Learning STRIPS action models from *state-invariants*

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Abstract

This paper addresses the learning of action models from *state-invariants* (i.e logic formulae that specify constraints about the possible states of a given domain) to cushion the negative impact of insufficient learning examples. Our approach is a *classical planning* compilation that is flexible to different kinds of input knowledge (e.g., partially observations of plan executions including partially observed intermediate states and/or actions) and outputs an action model that is *consistent* with the given input knowledge. The experimental results show that, even at unfavorable scenarios where input observations are minimal (just an *initial state* and the *goals*), *state-invariant* are helpful to learn better STRIPS action models.

1 Introduction

The specification of planning action models is a complex process that limits, too often, the application of *model-based planning* systems to real-world tasks [Kambhampati, 2007]. The *machine learning* of action models can relieve the *knowledge acquisition bottleneck* of planning and nowadays, there exists a wide range of effective approaches for learning action models [Arora *et al.*, 2018]. Many of the most successful approaches for learning planning action models are however purely *inductive* [Yang *et al.*, 2007; Pasula *et al.*, 2007; Mourao *et al.*, 2010; Zhuo and Kambhampati, 2013], meaning that their performance is linked to the *amount* and *quality* of the input examples (which normally are observations of plan executions generated by the aimed action model).

This paper addresses the learning of action models exploiting a different source of knowledge, *deductive* knowledge, with the form of *state-invariants* (i.e. logic formulae that specify constraints about the possible states of a given domain) to cushion the negative impact of insufficient learning examples. Given an action model, state-of-the-art planners infer *state-invariants* from that model to reduce search spaces and make the planning process more efficient [Helmert, 2009]. In this paper we follow the opposite direction and leverage *state-invariants* to learn the planning action model.

Our approach for learning STRIPS action models from *state-invariants* is building a classical planning compilation that is inspired by recent work by Aineto *et al.* 2018. Our compilation is flexible to different kinds of input knowledge (e.g., partially/fully observations of actions of plan executions as well as partially/fully observed intermediate states) and outputs an action model that is *consistent* with the given input knowledge. The experimental results show that, even at unfavorable scenarios where input observations are minimal (just an *initial state* and the *goals*), *state-invariant* help to learn better STRIPS models with the *classical planning* compilation.

2 Background

This section formalizes the *classical planning model* we follow in this work and the kind of *knowledge* that can be given as input to the task of learning STRIPS action models.

2.1 Classical planning with conditional effects

Let F be the set of propositional state variables (*fluents*) 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 (without loss of generality, we will assume that L does not contain conflicting values). Given L, let $\neg L = \{\neg l : l \in L\}$ be its complement. 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; $|s| = |F|$.

A *classical planning action* $a \in A$ has: a precondition $\mathsf{pre}(a) \in \mathcal{L}(F)$, a set of effects $\mathsf{eff}(a) \in \mathcal{L}(F)$, and a positive action cost $cost(a)$. The semantics of actions $a \in A$ is specified with two functions: $\rho(s, a)$ denotes whether action a is *applicable* in a state s and $\theta(s, a)$ denotes the *successor state* that results of applying action a in a state s. Then, $\rho(s, a)$ holds iff $\mathsf{pre}(a) \subseteq s$, i.e. if its precondition holds in s. The result of executing an applicable action $a \in A$ in a state s is a new state $\theta(s, a) = (s \setminus \neg\mathsf{eff}(a)) \cup \mathsf{eff}(a)$. Subtracting the complement of $\mathsf{eff}(a)$ from s ensures that $\theta(s, a)$ remains a well-defined state. The subset of action effects that assign a positive value to a state fluent is called *positive effects* and denoted by $\mathsf{eff}^+(a) \in \mathsf{eff}(a)$ while $\mathsf{eff}^-(a) \in \mathsf{eff}(a)$ denotes the *negative effects* of an action $a \in A$.

