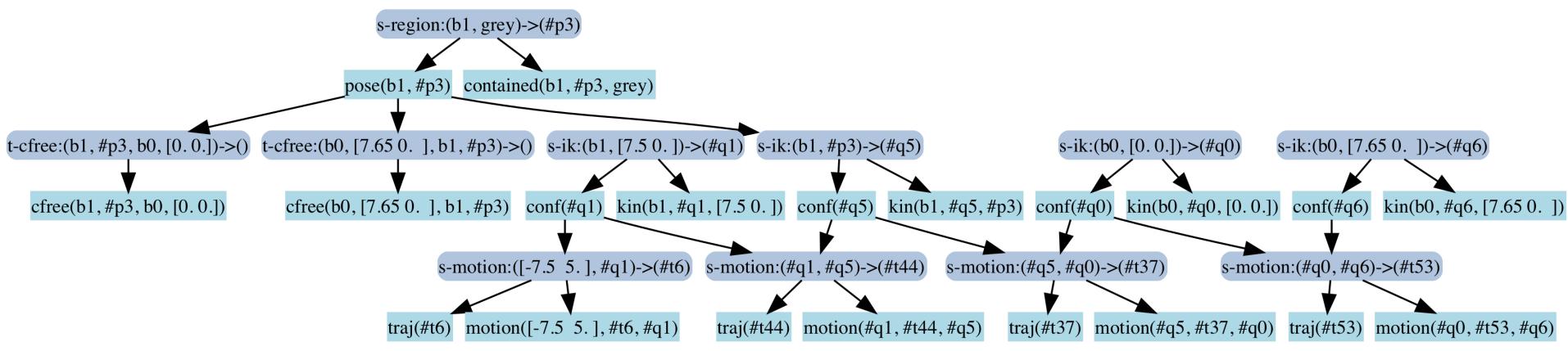


Stream evaluations:

- 1.s-region:(b0, red)->[([7.65 0.])]
- 2.t-cfree:(b0, [7.65 0.], b1, [7.5 0.])->[] (failed to produce an output) These stream instances are **removed** from subsequent searches

Focused Example: Iteration 2

Plan: [move([-7.5 5.], #t6, #q1), pick(b1, [7.5 0.], #q1), move(#q1, #t44, #q5), place(b1, #p3, #q5), move(#q5, #t37, #q0), pick(b0, [0. 0.], #q0), move(#q0, #t53, #q6), place(b0, [7.65 0.], #q6)]



Stream evaluations:

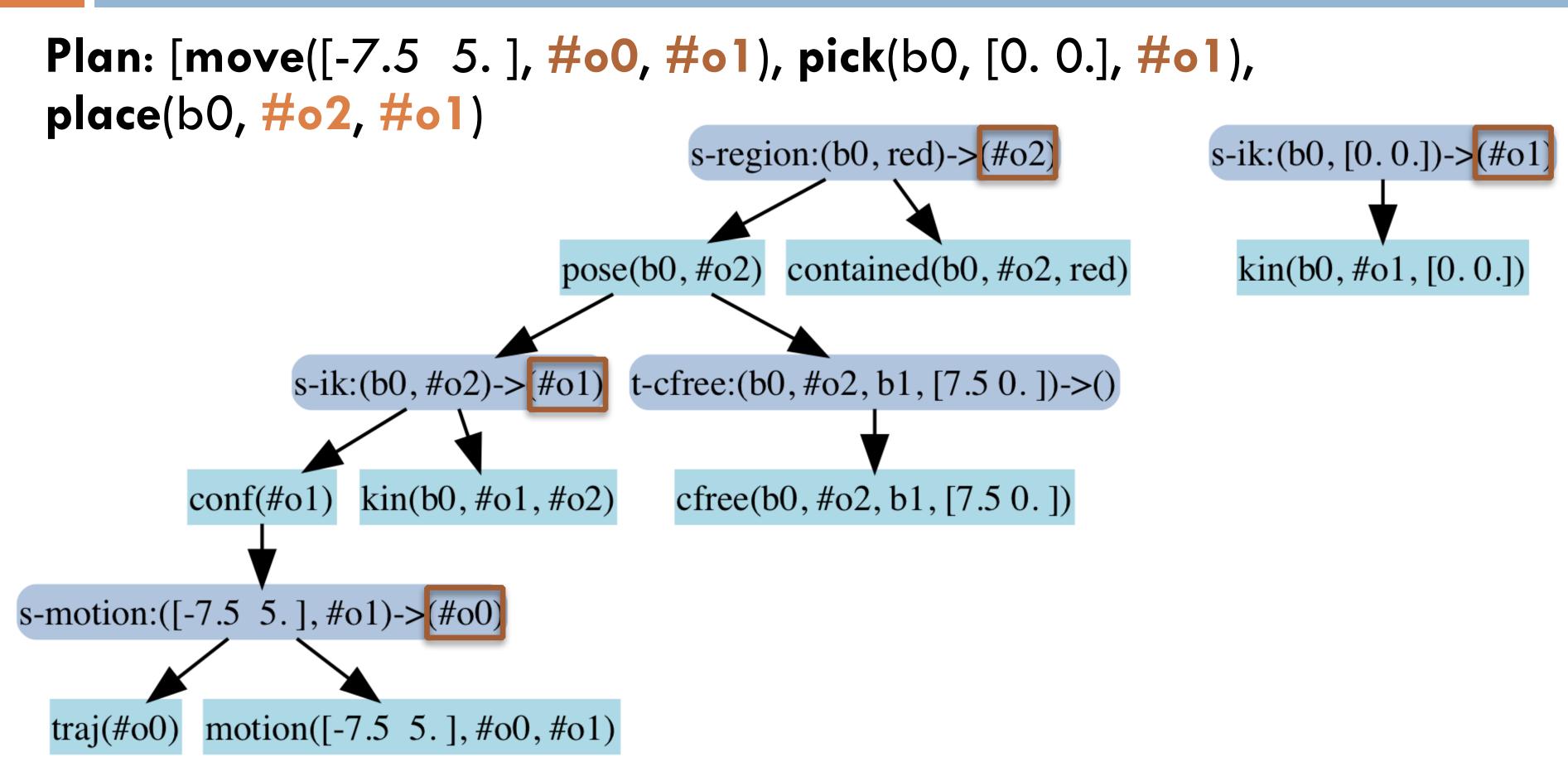
- 1. **s-region**:(b1, grey)->[([2.88 0.])]
- 2. t-cfree:(b1, [2.88 0.], b0, [0. 0.])->[()], t-cfree:(b0, [7.65 0.], b1, [2.88 0.])->[()]
- 3. s-ik:(b0, [7.65 0.])->[([7.65 2.5])], s-ik:(b1, [7.5 0.])->[([7.5 2.5])]
- 4. s-ik:(b1, [2.88 0.])->[([2.88 2.5])], s-ik:(b0, [0. 0.])->[([0. 2.5])]
- 5. s-motion:([7.5 2.5], [2.88 2.5])->[([[7.5 2.5], [7.5 5.], [2.88 5.], [2.88 2.5])]
- 6. s-motion:([-7.5 5.], [7.5 2.5])->[([[-7.5 5.], [-7.5 5.], [7.5 5.], [7.5 2.5]])]
- 7. s-motion:([0. 2.5], [7.65 2.5])->[([[0. 2.5], [0. 5.], [7.65 5.], [7.65 2.5])]
- 8. s-motion:([2.88 2.5], [0. 2.5])->[([[2.88 2.5], [2.88 5.], [0. 5.], [0. 2.5]])]

