Recognizing LTL$_f$/PLTL$_f$ Goals
in Fully Observable Non-Deterministic Domain Models

Ramon Fraga Pereira$^{1}$, Francesco Fuggitti$^{1,2}$, Giuseppe De Giacomo$^1$

$^1$Università degli Studi di Roma “La Sapienza”, Roma, Italy
$^2$York University, Toronto, ON, Canada

{pereira,degiacomo, fuggitti}@diag.uniroma1.it

Abstract

Goal Recognition is the task of discerning the correct intended goal that an agent aims to achieve, given a set of possible goals, a domain model, and a sequence of observations as a sample of the plan being executed in the environment. Existing approaches assume that the possible goals are formalized as a conjunction in deterministic settings. In this paper, we develop a novel approach that is capable of recognizing temporally extended goals in Fully Observable Non-Deterministic (FOND) planning domain models, focusing on goals on finite traces expressed in Linear Temporal Logic (LTL$_f$) and (Pure) Past Linear Temporal Logic (PLTL$_f$). We empirically evaluate our goal recognition approach using different LTL$_f$ and PLTL$_f$ goals over six common FOND planning domain models, and show that our approach is accurate to recognize temporally extended goals at several levels of observability.

1 Introduction

Goal Recognition is the task of recognizing the intentions of autonomous agents or humans by observing their interactions in an environment. Existing work on goal and plan recognition has been addressing this task over several different types of domain settings, such as plan-libraries (Mirska et al. 2016), plan tree grammars (Geib and Goldman 2009), classical planning domain models (Ramírez and Geffner 2009; 2010; E.-Martin, R.-Moreno, and Smith 2015; Sohrabi, Riabov, and Udrea 2016; Pereira, Oren, and Meneguzzi 2017), stochastic environments (Ramírez and Geffner 2011), and continuous domain models (Kaminka, Vered, and Agmon 2018).

In spite of the large literature, most existing approaches to Goal Recognition as Planning are not capable of recognizing temporally extended goals, goals formalized in terms of time, e.g., the exact order that a set of facts of a goal must be achieved in a plan. Furthermore, most of these approaches also assume that the outcomes of the observed actions are deterministic, and do not deal with unpredictable, possibly adversarial, environmental conditions.

Planning for temporally extended goals in deterministic and non-deterministic domain settings has been of increasing interest over the past years, starting with the pioneering work on planning for temporally extended goals (Bacchus and Kabanza 1998; 2000) and on planning via model checking (Cimatti et al. 1997; Pistore and Traverso 2001; Pistore, Bethin, and Traverso 2001); then, with the work on integrating LTL goals into standard planning tools (Gerevini et al. 2009; Patrizi et al. 2011; Patrizi, Lipovetzky, and Geffner 2013), and, more recently, with the work that relates planning in non-deterministic domains with synthesis, often focused on the finite trace variants of LTL (De Giacomo and Vardi 2013; 2015; Camacho et al. 2017; 2018; De Giacomo and Rubin 2018; Aminof, De Giacomo, and Rubin 2020).

In this paper, we introduce the task of goal recognition in discrete domain models that are fully observable and the outcomes of actions and observations are non-deterministic, possibly adversarial, i.e., Fully Observable Non-Deterministic (FOND), allowing the formalization of temporally extended goals using two types of temporal logic on finite traces: Linear-time Temporal Logic (LTL$_f$) and Pure-Past Linear-time Temporal Logic (PLTL$_f$), surveyed in (De Giacomo et al. 2020). Therefore, the goal recognition approach we develop in this paper is capable of recognizing not only the set of facts of a goal that an observed agent aims to achieve from a sequence of observations, but the temporal order (e.g., exact order) that this set of facts aims to be achieved.

The main contribution of this paper is three-fold. First, based on the standard definition of Plan Recognition as Planning introduced by Ramírez and Geffner in (2009; 2010), we propose a problem formalization for recognizing temporally extended goals (formalized in LTL$_f$ or PLTL$_f$) in FOND planning domain models, handling both stochastic (i.e., requiring strong-cyclic plans) and adversarial (i.e., requiring strong plans) environments, for a discussion see (Aminof, De Giacomo, and Rubin 2020). Second, we extend the probabilistic framework for goal recognition of Ramírez and Geffner (2010), and develop a probabilistic approach that reasons over executions of policies and returns a posterior probability distribution for the goals. Third, on a practical perspective, we propose an implementation of a compilation approach that generates an augmented FOND planning task compiling temporally extended goals together with the original planning problem. This compilation approach allows us to use any off-the-shelf FOND planner to perform the recognition task in FOND planning models with temporally extended goals. In particular, we focus on FOND domains with stochastic non-determinism (i.e., strong-cyclic plans), and conduct an extensive set of experiments. Thus, we empirically evaluate our approach using different LTL$_f$ and PLTL$_f$ goals over six FOND planning models, and show that our approach is
accurate to recognize temporally extended goals at several levels of observability.

2 Preliminaries

**LTL** and **PLTL**

Linear Temporal Logic on finite traces (LTL) is a variant of LTL introduced in (Pnueli 1977), but interpreted over finite, instead of infinite, traces (De Giacomo and Vardi 2013). Given a set \( AP \) of atomic propositions, the syntax of LTL formulas \( \varphi \) is defined as follows:

\[
\varphi ::= a \mid \neg \varphi \mid \varphi_1 \land \varphi_2 \mid \varphi_1 \lor \varphi_2
\]

where \( a \) denotes an atomic proposition in \( AP \), \( \circ \) is the next operator, and \( U \) is the until operator. Apart from the Boolean ones, we use the following abbreviations: eventually as \( \varphi \models \text{true} U \varphi \); always as \( \varphi \models \text{false} U \varphi \); weak next \( \circ \varphi \models \neg \text{false} U \varphi \), is a sequence of propositional interpretations, where \( \tau_m \models 2AP \) is the \( m \)-th interpretation of \( \tau \), and \( |\tau| \) represents the length of \( \tau \). A finite trace is formally denoted as \( \tau \in (2AP)^* \). Given a finite trace \( \tau \) and an LTL formula \( \varphi \), we inductively define when \( \varphi \) holds in \( \tau \) at position \( i \) (\( 0 \leq i < |\tau| \)), written \( \tau, i \models \varphi \) as follows:

- \( \tau, i \models \text{true} \varphi \text{ iff } a \in \tau_i \);
- \( \tau, i \models \text{false} \varphi \text{ iff } a \notin \tau_i \);
- \( \tau, i \models \varphi_1 \land \varphi_2 \text{ iff } \tau, i \models \varphi_1 \text{ and } \tau, i \models \varphi_2 \);
- \( \tau, i \models \varphi_1 \lor \varphi_2 \text{ iff } i + 1 < |\tau| \text{ and } \tau, i + 1 \models \varphi \);
- \( \tau, i \models \varphi_1 U \varphi_2 \text{ iff there exists } j \text{ such that } i < j < |\tau| \text{ and } \tau, j \models \varphi_2 \), and for all \( k, i < k < j \), we have \( \tau, k \models \varphi_1 \).

An LTL formula \( \varphi \) is true in \( \tau \), denoted by \( \tau \models \varphi \), if and only if \( \tau, 0 \models \varphi \).

As advocated in (De Giacomo et al. 2020), we also use the pure-past version of LTL, denoted as PLTL, due to its compelling computational advantage w.r.t to LTL when goal specifications are naturally expressed in a past fashion. PLTL refers only to the past and has a natural interpretation on finite traces: formulas are satisfied if they hold in the current (i.e., last) position of the trace.

