Representation Learning and Synthesis for Generalized Planning

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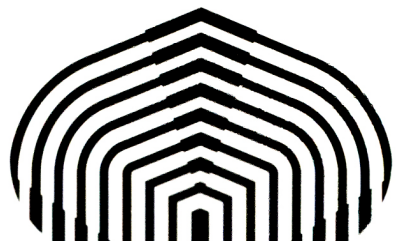
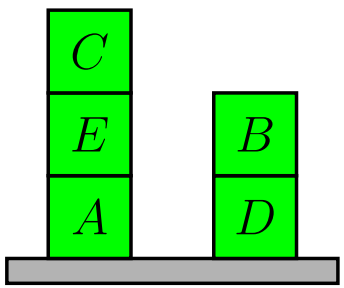


Collaborators

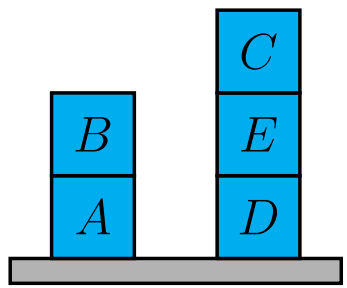
Generalized Planning: The Challenge

Generalized planning is about obtaining a **general plan or strategy** for solving collections of planning problems

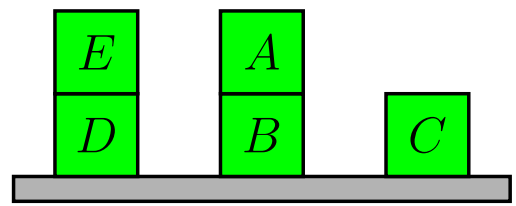
For example, find general strategy to achieve **fixed goal** in all Blocksworld problems, independently of number or initial configuration of blocks



Get A clear



Get A on B



Get tower A, B, C, D, E

Challenges:

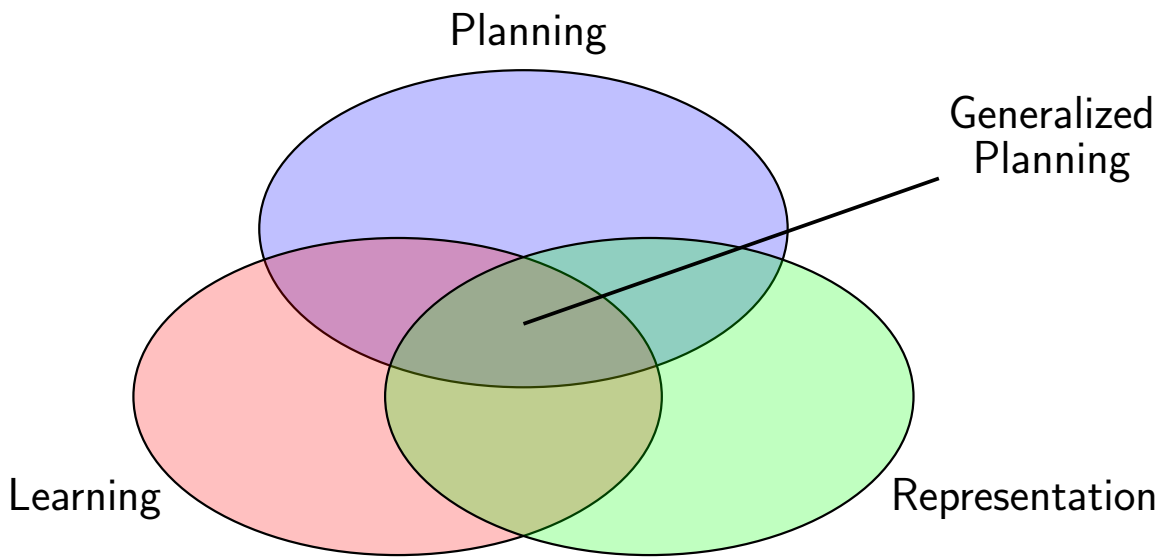
- How to formulate and represent the problem formally?
- What's the form of solutions?
- How to solve it?

Motivation

Why solve individual problems from scratch if it's possible to learn general plan in one shot?

Lots of current research in **deep (reinforcement) learning** is about computation of general plans or policies; e.g. [Espeholt et al., 2018; Groshev et al., 2018; Chevalier-Boisvert et al., 2019; François-Lavet et al. 2019]

Generalized planning gives us a crisp vocabulary to talk about general plans [Levesque, 2005; Hu & De Giacomo, 2011; B. & Geffner, 2015; Belle & Levesque, 2016; Jiménez et al., 2019; Illanes & McIlraith, 2019]

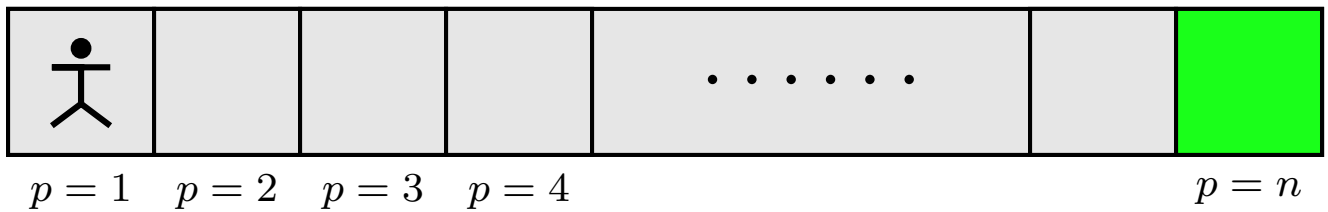


Outline

1. Non deterministic abstractions for families of classical planning problems
2. Qualitative Numerical Planning (QNP): concrete language for abstractions
3. First-order relational planning instances
4. Solving QNPs via reduction to FOND planning
5. Learning QNP abstractions from traces
6. Wrap Up

Example

Problem P_n: agent moves in $1 \times n$ grid, starts at $p = 1$ and goal is $p = n$



