Landmark-based Plan Recognition

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1 Introduction

As more computer systems require reasoning about what agents (both human and artificial) other than themselves are doing, the ability to accurately and efficiently recognize goals and plans from agent behavior becomes increasingly important. Plan recognition is the task of recognizing goals and plans based on often incomplete observations that include actions executed by agents and properties of agent behavior in an environment [10]. Accurate plan recognition is important to monitor and anticipate agent behavior, such as in crime detection and prevention, monitoring activities, and elderly care. Most plan recognition approaches [3, 1] employ plan libraries (i.e., a library with all plans for achieving a set of goals) to represent agent behavior, resulting in approaches to recognize plans that are analogous to language parsing. Recent work use planning domain definitions (domain theories) to represent potential agent behavior, bringing plan recognition closer to planning algorithms [8, 7, 6, 2].

In this paper, we develop a plan recognition approach that relies on planning landmarks [4] to filter candidate goals and plans from observations. Landmarks are properties (or actions) that every plan must satisfy (or execute) at some point in every plan execution to achieve a goal. In this way, we use this filtering algorithm in two settings. First, we build a landmark-based plan recognition heuristic that analyzes the amount of achieved landmarks to estimate the percentage of completion of each filtered candidate goal. Second, we show that the filter we develop can also be applied to other planning-based approaches, such as the approach from Ramírez and Geffner [8]. We evaluate our approach empirically against the current state-of-the-art [3] using their own datasets [8, 7, 6], and show that our approach has multiple advantages over existing approaches: it is more accurate than the state-of-the-art; it is substantially faster on its own; and it can also be used to speed up existing approaches [5].

2 Filtering Candidate Goals from Landmarks in Observations

Key to our approach to plan recognition is the ability to filter candidate goals based on the evidence of fact landmarks and partitioned facts in preconditions and effects of observed actions in a plan execution. This filtering process analyzes fact landmarks inferred from observed actions, and selects goals from a set of candidate goals with the highest number of observed landmarks having been achieved. We take as input a plan recognition problem $T_{PR}$, which is composed of a planning domain definition $\Xi$, an initial state $I$, a set of candidate goals $\mathcal{G}$, a set of observed actions $O$, and a filtering threshold $\theta$. The threshold gives us flexibility when dealing with incomplete observations and sub-optimal plans, which, when $\theta = 0$, may cause some potential goals to be filtered out before we get additional observations. Our algorithm iterates over the set of candidate goals $\mathcal{G}$, and, for each goal $g \in \mathcal{G}$, it extracts and classifies fact landmarks and partitions for $g$ from the initial state $I$. We then check whether the observed actions $O$ contain fact landmarks or partitioned facts of $g$ in either their preconditions or effects. As we deal with partial observations in a plan execution some executed actions may be missing from the observation, thus whenever we identify a fact landmark, we also infer that its predecessors have been achieved. Given the number of achieved fact landmarks of $g$, we estimate the percentage of fact landmarks that the observed actions $O$ have achieved according to the ratio between the amount of achieved fact landmarks and the total amount of landmarks. Finally, we return the goals from $\mathcal{G}$ with the highest percentage of achieved landmarks within threshold $\theta$.

3 Heuristic Plan Recognition using Landmarks

Our landmark-based heuristic method estimates the goal completion of every goal in the set of filtered goals. This estimate represents the percentage of sub-goals (atomic facts that are part of a conjunction of facts) in a goal that have been accomplished based on the evidence of achieved fact landmarks in observations. Our heuristic method estimates the percentage of completion towards a goal by using the set of achieved fact landmarks provided by the filtering process. We aggregate the percentage of completion of each sub-goal into an overall percentage of completion for all facts in a candidate goal. This heuristic, denoted as $h_{prl}$, is computed by Equation 1, where $\mathcal{AL}_g$ is the number of achieved landmarks from observations of every sub-goal $g$ of the candidate goal $G$, and $\mathcal{L}_g$ represents the number of necessary landmarks to achieve every sub-goal $g$. Thus, heuristic $h_{prl}(G)$ estimates the completion of a goal $G$ by calculating the ratio between the sum of the percentage of completion for every sub-goal $g \in G$, i.e., $\sum_{g \in G} \frac{|\mathcal{AL}_g|}{|\mathcal{L}_g|}$, and the number of sub-goals in $G$.

