Learning STRIPS Action Models from State-Constraints

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Abstract

This paper presents a classical planning compilation for learning STRIPS action models from state-constraints. The compilation approach does not require observations of the precise executed actions because an off-the-shelf classical planner leverages on the given constraints to determine the executed actions. In addition the paper introduces a novel evaluation method to asses the learning of STRIPS models even when actions are *reformulated* because the learning task is too low-constrained.

1 Introduction

Besides *plan synthesis* [Ghallab *et al.*, 2004], planning action models are also useful for *plan/goal recognition* [Ramírez, 2012]. At these 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 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 observations of the particular executed actions. An off-the-shelf classical planner leverages on the given constraints to determine the executed actions.
3. Can assess the learned STRIPS models with respect to a *reference model*, even when learning is so low constrained that actions are reformulated and still compliant with the learning inputs.

2 Background

This section defines the planning models used in this work as well as the input (the state constraints) and output (an STRIPS action model) of the addressed 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 the *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 $s_i = \theta(s_{i-1}, a_i)$. The *plan length* is denoted with $|\pi| = n$. 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 the plan π in the initial state 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 *International Planning Competition* [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. For instance to specify the states where a given action is applicable or that are considered goal states. A particular kind of state-constraints useful for planning is *invariants*. *State invariant* are traditionally used for computing more compact state representations [Helmert, 2009] and/or for making *satisfiability planning* and *backward search* more efficient [Rintanen, 2014; Alcázar and Torralba, 2015].

Given a classical planning problem $P = \langle F, A, I, G \rangle$, 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. The formula $\phi^*_{I,A}$ represents the *strongest invariant* and exactly characterizes the set of all states reachable from I using the actions in A. A *mutex* (mutually exclusive) is a state invariant that takes the form of a binary clause and indicates a pair of different properties that cannot be simultaneously true [Kautz and Selman, 1999]. For instance in a three-blocks *blocksworld*, $\phi_1 = \neg on(block_1, block_2) \vee \neg on(block_1, block_3)$ are mutex because $block_1$ can only be on top of a single block.

A *domain invariant* is an instance-independent state invariant, i.e. holds for any possible initial state. Domain invariants are often compactly defined as *lifted invariant* (also called schematic invariant) that is state invariants defined as a first order formula [Rintanen and others, 2017]. For instance in the *blocksworld*, $\phi_2 = \forall x : (\neg handempty \vee \neg holding(x))$, is a *domain mutex* because the robot hand is never empty and holding a block at the same time. In this work we exploit *domain invariants* to constrain the possible STRIPS action models and reduce then the learning hypothesis space.

```
(: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.

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 $pre(\xi) \cap add(\xi) = \emptyset$.

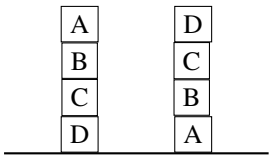
3 Learning STRIPS action models

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.

We formalize a more challenging learning task, where less input knowledge is available. This learning task corresponds to observing an agent acting in the world but watching only the results of its plan executions, the actual executed actions

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

;;; Label σ1 = (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 label and nine state-invariants.

are unobserved. Formally the addressed learning task is defined as $\Lambda = \langle \Psi, \Sigma, \Phi \rangle$:

- Ψ is the set of predicates that define the abstract state space of a given classical planning frame.
- $\Sigma = \{\sigma_1, \ldots, \sigma_\tau\}$ 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 unobserved plan π_t starting from the *initial* state s_0^t.
- Φ is a set of *domain invariants*, note that they do not necessary contain the *strongest invariant*.

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 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 can explain Σ and Φ. Figure 2 shows an example of a Λ task for learning a STRIPS action model in the blocksworld from a single label σ_1 and a set of nine state invariants.

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 starts with 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. A solution plan continues with, for every $\sigma_t \in \Sigma$, 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 the constraints $\phi \in \Phi$ 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 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.
  - Fluent $mode_{prog}$ indicating whether the operator schemes are programmed or validated (already programmed) and fluents $\{test_t\}_{1 \leq t \leq \tau}$, indicating the example where the action model is 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 $\xi \in \Xi$.

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

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

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

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 $1 \leq t \leq \tau$.

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

3.2 Constraining the learning hypothesis space

The compilation allows to reduce the space of the possible STRIPS action models and make learning more practicable using *state constraints*. The input constraints are introduced as new preconditions and goals of the classical planning task that results from the compilation.

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 $\xi \in \Xi$.
- 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* $\mathcal{O}_\pi = (s_0, s_1, \ldots, s_n)$ obtained 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 $\sigma_t = (s_i, s_{i+1})$, $0 \leq i < n$ s.t. only one $\mathsf{apply}_{\xi,\omega}$ action can be executed to produce the state s_{i+1} from state s_i. Introducing *state trajectories* as additional constraints to the compilation is done straightforward by:

```
(: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).

- Extending F_Λ with a new fluent $applied$.
- For every $\mathsf{apply}_{\xi,\omega}$ action, extending its precondition set with $\neg applied$ while its set of positive effects is extended with the $applied$ fluent.
- The $applied$ fluent is set to false at the initial state I_Λ. Likewise $\mathsf{validate}_{\mathsf{t}}$ actions set the $applied$ fluent to true while this fluent is added as an extra goal to the G_t, $1 \leq t \leq \tau$, goal sets.

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 (furthermore, effects 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 *computable from* $\Lambda = \langle \Psi, \Sigma, \Phi \rangle$ *can be obtained by solving the corresponding classical planning task* P_Λ.

Proof sketch. By definition, given the set of predicates Ψ, then $F_v \subseteq F_\Lambda$ fully captures the set of elements that can appear in a STRIPS action schema $\xi \in \Xi$. If $\Sigma = \emptyset$ and $\Phi = \emptyset$ are the empty set, any possible STRIPS action schema with the fluents in F_v can be computed because the compilation only constrains the application of $\mathsf{apply}_{\xi,\omega}$ actions iff they are not compliant with the Σ and Φ sets. If $\Sigma \neq \emptyset$ or $\Phi \neq \emptyset$ then a classical plan π that solves P_Λ cannot discard a possible STRIPS action schema $\xi \in \Xi$ that is compliant with Σ and Φ. □

4 Evaluation

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

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.

Precision and recall are often combined using the *harmonic mean*. This expression is called the *F-measure* (or the balanced *F-score*) and is formally defined as $F = 2 \times \frac{Precision \times Recall}{Precision + Recall}$. Given a reference STRIPS action model Ξ^* and the learned STRIPS action model Ξ we define the bijective function $f_{P\&R} : \Xi \mapsto \Xi^*$ such that $f_{P\&R}$ maximizes the accumulated *F-measure*. With this mapping defined we can compute the *precision* and *recall* of a learned STRIPS action $\xi \in \Xi$ with respect to the action $f_{P\&R}(\xi) \in \Xi^*$. This metric allow us to asses the quality of the learned models even if actions are reformulated in the learning process.

	Pre		Add		Del			
	P	**R**	**P**	**R**	**P**	**R**	**P**	**R**
Blocks	0.86	0.67	0.71	0.56	0.86	0.67	0.81	0.63
Driverlog	0.40	0.14	0.36	0.57	0.50	0.29	0.42	0.33
Ferry	0.50	0.29	0.33	0.50	0.50	0.50	0.44	0.43
Floortile	0.67	0.36	0.67	0.36	1.0	0.36	0.78	0.36
Grid	-	-	-	-	-	-	-	-
Gripper	1.0	0.67	0.75	0.75	0.75	0.75	0.83	0.72
Hanoi	1.0	0.5	1.0	1.0	1.0	1.0	1.0	0.83
Hiking	-	-	-	-	-	-	-	-
Parking	-	-	-	-	-	-	-	-
Satellite	0.40	0.14	0.43	0.60	0.67	0.50	0.50	0.41
Sokoban	-	-	-	-	-	-	-	-
Transport	0.75	0.30	0.67	0.80	1.0	0.60	0.81	0.57
Zenotravel	1.0	0.29	0.50	0.43	1.0	0.43	0.83	0.38
	0.73	0.36	0.60	0.62	0.81	0.57	0.71	0.52

Table 1: Precision and recall values obtained when learning from labels without computing the $f_{P\&R}$ mapping.