Agent can move **right** and **left**, and **senses** R when in last cell

Collection of problems: $\mathcal{Q} = \{P_n : n = 1, 2, \ldots\}$

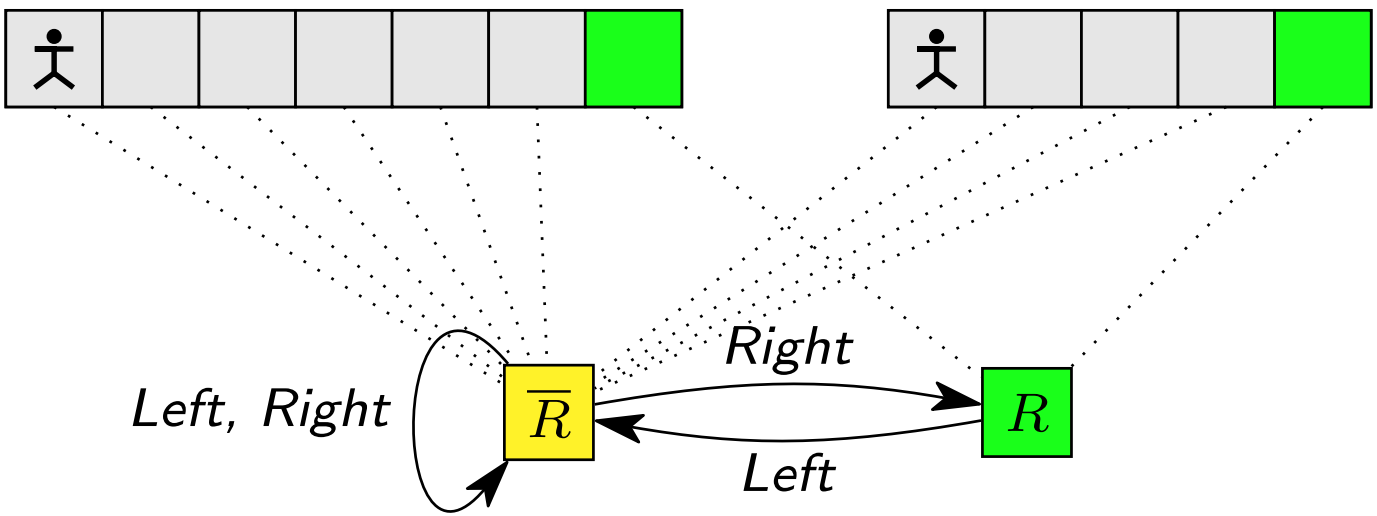
(Generalized) plan π:

While R not sensed do move right

What's the relation between the solution and the collection $\mathcal{Q}$?

Abstraction: Observable Projection

Policy π solves a **single abstract problem** that is **fully observable and non-deterministic (FOND)**



Fairness Assumptions in FOND problems

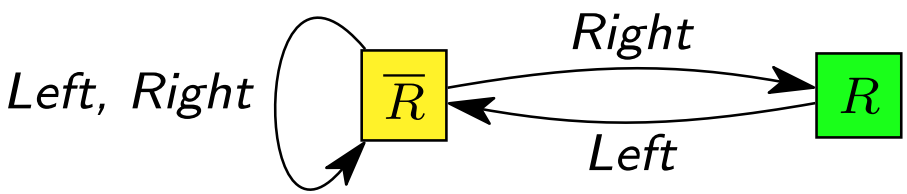
Solutions for FOND problems are either [Cimatti et al., 2003]:

– **Strong solutions:** acyclic and suitable for **adversarial planning**

– **Strong cyclic solutions:** assume **"strong fairness"** and suitable for MDPs when goal is to be reached with probability 1

Fairness assumptions in the projection doesn't correspond to either

Indeed, policy that interleaves *Right* and *Left* solves projection but doesn't solve any P_i as the agent won't get past the second cell

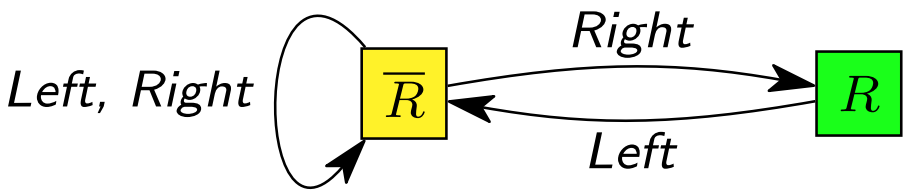


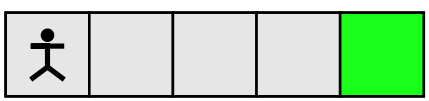
Local vs. Global Properties

Projection captures **local properties** of instances: each transition represents one or more transition in one or more instances

Global properties are lost in projection

Example: there is **no trajectory** (in some P) where *Right* applied infinitely often, *Left* only finitely, and goal isn't reached, but there is such in projection

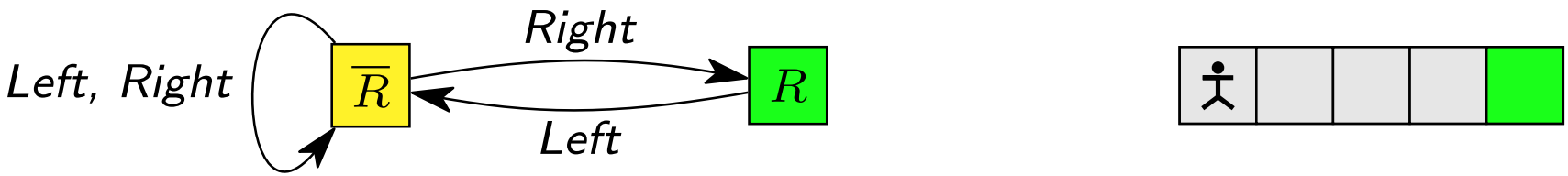




Trajectory Constraints

Global properties can be captured with **trajectory constraints** that filter out non-realizable trajectories [B. et al, 2017]

Example: if *Right* is applied infinitely often and *Left* only a finite number of times, goal is **eventually reached**



Solutions for $\mathcal{Q}$ are **strong-cyclic policies** whose induced trajectories that **comply with the constraints** are goal reaching

Different from standard fairness

Qualitative Numerical Planning

Simple and expressive language [Srivastava et al., 2011]:

- directly express the projection in compact form
- transparently adds the needed trajectory constraints
- after proper reduction to FOND, solved with off-the-shelf FOND planner
- models can be learned from sampled trajectories

A QNP problem is similar to STRIPS problem but extended with **numerical variables** that can be incremented or decremented **qualitatively**

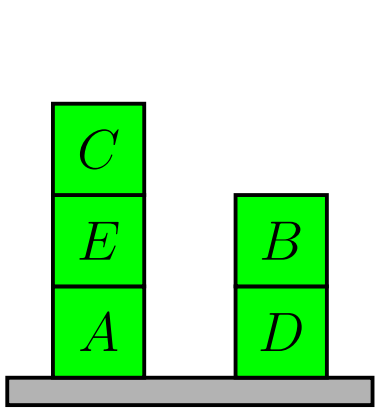
QNP Example: Clear-x

Goal: Remove all blocks above fixed block x

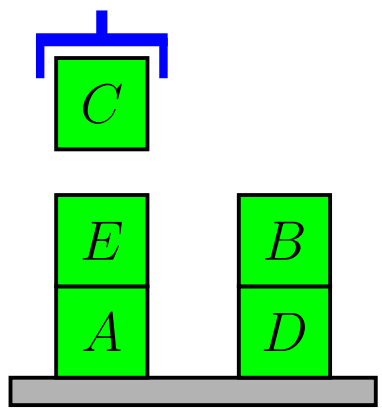
QNP $Q_{clear} = (F, V, I, A, G)$ captures all Blocksworld problems:

- $F = \{H\}$ where H denotes whether gripper holds a block
- $V = \{n\}$ where n **"counts"** blocks above x ($n{>}0$ iff some block above x)
- $I = \{\neg H, n > 0\}$
- $G = \{n{=}0\}$

