Model Recognition as Planning

Diego Aineto and **Sergio Jiménez** and **Eva Onaindia** and **Miquel Ramírez**
Departamento de Sistemas Informáticos y Computación
Universitat Politècnica de València.
Camino de Vera s/n. 46022 Valencia, Spain
{dieaigar,serjice,onaindia}@dsic.upv.es

Abstract

Given a partially observed plan execution and a set of possible planning models, *model recognition* is the task of identifying which model in the set produced the observed plan execution. The paper formalizes the *model recognition* task and proposes a novel method to assess the probability of a STRIPS model to produce a given partially observed plan execution. This method, that we called *model recognition as planning*, is robust to missing data in the observed plan execution (i.e. missing intermediate states and actions) given as input besides, it is computable with an off-the-shelf classical planner. The effectiveness of *model recognition as planning* is shown in a set of STRIPS models encoding different *Turing Machines*. We show that *model recognition as planning* succeeds to identify the executed *Turing Machine* despite the actual applied transitions, internal machine state or the values of several tape cells, are unknown.

Introduction

Plan recognition is the task of predicting the future actions of an agent provided observations of its current behaviour. Plan recognition is considered *automated planning* in reverse; while automated planning aims to compute a sequence of actions that accounts for a given goals, plan recognition aims to compute the goals that account for an observed sequence of actions (Geffner and Bonet 2013).

Diverse approaches has been proposed for plan recognition such as *rule-based systems*, *parsing*, *graph-covering*, *Bayesian nets*, etc (Carberry 2001). *Plan recognition as planning* is the model-based approach for plan recognition (Ramírez 2012; Ramírez and Geffner 2009). This approach assumes that the action model of the observed agent is known and leverages it to compute the most likely goal of the agent, according to the observed plan execution.

This paper introduces the task of *model recognition*. Given a partially observed plan execution and a set of possible planning models, *model recognition* is the task of identifying which model in the set has the highest probability of producing the input observation. *Model recognition* is of interest because:

- Once the planning model is recognized, then the model-based machinery for automated planning becomes applicable (Ghallab, Nau, and Traverso 2004).
- It enables indentifying algorithms by observing their execution. Diverse algorithm representations, like *finite state controllers*, *push-down automata* or GOLOG *programs*, can be encoded as classical planning models (Baier, Fritz, and McIlraith 2007; Bonet, Palacios, and Geffner 2010; Segovia-Aguas, Jiménez, and Jonsson 2017).

The paper introduces also *model recognition as planning*; a novel method to assess the probability of a given STRIPS model to produce an observed plan execution. The method is robust to missing data in the intermediate states and actions of the observed plan execution besides, it is computable with an off-the-shelf classical planner. The paper evaluates the effectiveness of *model recognition as planning* with a set of STRIPS models that represent different *Turing Machines*. All of these *Turing Machines* are defined within the same *tape alphabet* and same *machine states* but different *transition functions*. We show that *model recognition as planning* succeeds to identify the executed *Turing Machine* despite the actual applied transitions, the internal machine state or the values of several tape cells, are unknown.

Background

This section formalizes classical planning and the observation of the execution of a classical plan.

Classical planning

We use F to denote the set of *fluents* (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). 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; $|s| = |F|$, so the size of the state space is $2^{|F|}$. Explicitly including negative literals $\neg f$ in states simplifies subsequent definitions but often we will abuse of notation by defining a state s only in terms of the fluents that are true in s, as it is common in STRIPS planning.

A *classical planning problem* is a tuple $P = \langle F, A, I, G \rangle$, where I is an initial state, $G \subseteq \mathcal{L}(F)$ is a goal condition and A is a set of actions whose dynamics are specified with two functions: $App(s)$ that denotes the subset of actions applicable in a state s and $\theta(s, a)$ that denotes the *successor state* that results of applying a in s.

A *plan* for P is an action sequence $\pi = \langle a_1, \ldots, a_n \rangle$ that, when executed starting from the initial state I, induces the *state trajectory* $\langle s_0, s_1, \ldots, s_n \rangle$ such that $s_0 = I$ and forall $1 \leq i \leq n$, an action a_i is applicable in the corresponding state $a_i \in App(s_{i-1})$ and generates the successor state $s_i = \theta(s_{i-1}, a_i)$. The *plan length* is denoted with $|\pi| = n$.

