Learning Plan Rewriting Rules

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Abstract

Planning by Rewriting (PbR) is a new paradigm for efficient high-quality planning that exploits plan rewriting rules and efficient local search techniques to transform an easy-to-generate, but possibly suboptimal, initial plan into a high-quality plan. Despite the advantages of PbR in terms of scalability, plan quality, and anytime behavior, PbR requires the user to define a set of domain-specific plan rewriting rules which can be difficult and time-consuming. This paper presents an approach to automatically learning the plan rewriting rules based on comparing initial and optimal plans. We report results for several planning domains showing that the learned rules are competitive with manually-specified ones, and in several cases the learning algorithm discovered novel rewriting rules.

Introduction

Planning by Rewriting (PbR) (Ambite & Knoblock 1997; 1998; Ambite 1998) is a planning framework that has shown better scalability than other domain-independent approaches. In addition, PbR works with complex models of plan quality and has an anytime behavior. The basic idea of PbR is to first generate a possibly suboptimal initial plan, and then, iteratively rewrite the current plan using a set of declarative plan rewriting rules (until its quality is acceptable or some resource limit is reached).

Despite the advantages of PbR, the framework requires more inputs from the designer than other approaches. In addition to the operator specification, initial state, and goal that domain-independent planners take as input, PbR also requires an initial plan generator, a set of plan rewriting rules, and a search strategy (see Figure 1(a)). Although the plan rewriting rules can be conveniently specified in a high-level declarative language, designing and selecting which rules are the most appropriate requires a thorough understanding of the properties of the planning domain and requires the most effort by the designer. In this paper we address this limitation by providing a method for learning the rewriting rules from examples. The main idea is to solve a set of training problems for the planning domain using both the initial plan generator and an optimal planner. Then, the system compares the initial and optimal plan and hypothesizes a rewriting rule that would transform one into the other. An schematic of the resulting system is shown in Figure 1(b). Some ideas on automating the other inputs are discussed in the future work section.

The paper is organized as follows. First, we briefly review the Planning by Rewriting paradigm. Second, we present our approach to learning plan rewriting rules from examples. Third, we show empirical results in several domains. Finally, we discuss related work, future work, and conclusions.

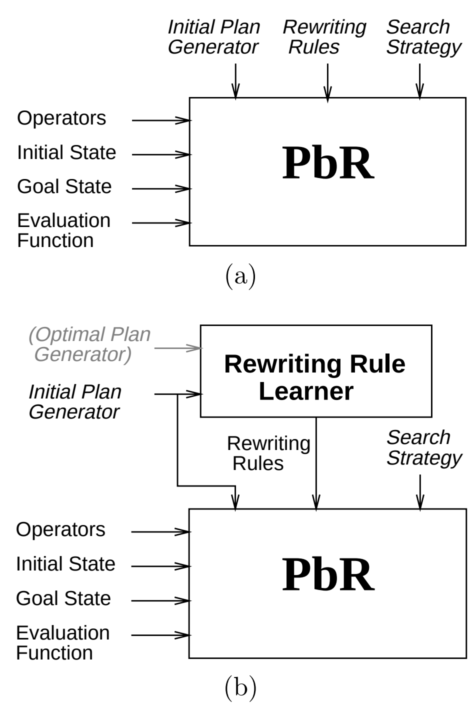


Figure 1: Basic PbR (a) and PbR with Rewriting Rule Learning (b)