	Pre		Add		Del			
	P	**R**	**P**	**R**	**P**	**R**	**P**	**R**
Blocks	0.86	0.67	0.71	0.56	0.86	0.67	0.81	0.63
Driverlog	0.40	0.14	0.36	0.57	0.50	0.29	0.42	0.33
Ferry	0.50	0.29	0.33	0.50	0.50	0.50	0.44	0.43
Floortile	0.67	0.36	0.67	0.36	1.0	0.36	0.78	0.36
Grid	-	-	-	-	-	-	-	-
Gripper	1.0	0.67	0.75	0.75	0.75	0.75	0.83	0.72
Hanoi	1.0	0.5	1.0	1.0	1.0	1.0	1.0	0.83
Hiking	-	-	-	-	-	-	-	-
Parking	-	-	-	-	-	-	-	-
Satellite	0.40	0.14	0.43	0.60	0.67	0.50	0.50	0.41
Sokoban	-	-	-	-	-	-	-	-
Transport	0.75	0.30	0.67	0.80	1.0	0.60	0.81	0.57
Zenotravel	1.0	0.29	0.50	0.43	1.0	0.43	0.83	0.38
	0.73	0.36	0.60	0.62	0.81	0.57	0.71	0.52

Table 2: Precision and recall values obtained when learning from labels but computing the $f_{P\&R}$ mapping.

4.1 Learning from labels

Tables 1 and 2 show the precision and recall values obtained when learning from a set of $(initial, final)$ state pairs. Precision (**P**) and recall (**R**) are computed separately for the preconditions (**Pre**), positive effects (**Add**) and negative Effects (**Del**) while the last two columns of each setting (and the last row) report averages values. The learning examples and learned models are the same for the both tables, the only difference here is the evaluation procedure for computing the *precision* and *recall* values. Table 1 does not use the $f_{P\&R}$ mapping which implies assuming that the learned actions are

	Total time	Preprocess	Plan length
Blocks	1.40	0.00	70
Driverlog	1.50	0.00	89
Ferry	1.49	0.00	64
Floortile	351.38	0.11	156
Grid	-	-	-
Gripper	0.04	0.00	59
Hanoi	2.33	0.01	49
Hiking	-	-	-
Parking	-	-	-
Satellite	78.36	0.03	98
Sokoban	-	-	-
Transport	285.61	0.10	106
Zenotravel	6.20	0.46	71

Table 3: Planning results obtained when learning from labels.

never reformulated. As the results show this is a too strong assumption.

Figure 3 shows the planning results obtained when learning from state-invariants. The table reports the total planning time, the preprocessing time (in seconds) invested by MADAGASCAR to solve the classical planning instances that result from our compilation as well as the number of actions in the solutions.

4.2 Learning from labels and state-invariants

For each domain we provide a set of *lifted domain invariants* that are computed using the TIM algorithm [Fox and Long, 1998]. Figure 4 shows the precision and recall values obtained when learning from state-invariants.