A plan π *solves* P iff $G \subseteq s_n$; i.e. if the goal condition is satisfied in the last state resulting from the execution of the plan π in the initial state I. A solution plan is *optimal* if it has minimum length.

The observation model

Given a classical planning problem $P = \langle F, A, I, G \rangle$ and a plan π that solves P, the observation of the execution of π on P is $\tau = \langle s_1, a_1, \ldots, a_n, s_m \rangle$, an interleaved combination of $1 \leq m \leq |\pi| + 1$ observed states and $1 \leq n \leq |\pi|$ observed actions:

- Observed states may be partial states. The value of certain fluents may be omitted in that states, i.e. $|s_i| \leq |F|$ for every $0 \leq i \leq m$.
- The sequence of observed states $\langle s_1, \ldots, s_m \rangle$ in τ is the same sequence of states traversed by π but certain states may also be omitted. Therefore the transitions between two consecutive observed states in τ may require the execution of more than a single action. Formally, $\theta(s_i, \langle a_1, \ldots, a_k \rangle) = s_{i+1}$, where $k \geq 1$ is unknown and unbound. This means that having τ does not implies knowing the actual length of π.
- The sequence of observed actions $\langle a_1, \ldots, a_n \rangle$ in τ is a sub-sequence of the solution plan π.

Definition 1 (Φ-observation)**.** *Given a subset of fluents $\Phi \subseteq F$ we say that τ is a Φ-observation of the execution of π on P iff, for every $0 \leq i \leq m$, each observed state s_i only contains fluents in Φ.*

Model Recognition

The *model recognition* task is a tuple $\langle P, M, \tau \rangle$ where:

- $P = \langle F, A, I, G \rangle$ is a classical planning problem such that the dynamics of the actions in A is unknown because functions $App(s)$ and/or $\theta(s, a)$ are undefined.
- $M = \{\mathcal{M}_1, \ldots, \mathcal{M}_m\}$ is a finite and non-empty set of models for the actions in A. Each model in $\mathcal{M} \in M$ defines a different function pair (App,θ).
- τ is an observation of the execution of a solution plan π for P.

A solution to the *model recognition* task is the discrete probability distribution $P(\mathcal{M}|\tau)$ that expresses, for each model $\mathcal{M} \in M$, its probability of producing the observation τ.

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

Figure 1: STRIPS action schema coded in PDDL.

According to the *Bayes* rule, the probability of an hypothesis $\mathcal{H}$, provided the observation $\mathcal{O}$, is given by the expression $P(\mathcal{H}|\mathcal{O}) = \frac{P(\mathcal{O}|\mathcal{H})P(\mathcal{H})}{P(\mathcal{O})}$. In the *model recognition* task, hypotheses are about the possible action models $\mathcal{M} \in M$ while the given observation is the partially observed plan execution τ. The $P(\mathcal{M}|\tau)$ probability distribution can then be estimated in three steps:

1. Computing the *a priori* probabilities. $P(\tau)$, that measures how surprising is the given observation and $P(\mathcal{M})$, that expresses if one model is a priori more likely than the others.
2. Computing the conditional probability $P(\tau|\mathcal{M})$. Our approach is to estimate this value according to the minimum amount of *edition* that is required by $\mathcal{M}$ to produce a plan π^*_τ such that:
   (a) π^*_τ is an optimal solution for the classical planning problem P.
   (b) τ is an observation of the execution of π^*_τ on the classical planning problem P.
3. Applying the Bayes rule to obtain the normalized posterior probabilities (the $P(\mathcal{M}|\tau)$ probabilities must sum 1 for all the $\mathcal{M} \in M$).

Note that the second step assumes that the observed agent is acting rationally, like in *plan recognition as planning* (Ramírez 2012; Ramírez and Geffner 2009). A related approach is recently followed for *model reconciliation* (Chakraborti et al. 2017) where model edition is used to conform the PDDL models of two different agents.