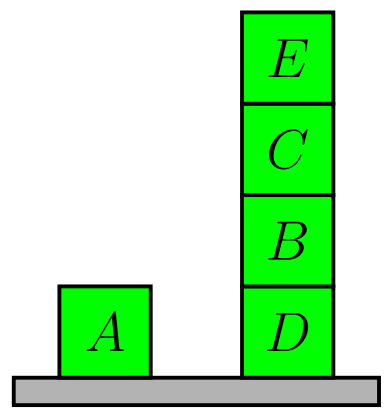
$x =$ block A



$\neg H,\ n = 2$



$H,\ n = 1$

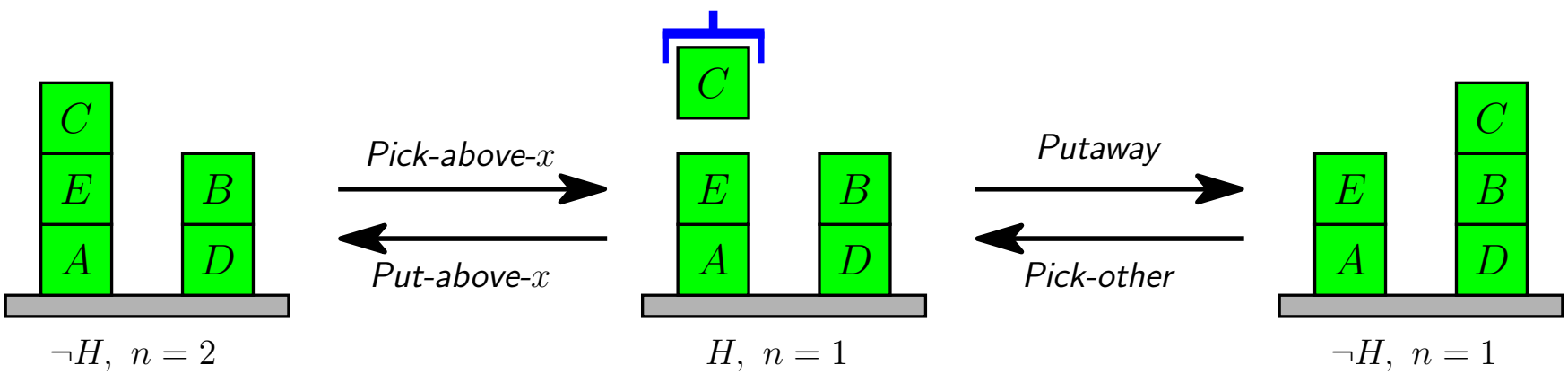


$\neg H,\ n = 0$

QNP Example: Actions

- *Putaway* $= \langle H; \neg H \rangle$ puts held block on table or block not above x
- *Pick-above-*$x = \langle \neg H, n > 0; H, n{\downarrow} \rangle$ picks the top block above x
- *Put-above-*$x = \langle H; \neg H, n{\uparrow} \rangle$ puts block being held on top block above x
- *Pick-other* $= \langle \neg H; H \rangle$ picks block not above x

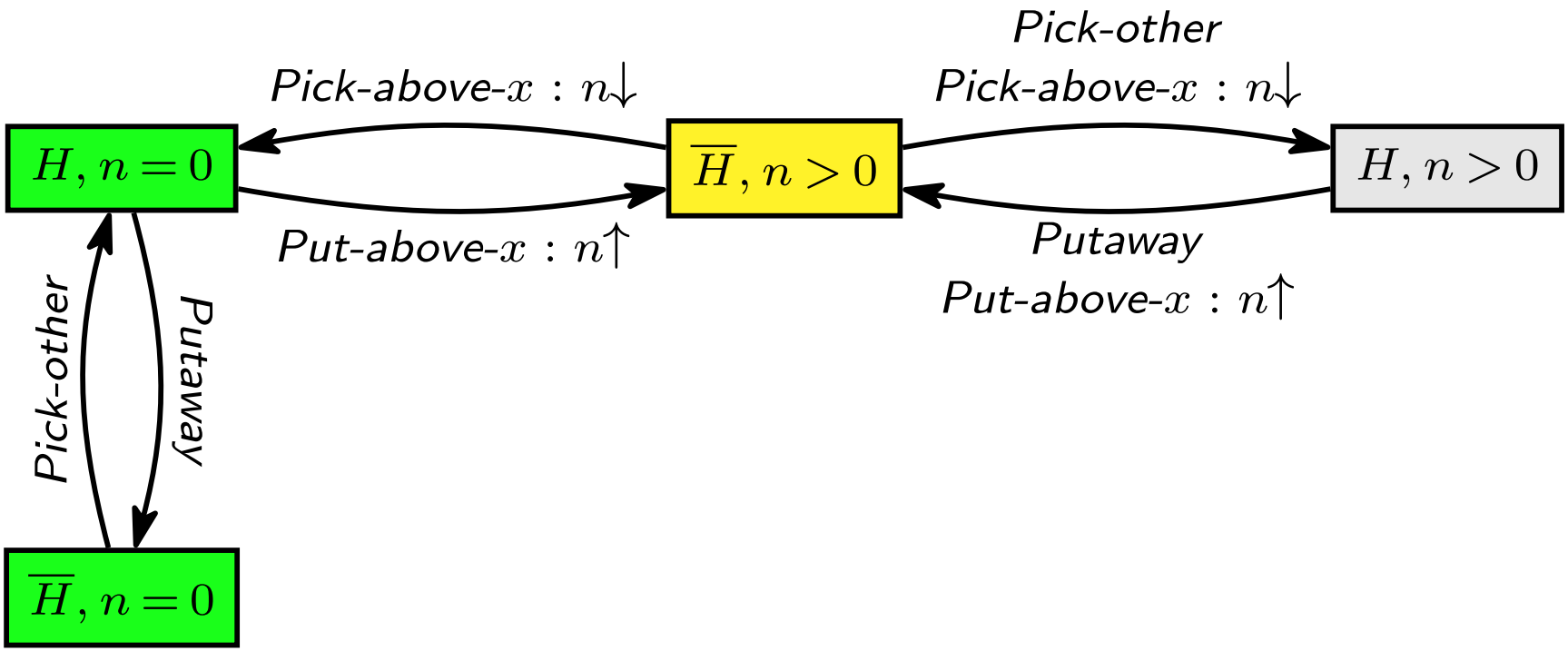
Block x is block A:



QNP Example: Projection

Observation projection for $Q_{clear} = (F, V, I, A, G)$ where

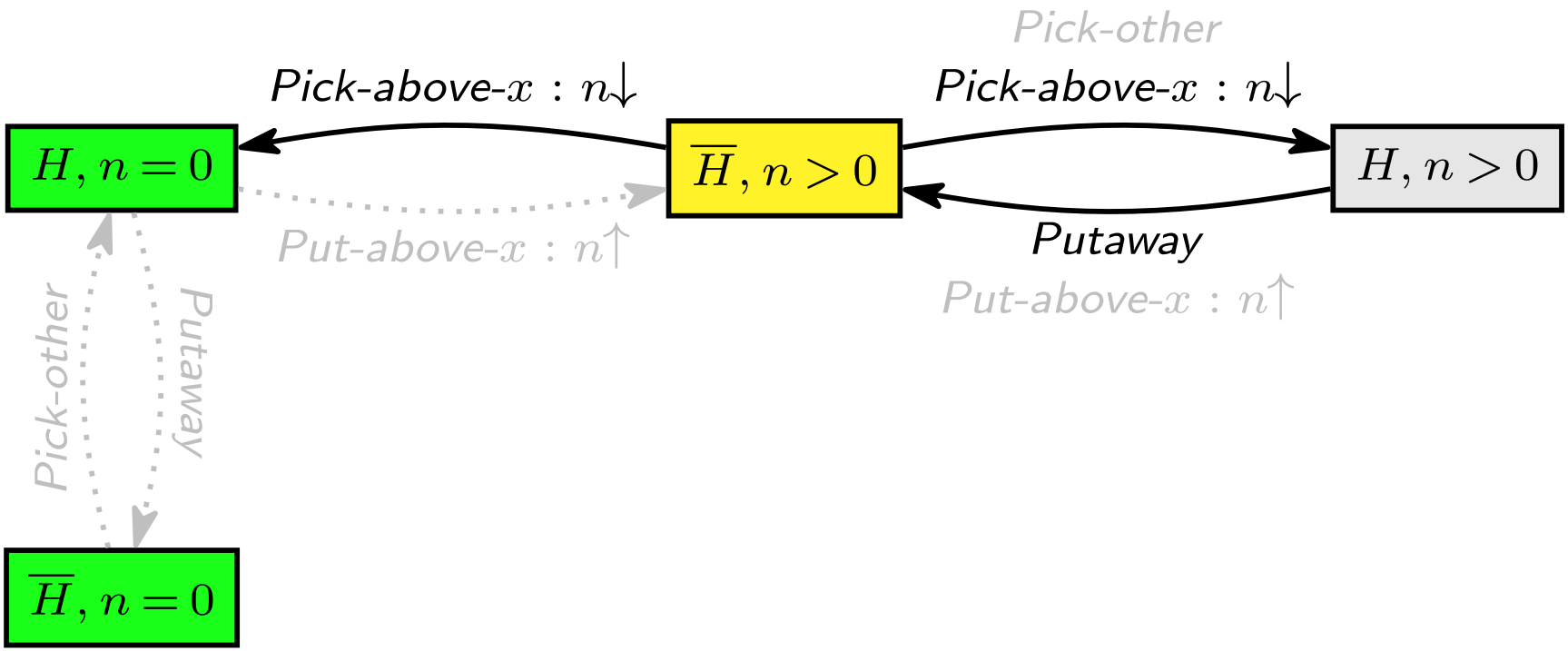
- $F = \{H\}$ and $V = \{n\}$
- $I = \{\overline{H}, n > 0\}$ and $G = \{n = 0\}$
- Actions in A: *Putaway* $= \langle H; \neg H \rangle$, *Pick-above-*$x = \langle \neg H, n > 0; H, n{\downarrow} \rangle$, *Put-above-*$x = \langle H; \neg H, n{\uparrow} \rangle$, and *Pick-other* $= \langle \neg H; H \rangle$



QNP Example: Solution

Observation projection for $Q_{clear} = (F, V, I, A, G)$ where

- $F = \{H\}$ and $V = \{n\}$
- $I = \{\overline{H}, n > 0\}$ and $G = \{n = 0\}$
- Actions in A: *Putaway* $= \langle H; \neg H \rangle$, *Pick-above-*$x = \langle \neg H, n > 0; H, n{\downarrow} \rangle$, *Put-above-*$x = \langle H; \neg H, n{\uparrow} \rangle$, and *Pick-other* $= \langle \neg H; H \rangle$



QNP Syntax

QNP is tuple $Q = (F, V, I, A, G)$ where

- F is a finite set of propositions
- V is a finite set of numerical variables
- I is a set of $F{+}V$-literals, where V-literals are $X{=}0$ or $X{>}0$ for X in V
- G is goal condition given by $F{+}V$-literals
- A is set of actions. Each has **precondition** *Pre* ($F{+}V$-literals), **boolean effects** *Eff* (F-literals), and **numerical effects** N (atoms $X{\uparrow}$ or $X{\downarrow}$) with restriction that if $X{\downarrow}$ in N, then $X > 0$ must be in *Pre*

Numerical vars affected only **qualitatively**, and tested for zero

Plan-existence for QNPs **decidable** [Srivastava et al., 2011] whereas it is **undecidable** for numerical planning [Helmert, 2002]

Trajectory Constraints for QNPs

Only **global property** that needs to be accounted for is: for each var X,

> *If X is decremented infinitely often but incremented only a finite number of times, eventually $X = 0$*

Constraint can be expressed in **Linear Temporal Logic (LTL)**, enabling automata-based approaches for solving QNPs [B. et al., 2017]

Theorem

A solution for QNP $Q = (F, V, I, A, G)$ can be obtained in time **doubly exponential** *in $|V| \times |A| + |G|$ and* **exponential** *in $|F| + |V|$*

Automata-based methods need to compute abstraction in explicit form and thus require **exponential space**

First-Order Relational Instances

QNPs also used on STRIPS domains where $\mathcal{Q}$ contains **ground instances** of common schema

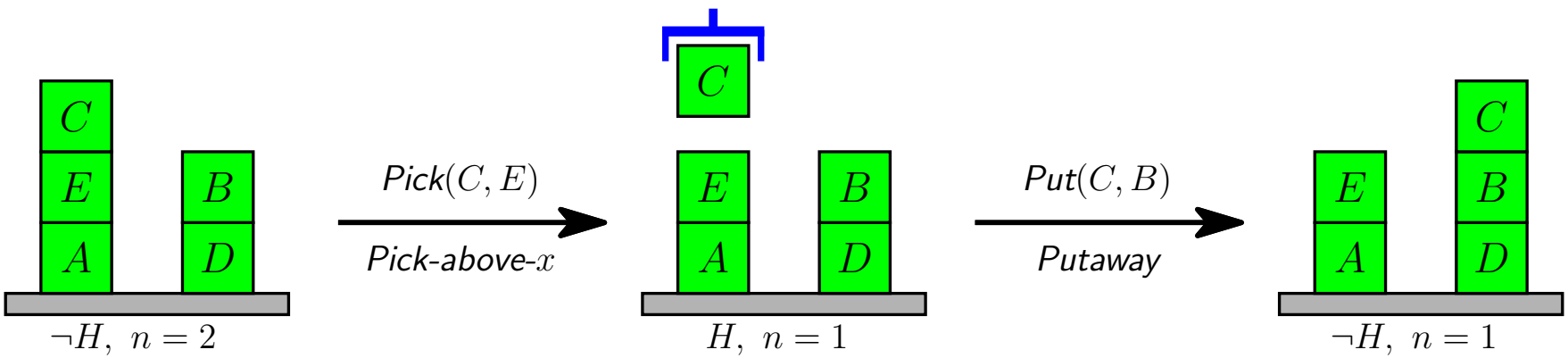
Each task P is associated with **interpretations** ϕ_p and ϕ_X for booleans p and numerical vars X that map embed P-states s into Q-states $\phi(s)$

Abstract actions in Q must **track** value change of variables

Sound Abstraction for Blocksworld

Q_{clear} is **sound abstraction** for Blocksworld instances defined with predicates *on*$(?x, ?y)$, *clear*$(?x)$, *ontable*$(?x)$ and *holding*$(?x)$

Q_{clear} has $F = \{H\}$ and $V = \{n\}$: H captures when gripper is holding a block, and n counts the number of blocks above block A



Pick-above-x **represents** *Pick*(C, E) while *Putaway* **represents** *Put*(C, B)

