Sequential Plan Recognition
(Extended Abstract)

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ABSTRACT

Plan recognition algorithms need to maintain all candidate hypotheses which are consistent with the observations, even though there is only a single hypothesis that is the correct one. Unfortunately, the number of possible hypotheses can be exponentially large in practice. This paper addresses the problem of how to disambiguate between many possible hypotheses that are all consistent with the actions of the observed agent. One way to reduce the number of hypotheses is to consult a domain expert or the acting agent directly about its intentions. This process can be performed sequentially, updating the set of hypotheses during the recognition process. The paper specifically addresses the problem of how to minimize the number of queries made that are required to find the correct hypothesis. It adapts a number of probing techniques for choosing which plan to query, such as maximal information gain and maximum likelihood. These approaches were evaluated on a domain from the literature using a well known plan recognition algorithm. The results showed that the information gain approach was able to find the correct plan using significantly fewer queries than the maximum likelihood approach as well as a baseline approach choosing random plans. Our technique can inform the design of future plan recognition systems that interleave the recognition process with intelligent interventions of their users.

Keywords

Plan Recognition; Activity Recognition; Human-Aware AI

1. INTRODUCTION

Plan recognition, the task of inferring agents' plans based on their observed actions, is a fundamental problem in AI, with a broad range of applications, such as advising in health care [1], or recognizing activities in gaming and educational software [4]. Many real world domains are ambiguous, in the sense that there are many possible hypotheses that are consistent with an observed agent's activities. Consider for example an e-learning software for chemistry education. Students' interactions in the lab consist of building models of chemical reactions, running the models, and analyzing the results. There can be many possible solution strategies that students can use to solve problems, and variations within each due to exploratory activities and mistakes carried out by the student. Given a set of actions performed by the student, one hypothesis may relate a given action to the solution of the problem, while another may relate this action to a failed attempt or a mistake. In general, the size of the hypothesis space can be very large. We focus on domains in which agents may pursue several goals at the same time. Thus a hypothesis includes a set of plans, one for each goal that the agent is pursuing.

In many domains it is possible to query the observed agent itself or a domain expert about certain aspects of the correct hypothesis. The query can be performed in real time (for example, the student may be asked about her solution strategy to a problem during her interaction with educational software), or offline after all observations were collected (for example, a system administrator observing suspicious behavior that can ask a cyber security expert for her opinion of these actions). Answers for such queries allow to reduce the set of possible hypotheses in a way that does not impede the completeness of the recognition process. Our approach is to query whether a given plan in one of the hypotheses is correct, and update all hypotheses in which this plan appears (or does not appear, depending on the answer to the query).

We evaluated these approaches in several domains from the plan recognition literature. We considered candidate plans to query that maximize the information gain as well as the likelihood of the resulting hypotheses given the expected query result. These approaches significantly decreased the number of queries compared to a baseline technique. In addition, once the number of hypotheses is large enough, the number of queries performed by the information-gain approach was significantly smaller than the other approaches. The potential impact of this work is to show how existing recognition systems can be extended to disambiguate the hypothesis space by intelligently querying their potential users in a way that minimizes the disruption and overhead.

2. SEQUENTIAL PLAN RECOGNITION

We define the sequential plan recognition process (SPRP) as a process with two stages: First, a plan recognizer receives a set of observations and returns a set of hypotheses that describe the observations. Second, the query process receives the set of hypotheses as input and sequentially chooses a plan p from the hypotheses set, to query whether it is part of the agent's plans. According to the answer of the query,

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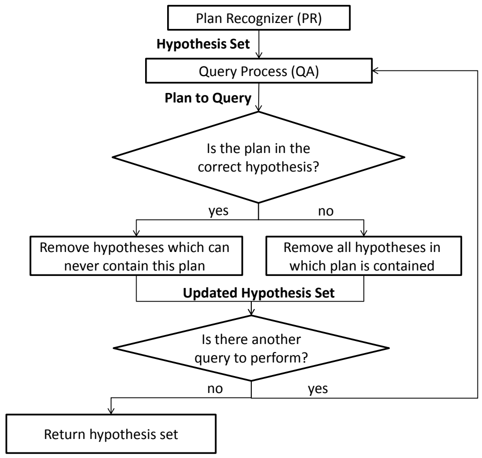

Figure 1: The SPRP Process

the set of hypotheses needs to be updated.