Review of Planning by Rewriting

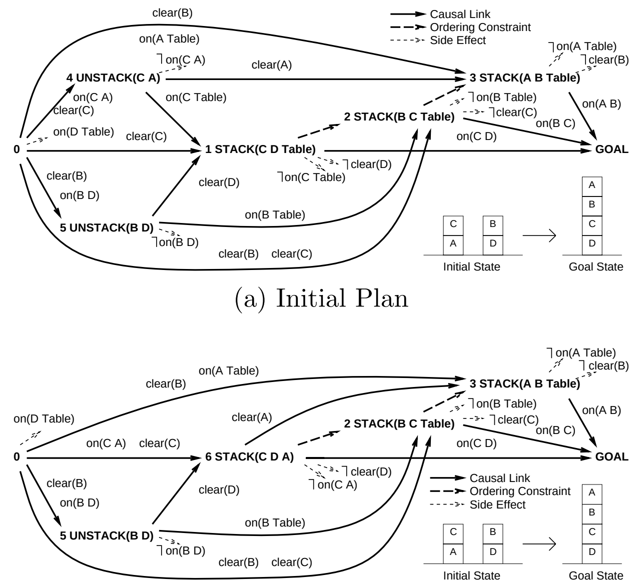
Planning by Rewriting is a local search method (Aarts & Lenstra 1997; Papadimitriou & Steiglitz 1982) for domain-independent plan optimization. A brief summary of the main issues follows (see (Ambite 1998) for a detailed description):

- *Efficient generation of an initial solution plan.* In many domains obtaining a possibly suboptimal initial plan is easy. For example, in the Blocks World it is straightforward to generate a solution in linear time using the naive algorithm: put all blocks on the table and build the desired towers from the bottom up (like the plan in Figure 3(a)).
- *Definition and application of the plan rewriting rules.* The user (or a learning algorithm) specifies the appropriate rewriting rules for a domain in a simple declarative rule definition language. These rules are matched against the current plan and generate new transformed plans of possibly better quality.
- *Plan quality measure.* This is the plan cost function of the application domain which is optimized during the rewriting process.
- *Searching of the space of rewritings.* There are many possible ways of searching the space of rewritten plans, for example, gradient descent, simulated annealing, etc.

In Planning by Rewriting a plan is represented by a graph, in the spirit of partial-order causal-link planners such as UCPOP (Penberthy & Weld 1992). The nodes are domain actions. The edges specify a temporal ordering relation among nodes, imposed by causal links and ordering constraints. The operator definition language of PbR is the same as that of Sage (Knoblock 1995), which adds resources and run-time variables to UCPOP. Figure 2 shows the specification of a simple Blocks World planning domain. Two sample plans using this domain appear in Figure 3.

```
(define (operator stack)
  :parameters (?X ?Y ?Z)
  :precondition
    (:and (on ?X ?Z) (clear ?X) (clear ?Y)
          (:neq ?Y ?Z) (:neq ?X ?Z) (:neq ?X ?Y)
          (:neq ?X Table) (:neq ?Y Table))
  :effect (:and (on ?X ?Y) (:not (on ?X ?Z))
                (clear ?Z) (:not (clear ?Y))))

(define (operator unstack)
  :parameters (?X ?Y)
  :precondition
    (:and (on ?X ?Y) (clear ?X) (:neq ?X ?Y)
          (:neq ?X Table) (:neq ?Y Table))
  :effect (:and (on ?X Table) (:not (on ?X ?Y))
                (clear ?Y)))
```

Figure 2: Planning Operators Specification



(a) Initial Plan

(b) Optimal Plan

Figure 3: PbR Plans

A plan rewriting rule specifies declaratively the replacement under certain conditions of a subplan by another subplan. These rules are intended to improve the quality of the plans. Plan rewriting rules arise from algebraic properties of the operators in a planning domain. For example, a rule may state that two subplans are equivalent for the purposes of achieving some goals, but one of the subplans is preferred. Figure 4 shows two rules for the Blocks World domain of Figure 2. Intuitively, the `avoid-move-twice` rule says that it is preferable to stack a block on top of another directly, rather than first moving it to the table. Similarly, the `avoid-undo` rule states that moving a block to the table and immediately putting it back to where it was originally is useless, and thus if two such steps appear in a plan, they can be removed. The application of the `avoid-move-twice` rule to the plan in Figure 3(a) produces the plan in Figure 3(b) (steps `4` and `1` are replaced by step `6`; `?b1 = C`, `?b2 = A`, `?b3 = D`).

PbR has been successfully applied to several planning domains, including query planning in mediators (Ambite & Knoblock 1998), but for clarity of exposition we will use examples from the Blocks World domain of Figure 2 throughout the paper. In the experimental results section we provide learning and performance results for the Blocks World, a process manufacturing domain, and a transportation logistics domain.