$$h_{prl}(G) = \left(\frac{\sum_{g \in G} |\mathcal{AL}_g|}{\sum_{g \in G} |\mathcal{L}_g|}\right)$$

4 Landmark-based Plan Recognition

Our plan recognition approach is detailed in Algorithm [1] which takes as input a plan recognition problem $T_{PR}$, and works in two stages. First, this algorithm filters candidate goals using the filtering process, which returns the candidate goals with the highest percentage of achieved landmarks within a given threshold $\theta$. Second, from the filtered candidates, this algorithm then uses $h_{prl}$ to return the recognized goals by estimating the percentage of completion using the set of achieved fact landmarks provided by the filter.
Landmarks provide key information about what cannot be avoided to achieve a goal, and we show that landmarks can be used efficiently for very accurate plan recognition. We have shown empirically that our approach yields not only superior accuracy results but also substantially faster recognition times for all domains used in evaluating against the state of the art [8] at varying observation levels.

There are multiple avenues for future work, such as: evaluating heuristics and symmetries in classical planning [2]; other landmark extraction techniques [3]; adding a probability interpretation to the observed landmarks and comparing to a recent work [2]; and account for information gain over multiple competing plan hypotheses.

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**REFERENCES**


Table 1: Comparison and experimental results of our landmark-based approach against Ramírez and Geffner [8] approach. R&G denotes their plan recognition approach and Filter + R&G denotes the same approach but using our filtering algorithm.

| Domain            | |G| | |L| | %Obs | |O| | Time | Accuracy | Time | Accuracy |
|-------------------|------------------|--------|------------------|-------------|------------------|--------|------------------|--------------|------------------|--------|------------------|----------|
| BLOCKS-WORLD      | 20               | 10     | 2                | 0.0%       | 100.0%           | 105     | 2                | 0.0%       | 100.0%           | 105     | 2                | 100.0%   | 100.0%           |
| (855)             |                  |        |                  |            |                  |        |                  |            |                  |        |                  |          |                  |
| CAMPUS            | 2                | 8.5    | 1                | 0.0%       | 100.0%           | 105     | 2                | 0.0%       | 100.0%           | 105     | 2                | 100.0%   | 100.0%           |
| (75)              |                  |        |                  |            |                  |        |                  |            |                  |        |                  |          |                  |
| EAST-UP-Campus    | 7.5              | 11.3   | 1                | 0.0%       | 100.0%           | 105     | 2                | 0.0%       | 100.0%           | 105     | 2                | 100.0%   | 100.0%           |
| (465)             |                  |        |                  |            |                  |        |                  |            |                  |        |                  |          |                  |
| INTRUSION-DETECTION | 15              | 16     | 1                | 0.0%       | 100.0%           | 105     | 2                | 0.0%       | 100.0%           | 105     | 2                | 100.0%   | 100.0%           |
| (465)             |                  |        |                  |            |                  |        |                  |            |                  |        |                  |          |                  |
| KITCHEN           | 3                | 5      | 1                | 0.0%       | 100.0%           | 105     | 2                | 0.0%       | 100.0%           | 105     | 2                | 100.0%   | 100.0%           |
| (75)              |                  |        |                  |            |                  |        |                  |            |                  |        |                  |          |                  |
| LOGISTICS         | 10               | 18.7   | 1                | 0.0%       | 100.0%           | 105     | 2                | 0.0%       | 100.0%           | 105     | 2                | 100.0%   | 100.0%           |
| (465)             |                  |        |                  |            |                  |        |                  |            |                  |        |                  |          |                  |

Algorithm 1 Recognize goals and plans using the filtering method and the landmark-based heuristic.

Input: \( \Xi = (\Sigma, A) \) planning domain, \( I \) initial state, \( G \) set of candidate goals, \( O \) observations, and \( \theta \) threshold.

Output: Recognized goal(s).

1: \( \text{function \textsc{recognize}}(\Xi, I, G, O, \theta) \)
2: \( \Lambda_G := \emptyset \rightarrow \text{Map goals to \% of landmarks achieved.} \)
3: \( \text{\textsc{filterCandidateGoals}}(\Xi, I, G, O, \theta) \)
4: \( \text{return arg max}_{G \in \Lambda_G} h_{\text{prl}}(G) \)