HOKAGE: A Heuristic Lifted Planning Algorithm for Generating Diverse Generalized Plans

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Abstract

This paper describes HOKAGE, a new planning algorithm that performs lifted (*i.e.*., grounding on the fly during planning and heuristic computations) search for generating solution plans. In doing so, unlike existing heuristic search algorithms, HOKAGE is able to perform arbitrary numeric reasoning during planning and can plan for mixed propositional and numeric goals (i.e., the truck needs to be at a particular location at any time less than 0900 hours). HOKAGE also generates generalized plans with limited looping structures. HOKAGE also is designed to generate diverse generalized plans, including looping, that are interestingly different. We are currently designing and developing HOKAGE and this paper provides a summary of our ongoing work.

Introduction

Over the years, there have been great strides in automated planning algorithms and planning heuristics that enable those algorithms to find high-quality plans very quickly [*e.g.*.](Gerevini, Saetti, and Serina 2003; Helmert 2006; Hoffmann and Nebel 2001). With a planning domain definition and problems as input, which are typically described in a form of PDDL, most of these methods first generate a fully-instantiated (ground) variant of those descriptions, typically amalgamating properties of domain definitions and relations with those in the particular planning problems and thereby creating symbolic but efficient data structures for heuristic search. Although this approach has been shown to be very effective and scalable in planning benchmarks, it is very limited in practical applications because of the *a priori* grounding schemes used and the limited expressivity those schemes require.

On the other hand, several early planners (*e.g.*., SNLP (McAllester and Rosenblitt 1991), SHOP2 (Nau et al. 2003), UCPOP (Penberthy and Weld 1992)) did not require such *a priori* grounding. Although these planners lacked the most recent and successful planning heuristics, they were able to instantiate planning models, control knowledge, and variables on the fly during the course of the planning process. By doing so, such lifted planners do not require to enumerate all possible objects or constant symbols in the problem definition. Among many, one of the benefits of this is that a planner can perform arbitrary numeric reasoning during because it can use the planning state during search as a database as it grounds variables in relevant contexts only.

HOKAGE is a new approach that aims to combine the benefits of both modern heuristic search methods and earlier lifted planning techniques. The following subsections discuss the benefits of this approach.

Lifted heuristic planning

HOKAGE uses a lifted relaxed planning graph method (an earlier lifted planning graph was in McDermott's PEDESTAL planner (McDermott 1991)) as a heuristic computation in a best-first search algorithm to generate heuristically-good plans. Starting from the initial state of an input planning problem, HOKAGE uses its lifted relaxed planning graph heuristic to compute heuristic values for all applicable actions in that state. First HOKAGE creates a state level in the relaxed planning graph from the facts of the initial state. HOKAGE is built on SHOP2's generalized automated theorem prover (Nau et al. 2003),[1] which provides Prolog-like functionality to identify the planning operators that are applicable in a state and generate ground instantiations of those planning operators as actions for a plan. HOKAGE uses the same theorem-proving expressivity and capabilities as SHOP2 and generates the subsequent action and state levels of the relaxed planning graph, until the goals of the planning problem can be satisfied. Once the relaxed planning graph is unfolded this way, the algorithm uses the same techniques for the heuristic values for every applicable action in the first state level of the graph. The planner then greedily chooses the action that has the highest heuristic value and the search continues with the subsequent state that arises by applying that action in the current state.

Numerical reasoning

These localized instantiations in HOKAGE during heuristic computation allow both the planner and the heuristic to evaluate arbitrary numeric formulas and computation in the preconditions or effects of the action. For example, the following shows a planning operator, using SHOP2's domain

[1] SIFT researchers have generalized this theorem-prover and made it available as an independent library for use outside the SHOP2 planner.

definition language, that models how a vehicle slows down given the weather effects:

```
(:op (!slow-down ?vehicle ?orig-eta)
 :precond ((monitor-eta ?vehicle ?orig-eta)
     (weather-impact ?vehicle ?force)
   (assign ?delay (/ ?force 10.0))
   (assign ?new-eta
    (+ ?orig-eta ?delay)))
 :delete ((monitor-eta ?vehicle ?orig-eta))
 :add ((monitor-eta ?vehicle ?new-eta)))
```

This operator computes the delay as a function of the forces exerted by the weather event on the vehicle. It also computes the new estimated time of arrival for the vehicle at its destination based on that delay. With the new information, the planning operator updates the state of the world.