Learning Plan Rewriting Rules

In this section we describe our algorithms for proposing plan rewriting rules and for converging on a set of useful rewriting rules.

```
(define-rule :name avoid-move-twice
  :if (:operators ((?n1 (unstack ?b1 ?b2))
                   (?n2 (stack ?b1 ?b3 Table)))
       :links (?n1 (on ?b1 Table) ?n2)
       :constraints ((possibly-adjacent ?n1 ?n2)
                     (:neq ?b2 ?b3)))
  :replace (:operators (?n1 ?n2))
  :with (:operators (?n3 (stack ?b1 ?b3 ?b2))))

(define-rule :name avoid-undo
  :if (:operators ((?n1 (unstack ?b1 ?b2))
                   (?n2 (stack ?b1 ?b2 Table)))
       :constraints ((possibly-adjacent ?n1 ?n2))
  :replace (:operators (?n1 ?n2))
  :with nil))
```

Figure 4: Rewriting Rules (Blocks World)

Rule Generation

The main assumption of our learning algorithm is that useful rewriting rules are of relatively small size (measured as the number of nodes and edges in the rule). If a domain requires large rewriting rules, it is probably not a good candidate for a local search, iterative repair algorithm such as PbR. Previous research also lends support for biases that favor conciseness (Minton & Underwood 1994). The rule generation algorithm follows these steps:

1. Problem Generation. To start the process, our algorithm needs a set of training problems for the planning domain. The choice of training problems determines the rules learned. Ideally, we would like problems drawn from the target problem distribution that generate plans gradually increasing in size (i.e., number of plan steps) in order to learn the smallest rewriting rules first. Towards this end we have explored two heuristics, based on a random problem generator, that work well in practice. For some domains the size of the plans can be controlled accurately by the number of goals. Thus, our system generates sets of problems increasing the number of goals up to a given goal size. For each goal size the system generates a number of random problems. We used this heuristic in our experiments. An alternative strategy is to generate a large number of problems with different goal sizes, sort the resulting plans by increasing size, and select the first N to be the training set.

2. Initial Plan Generation. For each domain, we define an initial plan generator. For example, the plan in Figure 3(a) was generated by putting all blocks on the table and building the desired towers from the bottom up. How to obtain in general such initial plan generators is beyond the scope of this paper, but see the discussion in the future work section and in (Ambite 1998) for some approaches.

3. Optimal Plan Generation. Our algorithm uses a general purpose planner performing a complete search according to the given cost metric to find the optimal plan. This is feasible only because the training problems are small; otherwise, the search space of the complete planner would explode. In our implementation we have used IPP (Koehler *et al.* 1997) and Sage (Knoblock 1995) as the optimal planners. Figure 3(b) shows the optimal plan for the problem in Figure 3(a).

4. Plan Comparison. Both the initial and optimal plans are ground labeled graphs (see Figure 3). Our algorithm performs graph differences between the initial and the optimal plans to identify nodes and edges present in only one of the plans. Formally, an intersection graph G_i of two graphs G_1 and G_2 is a maximal subgraph isomorphism between G_1 and G_2. If in a graph there are nodes with identical labels, there may be several intersection graphs. Given a graph intersection G_i, a graph difference $G_1 - G_2$ is the subgraph of G_1 whose nodes and edges are not in G_i.[1] In the example in Figure 3, the graph difference between the initial and the optimal plans, $G_{ini} - G_{opt}$, is the graph formed by the nodes: `unstack(C A)` and `stack(C D Table)`; and the edges: `(0 clear(C) 1)`, `(0 clear(C) 4)`, `(0 on(C A) 4)`, `(1 on(C D) Goal)`, `(4 clear(A) 3)`, `(4 on(C Table) 1)`, `(5 clear(D) 1)`, and `(1 2)`. Similarly, $G_{opt} - G_{ini}$ is formed by the nodes: `stack(C D A)`, and the edges: `(6 clear(A) 3)`, `(5 clear(D) 6)`, `(0 clear(C) 6)`, `(0 on(C A) 6)`, `(6 on(C D) Goal)`, and `(6 2)`.