Sound Abstractions

QNP Q is **sound abstraction** for STRIPS instance P iff

- if s_0 is initial state in P, then $\phi(s_0)$ is initial state in Q
- for each state s in P, if $\phi(s) \models G$ then s is goal in P
- for any reachable state s in P and any abstract action $\bar{a}$ in Q that is **applicable** in $\phi(s)$, there is action a in P that is **represented** by $\bar{a}$ at s

[B. & Geffner, 2018]

Theorem

If Q is sound for P and π solves Q, then the plan π' defined by $\pi'(s) = a$ where a is an action in P that is represented by $\pi(\phi(s)$ at s, **solves** *P. That is, π' solves $\mathcal{Q} = \{P : Q$ is sound abstraction for $P\}$*

Example: Gripper in STRIPS

Problem: Robot with grippers whose goal is to move balls from B to A:

STRIPS schema for Gripper:

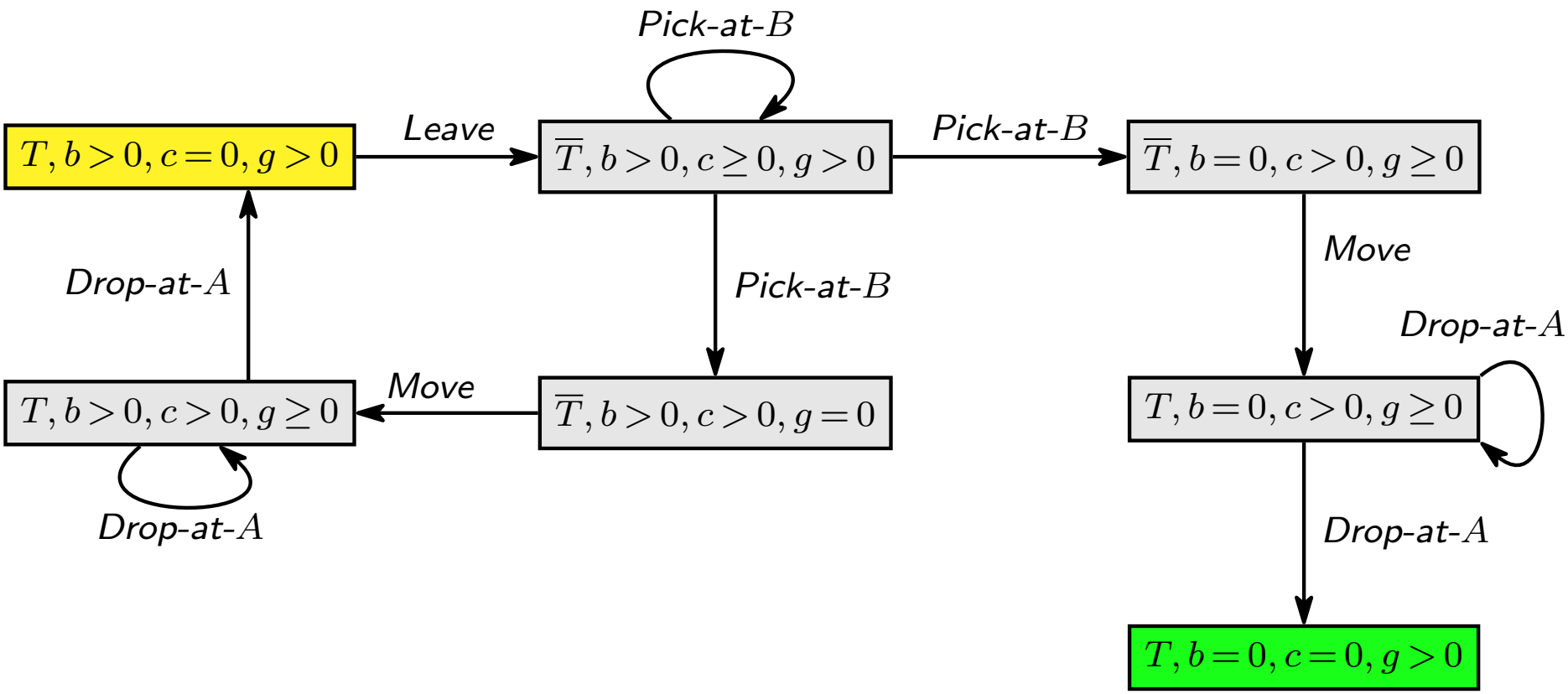
- Atoms: $\mathit{at}(?r)$, $\mathit{ball}(?b, ?r)$, $\mathit{empty}(?g)$, $\mathit{hold}(?b, ?g)$
- Actions:
  - $\mathit{Move}(?s, ?t) = \langle \mathit{at}(?s); \neg\mathit{at}(?s), \mathit{at}(?t) \rangle$
  - $\mathit{Pick}(?b, ?r, ?g) = \langle \mathit{empty}(?g), \mathit{at}(?r), \mathit{ball}(?b, ?r); \neg\mathit{empty}(?g), \neg\mathit{ball}(?b, ?r), \mathit{hold}(?b, ?g) \rangle$
  - $\mathit{Drop}(?b, ?r, ?g) = \langle \mathit{hold}(?b, ?g), \mathit{at}(?r); \neg\mathit{hold}(?b, ?g), \mathit{ball}(?b, ?r), \mathit{empty}(?g) \rangle$
- Initial state is robot at A and all balls at B
- Goal is to have all balls at A

Example: QNP for Gripper

QNP $Q_{gripper} = (F, V, I, A, G)$:

- $F = \{T\}$ where T iff *at*(A)
- $V = \{b, c, g\}$ where b counts balls at B, c balls held, and g free grippers
- $I = \{T, b > 0, c = 0, g > 0\}$ and $G = \{c = 0, b = 0\}$
- Abstract actions are:
  - *Move* $= \langle \neg T; T \rangle$ and *Leave* $= \langle T; \neg T \rangle$
  - *Pick-at-*$B = \langle \neg T, b > 0, g > 0; b\downarrow, c\uparrow, g\downarrow \rangle$
  - *Drop-at-*$B = \langle \neg T, c > 0; b\uparrow, c\downarrow, g\uparrow \rangle$
  - *Drop-at-*$A = \langle T, c > 0; c\downarrow, g\uparrow \rangle$

Example: Solution for Gripper



Solving QNPs with FOND Planners

Reduction from QNP into FOND planning

Reduction is function T : QNPs $\rightarrow$ FONDs such that:

- **Efficient:** given QNP Q returns FOND problem $P = T(Q)$ in polytime
- **Sound:** P has solution implies Q has solution
- **Complete:** Q has solution implies P has solution
- **Effective:** solution for Q can be recoverd in polytime from solution for P

