Learning STRIPS Action Models from State-Constraints

Diego Aineto and **Sergio Jiménez** and **Eva Onaindia**
Departamento de Sistemas Informáticos y Computación
Universitat Politècnica de València.
Camino de Vera s/n. 46022 Valencia, Spain
{dieaigar,serjice,onaindia}@dsic.upv.es

Abstract

This paper presents a classical planning compilation for learning STRIPS action models from state-constraints. A plan that solves the classical planning task resulting from the compilation induces a STRIPS action model compliant with the input constraints. Remarkably, the compilation approach does not require observations of the particular executed actions since they are guessed by an off-the-shelf classical planner leveraging on initial, final states, and the given set of state-constraints. The paper also shows that evaluating learned STRIPS models with respect to a *reference model* is non-trivial: when input constraints are too loose, actions can be *reformulated* interchanging and/or redefining their semantic. Last but not least, the paper introduces a novel evaluation method able to asses the learning of STRIPS models even when actions 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, automated planners are required to reason about an action model that correctly and completely captures 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 and nowadays, there exist 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 the automatic learning of 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 observations of the particular executed actions since they are guessed by an off-the-shelf classical planner leveraging on initial, final states, and the given set of state-constraints.
3. Assesses learned STRIPS models with respect to a *reference model*, even when learning is so low constrained that actions can be reformulated and still be compliant with the learning inputs.

2 Background

This section defines the planning models used in this work, the state constraints (input of the addressed learning task) and STRIPS action model (ouput of the learning task).

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* denoted by $\theta(s, a) = \{s \setminus \mathsf{eff}^-(a)) \cup \mathsf{eff}^+(a)\}$.

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 trajectory* $\langle s_0, s_1, \ldots, s_n \rangle$ 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 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 the 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 $a \in A$ is now defined as 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 *triggered effects* resulting from the action application 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 $\mathsf{eff}_c^-(s, a) \subseteq triggered(s, a)$ are the triggered *negative* effects and $\mathsf{eff}_c^+(s, a) \subseteq triggered(s, a)$ are the triggered *positive* effects.

2.3 State-constraints

The notion of *state-constraint* is very general and has been used in different areas of AI and for different purposes. If we restrict ourselves to planning, *state-constraints* are abstractions for compactly specifying sets of states. In this work we focus on invariants that constrain the set of possible states of a given planning task and help us to prune the space of possible STRIPS action models for that task. State invariants are traditionally useful in classical planning for computing more compact state representations [Helmert, 2009] and for making *satisfiability planning* and *backward search* more efficient [Rintanen, 2014; Alcázar and Torralba, 2015].

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 that is reachable from I. Given a planning problem $P = \langle F, A, I, G \rangle$, the *strongest invariant* is a formula $\phi^*_{I,A}$ that exactly characterizes the set of all states reachable from I and using the actions A. 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*, $\phi_1 = \neg on(block1, block2) \vee \neg on(block1, block3)$ are mutex because $block1$ can only be on top of a single block.

A *lifted invariant* (also called schematic invariant) is a state invariant defined using a first order formula [Rintanen and others, 2017]. A *domain invariant* is an instance-independent state invariant, i.e. holds for any possible initial state, so often they are lifted invariants. For instance in the *blocksworld*, $\phi_2 = \forall x : (\neg handempty \vee \neg holding(x))$, is a *lifted domain mutex* because the robot hand is never empty and holding a block at the same time.

```
(: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*.

2.4 STRIPS action schemes

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 *stack* action schema, coded in PDDL, 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 $pre(\xi) \cap add(\xi) = \emptyset$.

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.
- $\Sigma = \{\sigma_1, \ldots, \sigma_\tau\}$ is a set of $(initial, final)$ state pairs, that we call *labels*. Each label $\sigma_t = (s_0^t, s_n^t)$, $1 \leq t \leq \tau$, 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* that do not neccesary contain the *strongest invarriant*.

A solution to Λ is a set of operator schema Ξ compliant with the predicates in Ψ, the labels Σ, and the state-constraints Φ. A planning compilation is a suitable approach for addressing Λ learning tasks 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 can explain Σ and Φ.

3.1 Learning 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:

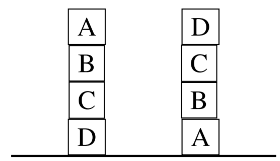
1. Programs the STRIPS action model Ξ. A solution plan has a *prefix* that, for each $\xi \in \Xi$, determines which fluents $f \in F_v$ belong to its $pre(\xi)$, $del(\xi)$ and $add(\xi)$ sets.
2. Validates the programmed STRIPS action model Ξ in Σ and Φ. For every $\sigma_t \in \Sigma$, a solution 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 any $\phi \in \Phi$ 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 (same fluents and actions but different initial state and/or 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

;;; 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 (on ?o1 ?o1))))

(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 ?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.

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 comprises three kinds of actions:
  1. Actions for *programming* operator schema $\xi \in \Xi$:
     - Actions for **removing** a *precondition* $f \in F_v$ from the action schema $\xi \in \Xi$.

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

     - 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 $1 \leq t \leq \tau$.

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

