Goal Recognition as Reasoning over Landmarks in Incomplete Domain Models

Doctoral Consortium

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ABSTRACT

Recent approaches to goal recognition have progressively relaxed the assumptions about the amount and correctness of domain knowledge and available observations, yielding accurate and efficient algorithms. These approaches, however, assume completeness and correctness of the domain theory against which their algorithms match observations: this is too strong for most real-world domains. In this work, we develop goal recognition techniques that are capable of recognizing goals using *incomplete* (and possibly incorrect) domain theories.

KEYWORDS

Goal Recognition; Incomplete Domain Models; Landmarks;

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1 INTRODUCTION

Goal recognition is the problem of recognizing the correct goal intended by an observed agent, given a sequence of observations as evidence of its behavior in an environment, and a domain model describing how the observed agent generates such behavior. Approaches to solve this problem vary on the amount and type of domain knowledge used in the agents' behavior (or plan generation). However, all recent planning-based approaches to goal and plan recognition assume that the domain model is correct and complete [1, 4, 6–10], preventing its application to realistic scenarios in which the domain modeler either has an incomplete or incorrect model of the agents' behavior under observation. Specifically, real world domains have two potential sources of uncertainty: (1) ambiguity in how actions performed by agents are realized; and (2) ambiguity in how imperfect sensor data reports features of the world. The former stems from an incomplete understanding of the action being modelled and requires a domain modeler to specify a number of alternate versions of the same action to cover the possibilities, *e.g.*, an action to turn on the gas burner in a cooker may or may not require the observed agent to press a spark button. The latter stems from imperfections in the way actions themselves may be interpreted from real-world noisy data, *e.g.*, if one uses machine learning algorithms to classify objects to be used as features (*e.g.*, logical facts) of the observations, certain features may not be recognizable reliably, so it is useful to model them as optional.

In this paper, we develop goal recognition approaches that can cope with incomplete planning domain models [5], and provide four main contributions. First, we formalize goal recognition in incomplete domains by combining the standard formalization of Ramírez and Geffner [8, 9] for plan recognition and that of Nguyen et al. [5]. Second, we develop an algorithm, adapted from [3], that extracts *possible* landmarks in incomplete domain models. Third, we develop a notion of *overlooked* landmarks that we can extract online as we process (*on the fly*) observations. Fourth, we develop two heuristic approaches to recognize goals that account for the various types of landmark as evidence.

2 GOAL RECOGNITION IN INCOMPLETE DOMAINS

Our approaches assume that the recognizer (observer) has an incomplete domain model while the observed agent is planning and acting in the environment with a complete domain model. To account for such uncertainty and incompleteness, the model available to the observer contains possible preconditions and effects, much like the incomplete domain models from previous planning approaches [5, 11]. We formalize the goal recognition problem over incomplete domain models in Definition 2.1.

*Definition 2.1 (**Goal Recognition Problem**).* A goal recognition problem with an incomplete domain model is a 5-tuple $\widetilde{\mathcal{T}} = \langle \widetilde{\mathcal{D}}, Z, \mathcal{I}, \mathcal{G}, O \rangle$, where: $\widetilde{\mathcal{D}} = \langle \mathcal{R}, \widetilde{\mathcal{O}} \rangle$ is an incomplete domain model, in which $\mathcal{R}$ is a set of predicates with typed variables, and $\widetilde{\mathcal{O}}$ is a set of incomplete operators with possible preconditions and effects; Z is the set of typed objects, in which $\mathcal{F}$ is the set instantiated predicates from $\mathcal{R}$ with objects from Z, and $\widetilde{\mathcal{A}}$ is the set of incomplete instantiated actions from $\widetilde{\mathcal{O}}$ with objects from Z; $\mathcal{I} \in \mathcal{F}$ is the initial state; $\mathcal{G}$ is the set of possible goals, including the correct hidden goal G^* ($G^* \in \mathcal{G}$); and $O = \langle o_1, o_2, ..., o_n \rangle$ is an observation sequence of executed actions, with each observation $o_i \in \widetilde{\mathcal{A}}$. O is a plan that achieves the correct hidden goal G^* in a complete domain in $\langle\langle \widetilde{\mathcal{D}} \rangle\rangle$.

