

Explanation-based learning of action models

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Abstract. The paper presents the classical planning compilation for learning STRIPS action models from observations of plan executions. The compilation is flexible to different amount and kind of available input knowledge; learning examples can range from a set of plans (with their corresponding initial and final states, as well as partially observed intermediate states) to just pairs of initial and final states where no intermediate action/state is observed. The compilation accepts also partially specified action models and it can be used to validate whether the observation of a plan execution follows a given STRIPS action model, even if this model is not fully specified or the input observation is incomplete.

Keywords: Learning action models · Classical planning.

1 Introduction

Besides *plan synthesis* [8], planning action models are also useful for *plan/goal recognition* [16]. In both tasks, an automated planner is required to reason about action models that correctly and completely capture the possible world transitions [7]. 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 [11].

Machine Learning (ML) has shown to be able to compute a wide range of different kinds of models from examples [14]. The application of inductive ML to learning STRIPS action models, the vanilla action model for planning [5], is not straightforward though:

- The *input* to ML algorithms (the learning/training data) is usually a finite vector that represents the value of some fixed object features. The input for learning planning action models is, however, observations of plan executions (where each plan possibly has a different length).
- The *output* of ML algorithms is usually a scalar value (an integer, in the case of *classification* tasks, or a real value, in the case of *regression* tasks). When learning action models the output is, for each action, the preconditions and effects that define the possible state transitions of a planning task.

Learning STRIPS action models is a well-studied problem with sophisticated algorithms such as ARMS [21], SLAF [2] or LOCM [4], which do not require full knowledge of the intermediate states traversed by the example plans. Motivated by recent advances on the synthesis of different kinds of generative models with classical planning [3, 18, 19], this paper describes an innovative planning compilation approach for learning STRIPS action models. The compilation approach is appealing by itself because it opens up the door to the bootstrapping of planning action models, but also because it is flexible to different amount and kind of available input knowledge:

1. Learning examples can range from a set of plans (with their corresponding initial and final states, as well as partially observed intermediate states) to just a pair of initial and final states where no intermediate state/action is observed.
2. Partially specified action models expressing *a priori* knowledge about the structure of actions can also be provided to the compilation. In the extreme, the compilation can validate whether an observed plan execution is valid for a given STRIPS action model, even if the model is not fully specified or the observation is incomplete.

2 Background

This section formalizes the models for *classical planning*, for the *observation* of the execution of a classical plan and for the explanation of an observation.

2.1 Classical planning with conditional effects

F is the set of *fluents* or *state variables* (propositional variables). A *literal* l is a valuation of a fluent $f \in F$, i.e. either $l = f$ or $l = \neg f$. L is a set of literals that represents a partial assignment of values to fluents, and $\mathcal{L}(F)$ is the set of all literals sets on F , i.e. all partial assignments of values to fluents. A *state* s is a full assignment of values to fluents. We explicitly include negative literals $\neg f$ in states and so $|s| = |F|$ and the size of the state space is $2^{|F|}$.

A *planning frame* is a tuple $\Phi = \langle F, A \rangle$, where F is a set of fluents and A is a set of *actions*. An action $a \in A$ is defined with *preconditions*, $\text{pre}(a) \in \mathcal{L}(F)$, and *effects* $\text{eff}(a) \in \mathcal{L}(F)$. 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 . Therefore $\rho(s, a)$ holds iff $\text{pre}(a) \subseteq s$ and the result of applying a in s is $\theta(s, a) = \{s \setminus \neg\text{eff}(a)\} \cup \text{eff}(a)\}$, with $\neg\text{eff}(a) = \{\neg l : l \in \text{eff}(a)\}$.

A *planning problem* is defined as a tuple $P = \langle F, A, I, G \rangle$, where I is the initial state in which all the fluents of F are assigned a value true/false and G is the goal set. A *plan* π for P is an action sequence $\pi = \langle a_1, \dots, a_n \rangle$, and $|\pi| = n$ denotes its *plan length*. The execution of π in the initial state I of P induces a *trajectory* $\tau(\pi, P) = \langle s_0, a_1, s_1, \dots, a_n, s_n \rangle$ 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 if the induced trajectory $\tau(\pi, P)$ holds that $G \subseteq s_n$. A solution plan is *optimal* iff its length is minimal.

Now we define actions with conditional effects because they allow to compactly define our compilation. An action $a_c \in A$ with conditional effects is defined as a set of preconditions $\text{pre}(a_c) \in \mathcal{L}(F)$ and a set of *conditional effects* $\text{cond}(a_c)$. Each conditional effect $C \triangleright E \in \text{cond}(a_c)$ is composed of two sets of literals: $C \in \mathcal{L}(F)$, the *condition*, and $E \in \mathcal{L}(F)$, the *effect*. An action $a_c \in A$ is applicable in a state s if and only if $\text{pre}(a_c) \subseteq s$, and the *triggered effects* resulting from the action application are the effects whose conditions hold in s :

$$\text{triggered}(s, a_c) = \bigcup_{C \triangleright E \in \text{cond}(a_c), C \subseteq s} E.$$

The result of applying a_c in state s follows the same definition of successor state, $\theta(s, a)$, but applied to the conditional effects in $\text{triggered}(s, a_c)$.