```
(: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).

3.2 Constraining the learning hypothesis space

Here we introduce the *state constraints* in the compilation to reduce the space of the possible STRIPS action models and make learning more practicable.

With regard to the *state invariants* Φ:

- Every invariant $\phi \in \Phi$ is added as an extra precondition of the $\mathsf{apply}_{\xi,\omega}$ actions for *applying* an already programmed operator schema.
- Every invariant $\phi \in \Phi$ is added as an extra goal to the G_t, $1 \leq t \leq \tau$, goal sets because ϕ must hold at every reached state, including the last state.

Additionally, if *state trajectories* $\mathcal{O}_\pi = (s_0, s_1, \ldots, s_n)$ resulting from observing the execution of an *unobserved* plan π are available, they can be included in the compilation to constrain further the learning hypothesis space. In this case $\Sigma = \{\sigma_1, \ldots, \sigma_\tau\}$ is no longer a set of $(initial, final)$ state pairs but a set of state pairs $\sigma_t = (s_i, s_{i+1})$, $1 \leq i<n$ so only one $\mathsf{apply}_{\xi,\omega}$ action can be used to produce a state s_{i+1} from a state s_i, for every $1 \leq i<n$. The introduction of *state trajectories* as new constraints to the compilation is done straigthforward by extending F_Λ with a new fluent $applied$ whose negation appears as a precondition of every $\mathsf{apply}_{\xi,\omega}$ action and that is added by the effects of these same actions.

Instead of enumerating the full sequence of states included in a trajectory, *state trajectory constraints* can also be implicitely defined using *Linear Temporal Logic* (LTL) [Bauer *et al.*, 2010]. For instance the LTL *eventually* operator, denoted by $\Diamond$, can define constraints that, unlike *state invariants*, must be true at least at one of the reached states. LTL constraints could be included in our compilation following the ideas for compiling 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) force the solution plans to always leave the LTL automata at an aceptor state by adding new goals to the classical planning task.

3.3 Compilation properties

Lemma 1. *Soundness. 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. □

Lemma 2. *Completeness. Any* STRIPS *action model Ξ is computable by solving the corresponding classical planning task P_Λ.*

Proof sketch. The compilation is *complete* in the sense that it does not discard any possible STRIPS action model. First, F_v completely captures the set of all the predicates that can appear in a STRIPS action schema $\xi \in \Xi$. Second, any conjunction of any length of the fluents F_v in the sets $pre(\xi)$,$del(\xi)$ and $add(\xi)$ is computable with a classical plan π that solves P_Λ given the proper Σ and Φ sets. □

4 Evaluation

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

Setup and Reproducibility

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.

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.

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.

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 $f_r(\xi)$.

4.1 Learning from state-invariants

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

4.2 Learning from state-trajectory constraints

5 Conclusions

References

[Alcázar and Torralba, 2015] Vidal Alcázar and Alvaro Torralba. A reminder about the importance of computing and exploiting invariants in planning. In *ICAPS*, pages 2–6, 2015.

