Learning STRIPS Action Models from State-Constraints

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Abstract

We present a classical planning compilation for learning STRIPS action models from state-constraints. Remarkably the compilation does not require the precise actions in the plan executions, despite they can be included to constraint further the space of possible action models. A plan that solves the classical planning task resulting from our compilation induces a STRIPS action model that is compliant with all the constraints given as input. The paper also shows that, when input constraints are too loose, evaluating learned STRIPS models with respect to reference model becomes non trivial (actions can be reformulated, i.e. their semantic can be swapped) and introduces a novel evaluation method that asses learned STRIPS models even if they are reformulated.

1 Introduction

Besides *plan synthesis* [Ghallab *et al.*, 2004], planning action models are also useful for *plan/goal recognition* [Ramírez, 2012]. At both planning tasks, an automated planner is required to reason about action models that correctly and completely capture the possible world transitions [Geffner and Bonet, 2013]. Unfortunately, building planning action models is complex, even for planning experts, and this knowledge acquisition task is a bottleneck that limits the potential of AI planning [Kambhampati, 2007].

The Machine Learning of planning action models is a promising alternative to hand-coding them with sophisticated algorithms like ARMS [Yang *et al.*, 2007], SLAF [Amir and Chang, 2008] or LOCM [Cresswell *et al.*, 2013]. Motivated by recent advances on the synthesis of different kinds of generative models with classical planning [Bonet *et al.*, 2009; Segovia-Aguas *et al.*, 2016; 2017], this paper introduces an innovative approach for learning STRIPS action models that:

1. Is defined as a classical planning compilation which opens the door to the bootstrapping of planning action models.
2. Does not require the actions applied in the observed plan executions but accepts this information to improve the quality of the learned models.
3. Assesses learned STRIPS models with respect to a reference model even when the learning hypothesis space is so low constrained that actions can be reformulated and still be compliant with the inputs.

2 Background

This section defines the planning models used on this work and the output of the learning tasks addressed in the paper.

2.1 Classical planning

We use F to denote the set of *fluents* (propositional variables) describing a state. A *literal* l is a valuation of a fluent $f \in F$, i.e. either $l = f$ or $l = \neg f$. A set of literals L represents a partial assignment of values to fluents (WLOG we assume that L does not assign conflicting values to any fluent). We use $\mathcal{L}(F)$ to denote the set of all literal sets on F, i.e. all partial assignments of values to fluents.

A *state* s is a full assignment of values to fluents, i.e. $|s| = |F|$, so the size of the state space is $2^{|F|}$. Explicitly including negative literals $\neg f$ in states simplifies subsequent definitions but often, we will abuse notation by defining a state s only in terms of the fluents that are true in s, as is common in STRIPS planning.

A *classical planning frame* is a tuple $\Phi = \langle F, A \rangle$, where F is a set of fluents and A is a set of actions. Each action $a \in A$ comprises three sets of literals:

- $\mathsf{pre}(a) \subseteq \mathcal{L}(F)$, called *preconditions*, the literals that must hold for the action $a \in A$ to be applicable.
- $\mathsf{eff}^+(a) \subseteq \mathcal{L}(F)$, called *positive effects*, that defines the fluents set to true by the application of the action $a \in A$.
- $\mathsf{eff}^-(a) \subseteq \mathcal{L}(F)$, called *negative effects*, that defines the fluents set to false by the action application.

We say that an action $a \in A$ is *applicable* in a state s iff $\mathsf{pre}(a) \subseteq s$. The result of applying a in s is the *successor state* $\theta(s, a) = \{s \setminus \mathsf{eff}^-(a)) \cup \mathsf{eff}^+(a)\}$.

A *classical planning problem* is a tuple $P = \langle F, A, I, G \rangle$, where I is an initial state and $G \subseteq \mathcal{L}(F)$ is a goal condition. A *plan* for P is an action sequence $\pi = \langle a_1, \ldots, a_n \rangle$ that induces a state sequence $\langle s_0, s_1, \ldots, s_n \rangle$ such that $s_0 = I$ and, for each $1 \leq i \leq n$, a_i is applicable in s_{i-1} and generates the successor state $s_i = \theta(s_{i-1}, a_i)$. We denote with $|\pi|$ the *plan length*. A plan π *solves* P iff $G \subseteq s_n$, i.e. if the goal

```
(:action stack
  :parameters (?v1 ?v2 - object)
  :precondition (and (holding ?v1) (clear ?v2))
  :effect (and (not (holding ?v1)) (not (clear ?v2))
               (handempty) (clear ?v1) (on ?v1 ?v2)))
```

Figure 1: STRIPS operator schema coding, in PDDL, the *stack* action from the *blocksworld*.

condition is satisfied at the last state reached after following the application of π in I.

