Using Classical Planners for Tasks with Continuous Actions in Robotics

Stuart Russell

Joint work with Siddharth Srivastava, Lorenzo Riano, Pieter Abbeel

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Real work done by
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Outline

- Can we apply classical planners to robotics problems?
  - Challenges: continuous action arguments, geometric reasoning
- Main ideas:
  - Symbolic references to continuous values
  - Optimistic model with symbolic corrections from low-level geometric motion planner, followed by replanning
- Why does this idea work? Can it be generalized?
  - Roughly analogous to theorem-proving with quantifier elimination
  - Current algorithm complete under strong assumptions
- Will it work for real-world problems?
  - Results on PR2 simulator, PR2

Combining Task and Motion Planners

- Discrete/classical planners:
  + Effective algorithms for combinatorial discrete spaces (e.g., automated heuristic generation)
  – Not directly applicable to continuous spaces
- Continuous/motion planners:
  + Effective algorithms for high-dimensional continuous space (e.g., PRM, RRT)
  – Not directly applicable to discrete spaces induced by contact changes (e.g., pickup/putdown)

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- Continuous/motion planners:
  - + Effective algorithms for high-dimensional continuous space (e.g., PRM, RRT)
  - – Not directly applicable to discrete spaces induced by contact changes (e.g., pickup/putdown)
- Obvious solution:
  - Use task planner for discrete actions
  - Implement those actions using continuous planner

Discrete blocks-world PickUp

PickUp(block1):

precondition $OnTable(block1) \wedge Empty(gripper)$

effect $Holding(block1) \wedge$
$\neg\ OnTable(block1) \wedge$
$\neg\ Empty(gripper)$

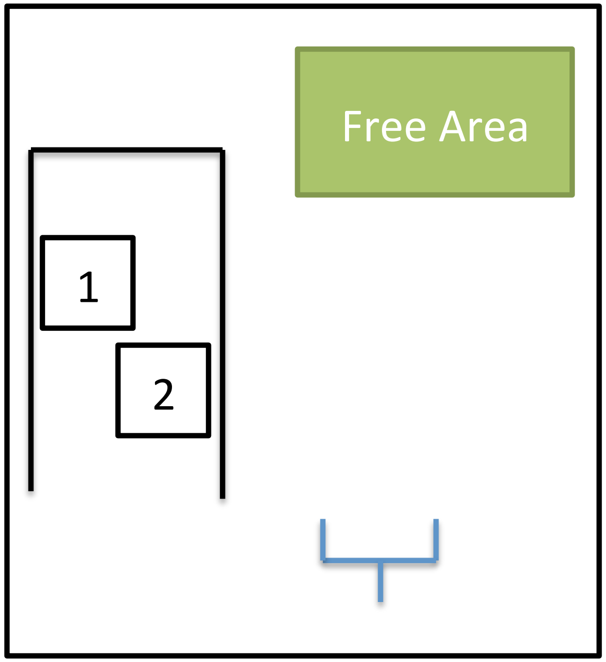
Geometric locations of robot, hand, or object
not considered

A Continuous Version of Blocks World

PickUp(b1, l1, l2, l3, p):

precondition GripperAt(l1) ∧
Empty(gripper) ∧
IsGraspingPose(l2, b1) ∧
At(b1, l3) ∧
∀b2 ¬ Obstructs(b2, p, l1, l2)

effect Holding(b1) ∧
¬ At(b1, l3) ∧
¬ Empty(gripper) ∧
GripperAt(l2)



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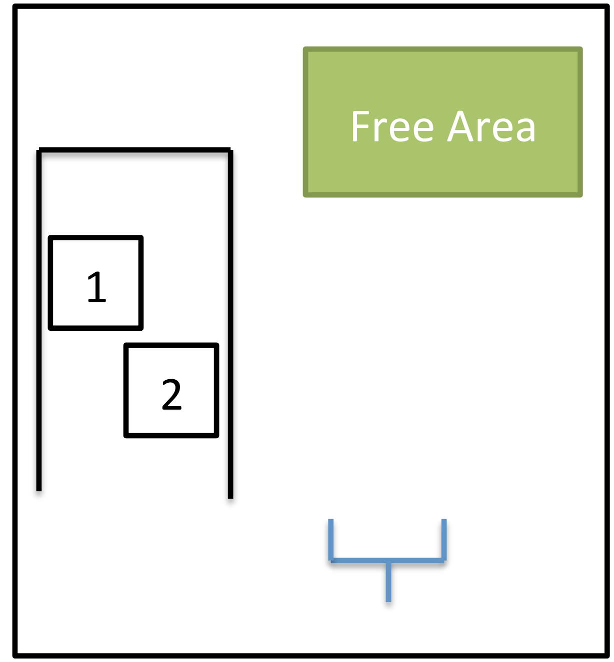