Given a set \( AP \) of propositional symbols, PLTL formulas are defined by the following syntax:

\[
\varphi ::= a \mid \neg \varphi \mid \varphi_1 \land \varphi_2 \mid \exists \varphi \mid \varphi_1 S \varphi_2
\]

where \( a \in AP \), \( \exists \) is the before operator, and \( S \) is the since operator. Similarly to LTL, common abbreviations are the once operator \( \varphi \models \text{true} S \varphi \) and the historically operator \( \varphi \models \text{false} S \varphi \). Given a finite trace \( \tau \) and a PLTL formula \( \varphi \), we inductively define when \( \varphi \) holds in \( \tau \) at position \( i \) (\( 0 \leq i < |\tau| \)), written \( \tau, i \models \varphi \) as follows. For atomic propositions and Boolean operators it is as for LTL. For past operators:

- \( \tau, i \models \exists \varphi \text{ iff } i - 1 \geq 0 \text{ and } \tau, i - 1 \models \varphi \);
- \( \tau, i \models \varphi_1 S \varphi_2 \text{ iff there exists } k \text{ such that } 0 \leq k < i \text{ and } \tau, k \models \varphi_2 \), and for all \( j, k < j \leq i \), we have \( \tau, j \models \varphi_1 \).

A PLTL formula \( \varphi \) is true in \( \tau \), denoted by \( \tau \models \varphi \), if and only if \( \tau, |\tau| - 1 \models \varphi \). A key property of temporal logics, that we are going to exploit in this paper, is that for every LTL/PLTL formula \( \varphi \) there exists a Deterministic Finite-state Automaton (DFA) \( A_\varphi \), accepting the traces \( \tau \) satisfying \( \varphi \) (see (De Giacomo and Vardi 2013, De Giacomo et al. 2020) for a complete description of the transformation).

**FOND Planning**

Following (Ghallab, Nau, and Traverso 2004), a Fully Observable Non-deterministic Domain planning model (FOND) is a tuple \( D = (2F, A, \alpha, tr) \), where \( 2F \) is the set of possible states and \( F \) is a set of fluents (atomic propositions); \( A \) is the set of actions; \( \alpha(s) \subseteq A \) represents the set of applicable actions in state \( s \); and \( tr(s, a) \) represents the non-empty set of successor states that follow action \( a \) in state \( s \). Such a domain model \( D \) is assumed to be compactly represented (e.g., in PDDL (McDermott et al. 1998)), hence its size is \( |F| \).

Given the set of literals of \( F \) as \( \text{Lits}(F) := F \cup \{ \neg f \mid f \in F \} \), every action \( a \in A \) is usually characterized by \( (\text{Pre}_a, \text{Eff}_a) \), where \( \text{Pre}_a \subseteq \text{Lits}(F) \) represents action preconditions and \( \text{Eff}_a \) represents action effects. An action \( a \) can be applied in a state \( s \) if the set of literals in \( \text{Pre}_a \) holds true in \( s \). The result of applying \( a \) in \( s \) is a successor state \( s' \) non-deterministically characterized by one of the \( \text{Eff}_a \)s in \( \text{Eff}^a = \{ \text{Eff}_a, \ldots, \text{Eff}_a \} \).

Unlike Classical Planning (Ghallab, Nau, and Traverso 2004), in which actions are deterministic (i.e., \( |tr(s, a)| = 1 \) in all states \( s \) for which \( a \) is applicable), in FOND planning, some actions have an uncertain outcome, namely they are non-deterministic (i.e., \( |tr(s, a)| \geq 1 \) in all states \( s \) in which \( a \) is applicable), and their effect cannot be predicted in advance. In PDDL, this uncertain outcome is expressed using the keyword \( oneof \) (Bryce and Buffet 2008), which is widely used by several FOND planners, such as PRP (Mousse, McIlraith, and Beck 2012), FOND-SAT (Geffner and Geffner 2018), and MyND (Mättmüller et al. 2010). We define a FOND planning problem as follows.

**Definition 1.** A FOND planning problem is a tuple \( P = (D, s_0, G) \), where \( D \) is a FOND domain model, \( s_0 \subseteq F \) is the initial state (initial assignment to fluents), and \( G \subseteq F \) is the goal state.

Solutions to a FOND planning problem \( P \) are called policies. A policy is usually denoted as \( \pi \), and formally defined as a partial function \( \pi : (2F)^* \rightarrow A \), where \( \pi \) maps states into applicable actions that eventually reach the goal state \( G \) from the initial state \( s_0 \). According to (Cimatti et al. 2003), there are three types of solutions to FOND planning problems: weak, strong and strong-cyclic solutions. In this paper, we focus on strong-cyclic solutions, where the environment acts in an unknown but stochastically based way. However, our approach applies to strong solutions as well, where the environment is purely adversarial.

As running example, we use the well-known TRIANGLE-TIREWORLD FOND domain model. In this domain, locations are connected by roads, and the agent can drive through them. The objective is to drive from a location to another. However, while driving between locations, a tire may be going flat, and if there is a spare tire in the location of the car, then the car can use it to fix the flat tire. Figure 1 illustrates an example of a FOND planning problem for the TRIANGLE-TIREWORLD domain, where circles are locations, roads are represented
by arrows, spare tires are depicted as tires, and the agent is depicted as a car. Figure 1B shows a policy $\pi$ to achieve location 22. Note that, to move from location 11 to location 21 there are two arrows labeled with the action \texttt{(move 11 21)}: (1) when moving does not cause the tire to go flat; (2) when moving causes the tire to go flat. The policy depicted in Figure 1B guarantees the success of achieving the location 22 despite the environment’s non-determinism. Given that the environment is non-deterministic, a strong-cyclic policy $\pi$ may induce to a set of plans to achieve a goal state $G$ from an initial state $s_0$.

In this work, we assume from Classical Planning that the cost is 1 for all instantiated actions $a \in A$. Also, we denote the set of possible executions of a policy $\pi$ as $E$. For instance, the policy $\pi$ depicted in Figure 1B has two possible executions in the set of executions $E$, namely $E = \{ \hat{e}_0, \hat{e}_1 \}$, such as: $\hat{e}_0$: \{(move 11 21), (move 21 22)\}; and $\hat{e}_1$: \{(move 11 21), (changetire 21), (move 21 22)\}.

### 3 FOND Planning for LTL$_f$ and PLTL$_f$

Our approach to goal recognition in FOND domains for LTL$_f$ and PLTL$_f$ goals is based on FOND planning for LTL$_f$ and PLTL$_f$ temporally extended goals (Camacho et al. 2017, 2018). De Giacomo and Rubin (2018).

Formally, a FOND planning problem for LTL$_f$/PLTL$_f$ goals as defined as follows:

**Definition 2.** A FOND planning problem for LTL$_f$/PLTL$_f$ goals is a tuple $\Gamma := (D, s_0, \varphi)$, where $D$ is a standard FOND domain model, $s_0$ is the initial state, and $\varphi$ is either an LTL$_f$ or a PLTL$_f$ formula.

A plan $\pi$ for $\Gamma$ achieves a formula $\varphi$ if and only if the sequence of states generated by $\pi$, despite the non-deterministic effects of the environment, is accepted by $L(A, \varphi)$ (i.e., the language accepted by the automaton $A, \varphi$).