A solution for a goal recognition problem in incomplete domain models $\widetilde{\mathcal{T}}$ is the correct hidden goal $G^* \in \mathcal{G}$ that the observation sequence *Obs* of a plan execution achieves.

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2.1 Landmark Extraction in Incomplete Domains

Planning landmarks are facts (or actions) that must be achieved (or executed) at some point along all valid plans to achieve a goal from an initial state [3]. Landmarks are often used to build heuristics for planning algorithms using complete and correct domain models. We adapt the extraction algorithm from [3] to extract landmarks from incomplete domains by building an Optimistic Relaxed Planning Graph (ORPG) instead of the original Relaxed Planning Graph (RPG) [2]. An ORPG is a levelled graph that deals with incomplete domain models by assuming the most *optimistic* conditions. Thus, besides ignoring the delete-effects of all actions, this graph also ignores possible preconditions and possible delete-effects, considering that all possible add effects occur. Replacing an RPG for an ORPG allows us to extract *definite* and *possible* landmarks, formalized in Definitions 2.2 and 2.3, respectively.

*Definition 2.2 (**Definite Landmark**).* A *definite* landmark L_D is a fact landmark extracted from a known add effect ($\mathit{eff}^+(a)$) of an achiever action[1] a in the ORPG.

*Definition 2.3 (**Possible Landmark**).* A *possible* landmark L_P is a fact landmark extracted from a possible add effect ($\widetilde{\mathit{eff}}^+(a)$) of an achiever action a in the ORPG.

2.2 Heuristic Goal Recognition Approaches

Key to our approaches is observing the evidence of achieved landmarks during observations to recognize which goal is more consistent with the observations. To do so, our approaches combine the concepts of *definite* and *possible* with that of *overlooked* landmarks. An overlooked landmark is an actual landmark, *i.e.*, a necessary fact for all valid plans towards a goal, that was not detected by approximate landmark extraction algorithms. Since we are dealing with incomplete domain models, and it is possible that they have few (or no) *definite* and/or *possible* landmarks, we extract *overlooked* landmarks from the evidence in the observations as we process them in order to enhance the set of landmarks useable by our heuristic. To find such landmarks we build a new ORPG removing observed actions that achieve a potentially *overlooked* fact landmark and checks the solvability of this modified problem. If the modified problem is indeed unsolvable, then this fact is an *overlooked* landmark.

2.3 Goal Completion Heuristic

We now combine our notions of landmarks to develop a goal recognition heuristic for recognizing goals in incomplete domain models. Our heuristic estimates the correct goal in the set of candidate goals by calculating the ratio between achieved *definite* ($\mathcal{AL}_G$), *possible* ($\widetilde{\mathcal{AL}}_G$), and *overlooked* ($\mathcal{ANL}_G$) landmarks and the amount of *definite* ($\mathcal{L}_G$), *possible* ($\widetilde{\mathcal{L}}_G$), and *overlooked* ($\mathcal{NL}_G$) landmarks. The estimate computed using Equation 1 represents the percentage of achieved landmarks for a candidate goal from observations.

$$h_{\widetilde{GC}}(G) = \left(\frac{\mathcal{AL}_G + \widetilde{\mathcal{AL}}_G + \mathcal{ANL}_G}{\mathcal{L}_G + \widetilde{\mathcal{L}}_G + \mathcal{NL}_G} \right) \quad (1)$$

[1] An achiever is an action at the level before a candidate landmark in the ORPG (or RPG) that can be used to achieve this candidate landmark.