[Amir and Chang, 2008] Eyal Amir and Allen Chang. Learning partially observable deterministic action models. *Journal of Artificial Intelligence Research*, 33:349–402, 2008.

[Baier and McIlraith, 2006] Jorge A Baier and Sheila A McIlraith. Planning with first-order temporally extended goals using heuristic search. In *Proceedings of the National Conference on Artificial Intelligence*, volume 21, page 788. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999, 2006.

[Bauer *et al.*, 2010] Andreas Bauer, Patrik Haslum, et al. Ltl goal specifications revisited. In *ECAI*, volume 10, pages 881–886, 2010.

[Bonet *et al.*, 2009] Blai Bonet, Héctor Palacios, and Héctor Geffner. Automatic derivation of memoryless policies and finite-state controllers using classical planners. In *ICAPS*, 2009.

[Cresswell *et al.*, 2013] Stephen N Cresswell, Thomas L McCluskey, and Margaret M West. Acquiring planning domain models using LOCM. *The Knowledge Engineering Review*, 28(02):195–213, 2013.

[Fox and Long, 2003] Maria Fox and Derek Long. PDDL2.1: An extension to PDDL for expressing temporal planning domains. *J. Artif. Intell. Res.(JAIR)*, 20:61–124, 2003.

[Geffner and Bonet, 2013] Hector Geffner and Blai Bonet. A concise introduction to models and methods for automated planning, 2013.

[Ghallab *et al.*, 2004] Malik Ghallab, Dana Nau, and Paolo Traverso. *Automated Planning: theory and practice*. Elsevier, 2004.

[Helmert, 2009] Malte Helmert. Concise finite-domain representations for pddl planning tasks. *Artificial Intelligence*, 173(5-6):503–535, 2009.

[Kambhampati, 2007] Subbarao Kambhampati. Model-lite planning for the web age masses: The challenges of planning with incomplete and evolving domain models. In *Proceedings of the National Conference on Artificial Intelligence*, 2007.

[Kautz and Selman, 1999] Henry Kautz and Bart Selman. Unifying sat-based and graph-based planning. In *IJCAI*, volume 99, pages 318–325, 1999.

[McDermott *et al.*, 1998] Drew McDermott, Malik Ghallab, Adele Howe, Craig Knoblock, Ashwin Ram, Manuela Veloso, Daniel Weld, and David Wilkins. PDDL – The Planning Domain Definition Language, 1998.

[Muise, 2016] Christian Muise. Planning. domains. *ICAPS system demonstration*, 2016.

[Ramírez, 2012] Miquel Ramírez. *Plan recognition as planning*. PhD thesis, Universitat Pompeu Fabra, 2012.

[Rintanen and others, 2017] Jussi Rintanen et al. Schematic invariants by reduction to ground invariants. In *AAAI*, pages 3644–3650, 2017.

[Rintanen, 2014] Jussi Rintanen. Madagascar: Scalable planning with sat. *Proceedings of the 8th International Planning Competition (IPC-2014)*, 2014.

[Segovia-Aguas *et al.*, 2016] Javier Segovia-Aguas, Sergio Jiménez, and Anders Jonsson. Hierarchical finite state controllers for generalized planning. In *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence*, pages 3235–3241. AAAI Press, 2016.

[Segovia-Aguas *et al.*, 2017] Javier Segovia-Aguas, Sergio Jiménez, and Anders Jonsson. Generating context-free grammars using classical planning. In *International Joint Conference on Artificial Intelligence*, 2017.

[Slaney and Thiébaux, 2001] John Slaney and Sylvie Thiébaux. Blocks world revisited. *Artificial Intelligence*, 125(1-2):119–153, 2001.

[Vallati *et al.*, 2015] Mauro Vallati, Lukáš Chrpa, Marek Grzes, Thomas L McCluskey, Mark Roberts, and Scott Sanner. The 2014 international planning competition: Progress and trends. *AI Magazine*, 36(3):90–98, 2015.

[Yang *et al.*, 2007] Qiang Yang, Kangheng Wu, and Yunfei Jiang. Learning action models from plan examples using weighted max-sat. *Artificial Intelligence*, 171(2-3):107–143, 2007.