Recognition of STRIPS models

Here we analyze the particular instantiation of the *model recognition* task where the dynamics of the actions A (i.e. the App and θ functions) are specified with STRIPS action schemas. Figure 1 shows the PDDL code for the *stack* actions, taken from a four-operator *blocksworld* (Slaney and Thiébaux 2001).

The space of STRIPS models

Like in PDDL (McDermott et al. 1998; Fox and Long 2003), we assume that fluents F are instantiated from a set of *predicates* Ψ. Each predicate $p \in \Psi$ has an argument list of arity $ar(p)$. Given a set of *objects* Ω, the set of fluents F is induced by assigning objects in Ω to the arguments of predicates in Ψ, i.e. $F = \{p(\omega) : p \in \Psi, \omega \in \Omega^{ar(p)}\}$ s.t. Ω^k is the k-th Cartesian power of Ω.

Let $\Omega_v = \{v_i\}_{i=1}^{\max_{a \in A} ar(a)}$ be an additional set of objects ($\Omega \cap \Omega_v = \emptyset$), that we denote as *variable names*,

```
(pre_holding_stack_v1) (pre_clear_stack_v2)
(del_holding_stack_v1) (del_clear_stack_v2)
(add_handempty_stack) (add_clear_stack_v1)
(add_on_stack_v1_v2)
```

Figure 2: Propositional encoding for the *stack* schema from a four-operator *blocksworld*.

and that is bound by the maximum arity of an action in a given planning frame. For instance, in a three-block four-operator *blocksworld* $\Omega = \{block_1, block_2, block_3\}$ while $\Omega_v = \{v_1, v_2\}$ because the `stack` and `unstack` actions have arity two. We define F_v, a new set of fluents, $F \cap F_v = \emptyset$, produced instantiating Ψ using only *variable names*. This set contains eleven elements for the mentioned *blocksworld*, F_v=`{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`)}`.

For a given action schema ξ, then $F_\xi \subseteq F_v$ defines the subset of elements that can appear in the preconditions and effects of that action schema. For instance $F_{\texttt{stack}} = F_v$ while $F_{\texttt{pickup}}$=`{handempty, holding(`v_1`), clear(`v_1`), ontable(`v_1`), on(`v_1`,`v_1`)}` excludes any element in F_v that involves v_2 because `pickup` actions have arity one.

Now we are ready to define the fluents $pre_f(\xi)$, $del_f(\xi)$ and $add_f(\xi)$, for every $f \in F_\xi$. These fluents represent a propositional encoding for the preconditions, negative and positive effects of an action schema ξ and hence, they specify the *App* and θ functions for all the actions $a \in A$ built from the corresponding STRIPS action schemas. In more detail, if a fluent $pre_f(\xi)/del_f(\xi)/add_f(\xi)$ holds, it means that f is a precondition/negative/positive effect in that schema. For instance, Figure 2 shows the conjunction of fluents representing the propositional encoding for the preconditions, negative and positive effects of the *stack* schema (see Figure 1).

The size of the space of possible STRIPS models for an action schema ξ is given by the expression, $2^{2\times|F_\xi|}$ (STRIPS constraints require negative effects appearing as preconditions, negative effects cannot be positive effects at the same time and also, positive effects cannot appear as preconditions). For the mentioned *blocksworld*, $2^{2\times|F_{\texttt{stack}}|} = 4,194,304$ while $2^{2\times|F_{\texttt{pickup}}|} = 1,024$. We say that two STRIPS schemes ξ and ξ' are *comparable* iff both share the same space of possible STRIPS models. For instance, we claim that blocksworld schemas `stack` and `unstack` are *comparable* while `stack` and `pickup` are not. Last but not least, two STRIPS models $\mathcal{M}$ and $\mathcal{M}'$ are *comparable* iff there exists a bijective function $\mathcal{M} \mapsto \mathcal{M}^*$ that maps every action schema $\xi \in \mathcal{M}$ to a comparable schema $\xi' \in \mathcal{M}'$ and vice versa.