Shared Optimistic Objects

- Focused still makes a large number of optimistic objects
 - Induce large discrete planning problems
- While many objects could be created, only a few will be used on a solution
- Let optimistic objects be the output of several streams
 - Typically overly optimistic, resolve through differentiation and additional search

- For example: single object #01 for each s-ik input
 - -s-ik:(b0, #o2)->(#o1)
 - s-ik:(b0, [0.0.])->(#o1)

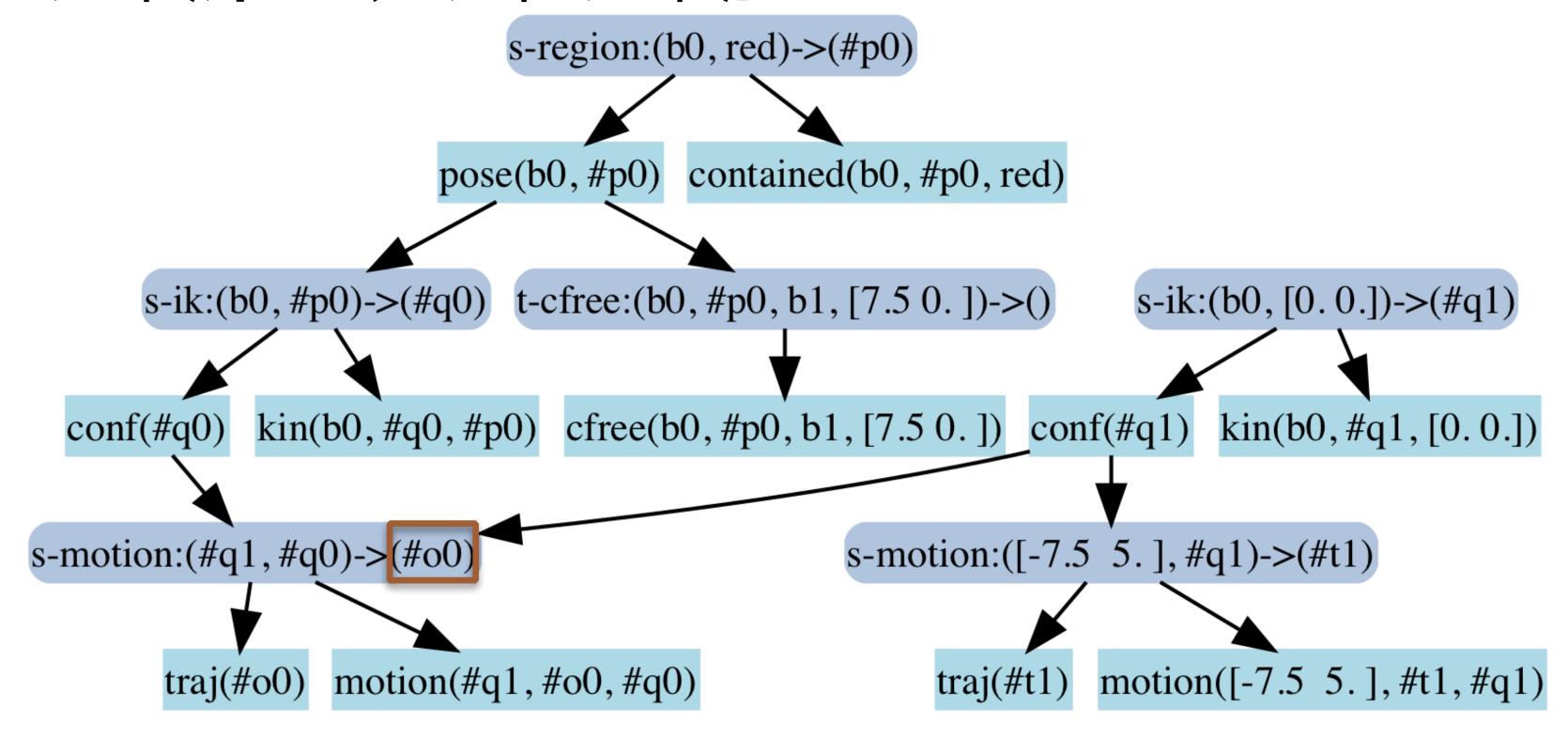
Focused Refinement: Step 1



Unique optimistic objects are created for: s-region:(b0, red)->(#o2), s-ik:(b0, [0. 0.])->(#o1)

Focused Refinement: Step 2

Plan: [move([-7.5 5.], #t1, #q1), pick(b0, [0. 0.], #q1), move(#q1, #o0, #q0), place(b0, #p0, #q0)]



Unique optimistic objects are created for:

s-motion:(#q1, #q0)->(#o0)

Focused Refinement: Step 3

```
Plan: [move([-7.5 5.], #t1, #q1), pick(b0, [0. 0.], #q1),
move(#q1, #t2, #q0), place(b0, #p0, #q0)]
                               s-region:(b0, red)->(#p0)
                            pose(b0, #p0) contained(b0, #p0, red)
           s-ik:(b0, #p0)->(#q0) t-cfree:(b0, #p0, b1, [7.5 0.])->()
                                                                   s-ik:(b0, [0.0.])->(\#q1)
                 kin(b0, #q0, #p0) cfree(b0, #p0, b1, [7.5 0.]) conf(#q1) kin(b0, #q1, [0. 0.])
     s-motion: (\#q1, \#q0) - (\#t2)
                                                  s-motion:([-7.5 5.], #q1)->(#t1)
             traj(#t2) motion(#q1, #t2, #q0)
                                                        traj(#t1) motion([-7.5 5.], #t1, #q1)
```

No more shared optimistic objects!