2.2 Classical planning with conditional effects

Our approach for learning STRIPS action models is compiling this leaning task into a classical planning task with conditional effects. Conditional effects allow us to compactly define actions whose effects depend on the current state. Supporting conditional effects is now a requirement of the IPC [Vallati *et al.*, 2015] and many classical planners cope with conditional effects without compiling them away.

An action $a \in A$ has now a set of *preconditions* $\mathsf{pre}(a) \in \mathcal{L}(F)$ and a set of *conditional effects* $\mathsf{cond}(a)$. Each conditional effect $C \rhd E \in \mathsf{cond}(a)$ is composed of two sets of literals $C \in \mathcal{L}(F)$, the *condition*, and $E \in \mathcal{L}(F)$, the *effect*.

An action $a \in A$ is *applicable* in a state s if and only if $\mathsf{pre}(a) \subseteq s$, and the resulting set of *triggered effects* are the effects whose conditions hold in s:

$$triggered(s,a) = \bigcup_{C \rhd E \in \mathsf{cond}(a), C \subseteq s} E,$$

The result of applying an action a in a state s is the *successor* state $\theta(s,a) = \{s \setminus \mathsf{eff}_c^-(s,a)) \cup \mathsf{eff}_c^+(s,a)\}$ where $\mathsf{eff}_c^-(s,a) \subseteq triggered(s,a)$ and $\mathsf{eff}_c^+(s,a) \subseteq triggered(s,a)$ are the triggered *negative* and *positive* effects, respectively.

2.3 STRIPS action schemes and *variable name* objects

This work addresses the learning of PDDL action schemes that follow the STRIPS requirement [McDermott *et al.*, 1998; Fox and Long, 2003]. Figure 1 shows the schema, coded in PDDL, for the *stack* action from a four-operator *blocksworld* [Slaney and Thiébaux, 2001].

To formalize the output of the learning task, we assume that fluents F are instantiated from a set of *predicates* Ψ, as in PDDL. Each predicate $p \in \Psi$ has an argument list of arity $ar(p)$. Given a set of *objects* Ω, the set of fluents F is induced by assigning objects in Ω to the arguments of predicates in Ψ, i.e. $F = \{p(\omega) : p \in \Psi, \omega \in \Omega^{ar(p)}\}$ s.t. Ω^k is the k-th Cartesian power of Ω.

Let $\Omega_v = \{v_i\}_{i=1}^{\max_{a\in A} ar(a)}$ be a new set of objects $\Omega \cap \Omega_v = \emptyset$, denoted as *variable names*, and that is bound by the maximum arity of an action in a given planning frame. For instance, in a three-block blocksworld $\Omega = \{block_1, block_2, block_3\}$ while $\Omega_v = \{v_1, v_2\}$ because the operators with the maximum arity, `stack` and `unstack`, have two parameters each.

Let us also define F_v, a new set of fluents $F \cap F_v = \emptyset$, that results from instantiating Ψ using only the objects in Ω_v and that defines the elements that can appear in an action schema. For instance, in the blocksworld, F_v={`handempty`, `holding`(v_1), `holding`(v_2), `clear`(v_1), `clear`(v_2), `ontable`(v_1), `ontable`(v_2), `on`(v_1,v_1), `on`(v_1,v_2), `on`(v_2,v_1), `on`(v_2,v_2)}.

Finally, we assume that actions $a \in A$ are instantiated from STRIPS operator schemes $\xi = \langle head(\xi), pre(\xi), add(\xi), del(\xi)\rangle$ where:

- $head(\xi) = \langle name(\xi), pars(\xi)\rangle$, is the operator *header* defined by its name and corresponding *variable names*, $pars(\xi) = \{v_i\}_{i=1}^{ar(\xi)}$. For instance, the headers for a four-operator blocksworld are: `pickup`(v_1), `putdown`(v_1), `stack`(v_1,v_2) and `unstack`(v_1,v_2).
- The preconditions $pre(\xi) \subseteq F_v$, the negative effects $del(\xi) \subseteq F_v$, and the positive effects $add(\xi) \subseteq F_v$ such that, $del(\xi) \subseteq pre(\xi)$, $del(\xi) \cap add(\xi) = \emptyset$ and $pre(\xi) \cap add(\xi) = \emptyset$.