The STRIPS edit distance

We define two edit *operations* on a STRIPS model $\mathcal{M} \in M$:

- *Deletion*. A fluent $pre_f(\xi)/del_f(\xi)/add_f(\xi)$ is removed from the operator schema $\xi \in \mathcal{M}$, such that $f \in F_\xi$.
- *Insertion*. A fluent $pre_f(\xi)/del_f(\xi)/add_f(\xi)$ is added to the operator schema $\xi \in \mathcal{M}$, s.t. $f \in F_\xi$.

We can now formalize an *edit distance* that quantifies how similar two given STRIPS action models are. The distance is symmetric and meets the *metric axioms* provided that the two *edit operations*, deletion and insertion, have the same positive cost.

Definition 2. *Let $\mathcal{M}$ and $\mathcal{M}'$ be two* comparable STRIPS *action models. The* **edit distance** *$\delta(\mathcal{M}, \mathcal{M}')$ is the minimum number of* edit operations *that is required to transform $\mathcal{M}$ into $\mathcal{M}'$.*

Since F_v is a bound set, the maximum number of edits that can be introduced to a given action model defined within F_v is bound as well.

Definition 3. *The **maximum edit distance** of an* STRIPS *model $\mathcal{M}$ built from the set of possible elements F_v is $\delta(\mathcal{M}, *) = \sum_{\xi\in\mathcal{M}} 3 \times |F_\xi|$.*

We define now an edit distance to asses the matching of a STRIPS model with respect to an observation of a plan execution.

Definition 4. *Given τ, an observation of the execution of a plan for solving P and $\mathcal{M}$, a* STRIPS *action model built from F_v. The* **observation edit distance***, $\delta(\mathcal{M}, \tau)$, is the minimal edit distance from $\mathcal{M}$ to any* comparable *model $\mathcal{M}'$ s.t. $\mathcal{M}'$ produces a plan π^*_τ optimal for P and compliant with τ;*

$$\delta(\mathcal{M}, \tau) = \min_{\forall \mathcal{M}' \to \tau} \delta(\mathcal{M}, \mathcal{M}')$$

The $\delta(\mathcal{M}, \tau)$ distance could also be defined assessing the edition required by the observed plan execution to match the given model. This implies defining *edit operations* that modify τ instead of $\mathcal{M}$ (Sohrabi, Riabov, and Udrea 2016). Our definition of the *observation edit distance* is more practical since normally F_v is smaller than F. In practice, the number of *variable objects* is smaller than the number of objects in a planning problem.

The $P(\mathcal{M}|\tau)$ probability for STRIPS models

Since we assume that the dynamics of the actions $A \in P$ is specified with STRIPS action schemas, we can estimate the $P(\mathcal{M}|\tau)$ probability as follows:

1. Assuming *a priori* all action models $\mathcal{M} \in M$ are equiprobable. There are no reasons to assume that one model is *a priori* more likely than the others so, $P(\mathcal{M}) = \frac{1}{\prod_{\xi\in\mathcal{M}} 2^{2\times|F_\xi|}}$.
2. Assuming that all the observations of plan executions with maximum n observed actions and m observed states are equiprobable then, $P(\tau) = \frac{1}{|A|^n \times 2^{m\times|F|}}$.
3. Estimating the conditional probability $P(\tau|\mathcal{M})$ by mapping the *observation edit distance* into a $[0, 1]$ likelihood, $1 - \frac{\delta(\mathcal{M},\tau)}{\delta(\mathcal{M},*)}$.

Model recognition as planning

This section shows that, when the dynamics of the actions $A \in P$ are specified with STRIPS action schemas, then

```
00 : (insert_add_handempty_stack)
01 : (insert_add_clear_stack_var1)
02 : (apply_unstack blockB blockA i1 i2)
03 : (apply_putdown blockB i2 i3)
04 : (apply_pickup blockA i3 i4)
05 : (apply_stack blockA blockB i4 i5)
06 : (validate_1)
```

Figure 3: Plan for editing (steps [0-1]) and validating (steps [2-6]) a given STRIPS planning model for the *blockswold*.