Focus proceeds as previously described

Theoretical Analysis

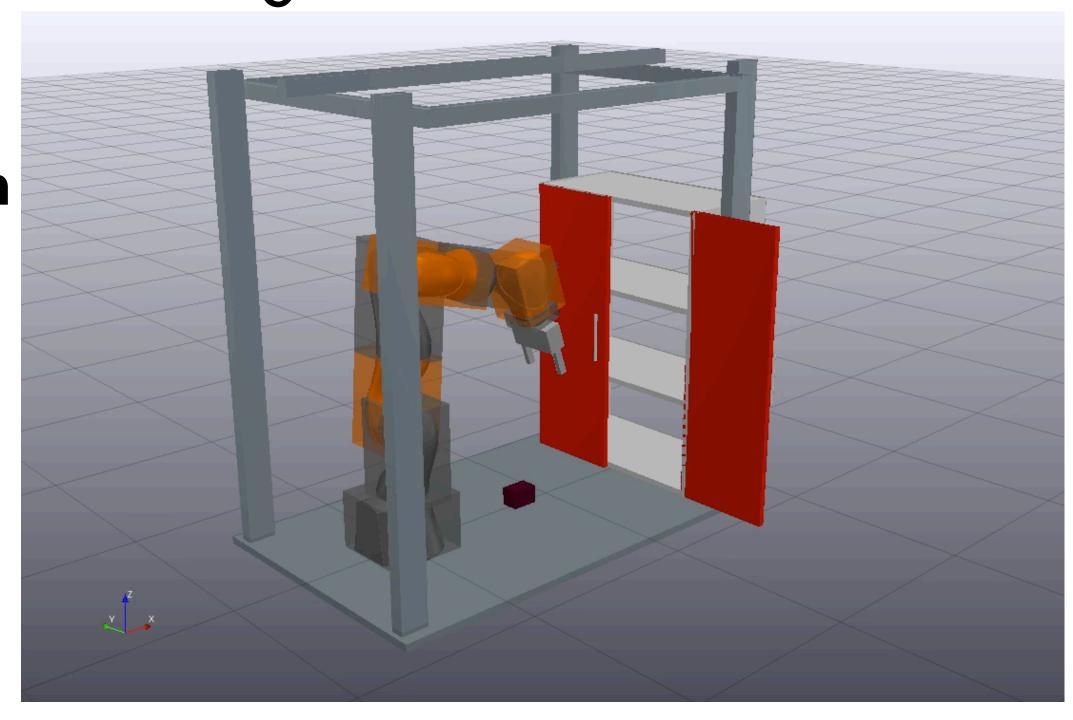
- PDDLStream plan existence is undecidable but semidecidable
 - Can encode halting problem within a stream
- Incremental and focused algorithms are semi-complete
 - Find a plan if streams will eventually produce one

- For TAMP, can lead to resolution complete and probabilistically complete algorithms
 - If robustly feasible, will find a plan with probability 1
 - Streams are part of the algorithm instead of input

Extensions

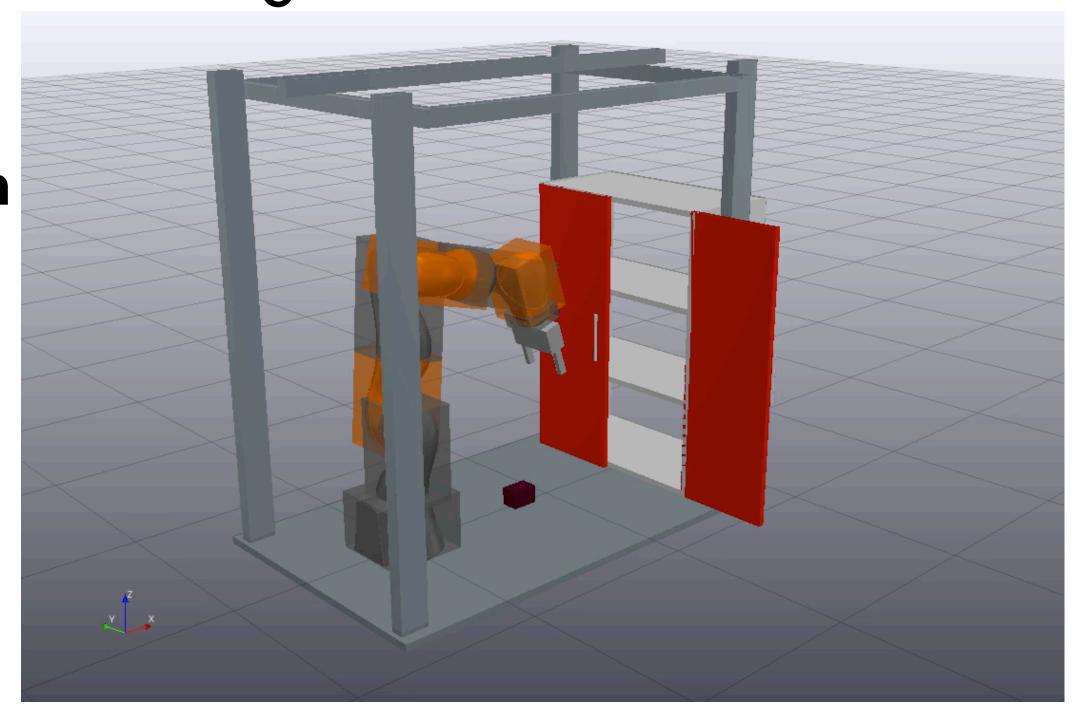
PDDLStream + Drake

- Goal: brick on the second cupboard shelf and robot
 + doors at initial joint positions
- Must open the left door to safely place and then close
- No need to manipulate the right door
- 1. Visual object detections
- 2. Point cloud pose estimation
- 3. **Solve** a TAMP problem to obtain joint trajectories
- 4. Convert to iiwa splines & gripper set points
- 5. Execute using controllers



PDDLStream + Drake

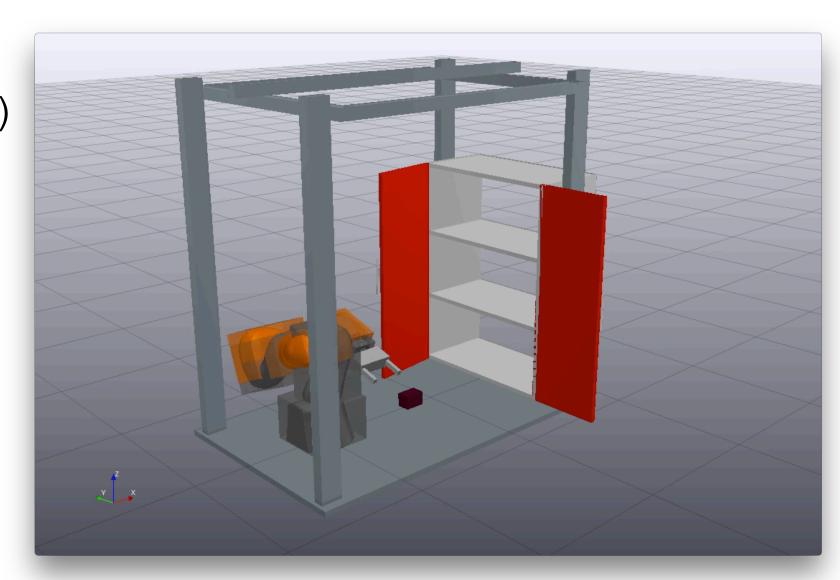
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- Problem formulation is very similar to the 2D pickand-place example
 - Configurations & poses simply have more DOFs