Oops: infinitely many facts, infinite branching factor

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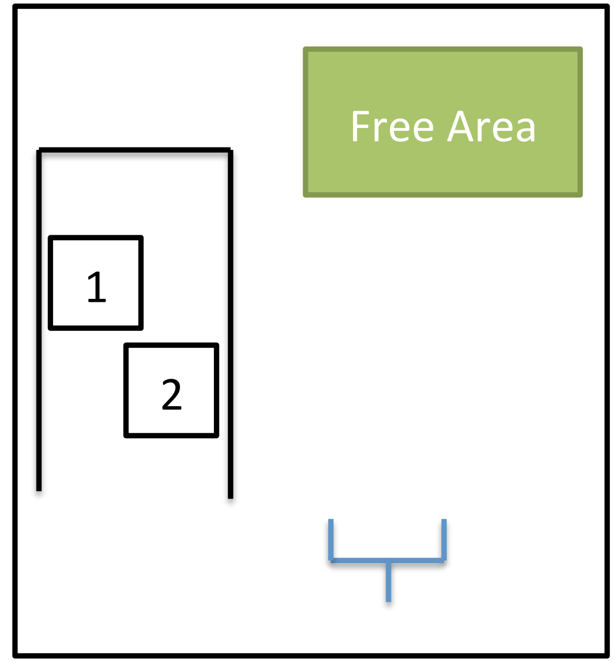
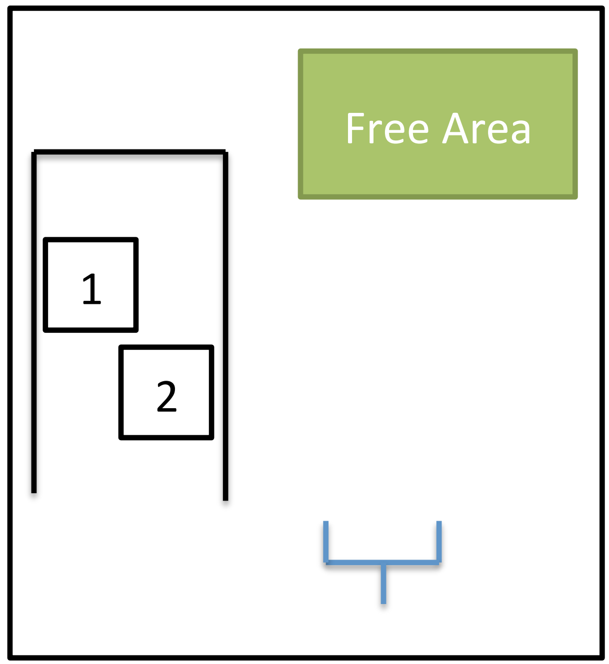


Oops: infinitely many facts, infinite branching factor

Solution: discretization

Discretization

- 10 points each in x, y
- Precompute
  - IsGraspingPose(l, b)
  - Obstructs(b, p, l1, l2)
- 5 objects = 50,000 facts