$\delta(\mathcal{M}, \tau)$ can be computed with a compilation of a classical planning with conditional effects. The intuition behind this compilation is that a solution to the resulting classical planning task is a sequence of actions that:

1. **Edits the action model $\mathcal{M}$ to build $\mathcal{M}'$.** A solution plan starts with a *prefix* that modifies the preconditions and effects of the action schemes in $\mathcal{M}$ using to the two *edit operations* defined above, *deletion* and *insertion*.
2. **Validates the edited model $\mathcal{M}'$ in the observation τ.** The solution plan continues with a postfix that validates the edited model $\mathcal{M}'$ on the given observations τ.

Figure 3 shows the plan for editing a given *blockswold* model where the positive effects (`handempty`) and (`clear ?v1`) of the `stack` schema are missing. The edited action model is validated at the observation of a four action plan for inverting a two-block tower where the intermediate states, s_1, s_2 and s_3, are unobserved.

Note that our interest is not in $\mathcal{M}'$, the edited model resulting from the compilation, but in the number of required *edit operations* (insertions and deletions) required by $\mathcal{M}'$ to be validated in the given observation, e.g. $\delta(\mathcal{M}, \tau) = 2$ for the example in Figure 3. In this case $\delta(\mathcal{M}, *) = 3 \times 2 \times (11 + 5)$ since there are 4 action schemes (`pickup`, `putdown`, `stack` and `unstack`) and $|F_v| = |F_{\texttt{stack}}| = |F_{\texttt{unstack}}| = 11$ while $|F_{\texttt{pickup}}| = |F_{\texttt{putdown}}| = 5$.

Conditional effects

Conditional effects allow us to compactly define our compilation. An action $a \in A$ with conditional effects is defined as a set of *preconditions* $\mathsf{pre}(a) \in \mathcal{L}(F)$ and a set of *conditional effects* $\mathsf{cond}(a)$. Each conditional effect $C \rhd E \in \mathsf{cond}(a)$ 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 $\mathsf{pre}(a) \subseteq s$, and the *triggered effects* resulting from the action application are the effects whose conditions hold in s:

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

The result of applying action a in state s is the *successor* state $\theta(s, a) = \{s \setminus \mathsf{eff}_c^-(s, a)) \cup \mathsf{eff}_c^+(s, a)\}$ 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.

The compilation formalization

Given a STRIPS model $\mathcal{M} \in M$ and the observation τ of the execution of a plan for solving $P = \langle F, A, I, G \rangle$, our compilation outputs a classical planning task $P' = \langle F', A', I', G' \rangle$ such that:

- F' contains:
  - The original fluents F.
  - Fluents $pre_f(\xi)/del_f(\xi)/add_f(\xi)$ modeling the space of STRIPS models.
  - The fluents $F_\pi = \{plan(name(a_i), \Omega^{ar(a_i)}, i)\}_{1 \le i \le n}$ to code the i^{th} action in τ. The static facts $next_{i,i+1}$ and the fluents at_i, $1 \le i < n$, are also added to iterate through the n steps of τ.
  - The fluents $\{test_j\}_{1 \le j \le m}$, indicating the state observation $s_j \in \tau$ where the action model is validated.
  - The fluents $mode_{edit}$ and $mode_{val}$ to indicate whether the operator schemas are edited or validated.
- I' extends the original initial state I with the fluent $mode_{edit}$ set to true as well as the fluents F_π plus fluents at_1 and $\{next_{i,i+1}\}$, $1 \le i < n$, for tracking the plan step where the action model is validated. Our compilation assumes that initially $\mathcal{M}'$ is defined as $\mathcal{M}$. Therefore fluents $pre_f(\xi)/del_f(\xi)/add_f(\xi)$ hold as given by $\mathcal{M}$.
- $G' = G \bigcup \{at_n, test_m\}$.
- A' comprises three kinds of actions with conditional effects:
  1. Actions for *editing* operator schema $\xi \in \mathcal{M}$:
     - Actions for adding a *precondition* $f \in F_v(\xi)$ from the action schema $\xi \in \mathcal{M}$.