5. Ground Rule Generation. After the plan comparison, the nodes and edges present only in the initial plan form the basis for the antecedent of the rule, and those present only in the optimal plan form the basis for the consequent. In order to maximize the applicability of the rule, not all the differences in nodes and edges of the respective graphs are included. Specifically, if there are nodes in the difference, only the edges internal to those nodes are included in the rule. This amounts to removing from consideration the edges that link the nodes to the rest of the plan. In other words, we are generating partially-specified rules.[2] In our example, the antecedent nodes are `unstack(C A)`

[1] Our implementation performs a simple but efficient approximation to graph difference. It simply computes the *set* difference on the set of labels of nodes (i.e., the ground actions) and on the "labeled" edges (i.e., the causal or ordering links with each node identifier substituted by the corresponding node action).

[2] A partially-specified rule (Ambite 1998) states only the most significant aspects of a transformation, as opposed to the fully-specified rules typical of graph rewriting systems. The PbR rewriting engine fills in the details and checks for plan validity. If a rule is overly general, it may fail to produce a rewriting for a plan that matches the rule's antecedent, but it would never produce an invalid plan.

(node 4) and `stack(C D Table)` (node 1). Therefore, the only internal edge is `(4 on(C Table) 1)`. This edge is included in the rule antecedent and the other edges are ignored. As the consequent is composed of only one node, there are no internal edges. Rule `bw-1-ground` in Figure 5 is the ground rule proposed from the plans of Figure 3.

If there are only edge (ordering or causal link) differences between the antecedent and the consequent, a rule including only edge specifications may be overly general. To provide some context for the application of the rule our algorithm includes in the antecedent specification those nodes participating in the differing edges (see rule `sc-14` in Figure 9 for an example).

The algorithm for proposing ground rules described in the preceding paragraphs is one point in a continuum from fully-specified rules towards more partially-specified rules. The main issue is that of context. In the discussion section we expand on how context affects the usefulness of the rewriting rules.

6. Rule Generalization. Our algorithm generalizes the ground rule conservatively by replacing constants by variables, except when the schemas of the operators logically imply a constant in some position of a predicate (similarly to EBL (Minton 1988)). Rule `bw-1-generalized` in Figure 5 is the generalization of rule `bw-1-ground` which was learned from the plans of Figure 3. The constant `Table` remains in the `bw-1-generalized` rule as is it imposed by the effects of `unstack` (see Figure 2).

```
(define-rule :name bw-1-ground
 :if (:operators ((?n1 (unstack C A))
                  (?n2 (stack C D Table)))
      :links (?n1 (on C Table) ?n2))
 :replace (:operators (?n1 ?n2))
 :with (:operators (?n3 (stack C D A))))

(define-rule :name bw-1-generalized
 :if (:operators ((?n1 (unstack ?b1 ?b2))
                  (?n2 (stack ?b1 ?b3 Table)))
      :links (?n1 (on ?b1 Table) ?n2))
 :replace (:operators (?n1 ?n2))
 :with (:operators (?n3 (stack ?b1 ?b3 ?b2))))
```

Figure 5: Ground vs. Generalized Rewriting Rules

Biasing towards Small Rules

There may be a large number of differences between an initial and an optimal plan. These differences are often better understood and explained as a sequence of small rewritings than as the application of a large monolithic rewriting. Therefore, in order to converge to a set of small "primitive" rewriting rules, our system applies the algorithm in Figure 6.