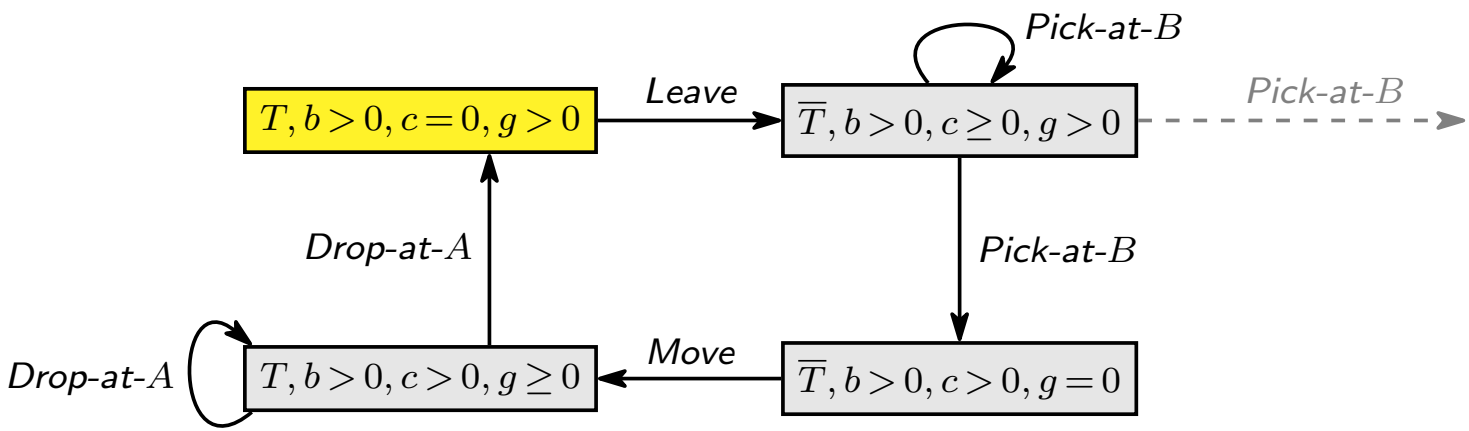
If conditions met, efficient algorithm for QNPs and establish upper bound on complexity

Termination of QNP Plans

QNP solutions are the strong-cyclic solutions that **terminate**

- π terminates if each infinite induced trajectory terminates
- Infinite trajectory denoted by $s_0, s_1, \ldots [s_i, \ldots, s_m]^*$ where $\{s_i, \ldots, s_m\}$ is **set of recurrent states (loop)**
- Such trajectory terminates iff there is variable X that is **decremented but not incremented** in loop

Example: loop terminates because variable b is decremented by *Pick-at-B* but not incremented in loop



Checking Termination with SIEVE

Termination checked with algorithm called SIEVE [Srivastava et al., 2011]

SIEVE works on policy graph $\mathcal{G}(\pi)$: subgraph of projection induced by π

SIEVE (Graph $\mathcal{G}(\pi)$):
repeat

- Compute the strongly connected components (SCC) of $\mathcal{G}(\pi)$
- Choose SCC C and variable X that is **decremented** in C but not **incremented** in C
- Remove edges (s, s') so that s and s' are in C, and $\pi(s)$ decrements X

until $\mathcal{G}(\pi)$ *is acyclic or there is no SCC* C *and variable* X *to choose*

Theorem

π terminates iff SIEVE *reduces $\mathcal{G}(\pi)$ to an acyclic graph. Hence, solution for Q can be obtained in* **exponential space** *by enumerating the strong-cyclic solutions and testing each for termination with* SIEVE

Reduction of QNPs into FOND

Reduction simulates way SIEVE removes edges to reduce SCCs. For this, a **bounded stack** and **bounded counters** are introduced [B. & Geffner, 2020]

Stack used to push/pop numeric vars, while counters used to bound number of operations on stack. The reduction is such that:

- actions that decrement vars must have **at least one such var** in stack
- actions that increment vars must have **none of such variables** in stack

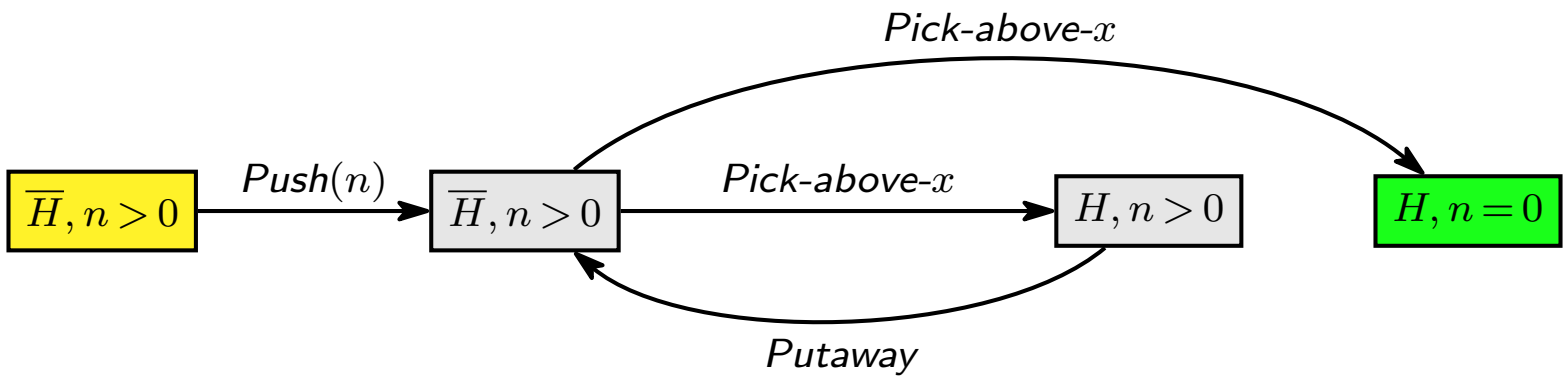
Max stack depth and max counter capacity implemented with polynomial number of propositions and actions

Theorem

QNP Q can be reduced in **polynomial time** *to FOND $P = T(Q)$ such that Q has solution iff P has solution. Moreover, solution for Q can be recovered in polytime from solution for P. Hence, QNPs can be solved in (worst-case)* **exponential time** *since FONDs can be solved in* **exponential time**