$$\begin{aligned}\mathsf{pre}(\mathsf{programPre}_{\mathsf{f},\xi}) &= \{\neg pre_f(\xi), \neg del_f(\xi), \neg add_f(\xi), mode_{edit}\},\\ \mathsf{cond}(\mathsf{programPre}_{\mathsf{f},\xi}) &= \{\emptyset\} \rhd \{pre_f(\xi)\}.\end{aligned}$$

     - Actions for adding a *negative* or *positive* effect $f \in F_v(\xi)$ to the action schema $\xi \in \mathcal{M}$.

$$\begin{aligned}\mathsf{pre}(\mathsf{programEff}_{\mathsf{f},\xi}) &= \{\neg del_f(\xi), \neg add_f(\xi), mode_{edit}\},\\ \mathsf{cond}(\mathsf{programEff}_{\mathsf{f},\xi}) &= \{pre_f(\xi)\} \rhd \{del_f(\xi)\},\\ &\qquad \{\neg pre_f(\xi)\} \rhd \{add_f(\xi)\}.\end{aligned}$$

     Besides these actions, the A' set also contains the actions for *deleting* a precondition and a negative/positive effect.
  2. Actions for *applying* an edited operator schema $\xi \in \mathcal{M}$ bound with objects $\omega \subseteq \Omega^{ar(\xi)}$. Since operators headers are given as input, the variables $pars(\xi)$ are bound to the objects in ω that appear at the same position. Figure 4 shows the PDDL encoding of the action for applying a programmed operator *stack* from *blocksworld*.

$$\begin{aligned}\mathsf{pre}(\mathsf{apply}_{\xi,\omega}) &= \{pre_f(\xi) \implies p(\omega)\}_{\forall p \in \Psi, f = p(pars(\xi))}\\ &\qquad \cup \{\neg mode_{val}\},\\ \mathsf{cond}(\mathsf{apply}_{\xi,\omega}) &= \{del_f(\xi)\} \rhd \{\neg p(\omega)\}_{\forall p \in \Psi, f = p(pars(\xi))},\\ &\qquad \{add_f(\xi)\} \rhd \{p(\omega)\}_{\forall p \in \Psi, f = p(pars(\xi))},\\ &\qquad \{mode_{edit}\} \rhd \{\neg mode_{edit}\},\\ &\qquad \{\emptyset\} \rhd \{mode_{val}\}.\end{aligned}$$

```
(:action apply_stack
  :parameters (?o1 - object ?o2 - object)
  :precondition
   (and (or (not (pre_on_stack_v1_v1)) (on ?o1 ?o1))
        (or (not (pre_on_stack_v1_v2)) (on ?o1 ?o2))
        (or (not (pre_on_stack_v2_v1)) (on ?o2 ?o1))
        (or (not (pre_on_stack_v2_v2)) (on ?o2 ?o2))
        (or (not (pre_ontable_stack_v1)) (ontable ?o1))
        (or (not (pre_ontable_stack_v2)) (ontable ?o2))
        (or (not (pre_clear_stack_v1)) (clear ?o1))
        (or (not (pre_clear_stack_v2)) (clear ?o2))
        (or (not (pre_holding_stack_v1)) (holding ?o1))
        (or (not (pre_holding_stack_v2)) (holding ?o2))
        (or (not (pre_handempty_stack)) (handempty)))
  :effect
   (and (when (del_on_stack_v1_v1) (not (on ?o1 ?o1)))
        (when (del_on_stack_v1_v2) (not (on ?o1 ?o2)))
        (when (del_on_stack_v2_v1) (not (on ?o2 ?o1)))
        (when (del_on_stack_v2_v2) (not (on ?o2 ?o2)))
        (when (del_ontable_stack_v1) (not (ontable ?o1)))
        (when (del_ontable_stack_v2) (not (ontable ?o2)))
        (when (del_clear_stack_v1) (not (clear ?o1)))
        (when (del_clear_stack_v2) (not (clear ?o2)))
        (when (del_holding_stack_v1) (not (holding ?o1)))
        (when (del_holding_stack_v2) (not (holding ?o2)))
        (when (del_handempty_stack) (not (handempty)))
        (when (add_on_stack_v1_v1) (on ?o1 ?o1))
        (when (add_on_stack_v1_v2) (on ?o1 ?o2))
        (when (add_on_stack_v2_v1) (on ?o2 ?o1))
        (when (add_on_stack_v2_v2) (on ?o2 ?o2))
        (when (add_ontable_stack_v1) (ontable ?o1))
        (when (add_ontable_stack_v2) (ontable ?o2))
        (when (add_clear_stack_v1) (clear ?o1))
        (when (add_clear_stack_v2) (clear ?o2))
        (when (add_holding_stack_v1) (holding ?o1))
        (when (add_holding_stack_v2) (holding ?o2))
        (when (add_handempty_stack) (handempty))
        (when (modeProg) (not (modeProg)))))
```