The main ideas behind the algorithm are to identify the smallest rule first and to simplify the current plans before learning additional rules. First, the algorithm generates initial and optimal plans for a set of sample problems. Then, it enters a loop that brings the initial plans increasingly closer to the optimal plans. The crucial steps are 6 and 3. In step 6 the smallest rewriting rule (`r`) is chosen first.[3] This rule is applied to each of the current plans. If it improves the quality of some plan, the rule enters the set of learned rules (`L`). Otherwise, the algorithm tries the next smallest rule in the current generation. Step 3 applies all previously learned rules to the current initial plans in order to simplify the plans as much as possible before starting a new generation of rule learning. This helps in generating new rules that are small and that do not subsume a previously learned rule. The algorithm terminates when no more cost-improving rules can be found.

```
Converge-to-Small-Rules:
1.  Generate a set of sample problems (P),
      initial plans (I), and optimal plans (O).
2.  Initialize the current plans (C)
      to the initial plans (I).
3.  Apply previously learned rules (L) to C
      (L is initially empty).
4.  Propose rewriting rules (R) for pairs of
      current initial (C) and optimal (O) plans
      (if their cost differ).
5.  If no cost-improving rules, Then Go to 10.
6.  S := Order the rules (R) by size.
7.  Extract the smallest rule (r) from S.
8.  Apply rule r to each current initial plan (in C)
      repeatedly until the rule does not produce
      any quality improvement.
9.  If r produced an improvement in some plan,
       Then Add r to the set of learned rules (L)
            The rewritten plans form the new C.
            Go to 3.
       Else Go to 7.
10. Return L
```

Figure 6: Bias towards small rules

Empirical Results

We tested our learning algorithm on three domains: the Blocks World domain used along the paper, the manufacturing process planning domain of (Minton 1988), and a restricted version of the logistics domain from the AIPS98 planning competition.

Blocks World

Our first experiment uses the Blocks World domain of Figure 2. The cost function is the number of steps in the plan. Note that although this domain is quite simple, generating optimal solutions is NP-hard (Gupta & Nau 1992). As initial plan generator, we used the

[3] If the size of two rules in the same, the rule with the smallest consequent is preferred (often a rewriting that reduces the number of operators also reduces the plan cost).

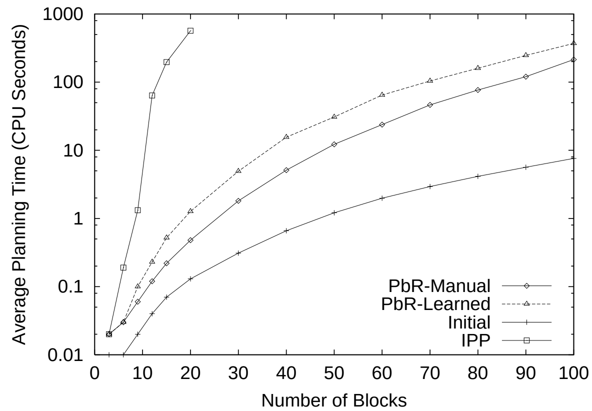
```
(define-rule :name bw-1 ;; avoid-move-twice-learned
  :if (:operators ((?n1 (unstack ?b1 ?b2))
                   (?n2 (stack ?b1 ?b3 Table)))
       :links ((?n1 (on ?b1 Table) ?n2)))
  :replace (:operators (?n1 ?n2))
  :with (:operators (?n3 (stack ?b1 ?b3 ?b2))))

(define-rule :name bw-2 ;; avoid-undo-learned
  :if (:operators ((?n1 (unstack ?b1 ?b2))
                   (?n2 (stack ?b1 ?b2 Table)))
       :links ((?n1 (on ?b1 Table) ?n2)
               (?n1 (clear ?b2) ?n2)))
  :replace (:operators ((?n1 ?n2)))
  :with nil)

(define-rule :name bw-3 ;; useless-unstack-learned
  :if (:operators ((?n1 (unstack ?b1 ?b2))))
  :replace (:operators ((?n1)))
  :with nil)
```

Figure 7: Learned Rewriting Rules (Blocks World)

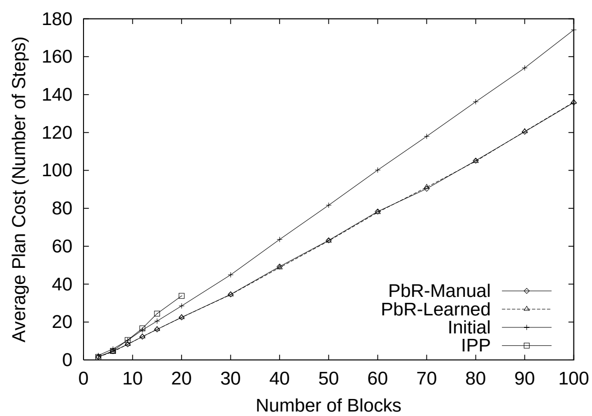
naive, but efficient, algorithm of putting all blocks on the table and building goal towers bottom up.