2.4 State-constraints

A *state invariant* is a formula ϕ that holds at the initial state of a given classical planning problem, $I \models \phi$, and at every state s reachable from I. State invariants are traditionally useful for making *satisfiability planning* and *backward search* more efficient [Rintanen, 2014; Alcázar and Torralba, 2015].

A *mutex* (mutually exclusive) is a particular state invariant that takes the form of a binary clause and that represents a pair of different properties that cannot be simultaneously true [Kautz and Selman, 1999]. For instance in a three-blocks blocksworld, $on(block1, block2)$ and $on(block1, block3)$ are mutex because $block1$ can only be on top of a single block.

A *lifted invariant* (also called schematic invariants in the literature) is a state invariant defined using a first order formula [Rintanen and others, 2017]. A *domain invariant* is a state invariant that is instance-independent (it holds for any possible initial state) and often, they are lifted invariants [Fox and Long, 1998]. For instance in the blocksworld, $\forall x : (\neg handempty \vee \neg holding(x))$, is a *lifted domain mutex* because the robot hand can never be empty and holding a block at the same time.

3 Learning STRIPS action models

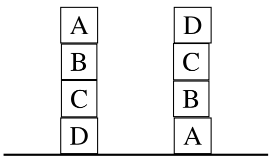
Learning STRIPS action models from fully available input knowledge, i.e. from plans where every action in the plan is available as well as its corresponding *pre-* and *post-states*, is straightforward. In this case, STRIPS operator schemes are derived lifting the literals that change between the pre and post-state of the corresponding action executions. Preconditions are derived lifting the minimal set of literals that appears in all the pre-states of the corresponding actions.

We formalize a more challenging learning task, where less input knowledge is available. This learning task, denoted by $\Lambda = \langle \Psi, \Sigma, \Phi\rangle$, corresponds to observing an agent acting in the world but watching only the results of its plan executions:

- Ψ is the set of predicates that define the abstract state space of a given planning domain.
- $\Sigma = \{\sigma_1, \dots, \sigma_\tau\}$ is a set of $(initial, final)$ state pairs, that we call *labels*. Each label $\sigma_t = (s_0^t, s_n^t)$, $1 \leq t \leq \tau$,

```
;;; Predicates in Ψ
(handempty) (holding ?o  - object)
(clear ?o - object) (ontable ?o - object)
(on ?o1 - object ?o2 - object)
```

;;; Label $\sigma_1 = (s_0^1, s_n^1)$




```
;;; Lifted domain invariants in Φ
 (forall (?o1 - object)
   (not (and (handempty) (holding ?o1)))))

 (forall (?o1 - object)
   (not (and (holding ?o1) (clear ?o1)))))

 (forall (?o1 - object)
   (not (and (holding ?o1) (ontable ?o1))))

 (forall (?o1 - object)
   (not (and (on ?o1 ?o1))))

 (forall (?o1 ?o2 - object)
   (not (and (on ?o1 ?o2) (holding ?o1))))

 (forall (?o1 ?o2 - object)
   (not (and (on ?o1 ?o2) (holding ?o2))))

 (forall (?o1 ?o2 - object)
    (not (and (on ?o1 ?o2) (clear ?o2))))

 (forall (?o1 ?o2 - object)
    (not (and (on ?o1 ?o2) (ontable ?o1))))

 (forall (?o1 ?o2 - object)
    (not (and (on ?o1 ?o2) (on ?o2 ?o1)))))
```

Figure 2: Example of a task for learning a STRIPS action model in the blocksworld from a single labeled plan.

comprises the *final* state s_n^t resulting from executing an unknown plan π_t starting from the *initial* state s_0^t.

- Φ is a set of *lifted domain invariants*.