2.2 The observation model

Given a planning problem $P = \langle F, A, I, G \rangle$ and a plan π , the *observation of the trajectory* $\tau(\pi, P)$ is a sequence of partial states that captures what is observed from the execution of π in P . Formally, $\mathcal{O}(\tau) = \langle s_0^o, s_1^o, \dots, s_m^o \rangle$, $s_0^o = I$ is a sequence of possibly *partially observable states* (except for the initial state s_0^o which is fully observable). 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.

This *observation model* comprises the case $|s_i^o| = 0$, when an intermediate state is fully unobservable. Further, this model consider also *observed actions* as fluents that indicate the action applied in a given state. This means that a sequence of *observed actions* $\langle a_1^o, \dots, a_l^o \rangle$ is a sub-sequence of π s.t. $a_i^o \in s_i^o$ ($0 \leq i < m$). The number of *observed actions*, l , can then range from 0 (in a fully unobservable action sequence) to $|\pi|$ (a fully observable action sequence).

The sequence of observed states $\mathcal{O}(\tau)$ must be *consistent* with the sequence of states in $\tau(\pi, P)$, meaning that $\forall i, s_i^o \subseteq s_i$. In practice, the number m of observed states ranges from 1 (the initial state, at least), to $|\pi| + 1$, and the observed intermediate states will comprise a number of fluents between $[1, |F|]$. This means that we assume a bijective monotone mapping between actions/states of trajectories and observations [15], 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 ($\theta(s_i^o, \langle a_1, \dots, a_k \rangle) = s_{i+1}^o$, where $k \geq 1$ is unknown but finite. In other words, having $\mathcal{O}(\tau)$ does not imply knowing the actual length of the trajectory τ .

This observation model can also distinguish between *observable state variables*, whose value may be read from sensors, and *hidden* (or *latent*) *state variables*, that cannot be observed. Given a subset of fluents $\Gamma \subseteq F$ we say that $\mathcal{O}(\tau)$ is a Γ -observation of the execution of π on P iff, for every $1 \leq i \leq m$, each observed state s_i^o only contains fluents in Γ .

2.3 The explanation model

Let $\Phi_{\mathcal{O}} = \langle F, A \rangle$ be a *classical planning frame* where the fluents F are deduced from the fully observed $s_0^o \in \mathcal{O}$. Let also $P_{\mathcal{O}}$ be the classical planning problem $P_{\mathcal{O}} = \langle F, A, s_0^o, s_m^o \rangle$.

Definition 1 (Explanation). *We say that a plan π explains \mathcal{O} (denoted $\pi \mapsto \mathcal{O}$) iff π is a solution for P that is consistent with the state trajectory constraints imposed by the sequence of partial states \mathcal{O} . If π is also optimal, we say that π is the best explanation for the input observation $\mathcal{O}(\tau)$.*

An *observation* can then be considered a sequence of ordered *landmarks* for the $P_{\mathcal{O}}$ classical planning problem, because the literals in the observation must be achieved by all the plans that solve this problem and in the same order [9].

3 Explanation-based learning of action models

The task of learning action models from the observation of a plan execution is defined as a tuple $\Lambda = \langle \mathcal{M}, \mathcal{O}, \kappa \rangle$, where:

- \mathcal{M} is the *initial empty model* that contains only the *header* (i.e., the corresponding *name* and *parameters*) of each action model to be learned.
- $\mathcal{O} = \langle s_0^o, s_1^o \dots, s_m^o \rangle$ is a sequence of partially observed states.
- κ is a set of logic formulae that define *domain-specific knowledge*.

A *solution* to a $\Lambda = \langle \mathcal{M}, \mathcal{O}, \kappa \rangle$ learning task is a model \mathcal{M}' s.t. it is consistent with the headers of \mathcal{M} and the given domain knowledge in κ and it explains \mathcal{O} . We say that a model \mathcal{M} *explains* an observation \mathcal{O} iff, when the $\langle \rho, \theta \rangle$ functions of the actions in $P_{\mathcal{O}}$ are given by \mathcal{M} , there exists a solution plan for $P_{\mathcal{O}}$ that *explains* \mathcal{O} .

3.1 The space of STRIPS action models

We analyze here the solution space of a learning task $\Lambda = \langle \mathcal{M}, \mathcal{O}, \Phi \rangle$; i.e., the space of STRIPS action models.

A STRIPS *action model* ξ is defined as $\xi = \langle name(\xi), pars(\xi), pre(\xi), add(\xi), del(\xi) \rangle$, where $name(\xi)$ and parameters, $pars(\xi)$, define the header of ξ ; and $pre(\xi)$, $del(\xi)$ and $add(\xi)$ are sets of fluents that represent the *preconditions*, *negative effects* and *positive effects*, respectively, of the actions induced from the action model ξ .

