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

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Abstract

1 Introduction

Given a 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 from a 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 observations that are given as input for the computation of the *least-commitment* action model.

2.1 Classical planning with conditional effects

Let F be 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 s.t. $|s| = |F|$ and the size of the state space is $2^{|F|}$.

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*. An action $a \in A$ is defined with *preconditions*, $\mathsf{pre}(a) \in \mathcal{L}(F)$, *positive effects*, $\mathsf{eff}^+(a) \in \mathcal{L}(F)$, and *negative 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 $\mathsf{pre}(a) \subseteq s$. And the result of applying a in s is $\theta(s, a) = \{s \setminus \mathsf{eff}^-(a)) \cup \mathsf{eff}^+(a)\}$.

A *classical planning problem* is a tuple $P = \langle F, A, I, G\rangle$, where I is 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 $C \rhd E \in \mathsf{cond}(a_c)$ is composed of two sets of literals: $C \in \mathcal{L}(F)$, the *condition*, and $E \in \mathcal{L}(F)$, the *effect*. An action a_c is applicable in a state s if $\rho(s, a_c)$ is true, and the *triggered effects* resulting from the action application are the effects whose conditions hold in s:

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

The result of applying action a_c in state s is $\theta(s, a_c) = \{s \setminus \mathsf{eff}_c^-(s, a)) \cup \mathsf{eff}_c^+(s, a)\}$, where $\mathsf{eff}_c^-(s, a) \subseteq triggered(s, a)$ and $\mathsf{eff}_c^+(s, a) \subseteq triggered(s, a)$ are, respectively, the triggered *negative* and *positive* effects.

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 partially observable state s_i^o is one in which $|s_i^o| < |F|$; i.e., a state in which at least a fluent of F is not observable. Note that this definition also comprises the case $|s_i^o| = 0$, when the state is fully unobservable. Whatever the sequence of observed states of $\mathcal{O}(\tau)$ is, it must be consistent with the sequence of states of $\tau(\pi, s_0)$, 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 $[1, |F|]$.

In other words, we assume 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 (Explaning a $\mathcal{O}(\tau)$ observation) *Given a* classical planning problem P *and a sequence of partially observed states $\mathcal{O}(\tau)$, we say that* P explains the observation *(denoted $P \mapsto \mathcal{O}(\tau)$) iff there exists a solution plan π for P that is consistent with $\mathcal{O}(\tau)$. If π is also optimal, we say that π is the* best explanation *for $\mathcal{O}(\tau)$.*

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 $\langle P, \mathcal{O}(\tau) \rangle$:

- $P = \langle F, A[\cdot], I, G \rangle$ is a classical planning problem where $A[\cdot]$ is a set of actions s.t. the semantics of each $a \in A[\cdot]$ is unknown; i.e. the corresponding $\langle \rho, \theta \rangle$ functions are undefined. The set of goals G can also be unknown.
- $\mathcal{O}(\tau)$ is a sequence of partial states that results from the observation of a trajectory $\tau(\pi, s_0)$ produced by the execution of certain unknown plan π that solves P.

Before formalizing the solution to this task, i.e. the *least-commitment* action model, we introduce several necessary definitions. We first start defining a *partially specified action model* inspired by the notion of *incomplete (annotated) model* [Sreedharan *et al.*, 2018].

Definition 2 (Partially specified action model) *Given a set of actions $A[\cdot]$ and a set of fluents F then, a* partially specified action model *M is a 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. (Note that if M is a singleton it represents a* fully specified action model*).*

