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 the *least-commitment* action model that is able to *explain* the given observation. This task is of interest because it allows the incremental learning of action models from arbitrary large sets of partial observations.

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 *conformant 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 $\mathsf{pre}(a) \in \mathcal{L}(F)$ and a set of effects $\mathsf{eff}(a) \in \mathcal{L}(F)$. 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. 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*. The execution of π on the initial state I of P induces a *trajectory* $\tau(\pi, s_0) = \langle s_0, a_1, s_1, \ldots, a_n, s_n \rangle$ 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 $\tau(\pi, s_0)$ reaches a final state $G \subseteq s_n$, where all goal conditions are met. A solution plan is optimal iff its length is minimal.

An action $a_c \in A$ with conditional effects is defined as 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 $C \triangleright E \in \mathsf{cond}(a_c)$ 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):

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

2.2 The observation model

Given a classical planning problem $P = \langle F, A, I, G \rangle$, a plan π 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 π on I. Formally, $\mathcal{O}(\tau) = \langle s_0^o, s_1^o \ldots, s_m^o \rangle$ where $s_0^o = I$.

A *partial state* s_i^o, $0 < i < m$, 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 $\forall i, s_i^o \subseteq s_i$. In practice, the number of observed states m, ranges from 1 (the initial state, at least), to $|\pi| + 1$, and the observed intermediate states will comprise a number of fluents between $[1, |F|]$.

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 $(\theta(s_i^o, \langle a_1, \ldots, a_k \rangle) = s_{i+1}^o$, where $k \geq 1$ is unknown but finite. In other words, having $\mathcal{O}(\tau)$ does not imply knowing the actual length of π.

Definition 1 (Explaining a $\mathcal{O}(\tau)$ observation) *Given a classical planning problem P and a sequence of partial states $\mathcal{O}(\tau)$, a plan π explains $\mathcal{O}(\tau)$ (denoted $\pi \mapsto \mathcal{O}(\tau)$) iff π is a solution for P consistent with $\mathcal{O}(\tau)$.*

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

Given a *classical planning frame* $\Phi = \langle F, A[\cdot] \rangle$ and a sequence of partial states $\mathcal{O}(\tau) = \langle s_0^o, s_1^o \ldots, s_m^o \rangle$, we can build the classical planning problem $P_{\mathcal{O}} = \langle F, A[\cdot], s_0^o, s_m^o \rangle$. We say that an action model $\mathcal{M}$ is a definition of the $\langle \rho, \theta \rangle$ functions of every action in $A[\cdot]$. Further we say that a model $\mathcal{M}$ *explains* a sequence of observations $\mathcal{O}(\tau)$ 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 $\mathcal{O}(\tau)$.

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 the uncertainty of the initial state) [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 Υ 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 $\pi = \langle a_1, \ldots, a_n \rangle$ is a *conformant plan* for P_c iff, for each possible *trajectory* $\tau(\pi, s_0) = \langle s_0, a_1, s_1, \ldots, a_n, s_n \rangle$ s.t. s_0 is a valuation of the fluents in F that satisfies Υ, then $\tau(\pi, s_0)$ reaches a final state $G \subseteq s_n$.

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

First, this section formalizes the notion of the *least-commitment* action model that is able to *explain* a sequence of partially observed states. Next, the section describes our approach to compute such model via *conformant planning*.

3.1 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 $\tau(\pi, s_0)$ defined within the *classical planning frame* Φ.

Before formalizing the solution to this task, i.e. the *least-commitment* action model, we introduce several necessary definitions.

Definition 2 (Model Space) *Given a classical planning frame $\Phi = \langle F, A[\cdot] \rangle$ the model space M is the set of possible models for the actions in $A[\cdot]$ such that: (1), any model $\mathcal{M} \in M$ is a definition of the $\langle \rho, \theta \rangle$ functions of every action in $A[\cdot]$ and (2), for every $\mathcal{M} \in M$ the $\langle \rho, \theta \rangle$ functions are defined in the set of state variables F.*

Now, we define a *partially specified action model* inspired by the notion of *incomplete (annotated) model* [Sreedharan *et al.*, 2018].

Definition 3 (Partially specified action model) *A partially specified action model is a subset of models in a given model space M.*

If the *partially specified action model* is a singleton, it represents a *fully specified action model*. On the other hand, if its size is $|M|$ the *partially specified action model* represents the full model space.

Now we are ready to define the *least-commitment* action model for an observation $\mathcal{O}(\tau)$.

Definition 4 (The *least-commitment* action model) *Given a $\langle \Phi, \mathcal{O}(\tau) \rangle$ task and the partially specified action model M that represents the full space of possible action models for the actions in $A[\cdot] \in \Phi$, then the least-commitment action model is another partially specified action model that represents the largest subset of models $M^* \subseteq M$ such that every model $\mathcal{M} \in M^*$ explains the input observation.*

3.2 The space of STRIPS action models

Despite previous definitions are general, this work focuses on the particular kind of action models that are specified as STRIPS action schemata.