A solution to Λ is a set of operator schema Ξ compliant with the predicates in Ψ, the labels Σ, and the set of state-constraints Φ. A planning compilation is a suitable approach for addressing the Λ learning task because a solution must not only determine the STRIPS action model Ξ but also, the *unobserved* plans $\pi_t = \langle a_1^t, \ldots, a_n^t \rangle$, $1 \leq t \leq \tau$ that explain Σ and Φ.

3.1 Learning STRIPS action models with classical planning

Our approach for addressing the learning task Λ, is compiling it into a classical planning task with conditional effects. The intuition behind the compilation is that a solution to the resulting classical planning task is a sequence of actions that:

1. Programs the STRIPS action model Ξ. A solution plan has a *prefix* that, for each $\xi \in \Xi$, determines which fluents $f \in F_v$ belong to its $pre(\xi)$, $del(\xi)$ and $add(\xi)$ sets.
2. Validates the programmed STRIPS action model Ξ in the input constraints (labels Σ and formulae Φ). For every $\sigma_t \in \Sigma$, a solution plan has a postfix that produces a final state s_n^t starting from the corresponding initial state s_0^t using the programmed action model Ξ and satisfying every $\phi \in \Phi$ at every reached state. We call this process the validation of the programmed STRIPS action model Ξ, at the t^{th} learning example $1 \leq t \leq \tau$.

To formalize our compilation we first define $1 \leq t \leq \tau$ classical planning instances $P_t = \langle F, \emptyset, I_t, G_t \rangle$ that belong to the same planning frame (i.e. same fluents and actions but differ in the initial state and goals). Fluents F are built instantiating the predicates in Ψ with the objects appearing in the input labels Σ. Formally $\Omega = \{o | o \in \bigcup_{1 \leq t \leq \tau} obj(s_0^t)\}$, where obj is a function that returns the set of objects that appear in a fully specified state. The set of actions, $A = \emptyset$, is empty because the action model is initially unknown. Finally, the initial state I_t is given by the state $s_0^t \in \sigma_t$ while goals G_t, are defined by the state $s_n^t \in \sigma_t$.

Now we are ready to formalize the compilation. Given a learning task $\Lambda = \langle \Psi, \Sigma, \Phi \rangle$ the compilation outputs a classical planning task $P_\Lambda = \langle F_\Lambda, A_\Lambda, I_\Lambda, G_\Lambda \rangle$:

- F_Λ extends F with:
  - Fluents representing the programmed action model $pre_f(\xi)$, $del_f(\xi)$ and $add_f(\xi)$, for every $f \in F_v$ and $\xi \in \Xi$. If a fluent $pre_f(\xi)/del_f(\xi)/add_f(\xi)$ holds, it means that f is a precondition/negative effect/positive effect in the STRIPS operator schema $\xi \in \Xi$. For instance, the preconditions of the $stack$ schema (Figure 1) are represented by fluents pre_holding_stack_v_1 and pre_clear_stack_v_2.
  - A fluent $mode_{prog}$ indicating whether the operator schemes are being programmed or validated (already programmed) and fluents $\{test_t\}_{1 \leq t \leq \tau}$, indicating the example where the action model is being validated.
- I_Λ contains the fluents from F that encode s_0^1 (the initial state of the first label) and every $pre_f(\xi) \in F_\Lambda$ and $mode_{prog}$ set to true. Our compilation assumes that initially operator schemas are programmed with every possible precondition, no negative effect and no positive effect.
- $G_\Lambda = \bigcup_{1 \leq t \leq \tau} \{test_t\}$, indicates that the programmed action model is validated in all the learning examples.
- A_Λ contains actions of three kinds:
  1. Actions for *programming* operator schema $\xi \in \Xi$:
     - Actions for **removing** a *precondition* $f \in F_v$ from the action schema $\xi \in \Xi$.

$$\begin{aligned}\mathsf{pre}(\mathsf{programPre}_{\mathsf{f},\xi}) =& \{\neg del_f(\xi), \neg add_f(\xi),\\ & mode_{prog}, pre_f(\xi)\},\\ \mathsf{cond}(\mathsf{programPre}_{\mathsf{f},\xi}) =& \{\emptyset\} \rhd \{\neg pre_f(\xi)\}.\end{aligned}$$

- Actions for **adding** a *negative* or *positive* effect $f \in F_v$ to the action schema $\xi \in \Xi$.