	Pre		**Add**		**Del**			
	P	**R**	**P**	**R**	**P**	**R**	**P**	**R**
Blocks	0.75	0.67	0.71	0.56	0.71	0.56	0.73	0.59
Driverlog	0.67	0.29	0.38	0.71	0.60	0.43	0.55	0.48
Ferry	0.75	0.43	0.75	0.75	0.75	0.75	0.75	0.64
Floortile	-	-	-	-	-	-	-	-
Grid	-	-	-	-	-	-	-	-
Gripper	1.0	0.67	1.0	1.0	1.0	1.0	1.0	0.89
Hanoi	0.50	0.25	0.0	0.0	0.50	0.50	0.33	0.25
Hiking	-	-	-	-	-	-	-	-
Parking	-	-	-	-	-	-	-	-
Satellite	0.40	0.14	0.43	0.60	0.67	0.50	0.50	0.41
Sokoban	-	-	-	-	-	-	-	-
Transport	-	-	-	-	-	-	-	-
Zenotravel	1.0	0.29	0.50	0.43	1.0	0.43	0.83	0.38
	0.72	0.39	0.54	0.58	0.72	0.60	0.67	0.52

Table 4: Precision and recall values obtained when learning from labels + invariants.

4.3 Learning from state-trajectory constraints

Figure 8 shows the precision and recall values obtained when learning from state trajectories and using the same state invariants from the previous evaluation.

5 Conclusions

We presented a novel approach for learning STRIPS action models from state constraints using classical planning. As far as we know, this is the first work on learning action models

	Total time	Preprocess	Plan length
Blocks	652.70	0.04	76
Driverlog	14.98	0.10	65
Ferry	1.70	0.03	58
Floortile	-	-	-
Grid	-	-	-
Gripper	0.14	0.00	47
Hanoi	55.30	0.14	43
Hiking	-	-	-
Parking	-	-	-
Satellite	84.57	0.22	98
Sokoban	-	-	-
Transport	-	-	-
Zenotravel	-	-	-

Table 5: Planning results obtained when learning from labels + invariants.

	Pre		**Add**		**Del**			
	P	**R**	**P**	**R**	**P**	**R**	**P**	**R**
Blocks	0.71	0.56	0.60	0.67	0.71	0.56	0.68	0.59
Ferry	0.75	0.43	0.50	0.75	0.75	0.75	0.67	0.64
Gripper	1.0	0.67	1.0	1.0	1.0	1.0	1.0	0.89
Hanoi	0.50	0.25	0.0	0.0	0.50	0.50	0.33	0.25
	0.74	0.48	0.53	0.61	0.74	0.70	0.67	0.57

Table 6: Precision and recall values obtained when learning from observations.

	Total time	Preprocess	Plan length
Blocks	13.36	0.00	73
Ferry	89.04	0.03	63
Gripper	0.66	0.00	43
Hanoi	98.66	0.11	45

Table 7: Planning results obtained when learning from observations.

	Pre		**Add**		**Del**			
	P	**R**	**P**	**R**	**P**	**R**	**P**	**R**
Blocks	-	-	-	-	-	-	-	-
Ferry	1.0	0.57	1.0	1.0	1.0	1.0	1.0	0.86
Gripper	0.75	0.50	0.75	0.75	0.75	0.75	0.75	0.67
Hanoi	0.50	0.25	0.0	0.0	0.50	0.50	0.33	0.25
	-	-	-	-	-	-	-	-

Table 8: Precision and recall values obtained when learning from observations + invariants.

	Total time	Preprocess	Plan length
Blocks	-	-	-
Ferry	253.04	0.21	61
Gripper	1.60	0.04	43
Hanoi	81.76	0.62	45

Table 9: Planning results obtained when learning from observations + invariants.

exclusively using an *off-the-shelf* classical planner and evaluated over a wide range of different domains. Recently, Stern and Juba 2017 proposed a classical planning compilation for learning action models but following the *finite domain* representation for the state variables and did not report experimental results since the compilation was not implemented.

The empirical results show that since our approach is strongly based on inference can generate non-trivial models from very small data sets. In addition, the SAT-based planner MADAGASCAR is particularly suitable for the approach because its ability to deal with planning instances populated with dead-ends and because many actions for programming the STRIPS model can be done in parallel since they do not interact reducing significantly the planning horizon.

Instead of enumerating the full sequence of states included in a trajectory, *state trajectory constraints* can be implicitly defined with *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. Despite this is beyond the scope of this paper, 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 acceptor state by adding new goals to the classical planning task.

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