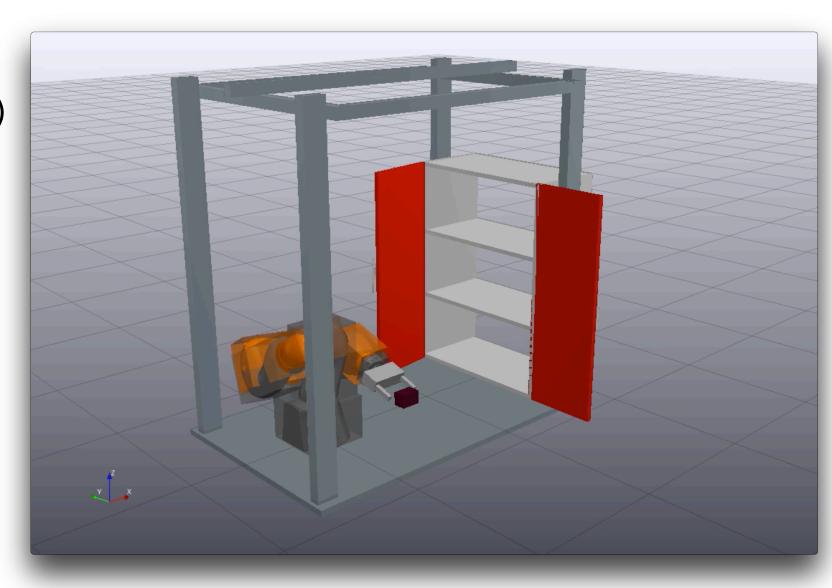
- Problem formulation is very similar to the 2D pickand-place example
 - Configurations & poses simply have more DOFs

```
(:action place
  :parameters (?r ?o ?p ?g ?q ?t)
  :precondition (and (Kin ?r ?o ?p ?g ?q ?t)
                 (AtGrasp ?r ?o ?g)
                 (AtConf ?r ?q)
                 (not (UnsafeTraj ?t)))
  :effect (and (AtPose ?o ?p)
          (HandEmpty ?r)
          (not (AtGrasp ?r ?o ?g))))
(:action pull
...; TODO: implementation
```



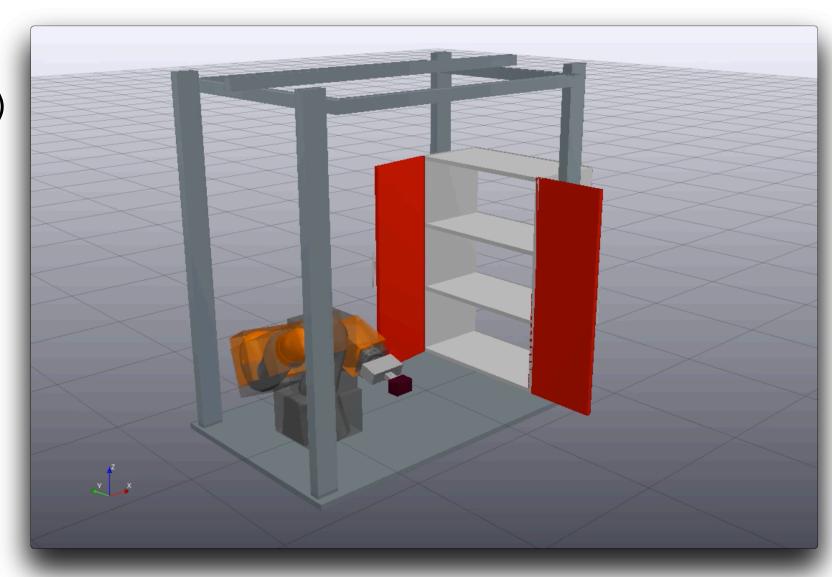
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```
(:action place
  :parameters (?r ?o ?p ?g ?q ?t)
  :precondition (and (Kin ?r ?o ?p ?g ?q ?t)
                 (AtGrasp ?r ?o ?g)
                 (AtConf ?r ?q)
                 (not (UnsafeTraj ?t)))
  :effect (and (AtPose ?o ?p)
          (HandEmpty ?r)
          (not (AtGrasp ?r ?o ?g))))
(:action pull
...; TODO: implementation
```



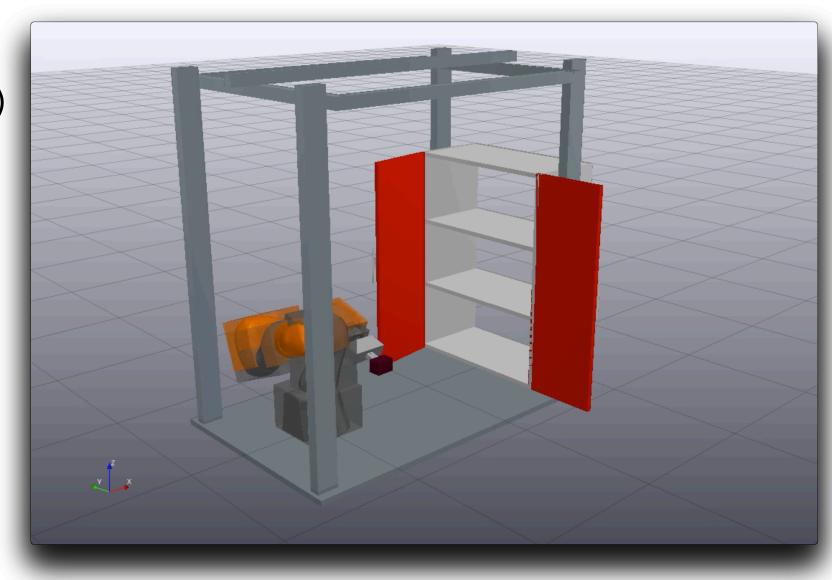
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```
(:action place
  :parameters (?r ?o ?p ?g ?q ?t)
  :precondition (and (Kin ?r ?o ?p ?g ?q ?t)
                 (AtGrasp ?r ?o ?g)
                 (AtConf ?r ?q)
                 (not (UnsafeTraj ?t)))
  :effect (and (AtPose ?o ?p)
          (HandEmpty ?r)
          (not (AtGrasp ?r ?o ?g))))
(:action pull
...; TODO: implementation
```