$$\begin{aligned}\mathsf{pre}(\mathsf{programEff_{f,\xi}}) =& \{\neg del_f(\xi), \neg add_f(\xi), \\ & mode_{prog}\},\\ \mathsf{cond}(\mathsf{programEff_{f,\xi}}) =& \{pre_f(\xi)\} \rhd \{del_f(\xi)\},\\ & \{\neg pre_f(\xi)\} \rhd \{add_f(\xi)\}.\end{aligned}$$

2. Actions for *applying* an already programmed operator schema $\xi \in \Xi$ bound with the objects $\omega \subseteq \Omega^{ar(\xi)}$. We assume operators headers are known so the binding of the operator schema is done implicitly by order of appearance of the action parameters, i.e. variables $pars(\xi)$ are bound to the objects in ω appearing at the same position. Figure 3 shows the PDDL encoding of the action for applying a programmed operator $stack$.

$$\begin{aligned}\mathsf{pre}(\mathsf{apply}_{\xi,\omega}) =& \{pre_f(\xi) \implies p(\omega)\}_{\forall p\in\Psi, f=p(pars(\xi))},\\ \mathsf{cond}(\mathsf{apply}_{\xi,\omega}) =& \{del_f(\xi)\} \rhd \{\neg p(\omega)\}_{\forall p\in\Psi, f=p(pars(\xi))},\\ & \{add_f(\xi)\} \rhd \{p(\omega)\}_{\forall p\in\Psi, f=p(pars(\xi))},\\ & \{mode_{prog}\} \rhd \{\neg mode_{prog}\}.\end{aligned}$$

3. Actions for *validating* learning example $1 \leq t \leq \tau$.

$$\begin{aligned}\mathsf{pre}(\mathsf{validate_t}) =& G_t \cup \{test_j\}_{j\in 1\leq j<t}\\ & \cup \{\neg test_j\}_{j\in t\leq j\leq \tau} \cup \{\neg mode_{prog}\},\\ \mathsf{cond}(\mathsf{validate_t}) =& \{\emptyset\} \rhd \{test_t\}.\end{aligned}$$

Lemma 1. *Any classical plan π that solves P_Λ induces an action model Ξ that solves the learning task Λ.*

Proof sketch. The compilation forces that once the preconditions of an operator schema $\xi \in \Xi$ are programmed, they cannot be altered. The same happens with the positive and negative effects that define an operator schema $\xi \in \Xi$ (besides they can only be programmed after preconditions are programmed). Once operator schemes are programmed they can only be applied because of the $mode_{prog}$ fluent. To solve P_Λ, goals $\{test_t\}$, $1 \leq t \leq \tau$ can only be achieved: executing an applicable sequence of programmed operator schemes that reaches the final state s_n^t, defined in σ_t, starting from s_0^t. If this is achieved for all the input examples $1 \leq t \leq \tau$, it means that the programmed action model Ξ is compliant with the provided input knowledge and hence, it is a solution to Λ. □

The compilation is *complete* in the sense that it does not discard any possible STRIPS action model.

4 Constraining the learning hypothesis space

Here we show that constraints can be used to reduce the space of possible action models and make the learning of STRIPS action models more practicable.