Our learning algorithm proposed the three rules shown in Figure 7, based on 15 random problems involving 3, 4, and 5 goals (5 problems each). Figure 4 shows the two manually-defined plan rewriting rules for this domains that appear in (Ambite 1998). Rules `bw-1` and `bw-2` in Figure 7 are essentially the same as rules `avoid-move-twice` and `avoid-undo` in Figure 4, respectively. The main difference is the interpreted predicate `possibly-adjacent` that acts as a filter to improve the efficiency of the manual rules, but is not critical to the rule efficacy.[4] The authors thought that the manual rules in Figure 4 were sufficient for all practical purposes, but our learning algorithm discovered an additional rule (`bw-3`) that addresses an optimization not covered by the two manual rules. Sometimes the blocks are in the desired position in the initial state, but our initial plan generator unstacks all blocks regardless. Rule `bw-3` would remove such unnecessary `unstack` operators. Note that our rewriting engine always produces valid plans. Therefore, if a plan cannot remain valid after removing a given `unstack`, this rule will not produce a rewriting.

We compared the performance of the manual and learned rules on the Blocks World as the number of blocks increases. The problem set consists of 25 random problems at 3, 6, 9, 12, 15, 20, 30, 40, 50, 60, 70, 80, 90, and 100 blocks for a total of 350 problems. The problems may have multiple towers in the initial state and in the goal state. We tested four planners: `Initial`, the initial plan generator described above; `IPP`, the efficient complete planner of (Koehler *et al.* 1997) with the GAM goal ordering heuristic (Koehler 1998); `PbR-Manual`, PbR with the manually-specified rules of Figure 4; and `PbR-Learned`, PbR with the learned rules of Figure 7. The results are shown in Figure 8.



(a) Planning Time



(b) Plan Cost

Figure 8: Performance (Blocks World)

Figure 8(a) shows the average planning time of the 25 problems for each block quantity. IPP cannot solve problems with more than 20 blocks within a time limit of 1000 CPU seconds. Both configurations of PbR scale much better than IPP, solving all the problems. Empirically, the manual rules were more efficient than the learned rules by a constant factor. The reason is that there are two manual rules versus three learned ones, and that the manual rules benefit from an additional filtering condition as we discussed above.

Figure 8(b) shows the average plan cost as the number of blocks increases. PbR improves considerably the quality of the initial plans. The optimal quality is only known for very small problems, where PbR approxi-

[4]Interpreted predicates are defined programmatically. The interpreted predicate `possibly-adjacent` ensures that the operators are consecutive in some linearization of the plan. Currently, we are not addressing the issue of learning interpreted predicates.

mates it.[5] The learned rules match the quality of the manual rules (the lines for PbR overlap in Figure 8(b)). Moreover, in some problems the learned rules actually produce lower cost plans due to the additional rule (`bw-3`) that removes unnecessary `unstack` operators.

Manufacturing Process Planning

For the second experiment we used a version of the manufacturing process planning domain of (Minton 1988) which models machines and objects as shared resources. This domain contains a variety of machines, such as a lathe, punch, spray painter, welder, etc, for a total of ten machining operations (see (Ambite 1998), pgs. 65–67, for the complete specification). The initial plan generator consists in solving the goals for each object independently and then concatenating these subplans. The cost function is the schedule length, that is, the time to manufacture *all* parts.