Our idea is to use off-the-shelf FOND planners for standard reachability goals to handle also temporally extended goals through an encoding of the automaton for the goal into an extended planning domain expressed in PDDL. Compiling automata and integrating them into the transition systems through symbolic encodings is standard in symbolic Model Checking. Moreover, doing such a compilation particularly into planning domains (e.g., PDDL) has a long history in the Planning community. Baier and McIlraith (2006) proposed a technique to encode non-deterministic Büchi Automata, needed for LTL, into deterministic planning domains. Forges and Baier (2015) adapted that technique to encode NFA corresponding to LTL$_f$ into deterministic planning domains. Camacho et al. (2017, 2018) proposed a technique that simultaneously determinizes on-the-fly the NFA for LTL$_f$ and encodes it into non-deterministic planning domains.

Here, we use a technique to encode directly the DFA into a non-deterministic PDDL planning domain, which takes advantage of the possibility of PDDL to write parametric domains that are instantiated (becoming propositional) when solving a specific task. Specifically, given a FOND planning problem $\Gamma$, compactly represented in PDDL, we solve $\Gamma$ as follows. First, we transform the LTL$_f$/PLTL$_f$ goal formula $\varphi$ into its corresponding DFA $A, \varphi$ through the highly-optimized MONA tool (Henriksen et al. 1995). Second, from the DFA $A, \varphi$ we build a “parametric” DFA (PDFA), which represents the lifted version of the DFA. Finally, the encoding of such a PDFA into PDDL results in an augmented FOND domain model $\Gamma'$. Thus, we reduce FOND planning for LTL$_f$/PLTL$_f$ to a classical FOND planning task for which any off-the-shelf FOND planner can be employed.

The use of parametric DFAs is based on the following observations. In temporal logic formulas and, hence, in the corresponding DFAs, propositions are represented by domain fluents grounded on specific objects of interest. We can replace these propositions with predicates using object variables, and then have a mapping function $m_{obj}$ that maps such variables into the objects of the problem instance. In this way, we get a lifted and parametric representation of the DFA, henceforth called PDDL, which is conveniently merged with the domain. Formally, given the mapping function $m_{obj}$, we can define a PDFA as follows:

**Definition 3.** A parametric DFA (PDFA) is a tuple $A^\varphi_p = (\Sigma^p, Q^p, q_0^p, \delta^p, F^p)$, where:

- $\Sigma^p = \{ \sigma_0^p, \ldots, \sigma_n^p \} = 2^F$ is the alphabet of planning domain fluents;
- $Q^p$ is a nonempty set of parametric states;
- $q_0^p$ is the parametric initial state;
- $\delta^p : Q^p \times \Sigma^p \rightarrow Q^p$ is the parametric transition function;
- $F^p \subseteq Q^p$ is the set of parametric final states.

$\Sigma^p, Q^p, q_0^p, \delta^p$ and $F^p$ can be obtained by applying $m_{obj}$ to all the components of the corresponding DFA.

**Example 1.** Given the LTL$_f$ formula $\Diamond(\forall x (A 21))$, the object of interest “21” is replaced by the object variable $x$ (i.e., $m_{obj}(21) = x$), and the corresponding DFA and PDFA are depicted in Figures 2a and 2b.

When the resulting new domain is instantiated, we implicitly get back the original DFA in the Cartesian product with the instantiated original domain. This is convenient since we leverage planners to handle the PDDL instantiation as they like. Note that this way of proceeding is somehow similar to what is done in (Baier and McIlraith 2006), where they handle LTL$_f$ goals expressed in a special FOL syntax, with the resulting automata parameterized by the variables in the LTL$_f$ formulas.

Once the PDFA has been computed, we encode its components within the planning problem $\Gamma$, specified in PDDL,
The transition function \( \Gamma' = \langle D', s_0', G' \rangle \), where \( D' = \{ 2^F, A', \alpha', tr' \} \). Intuitively, additional parts of \( \Gamma' \) are used to sequentially synchronize the dynamics between the domain and the automaton. Specifically, \( \Gamma' \) is composed by the following.

**Fluents.** \( F' \) has the same fluents in \( F \) plus fluents representing each state of the PDFA, and a fluent called “turnDomain”, which controls the alternation between domain’s actions and the PDFA’s synchronization action. Formally, \( F' = F \cup \{ q \mid q \in Q^p \} \cup \{ \text{turnDomain} \} \).

**Domain Actions.** Domain’s actions in \( A \) are modified by adding “turnDomain” in preconditions and the negated “turnDomain” in effects. Formally, \( \text{Pre}_a = \text{Pre}_a \cup \{ \text{turnDomain} \} \) and \( \text{Eff}_a = \text{Eff}_a \cup \{ \text{not} (\text{turnDomain}) \} \) for every \( a \in A \).

**Trans. Action.** The transition function \( \delta^p \) of a PDFA is encoded as a new domain action with conditional effects, called “trans”. Namely, \( \text{Pre}_{\text{trans}} = \{ \text{not} (\text{turnDomain}) \} \), \( \text{Eff}_{\text{trans}} = \{ \text{turnDomain} \} \cup \{ \text{when} (q^p, \sigma^p), \text{then} \delta^p(q^p, \sigma^p) \} \cup \{ \text{not} \text{turnDomain} \} \) for all \( (q^p, \sigma^p) \in \delta^p \).

**Initial and Goal States.** The new initial and goal states are specified as \( s'_0 = s_0 \cup \{ q_0^p \} \cup \{ \text{turnDomain} \} \) and \( G' = \{ q \mid q \in Q^p \} \cup \{ \text{turnDomain} \} \), respectively. Notice that the goal \( G \) of the starting planning problem \( \Gamma \) is completely ignored, and in the new planning task automaton states are grounded back on the objects of interest thanks to the mapping \( m^{obs} \).

Executions of a policy for our new FOND planning problem \( \Gamma' \) would be like \( \bar{e}: [a_1, t_1, a_2, t_2, \ldots, a_n, t_n] \), where \( a_1, \ldots, a_n \in A \) are the real domain actions, and \( t_1, \ldots, t_n \) are sequences of synchronization “trans” actions, which, at the end, can be easily removed to extract the desired execution \( e: [a_1, a_2, \ldots, a_n] \).

### 4 Goal Recognition in FOND Planning Domains with LTL/ and PLTL/ Goals

In this section, we introduce the task of goal recognition in FOND planning domains with LTL and PLTL goals. We formally define the task of goal recognition in planning domains with LTL and PLTL goals by extending the standard definition of Plan Recognition as Planning proposed by Ramírez and Geffner in (2009), as follows.

**Definition 4.** A goal recognition problem in a FOND planning domain model with temporally extended goals (LTL and/or PLTL) is a tuple \( T_p = (D, s_0, G_p, \text{Obs}) \), where:

- \( D = \{ 2^F, A, \alpha, tr \} \) is a FOND planning domain;
- \( s_0 \) is the initial state;
- \( G_p = \{ \varphi_0, \varphi_1, \ldots, \varphi_n \} \) is the set of possible goals formalized in LTL or PLTL. \( G_p \) also includes the actual intended hidden goal \( \varphi^* \), s.t. \( \varphi^* \in G_p \);
- \( \text{Obs} = \{ o_0, o_1, \ldots, o_n \} \) is a sequence of successfully executed (non-deterministic) actions of a strong-cyclic policy \( \pi^* \) that achieves the intended hidden goal \( \varphi^* \), s.t. \( o_i \in A \).