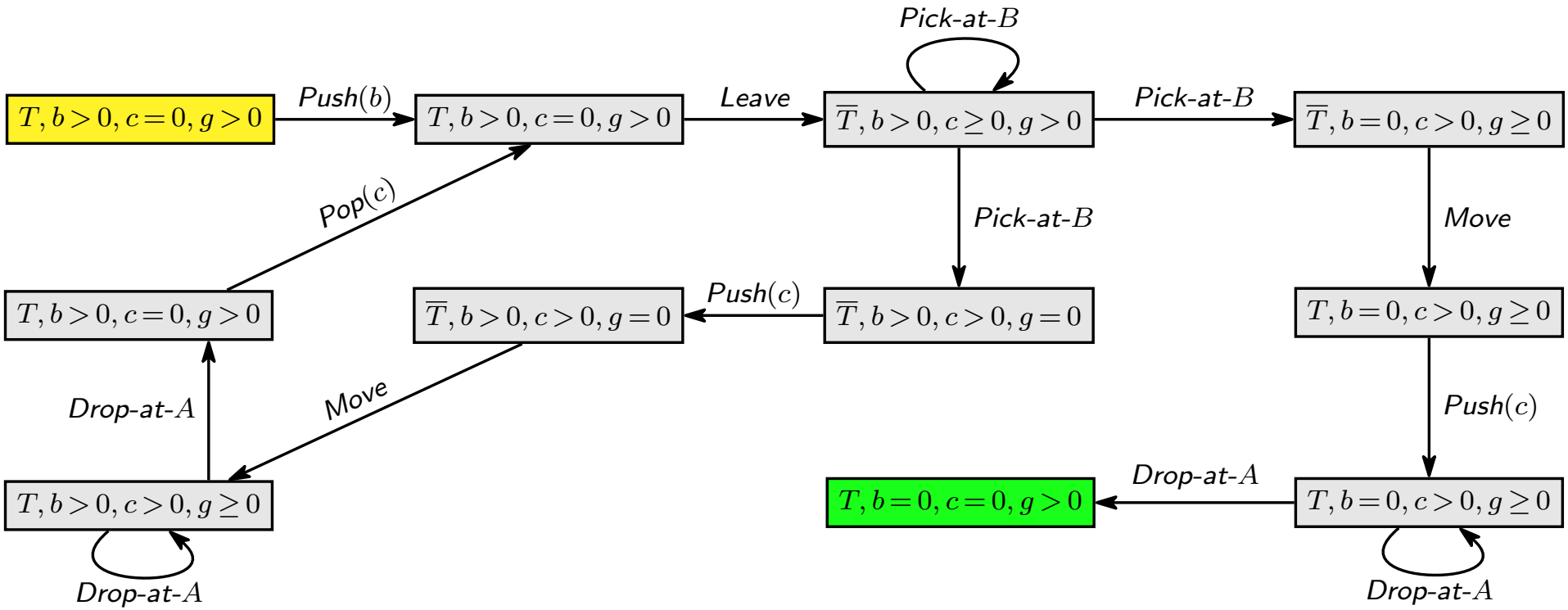
Example: Solving Clear-x

Q_{clear} fed to qnp2fond to get P solved with FOND-SAT [Geffner & Geffner, 2018]



qnp2fond translates Q in less than 0.01 secs. FOND-SAT solves P in 0.08 secs after 3 calls to SAT solver

Example: Solving Gripper



qnp2fond translates Q in less than 0.01 secs. FOND-SAT solves P in 11.25 secs after making 10 calls to SAT solver

Expressiveness and Limitations

Any $\mathcal{Q}$ can be captured with simple QNP Q with only **one variable** d:

– $I = \{d > 0\}$, $G = \{d = 0\}$ and **single action** *Get-closer* $= \langle d > 0; d\downarrow \rangle$

– d is **number of steps to goal**

Interpretation $\phi_d(s)$ performs computation that is **intractable:** compute distance in implicit graph

Makes sense to focus on abstractions whose features are **polynomial-time computable** from representation of states

Outline Recap

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2. Qualitative Numerical Planning (QNP): concrete language for abstractions
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Learning QNP Representations

QNPs are expressive and effective!

QNP models can be **learned from samples** [B., Francès & Geffner, 2019]

Main challenge is to learn **concepts** that define features (booleans and numericals); e.g. number of free grippers, distance to target, etc

From pool of concepts that define pool of features, select **minimal subset** that account for transitions in **sampled trajectories**

System learns QNP models that are translated into FOND and solved

QNP Learner

Input: STRIPS domain, sampled trajectories for small instances, and complexity bound N for concepts

Output: QNP model Q that explain trajectories

Method:

- Use atom schemas and fixed **concept grammar** to generate **pool of concepts:** all concepts with complexity $\leq N$
- Interpretation of concept C at state s is **subset of objects** $C(s)$; these define features:
  - **boolean feature** p when $|C(s)| \in \{0, 1\}$ for all states s
  - **numerical feature** $n = |C(s)|$ when $|C(s)| > 1$ for at least some state s
- From **pool of features**, construct SAT theory T that "separates" states and transitions in sample
- Recover QNP model from solution of SAT theory T

SAT Theory for Learning QNPs

Input:

– $\mathcal{S}$ = sample of transitions (s, s') from small instances in $\mathcal{Q}$
– $\mathcal{F}$ = pool of features f together with interpretations $f(s)$ at each s in $\mathcal{S}$

Propositional variables:

– $selected(f)$ for each f in $\mathcal{F}$ to select $\mathcal{F}$-subset
– $D_1(s, t)$ iff selected features distinguish states s and t in $\mathcal{S}$
– $D_2(s, s', t, t')$ iff selected features distinguish (s, s') and (t, t') in $\mathcal{S}$

Formulas:

– $D_1(s, t)$ (for states s and t such that only one is goal)
– $\bigwedge_{t'} D_2(s, s', t, t') \implies D_1(s, t)$ (for each (s, s') and t in $\mathcal{S}$)
– $D_1(s, t) \iff \bigvee_f selected(f)$ (for f's that distinguish s and t)
– $D_2(s, s', t, t') \iff \bigvee_f selected(f)$ (for f's that dist. (s, s') and (t, t'))

Theorem

$T(\mathcal{S}, \mathcal{F})$ is SAT iff there is **sound QNP** *abstraction relative to $\mathcal{S}$ and $\mathcal{F}$*

Learned QNPs: Gripper

Training set: 2 instances with 4 and 5 balls each

Learned features (selected) from $|\mathcal{S}| = 403$ and $|\mathcal{F}| = 130$:

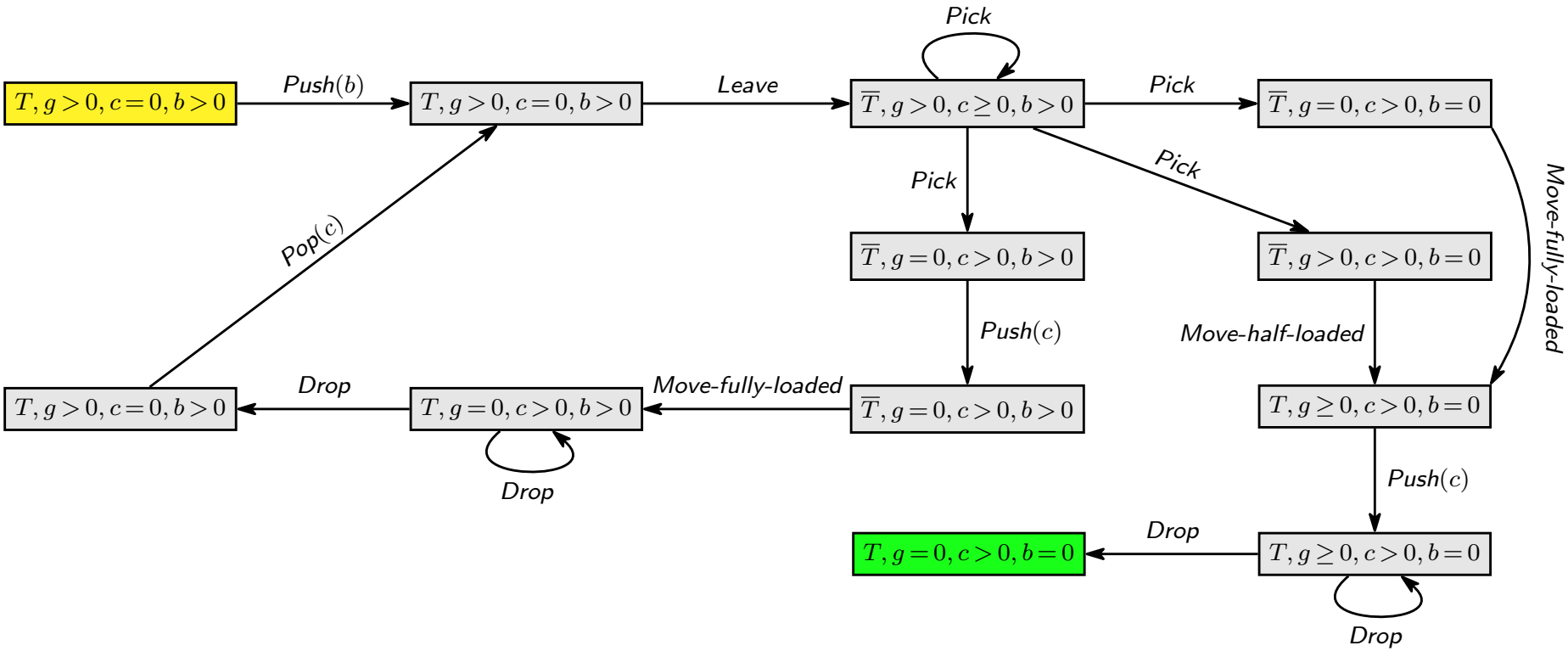
- $T =$ "whether robot is in target room"
- $b =$ "number of balls not in target room"
- $c =$ "number of balls being held by robot"
- $g =$ "number of free grippers (available capacity)"