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

Definition 3 (The *least-commitment* action model) *Given a $\langle P, \mathcal{O}(\tau) \rangle$ task and the* partially specified action model *M that represents the full space of possible action models for the actions in $A[\cdot] \in P$, 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` 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 constrained 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 $2^{2\times|\mathcal{I}_{\Psi,\xi}|}$.
2. *Domain-specific constraints*. One can introduce domain-specific knowledge to constrain further the space of possible schemata. For instance, in the *blocksworld* one can argue that `on(`v_1`,`v_1`)` and `on(`v_2`,`v_2`)` will not appear in the $pre(\xi)$, $del(\xi)$ and $add(\xi)$ lists of an action schema ξ because, in this particular domain, a block cannot be on top of itself. As a rule of thumb, *state invariants* constraining the possible states of a given planning domain belong to this second class of constraints [Fox and Long, 1998].

```
(: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.

3. *Observation constraints*. A sequence of state observations $\mathcal{O}(\tau)$ is *semantic knowledge* that constraints further the space of possible action schemata.

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

Given the set of actions $A[\cdot]$ (with unknown $\langle\rho,\theta\rangle$ functions) 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 $P_{\mathcal{O}} = \langle F, A[\cdot], s_0^o, s_m^o\rangle$. In other words, a classical planning problem such that $\mathcal{O}(\tau)$ is the observation of a $\tau(\pi, I)$ trajectory that solves that problem.

In this section we show that starting from a $\langle P_{\mathcal{O}}, \mathcal{O}(\tau)\rangle$ task we can build a *conformant planning problem* P_c whose solution induces the *least-commitment* action model for the input observation $\mathcal{O}(\tau)$. In more detail, we build a *conformant planning problem* $P_c = \langle F_c, A_c, \Upsilon, G\rangle$ such that:

- The set of fluents F_c 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 `pre_e_`ξ and `eff_e_`ξ (where $e \in \mathcal{I}_{\Psi,\xi}$) implementing a propositional encoding of the *preconditions*, *negative*, and *positive* effects of an action schema ξ. Our encoding exploits the syntactic constraint 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.
- The set of actions A_c contains now actions of three different kinds:
  - Actions for *committing* `pre_e_`ξ fluents to a positive/negative value (similar actions are also defined for *committing* `eff_e_`ξ fluents to a positive/negative value).

$$\begin{aligned}\mathsf{pre}(\mathsf{commit}\top\_\mathsf{pre\_e\_}\xi) =& \{mode_{commit}\},\\ \mathsf{cond}(\mathsf{commit}\top\_\mathsf{pre\_e\_}\xi) =& \{pre\_e\_\xi\} \rhd \{pre\_e\_\xi\},\\ & \{\neg pre\_e\_\xi\} \rhd \{pre\_e\_\xi\}.\end{aligned}$$

$$\begin{aligned}\mathsf{pre}(\mathsf{commit}\bot\_\mathsf{pre\_e\_}\xi) =& \{mode_{commit}\},\\ \mathsf{cond}(\mathsf{commit}\bot\_\mathsf{pre\_e\_}\xi) =& \{pre\_e\_\xi\} \rhd \{\neg pre\_e\_\xi\},\\ & \{\neg pre\_e\_\xi\} \rhd \{\neg pre\_e\_\xi\}.\end{aligned}$$

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

$$\begin{aligned}\mathsf{pre}(\mathsf{validate_j}) =& s_j \cup \{test_{j-1}\},\\ \mathsf{cond}(\mathsf{validate_j}) =& \{\emptyset\} \rhd \{\neg test_{j-1}, test_j,\\ & \{mode_{commit}\} \rhd \{\neg mode_{commit}, mode_{val}\}.\end{aligned}$$

  - *Editable* actions whose semantics is given by the value of `pre_e_`ξ, `eff_e_`ξ fluents at the current state. Figure 2 shows the PDDL encoding of an *editable* `stack(?v1,?v2)` schema. Note that this editable schema when `(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)` hold, then it behaves exactly as the original PDDL schema defined in Figure 1. Formally, given an operator schema $\xi \in \mathcal{M}$ its *editable* version is:

$$\begin{aligned}\mathsf{pre}(\mathsf{editable}_\xi) =& \{pre\_e\_\xi \implies e\}_{\forall e\in\mathcal{I}_{\Psi,\xi}}\\ \mathsf{cond}(\mathsf{editable}_\xi) =& \{pre\_e\_\xi, eff\_e\_\xi\} \rhd \{\neg e\}_{\forall e\in\mathcal{I}_{\Psi,\xi}},\\ & \{\neg pre\_e\_\xi, eff\_e\_\xi\} \rhd \{e\}_{\forall e\in\mathcal{I}_{\Psi,\xi}}.\end{aligned}$$

- The clauses in Υ comprises:
  1. The *unit clauses* given by the fluents that hold in the initial state $I = s_0$ and $mode_{commit}$ set to true.
  2. The clauses representing that the actual value of fluents `pre_e_`ξ, `eff_e_`ξ is unknown. In other words, that 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 ξ and $e \in \mathcal{I}_{\Psi,\xi}$, then Υ includes these two clauses:
     - `pre_e_`ξ xor $\neg$`pre_e_`ξ.
     - `eff_e_`ξ xor $\neg$`eff_e_`ξ.

  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 particular domain.
- The new goals are $G_c = \{test_m\}$.

3.4 Compilation properties

4 Evaluation

5 Conclusions

[Stern and Juba, 2017]

References

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```
(:action stack
 :parameters (?o1 - object ?o2 - object)
 :precondition
   (and (or (not (pre_on_v1_v1_stack)) (on ?o1 ?o1))
        (or (not (pre_on_v1_v2_stack)) (on ?o1 ?o2))
        (or (not (pre_on_v2_v1_stack)) (on ?o2 ?o1))
        (or (not (pre_on_v2_v2_stack)) (on ?o2 ?o2))
        (or (not (pre_ontable_v1_stack)) (ontable ?o1))
        (or (not (pre_ontable_v2_stack)) (ontable ?o2))
        (or (not (pre_clear_v1_stack)) (clear ?o1))
        (or (not (pre_clear_v2_stack)) (clear ?o2))
        (or (not (pre_holding_v1_stack)) (holding ?o1))
        (or (not (pre_holding_v2_stack)) (holding ?o2))
        (or (not (pre_handempty_stack)) (handempty)))
 :effect (and
   (when (and (pre_on_v1_v1_stack)(eff_on_v1_v1_stack)) (not (on ?o1 ?o1)))
   (when (and (pre_on_v1_v2_stack)(eff_on_v1_v2_stack)) (not (on ?o1 ?o2)))
   (when (and (pre_on_v2_v1_stack)(eff_on_v2_v1_stack)) (not (on ?o2 ?o1)))
   (when (and (pre_on_v2_v2_stack)(eff_on_v2_v2_stack)) (not (on ?o2 ?o2)))
   (when (and (pre_ontable_v1_stack)(eff_ontable_v1_stack)) (not (ontable ?o1)))
   (when (and (pre_ontable_v2_stack)(eff_ontable_v2_stack)) (not (ontable ?o2)))
   (when (and (pre_clear_v1_stack)(eff_clear_v1_stack)) (not (clear ?o1)))
   (when (and (pre_clear_v2_stack)(eff_clear_v2_stack)) (not (clear ?o2)))
   (when (and (pre_holding_v1_stack)(eff_holding_v1_stack)) (not (holding ?o1)))
   (when (and (pre_holding_v2_stack)(eff_holding_v2_stack)) (not (holding ?o2)))
   (when (and (pre_handempty_stack)(eff_handempty_stack)) (not (handempty)))
   (when (and (not(pre_on_v1_v1_stack))(eff_on_v1_v1_stack)) (on ?o1 ?o1))
   (when (and (not(pre_on_v1_v2_stack))(eff_on_v1_v2_stack)) (on ?o1 ?o2))
   (when (and (not(pre_on_v2_v1_stack))(eff_on_v2_v1_stack)) (on ?o2 ?o1))
   (when (and (not(pre_on_v2_v2_stack))(eff_on_v2_v2_stack)) (on ?o2 ?o2))
   (when (and (not(pre_ontable_v1_stack))(eff_ontable_v1_stack)) (ontable ?o1))
   (when (and (not(pre_ontable_v2_stack))(eff_ontable_v2_stack)) (ontable ?o2))
   (when (and (not(pre_clear_v1_stack))(eff_clear_v1_stack)) (clear ?o1))
   (when (and (not(pre_clear_v2_stack))(eff_clear_v2_stack)) (clear ?o2))
   (when (and (not(pre_holding_v1_stack))(eff_holding_v1_stack)) (holding ?o1))
   (when (and (not(pre_holding_v2_stack))(eff_holding_v2_stack)) (holding ?o2))
   (when (and (not(pre_handempty_stack))(eff_handempty_stack)) (handempty))))
```

Figure 2: PDDL encoding of the editable version of the `stack(?v1,?v2)` schema.

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