We ran our learning algorithm on 200 random problems involving 2, 3, 4, and 5 goals (50 problems each) on ten objects. The system produced a total of 18 rewriting rules, including some of the most interesting manual rules in (Ambite 1998). For example, the rule `lathe+SP-by-SP`, shown in Figure 9, was manually specified after a careful analysis of the depth-first search used by the initial plan generator. In this domain, in order to spray paint a part, the part must have a regular shape so that it can be clamped to the machine. Being cylindrical is a regular shape, therefore the initial planner may decide to make the part cylindrical, by lathing it, in order to paint it (!). However, this may not be necessary as the part may already have a regular shape. Thus, `lathe+SP-by-SP` substitutes the pair `spray-paint` and `lathe` by a single `spray-paint` operation. Our learning algorithm discovered the corresponding rule `sc-8` (Figure 9). The learned rule does not use the `regular-shapes` interpreted predicate (which enumerates the regular shapes), but it is just as general because the free variable `?shape2` in the rule consequent will capture any valid constant.

The rules `machine-swap` and `sc-14` in Figure 9 show a limitation of our current learning algorithm, namely, that it does not learn over the resource specifications in the operators. The manually-defined `machine-swap` rule allows the system to explore the possible orderings of operations that require the same machine. This rule finds two consecutive operations on the same machine and swaps their order. Our system produced more specific rules that are versions of this principle, but it did not capture all possible combinations. Rule `sc-14` is one such learned rule. This rule would be subsumed by the `machine-swap`, because the `punch` is a machine resource. This is not a major limitation of our framework and we plan to extend the basic rule generation mechanism to also learn over resource specifications.

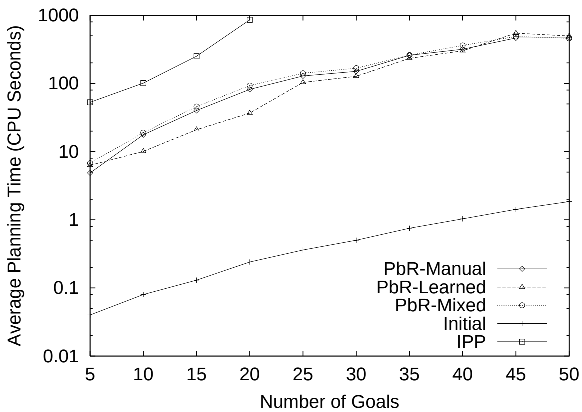
[5] We ran Sage for the 3 and 6-block problems. We used IPP for the purpose of comparing planning time. However, IPP optimizes a different cost metric, shortest parallel timesteps, instead of number of plan steps.

```
(define-rule :name lathe+SP-by-SP  ;; Manual
  :if (:operators
        ((?n1 (lathe ?x))
         (?n2 (spray-paint ?x ?color ?shape1)))
       :constraints ((regular-shapes ?shape2)))
  :replace (:operators (?n1 ?n2))
  :with (:operators
          (?n3 (spray-paint ?x ?color ?shape2))))

(define-rule :name sc-8           ;; Learned
  :if (:operators
        ((?n1 (lathe ?x))
         (?n2 (spray-paint ?x ?color Cylindrical))))
  :replace (:operators (?n1 ?n2))
  :with (:operators
          (?n3 (spray-paint ?x ?color ?shape2))))

(define-rule :name machine-swap    ;; Manual
  :if (:operators ((?n1 (machine ?x) :resource)
                   (?n2 (machine ?x) :resource))
       :links ((?n1 :threat ?n2))
       :constraints
         ((adjacent-in-critical-path ?n1 ?n2)))
  :replace (:links (?n1 ?n2))
  :with (:links (?n2 ?n1)))

(define-rule :name sc-14           ;; Learned
  :if (:operators ((?n1 (punch ?x ?w1 ?o))
                   (?n2 (punch ?y ?w1 ?o)))
       :links ((?n1 ?n2)))
  :replace (:links ((?n1 ?n2)))
  :with (:links ((?n2 ?n1))))
```

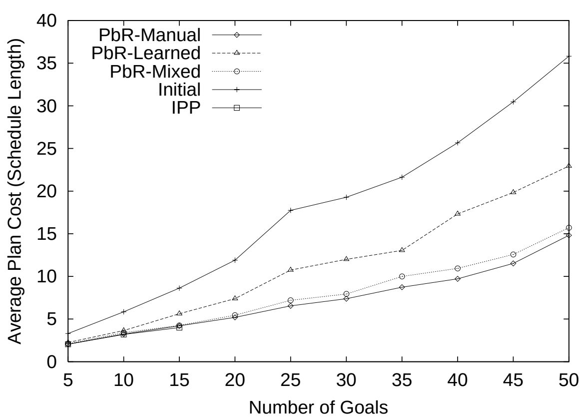
Figure 9: Manual vs. Learned Rewriting Rules