As pointed out by Ramírez and Geffner in (2009), an ideal solution for a goal recognition problem is finding the single actual intended hidden goal \( G^* \in G \) that the observation sequence \( \text{Obs} \) of a plan execution achieves. Approaches to goal and plan recognition often return either a probability distribution over the set of possible goals (Ramírez and Geffner 2009; 2010; E.-Martín, R.-Moreno, and Smith 2015; Sohrabi, Riabov, and Udrea 2016), or scores associated to each possible goal (Pereira, Oren, and Meneguzzi 2017). Here, we return a probability distribution over the possible temporally extended goals \( G_p \) (Section 5).

Since we are dealing with non-deterministic domain models, we note that an observation sequence \( \text{Obs} \) corresponds to a successful execution \( \bar{e} \) in the set of all possible executions \( \bar{E} \) of a strong-cyclic policy \( \pi \) that achieves the actual intended hidden goal \( \varphi^* \). As usual in Goal Recognition, we define that an observation sequence \( \text{Obs} \) can be either full or partial – in a full observation sequence we observe all actions of an agent’s plan, whereas in a partial observation sequence, only a sub-sequence of actions are observed.

**Probabilistic Goal Recognition**

We now recall the probabilistic framework for Plan Recognition as Planning proposed by Ramírez and Geffner (2010). This probabilistic framework sets the probability distribution for every goal \( G \) in the set of possible goals \( G \), and the observation sequence \( \text{Obs} \) to be a Bayesian posterior conditional probability, as follows:

\[
P(G \mid \text{Obs}) = \eta \ast P(\text{Obs} \mid G) \ast P(G)
\]

where \( P(G) \) is the *a priori* probability assigned to goal \( G \), \( \eta \) is a normalization factor inversely proportional to the probability of \( \text{Obs} \), and \( P(\text{Obs} \mid G) \) is

\[
P(\text{Obs} \mid G) = \sum_{\pi} P(\text{Obs} \mid \pi) \ast P(\pi \mid G)
\]

\( P(\text{Obs} \mid \pi) \) is the probability of obtaining \( \text{Obs} \) by executing a policy \( \pi \) and \( P(\pi \mid G) \) is the probability of an agent pursuing \( G \) to select \( \pi \). Next, we show how we extend the probabilistic framework presented above for recognizing temporally extended goals in FOND planning domain models.

### 5 Solution Approach

In this section, we develop a recognition approach that is capable of recognizing temporally extended goals (specified either in LTL or in PLTL) in FOND planning domain models. Our approach extends the probabilistic framework of Ramírez.
and Geffner (2010) to compute posterior probabilities over the possible goals $G_\varphi$ by reasoning over the set of possible executions $\hat{E}$ of policies $\pi$ and the observations $Ob$. To extract policies, our approach can use any off-the-shelf FOND planner, thanks to the compilation approach developed in Section 3. Our goal recognition approach works in two stages, compilation stage and recognition stage. In the next sections, we describe in detail how these two stages work.

Compilation Stage

We perform a compilation stage that allows us to use off-the-shelf FOND planners to extract policies for temporally extended goals. To this end, we compile and generate new FOND planning domains $D'$ and problems $\Gamma'$ for the set of possible temporally extended goals $G_\varphi$ using the compilation approach described in Section 3. More specifically, for every goal $\varphi \in G_\varphi$, our compilation approach takes as input a FOND planning problem $\Gamma$, where $\Gamma$ contains the FOND planning domain model $D$ along with the pair initial state $s_0$ and temporally extended goal $\varphi$. Finally, as a result, we obtain a new FOND planning problem $\Gamma'$ associated with the new domain $D'$ and the respective temporally extended goal $\varphi$.

Recognition Stage

We now present the stage in which we perform the task of goal recognition. In this stage, we extract policies for every goal $\varphi \in G_\varphi$ by using the new FOND planning domains $D'$ and problems $\Gamma'$ generated in the compilation stage. From these extracted policies, along with the observations $Ob$, we compute the posterior probabilities for the set of goals $G_\varphi$ by matching the observations $Ob$ with all possible executions in the set of executions $\hat{E}$ of the policies. Next, we describe in detail the recognition stage.

Computing Policies and the Set of Executions $\hat{E}$ for $G_\varphi$

We extract policies for every goal $\varphi \in G_\varphi$ by using the new FOND planning domains $D'$ and problems $\Gamma'$, and from each of these policies, we enumerate the set of possible executions $\hat{E}$. The aim of enumerating the set of possible executions $\hat{E}$ for a policy $\pi$ is to attempt to infer what execution $\hat{e} \in \hat{E}$ the observed agent is performing in the environment. Since the environment is non-deterministic, we do not know what execution $\hat{e}$ the observed agent will perform to achieve its temporally extended goals.

After enumerating the set of possible executions $\hat{E}$ for a policy $\pi$, we compute the average distance of all actions in the set of executions $\hat{E}$ to the goal state $\varphi$ from initial state $s_0$. We note that strong-cyclic solutions may have infinite possible executions, however, here we consider executions that do not enter loops, and for those entering possible loops, we consider only the ones entering loops at most once. Indeed, possibly repeated actions present in loops do not affect the computation of the average distance because even if the observed agent executes the same action repeatedly often, it does not change its distance to the goal. The average distance aims to estimate “how far” every observation $o \in Ob$ is to a goal state $\varphi$. This average distance is computed because some executions $\hat{e} \in \hat{E}$ may share the same action in execution sequences but at different time steps. We refer to this average distance as $d$. For example, consider the policy $\pi$ depicted in Figure 1B. As mentioned before, this policy $\pi$ has two possible executions for achieving the goal state from the initial state, and these two executions share some actions, such as: (move 11 21). In particular, this action appears twice in Figure 1B due to its uncertain outcome. Therefore, this action has two different distances (if we count the number of remaining actions towards the goal state) to the goal state: distance = 1, if the outcome of this action generates the state $s_2$; and distance = 2, if the outcome of this action generates the state $s_3$. Thus, since this policy $\pi$ has two possible executions, and the sum of the distances is 3, the average distance for this action to the goal state is $d = 1.5$. The average distances for the other actions in this policy are: $d = 1$ for (change tire 21), because it appears only in one execution; and $d = 0$ for (move 21 22), because the execution of this action achieves the goal state.

We use the average distance $d$ to compute an estimated score that expresses “how far” every observed action in the observation sequence $Ob$ is to a temporally extended goal $\varphi$ in comparison to the other goals in the set of possible goals $G_\varphi$. This means that, the goal(s) with the lowest score(s) along the execution of the observed actions $o \in Ob$ is (are) the one(s) that, most likely, the observation sequence $Ob$ aims to achieve. We note that, the average distance $d$ for those observations $o \in Ob$ that are not in the set of executions $\hat{E}$ of a policy $\pi$, is set to a large constant number, i.e., to $d = e_o$.