Generating diverse plans

Unlike many existing approaches that are designed to generate the first good solution heuristically very fast, HOKAGE is designed to generate many diverse solutions to an input planning problem. We use a plan-adaptation approach as in the LPG-d diverse planner (Nguyen et al. 2012); once HOKAGE generates the first heuristic plan, it uses local-search to continually adapt it to find for new different plans.

The algorithm first selects a plan from the pool of solutions it has generated so far as the candidate plan for adaptation. Note that since HOKAGE always generates a first heuristically-good solution to the planning problem, there is always an opportunity for diverse planning (if the problem is solvable). Then, the algorithm selects a point in the plan and adapts the postfix of the plan from that point on. In our current implementation, both the candidate plan and the adaptation point are chosen randomly during local search.

Aside from this initial implementation, generating diverse plans, and comparing different approaches to doing so requires a domain-independent, theoretically motivated definition of the diversity (distance) between plans. Previously proposed diversity measures are not theoretically motivated, provide inconsistent results on the same plan sets, and suffer from a number of pathologies. As next steps beyond HOKAGE's current random selections for diverse search, we plan to incorporate our previous work on plan-to-plan distance measure that we developed based on compression theory and Kolmogorov complexity (Goldman and Kuter 2015). In that work, we defined the diversity of plans in terms of how surprising one plan is given another or, its inverse, the conditional information in one plan given another. Kolmogorov complexity provides a domain independent theory of conditional information. While Kolmogorov complexity is not computable, a related metric, Normalized Compression Distance (NCD), provides a well-behaved approximation. In our previous paper, we exhibited a number of pathological cases we have found in existing diversity measures, introduced NCD as an alternative diversity metric, and demonstrated that NCD does not admit those pathologies and that it provides better diversity information. We plan to investigate how NCD could be used incorporated in the heuristic selection mechanism of diverse planning: in our previous work it was only used as a plan comparison metric.

Plans with looping behavior

Diverse planning has been typically explored in existing works on classical plans, i.e., sequences of actions, including our previous works. However, in many practical applications plans involve repeating actions or plan segments in which some of the action parameters remain the same and some change, until some subgoaling criterion is achieved. Such repeating actions or action subsequences constitute looping behavior. When plans do not capture that structure, they are typically excessively long, are not efficiently constructed by existing planners. In addition, existing measures of plan diversity do not take repeated structure into account in their assessments of how different plans are.

HOKAGE implements our first step to address this issue. In particular, HOKAGE analyzes plans generated heuristically and attempts to identify looping behaviors in them. For example, the following is an example generated by the planner in our weather scenario:

```
((!CLOUD-COVER-FORMED CLOUD-COVER
  ;; Latitude and longitude
  356536189N 1177322804W
  3000) ; Altitude
 (:LOOP
   (:FOR ?LOOPVAR120995)
   (:FROM 1500) ;; time
   (:TO 1515.0)
   (:DO
    ((!SLOW-DOWN UAV-1 ?LOOPVAR120995)))))
```

The above plan shows a weather event with cloud cover forming at a particular location and causing delay to a UAV in that location, over a certain time. A classical plan represents this plan with a series of SLOW-DOWN actions whereas it's really a looping behavior. Our work here is similar to Srivastava, *et al.*. (2008), however, HOKAGE like most planners, aims to solve individual planning problems, rather than generalize plans to cover multiple situations.

From a diverse planning perspective, different timelines that could be exhibited by these kinds of plans could generate different lengths of actions. In our opinion, that should not impact the diversity of the plans because in all of those cases, the looping behavior and characteristics will be the same in the plans. Our intent for HOKAGE is to fully take the generalized plan structures into account during diverse planning semantically and theoretically.

Conclusions and Ongoing Work

Our work with the HOKAGE system is just beginning. HOKAGE is fully implemented, but we continue to work to improve it. We are also working to provide a formal characterization of the class of problems that HOKAGE can solve. After this process has been completed, we will begin conducting experiments to probe HOKAGE's efficiency.

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