Figure 4: PDDL action for applying an already programmed schema *stack* (implications are coded as disjunctions).

	q_0	q_1	q_2	q_3	q_4	$\underline{q_5}$
a	x,r,q_1	a,r,q_1	-	a,l,q_3	-	-
b	-	y,r,q_2	b,r,q_2	b,l,q_3	-	-
c	-	-	z,l,q_3	-	-	-
x	-	-	-	x,r,q_0	-	-
y	y,r,q_4	y,r,q_1	-	y,l,q_3	y,r,q_4	-
z	-	-	z,r,q_2	z,l,q_3	z,r,q_4	-
$\square$	-	-	-	-	$\square$,r,q_5	-

Figure 5: Seven-symbol six-state *Turing Machine* for recognizing the $\{a^n b^n c^n : n \geq 1\}$ language ($\underline{q_5}$ is the only acceptor state).

When the observation τ includes observed actions, then the extra conditional effects $\{at_i, plan(name(a_i), \Omega^{ar(a_i)}, i)\} \rhd \{\neg at_i, at_{i+1}\}_{\forall i \in [1,n]}$ are included in the $\mathsf{apply}_{\xi,\omega}$ actions to validate that actions are applied, exclusively, in the same order as they appear in τ.

3. Actions for *validating* the partially observed state $s_j \in \tau$, $1 \leq j < m$.

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

Evaluation

To evaluate the empirical performance of *model recognition as planning* we defined a set of possible STRIPS models, each representing a different *Turing Machine*, but all sharing the same set of *machine states* and same *tape alphabet*.

Modeling *Turing Machines* with STRIPS

A *Turing machine* is a tuple $\mathcal{M} = \langle Q, q_o, Q_\perp, \Sigma, \Upsilon, \square, \delta \rangle$:

- Q, is a finite and non-empty set of machine states such that $q_0 \in Q$ is the initial state of the machine and $Q_\perp \subseteq Q$ is the subset of acceptor states.
- Σ is the *tape alphabet*, that is a finite non-empty set of symbols that contains the *input alphabet* $\Upsilon \subseteq \Sigma$ (the subset of symbols allowed to initially appear in the tape) and the *blank symbol* $\square \in \Upsilon$ (the only symbol allowed to occur on the tape infinitely often).
- $\delta : \Sigma \times (Q \setminus Q_\perp) \rightarrow \Sigma \times Q \times \{left, right\}$ is the *transition function*. For each possible pair of tape symbol and non-terminal machine state δ defines (1), the tape symbol to print at the current position of the header (2), the new state of the machine and (3), whether the header is shifted *left* or *right* after the print operation. If δ is not defined for the current pair of tape symbol and machine state, the machine halts.

Figure 5 shows the δ function of a *Turing Machine* for recognizing the $\{a^n b^n c^n : n \geq 1\}$ language. The *tape alphabet* is $\Sigma = \{a, b, c, x, y, z, \square\}$, the *input alphabet* $\Upsilon = \{a, b, c, \square\}$ and the possible machine states are $Q = \{q_0, q_1, q_2, q_3, q_4, \underline{q_5}\}$ where $\underline{q_5}$ is the only acceptor state.

```
(:action transition-1      ;;; a,q0 → x,r,q1
  :parameters (?xl ?x ?xr)
  :precondition (and (head ?x) (symbol-a ?x) (state-q0)
                     (next ?xl ?x) (next ?x ?xr))
  :effect (and (not (head ?x))
               (not (symbol-a ?x)) (not (state-q0))
               (head ?xr) (symbol-x ?x) (state-q1)))
```

Figure 6: STRIPS action schema that models the transition $a, q_0 \rightarrow x, r, q_1$ of the Turing Machine defined in Figure 5.