Querying about p means that we wish to know if the agent is executing a set of plans that include p. In SPRP, querying about p might also return True if p is a partial plan in the agent's set: $QA(p)$=True if there exists a plan p' in the agent's true set of plans such that p can be extended to p' if the agent executes additional actions. Accordingly, if the result of the query is True, we cannot discard all hypotheses that do not contain p, but only those which will never contain p, no matter what future actions will be taken. Similarly, if a query about p returns False, we can discard all plans that equal to p or extend it.

The query process continues until there are no more plans to query about in the remaining hypotheses set. The complete SPRP process is described in Figure 1.

Using SPRP, we can define the *sequential plan recognition problem*: how to minimize the set of queries required to reach the correct hypothesis.

We propose several heuristic methods for generating a policy that aim to minimize the number of queries required to achieve the minimal set of hypotheses that are consistent with the observations. These methods rely on the standard assumption that each hypothesis h is associated with a probability $P(h)$ that is assigned by the PR (such as PHATT [2]).

Most Probable Hypothesis (MPH). Choose a plan from the hypothesis h that is associated with the highest probability and was not yet queried about.

Most Probable Plan (MPP). Choose the plan that is associated with the highest cumulative probability across all hypotheses: $\text{argmax}_{t \in T} P(t)$, where T is the union set of all plans in all of the hypotheses H, and $P(t)$ denotes the cumulative probability assigned to all hypotheses that contain the plan t.

Minimal Entropy. Choose the plan with the maximal information gain (or minimal entropy) given the resulting hypothesis set.

We show an evaluation of the probing approach on the simulated domain used by Kabanza et al. [3]. This domain includes 100 instances with a fixed number of actions, 10 identified goals, and a branching factor of 3 for rules in the grammar. We used the Most Probable Plan (MPP), the Most Probable Hypothesis (MPH) and the Minimal Entropy (Entropy) approaches, as well as a baseline approach that picked a tree to query at random. For the plan recognition process, we used the PHATT algorithm [2].

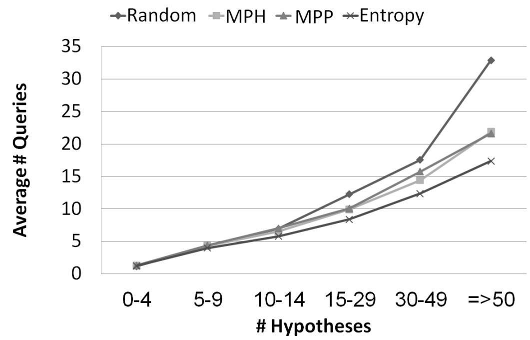

Figure 2: Queries until convergence given explanations for simulated domain

Figure 2 shows the average number of queries until converging to the single correct hypothesis in both of the domains, as a function of the number of hypotheses. As shown by the figure, in both domains, the random baseline generated significantly more queries than did the other approaches.

In particular, the number of queries needed for convergence grew exponentially for the random approach in the VirtualLabs domain. At first there is not enough ambiguity between the different explanations to make the insights from the queries useful, thus no method is significantly better than the others. As we increase the number of hypotheses, we see a difference between the more informed query approaches. As shown by the figure, although there is a monotonous increase in the number of queries required by all approaches, the growth rate of the Entropy query approach is the smallest. In total, the number of queries that were generated by the Entropy approach were significantly less than the number of queries generated by the MPP and MPH approaches (two-sided t-test $p < 0.05$).

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