

# Computing the *least-commitment* action model from state observations

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## Abstract

## 1 Introduction

Given an input sequence of partially observed states, this paper formalizes the task of computing a compact representation of the set of all action models that are consistent with that input observation. That is the *least-commitment* action model.

This task is of interest because, if we can compute the *least-commitment* action model, then a new input observation has either no effect on the *least-commitment* action model or eliminates some models from it. This property allows to implement an incremental algorithm for learning planning action models from arbitrary large sets of partial observations (one has never to go back and re-process old observations) [Mitchell, 1982].

In addition, the paper introduces a new method to compute the *least-commitment* action model for an input sequence of partially observed states. The method assumes that action models are specified as STRIPS action schemata and it is built on top of off-the-shelf algorithms for *classical planning*.

## 2 Background

This section formalizes the *planning models* we use in the paper as well as the kind of state *observations* that are given as input for computing the *least-commitment* action model.

### 2.1 Classical planning with conditional effects

Let  $F$  be the set of *fluents* or *state variables* (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 (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 frame* is a tuple  $\Phi = \langle F, A \rangle$ , where  $F$  is a set of fluents and  $A$  is a set of *actions*. Each classical planning action  $a \in A$  has a precondition  $\text{pre}(a) \in \mathcal{L}(F)$ , a set of effects  $\text{eff}(a) \in \mathcal{L}(F)$ , and a positive action cost

$\text{cost}(a)$ . 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  $\text{pre}(a) \subseteq s$ , 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  $\theta(s, a) = (s \setminus \neg \text{eff}(a)) \cup \text{eff}(a)$ . Subtracting the complement of  $\text{eff}(a)$  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  $\text{eff}^+(a) \in \text{eff}(a)$  while  $\text{eff}^-(a) \in \text{eff}(a)$  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*  $\pi$  is an action sequence  $\pi = \langle a_1, \dots, a_n \rangle$ , with  $|\pi| = n$  denoting its *plan length* and  $\text{cost}(\pi) = \sum_{a \in \pi} \text{cost}(a)$  its *plan cost*. The execution of  $\pi$  on the initial state  $I$  of  $P$  induces a *trajectory*  $\tau(\pi, s_0) = \langle s_0, a_1, s_1, \dots, a_n, s_n \rangle$  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  $\pi$  solves  $P$  iff the induced *trajectory*  $\tau(\pi, s_0)$  reaches a final state  $G \subseteq s_n$ , where all goal conditions are met. A solution plan is *optimal* iff it minimizes the sum of action costs.

An *action with conditional effects*  $a_c \in A$  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  $a_c$  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  $\theta(s, a_c) = \{s \setminus \neg \text{eff}_c(s, a) \cup \text{eff}_c(s, a)\}$  where  $\text{eff}_c(s, a)$  are the *triggered effects* resulting from the action application (conditional effects whose conditions hold in  $s$ ):

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

### 2.2 The observation model

Given a classical planning problem  $P = \langle F, A, I, G \rangle$ , a plan  $\pi$  and a trajectory  $\tau(\pi, s_0)$ , we define the *observation of the trajectory* as a sequence of partial states that results from observing the execution of  $\pi$  on  $I$ . Formally,  $\mathcal{O}(\tau) = \langle s_0^o, s_1^o, \dots, s_m^o \rangle$  where  $s_0^o = I$  and  $m$  ranges from 1 (the initial state, at least) to  $|\pi| + 1$ . The observed intermediate states are *partial states*.

A partial state  $s_i^o$ ,  $0 < i < m$  resulting from observing the corresponding state  $s_i$ , 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  $\tau(\pi, s_0)$ , meaning that  $\forall i, s_i^o \subseteq s_i$ .

We are assuming then that there is a *bijective monotone mapping* between 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 ( $\theta(s_i^o, \langle a_1, \dots, a_k \rangle) = s_{i+1}^o$ , where  $k \geq 1$  is unknown but finite. In other words, having  $\mathcal{O}(\tau)$  does not imply knowing the actual length of  $\pi$ .