Let Ψ be the set of *predicates* that shape the fluents F (the initial state of an observation is a full assignment of values to fluents, $|s_0^o| = |F|$, and so the predicates Ψ are extractable from the observed state s_0^o). The set of propositions that can appear in $pre(\xi)$, $del(\xi)$ and $add(\xi)$ of a given ξ , denoted as $\mathcal{I}_{\xi, \Psi}$, are FOL interpretations of Ψ over the parameters $pars(\xi)$. For instance, in a four-operator *blocksworld* [20], the $\mathcal{I}_{\xi, \Psi}$ set contains five elements for the *pickup*(v_1) model,

$\mathcal{I}_{pickup,\Psi} = \{\text{handempty}, \text{holding}(v_1), \text{clear}(v_1), \text{ontable}(v_1), \text{on}(v_1, v_1)\}$ and eleven elements for the model of $\text{stack}(v_1, v_2)$, $\mathcal{I}_{stack,\Psi} = \{\text{handempty}, \text{holding}(v_1), \text{holding}(v_2), \text{clear}(v_1), \text{clear}(v_2), \text{ontable}(v_1), \text{ontable}(v_2), \text{on}(v_1, v_1), \text{on}(v_1, v_2), \text{on}(v_2, v_1), \text{on}(v_2, v_2)\}$. Hence, solving a $\Lambda = \langle \mathcal{M}, \mathcal{O}, \kappa \rangle$ learning task is determining which elements of $\mathcal{I}_{\xi,\Psi}$ will shape the preconditions, positive and negative effects of each action model $\xi \in \mathcal{M}$.

In principle, for a given STRIPS action model ξ , any element of $\mathcal{I}_{\xi,\Psi}$ can potentially appear in $\text{pre}(\xi)$, $\text{del}(\xi)$ and $\text{add}(\xi)$. In practice, the actual space of possible STRIPS schemata is bounded by:

1. **Syntactic constraints.** The solution \mathcal{M}' must be consistent with the STRIPS constraints: $\text{del}(\xi) \subseteq \text{pre}(\xi)$, $\text{del}(\xi) \cap \text{add}(\xi) = \emptyset$ and $\text{pre}(\xi) \cap \text{add}(\xi) = \emptyset$. *Typing constraints* would also be a type of syntactic constraint [13].
2. **Observation constraints.** The solution \mathcal{M}' must be consistent with these *semantic constraints* derived from the learning samples \mathcal{O} , which in our case is a single plan observation. Specifically, the states induced by the plan computable with \mathcal{M}' must comprise the observed states of the sample, which further constrains the space of possible action models.

Considering only the syntactic constraints, the size of the space of possible STRIPS models is given by $2^{2 \times |\mathcal{I}_{\Psi,\xi}|}$ because one element in $\mathcal{I}_{\xi,\Psi}$ can appear both in the preconditions and effects of ξ . The belonging of an $e \in \mathcal{I}_{\Psi,\xi}$ to the preconditions, positive effects or negative effects of ξ is handled with a refined propositional encoding that uses fluents of two types, $\text{pre}_{\xi}e$ and $\text{eff}_{\xi}e$, instead of the three fluents used in the original compilation [1]. The four possible combinations of these two fluents are summarized in Figure 1. This compact encoding allows for a more effective exploitation of the syntactic constraints, and also yields the solution space of Λ to be the same as its search space.

	Meaning
$\neg \text{pre}_{\xi}e \wedge \neg \text{eff}_{\xi}e$	e belongs neither to the preconditions nor effects of ξ ($e \notin \text{pre}(\xi) \wedge e \notin \text{add}(\xi) \wedge e \notin \text{del}(\xi)$)
$\text{pre}_{\xi}e \wedge \neg \text{eff}_{\xi}e$	e is only a precondition of ξ ($e \in \text{pre}(\xi) \wedge e \notin \text{add}(\xi) \wedge e \notin \text{del}(\xi)$)
$\neg \text{pre}_{\xi}e \wedge \text{eff}_{\xi}e$	e is a positive effect of ξ ($e \notin \text{pre}(\xi) \wedge e \in \text{add}(\xi) \wedge e \notin \text{del}(\xi)$)
$\text{pre}_{\xi}e \wedge \text{eff}_{\xi}e$	e is a negative effect of ξ ($e \in \text{pre}(\xi) \wedge e \notin \text{add}(\xi) \wedge e \in \text{del}(\xi)$)

Fig. 1. Combinations of the fluent propositional encoding and their meaning

3.2 The sampling space

According to our *observation model* the minimal expression of an observation must comprise at least two state observations, a full initial state s_0^o and a partially observed final state s_m^o so $m \geq 1$. The maximal expression of an observation corresponds to a fully observed trajectory $\mathcal{O}(\tau) = \tau$ (meaning that all traversed states and applied actions are fully observed). In between there is a grey scale of different kind of possible observations, including the observation of the initial state and a plan that is frequently used for previous system that learn planning action models such as ARMS [21] or SLAF [2].