- Problem formulation is very similar to the 2D pickand-place example
 - Configurations & poses simply have more DOFs

```
(:action place
  :parameters (?r ?o ?p ?g ?q ?t)
  :precondition (and (Kin ?r ?o ?p ?g ?q ?t)
                 (AtGrasp ?r ?o ?g)
                 (AtConf ?r ?q)
                 (not (UnsafeTraj ?t)))
  :effect (and (AtPose ?o ?p)
          (HandEmpty ?r)
          (not (AtGrasp ?r ?o ?g))))
(:action pull
...; TODO: implementation
```



PDDLStream + Drake Streams

- Stream implementations have similar declarations but more complex Python implementations
 - Randomize initial guess to sample many solutions

```
(:stream inverse-kinematics
  :inputs (?r ?o ?p ?g)
  :domain (and (Robot ?r) (Pose ?o ?p) (Grasp ?o ?q))
  :outputs (?q ?t)
  :certified (and (Conf ?r ?q) (Traj ?t) (Kin ?r ?o ?p ?g ?q ?t)))
   from pydrake.multibody.inverse_kinematics import InverseKinematics
   def get_ik_gen_fn(diagram, context, plant, scene_graph):
       def get_fn(robot_name, obj_name, obj_pose, obj_grasp):
           robot_model = plant.GetModelInstanceByName(robot_name)
           obj_model = plant.GetModelInstanceByName(obj_name)
          while True:
               ik_scene = InverseKinematics(plant)
               ... # TODO: implementation
              yield (robot_conf, robot_traj)
       return get_fn
```