**Definition 1 (Plan explanation)** Given a classical planning problem  $P$  and an observation  $\mathcal{O}(\tau)$ , a plan  $\pi$  explains  $\mathcal{O}(\tau)$  (denoted  $\pi \mapsto \mathcal{O}(\tau)$ ) iff  $\pi$  is a solution for  $P$  that is consistent with the state trajectory constraints imposed by the sequence of partial states  $\mathcal{O}(\tau)$ .

If  $\pi$  is also optimal, we say that  $\pi$  is the *best explanation* for the input observation  $\mathcal{O}(\tau)$ .

### 2.3 Conformant planning

*Conformant planning* is planning with incomplete information about the initial state, no sensing, and validating that goals are achieved with certainty (despite there is uncertainty at the initial state and no sensing is available) [Goldman and Boddy, 1996; Smith and Weld, 1998; Bonet and Geffner, 2000].

Syntactically, conformant planning problems are expressed in compact form through a set of state variables. A *conformant planning problem* can be defined as a tuple  $P_c = \langle F, A, \Upsilon, G \rangle$  where  $F$ ,  $A$  and  $G$  are the set of *fluents*, *actions* and *goals* (as previously defined for *classical planning*). Now  $\Upsilon$  is a set of clauses over literals  $l = f$  or  $l = \neg f$  (for  $f \in F$ ) that define the set of possible initial states.

A solution to a conformant planning problem is an action sequence that maps each possible initial state into a goal state. More precisely, an action sequence  $\pi = \langle a_1, \dots, a_n \rangle$  is a *conformant plan* for  $P_c$  iff, for each possible trajectory  $\tau(\pi, s_0) = \langle s_0, a_1, s_1, \dots, a_n, s_n \rangle$  s.t.  $s_0$  is a valuation of the fluents in  $F$  that satisfies  $\Upsilon$ , then  $\tau(\pi, s_0)$  reaches a final state  $G \subseteq s_n$ .

## 3 The least-commitment action model

The task of computing the *least-commitment* action model from a sequence of state observations is defined as  $\langle \Phi, \mathcal{O}(\tau) \rangle$ :

- $\Phi = \langle F, A[\cdot] \rangle$  is a *classical planning frame* where the semantics of each action  $a \in A[\cdot]$  is unknown; i.e. the corresponding  $\langle \rho, \theta \rangle$  functions are undefined.
- $\mathcal{O}(\tau)$  is a sequence of partial states that results from the partial observation of a trajectory  $\tau(\pi, s_0)$  within the *classical planning frame*  $\Phi$ .

**Definition 2 (Action model)** An action model  $\mathcal{M}$  is a definition of the  $\langle \rho, \theta \rangle$  functions of every action in  $A[\cdot]$ .

Given a *classical planning frame*  $\Phi = \langle F, A[\cdot] \rangle$  and an observation  $\mathcal{O}(\tau) = \langle s_0^o, s_1^o, \dots, s_m^o \rangle$  let  $P_{\mathcal{O}}$  be the classical planning problem  $P_{\mathcal{O}} = \langle F, A[\cdot], s_0^o, s_m^o \rangle$ . A model  $\mathcal{M}$  *explains* an observation  $\mathcal{O}(\tau)$  iff, when the  $\langle \rho, \theta \rangle$  functions of the actions in  $P_{\mathcal{O}}$  are defined by  $\mathcal{M}$ , there exists a solution plan for  $P_{\mathcal{O}}$  that *explains*  $\mathcal{O}(\tau)$ .

**Definition 3 (The least-commitment action model)** Given a  $\langle \Phi, \mathcal{O}(\tau) \rangle$  task (and let  $M$  be the set of action models that represents the full space of possible action models for the actions in  $A[\cdot] \in \Phi$ ), the *least-commitment action model* is the largest subset of models  $M^* \subseteq M$  such that every model  $\mathcal{M} \in M^*$  explains the input observation.

### 3.1 The space of STRIPS action models

This work focuses on the particular task of computing the *least-commitment* action model when action models are specified as STRIPS action schemata.