4.1 State constraints

Every state invariant $\phi \in \Phi$ is added as an extra precondition of actions $\mathsf{apply}_{\xi,\omega}$ for *applying* an already programmed operator schema. Likewise, every state invariant $\phi \in \Phi$ is also added as an extra goal in G_Λ because formulae $\phi \in \Phi$ must hold at every reached state, including the last reached state.

```
(:action apply_stack
  :parameters (?o1 - object ?o2 - object)
  :precondition
   (and (or (not (pre_on_stack_v1_v1)) (on ?o1 ?o1))
        (or (not (pre_on_stack_v1_v2)) (on ?o1 ?o2))
        (or (not (pre_on_stack_v2_v1)) (on ?o2 ?o1))
        (or (not (pre_on_stack_v2_v2)) (on ?o2 ?o2))
        (or (not (pre_ontable_stack_v1)) (ontable ?o1))
        (or (not (pre_ontable_stack_v2)) (ontable ?o2))
        (or (not (pre_clear_stack_v1)) (clear ?o1))
        (or (not (pre_clear_stack_v2)) (clear ?o2))
        (or (not (pre_holding_stack_v1)) (holding ?o1))
        (or (not (pre_holding_stack_v2)) (holding ?o2))
        (or (not (pre_handempty_stack)) (handempty)))
  :effect
   (and (when (del_on_stack_v1_v1) (not (on ?o1 ?o1)))
        (when (del_on_stack_v1_v2) (not (on ?o1 ?o2)))
        (when (del_on_stack_v2_v1) (not (on ?o2 ?o1)))
        (when (del_on_stack_v2_v2) (not (on ?o2 ?o2)))
        (when (del_ontable_stack_v1) (not (ontable ?o1)))
        (when (del_ontable_stack_v2) (not (ontable ?o2)))
        (when (del_clear_stack_v1) (not (clear ?o1)))
        (when (del_clear_stack_v2) (not (clear ?o2)))
        (when (del_holding_stack_v1) (not (holding ?o1)))
        (when (del_holding_stack_v2) (not (holding ?o2)))
        (when (del_handempty_stack) (not (handempty)))
        (when (add_on_stack_v1_v1) (on ?o1 ?o1))
        (when (add_on_stack_v1_v2) (on ?o1 ?o2))
        (when (add_on_stack_v2_v1) (on ?o2 ?o1))
        (when (add_on_stack_v2_v2) (on ?o2 ?o2))
        (when (add_ontable_stack_v1) (ontable ?o1))
        (when (add_ontable_stack_v2) (ontable ?o2))
        (when (add_clear_stack_v1) (clear ?o1))
        (when (add_clear_stack_v2) (clear ?o2))
        (when (add_holding_stack_v1) (holding ?o1))
        (when (add_holding_stack_v2) (holding ?o2))
        (when (add_handempty_stack) (handempty))
        (when (modeProg) (not (modeProg)))))
```

Figure 3: Action for applying an already programmed schema $stack$ as encoded in PDDL (implications coded as disjunctions).

If the state trajectory corresponding to a plan execution is available it can also be included in the compilation. In this case $\Sigma = \{\sigma_1, \ldots, \sigma_\tau\}$ is no longer a set of $(initial, final)$ state pairs but a set of state trajectories $\sigma_t = (s_0^t, s_1^t, \ldots, s_n^t)$, $1 \leq t \leq \tau$, that comprises the sequence of states resulting from executing the *unobserved* plan $\pi_t = \langle a_1^t, \ldots, a_n^t \rangle$ starting from the *initial* state s_0^t.

- Fluents at_j and $next_{j,j_2}$, $1 \leq j < j2 \leq n$, are added to F_Λ to iterate through the state trajectories. Likewise I_Λ includes also now the fluents at_1 and $\{next_{j,j_2}\}$, $1 \leq j < j2 \leq n$
- Actions $\mathsf{apply}_{\xi,\omega}$ for *applying* an already programmed operator schema have extra conditional effects $\{at_j\} \rhd \{\neg at_j, at_{j+1}\}_{\forall j \in [1,n]}$. Actions $\mathsf{validate_t}$ for *validating* the t^{th} learning example add at_1 and delete $at_{|\pi_t|}$.

Linear Temporal Logic (LTL) allows to represent more expressive state-constraints [Bauer *et al.*, 2010]. For instance the LTL *eventually* operator, denoted by $\Diamond$, can define state-constraints that, unlike *state invariants*, must be true at least at one of the reached states. LTL constraints can be included in our compilation following the ideas for compiling first-order temporally extended goals into classical planning [Baier and McIlraith, 2006] that (1) transform the given LTL formula into an equivalent automata, (2) compute the cross product of this automata with the given classical planning task and (3) adds as new goals classical planning goals the aceptor states of the equivalent automata.

4.2 Plan constraints

Here we show that our classical planning compilation is also flexible to include as input constraints, if available, the actions in the plans executed by the observed agent. Now the learning task is defined as $\Lambda = \langle \Psi, \Sigma, \Phi, \Pi \rangle$, where:

- $\Pi = \{\pi_1, \ldots, \pi_\tau\}$ is a given set of example plans where each plan $\pi_t = \langle a_1^t, \ldots, a_n^t \rangle$, $1 \leq t \leq \tau$, is an action sequence that induces the corresponding state sequence $\langle s_0^t, s_1^t, \ldots, s_n^t \rangle$ such that, for each $1 \leq i \leq n$, a_i^t is applicable in s_{i-1}^t and generates $s_i^t = \theta(s_{i-1}^t, a_i^t)$.