As part of the computation of this estimated score, we compute a penalty value that directly affects the estimated score. This penalty value represents a penalization that aims to increase the estimated score for those goals in which each pair of subsequent observations $\langle o_{i-1}, o_i \rangle$ in $Ob$ does not have any relation or order in the set of executions $\hat{E}$ of these goals. We use the Euler constant $e$ to compute this penalty value, formally defined as $e^{p(o_{i-1}, o_i)}$, in which we use $R(\hat{e})$ as the set of order relation of an execution $\hat{e}$, where

$$p(o_{i-1}, o_i) = \begin{cases} 1, & \text{if } \exists \hat{e} \in \hat{E}((o_{i-1} < o_i) \notin R(\hat{e})) \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Equation 3 formally defines the computation of the estimated score for every goal $\varphi \in G_\varphi$ given a pair of subsequent observations $\langle o_{i-1}, o_i \rangle$ in $Ob$ does not have any relation or order in the set of executions $\hat{E}$ of these goals.

$$e^{p(o_{i-1}, o_i)} \ast d(o_i, \varphi) \sum_{\varphi' \in G_\varphi} d(o_i, \varphi') \quad (4)$$

Example 2. To exemplify how we compute the estimated score for every goal $\varphi \in G_\varphi$, consider the following goal recognition problem for the TRIANGLE-TIREWORLD domain example in Figure 3. The initial state $s_0$ is $vAt(11)$; the temporally extended goals $G_\varphi$ are expressed as $\text{LTL}_f$ goals, such that $\varphi_0 = \diamond vAt(51)$, $\varphi_1 = \diamond vAt(33)$, and $\varphi_2 = \diamond vAt(15)$; $Ob = \langle o_1 : \text{move 11 21}, o_1 : \text{change tire 22} \rangle$. The intended goal $\varphi^*$ is $\varphi_1$.

Before computing the estimated score for the goals, we first perform the compilation process presented in Compilation Stage. Afterward, we extract policies $\pi$ for every goal $\varphi \in G_\varphi$, enumerate the possible executions $\hat{E}$ for the goals $G_\varphi$ from
the extracted policies, and then compute the average distance \( d \) of all actions in the set of executions \( E \) for the goals \( G_\varphi \), from initial state \( s_0 \). The number of possible executions \( E \) for the goals are: \( \varphi_0 : |E| = 8, \varphi_1 : |E| = 8, \) and \( \varphi_2 : |E| = 16 \).

The average distances \( d \) of all actions in \( E \) for the goals are as follows:

- \( \varphi_0 \): \( \text{move 11 21} = 4.5, \text{changetire 21} = 4, \text{move 21 31} = 3, \text{changetire 31} = 2.5, \text{move 31 41} = 1.5, \text{changetire 41} = 1, \text{move 41 51} = 0 \);
- \( \varphi_1 \): \( \text{move 11 21} = 4.5, \text{changetire 21} = 4, \text{move 21 22} = 3, \text{changetire 22} = 2.5, \text{move 22 23} = 1.5, \text{changetire 23} = 1, \text{move 23 33} = 0 \);
- \( \varphi_2 \): \( \text{move 11 21} = 6, \text{changetire 21} = 5.5, \text{move 21 22} = 4.5, \text{changetire 22} = 4, \text{move 22 23} = 3, \text{changetire 23} = 2.5, \text{changetire 24} = 1.5, \text{move 24 15} = 0 \).

Once we have the average distances \( d \) of all actions in \( E \) for all goals, we can then compute the estimated score for \( G_\varphi \) for every observation \( o \in \text{Obs} \), for every observation \( o \in \text{Obs} \): \( \varphi_0 \) (move 11 21): \( \varphi_0 = \frac{4.5}{4.5+6} = 0.43 \), \( \varphi_1 = \frac{4.5}{4.5+6} = 0.43 \), \( \varphi_2 = \frac{6}{4.5+6} = 0.57 \); and \( \varphi_1 \) (changetire 22): \( \varphi_0 = \frac{e^5}{e^5+0.6} = 61.87 \), \( \varphi_1 = \frac{2.5}{e^{0.5} + 2} = 0.016 \), \( \varphi_2 = \frac{0.5}{e^{1.5} + 2} = 0.026 \).

Note that for the observation \( o_1 \), the average distance \( d \) for \( \varphi_0 \) is \( e^5 = 148.4 \) because this observed action is not an action for one of the executions in the set of executions for this goal (Obs aims to achieve the intended goal \( \varphi^* = \varphi_1 \)). Furthermore, the penalty value is applied to \( \varphi_0 \), namely, \( e^1 = 2.71 \). We can see that the estimated score of the correct intended goal \( \varphi_1 \) is always the lowest for all observations Obs, especially when we observe the second observation \( o_1 \). As a result, we have only the correct goal \( \varphi_1 \) with the lowest score. We can also see that our approach correctly infers the intended goal \( \varphi^* \), even when observing with just few actions.

Next, we present how we use the estimated score to compute posterior probabilities for the set of possible temporally extended goals \( G_\varphi \).

**Computing the Posterior Probabilities for \( G_\varphi \).** To compute the posterior probabilities over the set of possible temporally extended goals \( G_\varphi \), we start by computing the average estimated score for every goal \( \varphi \in G_\varphi \) for every observation \( o \in \text{Obs} \), and we formally define this computation as \( \mathcal{E}(\varphi, \text{Obs}, G_\varphi) \), in the following equation.

\[
\mathcal{E}(\varphi, \text{Obs}, G_\varphi) = \left( \frac{\sum_{o \in \text{Obs}} e^{P(o, \varphi)| o} - d(o, \varphi)}{|\text{Obs}|} \right)
\]

The average estimated score \( \mathcal{E} \) aims to estimate “how far” a goal \( \varphi \) is to be achieved compared to other goals (\( G_\varphi \setminus \{\varphi\} \)) averaging among all the observations in \( \text{Obs} \). The lower the average estimated score \( \mathcal{E} \) to a goal \( \varphi \), the more likely such a goal is to be the one that the observed agent aims to achieve. Based on this, we now state two important properties of \( \mathcal{E} \), formally defined in Equation (5) as follows:

1. Given that the sequence of observations \( \text{Obs} \) corresponds to an optimal execution \( \bar{e} \in \hat{E} \) that aims to achieve the actual intended hidden goal \( \varphi^* \in G_\varphi \), the average estimated score outputted by \( \mathcal{E} \) will tend to be the lowest for \( \varphi^* \) in comparison to the scores of the other goals (\( G_\varphi \setminus \{\varphi^*\} \)), as observations increase in length; and

2. If we restrict the recognition setting and define that the possible goals \( G_\varphi \) are not sub-goals of each other, and observe all observations in \( \text{Obs} \) (i.e., full observability), we will have the intended goal \( \varphi^* \) with the lowest score among all possible goals, i.e., for \( \varphi \in G_\varphi \) is the case that \( \mathcal{E}(\varphi^*, \text{Obs}, G_\varphi) \leq \mathcal{E}(\varphi, \text{Obs}, G_\varphi) \).