A STRIPS *action schema*  $\xi$  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  $\Psi$  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  $\xi$  is given by FOL interpretations of  $\Psi$  over the parameters  $pars(\xi)$  and is denoted as  $\mathcal{I}_{\Psi, \xi}$ .

For instance, in the *blocksworld* the  $\mathcal{I}_{\Psi, \xi}$  set contains five elements for a  $pickup(v_1)$  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 a  $stack(v_1, v_2)$  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  $\xi$ , the 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  $\xi$  because, in this specific domain, a block cannot be on top of itself. *State invariants* are also constraints of this kind [Fox and Long, 1998].
3. *Observation constraints.* An observations  $\mathcal{O}(\tau)$  depicts *semantic knowledge* that constraints further the space of possible action schemata.

```

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

In this work we introduce a propositional encoding of the *preconditions*, *negative*, and *positive* effects of a STRIPS action schema  $\xi$  using only fluents of two kinds  $\text{pre}_e.\xi$  and  $\text{eff}_e.\xi$  (where  $e \in \mathcal{I}_{\Psi, \xi}$ ). This encoding exploits the syntactic constraints of STRIPS so is more compact than the one previously proposed by Aineto *et al.* 2018. In more detail, if  $\text{pre}_e.\xi$  and  $\text{eff}_e.\xi$  holds it means that  $e \in \mathcal{I}_{\Psi, \xi}$  is a negative effect in  $\xi$  while if  $\text{pre}_e.\xi$  does not hold but  $\text{eff}_e.\xi$  holds, it means that  $e \in \mathcal{I}_{\Psi, \xi}$  is a positive effect in  $\xi$ . Figure 1 shows the PDDL encoding of the `stack(?v1, ?v2)` schema and our propositional representation for this same schema with  $\text{pre}_e.\text{stack}$  and  $\text{eff}_e.\text{stack}$  fluents ( $e \in \mathcal{I}_{\Psi, \text{stack}}$ ).

### 3.2 Partially specified STRIPS action models

A set of action models can be defined *explicitly*, enumerating all the models that belong to the set or *implicitly*, enumerating all the constraints that must satisfy any model that belongs to the set. Inspired by the notion of *incomplete (annotated) model* [Sreedharan *et al.*, 2018], we define here a *partially specified* STRIPS action model, a formalism for the *implicit* representation of a set of STRIPS schemes.

Extending our propositional encoding of STRIPS action schemes to the *knowledge level*, we can compactly represent a set of STRIPS schema. The extension defines, for each proposition  $\text{pre}_e.\xi$ , two propositions  $K\text{pre}_e.\xi$  and  $K\neg\text{pre}_e.\xi$ , meaning that is *known* that  $e \in \mathcal{I}_{\Psi, \xi}$  is a precondition of  $\xi$  and that is *known* that  $e \in \mathcal{I}_{\Psi, \xi}$  is not a precondition of  $\xi$ . Likewise  $K\text{eff}_e.\xi$  and  $K\neg\text{eff}_e.\xi$  represent that is *known* that  $e \in \mathcal{I}_{\Psi, \xi}$  is an effect of  $\xi$  and that is *known* that  $e \in \mathcal{I}_{\Psi, \xi}$  is not an effect of  $\xi$ .

**Definition 4 (Partially specified STRIPS model)** A partially specified action schema  $\xi[\cdot]$  is an arbitrary formula over the  $K\text{pre}_e.\xi$ ,  $K\neg\text{pre}_e.\xi$ ,  $K\text{eff}_e.\xi$  and  $K\neg\text{eff}_e.\xi$  propositions ( $e \in \mathcal{I}_{\Psi, \xi}$ ) whose valuations enumerate the set of action models  $M_\xi$ .

With respect to this formalization, the *full space* of possible STRIPS schemas for  $\xi$  is compactly represented by the *partially specified action schema*  $\bigcap_{e \in \mathcal{I}_{\Psi, \xi}} \neg K\text{pre}_e.\xi \wedge \neg K\neg\text{pre}_e.\xi \wedge \neg K\text{eff}_e.\xi \wedge \neg K\neg\text{eff}_e.\xi$ . Figure 2 shows a *partially specified* STRIPS model that represents of a set of action models for the `stack(?v1, ?v2)` schema. This *partially specified* STRIPS model compactly represents a set of  $2^5$  models since (1), the actual five effects of the action are *unknown*, (2) preconditions are known to appear as in the actual definition of the `stack(?v1, ?v2)` schema for the *blocksworld* and (3), it is *known* that the preconditions and effects that are not part of the actual definition of the