Figure 2 shows a learning example that contains an initial state of the blocksworld where the robot hand is empty and three blocks (namely `blockA`, `blockB` and `blockC`) are on top of the table and clear. The observation represents a partially observable final state in which `blockA` is on top of `blockB` and `blockB` on top of `blockC`.

```
(:predicates (on ?x ?y) (ontable ?x) (clear ?x) (handempty) (holding ?x))

(:objects blockA blockB blockC)

(:init (ontable blockA) (clear blockA) (ontable blockB) (clear blockB)
        (ontable blockC) (clear blockC) (handempty))

(:observation (on blockA blockB) (on blockB blockC))
```

Fig. 2. Example of a two-state observation for the learning of STRIPS action models in the *blocksworld* domain.

3.3 The domain-specific knowledge

One can introduce domain-specific knowledge to constrain further the space of possible schemata. For instance, back to the *blocksworld* domain, one can argue that $\text{on}(v_1, v_1)$ and $\text{on}(v_2, v_2)$ will not appear in the $\text{pre}(\xi)$, $\text{del}(\xi)$ and $\text{add}(\xi)$ of any action model ξ because, in this specific domain, a block cannot be on top of itself. In addition, *domain-specific knowledge* can be used to complete partially observed states.

A compact formalism for expressing domain-specific knowledge are *schematic invariants*. For instance *schematic invariants* can identify mutually exclusive properties of a given type of objects [6] (Figure 3 shows an example of four clauses that define schematic invariants for the *blocksworld* domain).

$$\begin{aligned}
 &\forall x_1, x_2 \neg \text{ontable}(x_1) \vee \neg \text{on}(x_1, x_2). \\
 &\forall x_1, x_2 \neg \text{clear}(x_1) \vee \neg \text{on}(x_2, x_1). \\
 &\forall x_1, x_2, x_3 \neg \text{on}(x_1, x_2) \vee \neg \text{on}(x_1, x_3) \text{ such that } x_2 \neq x_3. \\
 &\forall x_1, x_2, x_3 \neg \text{on}(x_2, x_1) \vee \neg \text{on}(x_3, x_1) \text{ such that } x_2 \neq x_3.
 \end{aligned}$$

Fig. 3. Schematic mutexes for the *blocksworld* domain.

4 Learning Strips action models with classical planning

Our proposal to address a learning task $\Lambda = \langle \mathcal{M}, \tau \rangle$ is to transform Λ into a planning task P_Λ . The intuition behind the compilation is that when P_Λ is solved with a planner, the solution plan π_Λ is a sequence of actions that build the action models of the output domain model \mathcal{M}' and verify that \mathcal{M}' is consistent with the actions and states of the observed plan trace $\tau = \langle s_0, \dots, s_n \rangle$. Hence, π_Λ will comprise two differentiated blocks of actions: a first set of actions each defining the **insertion** of a fluent as a precondition, a positive effect or a negative effect of an action model $\xi \in \mathcal{M}'$; and a second set of actions that determine the **application** of the learned ξ s while successively **validating** the effects of the action application in every observable point of τ , including that the final reached state comprises s_n . Roughly speaking, in the *blocksworld* domain, the format of the first set of actions of π_Λ will look like `(insert_pre_stack_holding_v1), (insert_eff_stack_clear_v1), (insert_eff_stack_clear_v2)`, where the first effect denotes a positive effect and the second one a negative effect to be inserted in $\text{name}(\xi) = \text{stack}$; and the format of the second set of actions of π_Λ will be like `(apply_unstack_blockB_blockA), (apply_putdown_blockB)` and `(validate.1), (validate.2)`, where the last two actions denote the points at which the states generated through the action application must be validated with the observed states of τ .

4.1 Compilation

Our compilation scheme builds upon the approach presented in [1] but FAMA comes up with a more general and flexible scheme able to capture any type of input plan trace.

A learning task $\Lambda = \langle \mathcal{M}, \tau \rangle$ is compiled into a planning task P_Λ with conditional effects in the context of a planning frame $\Phi = \langle F, A \rangle$. We use conditional effects because they allow us to compactly define actions whose effects depend on the current state. An action $a \in A$ with conditional effects is defined as a set of preconditions $\text{pre}(a) \in \mathcal{L}(F)$ and a set of *conditional effects* $\text{cond}(a)$. Each conditional effect $C \triangleright E \in \text{cond}(a)$ 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 $\text{pre}(a) \subseteq s$, and the *triggered effects* resulting from the action application are the effects whose conditions hold in s ; that is, $\text{triggered}(s, a) = \bigcup_{C \triangleright E \in \text{cond}(a), C \subseteq s} E$. The result of applying a in state s follows

the same definition of successor state, $\theta(s, a)$, introduced in section ?? but applied to the conditional effects in $triggered(s, a)$.

A solution plan π_A to P_A induces the output domain model \mathcal{M}' that solves the learning task A . Specifically, a solution plan π_A serves two purposes:

1. **To build the action models of \mathcal{M}' .** π_A comprises a first block of actions (plan *prefix*) that set the predicates $p \in \Psi_\xi$ of $pre(\xi)$, $del(\xi)$ and $add(\xi)$ for each $\xi \in \mathcal{M}$.
2. **To validate the action models of \mathcal{M}' .** π_A also comprises a second block of actions (plan *postfix*) which is aimed at validating of the observed plan trace τ with the built action models \mathcal{M}' .