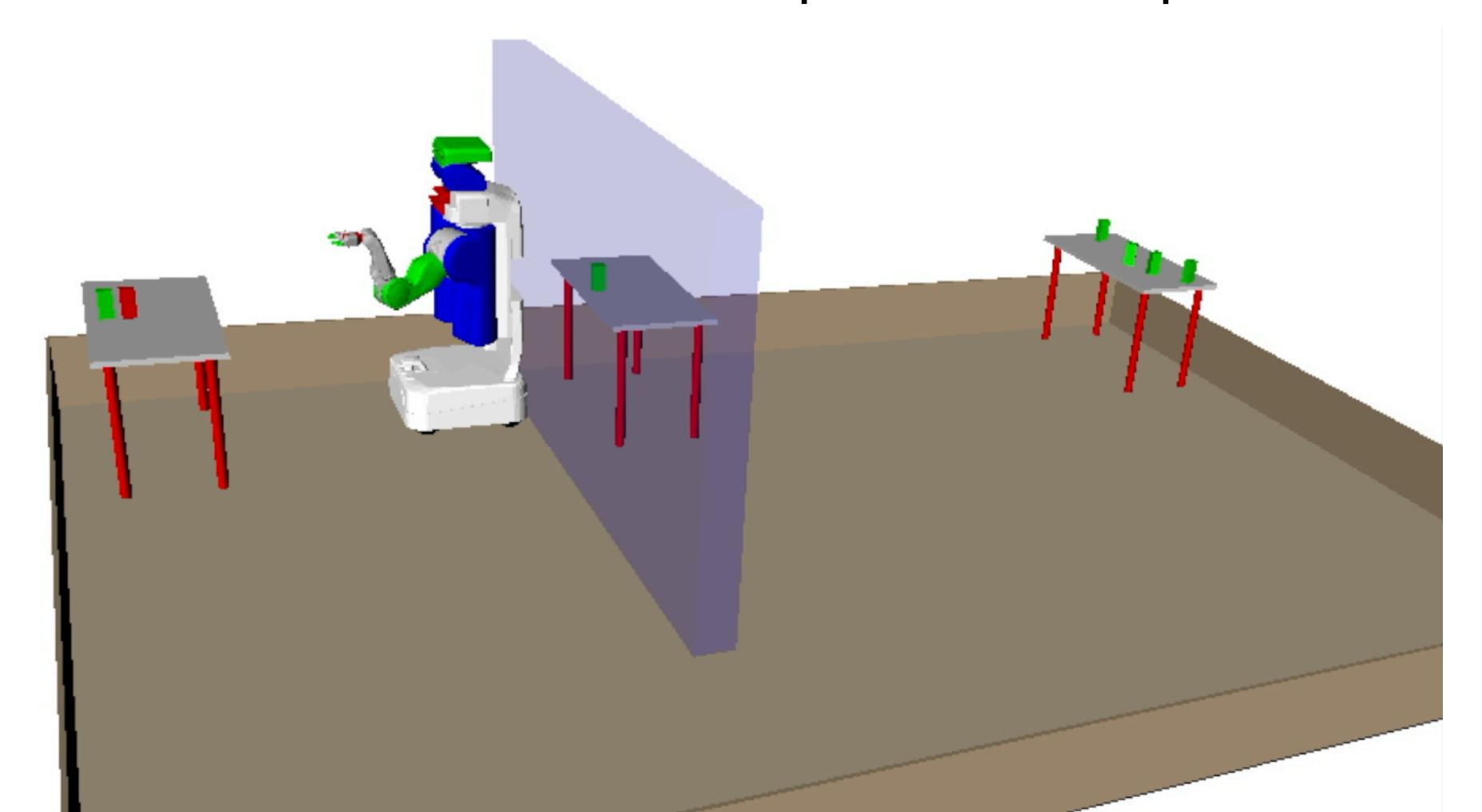
Cost-Sensitive Planning

Actions may have costs specified as nonnegative functions

Function specification similar to derived predicates

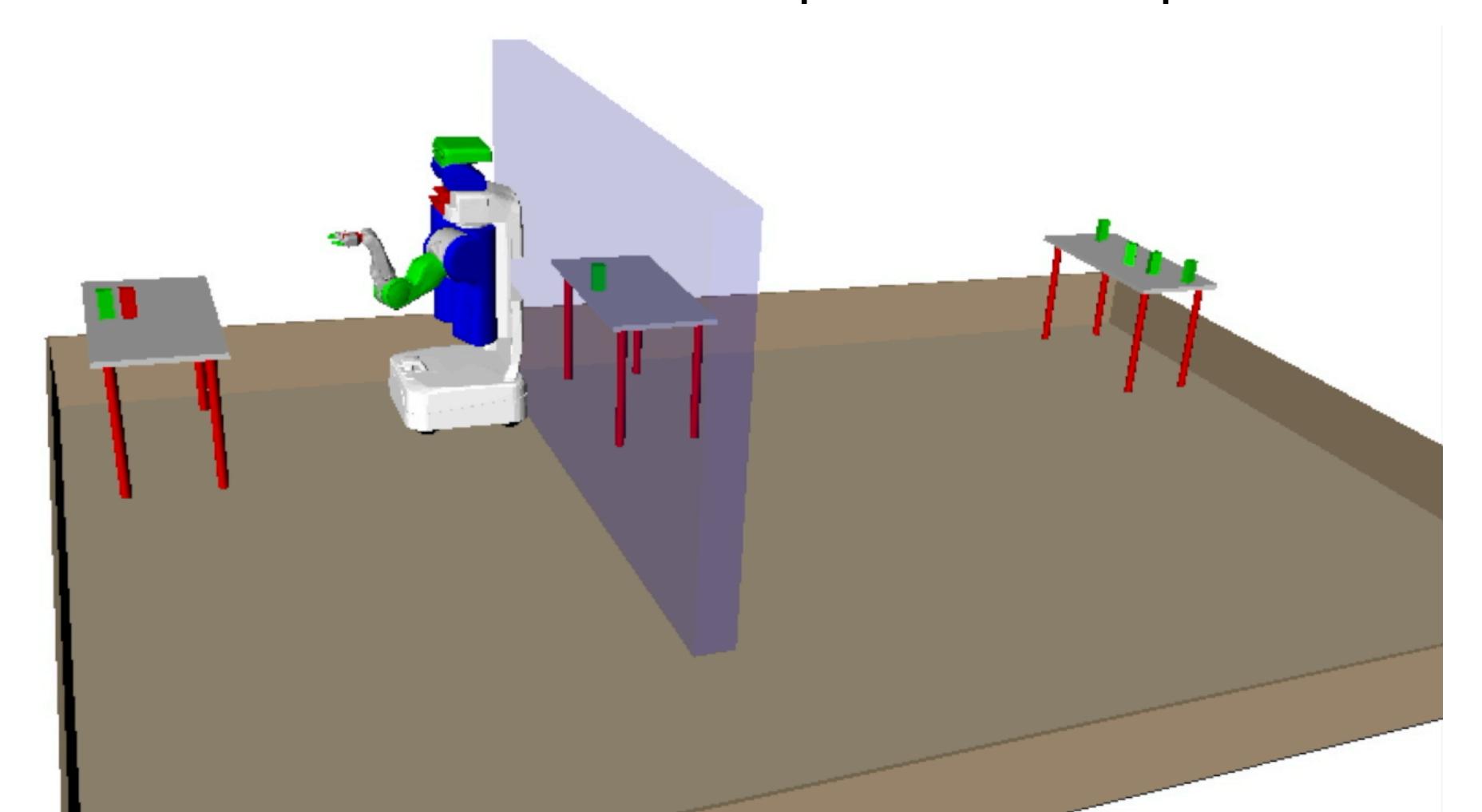
Goal: Hold Any Green Block

Lower bounds on costs improve focused performance



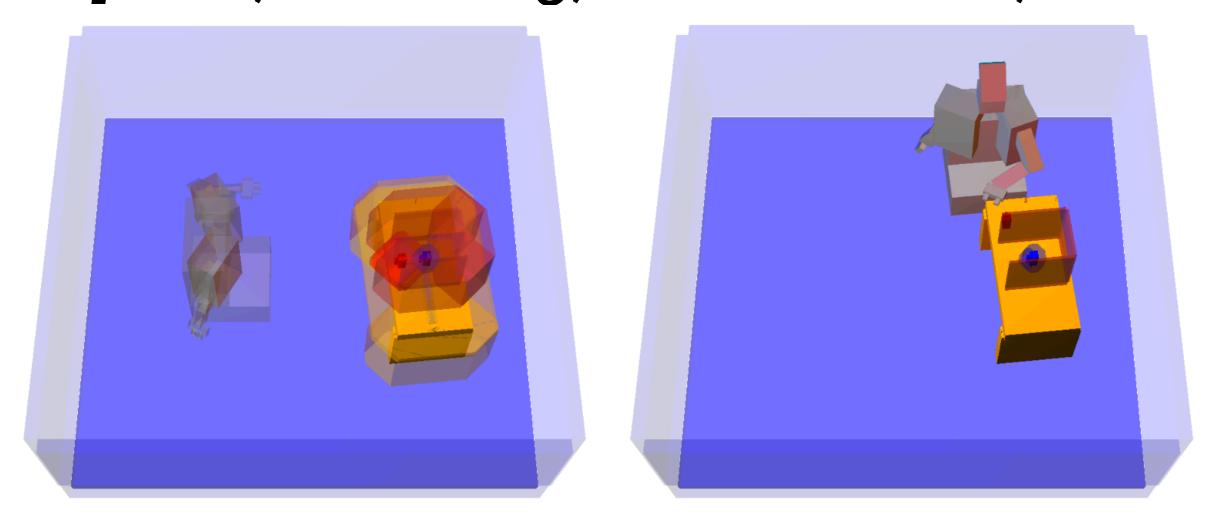
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Lower bounds on costs improve focused performance