A *classical planning problem* is a tuple $P = \langle F, A, I, G\rangle$, where I is the initial state and $G \in \mathcal{L}(F)$ is the set of goal conditions over the state variables. A *plan* π is an action sequence $\pi = \langle a_1, \ldots, a_n \rangle$, with $|\pi| = n$ denoting its *plan length* and $cost(\pi) = \sum_{a \in \pi} cost(a)$ its *plan cost*. The execution of π on the initial state of P induces a *trajectory* $\tau(\pi, P) = \langle s_0, a_1, s_1, \ldots, a_n, s_n \rangle$ such that $s_0 = I$ and, for each $1 \leq i \leq n$, it holds $\rho(s_{i-1}, a_i)$ and $s_i = \theta(s_{i-1}, a_i)$. A plan π solves P iff the induced *trajectory* $\tau(\pi, P)$ reaches a final state $G \subseteq s_n$, where all goal conditions are met. A solution plan is *optimal* iff its cost is minimal.

We also define *actions with conditional effects* because they are useful to compactly formulate our approach for *goal recognition with unknown domain models*. An action $a_c \in A$ with conditional effects is a set of preconditions $\mathsf{pre}(a_c) \in \mathcal{L}(F)$ and a set of *conditional effects* $\mathsf{cond}(a_c)$. Each conditional effect $C \rhd E \in \mathsf{cond}(a_c)$ 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_c is applicable in a state s if $\rho(s, a_c)$ is true, and the result of applying action a_c in state s is $\theta(s, a_c) = \{s \setminus \neg\mathsf{eff}_c(s, a) \cup \mathsf{eff}_c(s, a)\}$ where $\mathsf{eff}_c(s, a)$ are the *triggered effects* resulting from the action application (conditional effects whose conditions hold in s):

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

2.2 State-invariants

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, *state-constraints* in planning allow to specify the set of states where a given action is applicable, the set of states where a given *derived predicate* holds or the set of states that are considered goal states.

State invariants is a kind of state-constraints useful for computing more compact state representations [Helmert, 2009] or 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, built from F, that is reachable from I by applying actions in A.

The formula $\phi^*_{I,A}$ represents the *strongest invariant* and exactly characterizes the set of all states reachable from I with the actions in A. For instance Figure 1 shows five clauses that define the *strongest invariant* for the *blocksworld* planning domain [Slaney and Thiébaux, 2001]. There are infinitely many strongest invariants, but they are all logically equivalent, and computing the strongest invariant is PSPACE-hard (as hard as testing plan existence [Bylander, 1994]).

$\forall x_1, x_2\ ontable(x_1) \leftrightarrow \neg on(x_1, x_2)$.
$\forall x_1, x_2\ clear(x_1) \leftrightarrow \neg on(x_2, x_1)$.
$\forall x_1, x_2, x_3\ \neg on(x_1, x_2) \vee \neg on(x_1, x_3)\ such\ that\ x_2 \neq x_3$.
$\forall x_1, x_2, x_3\ \neg on(x_2, x_1) \vee \neg on(x_3, x_1)\ such\ that\ x_2 \neq x_3$.
$\forall x_1, \ldots, x_n\ \neg(on(x_1, x_2) \wedge on(x_2, x_3) \wedge \ldots \wedge on(x_{n-1}, x_n) \wedge on(x_n, x_1))$.

Figure 1: *Strongest invariant* for the *blocksworld* domain.

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-block *blocksworld*, $\phi_1 = \neg on(block_A, block_B) \vee \neg on(block_A, block_C)$ is a mutex because $block_A$ can only be on top of a single block.

A *domain invariant* is an instance-independent invariant, i.e. holds for any possible initial state and set of objects. Therefore, if a given state s holds $s \not\models \phi$ such that ϕ is a *domain invariant*, it means that s is not a valid state. Domain invariants are often compactly defined as *lifted invariants* (also called schematic invariants) [Rintanen and others, 2017]. For instance, $\phi_2 = \forall x :\ (\neg handempty \vee \neg holding(x))$, is a *domain mutex* for the *blocksworld* because the robot hand is never empty and holding a block at the same time.

3 Learning STRIPS action models from *state-invariants*

We define the task of learning a planning action model from *state-invariants* as a tuple $\Lambda = \langle P, \Phi, M \rangle$, where:

- $P = \langle F, A[\cdot], I, G \rangle$, is a *classical planning problem* where $A[\cdot]$ is a set of actions s.t., the *dynamics* of each action $a \in A[\cdot]$ is *unknown* (i.e. functions ρ and/or θ are undefined for $a \in A[\cdot]$).
- Φ is a set of *state-invariants* that define constraints about the set of possible states.
- M is the *space of possible action models* for the $A[\cdot]$ actions (i.e., the set of possible specifications of the ρ and/or θ functions for each $a \in A[\cdot]$ action).

A model $\mathcal{M} \in M$ is a *solution* to the $\Lambda = \langle P, \Phi, M \rangle$ learning task iff there exists a plan π that solves $P = \langle F, A[\cdot], I, G \rangle$, when the semantics of each action $a \in A[\cdot]$ is given by $\mathcal{M}$, and such that any state traversed by the trajectory $\tau(\pi, P)$ is *consistent* with the *state-invariants* Φ.

Next, we show that the set M of possible action models can be compactly encoded as a set of propositional variables and a set of constraints over those variables. Then, we show how to exploit this compact encoding to solve a $\Lambda = \langle P, \Phi, M \rangle$ learning task with an off-the-shelf classical planner.

3.1 A propositional encoding for the space of STRIPS action models

A STRIPS *action schema* ξ is defined by four lists: A list of *parameters* $pars(\xi)$, and three list of predicates (namely $pre(\xi)$, $del(\xi)$ and $add(\xi)$) that shape the kind of fluents that can appear in the *preconditions*, *negative effects* and *positive effects* of the actions induced from that schema. Let be Ψ the set of *predicates* that shape the propositional state variables F, and a list of *parameters*, $pars(\xi)$. The set of elements that can appear in $pre(\xi)$, $del(\xi)$ and $add(\xi)$ of the STRIPS action schema ξ is the set of FOL interpretations of Ψ over the parameters $pars(\xi)$ and is denoted as $\mathcal{I}_{\Psi,\xi}$.

For instance in a four-operator *blocksworld* [Slaney and Thiébaux, 2001], the $\mathcal{I}_{\Psi,\xi}$ set contains only five elements for the `pickup`(v_1) schemata, $\mathcal{I}_{\Psi,pickup}$={`handempty`, `holding`($v_1$), `clear`($v_1$), `ontable`($v_1$), `on`($v_1, v_1$)} while it contains eleven elements for

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


(pre_holding_v1_stack) (pre_clear_v2_stack)
(eff_holding_v1_stack) (eff_clear_v2_stack)
(eff_clear_v1_stack) (eff_handempty_stack) (eff_on_v1_v2_stack)
```

Figure 2: PDDL encoding of the `stack(?v1,?v2)` schema and our propositional representation for this same schema.

the `stack(`v_1`,`v_2`)` schemata, $\mathcal{I}_{\Psi,stack}$={`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`)`}.

Despite any element of $\mathcal{I}_{\Psi,\xi}$ can *a priori* appear in the $pre(\xi)$, $del(\xi)$ and $add(\xi)$ of schema ξ, in practice the actual space of possible STRIPS schemata is bounded by constraints of three kinds:

1. **Syntactic constraints**. STRIPS constraints require $del(\xi) \subseteq pre(\xi)$, $del(\xi) \cap add(\xi) = \emptyset$ and $pre(\xi) \cap add(\xi) = \emptyset$. Considering exclusively these syntactic constraints, the size of the space of possible STRIPS schemata is given by $2^{2\times|\mathcal{I}_{\Psi,\xi}|}$. *Typing constraints* are also of this kind [McDermott *et al.*, 1998].
2. **Domain-specific constraints**. One can introduce domain-specific knowledge to constrain further the space of possible schemata. For instance, in the *blocksworld* one can argue that `on(`v_1`,`v_1`)` and `on(`v_2`,`v_2`)` will not appear in the $pre(\xi)$, $del(\xi)$ and $add(\xi)$ lists of an action schema ξ because, in this specific domain, a block cannot be on top of itself. *State invariants* are constraints of this kind.
3. **Observation constraints**. The observation of the actions and states resulting from the execution of a plan depicts *semantic knowledge* that constraints further the space of possible action schemata.

In this work we introduce a propositional encoding of the *preconditions*, *negative*, and *positive* effects of a STRIPS action schema ξ using only fluents of two kinds `pre_e_`ξ and `eff_e_`ξ (where $e \in \mathcal{I}_{\Psi,\xi}$). This encoding exploits the syntactic constraints of STRIPS so it is more compact that the one previously proposed by Aineto *et al.* 2018 for learning STRIPS action models with classical planning. In more detail, if `pre_e_`ξ holds it means that $e \in \mathcal{I}_{\Psi,\xi}$ is a *precondition* in ξ. If `pre_e_`ξ and `eff_e_`ξ holds it means that $e \in \mathcal{I}_{\Psi,\xi}$ is a *negative effect* in ξ while if pre_e_ξ does not hold but `eff_e_`ξ holds, it means that $e \in \mathcal{I}_{\Psi,\xi}$ is a *positive effect* in ξ. Figure 2 shows the PDDL encoding of the `stack(?v1,?v2)` schema and our propositional representation for this same schema using the `pre_e_stack` and `eff_e_stack` fluents ($e \in \mathcal{I}_{\Psi,stack}$).

3.2 Learning STRIPS action models with classical planning

Our approach for computing an action model $\mathcal{M} \in M$ that solves the $\Lambda = \langle P, \Phi, M\rangle$ learning task is to build and solve a classical planning problem $P_\Lambda = \langle F_\Lambda, A_\Lambda, I, G_\Lambda\rangle$ such that:

- F_Λ extends F with a fluent $mode_{inval}$, to indicate whether an action model is *inconsistent* with the input *state-invariants* Φ, a fluent $mode_{insert}$, to indicate whether action models are being programmed, and the fluents for the propositional encoding of the corresponding space of STRIPS action models. As explained, this is a set of fluents of the type $\{pre\_e\_\xi, eff\_e\_\xi\}_{\forall e\in\mathcal{I}_{\Psi,\xi}}$.
- $G_\Lambda = G \cup \{\neg mode_{inval}\}$ extends the original goals G with the $\neg mode_{inval}$ literal to validate that only states *consistent* with the state constraints Φ are traversed by P_Λ solutions.
- A_Λ replaces the actions in A with two types of actions.
  1. Actions for *inserting* a *precondition*, *positive* effect or *negative* effect in ξ following the syntactic constraints of STRIPS models.
     - Actions which support the addition of a *precondition* $p \in \mathcal{I}_{\Psi,\xi}$ to the action model ξ. A precondition p is inserted in ξ when neither pre_p, eff_p exist in ξ.

$$\begin{aligned}\mathsf{pre}(\mathsf{insertPre}_{\mathsf{p},\xi}) =& \{\neg pre\_p\_\xi, \neg eff\_p\_\xi, mode_{insert}\},\\ \mathsf{cond}(\mathsf{insertPre}_{\mathsf{p},\xi}) =& \{\emptyset\} \rhd \{pre\_p\_\xi\}.\end{aligned}$$

     - Actions which support the addition of a *negative* or *positive* effect $p \in \mathcal{I}_{\Psi,\xi}$ to the action model ξ.

$$\begin{aligned}\mathsf{pre}(\mathsf{insertEff}_{\mathsf{p},\xi}) =& \{\neg eff\_p\_\xi, mode_{insert}\},\\ \mathsf{cond}(\mathsf{insertEff}_{\mathsf{p},\xi}) =& \{\emptyset\} \rhd \{eff\_p\_\xi\}.\end{aligned}$$

  2. Actions for *applying* an action model ξ built by the *insert* actions and bounded to objects $\omega \subseteq \Omega^{|pars(\xi)|}$ (where Ω is the set of *objects* used to induce the fluents F by assigning objects in Ω to the Ψ predicates, and Ω^k is the k-th Cartesian power of Ω). The action parameters, $pars(\xi)$, are bound to the objects in ω that appear in the same position. These actions validate also that any state traversed by P_Λ solutions is *consistent* with the *state-invariants* Φ.

$$\begin{aligned}\mathsf{pre}(\mathsf{apply}_{\xi,\omega}) =& \{\neg mode_{inval}\},\\ \mathsf{cond}(\mathsf{apply}_{\xi,\omega}) =& \{pre\_p\_\xi \wedge eff\_p\_\xi\} \rhd \{\neg p(\omega)\}_{\forall p\in\mathcal{I}_{\Psi,\xi}},\\ & \{\neg pre\_p\_\xi \wedge eff\_p\_\xi\} \rhd \{p(\omega)\}_{\forall p\in\mathcal{I}_{\Psi,\xi}}\},\\ & \{pre\_p\_\xi \wedge \neg p(\omega)\} \rhd \{mode_{inval}\}_{\forall p\in\mathcal{I}_{\Psi,\xi}},\\ & \{\neg\phi\} \rhd \{mode_{inval}\}_{\forall\phi\in\Phi},\\ & \{\emptyset\} \rhd \{\neg mode_{insert}\},\end{aligned}$$

3.3 Effective prunning of inconsistent action models with *domain mutex*

We define a *domain mutex* as a (p, q) predicates pair where both $p \in \Psi$ and $q \in \Psi$ are predicates that shape the set of fluents F of a given planning problem and such that they satisfy the following formulae $p \leftrightarrow \neg q$ where are the predicate variables are universally quantified. For instance, predicates $holding(x)$ and $clear(x)$ from the *blocksworld* are *domain mutex* since they satisfy $\forall x \; holding(x) \leftrightarrow \neg clear(x)$ while predicates $clear(x)$ and $ontable(x)$ (also from the *blocksworld*) are not *domain mutex* because they do not always satisfy $\forall x \; clear(x) \leftrightarrow \neg ontable(x)$.

We pay attention to this particular class of *state-invariants* because they define the *state-properties* of a given type of objects [Fox and Long, 1998] and because they enable an effectively pruning of inconsistent /strips/ action models. Our approach to implement this pruning is extending the conditional effects of the $\mathsf{insertPre}_{\mathsf{p},\xi}$ and $\mathsf{insertPre}_{\mathsf{p},\xi}$ actions (i.e., the actions that determine a solution model $\mathcal{M}$) with extra conditional effects indicating that the programmed model is *invalid* (i.e., inconsistent with a *domain mutex* in Φ). Note that this *consistency* checking is more effective than the one implemented at the $\mathsf{apply}_{\xi,\omega}$ actions since $\mathsf{insertPre}_{\mathsf{p},\xi}$ and $\mathsf{insertPre}_{\mathsf{p},\xi}$ actions appear at an earlier stage of the planning process.

Formally, given a *domain mutex* (p,q), s.t. both p and q belong to $\in \mathcal{I}_{\Psi,\xi}$, we extend the actions for setting a precondition p in a given action schema ξ as follows:

$$\begin{aligned}\mathsf{pre}(\mathsf{insertPre}_{\mathsf{p},\xi}) =& \{\neg pre_p(\xi), \neg eff_p(\xi),\\ & mode_{insert}, \neg mode_{inval}\},\\ \mathsf{cond}(\mathsf{insertPre}_{\mathsf{p},\xi}) =& \{\emptyset\} \rhd \{pre_p(\xi)\},\\ & \{pre_q(\xi)\} \rhd \{mode_{inval}\}.\end{aligned}$$

The same procedure is applied for action $insertPre_{q,\xi}$ to ban programming precondition q iff $pre_p(\xi)$ precondition is already set. A similar procedure is also applied to $\mathsf{insertEff}_{\mathsf{p},\xi}$ and $\mathsf{insertEff}_{\mathsf{q},\xi}$ actions for banning in this case, two *negative effects* (or two *positive effects*) that are *domain mutex*. Now we show the actions that ban programming a positive (or negative) p effect if its corresponding q effect is already programmed:

$$\begin{aligned}\mathsf{pre}(\mathsf{insertEff}_{\mathsf{p},\xi}) =& \{\neg eff_p(\xi), mode_{insert}, \neg mode_{inval}\},\\ \mathsf{cond}(\mathsf{insertEff}_{\mathsf{p},\xi}) =& \{\emptyset\} \rhd \{eff_p(\xi),\\ & \{pre_q(\xi), eff_q(\xi), pre_p(\xi)\} \rhd \{mode_{inval}\},\\ & \{\neg pre_q(\xi), eff_q(\xi), \neg pre_p(\xi)\} \rhd \{mode_{inval}\}.\end{aligned}$$

3.4 Learning from partiallly specified models

The compilation is defined assuming M represents the *full* space of STRIPS action models. In some contexts it is however reasonable to assume that the action model is not learned from scratch, e.g. because some parts of the action model are known [Zhuo *et al.*, 2013; Sreedharan *et al.*, 2018]. Here we show that the compilation approach is also flexible to this particular learning scenario.

When the action model for a STRIPS schema ξ is partially specified, the known preconditions and effects are encoded setting the corresponding fluents $\{pre\_e\_\xi, eff\_e\_\xi\}_{\forall e \in \mathcal{I}_{\Psi,\xi}}$ to true in the initial state. Further, the corresponding insert actions, $\mathsf{insertPre}_{\mathsf{p},\xi}$ and $\mathsf{insertEff}_{\mathsf{p},\xi}$, become unnecessary and are removed from A_Λ, making the classical planning task P_Λ easier to be solved.

For example, suppose that the preconditions of the *blocksworld* action schema `stack` are known, then the initial state I is extended with literals, `(pre_holding_v1_stack)` and `(pre_clear_v2_stack)` and the associated actions $\mathsf{insertPre}_{\mathsf{holding_v1,stack}}$ and $\mathsf{insertPre}_{\mathsf{clear_v2,stack}}$ can be safely removed from the A_Λ action set without altering the *soundness* and *completeness* of the P_Λ compilation.

3.5 Compilation properties

Lemma 1. *Soundness. Any classical plan π_Λ that solves P_Λ produces a* STRIPS *model $\mathcal{M}$ that solves the $\Lambda = \langle P, \Phi, M\rangle$ learning task.*

Proof. According to the P_Λ compilation, once a given precondition or effect is inserted into the action model $\mathcal{M}$ it cannot be removed back. In addition, once the action model $\mathcal{M}$ is applied it cannot be *reprogrammed*. In the compiled planning problem P_Λ, the value of the original fluents F can exclusively be modified via $\mathsf{apply}_{\xi,\omega}$ actions. Therefore, the goals of the original P classical planning task can only be achieved executing an applicable sequence of $\mathsf{apply}_{\xi,\omega}$ actions that, starting in the corresponding initial state $I = s_0$ reach a state $G \subseteq s_n$ validating that every generated intermediate state s_i, s.t. $0 \leq i \leq n$, is consistent with the input *state-invariants*. This is exactly the definition of the solution condition for an action model $\mathcal{M}$ to solve the $\Lambda = \langle P, \Phi, M\rangle$ learning task. □

Lemma 2. *Completeness. Any* STRIPS *model $\mathcal{M}$ that solves the $\Lambda = \langle P, \Phi, M\rangle$ learning task can be computed with a classical plan π_Λ that solves P_Λ.*

Proof. By definition $\mathcal{I}_{\Psi,\xi}$ fully captures the set of elements that can appear in a STRIPS action schema ξ using predicates Ψ. In addition the P_Λ compilation does not discard any possible action model $\mathcal{M}$ definable within $\mathcal{I}_{\Psi,\xi}$ while it can satisfy the domain mutex in Φ. This means that for every STRIPS model $\mathcal{M}$ that solves the $\Lambda = \langle P, \Phi, M\rangle$, we can build a plan π_Λ that solves P_Λ by selecting the appropriate $\mathsf{insertPre}_{\mathsf{p},\xi}$ and $\mathsf{insertEff}_{\mathsf{p},\xi}$ actions for *programming* the precondition and effects of the corresponding action model $\mathcal{M}$ and then, selecting the corresponding $\mathsf{apply}_{\xi,\omega}$ actions that transform the initial state I into a state that satisfies the goals G. □

The size of the classical planning task P_Λ output by our compilation depends on the arity of the given *predicates* Ψ, that shape the propositional state variables F, and the number of parameters of the action models, $|pars(\xi)|$. The larger these arities, the larger $|\mathcal{I}_{\Psi,\xi}|$. The size of the $\mathcal{I}_{\Psi,\xi}$ set is the term that dominates the compilation size because it defines the pre_e_ξ/eff_e_ξ fluents, the corresponding set of *insert* actions, and the number of conditional effects in the $\mathsf{apply}_{\xi,\omega}$ actions. Note that *typing* can be used straightforward to constrain the FOL interpretations of Ψ over the parameters $pars(\xi)$ which significantly reduces $|\mathcal{I}_{\Psi,\xi}|$ and hence, the size of the classical planning task output by the compilation.

4 Learning from observations of plan executions

So far we have explained the compilation for learning from a single input trace. However, the compilation is extensible to the more general case $\Lambda = \langle\mathcal{M}, \mathcal{T}\rangle$, where $\mathcal{T} = \{\tau_1, \ldots, \tau_k\}$ is a set of plan traces. Taking this into account, a small modification is required in our compilation approach. In particular, the actions in P_Λ for *validating* the last state $s_m^t \in \tau_t$, $1 \leq t \leq k$ of a plan trace τ_t reset the current state and the current plan. These actions are now redefined as:

Inductive approaches for the learning planning action models compute an action model that maximizes some notion of *statistical consistency* over a set of observations of plan executions so output an action model in our case a solution to the addressed learning task is an action model that is *consistent* with the input knowledge.

4.1 The observation model

Given a planning problem $P = \langle F, A, I, G\rangle$, a plan π and a trajectory $\tau(\pi, P)$, we define the *observation of the trajectory* as an interleaved combination of actions and states that represents the observation from the execution of π in P. Formally, $\mathcal{O}(\tau) = \langle s_0^o, a_1^o, s_1^o \ldots, a_l^o, s_m^o\rangle$, $s_0^o = I$, and:

- The **observed actions** are consistent with π, which means that $\langle a_1^o, \ldots, a_l^o\rangle$ is a sub-sequence of π. The number of observed actions, l, ranges from 0 (fully unobserved action sequence) to $|\pi|$ (fully observed action sequence).
- The **observed states** $\langle s_0^o, s_1^o, \ldots, s_m^o\rangle$ is a sequence of possibly *partially observable states*, except for the initial state s_0^o, which is fully observed. A partially observable state s_i^o is one in which $|s_i^o| < |F|$; i.e., a state in which at least a fluent of F is not observable. Note that this definition also comprises the case $|s_i^o| = 0$, when the state is fully unobservable. Whatever the sequence of observed states of $\mathcal{O}(\tau)$ is, it must be consistent with the sequence of states of $\tau(\pi, P)$, meaning that $\forall i, s_i^o \subseteq s_i$. The number of observed states, m, range from 1 (the initial state, at least), to $|\pi|+1$, and each *observed* states comprises $[1, |F|]$ fluents (the observation can still miss intermediate states that are *unobserved*).

We assume a bijective monotone mapping between actions/states of trajectories and observations [Ramírez and Geffner, 2009], thus also granting the inverse consistency relationship (the trajectory is a superset of the observation). Therefore, transiting between two consecutive observed states in $\mathcal{O}(\tau)$ may require the execution of more than a single action ($\theta(s_i^o, \langle a_1, \ldots, a_k\rangle) = s_{i+1}^o$, where $k \geq 1$ is unknown but finite. In other words, having an input observation $\mathcal{O}(\tau)$ does not imply knowing the actual length of π.

4.2 Learning from observations with *classical planning*

The work on *plan recognition as planning* usually assumes an observation model that is referred only to logs of executed actions. However, the approach applies also to more expressive observation models that consider state observations as well, like the observation model defined above, with a simple three-fold extension:

- One fluent $\{validated_j\}_{0\leq j\leq m}$ to point at every $s_j^o \in \mathcal{O}(\tau)$ state observation. Two fluents, at_i and $next_{i,i+1}$, $1 \leq i \leq n$, to iterate through the n observed actions of τ. The former is used to ensure that actions are executed in the same order as they are observed in τ. The latter is used to iterate to the next planning step when solving P_Λ.
- Adding at_1 and $\{next_{i,i+1}\}$, $1 \leq i \leq n$ to the initial state and $validated_m$ to every possible goal $G \in G[\cdot]$ to constrain solution plans $\pi^\top$ to be consistent with all the state observations.
- When the input plan trace contains observed actions, the extra conditional effects $\{at_i, plan(name(a_i), \Omega^{ar(a_i)}, i)\} \rhd \{\neg at_i, at_{i+1}\}_{\forall i\in[1,n]}$ are included in the $\mathsf{apply}_{\xi,\omega}$ actions to ensure that actions are applied in the same order as they appear in τ.

- Actions for *validating* the partially observed state $s_j \in \tau$, $1 \leq j < m$. These actions are also part of the postfix of the solution plan π_Λ and they are aimed at checking that the observable data of the input plan trace τ follows after the execution of the apply actions.
- One $\mathsf{validate_j}$ action to constraint $\pi^\top$ to be consistent with the $s_j^o \in \mathcal{O}(\tau)$ input state observation, $(1 \leq j \leq m)$.

$$\begin{aligned}\mathsf{pre(validate_j)} =& s_j^o \cup \{validated_{j-1}\},\\ \mathsf{cond(validate_j)} =& \{\emptyset\} \rhd \{\neg validated_{j-1}, validated_j\}.\end{aligned}$$

domain mutex are useful to reduce the amount of applicable actions for programming a precondition or an effect for a given action schema. For example given the *domain mutex* $\phi = (\neg f_1 \vee \neg f_2)$ such that $f_1 \in F_v(\xi)$ and $f_2 \in F_v(\xi)$, we can redefine the corresponding programming actions for **removing** the *precondition* $f_1 \in F_v(\xi)$ from the action schema $\xi \in \mathcal{M}$ as:

5 Evaluation

6 Related work

State-invariants have been previously used to infer a HTN lanning model [Lotinac and Jonsson, 2016].

In *Inductive Logic Programming* it is very common to make the hypothesis be consistent with some form deductive knowledge apart from the examples, what is ussually called *background knowledge* [Muggleton and De Raedt, 1994].

7 Conclusions

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