```

(Kpre_holding_v1_stack) (Kpre_clear_v2_stack)
(Knegpre_holding_v2_stack) (Knegpre_clear_v1_stack)
(Knegpre_handempty_stack)
(Knegpre_ontable_v1_stack) (Knegpre_ontable_v2_stack)
(Knegpre_on_v1_v2_stack) (Knegpre_on_v2_v1_stack)
(Knegpre_on_v1_v1_stack) (Knegpre_on_v2_v2_stack)

(Knegeff_holding_v2_stack) (Knegeff_clear_v2_stack)
(Knegeff_clear_v2_stack) (Knegeff_on_v2_v2_stack)
(Knegeff_on_v1_v1_stack) (Knegeff_on_v2_v1_stack)

```

Figure 2: *Partially specified* STRIPS model that represents of a set of action models for the `stack(?v1, ?v2)` schema.

`stack(?v1, ?v2)` schema are not part of this *partially specified* STRIPS model.

**Definition 5 (Partially specified model explanation)** A *partially specified action schema*  $\xi[\cdot]$  explains a given observation  $\mathcal{O}(\tau)$ , iff every model  $\mathcal{M} \in M_\xi$  explains that observation.

## 4 Batch learning of action models

Given a *classical planning frame*  $\Phi = \langle F, A[\cdot] \rangle$  and a batch of state observations  $\mathcal{O}_1, \dots, \mathcal{O}_T$  within this frame, this section shows a model learning algorithm that incrementally eliminates action models that are not *consistent* with the input observations. The algorithm is defined as follows.

1. Initialize a *partially specified* model to the full space of possible action models,  $\xi[\cdot] := M$ .
2. For each input observation  $\mathcal{O}_t$ ,  $1 \leq t \leq T$ :
  - (a) Compute  $M_t^*$ , the *least-commitment* model that solves the corresponding  $\langle \Phi, \mathcal{O}_t \rangle$  task.
  - (b) Update the *partially specified* model intersecting it with the computed *least-commitment* model,  $\xi[\cdot] := \xi[\cdot] \cap M_t^*$ .
  - (c) Continue until the *partially specified* model  $\xi[\cdot]$  is a singleton, or no more observations left ( $t = T$ ).
3. Return  $\xi[\cdot]$

This model learning algorithm is *sound* given that, by definition, all the action models defined by  $M_t^*$  are *consistent* with observation  $\mathcal{O}_t$  and always holds that  $\xi[\cdot]_t \subseteq \xi[\cdot]_{t-1}$ , where  $\xi[\cdot]_t$  is the value of the *partially specified* model after the  $t^{\text{th}}$  iteration. The algorithm is also *complete* because it only discards from  $\xi[\cdot]_0$  (the full space of possible action models) models that are not consistent with a given input observation. Further the complexity of our model learning algorithm depends only linearly on  $T$ , the number of input observations, since it has never to re-process old observations.

The challenge to implement this algorithm is then the computation of  $M_t^*$ , the *least-commitment* model that solves the corresponding  $\langle \Phi, \mathcal{O}_t \rangle$  task.

### 4.1 Computing the least-commitment model via conformant planning

The compilation for learning STRIPS action models defined by Aineto *et al.* 2018 can be used to compute a *partially specified model* that explains a given observation by producing a conformant planning task instead of a classical planning