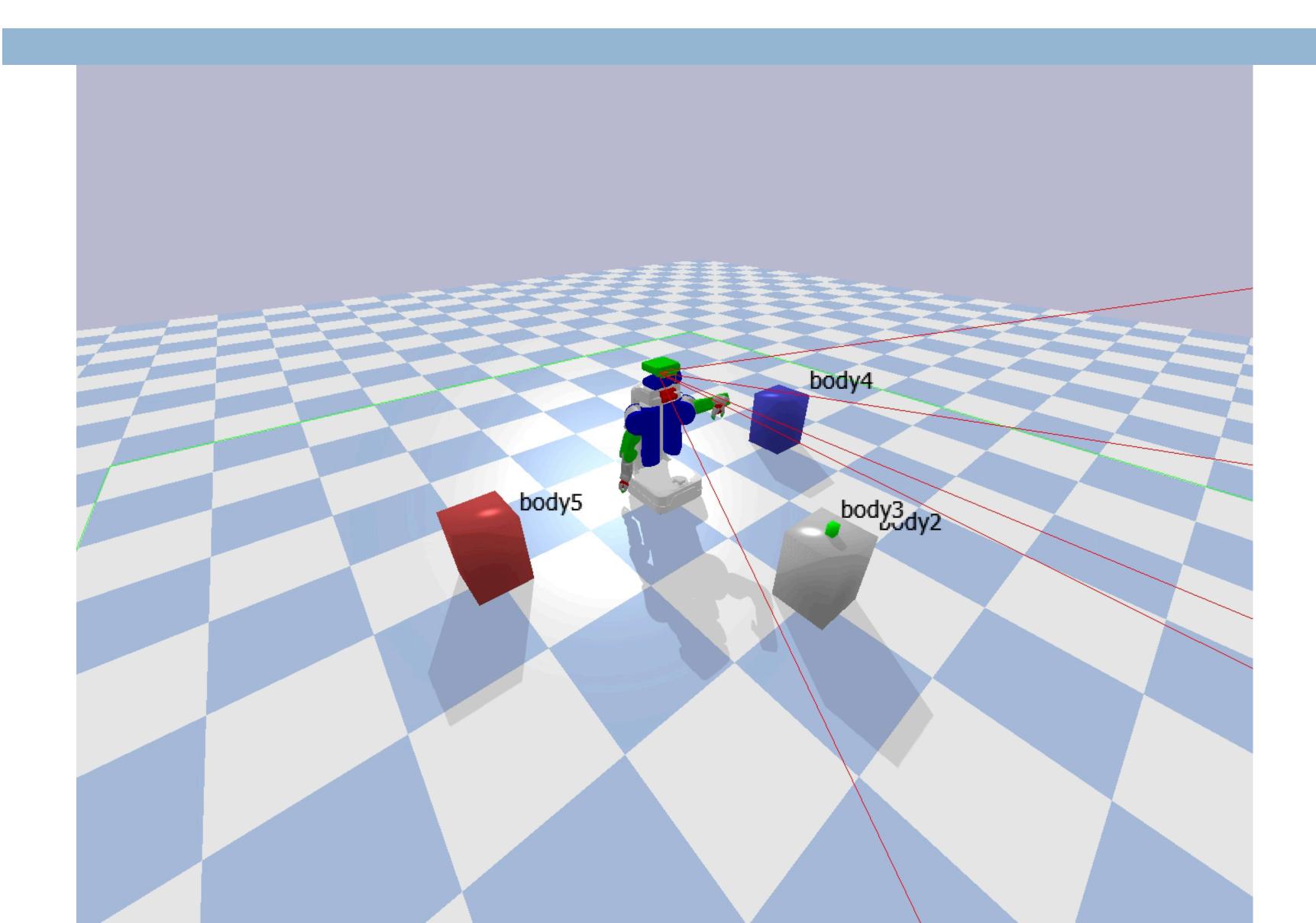


Planning in the Real World

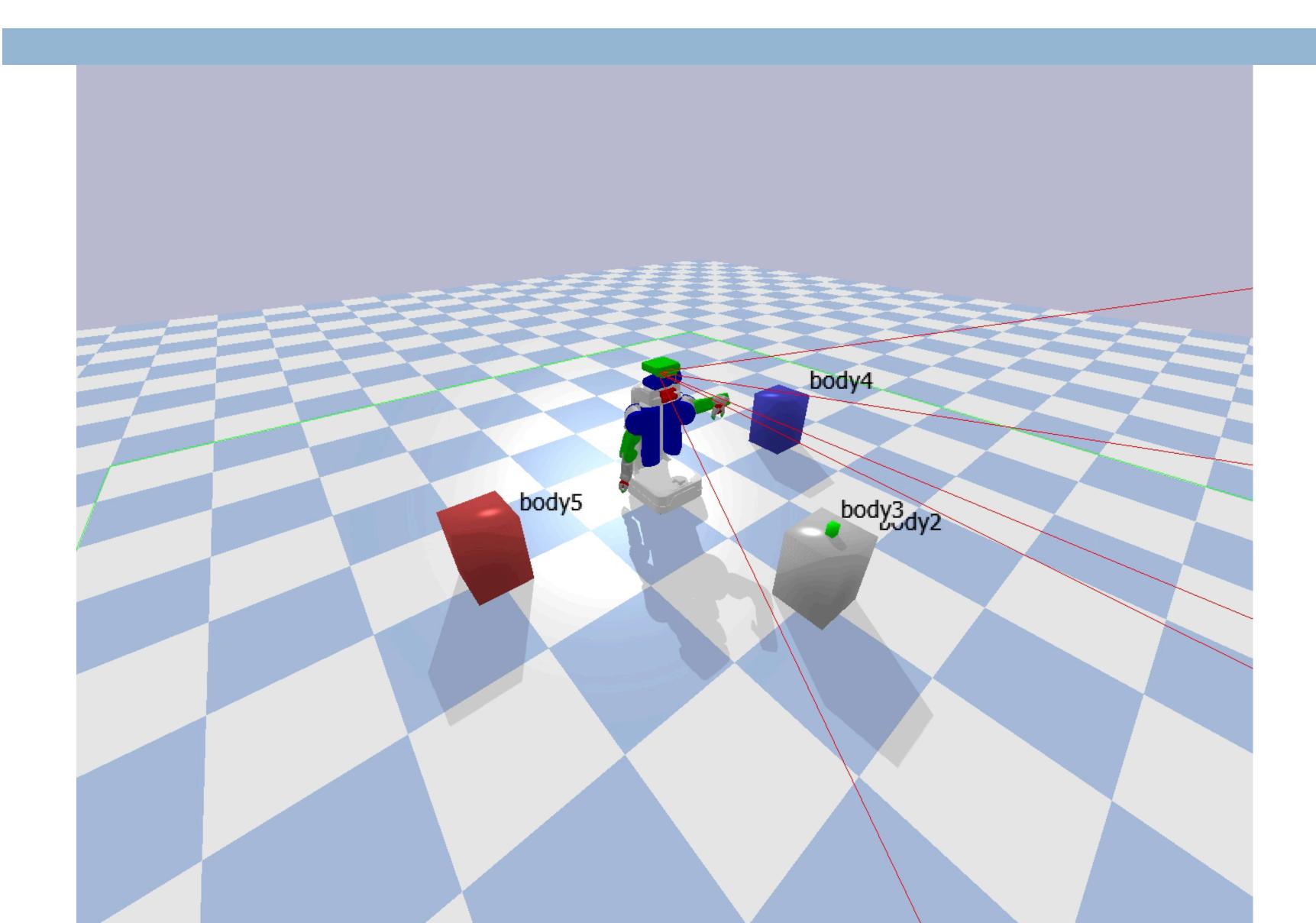
- Nondeterministic outcomes stochastic effects
- Partial observability
 - The true state is unknown. Must perform inference.
- Belief space planning (11/29/18)
 - Update and control a probability distribution over states [Platt, Kaelbling, Lozano-Perez, Tedrake]