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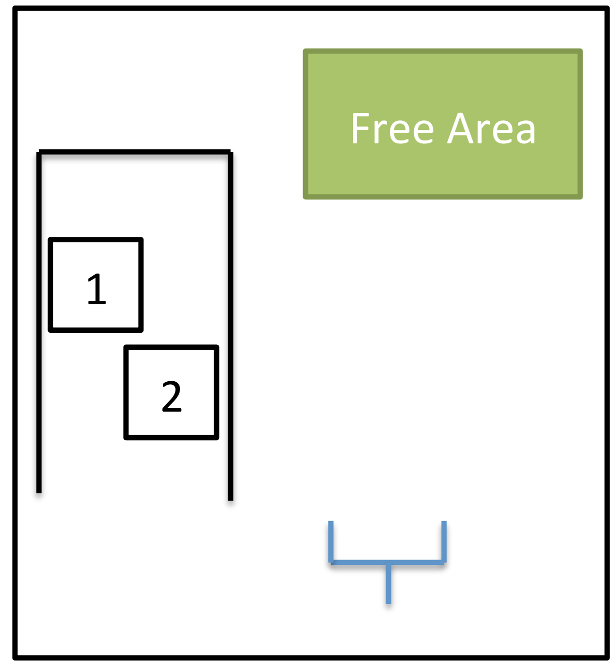
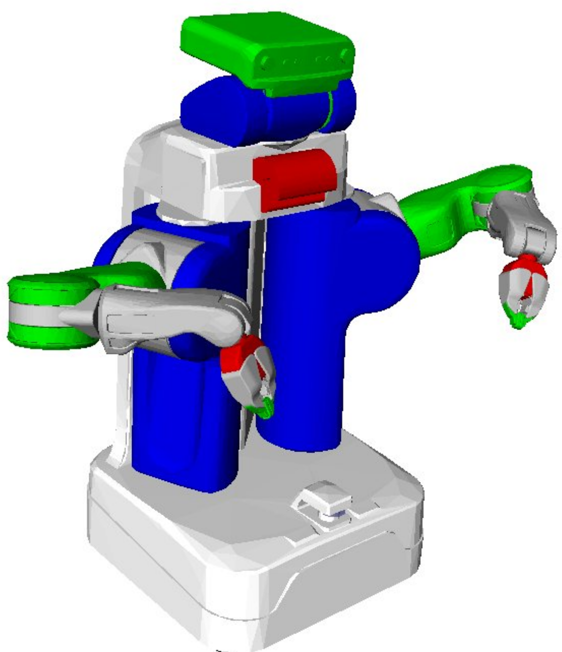
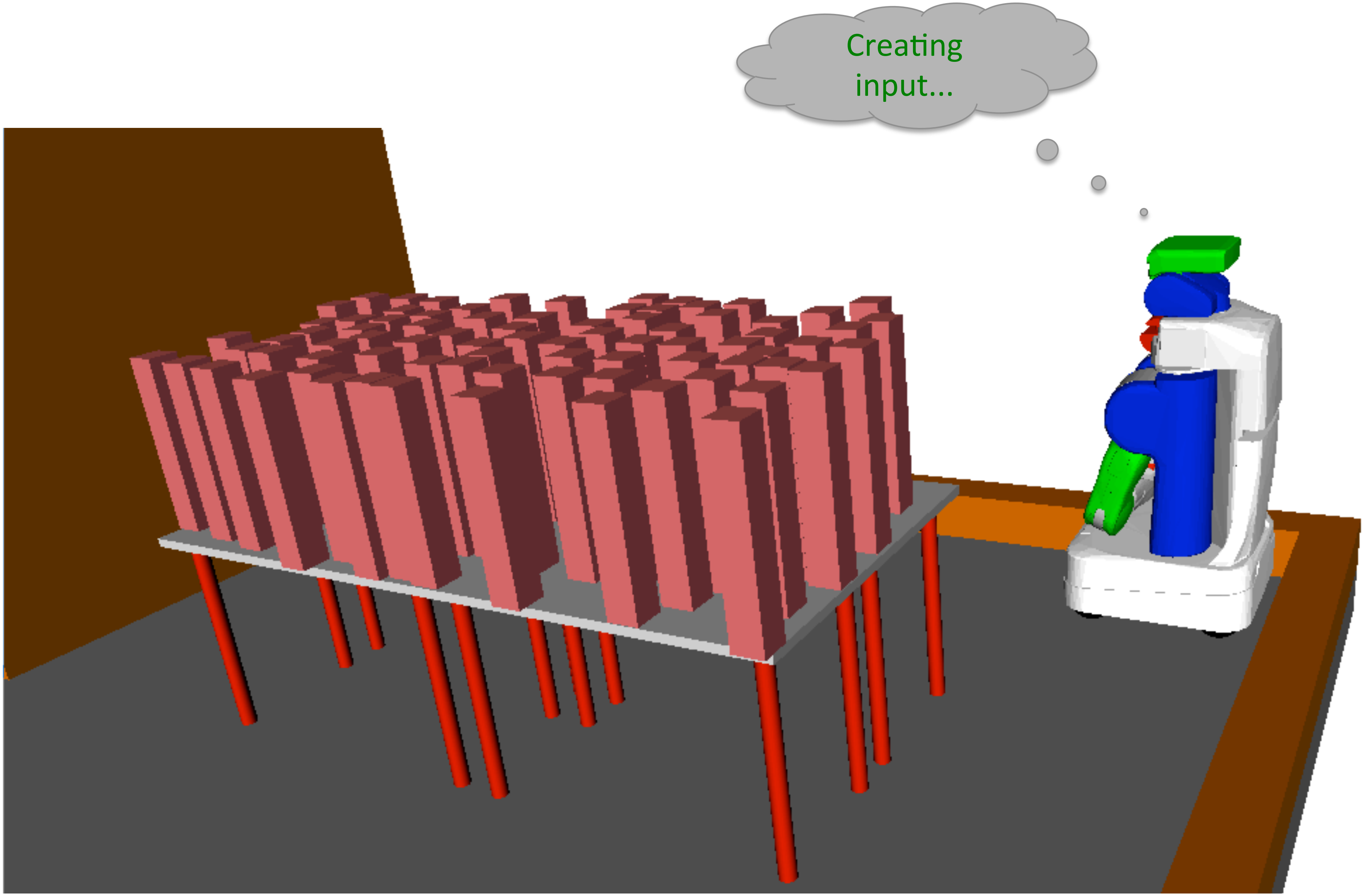




7DOF arm + 4DOF base/torso + 80 objects =~ 10^{14} facts


Creating
input...

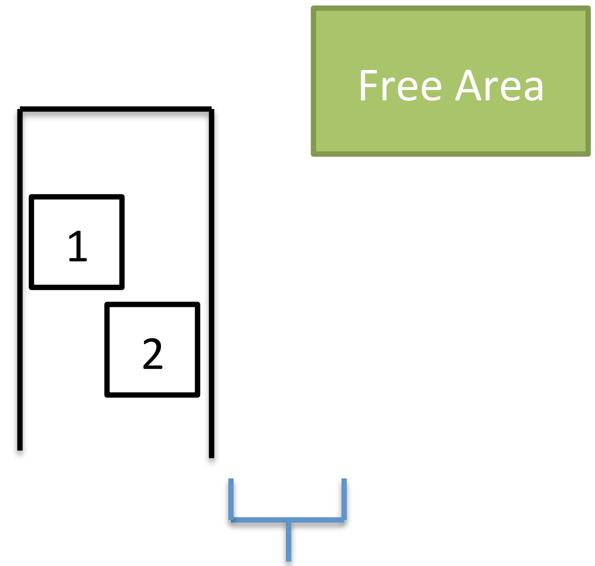
Our approach

- PDDL planner uses "location references"
  - Number of references depends on number of objects and on discrete plan size – no discretization
  - Low-level motion planner interprets these references
- Low-level infeasibility is re-expressed as new PDDL facts about obstructions
  - Expressed using location references
- PDDL planner replans with new information

A SIMPLE EXAMPLE

Discrete state: GripperAt(initLoc), At(block1, block1_loc), At(block2, block2_loc)

- High level intuitive plan:
  - pick block1 after going to its grasping pose



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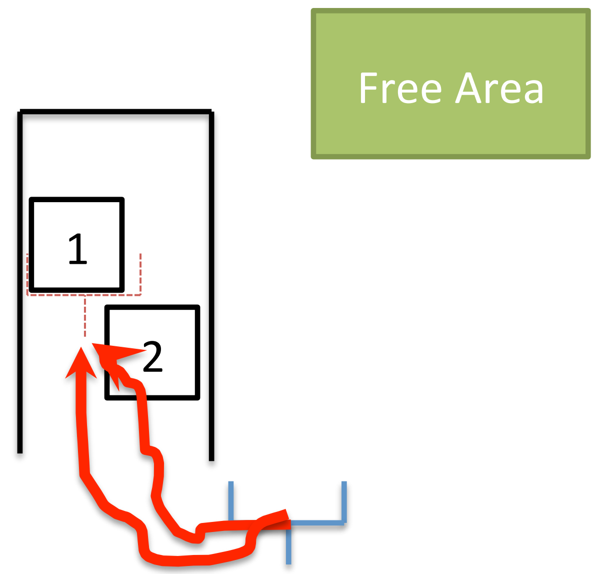
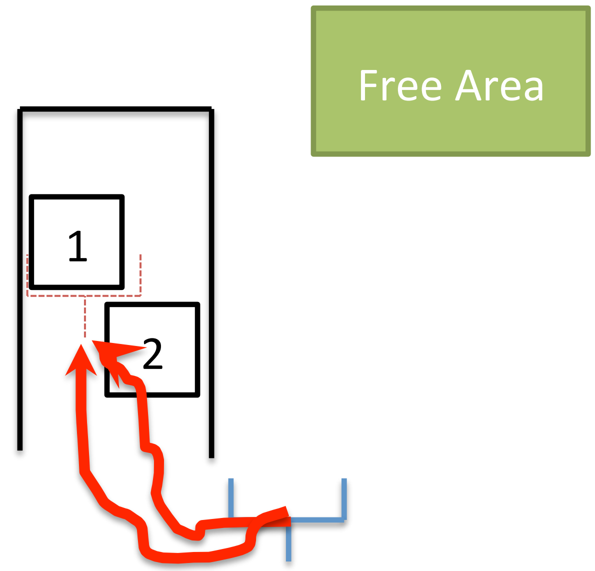


1. Low level instantiates a grasping pose for block 1 independent of other block
2. Low level searches for a motion plan to reach grasping pose; finds no collision-free solution

Discrete state += “block2 obstructs grasping pose for block1 in path from initial location”

- High level intuitive plan:
  - ~~pick block1 after going to its grasping pose~~

Failed



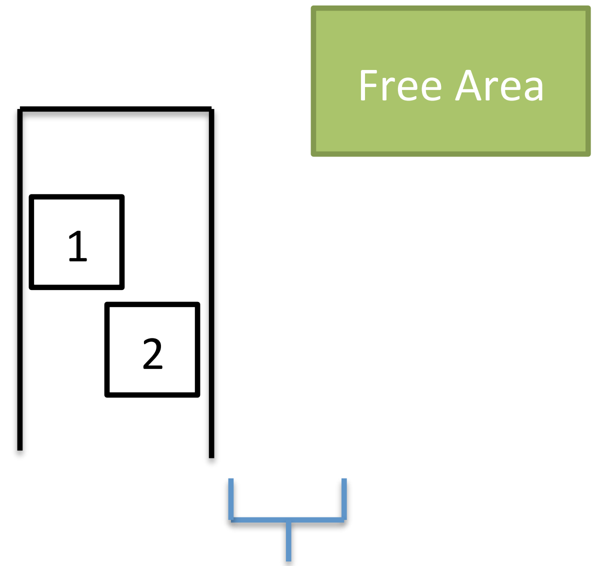
1. Low level instantiates a grasping pose for block 1 independent of other block
2. Low level searchers for a motion plan to reach grasping pose; finds no collision-free solution
3. Reports obstruction to high level

“block2 obstructs grasping pose for block1 from initial location”

Discrete state += “block2 obstructs grasping pose for block1 in path from initial location”

- High level intuitive plan:
  - ~~pick block1 after going to its grasping pose~~

  REPLAN
  - pick block2 after going to its grasping pose
  - release block2 in after going to release pose for free area
  - pick block1 after going to its grasping pose



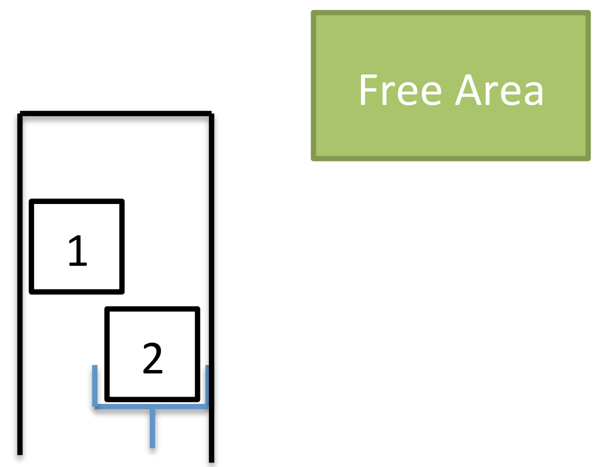
1. Low level instantiates a grasping pose for block 1 independent of other block
2. Low level searchers for a motion plan to reach grasping pose; finds no collision-free solution
3. Reports obstruction to high level
4. High level updates state, replans

Discrete state diff: GripperAt “grasping pose for block2”, Holding(block2)

- High level intuitive plan:
  - ~~pick block1 after going to its grasping pose~~

  REPLAN

  - pick block2 after going to its grasping pose
  - release block2 in after going to release pose for free area
  - pick block1 after going to its grasping pose

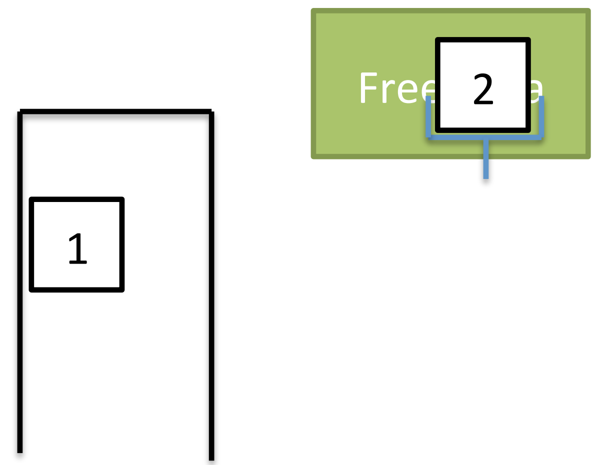


Discrete state diff: At(block2, FreeArea), Empty(gripper)

- High level intuitive plan:
  - ~~pick block1 after going to its grasping pose~~

  REPLAN

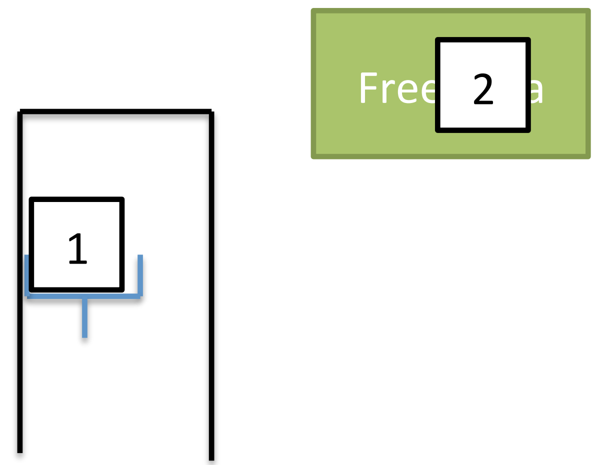
  - pick block2 after going to its grasping pose
  - release block2 in after going to release pose for free area
  - pick block1 after going to its grasping pose



Discrete state diff: GripperAt “grasping pose for 1”, Holding(block1)

- High level intuitive plan:
  - ~~pick block1 after going to its grasping pose~~

  REPLAN
  - pick block2 after going to its grasping pose
  - release block2 in after going to release pose for free area
  - pick block1 after going to its grasping pose



Goal Reached!

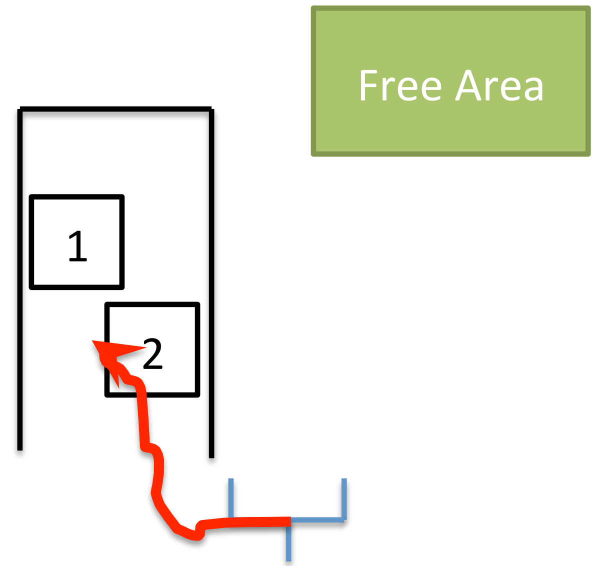
SAME EXAMPLE IN FORMAL SYNTAX

Discrete state += Obstructs(block2, initLoc, gp(block1), path(initLoc, gp(block1)))

- High level intuitive plan:
  - ~~PickUp(block1, initLoc, gp(block1), loc(block1),path(initLoc,gp(block1)))~~ Failed

  REPLAN

  - PickUp(block2, initLoc, gp(block2), loc(block2),path(initLoc,gp(block2)))
  - PutDown(gp(block2), free_area, rp(free_area),path(gp(block2), rp(free_area)))
  - PickUp(block1, rp(free_area), gp(block1), loc(block1), path(rp(free_area), gp(block1)))

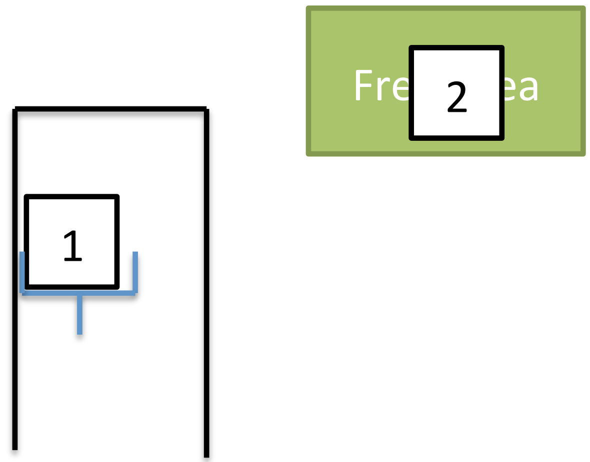


Discrete state diffs: GripperAt(gp(block1)), Empty(gripper), Holding(block1)

- High level intuitive plan:
  - ~~PickUp(block1, initLoc, gp(block1), loc(block1),path(initLoc,gp(block1)))~~

  REPLAN

  - PickUp(block2, initLoc, gp(block2), loc(block2),path(initLoc,gp(block2)))
  - PutDown(gp(block2), free_area, rp(free_area),path(gp(block2), rp(free_area)))
  - PickUp(block1, rp(free_area), gp(block1), loc(block1), path(rp(free_area), gp(block1)))



Goal Reached!

WHY DOES IT WORK??

Actions with Continuous Arguments

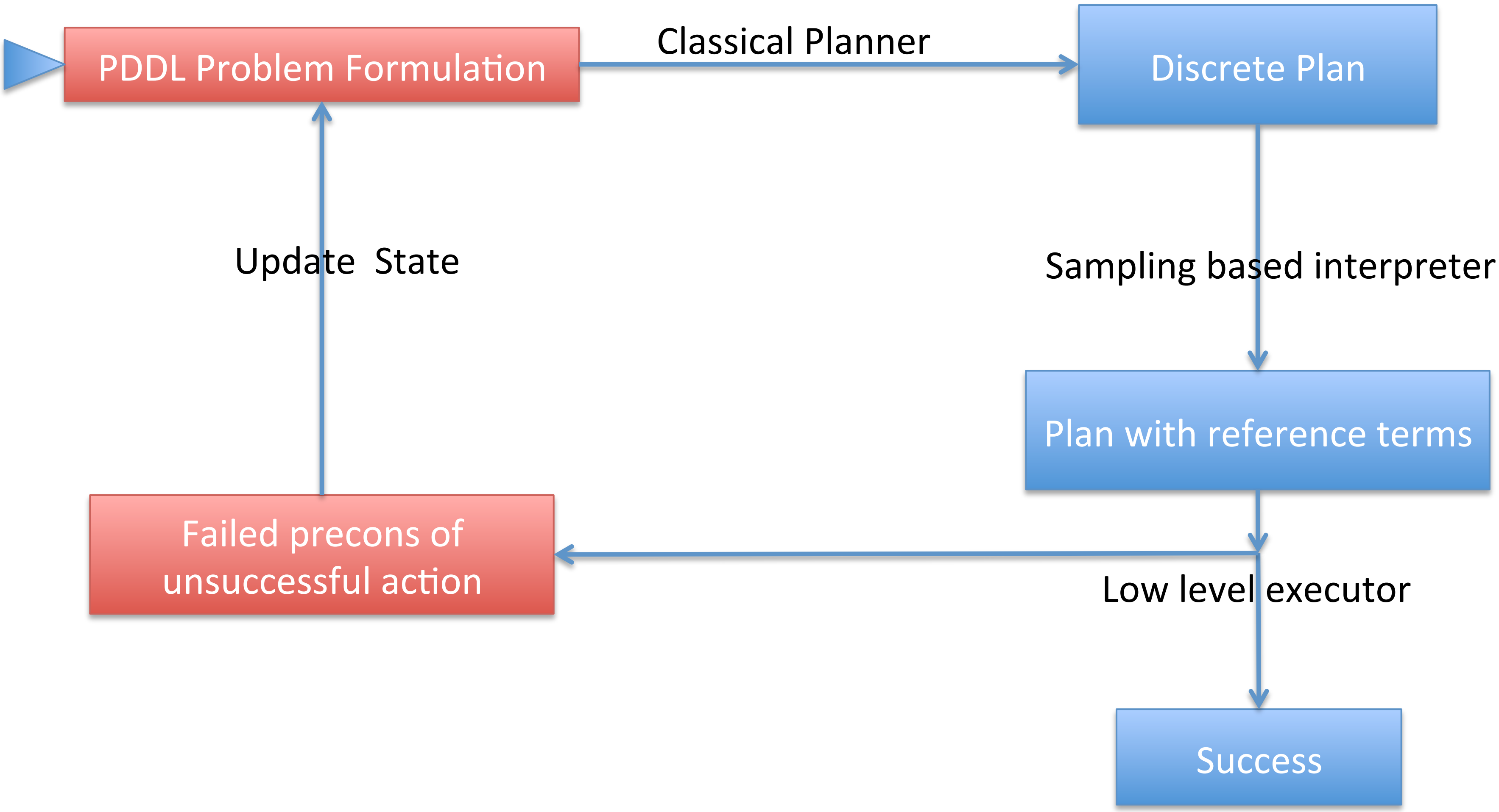
- Effect axioms for actions like "grasp" have the form

  $\forall x \forall y\ (p(x,y) \Rightarrow q(x) \wedge r(x,g(y)))$

  where p is the precondition, q is the post-condition

  x: object, y: continuous arguments
- In order to apply the action to achieve $q(x)$, need to find *some* y (from infinitely many) satisfying $p(x,y)$
- Treat low-level motion planner as an unknown function $f()$ s.t. $p(x, f(x))$ holds
- Planner can assume facts: $p(x, f(x))$ for each x
  - Treat "$f(x)$" like any other object in the world

Overall Approach



Sufficient Conditions for Guaranteed Solutions

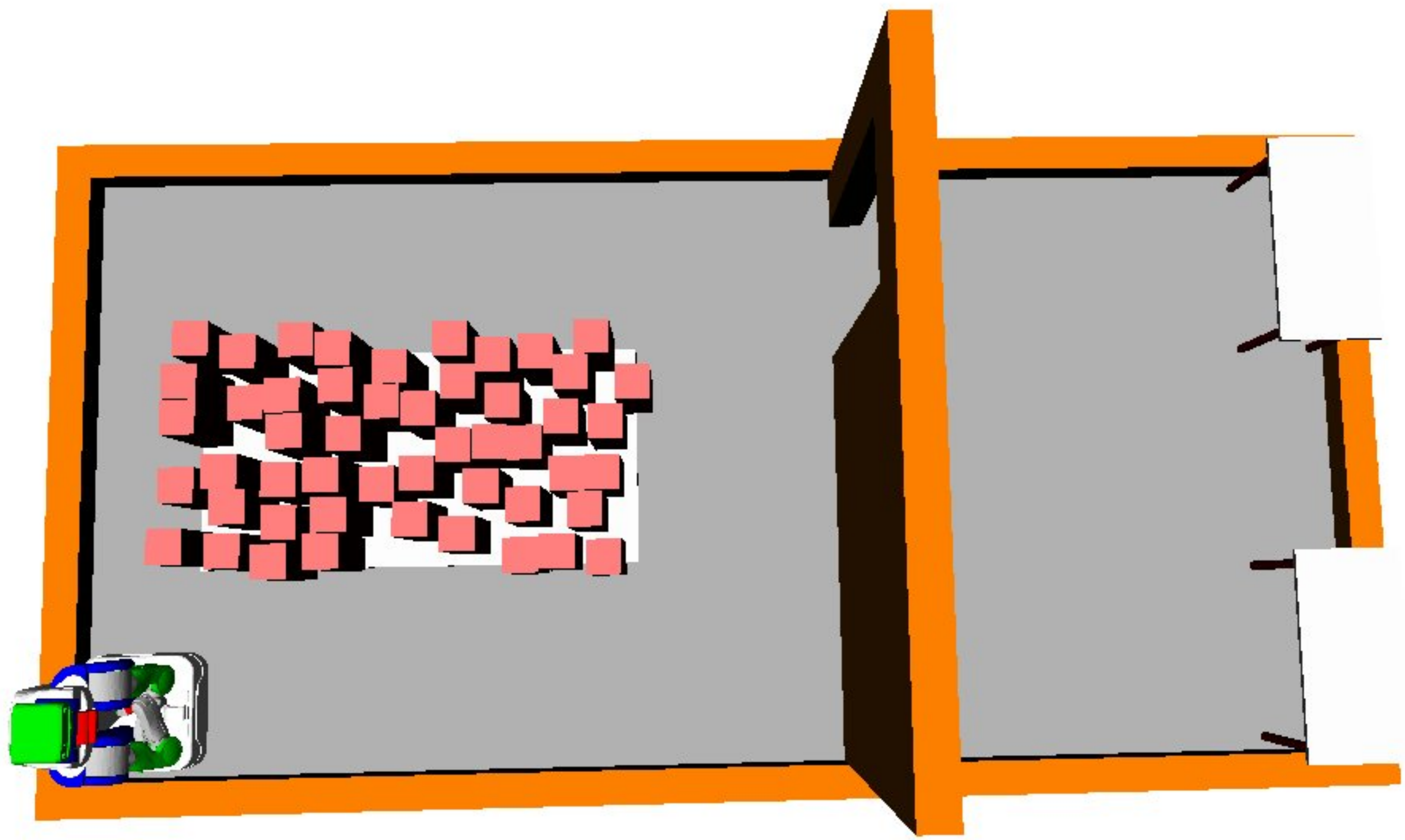
- Standard limitations of replanning:
  - Initial PDDL model is incorrect, but algorithm may act anyway
  - Can fail with dead ends and infinite loops
- BUT the model does improve with every non-executable action
- Theorem: Algorithm is sound and complete provided:
  - Low level sampling terminates, succeeds when possible
  - Problem has no dead ends
  - Negative geometric preconditions can be deleted but not added
  - Positive geometric preconditions can be added but not deleted
- For details, see paper or ask Siddharth

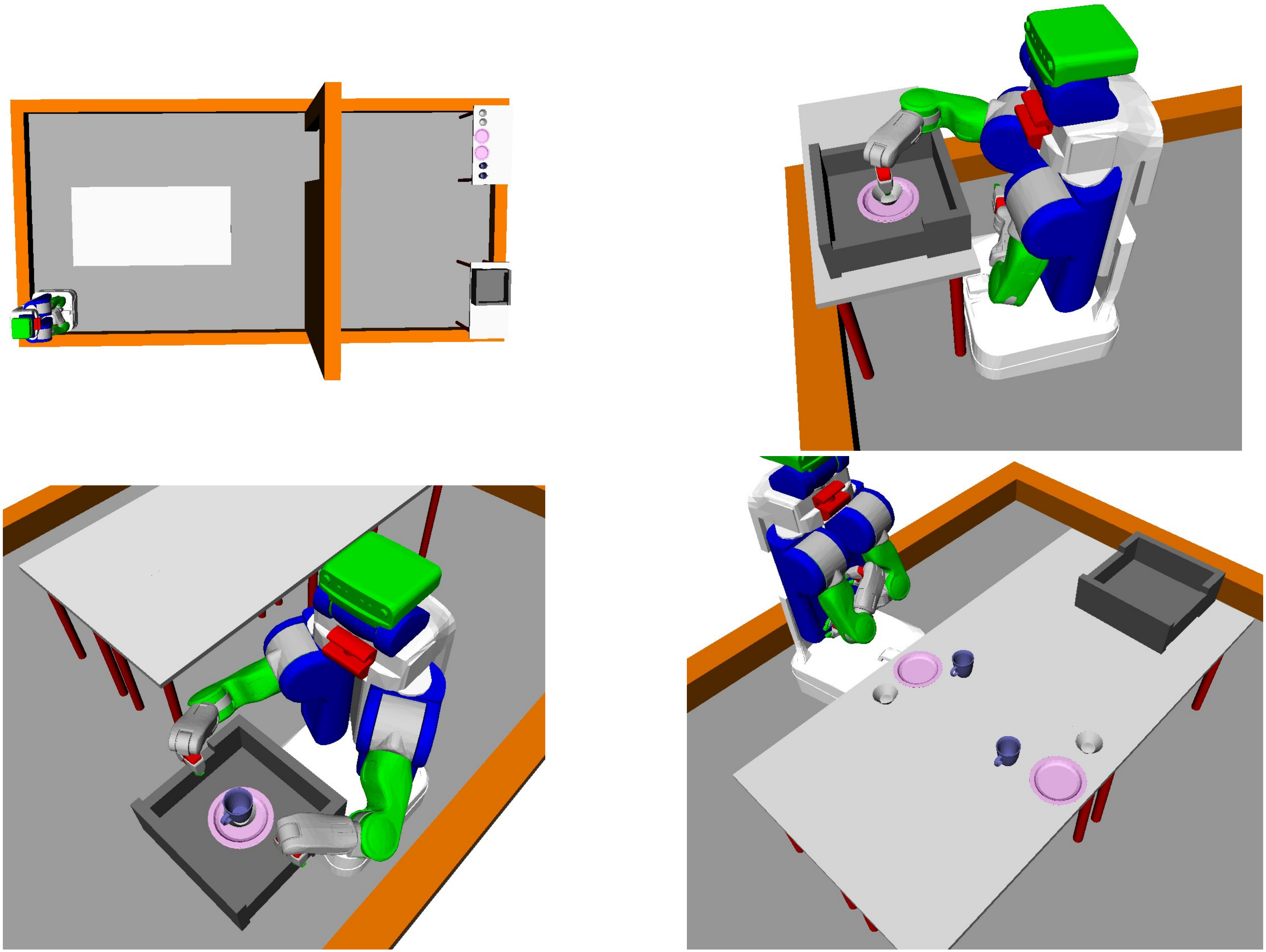
RESULTS ON A PR2 SIMULATOR

Experiments

- Used OpenRave for simulation, IK and grasp computation
- Scenario 1: pick and place with obstructions
  - Many (50, 65, 80) randomly placed objects
  - 3 tests (50, 65, 80 objects), 10 runs each
  - Used FF planner (optimality not a concern)
- Scenario 2: setting a dinner table
  - 2 cups, 2 mugs, 2 plates to be placed at predefined locations
  - Tray available to carry multiple objects
  - Stability constraints for item stacking not known a priori
  - Used FD anytime planner with timeout

Cluttered Table, 50 Objects





Results

- Cluttered table, averages over 10 runs:

#Objects	Time(s)	#Replan	# Obstrns
50	139	2.1	1.8
65	228	2.6	2.0
80	602	2.3	2.6

  - Most of the time spent in low level planning*
- Dinner table: planning + execution time ~230s
  - Most of the time was spent in high level planning

Simulations

Non-simulations

Conclusions

- A method for using classical planners with motion planners in a modular fashion
  - Avoiding exponential discretization complexity
  - Solution based on naming just the discrete-plan-relevant locations with uninterpreted functions
  - Execution errors must be observable and expressible as new PDDL facts

- Still works with no internal low-level model
- Alternative algorithmic approaches could yield stronger guarantees given a low-level simulator