task. The initial state  $\Upsilon$  of the conformant planning task does not code an *initial* action model (typically *empty*) but the full space of action models. In more detail, the clauses in  $\Upsilon$  are:

1. The *unit clauses* given by the fluents that hold in the initial state  $I = s_0$ .
2. The clauses representing that the actual value of fluents  $\text{pre\_e\_}\xi$ ,  $\text{eff\_e\_}\xi$  is unknown. Any model from the STRIPS space of models (following the previously mentioned *syntactic constraints*) can initially be part of the *least-commitment* action model. Formally, for every  $\xi$  and  $e \in \mathcal{I}_{\Psi, \xi}$ ,  $\Upsilon$  includes these two clauses:

- $\text{pre\_e\_}\xi \vee \neg \text{pre\_e\_}\xi$
- $\text{eff\_e\_}\xi \vee \neg \text{eff\_e\_}\xi$

One can also add here clauses that encode *domain-specific constraints* (as mentioned in the previous section) to make the conformant planning problem easier to be solved for a specific domain.

A conformant plan that solves this task only induces a *partially specified model* that *explains* the given input observation. To get a *partially specified model* that is *least-commitment*, we have to compute the *optimal* plan for this same conformant planning task using the following action costs: All actions have zero cost, except the actions that *program* a given precondition (or effect) of an action schema. These actions represent now a reduction of one unit in the *uncertainty* of the initial state and hence, have an associated cost of 1. In other words, each of these actions implement an *immediate specification* of the current *partially specified model*.

#### 4.2 Computing a superset of the least-commitment action models via classical planning

Inspired by the *classical planning compilation*  $K_0$  for conformant planning [Palacios and Geffner, 2009], this section shows that we can build a *classical planning problem*  $P = \langle F', A', I', G' \rangle$  whose optimal solution induces a *superset* of the *least-commitment* action model for an input observation  $\mathcal{O}(\tau)$  (all actions in  $A'$  have zero cost except *commit* actions that have a cost of one):

- The set of fluents  $F'$  extends  $F$  with two new sets of fluents:
  - $\{test_j\}_{1 \leq j \leq m}$ , indicating the state observation  $s_j \in \mathcal{O}(\tau)$  where the action model is validated
  - The *knowledge level* fluents  $K\text{pre\_e\_}\xi$ ,  $K\neg\text{pre\_e\_}\xi$ ,  $K\text{eff\_e\_}\xi$  and  $K\neg\text{eff\_e\_}\xi$  encoding the space of possible *partially specified* action models.
- The set of actions  $A'$  contains now actions of three different kinds:
  - Actions for *committing*  $\text{pre\_e\_}\xi$  to a positive/negative value. Similar actions are also defined for *committing*  $\text{eff\_e\_}\xi$  to a positive/negative value but the value of  $\text{eff\_e\_}\xi$  can only be committed once the value of the corresponding  $\text{pre\_e\_}\xi$  is committed

