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 plan recognition approaches, such as the approach from Ramírez and Geffner [8]. We evaluate our approach empirically against the current state-of-the-art [8] using their own datasets [8, 7], 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. A complete discussion of our plan recognition approach and experiments is provided in the full paper.

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. Our 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 \( G \), 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 \( G \) and, for each goal \( g \) in \( G \), it extracts and classifies fact landmarks and partitions for \( g \) from the initial state \( I \). Then we 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 \( G \) with the highest percentage of achieved landmarks within threshold \( \theta \).

3 Heuristic Plan Recognition using Landmarks

We now develop a landmark-based heuristic method that 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 \( \mathcal{L}_g \) 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 \( g \) of \( G \). 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., \( \sum_{g \in G} \frac{|\mathcal{L}_g|}{|\mathcal{L}_g|} \), and the number of sub-goals in \( G \).

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

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
of Ramírez and Geffner [8] on its own, and this approach combined
the correct hidden goal (of observability). We use two metrics, the accuracy of recognizing
ent filtering thresholds (0%, 10%, 20% and 30%). If threshold
with our filter. More specifically, we use their faster and most accu-

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

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

Output: Recognized goal(s).

1. function \( \text{recognize}(\Xi, I, \mathcal{G}, O, \theta) \) \( \triangleright \) Map goals to % of landmarks achieved.
2. \( \mathcal{G} := \{ \mathcal{G} \} \) and \( \mathcal{G} := \text{FILTERCANDIDATEGOALS}(\Xi, I, \mathcal{G}, O, \theta) \)
3. return \( \arg \max_{G \in \mathcal{G}} h_{prl}(G) \)

The filtered candidates, this algorithm then uses \( h_{prl} \) to return the rec-
ognized goals by estimating the percentage of completion using the
set of achieved fact landmarks provided by the filtering process.

Table 1 shows the result of our experiments, which uses six do-
main datasets provided by Ramírez and Geffner [8, 7], com-
prising hundreds of plan recognition problems, i.e., a domain descrip-
tion, an initial state, a set of candidate goals \( \mathcal{G} \), a hidden goal \( G \) in
\( \mathcal{G} \), and an observation sequence \( O \) (10%, 30%, 50%, 70%, or 100%
of observability). We use two metrics, the accuracy of recognizing
the correct hidden goal \( G \) in \( \mathcal{G} \) and the speed to recognize a goal,
and compare our approach to two other approaches: the approach
of Ramírez and Geffner [8] on its own, and this approach combined
with our filter. More specifically, we use their fastest and most ac-
curate approach. For our approach, we show the accuracy under
different filtering thresholds (0%, 10%, 20% and 30%). If threshold \( \theta = 0 \),
our approach gives no flexibility for filtering candidate goals, return-
ning only the goals with the highest percentage of achieved landmarks.
Each row of this table shows the observability (% Obs) and averages
of the number of candidate goals \( |G| \), the number of observed actions
\( |O| \), recognition time (seconds), and accuracy. We can see from the
table that our approach is both faster and more accurate than Ramírez
and Geffner [8], and, when we combine their algorithm with our fil-
ter, the resulting approach gets a substantial speedup.

5 Conclusion

We have developed an approach for plan recognition that relies on
planning landmarks and a new heuristic based on these landmarks.

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 sub-
stantially 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 [9]; other landmark
extraction techniques [5]; 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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