A classical planning frame $\Phi = \langle F, A \rangle$ can encode the *transition function* δ of a *Turing Machine* $\mathcal{M}$ as follows:

- Fluents F are instantiated from a set of four *predicates* Ψ: `(head ?x)` that encodes the current position of the header in the tape. `(next ?x1 ?x2)` encoding that the cell `?x2` follows cell `?x1` in the tape. `(symbol-`σ `?x)` encoding that the tape cell `?x` contains the symbol $\sigma \in \Sigma$. `(state-`q`)` encoding that $q \in Q$ is the current machine state. Given a set of *objects* Ω that represent the cells in the tape of the given Turing Machine, the set of fluents F is induced by assigning objects in Ω to the arguments of the predicates in Ψ.
- Actions A are instantiated from STRIPS operator schema. For each transition in δ, a STRIPS schema is defined:
  - The **header** is `transition-id(?xl ?x ?xr)` where id uniquely identifies the transition in δ. Parameters $?xl$, $?x$ and $?xr$ are tape cells.
  - The **preconditions** are `(head ?x)` and `(next ?xl ?x) (next ?x ?xr)` to make $?x$ the tape cell pointed by the header and $?xl/?xr$ its left/right neighbors. Preconditions `(symbol-`σ `?x)` and `(state-`q`)` are also included to capture the symbol currently pointed by the header and the current machine state.
  - The **delete effects** remove the symbol currently pointed by the header and the current machine state while the **positive effects** set the new symbol pointed by the header and the new machine state according to δ.

The STRIPS action schema of Figure 6 models the rule $a, q_0 \rightarrow x, r, q_1$ of the *Turing Machine* defined in Figure 5 (the full encoding of the *Turing Machine* of Figure 5 produces a total of sixteen STRIPS action schema).

Since the *transition function* of a *Turing Machine* can be encoded as a classical planning frame $\Phi = \langle F, A \rangle$, executions of that *Turing Machine* are definable as an action sequence $\langle a_1, \ldots, a_n \rangle$ that induces the *state trajectory* $\langle s_0, s_1, \ldots, s_n \rangle$ such that a_i $(1 \leq i \leq n)$ is applicable in s_{i-1} and generates the successor state $s_i = \theta(s_{i-1}, a_i)$.

Experimental setup

We randomly generated a $M = \{\mathcal{M}_1, \ldots, \mathcal{M}_{100}\}$ set of one-hundred different *Turing Machines* where each $\mathcal{M} \in M$ is a seven-symbol six-state *Turing Machine*. The classical planning frame $\Phi = \langle F, A \rangle$ is the same for all the *Turing Machines*, there is an $a \in A$ action for each pair of tape symbol and non-terminal state machine, while the $\theta(s, a)$ function is defined differently for each the machines (using a different STRIPS action model).

We randomly choose a machine $\mathcal{M} \in M$ and produce the observation τ of a fifty-step execution plan. Finally, we follow our *model recognition as planning* method to identify the *Turing Machine* that produced τ. This experiment is repeated for different amounts of missing information in the input trace τ: unknown applied transitions, unknown internal machine state and unknown values of several tape cells.

Reproducibility MADAGASCAR is the classical planner we used to solve the instances that result from our compilations for its ability to deal with dead-ends (Rintanen 2014). Due to its SAT-based nature, MADAGASCAR can apply the actions for editing preconditions in a single planning step (in parallel) because there is no interaction between them. Actions for editing effects can also be applied in a single planning step, thus significantly reducing the planning horizon.

The compilation source code, evaluation scripts and benchmarks (including the used training and test sets) are fully available at this anonymous repository so any experimental data reported in the paper can be reproduced.

Results

Conclusions

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