Given a learning task $A = \langle \mathcal{M}, \tau \rangle$, with τ formed by an n -action sequence $\langle a_1, \dots, a_n \rangle$ and a m -state trajectory $\langle s_0, s_1, \dots, s_m \rangle$ ($\tau = \langle s_0, a_1, \dots, a_n, s_m \rangle$), the compilation outputs a classical planning task $P_A = \langle F_A, A_A, I_A, G_A \rangle$ such that:

- F_A extends F with the model fluents to represent the preconditions and effects of each $\xi \in \mathcal{M}$ as well as some other fluents to keep track of the validation of τ . Specifically, F_A contains:
 - The set of fluents obtained from s_0 ; i.e., F .
 - The model fluents $pre_p(\xi)$, $del_p(\xi)$ and $add_p(\xi)$, for every $\xi \in \mathcal{M}$ and $p \in \Psi_\xi$, defined as explained in section ??
 - A set of fluents $F_\pi = \{plan(name(a_i), \Omega^{ar(a_i)}, i)\}_{1 \leq i \leq n}$ to represent the i^{th} observable action of τ . In the example of Figure ??, the two observed actions (**putdown B**) and (**stack A B**) would be encoded as fluents (**plan-putdown B i1**) and (**plan-stack A B i2**) to indicate that (**putdown B**) is observed in the first place and (**stack A B**) is the second observed action.
 - 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_A .
 - A set of fluents $\{test_j\}_{0 \leq j \leq m}$, to point at the state observation $s_j \in \tau$ where the action model is validated. In the example of Figure ?? two tests are required to validate the programmed action model, one test at s_0 and another one at s_4 .
 - A fluent, $mode_{prog}$, to indicate whether action models are being programmed or validated.
- I_A encodes s_0 and the following fluents set to true: $mode_{prog}$, $test_0$, F_π , at_1 and $\{next_{i,i+1}\}$, $1 \leq i \leq n$. Our compilation assumes that action models are initially programmed with no precondition, no negative effect and no positive effect.
- G_A includes the positive literals at_n and $test_m$. When these two goals are achieved by the solution plan π_A , we will be certain that the action models of \mathcal{M}' are validated in all the actions and states observed in the input plan trace τ .

- A_A includes three types of actions that give rise to the actions of π_A .
- 1. Actions for *inserting* a component (precondition, positive effect or negative effect) in $\xi \in \mathcal{M}$ following the syntactic constraints of STRIPS models. These actions will form the prefix of the solution plan π_A . Among the *inserting* actions, we find:
 - Actions which support the addition of a *precondition* $p \in \Psi_\xi$ to the action model $\xi \in \mathcal{M}$. A precondition p is inserted in ξ when neither pre_p , del_p nor add_p exist in ξ .

$$\begin{aligned} \text{pre}(\text{insertPre}_{p,\xi}) &= \{\neg pre_p(\xi), \neg del_p(\xi), \neg add_p(\xi), mode_{prog}\}, \\ \text{cond}(\text{insertPre}_{p,\xi}) &= \{\emptyset\} \triangleright \{pre_p(\xi)\}. \end{aligned}$$

- Actions which support the addition of a *negative* or *positive* effect $p \in \Psi_\xi$ to the action model $\xi \in \mathcal{M}$. A positive effect is inserted in ξ under the same conditions of a precondition insertion, and a negative effect is inserted in ξ when neither del_p nor add_p appear in ξ but pre_p does.

$$\begin{aligned} \text{pre}(\text{insertEff}_{p,\xi}) &= \{\neg del_p(\xi), \neg add_p(\xi), mode_{prog}\}, \\ \text{cond}(\text{insertEff}_{p,\xi}) &= \{pre_p(\xi)\} \triangleright \{del_p(\xi)\}, \\ &\quad \{\neg pre_p(\xi)\} \triangleright \{add_p(\xi)\}. \end{aligned}$$

For instance, given $name(\xi) = \text{stack}$ and $C_{pre-stack} = \{(\text{pre_stack_holding_v1}), (\text{pre_stack_holding_v2}), (\text{pre_stack_on_v1_v2}), (\text{pre_stack_clear_v1}), (\text{pre_stack_clear_v1}), \dots\}$, the insertion of each item $c \in C_{pre-stack}$ in ξ will generate a different alternative in the search space when solving P_A as long as $c \notin pre(\xi)$, $c \notin add(\xi)$ and $c \notin del(\xi)$. The same applies to effects with respect to sets $C_{add-stack}$ and $C_{del-stack}$ that would include all fluents starting with prefix **add** and **del**, respectively.