We extend the compilation to consider the actions in the executed plans. Given a learning task $\Lambda = \langle \Psi, \Sigma, \Phi, \Pi \rangle$, the compilation outputs a classical planning task $P_\Lambda = \langle F_\Lambda, A_\Lambda, I_\Lambda, G_\Lambda \rangle$ that extends P_Λ as follows:

- F_Λ is extended with $F_\Pi = \{plan(name(\xi), \Omega^{ar(\xi)}, j)\}$, the fluents to code the steps of the plans in Π, where $F_{\pi_t} \subseteq F_\Pi$ encodes $\pi_t \in \Pi$ and $1 \leq j \leq |\pi_t|$.
- I_Λ is extended with fluents F_{π_1}. Goals are $G_\Lambda = \bigcup_{1 \leq t \leq \tau} \{test_t\}$, as in the original compilation.
- With respect to A_Λ.
  1. The actions for *programming* the preconditions/effects of a given schema $\xi \in \Xi$ are the same.
  2. The actions for *applying* an already programmed operator have an extra precondition $f \in F_\Pi$, that encodes the current plan step. This mechanism forces that these actions are only applied as in the example plans.
  3. The actions for *validating* the current learning example have an extra conditional effects to unload plan π_t and load the next plan π_{t+1}:

$$\{f\} \rhd \{\neg f\}_{f \in F_{\pi_t}}, \{\emptyset\} \rhd \{f\}_{f \in F_{\pi_{t+1}}}.$$

5 Evaluation

This section evaluates the performance of our approach for learning STRIPS action models starting from different amounts of available input knowledge.

Setup.
The domains used in the evaluation are IPC domains that satisfy the STRIPS requirement [Fox and Long, 2003], taken from the PLANNING.DOMAINS repository [Muise, 2016]. We only use 5 learning examples for each domain and they are fixed for all the experiments so we can evaluate the impact of the input knowledge in the quality of the learned models. All experiments are run on an Intel Core i5 3.10 GHz x 4 with 4 GB of RAM.

Reproducibility.
We make fully available the compilation source code, the evaluation scripts and the used benchmarks at this anonymous repository *https://github.com/anonsub/strips-learning* so any experimental data reported in the paper is fully reproducible.

Planner.
The classical planner we use to solve the instances that result from our compilations is MADAGASCAR [Rintanen, 2014]. We use MADAGASCAR because its ability to deal with planning instances populated with dead-ends. In addition, SAT-based planners can apply the actions for programming preconditions in a single planning step (in parallel) because these actions do not interact. Actions for programming action effects can also be applied in a single planning step reducing significantly the planning horizon.

Metrics.
The quality of the learned models is quantified with the *precision* and *recall* metrics. Intuitively, precision gives a notion of *soundness* while recall gives a notion of the *completeness* of the learned models. Formally, $Precision = \frac{tp}{tp+fp}$, where tp is the number of true positives (predicates that correctly appear in the action model) and fp is the number of false positives (predicates appear in the learned action model that should not appear). Recall is formally defined as $Recall = \frac{tp}{tp+fn}$ where fn is the number of false negatives (predicates that should appear in the learned action model but are missing).

When the learning hypothesis space is low constrained, the learned actions can be reformulated and still be compliant with the inputs. For instance in the *blocksworld*, given a low amount of input knowledge, operator `stack` could be *learned* with the preconditions and effects of the `unstack` operator (and vice versa) making non trivial to compute *precision* and *recall* with respect to a reference model. To address this issue we define the following evaluation methodology that deals with action reformulation.

Given a reference STRIPS action model Ξ^* and the learned STRIPS action model Ξ we define these two bijective functions $f_p : \Xi \mapsto \Xi^*$ and $f_r : \Xi \mapsto \Xi^*$ such that f_p and f_r respectively maximize the the accumulated *precision* and *recall*. With this defined we compute the *precision* of an STRIPS action ξ with respect to the action $f_p(\xi)$. Likewise, the *recall* of an STRIPS action ξ is computed with respect to the action $f_r(\xi)$.

5.1 Learning with state-constraints

For each domain we provide a set of *lifted domain invariants*.

5.2 Learning with plans

6 Conclusions

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