After defining how we compute the average estimated score \( \mathcal{E} \) for the goals using Equation (5), we can use the average estimated score \( \mathcal{E} \) to attempt to maximize the probability of observing a sequence of observations \( \text{Obs} \) for a given goal \( \varphi \), as we formally define in Equation (6)

\[
P(Obs \mid \varphi) = [1 + \mathcal{E}(\varphi, \text{Obs}, G_\varphi)]^{-1}
\]

Thus, by using the estimated score in Equation (5) we can infer that the goals \( \varphi \in G_\varphi \) with the lowest estimated score will be the most likely to be achieved according to the probability interpretation we propose in Equation (5) For instance, consider the goal recognition problem presented in Example 2 and the estimated scores we computed for the temporally extended goals \( \varphi_0, \varphi_1, \) and \( \varphi_2 \) based on the observation sequence \( \text{Obs} \). From this, we have the following probabilities \( P(Obs \mid \varphi) \) for the goals:

- \( P(Obs \mid \varphi_0) = [1 + (31.15)]^{-1} = 0.00003 \)
- \( P(Obs \mid \varphi_1) = [1 + (0.216)]^{-1} = 0.82 \)
- \( P(Obs \mid \varphi_2) = [1 + (0.343)]^{-1} = 0.74 \)

After normalizing these computed probabilities using \( \gamma^2 \eta \) and assuming that the prior probability \( P(\varphi) \) is equal to every goal in the set of goals \( G_\varphi \), we can use Equation (5) to compute the posterior probabilities (Equation 6) for the temporally extended goals. The solution to a recognition problem \( T_\varphi \) (Definition 3) is a set of temporally extended goals \( G_\gamma \) with the maximum probability, formally:

\[
\eta^2 = \left[ \sum_{\varphi \in G_\varphi} P(Obs \mid \varphi) \ast P(\varphi) \right]^{-1}
\]
domain models, in which most of them are commonly used to experiment and evaluation, we use six sands of goal recognition problems using well-known planners, such as: blocks-world, logistics, tidy-up, fireworld, triangle-fireworld, and zeno-travel. Based on these fond planning domain models, we build different recognition datasets: a baseline dataset using conjunctive goals ($\phi_1 \land \phi_2$) and datasets with LTL and PLTL goals.

For the LTL datasets, we use three types of goals:

- $\diamond \phi$, where $\phi$ is a propositional formula expressing that eventually $\phi$ will be achieved. This temporal formula is analogous to a conjunctive goal;
- $\diamond (\phi_1 \land \diamond (\diamond \phi_2))$, expressing that $\phi_1$ must hold before $\phi_2$ holds. For instance, we can define a temporal goal that expresses the order in which a set of packages in logistics domain should be delivered;
- $\phi_1 \land \phi_2$, expressing that $\phi_1$ must hold until $\phi_2$ is achieved. For instance, in the tidy-up domain, we can define a temporal goal expressing that no one can be in the kitchen until the kitchen is cleaned by the robot.

For the PLTL datasets, we use two types of goals:

- $\phi_1 \land \diamond \phi_2$, expressing that $\phi_1$ holds and $\phi_2$ held once. For instance, in the blocks-world domain, we can define a past temporal goal that only allows stacking a set of blocks $(a, b, c)$ once another set of blocks has been stacked $(a, e)$;
- $\phi_1 \land (\neg \phi_2 S \phi_3)$, expressing that the formula $\phi_1$ holds and since $\phi_1$ held $\phi_2$ was not true anymore. For instance, in zeno-travel, we can define a past temporal goal expressing that person 1 is at city 1 and since the person 2 is at city 1, the aircraft must not pass through city 2 anymore.

Thus, in total, we have 6 different recognition datasets over the six fond domains presented above. Each of these datasets contains hundreds of recognition problems ($\approx 390$ recognition problems per dataset), such that each recognition problem $T$ in these datasets is comprised of a fond planning domain model $D$, an initial state $s_0$, a set of possible goals $G_\phi$ (expressed in either LTL or PLTL), the actual intended hidden goal in the set of possible goals $\phi^* \in G_\phi$, and the observation sequence $O$. An observation sequence contains a sequence of actions that represent an execution $\hat{e}$ in the set of possible executions $\hat{E}$ of policy $\pi$ that achieves the actual intended hidden goal $\phi^*$, and as we stated before, this observation sequence $O$ can be full or partial. To generate the observations $O$ for $\phi^*$ and build the recognition problems, we extract strong cyclic policies using different fond planners, such as PRP and MyND. A full observation sequence represents an execution (a sequence of executed actions) of a strong cyclic policy that achieves the actual intended hidden goal $\phi^*$, i.e., 100% of the actions of $\hat{e}$ having been observed. A partial observation sequence is represented by a sub-sequence of actions of a full execution that aims to achieve the actual intended hidden goal $\phi^*$ (e.g., an execution with “missing” actions, due to a sensor malfunction). We

We note that the set of possible goals $G_\phi$ contains very similar goals (i.e., $\phi_0 = \phi_1 \land \phi_2$ and $\phi_1 = \phi_2 \land \phi_1$), and all possible goals can be achieved from the initial state by a strong-cyclic policy.

$G_\phi = \arg\max_{G \in G_\phi} P(\phi \mid \text{Obs})$. Hence, considering $\eta$ and the probabilities $P(\text{Obs} \mid \phi)$ computed before, we then have the following posterior probabilities for the goals in Exemplar $\mathbb{P}(\phi_0 \mid \text{Obs}) = 0.001$; $P(\phi_1 \mid \text{Obs}) = 0.524$; and $P(\phi_2 \mid \text{Obs}) = 0.475$. Recall that for Example 2 $\phi^* = \phi_1$, and according to the computed posterior probabilities, we have $G_\phi = \{\phi_1\}$, so our approach yields only the correct intended goal by observing just two observations.

We note that the use of the average distance $d$ and the penalty value $p$ to compute the estimated score $E$ allows our approach to disambiguate similar goals during the recognition stage. For instance, consider the following possible temporally extended goals: $\phi_0 = \phi_1 \cup \phi_2$ and $\phi_1 = \phi_2 \cup \phi_1$. It is possible to see that both goals have the same formulas to be achieved, i.e., $\phi_1$ and $\phi_2$, but in a different order. Thus, even having the same formulas to be achieved, the sequences of executions of their policies are different. Therefore, the average distances are also different, possibly a smaller value for the temporally extended goal that the agent aims to achieve, and the penalty value may also be applied to the other goal if two subsequent observations do not have any order relation in the set of executions for this goal.

Computational Complexity. In essence, the most expensive computational part of our recognition approach is computing the policies $\pi$ for the possible goals $G_\phi$ from an initial state $s_0$. Therefore, we can say that our approach requires $|G_\phi|$ calls to an off-the-shelf FOND planner. Thus, the computational complexity of our recognition approach is linear in the number of possible goals $|G_\phi|$, namely $O(|G_\phi|)$.

In contrast, for recognizing goals in classical planning settings, the approach of Ramirez and Geffner (2010) requires $2 \times |G|$ calls to an off-the-shelf Classical planner, i.e., $O(2 \times |G_\phi|)$. Concretely, to compute $P(\text{Obs} \mid G)$, Ramirez and Geffner’s approach computes two plans for every goal, and based on these two plans, they compute a cost-difference between these plans and plug it into a Boltzmann equation, namely, Equation 5 in [Ramirez and Geffner 2010]. For computing these two plans, this approach requires a non-trivial transformation process that modifies both the domain and problem, i.e., an augmented domain and problem that compute a plan that complies with the observations, and another augmented domain and problem to compute a plan that does not comply with the observations. The intuition of Ramirez and Geffner’s approach is that the lower the cost-difference for a goal, the higher the probability for this goal, much similar to the intuition of our estimated score $E$.

6 Experiments and Evaluation

In this section, we present experiments and evaluations we carried out to validate the effectiveness of our recognition approach. We empirically evaluate our approach over thousands of goal recognition problems using well-known FOND planning domain models with different types of temporal extended goals expressed in LTL and PLTL.