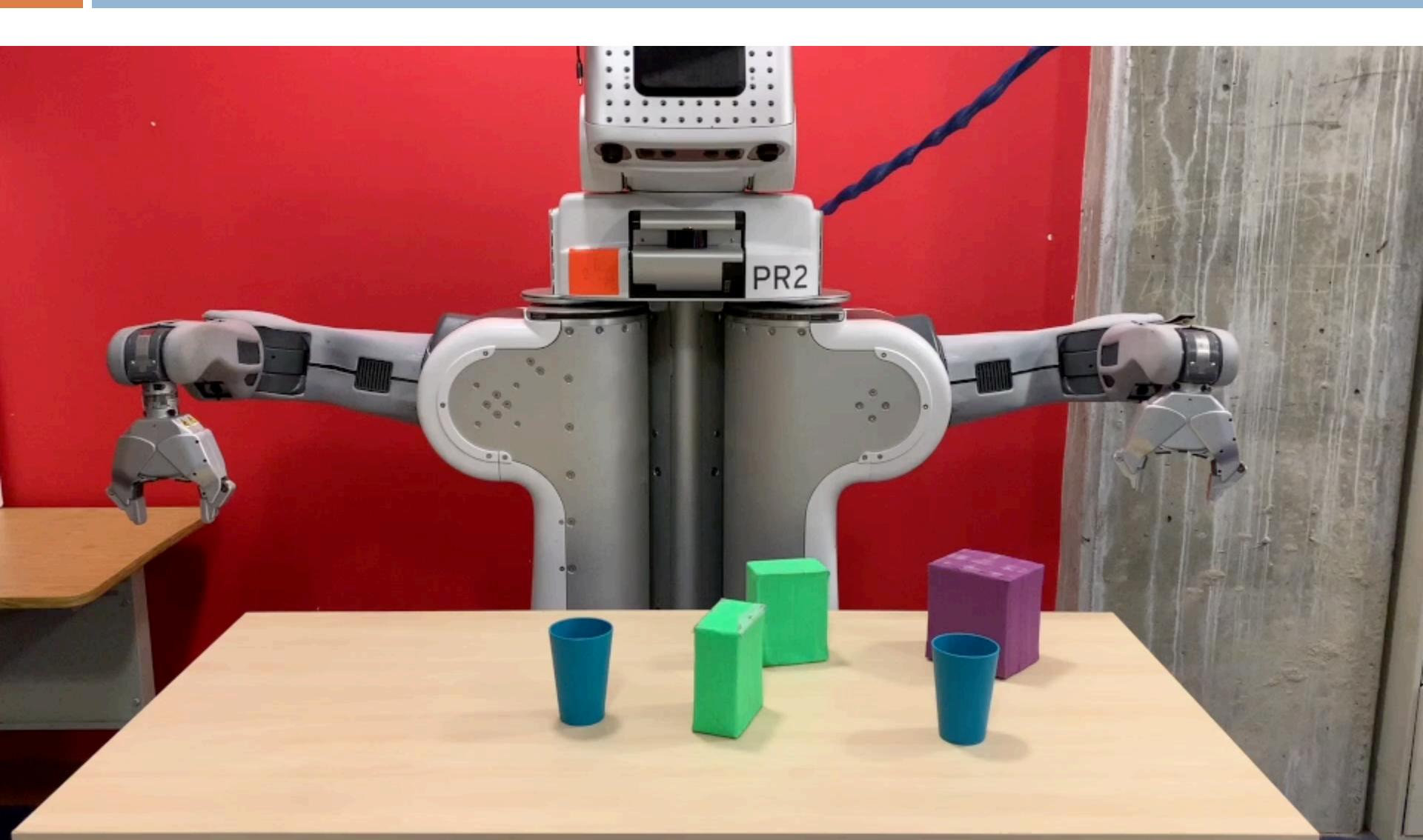
Observing, Planning, & Executing



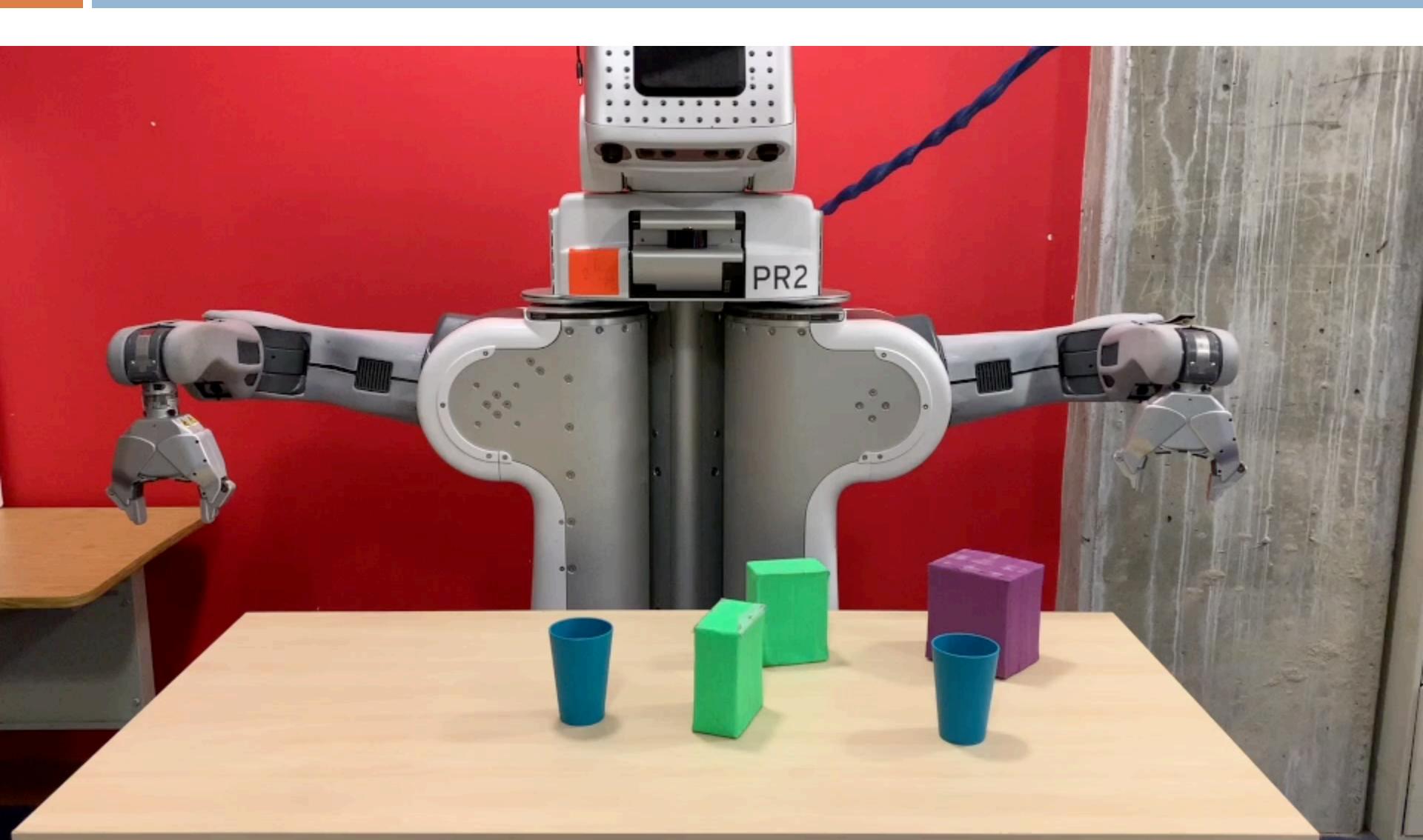
Observing, Planning, & Executing



PR2 Manipulation Outtakes



PR2 Manipulation Outtakes



PR2 Manipulation Outtakes