(i.e. once either  $K\text{pre\_e\_}\xi$  or  $K\neg\text{pre\_e\_}\xi$  holds).

$$\begin{aligned} \text{pre}(\text{commit}\top\text{pre\_e\_}\xi) &= \{mode_{commit}, \\ &\quad \neg K\text{pre\_e\_}\xi, \neg K\neg\text{pre\_e\_}\xi\}, \\ \text{cond}(\text{commit}\top\text{pre\_e\_}\xi) &= \{\emptyset\} \triangleright \{K\text{pre\_e\_}\xi\}. \end{aligned}$$

$$\begin{aligned} \text{pre}(\text{commit}\perp\text{pre\_e\_}\xi) &= \{mode_{commit}, \\ &\quad \neg K\text{pre\_e\_}\xi, \neg K\neg\text{pre\_e\_}\xi\}, \\ \text{cond}(\text{commit}\perp\text{pre\_e\_}\xi) &= \{\emptyset\} \triangleright \{K\neg\text{pre\_e\_}\xi\}. \end{aligned}$$

- Actions for *validating* that committed models explain the  $s_j$  observed states,  $0 \leq j < m$ .

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

- *Editable* actions whose semantics is given by the value of the *knowledge level* fluents ( $K\text{pre\_e\_}\xi$ ,  $K\neg\text{pre\_e\_}\xi$ ,  $K\text{eff\_e\_}\xi$  and  $K\neg\text{eff\_e\_}\xi$ ) at the current state. Figure 3 shows the PDDL encoding of an *editable stack* ( $?v1, ?v2$ ) schema. This editable schema behaves exactly as the original PDDL schema defined in Figure 1 when the set of fluents  $(K\text{pre\_holding\_v1\_stack}) (K\text{pre\_clear\_v2\_stack}) (K\text{eff\_holding\_v1\_stack}) (K\text{eff\_clear\_v2\_stack}) (K\text{eff\_clear\_v1\_stack}) (K\text{eff\_handempty\_stack}) (K\text{eff\_on\_v1\_v2\_stack})$  hold at the current state as well as the remaining  $K\neg\text{pre\_e\_}\xi$  and  $K\neg\text{eff\_e\_}\xi$  for all the preconditions and effects that are not part of the actual  $\text{stack}(?v1, ?v2)$  schema. Formally, given an operator schema  $\xi \in \mathcal{M}$  its *editable* version is:

$$\begin{aligned} \text{pre}(\text{editable}_\xi) &= \{\neg K\neg\text{pre\_e\_}\xi \implies e\}_{e \in \mathcal{I}_{\Psi, \xi}} \\ \text{cond}(\text{editable}_\xi) &= \{K\text{pre\_e\_}\xi, K\text{eff\_e\_}\xi\} \triangleright \{\neg e\}_{e \in \mathcal{I}_{\Psi, \xi}}, \\ &\quad \{K\neg\text{pre\_e\_}\xi, K\text{eff\_e\_}\xi\} \triangleright \{e\}_{e \in \mathcal{I}_{\Psi, \xi}}. \end{aligned}$$

- The new initial state  $I' = I \cup \{mode_{commit}\}$  while the new goals are  $G' = s_m \cup \{test_m\}$ .

#### 4.3 Compilation properties

#### 5 Evaluation

#### 6 Conclusions

Related work [Stern and Juba, 2017].

#### References

- [Aineto et al., 2018] Diego Aineto, Sergio Jiménez, and Eva Onaindia. Learning STRIPS action models with classical planning. In *International Conference on Automated Planning and Scheduling, (ICAPS-18)*, pages 399–407. AAAI Press, 2018.
- [Bonet and Geffner, 2000] Blai Bonet and Hector Geffner. Planning with incomplete information as heuristic search in belief space. In *Proceedings of the Fifth International Conference on Artificial Intelligence Planning Systems*, pages 52–61. AAAI Press, 2000.

```

(:action stack
:parameters (?o1 - object ?o2 - object)
:precondition
  (and (or (Knotpre_on_v1_v1_stack) (on ?o1 ?o1))
        (or (Knotpre_on_v1_v2_stack) (on ?o1 ?o2))
        (or (Knotpre_on_v2_v1_stack) (on ?o2 ?o1))
        (or (Knotpre_on_v2_v2_stack) (on ?o2 ?o2))
        (or (Knotpre_ontable_v1_stack) (ontable ?o1))
        (or (Knotpre_ontable_v2_stack) (ontable ?o2))
        (or (Knotpre_clear_v1_stack) (clear ?o1))
        (or (Knotpre_clear_v2_stack) (clear ?o2))
        (or (Knotpre_holding_v1_stack) (holding ?o1))
        (or (Knotpre_holding_v2_stack) (holding ?o2))
        (or (Knotpre_handempty_stack) (handempty)))
:effect (and
  (when (and (Kpre_on_v1_v1_stack) (Keff_on_v1_v1_stack)) (not (on ?o1 ?o1)))
  (when (and (Kpre_on_v1_v2_stack) (Keff_on_v1_v2_stack)) (not (on ?o1 ?o2)))
  (when (and (Kpre_on_v2_v1_stack) (Keff_on_v2_v1_stack)) (not (on ?o2 ?o1)))
  (when (and (Kpre_on_v2_v2_stack) (Keff_on_v2_v2_stack)) (not (on ?o2 ?o2)))
  (when (and (Kpre_ontable_v1_stack) (Keff_ontable_v1_stack)) (not (ontable ?o1)))
  (when (and (Kpre_ontable_v2_stack) (Keff_ontable_v2_stack)) (not (ontable ?o2)))
  (when (and (Kpre_clear_v1_stack) (Keff_clear_v1_stack)) (not (clear ?o1)))
  (when (and (Kpre_clear_v2_stack) (Keff_clear_v2_stack)) (not (clear ?o2)))
  (when (and (Kpre_holding_v1_stack) (Keff_holding_v1_stack)) (not (holding ?o1)))
  (when (and (Kpre_holding_v2_stack) (Keff_holding_v2_stack)) (not (holding ?o2)))
  (when (and (Kpre_handempty_stack) (Keff_handempty_stack)) (not (handempty)))
  (when (and (Knot_pre_on_v1_v1_stack) (Keff_on_v1_v1_stack)) (on ?o1 ?o1))
  (when (and (Knot_pre_on_v1_v2_stack) (Keff_on_v1_v2_stack)) (on ?o1 ?o2))
  (when (and (Knot_pre_on_v2_v1_stack) (Keff_on_v2_v1_stack)) (on ?o2 ?o1))
  (when (and (Knot_pre_on_v2_v2_stack) (Keff_on_v2_v2_stack)) (on ?o2 ?o2))
  (when (and (Knot_pre_ontable_v1_stack) (Keff_ontable_v1_stack)) (ontable ?o1))
  (when (and (Knot_pre_ontable_v2_stack) (Keff_ontable_v2_stack)) (ontable ?o2))
  (when (and (Knot_pre_clear_v1_stack) (Keff_clear_v1_stack)) (clear ?o1))
  (when (and (Knot_pre_clear_v2_stack) (Keff_clear_v2_stack)) (clear ?o2))
  (when (and (Knot_pre_holding_v1_stack) (Keff_holding_v1_stack)) (holding ?o1))
  (when (and (Knot_pre_holding_v2_stack) (Keff_holding_v2_stack)) (holding ?o2))
  (when (and (Knot_pre_handempty_stack) (Keff_handempty_stack)) (handempty)))

```

Figure 3: PDDL encoding of the editable version of the stack(?v1, ?v2) schema.

*Automated Planning and Scheduling, (ICAPS-18)*, pages 518–526, 2018.

[Stern and Juba, 2017] Roni Stern and Brendan Juba. Efficient, safe, and probably approximately complete learning of action models. In *International Joint Conference on Artificial Intelligence, (IJCAI-17)*, pages 4405–4411, 2017.

[Fox and Long, 1998] Maria Fox and Derek Long. The automatic inference of state invariants in tim. *Journal of Artificial Intelligence Research*, 9:367–421, 1998.

[Goldman and Boddy, 1996] Robert P Goldman and Mark S Boddy. Expressive planning and explicit knowledge. In *AIPS*, volume 96, pages 110–117, 1996.

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

[Mitchell, 1982] Tom M Mitchell. Generalization as search. *Artificial intelligence*, 18(2):203–226, 1982.

[Palacios and Geffner, 2009] Héctor Palacios and Héctor Geffner. Compiling uncertainty away in conformant planning problems with bounded width. *Journal of Artificial Intelligence Research*, 35:623–675, 2009.

[Ramírez and Geffner, 2009] Miquel Ramírez and Hector Geffner. Plan recognition as planning. In *International Joint conference on Artificial Intelligence, (IJCAI-09)*, pages 1778–1783. AAAI Press, 2009.

[Smith and Weld, 1998] David E Smith and Daniel S Weld. Conformant graphplan. In *AAAI/IAAI*, pages 889–896, 1998.

[Sreedharan *et al.*, 2018] Sarath Sreedharan, Tathagata Chakraborti, and Subbarao Kambhampati. Handling model uncertainty and multiplicity in explanations via model reconciliation. In *International Conference on*