Domains and Recognition Datasets

For experiments and evaluation, we use six FOND planning domain models, in which most of them are commonly used to evaluate FOND planners (Mattmüller et al. 2010; Muise, McIlraith, and Beck 2012; Geffner and Geffner 2018), such as: BLOCKS-WORLD, LOGISTICS, TIDY-UP, FIREWORLD, TRIANGLE-FIREWORLD, and ZENO-TRAVEL. Based on these FOND planning domain models, we build different recognition datasets: a baseline dataset using conjunctive goals ($\phi_1 \land \phi_2$) and datasets with LTL and PLTL goals.

For the LTL datasets, we use three types of goals:

- $\diamond \phi$, where $\phi$ is a propositional formula expressing that eventually $\phi$ will be achieved. This temporal formula is analogous to a conjunctive goal;
- $\diamond (\phi_1 \land \circ(\diamond \phi_2))$, expressing that $\phi_1$ must hold before $\phi_2$ holds. For instance, we can define a temporal goal that expresses the order in which a set of packages in logistics domain should be delivered;
- $\phi_1 \land \phi_2$, expressing that $\phi_1$ must hold until $\phi_2$ is achieved. For instance, in the tidy-up domain, we can define a temporal goal expressing that no one can be in the kitchen until the kitchen is cleaned by the robot.

For the PLTL datasets, we use two types of goals:

- $\phi_1 \land \diamond \phi_2$, expressing that $\phi_1$ holds and $\phi_2$ held once. For instance, in the blocks-world domain, we can define a past temporal goal that only allows stacking a set of blocks $(a, b, c)$ once another set of blocks has been stacked $(a, e)$;
- $\phi_1 \land (\neg \phi_2 S \phi_3)$, expressing that the formula $\phi_1$ holds and since $\phi_1$ held $\phi_2$ was not true anymore. For instance, in zeno-travel, we can define a past temporal goal expressing that person 1 is at city 1 and since the person 2 is at city 1, the aircraft must not pass through city 2 anymore.

Thus, in total, we have 6 different recognition datasets over the six FOND domains presented above. Each of these datasets contains hundreds of recognition problems ($\approx 390$ recognition problems per dataset), such that each recognition problem $T$ in these datasets is comprised of a FOND planning domain model $D$, an initial state $s_0$, a set of possible goals $G_\phi$ (expressed in either LTL or PLTL), the actual intended hidden goal in the set of possible goals $\phi^* \in G_\phi$, and the observation sequence $O$. An observation sequence contains a sequence of actions that represent an execution $\hat{e}$ in the set of possible executions $\hat{E}$ of policy $\pi$ that achieves the actual intended hidden goal $\phi^*$, and as we stated before, this observation sequence $O$ can be full or partial. To generate the observations $O$ for $\phi^*$ and build the recognition problems, we extract strong cyclic policies using different FOND planners, such as PRP and MyND. A full observation sequence represents an execution (a sequence of executed actions) of a strong cyclic policy that achieves the actual intended hidden goal $\phi^*$, i.e., 100% of the actions of $\hat{e}$ having been observed. A partial observation sequence is represented by a sub-sequence of actions of a full execution that aims to achieve the actual intended hidden goal $\phi^*$ (e.g., an execution with “missing” actions, due to a sensor malfunction). We

We note that the set of possible goals $G_\phi$ contains very similar goals (i.e., $\phi_0 = \phi_1 \land \phi_2$ and $\phi_1 = \phi_2 \land \phi_1$), and all possible goals can be achieved from the initial state by a strong-cyclic policy.
define four levels of observability for a partial observations: 10%, 30%, 50%, or 70% of its actions having been observed.

Evaluation Metrics
We use four metrics, as follows: Recognition time (Time), the average time in seconds to perform the recognition task (including the calls to the FOND planner); True Positive Rate (TPR), that measures the fraction of times that the intended hidden goal $\varphi^*$ was correctly recognized, e.g., the percentage of recognition problems that our approach correctly recognized the intended goal. A higher TPR indicates better accuracy, measuring how often the intended hidden goal had the highest probability $P(\varphi | \text{Obs})$ among the possible goals; False Positive Rate (FPR), that measures how often goals other than the intended goal are recognized (wrongly) as the intended ones. A lower FPR indicates better accuracy; False Negative Rate (FNR), measuring the fraction of times in which the intended goal was recognized incorrectly.

Goal Recognition Results
Table 1 shows three inner tables that summarize and aggregate the average results of all six datasets for all four metrics (Time, TPR, FPR, and FNR). $|\text{Obs}|$ represents the average number of goals in the datasets, and $|\text{Obs}|$ the average number of observations. Each row in these inner tables represents the observation level, varying from 10% to 100%. We note that we are unable to provide a direct comparison of our approach against existing recognition approaches in the literature because most of these approaches perform a non-trivial process that transforms a recognition problem into planning problems to be solved by a planner (Ramírez and Gelfin[2010] Sohrabi, Riabov, and Udrea[2016]). Even adapting such a transformation to work in FOND settings with temporally extended goals, we cannot guarantee that it will work properly in the problem setting we propose in this paper.

Conjunctive and Eventuality Goals. The first inner table shows the average results comparing the performance of our approach between conjunctive goals and temporally extended goals using the temporal operator $\Diamond$ (eventually). We refer to this comparison as baseline, since these two types of goals have the same semantics. We can see that the results for these two types of goals are very similar for all metrics. Moreover, it is also possible to see that our recognition approach is very accurate and performs well at all levels of observability, yielding high TPR values, and low FPR and FNR values for more than 10% of observability. Note that for 10% of observability and LTL$_f$ goals for $\Diamond \varphi$, the TPR average value is 0.74, and it means for 74% of the recognition problems our approach recognized correctly the intended temporally extended goal when observing, on average, only 3.85 actions.

Results for LTL$_f$ Goals. Regarding the results for the two types of LTL$_f$ goals (second inner table), we can see that our approach shows to be accurate for all metrics at all levels of observability, apart from the results for 10% of observability for LTL$_f$ goals in which the formulas must be recognized in a certain order. Note that even when observing just a few actions (2.1 for 10% and 5.4 for 30%) our approach is accurate, but not as accurate as for more than 30% of observability.

Results for PLTL$_f$ Goals. Finally, as for the results for the two types of PLTL$_f$ goals, we can see in the last inner table that, the overall average number of observations $|\text{Obs}|$ is less than the average for the other datasets, making the task of goal recognition more difficult for the PLTL$_f$ datasets. Yet, we can see that our recognition approach remains accurate when dealing with fewer observations. We can also see that the values of FNR increase for low observability, but the FPR values, are, on average, inferior to 0.15.

| $|\text{Obs}|$ | Time TPR FPR FNR | Time TPR FPR FNR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 10 | 3.85 | 199.8 | 0.76 | 0.13 | 243.5 | 0.74 | 0.14 | 0.26 | 10 | 3.85 | 199.8 | 0.76 | 0.13 | 243.5 | 0.74 | 0.14 | 0.26 |
| 30 | 10.7 | 187.2 | 0.85 | 0.08 | 1.15 | 235.1 | 0.86 | 0.10 | 0.14 | 30 | 10.7 | 187.2 | 0.85 | 0.08 | 1.15 | 235.1 | 0.86 | 0.10 | 0.14 |
| 50 | 17.4 | 188.4 | 0.83 | 0.09 | 0.17 | 242.1 | 0.89 | 0.07 | 0.11 | 50 | 17.4 | 188.4 | 0.83 | 0.09 | 0.17 | 242.1 | 0.89 | 0.07 | 0.11 |
| 70 | 24.3 | 187.8 | 0.86 | 0.08 | 0.14 | 232.1 | 0.92 | 0.08 | 0.08 | 70 | 24.3 | 187.8 | 0.86 | 0.08 | 0.14 | 232.1 | 0.92 | 0.08 | 0.08 |
| 100 | 34.7 | 190.4 | 0.85 | 0.09 | 0.15 | 272.8 | 0.95 | 0.09 | 0.05 | 100 | 34.7 | 190.4 | 0.85 | 0.09 | 0.15 | 272.8 | 0.95 | 0.09 | 0.05 |

Table 1: Results for Conjunctive, LTL$_f$, and PLTL$_f$ goals.