We compared the performance of the manual and learned rules for the manufacturing process planning domain on a set of 200 problems, for machining 10 parts, ranging from 5 to 50 goals. We tested five planners: `Initial`, the initial plan generator described above; `IPP` (Koehler *et al.* 1997), which produces the optimal plans in this domain; `PbR-Manual`, PbR with the manually-specified rules in (Ambite 1998); `PbR-Learned`, PbR with the learned rules; and `PbR-Mixed`, which adds to the learned rules the two rules that deal with resources in (Ambite 1998) (the `machine-swap` rule in Figure 9, and a similar one on objects).

The results are shown in Figure 10. In these graphs each data point is the average of 20 problems for each given number of goals. There were 10 provably unsolvable problems. Initial, and thus PbR, solved all the 200 problems (or proved them unsolvable). IPP only solved 65 problems under the 1000 CPU seconds time limit: all problems at 5 and 10 goals, 19 at 15 goals, and 6 at 20 goals. Figure 10(a) shows the average planning time on the solvable problems. Figure 10(b) shows the average schedule length for the problems solved by the planners for the 50 goal range.[6] The fastest planner is Initial, but it produces plans with a cost of more that twice the optimal (which is produced by IPP). The three configurations of PbR scale much better than IPP solving all problems. The manual rules achieve a quality very close to the optimal (where optimal cost is known, and scale gracefully thereafter). The learned rules improve significantly the quality of the initial plans, but they do not reach the optimal quality because many of the resource-swap rules are missing. Finally, when we add the two general resource-swap rules to the the learned rules (`PbR-Mixed`), the cost achieved approaches that of the manual rules.



(a) Average Planning Time



(b) Average Plan Cost

Figure 10: Performance (Manufacturing)

[6]We don't show cost for IPP at 20 goals because as it only solves 6 problems the average value is not meaningful.

Logistics

For our third experiment we used a version of the `logistics-strips` planning domain of the AIPS98 planning competition which we restricted to using only trucks but not planes. The domain consists of the operators `load-truck`, `drive-truck`, and `unload-truck`. The goals are to transport several packages from their initial location to a their desired destinations. A package is transported from one location to another by loading it into a truck, driving the truck to the destination, and unloading the truck. A truck can load any number of packages. The cost function is the time to deliver all packages (measured as the number of operators in the critical path of a plan).

The initial plan generator picks a distinguished location and delivers packages one by one starting and returning to the distinguished location. For example, assume that truck t1 is at the distinguished location l1, and package p1 must be delivered from location l2 to location l3. The plan would be: drive-truck(t1 l1 l2 c), load-truck(p1 t1 l2), drive-truck(t1 l2 l3 c), unload-truck(p1 t1 l3), drive-truck(t1 l3 l1 c). The initial plan generator would keep producing this circular trips for the remaining packages. Although this algorithm is very efficient it produces plans of very low quality.

By inspecting the domain and several initial and optimal plans, the authors manually defined the rules in Figure 11. The `loop` rule states that driving to a location and returning back immediately after is useless. The fact that the operators must be adjacent is important because it implies that no intervening `load` or `unload` was performed. In the same vein, the `triangle` rule states that it is better to drive directly between two locations than through a third point if no other operation is performed at such point. The `load-earlier` rule captures the situation in which a package is not loaded in the truck the first time that the package's location is visited. This occurs when the initial planer was concerned with a trip for another package. The `unload-later` rule captures the dual case.

Our system learned the rules in Figure 12 from a set of 60 problems with 2, 4, and 5 goals (20 problems each). Rules `logs-1` and `logs-3` capture the same transformations as rules `loop` and `triangle`, respectively. Rule `logs-2` chooses a different starting point for a trip. