Task and Motion Planning (TAMP)

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Slides modified from: Caelan Reed Garrett
github.com/caelan/pddlstream

NVIDIA

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Introduction

- "Robot, cook me a bowl of tomato soup"
- Must find out a sequence of grasps and motions that will result in a cooked can of soup
- In this case: grabs soup, pours it out into the red bowl, puts the red bowl on the stove, and then takes it off.
- Easy, right?

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Planning for Autonomous Robots

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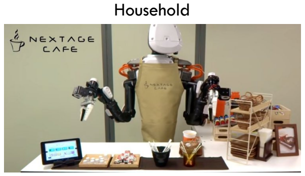
- Robot must select both **high-level** actions & **low-level** controls
- **Application areas:** semi-structured and human environments

Household

Warehouse fulfilment



Food service

Construction

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Task and Motion Planning (TAMP)

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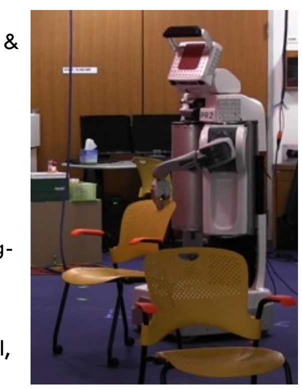
- Plan in a **factored, hybrid** space
  - **Discrete** and **continuous** variables & actions
- **Variables**
  - **Continuous:** robot configuration, object poses, door joint positions,
  - **Discrete:** is-on, is-in-hand, is-holding-water, is-cooked, …
- **Actions:** move, pick, place, push, pull, pour, detect, cook, …



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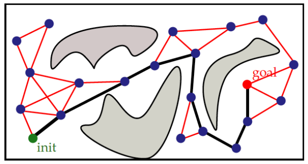
(Probable) Roadmap

1. **Background**
   1. Task Planning
   2. Motion Planning
2. **Hybrid Planning**
   1. Prediscretized & Numeric Planning
   2. Multi-Modal Motion Planning
   3. Integrated TAMP
3. **STRIPStream**
4. Temporal TAMP
5. TAMP under Uncertainty



[Fig from Erion Plaku]

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Cooking and Stacking

6

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Preparing Coffee

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Automated Fabrication

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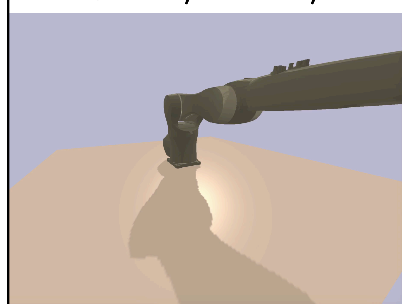
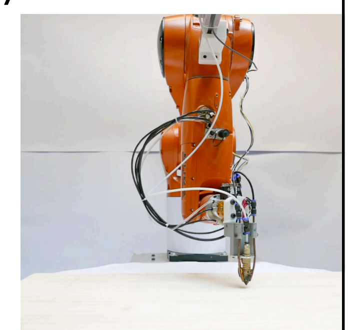
- Plan sequence of **306** 3D printing extrusions (actions)
- Collision, kinematic, **stability** and **stiffness** constraints



[Huang, Garrett, & Mueller 2018]



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Problem Class

- **Discrete-time**
  - Plans are finite sequences of controls
- **Deterministic** (for now)
  - Actions always produce the intended effect
  - Solutions are **plans** (instead of policies)
- **Observable** (for now)
  - Access to the full world state
- **Hybrid**
  - States & controls composed of **mixed discrete-continuous variables**

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Classical (Task) Planning

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- Key focus: **discrete** problems with **many variables**
  - Often enormous, but **finite,** state-spaces
- Problems typically described using an **action language**
  - **Propositional Logic** (STRIPS) [Fikes 1971]
  - **Planning Domain Description Language** (PDDL) [Aeronautiques 1998]
- Develop **domain-independent** algorithms
  - Can apply to **any problem** expressible using PDDL
- Exploit **factored** and **sparse** structure to develop efficient algorithms

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Classical Planning Representations

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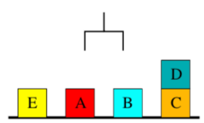
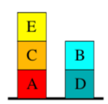


Initial State



Goal State

- Facts: $on(x, y)$, $onTable(x)$, $clear(x)$, $holding(x)$, $armEmpty()$.
- Initial state: $\{onTable(E), clear(E), \ldots, onTable(C), on(D, C), clear(D), armEmpty()\}$.
- Goal: $\{on(E, C), on(C, A), on(B, D)\}$.
- Actions: $stack(x, y)$, $unstack(x, y)$, $putdown(x)$, $pickup(x)$.
- $stack(x, y)$? $pre : \{holding(x), clear(y)\}$
  $add : \{on(x, y), armEmpty()\}$
  $del : \{holding(x), clear(y)\}$.

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First-Order Action Languages

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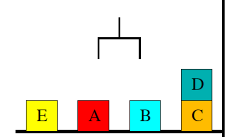
- **Predicate:** boolean function `(On ?b1 ?b2)=True/False`
- **Facts** (literals)**:** instantiated predicates `(On D C)=True`
- **State:** set of facts `{(On A B)=False, (On D C)=True, …}`
  - Equivalently, boolean state variables
  - **Closed-world** assumption: unspecified facts are **false**
- Example: **Blocksworld** domain



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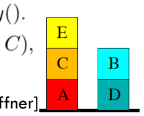
Goal: $\{on(E, C), on(C, A), on(B, D)\}$. [Figs from Hector Geffner]
Actions: $stack(x, y)$, $unstack(x, y)$, $putdown(x)$, $pickup(x)$.



Goal State

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(Lifted) Action Schema

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- A tuple of free **parameters**
- A **precondition** formula tests applicability
- An **effect** formula modifies the state
- Logical **conjunctions** enable factoring
- Effects are **deltas**

```
(:action stack
  :parameters (?b1 ?b2)
  :precondition (and
    (Holding ?b1) (Clear ?b2))
  :effect (and
    (ArmEmpty)
    (On ?b1 ?b2) (Clear ?b1)
    (not (Holding ?b1))
    (not (Clear ?b2))))
```

```
(:action unstack
  :parameters (?b1 ?b2)
  :precondition (and
    (ArmEmpty) (On ?b1 ?b2)
    (Clear ?b1))
  :effect (and
    (Holding ?b1) (Clear ?b2)
    (not (Clear ?b1))
    (not (ArmEmpty))
    (not (On ?b1 ?b2))))
```

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Planning Approaches

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- **State-space** search: [Bonet 2001] [Hoffman 2001] [Helmert 2006]
  - **Progression** (forward) or regression (backward)
  - Best-first **heuristic search** algorithms
- **Partial-order** planning [Penberthy 1992]
  - Search directly over plans (**plan-space**)
- Planning as **Satisfiability** [Kautz 1999]
  - Compile to **fixed-horizon** SAT instance
  - SAT is **NP-Complete**
  - Planning is **PSPACE-Complete**
  - **Increase horizon if formula unsatisfiable**

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Forward Best-First Search

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- For a state s
  - Path **cost**: $g(s)$
  - **Heuristic** estimate: $h(s)$
  - Open list **sorted** by priority $f(s)$
- **Weighted A***: $f(s) = g(s) + wh(s)$
  - Uniform cost search: $w = 0 \implies f(s) = g(s)$
  - A* search: $w = 1 \implies f(s) = g(s) + h(s)$
  - **Greedy** best-first search: $w = \infty \implies f(s) = h(s)$
- How do we estimate $h(s)$?
  - No obvious metric (no metric-space embedding)

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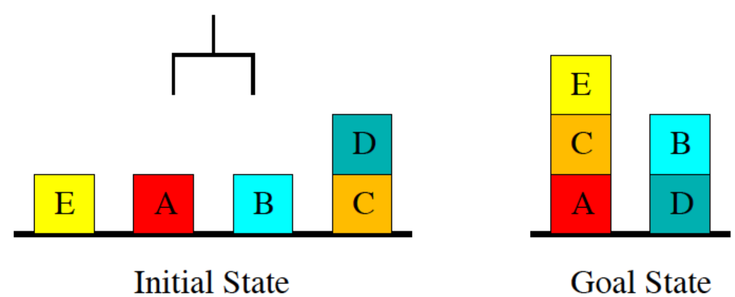
Predict the Minimum Plan Length

17

- Can stack / unstack anywhere on the ground
- Hint: is an **even** number



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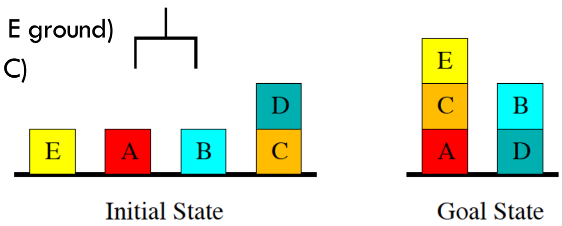
Predict the Minimum Plan Length

18

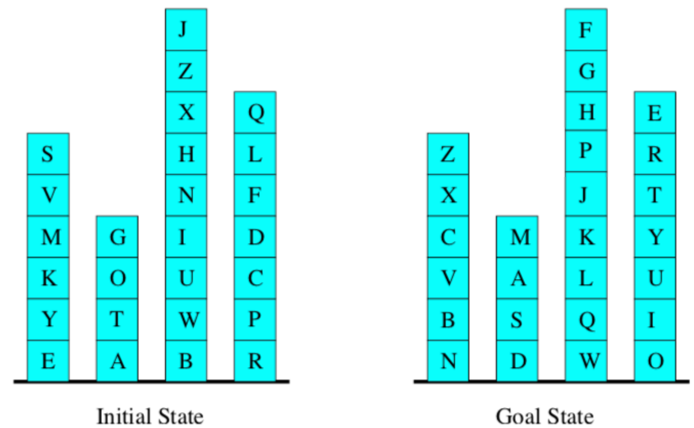
- **Solution** (length=6):
  - (unstack D C)
  - (stack D B)
  - (unstack C ground)
  - (stack C A)
  - (unstack E ground)
  - (stack E C)



18

Predict the Minimum Plan Length

19



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Domain-Independent Heuristics

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- Estimating $h(s)$ is **nontrivial**
- Can we do it in an a **domain-independent** manner?
- Solve a related, **approximate** planning problem
  - Primary focus for almost all of classical planning
- Suggestions for how to do this?
  - **Independently** plan for each goal
  - **Remove** some action preconditions [Helmert 2006]
  - Remove negative (**delete**) **effects** [Bonet 2001] [Hoffman 2001]
  - …

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Delete-Relaxation Heuristics

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- Remove all negative (**not**) effects
  - Solving optimally is **NP-Complete**
  - Can greedily find a short plan in polynomial time
- Basis for both **admissible** and **greedier,** non-admissible heuristics

(**:action** stack
  :parameters (?b1 ?b2)
  :precondition (**and**
    (Holding ?b1) (Clear ?b2))
  :effect (**and**
    (ArmEmpty)
    (On ?b1 ?b2) (Clear ?b1)
    ~~(**not** (Holding ?b1))~~
    ~~(**not** (Clear ?b2))~~))

(**:action** unstack
  :parameters (?b1 ?b2)
  :precondition (**and**
    (ArmEmpty) (On ?b1 ?b2)
    (Clear ?b1))
  :effect (**and**
    (Holding ?b1) (Clear ?b2)
    ~~(**not** (Clear ?b1))~~
    ~~(**not** (ArmEmpty))~~
    ~~(**not** (On ?b1 ?b2))~~))

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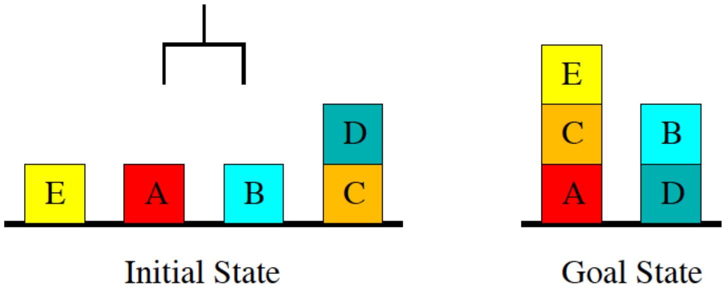
Predict the Minimum Delete-Relaxed Plan Length

22

- Can stack / unstack anywhere on the ground
- Hint: is **no greater** than 6



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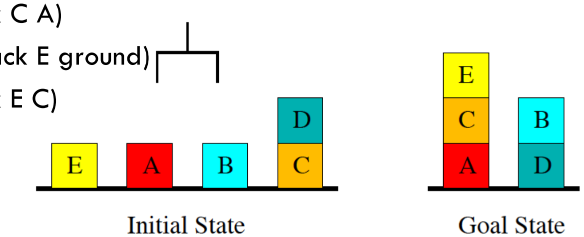
Predict the Minimum Delete-Relaxed Plan Length

23

- **Solution** (length=6):
  - (unstack D C)
  - (stack D B)
  - (unstack C ground)
  - (stack C A)
  - (unstack E ground)
  - (stack E C)



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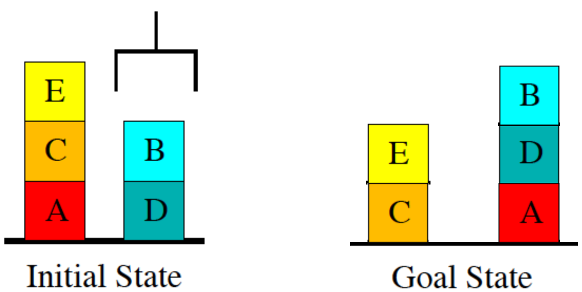
Predict the Minimum Plan Length

24

- Can stack / unstack anywhere on the ground
- Hint: is an **even** number



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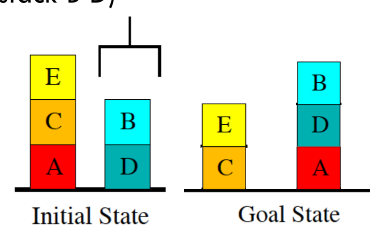
Predict the Minimum Plan Length

25

- **Solution** (length=12):
  - (unstack E C)
  - (stack E ground)
  - (unstack C A)
  - (stack C ground)
  - (unstack E ground)
  - (stack E C)
  - (unstack B D)
  - (stack B ground)
  - (unstack D ground)
  - (stack D A)
  - (unstack B ground)
  - (stack B D)



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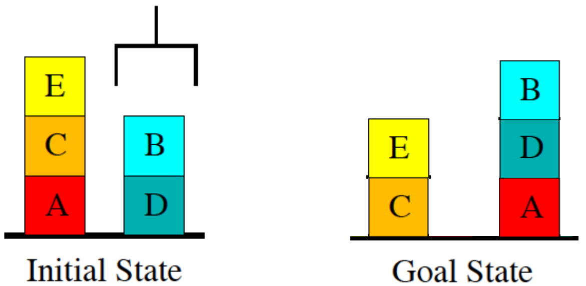
Predict the Minimum Delete-Relaxed Plan Length

26

- Can stack / unstack anywhere on the ground
- Hint: is **no greater** than 12



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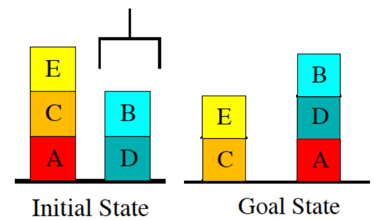
Predict the Minimum Delete-Relaxed Plan Length

27

- **Solution** (length=5):
  - (unstack E C)
  - (unstack C A)
  - (unstack B D)
  - (unstack D ground)
  - (stack D A)



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Review: Motion Planning

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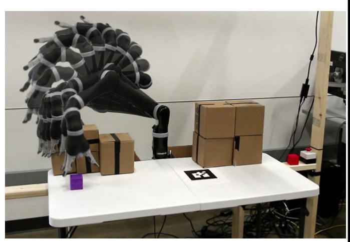
- Plan a **path** for a robot from an initial configuration to a goal configuration that **avoids obstacles**
  - Sequence of **<u>continuous</u>** configurations
  - Configurations often are **high-dimensional**
    - Example: 7 DOFs
- High-level approaches:
  - Geometric decomposition
  - **Sampling-based**
  - Optimization-based



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Sampling-Based Motion Planning

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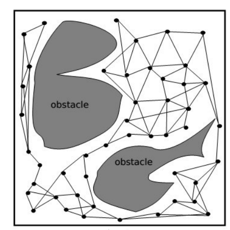
- **Discretize** configuration space by **sampling**
  - Sampling be deterministic or **random**
- **Implicitly** represent the collision-free configuration space using an blackbox **collision checker**
  - **Abstracts away** complex robot geometry
- Algorithms
  - Probabilistic Roadmap (PRM)
  - Rapidly-Exploring Random Tree (RRT)
  - Bidirectional RRT (BiRRT)



[Kavraki 1994][Kuffner 2000][LaValle 2006]

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Probabilistic Roadmap (1/7)

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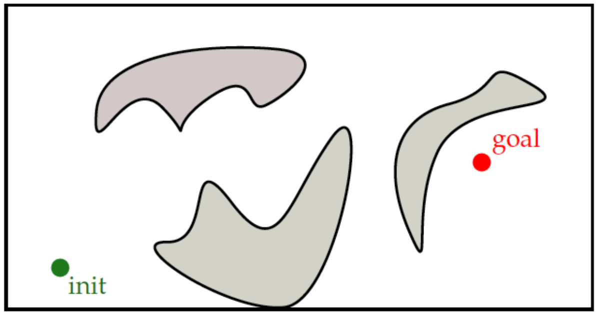

[Fig from Erion Plaku]

Find a path from init to goal that avoids the obstacles

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Probabilistic Roadmap (2/7)

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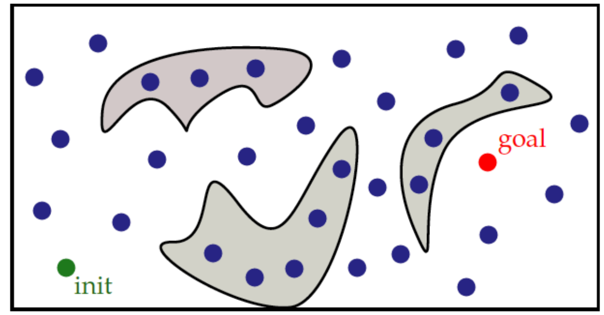

[Fig from Erion Plaku]

Sample a set of configurations

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Probabilistic Roadmap (3/7)

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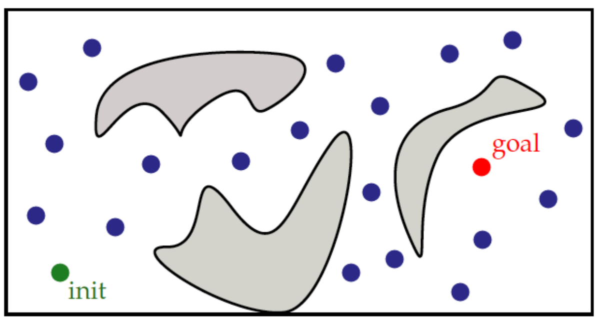

[Fig from Erion Plaku]

Remove configurations that collide with the obstacles

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Probabilistic Roadmap (4/7)

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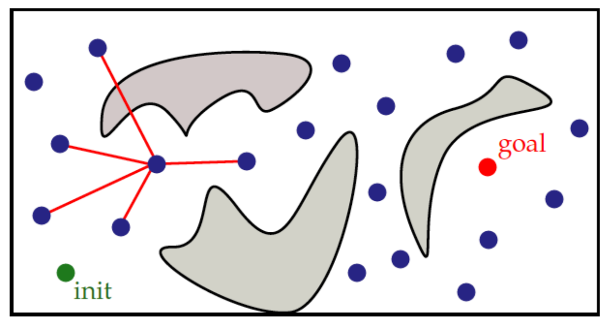

[Fig from Erion Plaku]

Connect nearby configurations

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Probabilistic Roadmap (5/7)

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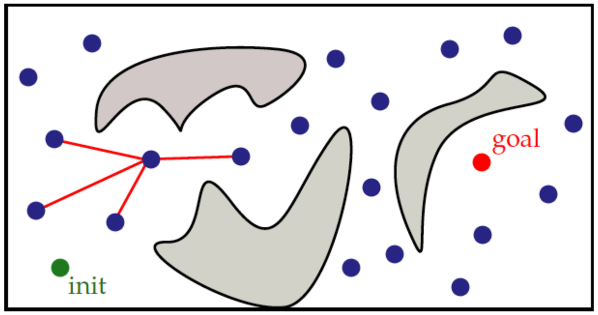

[Fig from Erion Plaku]

Prune connections that collide with the obstacles

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Probabilistic Roadmap (6/7)

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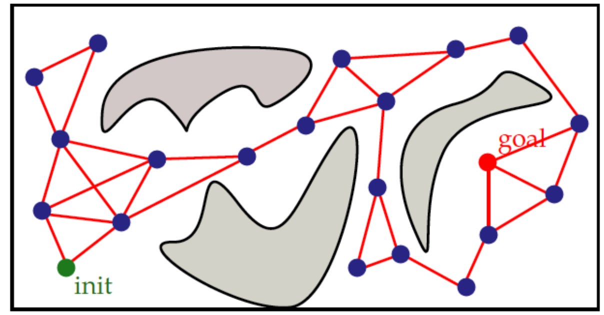

[Fig from Erion Plaku]

The resulting structure is a finite roadmap (graph)

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Probabilistic Roadmap (7/7)

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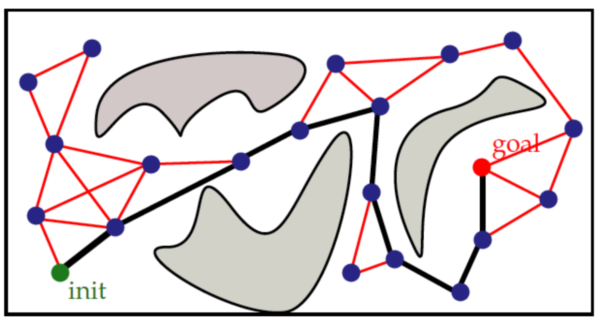

[Fig from Erion Plaku]

Search for the shortest-path on the roadmap

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Task and Motion Planning (TAMP)

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Shakey the Robot (1969)

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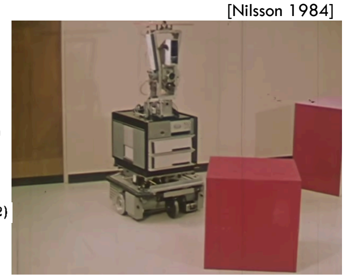
- **First autonomous mobile manipulator** (via pushing)
  - Visibility graph, A* search, and STRIPS!
- **Decoupled** task and motion planning
  - Task planning **then** motion planning

[Fikes 1971]
[Nilsson 1984]

```
type(robot robot)   type(o1 object)
name(robot shakey)  name(o1 box1)
at(robot 4.1 7.2)   at(o1 3.1 5.2)
theta(robot 90.1)   inroom(o1 r1)
                    shape(o1 wedge)
                    radius(o1 3.1)
```

GOTHRU(d,r1,r2)
- Precondition: INROOM(ROBOT,r1) ∧ CONNECTS(d,r1,r2)
- Delete List: INROOM(ROBOT,$)
- Add List: INROOM(ROBOT,r2)



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Obstacle Blocks Shakey's Path

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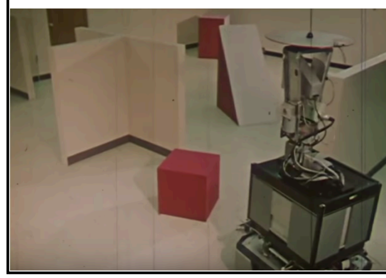
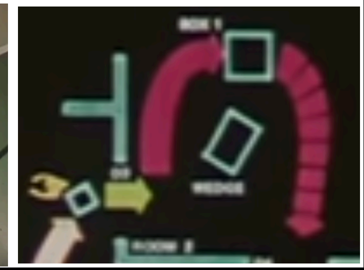
- What if a movable block **prevented** Shakey from safely moving into the adjacent room?
- Shakey could **push** it out of the way or **go around** it
  - What's more efficient? How to push it? …





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Decoupled vs Integrated TAMP

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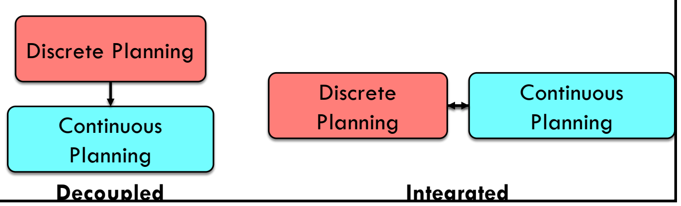
- **Decoupled:** discrete (task) planning **then** continuous (motion) planning
- Requires a strong **downward refinement** assumption
  - **Every** correct discrete plan can be **refined** into a correct continuous plan (from hierarchal planning)
- **Integrated:** **simultaneous** discrete & continuous planning



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Geometric Constraints Affect Plan

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- **Inherits challenges** of both motion & classical planning
  - **High-dimensional, continuous** state-spaces
  - State-space **exponential** in number of variables
  - **Long horizons**
- Continuous constraints **limit high-level strategies**
  - Kinematics, reachability, joint limits, collisions grasp, visibility, stability, stiffness, torque limits, …

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Pouring Among Obstacles

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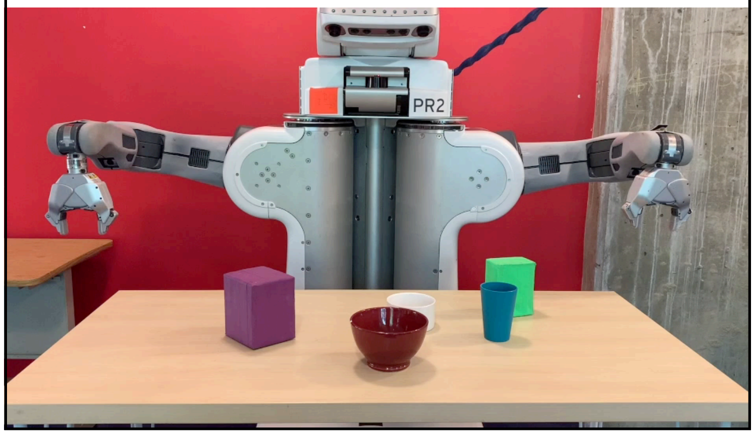

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Preparing a Meal for Two

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Breaking Down "Preparing a Meal"

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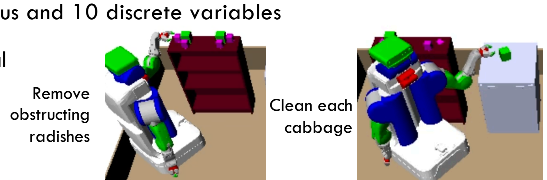
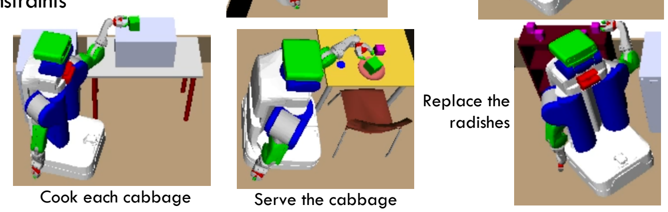
- Clean 3 blue cups and clean/cook 2 green cabbages
- 64 continuous and 10 discrete variables

1. High-dimensional
2. Long horizon
3. Discrete state
4. Geometric constraints





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Block in Left Cabinet & Doors Closed

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- Robot forced to **regrasp** the object
  - Change from a **top** grasp to a **side** grasp
- **Non-monotonic** problem
  - Plan must **undo goals** to solve
  - **Open** then **close** the cabinet door
- Physical constraints can be subtle!

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Hybrid Planning Spectrum

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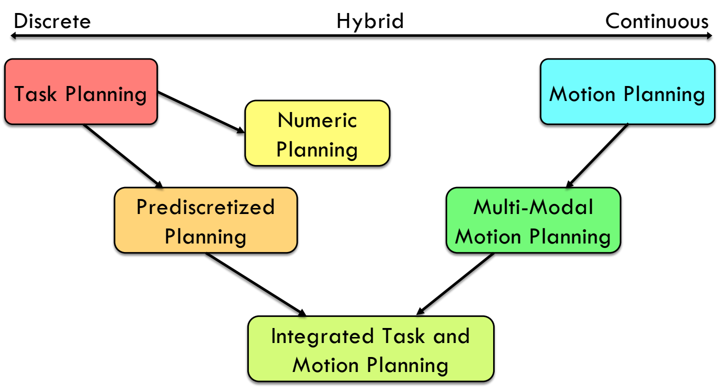

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Prediscretized & Numeric Planning

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Prediscretized Planning

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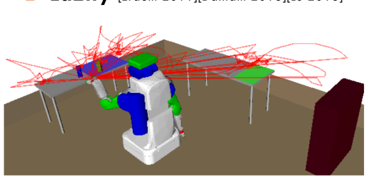
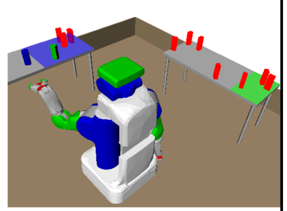
- Assumes that a **finite set** of object placements, object grasps, and (sometimes) robot configurations are **given**
- Can **directly** perform discrete task planning
- Still need to evaluate **reachability**
  - Eagerly in **batch** [Lozano-Pérez 2014][Garrett 2017][Ferrer-Mestres 2017]
  - Eagerly during **search** [Dornhege 2009]
  - **Lazily** [Erdem 2011][Dantam 2018][Lo 2018]

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Multi-Modal Motion Planning

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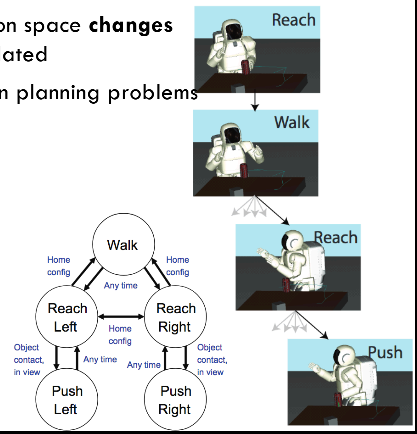
Multi-Modal Motion Planning

73

- Collision-free configuration space **changes** when objects are manipulated
- Use a **sequence** of motion planning problems each defined by a **mode**
- **Mode:** a set of motion constraints
  - Gripper is empty
  - Relative object pose remains **constant**



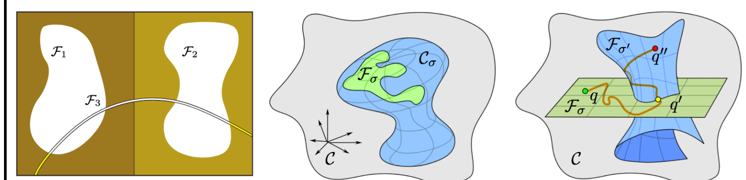
[Alami 1994][Siméon 2004][Hauser 2011]
[Barry 2013][Vega-Brown 2016]

73

Low-dimensional Intersections

74

- Need samples that **connect** adjacent modes
- Intersection of two modes is often **low-dimensional**
  - **Special-purpose** samplers are needed
- **Example:** transition from gripper **empty** to **holding**
- Configurations at the **intersection** obtained using **inverse kinematics** (IK)



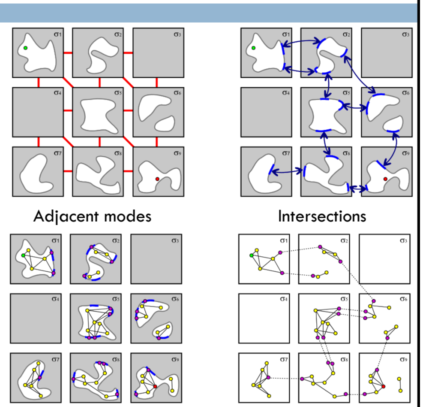
[Hauser 2011]

74

Sampling-Based Multi-Modal Planning

75

1. Sample from the set of **modes**
2. Sample at the **low-dimensional intersection** of adjacent modes
3. Sample a roadmap **within** each mode
4. Discrete search on the multi-modal **roadmap**



Adjacent modes

Intersections

Individual mode roadmaps

Combined Roadmap

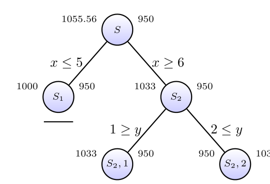
[Hauser 2011]

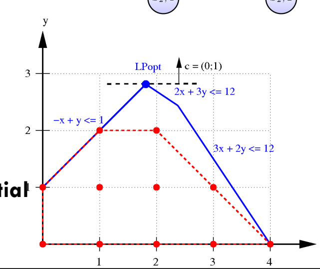
75

Mixed Integer Programming (MIP)

76

- Continuous and integer variables
- Convex constraints and costs
- **Branch-and-bound**
  - Split on integer variables
- **Integrality relaxation**
  - Lower bound on cost
  - Loose when **logical** operations
- Planning limitation
  - \# of variables may be **exponential** in problem size





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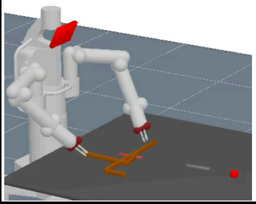
Optimization-Based Multi-Modal Motion Planning

77

- Discrete search over sequences of **mode switches**
  - Sequences have **varying length**
  - Each sequence induces a **non-convex constrained optimization problem**
- Sequences can be pruned using **lower bounds** obtained by **relaxing** some constraints [Lagriffoul 2014]



[Toussaint 2015]
[Toussaint 2018]

$$\begin{aligned}\min_{x,a_{1:K},s_{1:K}} \quad & \int_0^T f_{\text{path}}(\bar{x}(t))\ dt + f_{\text{goal}}(x(T)) \\ \text{s.t.} \quad & x(0)=x_0,\ h_{\text{goal}}(x(T))=0,\ g_{\text{goal}}(x(T))\le 0, \\ & \forall t\in[0,T]:\ h_{\text{path}}(\bar{x}(t),s_{k(t)})=0, \\ & \qquad g_{\text{path}}(\bar{x}(t),s_{k(t)})\le 0 \\ & \forall k\in\{1,..,K\}:\ h_{\text{switch}}(\hat{x}(t_k),a_k)=0, \\ & \qquad g_{\text{switch}}(\hat{x}(t_k),a_k)\le 0, \\ & \qquad s_k\in \text{succ}(s_{k\text{-}1},a_k)\ .\end{aligned}$$

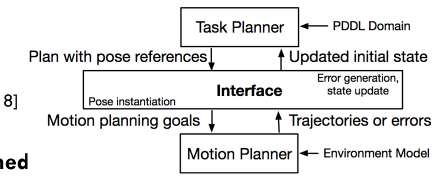
77

Integrated TAMP

78

- Geometric search **guided** by classical planning
  - Both heuristic and sampling guidance [Gravot 2005][Plaku 2010]
- Task and motion planning **interface**
  - Maintain **separate** discrete and continuous descriptions
  - Custom interface to communicate between the two
  - How are failures **diagnosed?**

[Erdem 2011][De Silva 2013]
[Srivastava 2014][Dantam 2018]



- Direct search in **combined**

[Kaelbling 2011] [Garrett 2018a] [Garrett 2018b]

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Hybrid Planning Spectrum Revisited

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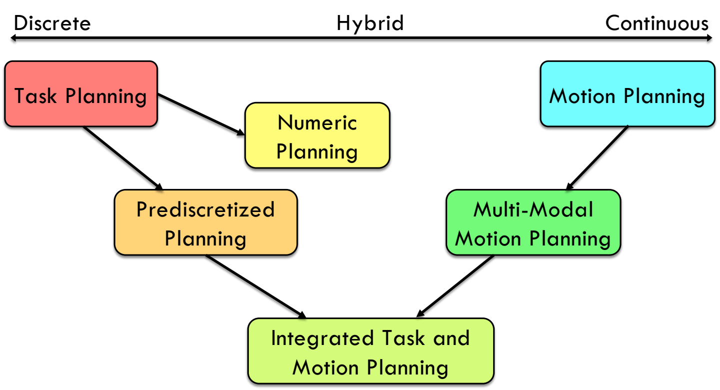

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One Approach: STRIPStream

83

- **No general-purpose, flexible framework** for planning in a variety of TAMP domains
- Extends **PDDL** to incorporate **sampling procedures**
  - Can model domains with **infinitely-many** actions
- Develop **domain-independent** algorithms that treat the samplers as **blackbox inputs**
- Algorithms solve a **sequence of finite** PDDL problems
  - Leverage existing **classical planners** as subroutines
- Algorithms are particularly **fast when downward refinement holds** while remaining **complete**

83

STRIPStream Language

85

Benefits of Extending PDDL

- **Standardized** action description language
- Emphasis on describing and solving problems in a **domain-independent** way
- Large wealth of efficient, **existing algorithms** that exploit **factored** state & action structure
- Encodes the **difference** between two states using preconditions & effects
  - Most variables are **unchanged**
  - Actions can be described using **few parameters**

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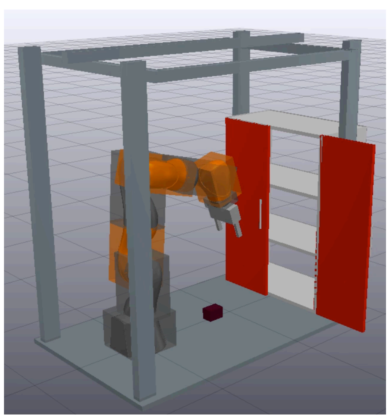
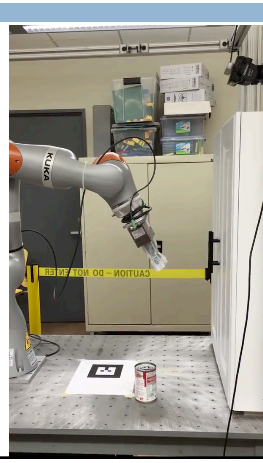
STRIPStream + Drake





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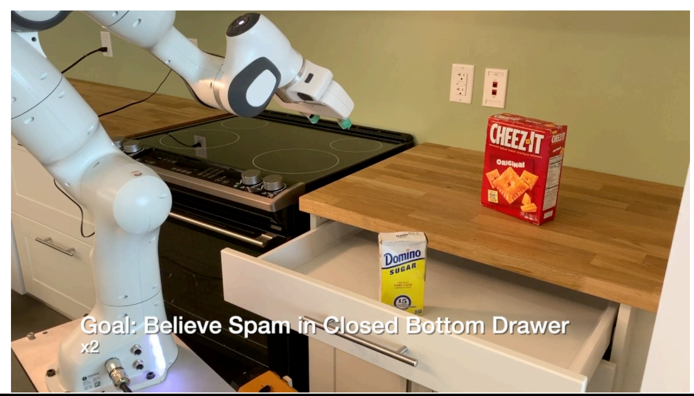
Solved Using the Same Algorithm

Framework not specific to a single robot or robotics at all!



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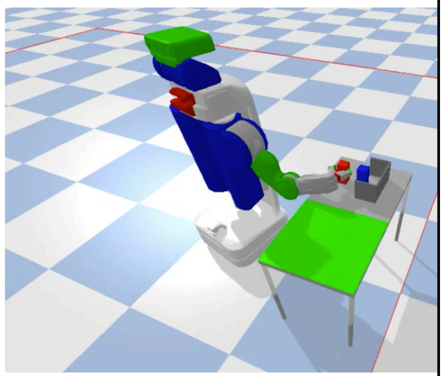
Motivating Pick & Place Example

91

- Single object **prevents** a goal object from being reachable
- Focus on a compact 2D version
- Formulation almost the same for 3D
- Algorithms agnostic to number of DOFs

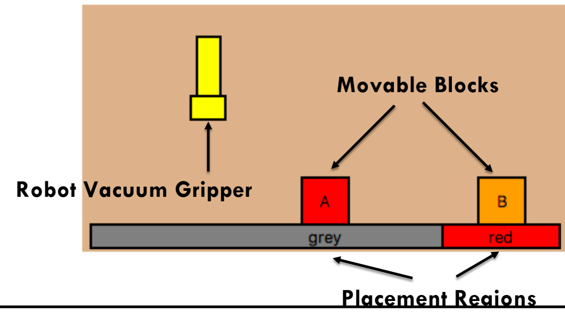


91

2D Pick-and-Place Example

92

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

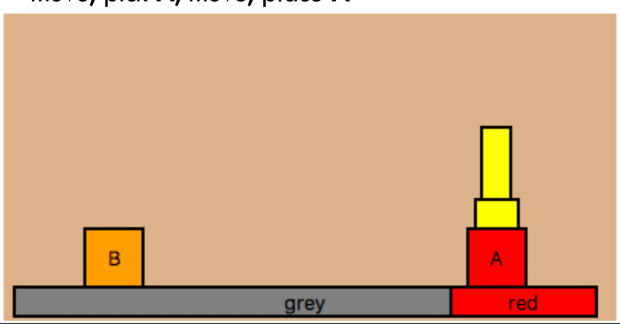


92

2D Pick-and-Place Solution

93

- One (of infinitely many) possible solutions
  - move, pick **B**, move, place **B**, move, pick **A**, move, place **A**



93

2D Pick-and-Place Initial & Goal

94

- Some constants are **numpy arrays**
- **Static initial facts** - value is **constant** over time
  - (Block, A), (Block, B), (Region, red), (Region, grey), (Conf, [-7.5 5.]), (Pose, A, [0. 0.]), (Pose, B, [7.5 0.]), (Grasp, A, [0. -2.5]), (Grasp, B, [0. -2.5])
- **Fluent initial facts** - value **changes** over time
  - (AtConf, [-7.5 5.]), (HandEmpty), (AtPose, A, [0. 0.]), (AtPose, B, [7.5 0.])
- **Goal formula:** `(exists (?p) (and (Contained A ?p red) (AtPose A ?p)))`

94

2D Pick-and-Place Actions

95

- Typical PDDL action description except that arguments are **high-dimensional** & **continuous**!
- To use the actions, must **prove** the following **static facts:**

```
(Motion ?q1 ?t ?q2), (Kin ?b ?p ?g ?q)
```

```
(: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 ?g ?q)
  :precondition (and (Kin ?b ?p ?g ?q)
                     (AtConf ?q) (AtPose ?b ?p) (HandEmpty))
  :effect (and (AtGrasp ?b ?g)
               (not (AtPose ?b ?p)) (not (HandEmpty))))
```

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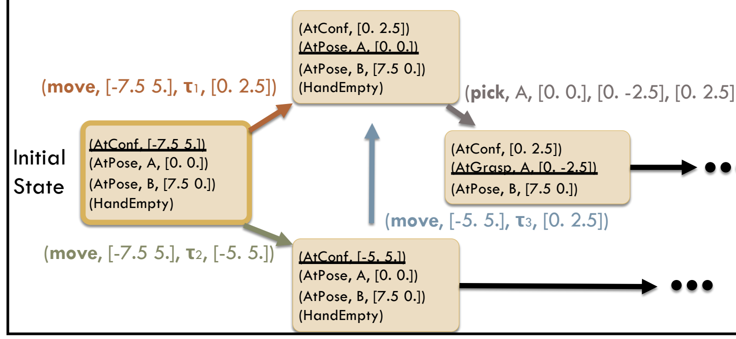
BFS in Discretized State-Space

96

- Suppose we were **given** the following additional static facts:
  - (Motion, [-7.5 5.], τ_1, [0. 2.5]), (Motion, [-7.5 5.], τ_2, [-5. 5.]), (Motion, [-5. 5.], τ_3, [0. 2.5]), (Kin, A, [0. 0.], [0. -2.5], [0. 2.5]), …



96

No a Priori Discretization

- **Values given at start:**
  - 1 initial configuration: (Conf, **[-7.5 5.]**)
  - 2 initial poses: (Pose, A, **[0. 0.]**), (Pose, B, **[7.5 0.]**)
  - 2 grasps: (Grasp, A, **[0. -2.5]**), (Grasp, B, **[0. -2.5]**)
- **Planner needs to find:**
  - 1 pose within a region: `(Contain A ?p red)`
  - 1 collision-free pose: `(CFree A ?p ? B ?p2)`
  - 4 grasping configurations: `(Kin ?b ?p ?g ?q)`
  - 4 robot trajectories: `(Motion ?q1 ?t ?q2)`

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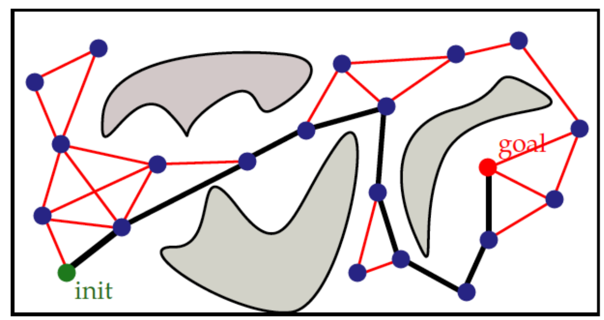
Intuition: Build a Roadmap

98



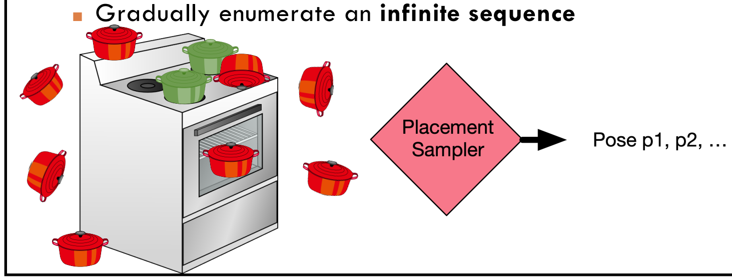
[Fig from Erion Plaku]

Search for the shortest-path on the roadmap

98

What Samplers Do We Need?

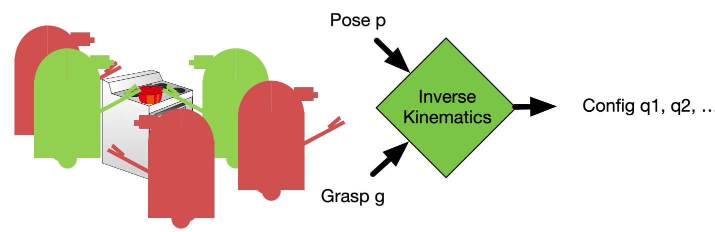
- **Low-dimensional** placement stability constraint (`Contain`)
  - *i.e.* 1D manifold embedded in 2D pose space
- Directly **sample values that satisfy the constraint**
- May need **arbitrarily many** samples
  - Gradually enumerate an **infinite sequence**



99

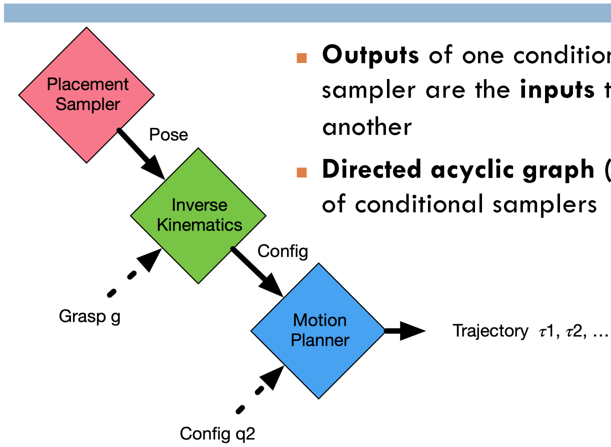
Intersection of Constraints

- **Kinematic constraint** (`Kin`) involves poses, grasps, and configurations
- **Conditional samplers** - samplers with inputs



100

Composing Conditional Samplers



- **Outputs** of one conditional sampler are the **inputs** to another
- **Directed acyclic graph (DAG)** of conditional samplers

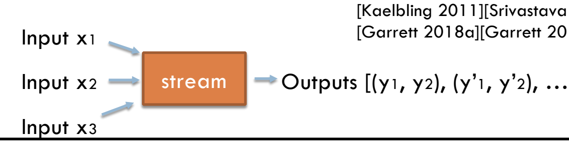
101

Stream: a function to a generator

- **Advantages**
  - Programmatic implementation
  - Compositional
  - Supports infinite sequences
- **Stream** - function from an **input object tuple** (x_1, x_2, x_3) to a (potentially infinite) sequence of **output object tuples** [(y_1, y_2), (y'_1, y'_2), …]

```
def stream(x1, x2, x3):
    i = 0
    while True:
        y1 = i*(x1 + x2)
        y2 = i*(x2 + x3)
        yield (y1, y2)
        i += 1
```

[Kaelbling 2011][Srivastava 2014]
[Garrett 2018a][Garrett 2018b]



102

Stream Certified Facts

103

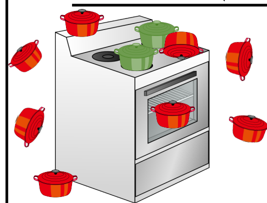
- Objects alone aren't helpful: **what do they represent?**
  - Communicate semantics using **predicates**!
- Augment stream specification with:
  - **Domain facts** - static facts declaring legal **inputs**
    - *e.g.* only configurations can be motion inputs
  - **Certified facts** - static facts that all **outputs** satisfy with their corresponding **inputs**
    - *e.g.* poses sampled from a region are within it

103

Sampling Contained Poses

104

```
(:stream sample-region
  :inputs (?b ?r)
  :domain (and (Block ?b) (Region ?r))
  :outputs (?p)
  :certified (and (Pose ?b ?p) (Contain ?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_
      p = np.array([x, 0.])
      yield (p,)
```

Block b → sample-region → Pose [(p), (p'), (p''), …]
Region r → sample-region

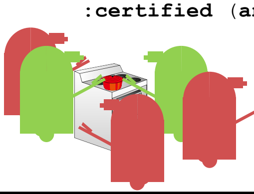
104

Sampling IK Solutions

105

- **Inverse kinematics** (IK) to produce robot grasping configuration
  - Trivial in 2D, non-trial in general (*e.g.* 7 DOF arm)

```
(:stream sample-ik
  :inputs (?b ?p ?g)
  :domain (and (Pose ?b ?p) (Grasp ?b ?g))
  :outputs (?q)
  :certified (and (Conf ?q) (Kin ?b ?p ?g ?q)))
```



Block b → sample-ik → Conf [(q'), (q'')]
Pose p → sample-ik
Grasp g → sample-ik

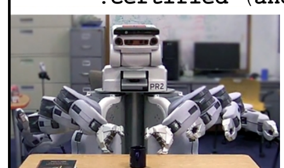
105

Calling a Motion Planner

106

- "Sample" (*e.g.* via a PRM) **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)))
```



Conf q_1 → sample-motion → Trajectory [(t)]
Conf q_2 → sample-motion

106

2D Place Collisions

107

- Add parameters for the pose of each block - **bad!**
- Use a **derived predicate** for whether currently **unsafe**
  - Predicate defined by **logical formula** [Fox 2003] [Thiébaux 2005]
  - Enables lightweight **logical inference**
  - Decomposes collision checking into a logical **AND**

```
(:action place
  :parameters (?b ?p ?g ?q)
  :precondition (and ... (not (UnsafePose ?b ?p)))
  :effect (and ...)

(:derived (UnsafePose ?b1 ?p1)
  (exists (?b2 ?p2) (and (Pose ?b1 ?p1) (Pose ?b2 ?p2)
                         (not (= ?b1 ?b2)) (AtPose ?b2 ?p2)
                         (not (CFree ?b1 ?p1 ?b2 ?p2)))))
```

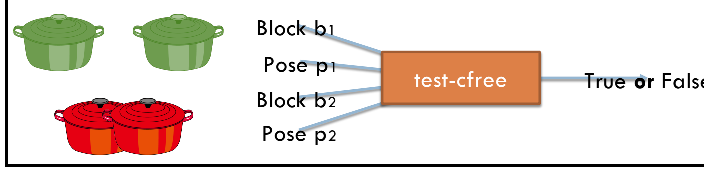
107

Check Block Collisions

108

- **Test stream:** stream without output objects
- Return True if **collision-free** placement (e.g. via querying a collision checker)

```
(:stream test-cfree
  :inputs (?b1 ?p1 ?b2 ?p2)
  :domain (and (Pose ?b1 ?p1) (Pose ?b2 ?p2))
  :outputs ()
  :certified (CFree ?b1 ?p1 ?b2 ?p2))
```

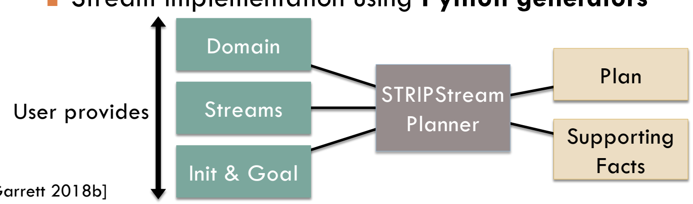


108

STRIPStream = STRIPS + Streams

109

- **Domain dynamics** *(domain.pddl): declares* actions
- **Stream properties** (*stream.pddl*)
  - Declares stream inputs, outputs, and certified facts
- **Problem** and **stream implementation** (*problem.py*)
  - Initial state, **Python constants,** & goal formula
  - Stream implementation using **Python generators**



[Garrett 2018b]

109

STRIPStream Algorithms

110

Two STRIPStream Algorithms

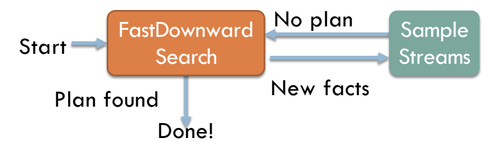
- **STRIPStream planners decide** which streams to use
- Algorithms alternate between **searching & sampling:**
  1. **Search** a finite PDDL problem for plan
  2. **Modify** the PDDL problem (depending on the plan)
- Search implemented using **off-the-shelf algorithms**
  - **Off-the-shelf AI planner** - FastDownward
    - Exploits factoring in its search heuristics (e.g. hFF)
    - http://www.fast-downward.org/
  - **Probabilistically complete** given *sufficient* samplers

[Garrett 2018a]
[Garrett 2018b]

111

Incremental Algorithm

- Incrementally construct all possible initial facts
- Periodically check if a solution exists
- 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



[Garrett 2018a]
[Garrett 2018b]

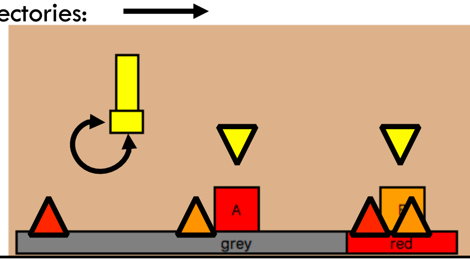
112

Incremental: Sampling Iteration 1

113

Iteration 1 - 14 stream evaluations

- **Sampled:**
  - 2 new robot configurations: 
  - 4 new block poses: 
  - 2 new trajectories: 

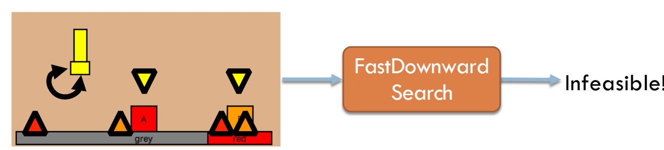


113

Incremental: Search Iteration 1

114

- Pass current discretization to FastDownward
- If **infeasible,** the current set of samples is insufficient



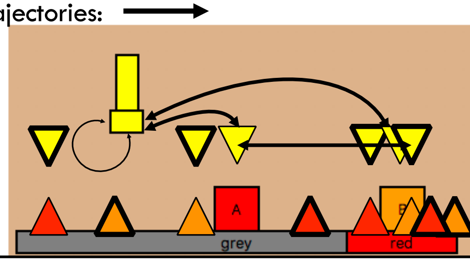
114

Incremental: Sampling Iteration 2

115

Iteration 2 - 54 stream evaluations

- **Sampled:**
  - 4 new robot configurations:
  - 4 new block poses:
  - 10 new trajectories:



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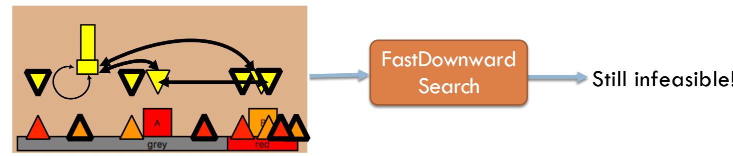
Incremental: Search Iteration 2

116

- Pass current discretization to FastDownward
- If **infeasible,** the current set of samples is insufficient



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Incremental Example: Iterations 3-4

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Iteration 3 - 118 stream evaluations
Iteration 4 - 182 stream evaluations

Solution:
1) **move** [-7.5 5.] [[-7.5 5.], [-7.5 5.], [7.5 5.], [7.5 2.5]] [7.5 2.5]
2) **pick B** [7.5 0.] [0. -2.5] [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 B** [10.97 0.] [0. -2.5] [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 A** [0. 0.] [0. -2.5] [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 A** [7.65 0.] [0. -2.5] [7.65 2.5]

- **Drawback** - many unnecessary samples produced
  - **Computationally expensive** to generate
  - Induces **large discrete-planning problems**

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Optimistic Stream Outputs

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- Many TAMP streams are exceptionally **expensive**
  - Inverse kinematics, motion planning, collision checking
- **Only** query streams that are **identified** as useful
  - Plan with **optimistic hypothetical** outputs [Srivastava 2014]
- 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.], [0. -2.5])->(**#q0**),
3. **s-ik:**(b0, **#p0**, [0. -2.5]) ->(**#q2**)

[Garrett 2018a]
[Garrett 2018b]

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Focused Algorithm

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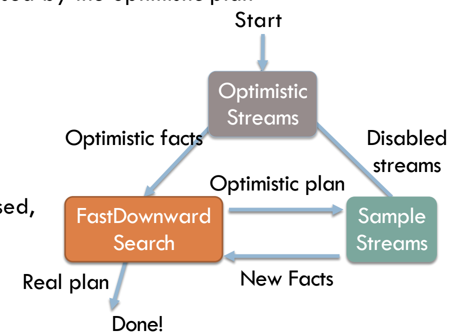
- **Lazily** plan using optimistic outputs **before** real outputs
- **Recover** set of streams used by the optimistic plan
- Repeat:
  1. Construct active **optimistic** objects
  2. **Search** with **real & optimistic** objects
  3. If **only real objects** used, **return plan**
  4. **Sample** used streams
  5. **Disable** used streams



[Garrett 2018a][Garrett 2018b]

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Focused Example 1

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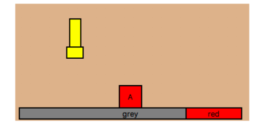
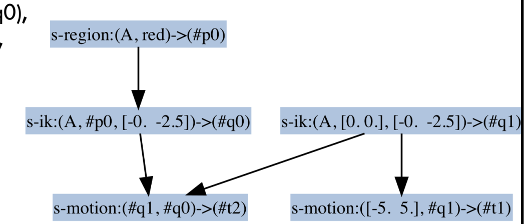
Optimistic Plan:
move([-5. 5.], #t0, #q0), **pick**(A, [0. 0.], [-0. -2.5], #q0),
move(#q0, #t2, #q1), **place**(A, #p0, [-0. -2.5], #q1)

Constraints:
(kin, A, #q0, #p0, [-0. -2.5]),
(kin, A, #q1, [0. 0.], [-0. -2.5]),
(motion, [-5. 5.], #t1, #q1),
(motion, #q1, #t2, #q0),
(contain, A, #p0, red),





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Focused Example 2: Iteration 1

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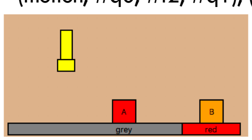
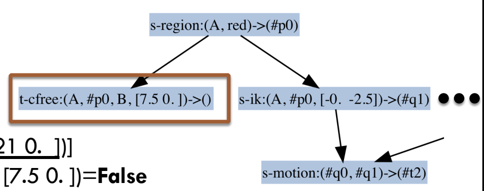
Optimistic Plan:
move([-5. 5.], #t0, #q0), **pick**(A, [0. 0.], [-0. -2.5], #q0), **move**(#q0, #t2, #q1), **place**(A, #p0, [-0. -2.5], #q1)

Constraints:
(cfree, A, #p0, B, [7.5 0.]), (contain, A, #p0, red),
(kin, A, #q0, [0. 0.], [-0. -2.5]), (kin, A, #q1, #p0, [-0. -2.5]),
(motion, #q0, #t2, #q1), (motion, [-5. 5.], #t0, #q0)





Stream evaluations:
1. **s-region:**(A, red)->[([8.21 0.])]
2. **t-cfree:**(A, [8.21 0.], B, [7.5 0.])=**False**

These stream instances are **removed** from subsequent searches

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Focused Example: Iteration 2

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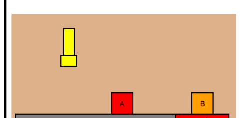
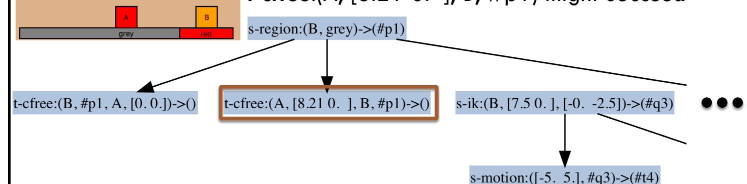
Optimistic Plan:
move([-5. 5.], #t4, #q2), **pick**(B, [7.5 0.], [-0. -2.5], #q2),
move(#q2, #t9, #q3), **place**(B, #p1, [-0. -2.5], #q3),
move(#q3, #t6, #q0), **pick**(A, [0. 0.], [-0. -2.5], #q0),
move(#q0, #t8, #q4), **place**(A, [8.21 0.], [-0. -2.5], #q4)



t-cfree:(A, [8.21 0.], B, [7.5 0.]) previously **failed**
t-cfree:(A, [8.21 0.], B, #p1) might **succeed**



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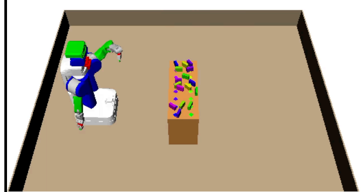
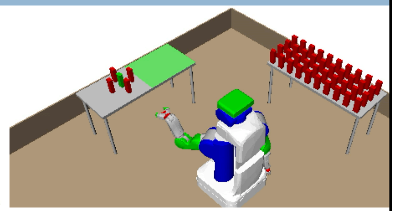
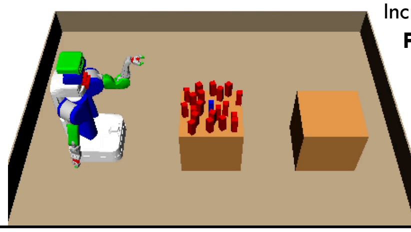
Focused Outperforms Incremental





Incremental ~20 s
Focused ~10 s

Incremental N/A
Focused ~25s



Incremental N/A
Focused ~20s

[Garrett 2018a]

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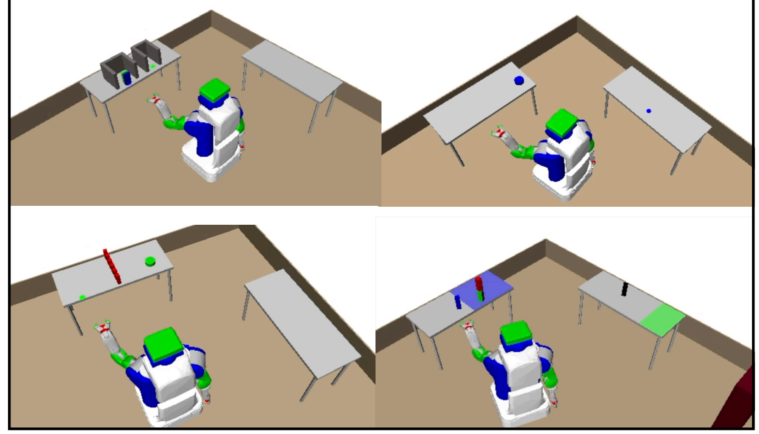
Diverse Experiments



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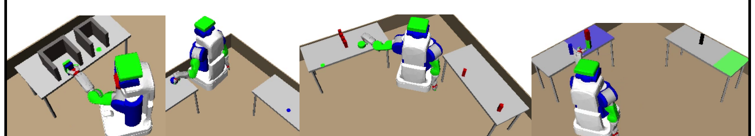
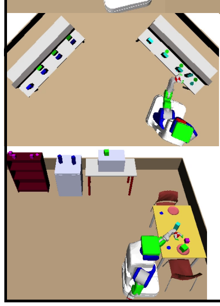
Diverse Experiments





	Incr.		*Incr. - H*		*Focus*		*Focus - H*	
Problem	**%**	**t**	**%**	**t**	**%**	**t**	**%**	**t**
Regrasp	98	1	100	2	98	1	95	1
Push	100	11	100	13	100	13	100	9
Wall	95	10	98	13	100	6	100	8
Stacking	100	9	100	9	100	2	100	3
Nonmon.	25	21	98	15	0	-	88	43
Dinner	0	-	100	27	0	-	98	22

Success percentage (%), Average runtime in sec. (t)

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Cost-Minimizing Planning

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- Actions costs specified as **nonnegative functions**

```
(:action move                                  (:function (Length ?t)
  :parameters (?q1 ?t ?q2)                         (Traj ?t))
  :precondition (and (Motion ?q1 ?t ?q2)
                     (AtConf ?q1))
  :effect (and (AtConf ?q2)
               (not (AtConf ?q1)))
               (increase (total-cost) (Length ?t))))
```

- Function specification similar to derived predicates

```
def Length(t):
    return sum(np.linalg.norm(q2 - q1)
               for q1, q2 in zip(t[:-1], t[1:]))
```

- **Asymptotically optimal** algorithms

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Goal: Hold Any Green Block

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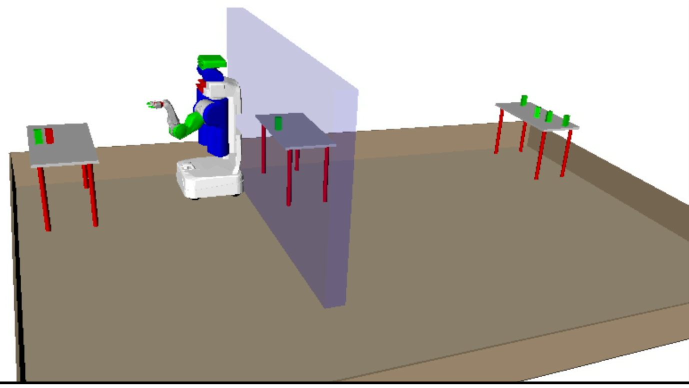
- **Lower bounds on costs** improve focused performance



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TAMP Under Uncertainty

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A Real World Example

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In the real world…

Three big problems:

1) Partially observability: we don't have full knowledge of the world; objects not visible.
2) Stochastic actions: objects or the robot will not appear where we expect when grasped, placed, or detected. This means we must be able to re-plan efficiently.
3) Problem complexity: plans are long, with many free parameters. It's impossible to explore all possible results of our actions.

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POMDP: Partially-Observable State

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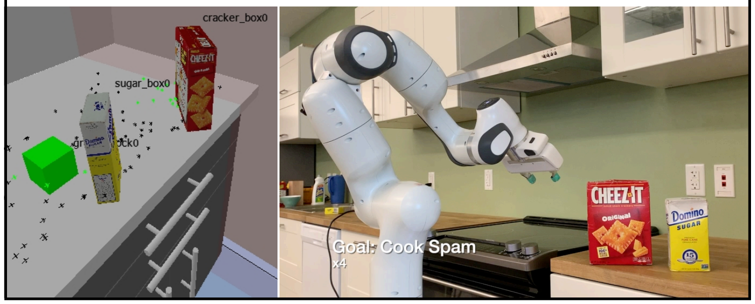
- Update a **belief** (probability distribution) over states
- Plan in the **space of beliefs** (belief space planning)
  - Intentionally take observation actions



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MDP: Stochastic Action Effects

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- Approximate as cost-sensitive **deterministic** problem
- **Policy** computed online via **replanning**

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Geometric & Probabilistic Constraints

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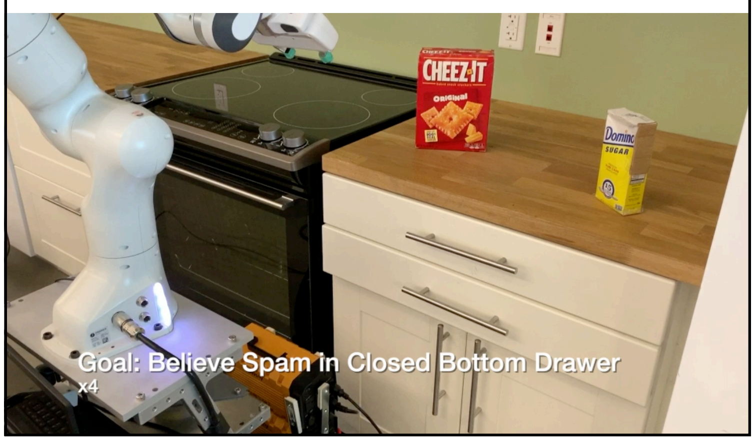

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Three Insights

1) **Particle-based belief representation:** allows us to represent belief over where objects might be, given a prior based on the environment. Determinize this belief before planning.
2) **Online replanning:** we constrain new plans to be decreasing in length, and re-use elements of the plan structure. This prevents issues with (1).
3) **Deferred evaluation:** only evaluate *streams*, i.e. find continuous values, for actions that occur before the next time we will need to replan.

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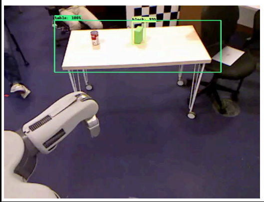
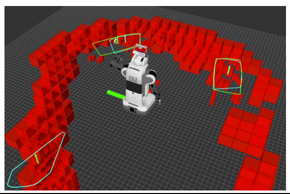
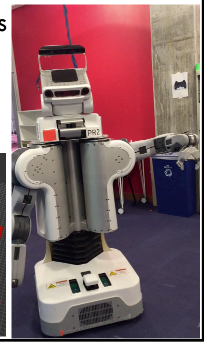
Belief-Space TAMP System

- Convolutional Neural Network (**CNN**) Object Detector
- Point cloud **plane estimation** to identify surfaces
- Point cloud **pose estimation** for objects
- **Occupancy grid** for non-manipulable
- Plan, execute, & observe in **real time**







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Takeaways

- **Task and Motion Planning (TAMP):** hybrid planning where <u>continuous constraints affect discrete decisions</u>
- **Sampling** is powerful for exploring continuous spaces
- **STRIPStream:** planning language that supports **sampling procedures** as blackbox streams
  - **Domain-independent** algorithms
  - **Lazy/optimistic** planning intelligently queries only a small number of samplers (focused algorithm)
- Ongoing work involving **cost-sensitive, multi-agent, probabilistic & partially observable** TAMP

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Other Directions

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Robustness and Reactivity

Task-Level Disturbances

Action-Level Disturbances

Sensors can be wrong, actions can have unpredictable effects, and external factors can interfere with execution.

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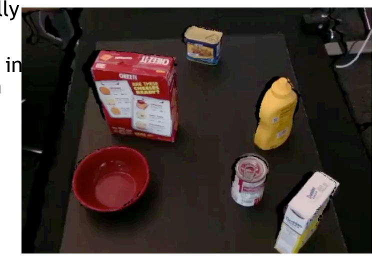
Goal-Based Imitation Learning

- Goal-based imitation allows us to map from human demonstrations to dramatically different environments.
- Take a human demonstration in one environment, use motion planning to determine what their intentions were.



Huang, D., Chao, Y., Paxton, C., Deng, X., Li, F., Naebles, J., Garg, A., Fox, D. Motion Reasoning for Goal-Based Imitation Learning. ICRA 2020

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Goal-Based Imitation Learning

- Goal-based imitation allows us to map from human demonstrations to dramatically different environments.
- Take a human demonstration in one environment, use motion planning to determine what their intentions were.
- Use the inferred logical goal and execute robustly in the new environment.

Huang, D., Chao, Y., Paxton, C., Deng, X., Li, F., Naebles, J., Garg, A., Fox, D. Motion Reasoning for Goal-Based Imitation Learning. ICRA 2020

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Deep Planning Domain Learning

- Learn symbols for high-level task planning, as well as low-level policies for reactive execution.
- Advantage: highly reactive learned hierarchical architecture that can generate plans for held-out tasks.

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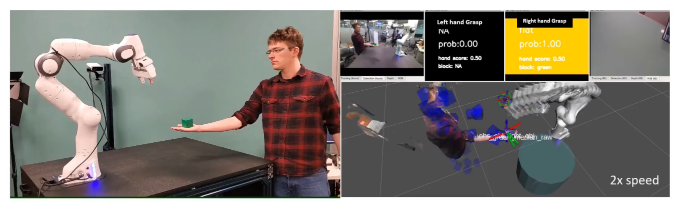
Collaborating with Humans

Human Grasp Classification for Reactive Human-to-Robot Handovers

Wei Yang[*1], Chris Paxton[*1], Maya Cakmak[1,2], and Dieter Fox[1,2]



NVIDIA. UNIVERSITY of WASHINGTON

[*] Equal contribution | [1] NVIDIA, USA | [2] University of Washington, USA

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Questions? (and Outtakes!)

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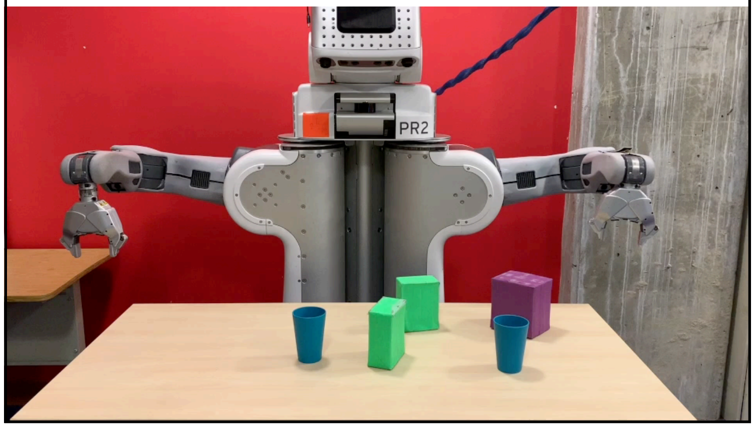

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