Note that executing an insert action, e.g. $(\text{insert_pre_stack_holding_v1})$, will add the corresponding model fluent $(\text{pre_stack_holding_v1})$ to the successor state. Hence, the execution of the insert actions of π_A yield a state containing the valuation of the model fluents that shape every $\xi \in \mathcal{M}$. For example, executing the insert actions that shape the action model $name(\xi) = \text{putdown}$ leads to a state containing the positive literals $(\text{pre_putdown_holding_v1}), (\text{eff_putdown_holding_v1}), (\text{eff_putdown_clear_v1}), (\text{eff_putdown_ontable_v1}), (\text{eff_putdown_handempty})$.

- 2. Actions for *applying* the action models $\xi \in \mathcal{M}$ built by the insert actions and bounded to objects $\omega \subseteq \Omega^{ar(\xi)}$. Since action headers are known, the variables $pars(\xi)$ are bounded to the objects in ω that appear in the same position.

$$\begin{aligned}
\text{pre}(\text{apply}_{\xi,\omega}) &= \{pre_p(\xi) \implies p(\omega)\}_{\forall p \in \Psi_\xi}, \\
\text{cond}(\text{apply}_{\xi,\omega}) &= \{del_p(\xi)\} \triangleright \{\neg p(\omega)\}_{\forall p \in \Psi_\xi}, \\
&\quad \{add_p(\xi)\} \triangleright \{p(\omega)\}_{\forall p \in \Psi_\xi}, \\
&\quad \{mode_{prog}\} \triangleright \{\neg mode_{prog}\}.
\end{aligned}$$

These actions will be part of the postfix of the plan π_A and they determine the application of the learned action models according to the values of the model fluents in the current state configuration. Figure 4 shows the PDDL encoding of (`apply_stack`) for applying the action model of the *stack* operator.

Note that executing an apply action, e.g. (`apply_stack blockB blockA`), will add the literals (`on blockB blockA`), (`clear blockB`), (`not(clear blockA)`), (`handempty`) and (`not(clear blockB)`) to the successor state if $name(\xi) = \text{stack}$ has been correctly programmed by the insert actions. Hence, while **insert actions** add the values of the **model fluents** that shape ξ , the **apply actions** add the values of the **fluents of F** that result from the execution of ξ .

When the input plan trace contains observed actions, the extra conditional effects

$\{at_i, plan(name(a_i), \Omega^{ar(a_i)}, i)\} \triangleright \{\neg at_i, at_{i+1}\}_{\forall i \in [1,n]}$ are included in the $\text{apply}_{\xi,\omega}$ actions to ensure that actions are applied in the same order as they appear in τ .

3. 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_A and they are aimed at checking that the observable data of the input plan trace τ follows after the execution of the apply actions.

$$\begin{aligned}
\text{pre}(\text{validate}_j) &= s_j \cup \{test_{j-1}\}, \\
\text{cond}(\text{validate}_j) &= \{\emptyset\} \triangleright \{\neg test_{j-1}, test_j\}.
\end{aligned}$$

There will be a validate action in π_A for every observed state in τ . The position of the validate actions in π_A will be determined by the planner by checking that the state resulting after the execution of an apply action comprises the observed state $s_j \in \tau$.

In some contexts, it is reasonable to assume that some parts of the action model are known and so there is no need to learn the entire model from scratch [22]. In FAMA, when an action model ξ is partially specified, the known preconditions and effects are encoded as fluents $pre_p(\xi)$, $del_p(\xi)$ and $add_p(\xi)$ set to true in the initial state I_A . In this case, the corresponding insert actions, $\text{insertPre}_{p,\xi}$

```

(:action apply_stack
:parameters (?o1 - object ?o2 - object)
:precondition
  (and (or (not (pre_stack_on_v1_v1)) (on ?o1 ?o1))
        (or (not (pre_stack_on_v1_v2)) (on ?o1 ?o2))
        (or (not (pre_stack_on_v2_v1)) (on ?o2 ?o1))
        (or (not (pre_stack_on_v2_v2)) (on ?o2 ?o2))
        (or (not (pre_stack_ontable_v1)) (ontable ?o1))
        (or (not (pre_stack_ontable_v2)) (ontable ?o2))
        (or (not (pre_stack_clear_v1)) (clear ?o1))
        (or (not (pre_stack_clear_v2)) (clear ?o2))
        (or (not (pre_stack_holding_v1)) (holding ?o1))
        (or (not (pre_stack_holding_v2)) (holding ?o2))
        (or (not (pre_stack_handempty)) (handempty))))
:effect
  (and (when (del_stack_on_v1_v1) (not (on ?o1 ?o1)))
        (when (del_stack_on_v1_v2) (not (on ?o1 ?o2)))
        (when (del_stack_on_v2_v1) (not (on ?o2 ?o1)))
        (when (del_stack_on_v2_v2) (not (on ?o2 ?o2)))
        (when (del_stack_ontable_v1) (not (ontable ?o1)))
        (when (del_stack_ontable_v2) (not (ontable ?o2)))
        (when (del_stack_clear_v1) (not (clear ?o1)))
        (when (del_stack_clear_v2) (not (clear ?o2)))
        (when (del_stack_holding_v1) (not (holding ?o1)))
        (when (del_stack_holding_v2) (not (holding ?o2)))
        (when (del_stack_handempty) (not (handempty)))
        (when (add_stack_on_v1_v1) (on ?o1 ?o1))
        (when (add_stack_on_v1_v2) (on ?o1 ?o2))
        (when (add_stack_on_v2_v1) (on ?o2 ?o1))
        (when (add_stack_on_v2_v2) (on ?o2 ?o2))
        (when (add_stack_ontable_v1) (ontable ?o1))
        (when (add_stack_ontable_v2) (ontable ?o2))
        (when (add_stack_clear_v1) (clear ?o1))
        (when (add_stack_clear_v2) (clear ?o2))
        (when (add_stack_holding_v1) (holding ?o1))
        (when (add_stack_holding_v2) (holding ?o2))
        (when (add_stack_handempty) (handempty))
        (when (modeProg) (not (modeProg)))))