2.4 Uniqueness Heuristic

Most goal recognition problems contain multiple candidate goals that share common fact landmarks, generating ambiguity that jeopardizes the goal completion heuristic. Clearly, landmarks that are common to multiple candidate goals are less useful for recognizing a goal than landmarks that exist for only a single goal. As a consequence, computing how unique (and thus informative) each landmark is can help disambiguate similar goals for a set of candidate goals. Our uniqueness heuristic is based on this intuition, using the concept of *landmark uniqueness*, which is the inverse frequency of a landmark among the landmarks found in a set of candidate goals. Intuitively, a landmark L that occurs only for a single goal within a set of candidate goals has the maximum uniqueness value of 1. We calculate the *landmark uniqueness value* for a landmark L and a set of landmarks for all candidate goals $K_{\mathcal{G}}$ using the following equation: $L_{Uniq}(L, K_{\mathcal{G}}) = \frac{1}{\sum\limits_{\mathcal{L} \in K_{\mathcal{G}}} |\{L | L \in \mathcal{L}\}|}$.

Using the concept of *landmark uniqueness value*, we estimate which candidate goal is the intended one by summing the uniqueness values of the landmarks achieved in the observations. Unlike our previous heuristic, which estimates progress towards goal completion by analyzing just the set of achieved landmarks, the landmark-based uniqueness heuristic estimates the goal completion of a candidate goal G by calculating the ratio between the sum of the uniqueness value of the achieved landmarks of G and the sum of the uniqueness value of all landmarks of a goal G. Our new uniqueness heuristic also uses the concepts of *definite*, *possible*, and *overlooked* landmarks. We store the set of *definite* and *possible* landmarks of a goal G separately into $\mathcal{L}_G$ and $\widetilde{\mathcal{L}}_G$, and the set of *overlooked* landmarks into $\mathcal{NL}_G$. Thus, the uniqueness heuristic effectively weighs the completion value of a goal by the informational value of a landmark so that unique landmarks have the highest weight. To estimate goal completion using the *landmark uniqueness value*, we calculate the uniqueness value for every extracted (*definite*, *possible*, and *overlooked*) landmark in the set of landmarks of the candidate goals using the equation we mentioned before. Since we use three types of landmarks and they are stored in three different sets, we compute the *landmark uniqueness value* separately for them, storing the uniqueness value of *definite* landmarks $\mathcal{L}_G$ into $\Upsilon_{\mathcal{L}}$, the landmark uniqueness value of *possible* landmarks $\widetilde{\mathcal{L}}_G$ into $\Upsilon_{\widetilde{\mathcal{L}}}$, and the landmark uniqueness value of *overlooked* landmarks $\mathcal{NL}_G$ into $\Upsilon_{\mathcal{NL}_G}$. Our uniqueness heuristic $h_{\widetilde{UNIQ}}$ is computed as follows:

$$h_{\widetilde{UNIQ}}(G) = \left(\frac{\sum\limits_{\mathcal{A}_L \in \mathcal{AL}_G} \Upsilon_{\mathcal{L}}(\mathcal{A}_L) + \sum\limits_{\widetilde{\mathcal{A}_L} \in \widetilde{\mathcal{AL}_G}} \Upsilon_{\widetilde{\mathcal{L}}}(\widetilde{\mathcal{A}_L}) + \sum\limits_{\mathcal{ANL} \in \mathcal{ANL}_G} \Upsilon_{\mathcal{NL}_G}(\mathcal{ANL})}{\sum\limits_{L \in \mathcal{L}_G} \Upsilon_{\mathcal{L}}(L) + \sum\limits_{\tilde{L} \in \widetilde{\mathcal{L}}_G} \Upsilon_{\widetilde{\mathcal{L}}}(\tilde{L}) + \sum\limits_{\mathcal{NL} \in \mathcal{NL}_G} \Upsilon_{\mathcal{NL}_G}(\mathcal{NL})} \right) \quad (3)$$

3 CONCLUSIONS

We have developed novel heuristics to goal recognition that deal with incomplete domains that have *possible*, rather than *known*, preconditions and effects. Recent approaches differ from ours in that they only deal with complete (even if modified) domain models, and most of them transform or compile the recognition problems into planning problems for a classical planner. Such transformation process may not necessarily work with incomplete domains, given the very large number of potential models.

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