Learned abstract actions:

- *Drop* $= \langle T, c > 0; c\downarrow, g\uparrow \rangle$
- *Move-fully-loaded* $= \langle \neg T, c > 0, g = 0; T \rangle$
- *Move-half-loaded* $= \langle \neg T, c > 0, g > 0, b = 0; T \rangle$
- *Pick* $= \langle \neg T, b > 0, g > 0; b\downarrow, g\downarrow, c\uparrow \rangle$
- *Leave* $= \langle T, c = 0, g > 0; \neg T \rangle$

Solution works for any number of balls and grippers!

Example: Solution for (Learned) Gripper



Model Q learned and translated into FOND in less than 1 sec. `FOND-SAT` solves the FOND problem in less than 13 secs after 11 calls to SAT solver

Learned QNPs: Pick Rewards in Grid

Inspired from RL work [Garnelo, Arulkumaran & Shanahan, 2016]

Training set: 2 instances 4×4, 5×5, diff. dist. of blocked cells and rewards

Learned Features (selected) from $|\mathcal{S}| = 568$ and $|\mathcal{F}| = 280$:

– $r =$ "number of remaining rewards"

– $d =$ "minimum distance to closest reward along unblocked path"

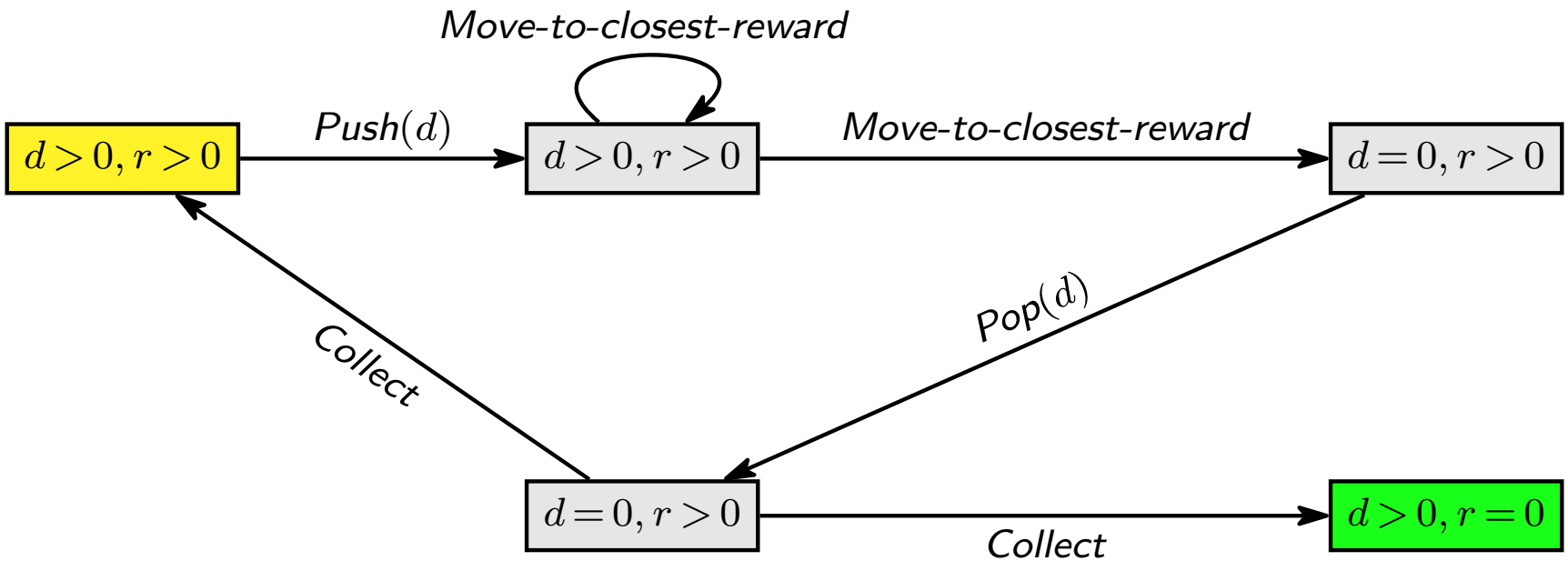
Learned abstract actions:

– *Move-to-closest-reward* $= \langle r > 0, d > 0; d{\downarrow} \rangle$

– *Collect* $= \langle d = 0, r > 0; r{\downarrow}, d{\uparrow} \rangle$

Solution works for any grid dimension, number of rewards, and distribution of blocked cells!

Example: Solution for (Learned) Rewards



Model Q is learned and translated into FOND is less than 1 sec. `FOND-SAT` solves the FOND problem in less than 1 sec after 4 calls to SAT solver

Wrap Up

- Collections of planning problems expressed as non-det abstractions with trajectory constraints
- QNP is suitable language for expressing abstractions and constraints compactly
- QNPs solved with reduction to FOND
- QNP models can be learned

Related Work

- LTL can be used to express more general abstractions and constraints [B. et al, 2017, Aminof et al., 2019; Illanes & McIlraith, 2019, Camacho et al, 2018]
- Model-based learning of general policies from examples [Khardon, 1999; Martín & Geffner, 2004; Fern et al., 2004; Jiménez et al., 2019]
- Deep RL for general policies [Toyer et al., 2018; Issakkimuthu et al., 2018; Bueno et al., 2019; Garg et al., 2020]
- Learning general policies from images without PDDL/STRIPS first-order representations [Ross et al, 2011; Hussein et al., 2017] and DRL

Current Work

Learn QNP models directly from image traces provided by a teacher:

- Use SAT to learn QNP model + solution that **imitates** teacher on traces
- Model has **uninterpreted** variables, but SAT solution gives interpretations for images in traces
- Use interpretations provided by SAT to learn **interpretation functions:**
  - Classifier from state images into valuations for variables
  - Classifier from image transitions into qualitative effects
- Solution + classifiers sufficient for applying policy on new instances

SAT task similar and inspired by work on learning STRIPS representations from non-symbolic traces (ECAI 2020)

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