```

Fig. 4. PDDL action for applying an already programmed model for *stack* (implications are coded as disjunctions).

and $\text{insertEff}_{p,\xi}$, become unnecessary and are removed from A_A , thereby making the classical planning task P_A easier to be solved.

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 $\mathcal{T} = \{\tau_1, \dots, \tau_k\}$ 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_A 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:

$$\begin{aligned}
\text{pre}(\text{validate}_j) &= s_m^t \cup \{test_{j-1}\} \cup \{\neg mode_{prog}\}, \\
\text{cond}(\text{validate}_j) &= \{\emptyset\} \triangleright \{\neg test_{j-1}, test_j\} \cup \\
&\quad \{\neg f\}_{\forall f \in s_m^t, f \notin s_0^{t+1}} \cup \{f\}_{\forall f \in s_0^{t+1}, f \notin s_m^t}, \\
&\quad \{\neg f\}_{\forall f \in F_{\pi_t}} \cup \{f\}_{\forall f \in F_{\pi_{t+1}}}.
\end{aligned}$$

Finally, we will detail the composition of a solution plan π_A to a planning task P_A and the mechanism to extract the action models of \mathcal{M}' from π_A . The plan of Figure 5 shows a solution to the task P_A that encodes a learning task $\Lambda = \langle \mathcal{M}, \tau \rangle$ for obtaining the action models of the *blocksworld* domain, where the models for *pickup*, *putdown* and *unstack* are already specified in \mathcal{M} . Therefore, the plan shows the insert actions and validate action for the action model *stack* using the input plan trace of Figure ?? . Plan steps 00 – 01 insert the preconditions of the *stack* model, steps 02 – 06 insert the action model effects, and steps 07 – 11 form the plan postfix that applies the action models (only the *stack* model is learned) and validates the result in the plan trace of Figure ?? .

```

00 : (insert_pre_stack_holding.v1)
01 : (insert_pre_stack_clear.v2)
02 : (insert_eff_stack_clear.v1)
03 : (insert_eff_stack_clear.v2)
04 : (insert_eff_stack_hanempty)
05 : (insert_eff_stack_holding.v1)
06 : (insert_eff_stack_on.v1.v2)
07 : (apply_unstack blockB blockA i1 i2)
08 : (apply_putdown blockB i2 i3)
09 : (apply_pickup blockA i3 i4)
10 : (apply_stack blockA blockB i4 i5)
11 : (validate.1)

```

Fig. 5. Plan for programming and validating the *stack* action model (using the plan trace τ of Figure ??) as well as previously specified action models for *pickup*, *putdown* and *unstack*.

Given a solution plan π_A that solves P_A , the set of action models \mathcal{M}' that solves $\Lambda = \langle \mathcal{M}, \tau \rangle$ are computed in linear time and space. In order to do so, π_A is executed in the initial state I_A and the action model \mathcal{M}' will be given by the fluents $pre_f(\xi)$, $del_f(\xi)$ and $add_f(\xi)$ that are set to true in the last state reached by π_A , $s_g = \theta(I_A, \pi_A)$. For each $\xi \in \mathcal{M}'$, we build the sets of preconditions, positive effects and negative effects as follows:

$$\begin{aligned}
pre(\xi) &= \{p \mid pre_p(\xi) \in s_g\}_{\forall p \in \Psi_\xi}, \\
add(\xi) &= \{p \mid add_p(\xi) \in s_g\}_{\forall p \in \Psi_\xi}, \\
del(\xi) &= \{p \mid del_p(\xi) \in s_g\}_{\forall p \in \Psi_\xi}.
\end{aligned}$$

The logical inference process our approach is based on has trouble learning preconditions that do not appear as negative effects since in this case no change is observed between the pre-state and post-state of an action. This is specially relevant for static predicates that never change and, hence, only appear as preconditions in the actions. In order to address this shortcoming and complete the

list of learned preconditions, we apply a post-process based on the one proposed in [12]. The idea lies in going through every action and counting the number of cases where a literal is present before the action is executed and the number of cases where it is not present. If a literal is present in all the cases before the action, the literal is considered to be a precondition.

In order to obtain a complete trace, the proposal in [12] applies the sequence of actions of the input trace and infers the preconditions from this action sequence. In our case, since the sequence of actions of the input trace might not be fully observable, we produce the traces by applying the actions found in the validation part of the solution plan. For instance, in the example of the figure 5, the sequence of actions used to produce the complete trace would be `(unstack blockB blockA)`, `(put-down blockB)`, `(pick-up blockA)`, and `(stack blockA blockB)`.

4.2 Properties of the compilation

Lemma 1. *Soundness. Any classical plan π that solves P' (planning task that results from the compilation) produces a model \mathcal{M}' that solves the $\Lambda = \langle \mathcal{M}, \mathcal{O}, \Phi \rangle$ learning task.*

Proof (Proof). According to the P' compilation, once a given precondition or effect is inserted into the domain model \mathcal{M} it cannot be undone. In addition, once an action model is applied it cannot be modified. In the compiled planning task P' , only `(apply) ξ, ω` actions can update the value of the state fluents F . This means that a state consistent with an observation s_m^o can only be achieved executing an applicable sequence of `(apply) ξ, ω` actions that, starting in the corresponding initial state s_0^o , validates that every generated intermediate state s_j ($0 < j \leq m$), is consistent with the input state observations and *state-invariants*. This is exactly the definition of the solution condition for model \mathcal{M}' to solve the $\Lambda = \langle \mathcal{M}, \mathcal{O}, \Phi \rangle$ learning task.

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

Proof (Proof). By definition $\mathcal{I}_{\xi, \Psi}$ fully captures the set of elements that can appear in an action model ξ using predicates Ψ . In addition the P' compilation does not discard any model \mathcal{M}' definable within $\mathcal{I}_{\xi, \Psi}$ that satisfies the mutexes in Φ . This means that, for every model \mathcal{M}' that solves the $\Lambda = \langle \mathcal{M}, \mathcal{O}, \Phi \rangle$, we can build a plan π that solves P' by selecting the appropriate `(insert_pre) ξ, e` and `(insert_eff) ξ, e` actions for programming the precondition and effects of the corresponding action models in \mathcal{M}' and then, selecting the corresponding `(apply) ξ, ω` actions that transform the initial state observation s_0^o into the final state observation s_m^o .

The size of P' depends on the arity of the predicates in Ψ , that shape variables F , and the number of parameters of the action models, $|pars(\xi)|$. The larger these arities, the larger $|\mathcal{I}_{\xi, \Psi}|$. The size of $\mathcal{I}_{\xi, \Psi}$ is the most dominant factor of the compilation because it defines the *pre- ξ -e/eff- ξ -e* fluents, the corresponding set of insert actions, and the number of conditional effects in the `(apply) ξ, ω` actions. Note that

typing can be used straightforward to constrain the FOL interpretations of Ψ over the parameters $\text{pars}(\xi)$, which will significantly reduce $|\mathcal{I}_{\xi,\Psi}|$ and hence the size of P' output by the compilation.

Classical planners tend to prefer shorter solution plans, so our compilation (as well as the BLS) may introduce a bias to $\Lambda = \langle \mathcal{M}, \mathcal{O}, \Phi \rangle$ learning tasks preferring solutions that are referred to action models with a shorter number of preconditions/effects. In more detail, all $\{\text{pre-}\xi\text{-e}, \text{eff-}\xi\text{-e}\}_{\forall e \in \mathcal{I}_{\xi,\Psi}}$ fluents are false at the initial state of our P' compilation so classical planners tend to solve P' with plans that require a smaller number of insert actions.

This bias can be eliminated defining a cost function for the actions in P' (e.g. insert actions have *zero cost* while $(\text{apply})_{\xi,\omega}$ actions have a *positive constant cost*). In practice we use a different approach to disregard the cost of insert actions since classical planners are not proficient at optimizing plan cost with zero-cost actions. Instead, our approach is to use a SAT-based planner [17] that can apply all actions for inserting preconditions in a single planning step (these actions do not interact). Further, the actions for inserting action effects are also applied in another single planning step. The plan horizon for programming any action model is then always bounded to 2. The SAT-based planning approach is also convenient for its ability to deal with planning problems populated with dead-ends and because symmetries in the insertion of preconditions/effects into an action model do not affect the planning performance.

An interesting aspect of our approach is that when a *fully* or *partially specified* STRIPS action model \mathcal{M} is given in Λ , the P_Λ compilation also serves to validate whether the observed τ follows the given model \mathcal{M} :

- \mathcal{M} is proved to be a *valid* action model for the given input data in τ iff a solution plan for P_Λ can be found.
- \mathcal{M} is proved to be a *invalid* action model for the given input data τ iff P_Λ is unsolvable. This means that \mathcal{M} cannot be consistent with the given observation of the plan execution.

The validation capacity of our compilation is beyond the functionality of VAL (the plan validation tool [10]) because our P_Λ compilation is able to address *model validation* of a partial (or even an empty) action model with a partially observed plan trace. VAL, however, requires a full plan and a full action model for plan validation.

5 Experimental results

6 Conclusions

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