7 Conclusions
In this paper, we have studied goal recognition for temporally extended goals, specified in both LTL$_f$ and PLTL$_f$, in FOND planning domain models. We also have developed a novel probabilistic recognition framework in such a setting. On a practical perspective, we have implemented a compilation of temporally extended goals that allows us to reduce the problem of FOND planning for LTL$_f$/PLTL$_f$ goals to standard FOND planning, and have performed extensive experiments that show the feasibility of the approach. Indeed, we have shown that, for all evaluated domains, our recognition approach yields high accuracy for recognizing temporally extended goals at several levels of observability, for both LTL$_f$ and PLTL$_f$ goals. As future work, we intend to address noisy observations, and recognize not only the temporal goal that the observed agent aims to achieve, but also anticipate the sequence of actions that the agent is executing.
Acknowledgments
Research partially supported by the ERC Advanced Grant WhiteMech (No. 834228) and by the EU ICT-48 2020 project TAILOR (No. 952215).

References
Aminof, B.; De Giacomo, G.; and Rubin, S. 2020. Stochastic Fairness and Language-Theoretic Fairness in Planning in Non-deterministic Domains. In IJCAI.

Bacchus, F.; and Kabanza, F. 1998. Planning for temporally extended goals. Annals of Mathematics and Artificial Intelligence 22(1-2).

Bacchus, F.; and Kabanza, F. 2000. Using temporal logics to express search control knowledge for planning. Artificial Intelligence 116(1-2).

Baier, J. A.; and McIlraith, S. A. 2006. Planning with First-Order Temporally Extended Goals using Heuristic Search. In AAAI.

Bryce, D.; and Buffet, O. 2008. 6th International Planning Competition: Uncertainty Part. International Planning Competition (IPC).

Camacho, A.; Baier, J.; Muise, C.; and McIlraith, S. 2018. Finite LTL Synthesis as Planning. In ICAPS.

Camacho, A.; Triantafillou, E.; Muise, C.; Baier, J.; and McIlraith, S. 2017. Non-Deterministic Planning with Temporally Extended Goals: LTL over Finite and Infinite Traces. In AAAI.

Cimatti, A.; Giunchiglia, E.; Giunchiglia, F.; and Traverso, P. 1997. Planning via model checking: A decision procedure for AR. In ECP.

Cimatti, A.; Pistore, M.; Roveri, M.; and Traverso, P. 2003. Weak, Strong, and Strong Cyclic Planning via Symbolic Model Checking. Artificial Intelligence 147(1-2).

De Giacomo, G.; Di Stasio, A.; Fuggitti, F.; and Rubin, S. 2020. Pure-Past Linear Temporal and Dynamic Logic on Finite Traces. In IJCAI. Survey Track.

De Giacomo, G.; and Rubin, S. 2018. Automata-Theoretic Foundations of FOND Planning for LTLf and LDLf Goals. In IJCAI.

De Giacomo, G.; and Vardi, M. 2013. Linear Temporal Logic and Linear Dynamic Logic on Finite Traces. In IJCAI.

De Giacomo, G.; and Vardi, M. 2015. Synthesis for LTL and LDL on finite traces. In IJCAI.

E.-Martín, Y.; R.-Moreno, M. D.; and Smith, D. E. 2015. A Fast Goal Recognition Technique Based on Interaction Estimates. In IJCAI.

Geffner, T.; and Geffner, H. 2018. Compact Policies for Fully Observable Non-Deterministic Planning as SAT. In ICAPS.

Geib, C. W.; and Goldman, R. P. 2009. A Probabilistic Plan Recognition Algorithm Based on Plan Tree Grammars. Artificial Intelligence 173(11).

Gerevini, A. E.; Haslum, P.; Long, D.; Saetti, A.; and Dimopoulos, Y. 2009. Deterministic planning in the fifth international planning competition: PDDL3 and experimental evaluation of the planners. Artificial Intelligence.

Ghallab, M.; Nau, D. S.; and Traverso, P. 2004. Automated Planning - Theory and Practice. Elsevier, 1st edition. 635p.

Henriksen, J.; Jensen, J.; Jørgensen, M.; Klarlund, N.; Paige, B.; Rauhe, T.; and Sandholm, A. 1995. Mona: Monadic Second-order logic in practice. In TACAS.

Kaminka, G. A.; Vered, M.; and Agmon, N. 2018. Plan Recognition in Continuous Domains. In AAAI.

Mattmüller, R.; Ortlieb, M.; Helmert, M.; and Bercher, P. 2010. Pattern Database Heuristics for Fully Observable Non-deterministic Planning. In ICAPS.

McDermott, D.; Ghallab, M.; Howe, A.; Knoblock, C.; Ram, A.; Veloso, M.; Weld, D.; and Wilkins, D. 1998. PDDL – The Planning Domain Definition Language. In AIPS.

Mirsky, R.; Stern, R.; Gal, Y. K.; and Kalech, M. 2016. Sequential Plan Recognition. In IJCAI.

Muise, C.; McIlraith, S. A.; and Beck, J. C. 2012. Improved Non-deterministic Planning by Exploiting State Relevance. In ICAPS.

Nebel, B.; Dornhege, C.; and Hertle, A. 2013. How Much Does a Household Robot Need To Know In Order To Tidy Up Your Home? In AAAI Workshop on Intelligent Robotic Systems.

Patrizi, F.; Lipovetzky, N.; and Geffner, H. 2013. Fair LTL Synthesis for Non-Deterministic Systems using Strong Cyclic Planners. In IJCAI.

Patrizi, F.; Lipovetzky, N.; Giacomo, G. D.; and Geffner, H. 2011. Computing Infinite Plans for LTL Goals Using a Classical Planner. In IJCAI.

Pereira, R. F.; Oren, N.; and Meneguzzi, F. 2017. Landmark-Based Heuristics for Goal Recognition. In AAAI.

Pistore, M.; Bettin, R.; and Traverso, P. 2001. Symbolic techniques for planning with extended goals in non-deterministic domains. In ECP.

Pistore, M.; and Traverso, P. 2001. Planning as model checking for extended goals in nondeterministic domains. In IJCAI.

Pnueli, A. 1977. The Temporal Logic of Programs. In FOCS.

Ramírez, M.; and Geffner, H. 2009. Plan Recognition as Planning. In IJCAI.

Ramírez, M.; and Geffner, H. 2010. Probabilistic Plan Recognition Using Off-the-Shelf Classical Planners. In AAAI.

Ramírez, M.; and Geffner, H. 2011. Goal Recognition over POMDPs: Inferring the Intention of a POMDP Agent. In IJCAI.

Sohrabi, S.; Riabov, A. V.; and Udrea, O. 2016. Plan Recognition as Planning Revisited. In IJCAI.

Torres, J.; and Baier, J. A. 2015. Polynomial-Time Reformulations of LTL Temporally Extended Goals into Final-State Goals. In IJCAI.