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 given by FOL interpretations of Ψ over the parameters $pars(\xi)$. We denote this set of FOL interpretations as $\mathcal{I}_{\Psi,\xi}$. For instance, in the *blocksworld* the $\mathcal{I}_{\Psi,\xi}$ set contain eleven elements for 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, the space of possible STRIPS schemata is bounded by constraints of three kinds:

```
(: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.

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 $2^{2 \times |\mathcal{I}_{\Psi,\xi}|}$. With this regard, we implement a propositional encoding of the *preconditions*, *negative*, and *positive* effects of an action schema ξ using only fluents pre_e_ξ and eff_e_ξ (where $e \in \mathcal{I}_{\Psi,\xi}$). This encoding exploits the syntactic constraints of STRIPS so, 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 1 shows the PDDL encoding of the stack(?v1,?v2) schema and our propositional representation for this same schema.

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(v1,v1) and on(v2,v2) 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. As a rule of thumb, *typing constraints* and *state invariants* belong to this second class of constraints [Fox and Long, 1998].

3. *Observation constraints.* A sequence of state observations $\mathcal{O}(\tau)$ depicts *semantic knowledge* that constraints further the space of possible action schemata. For instance, since we assume that the initial state s_0 is fully observed, we have that $\bigcup_\xi \neg pre\_e\_\xi \wedge eff\_e\_\xi$ if there is an instantiation of e that holds in s_i^o $(0 < i)$ but not in s_0.

3.3 Computing the *least-commitment* model via classical planning

Inspired by the *classical planning compilation* K_{s_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 solution induces the *least-commitment* action model for an observation $\mathcal{O}(\tau)$:

- 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
  - Fluents $K pre\_e\_\xi$, $K \neg pre\_e\_\xi$ and $K eff\_e\_\xi$ encoding the *knowledge level* representation of the space of possible STRIPS action models (note that fluents $K \neg eff\_e\_\xi$ are not necessary in our encoding).

- The set of actions A' contains now actions of three different kinds:
  - Actions for *committing* pre_e_ξ to a positive/negative value. Similar actions are also defined for *committing* eff_e_ξ but only to a positive value (recall that fluents $K \neg eff\_e\_\xi$ are not necessary in our encoding). The value of an effect eff_e_ξ can only be committed once the value of the corresponding precondition pre_e_ξ is committed (i.e. once either $K pre\_e\_\xi$ or $K \neg pre\_e\_\xi$ hold in the current state).

    $pre(\text{commit}\top\_pre\_e\_\xi) = \{mode_{commit},$
    $\qquad\qquad\qquad\qquad \neg K pre\_e\_\xi, \neg K \neg pre\_e\_\xi\},$
    $cond(\text{commit}\top\_pre\_e\_\xi) = \{\emptyset\} \triangleright \{K pre\_e\_\xi\}.$

    $pre(\text{commit}\bot\_pre\_e\_\xi) = \{mode_{commit},$
    $\qquad\qquad\qquad\qquad \neg K pre\_e\_\xi, \neg K \neg pre\_e\_\xi\},$
    $cond(\text{commit}\bot\_pre\_e\_\xi) = \{\emptyset\} \triangleright \{K \neg pre\_e\_\xi\}.$

    $pre(\text{commit}\top\_eff\_e\_\xi) = \{mode_{commit},$
    $\qquad\qquad\qquad\qquad \neg K eff\_e\_\xi,$
    $\qquad\qquad\qquad\qquad K pre\_e\_\xi \vee K \neg pre\_e\_\xi\},$
    $cond(\text{commit}\top\_eff\_e\_\xi) = \{\emptyset\} \triangleright \{K eff\_e\_\xi\}.$

  - Actions for *validating* that committed models explain the s_j observed states, $0 \leq j < m$.
    $pre(\text{validate}_j) = s_j \cup \{test_{j-1}\},$
    $cond(\text{validate}_j) = \{\emptyset\} \triangleright \{\neg test_{j-1}, test_j\},$
    $\qquad\qquad\qquad \{mode_{commit}\} \triangleright \{\neg mode_{commit}, mode_{val}\}.$

  - *Editable* actions whose semantics is given by the value of fluents $K pre\_e\_\xi$, $K \neg pre\_e\_\xi$ and $K eff\_e\_\xi$ at the current state. Figure 2 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 (Kpre_holding_v1_stack) (Kpre_clear_v2_stack) (Keff_holding_v1_stack) (Keff_clear_v2_stack) (Keff_clear_v1_stack) (Keff_handempty_stack) (Keff_on_v1_v2_stack) hold at the current state. Formally, given an operator schema $\xi \in \mathcal{M}$ its *editable* version is:

    $pre(\text{editable}_\xi) = \{K pre\_e\_\xi \implies e\}_{\forall e \in \mathcal{I}_{\Psi,\xi}}$
    $cond(\text{editable}_\xi) = \{K pre\_e\_\xi, K eff\_e\_\xi\} \triangleright \{\neg e\}_{\forall e \in \mathcal{I}_{\Psi,\xi}},$
    $\qquad\qquad \{K \neg pre\_e\_\xi, K eff\_e\_\xi\} \triangleright \{e\}_{\forall e \in \mathcal{I}_{\Psi,\xi}}.$

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

3.4 Compilation properties

4 Evaluation

5 Conclusions

Related work [Stern and Juba, 2017].

```
(:action stack
 :parameters (?o1 – object ?o2 – object)
 :precondition
   (and (or (not (Kpre_on_v1_v1_stack)) (on ?o1 ?o1))
        (or (not (Kpre_on_v1_v2_stack)) (on ?o1 ?o2))
        (or (not (Kpre_on_v2_v1_stack)) (on ?o2 ?o1))
        (or (not (Kpre_on_v2_v2_stack)) (on ?o2 ?o2))
        (or (not (Kpre_ontable_v1_stack)) (ontable ?o1))
        (or (not (Kpre_ontable_v2_stack)) (ontable ?o2))
        (or (not (Kpre_clear_v1_stack)) (clear ?o1))
        (or (not (Kpre_clear_v2_stack)) (clear ?o2))
        (or (not (Kpre_holding_v1_stack)) (holding ?o1))
        (or (not (Kpre_holding_v2_stack)) (holding ?o2))
        (or (not (Kpre_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 2: PDDL encoding of the editable version of the `stack(?v1,?v2)` schema.

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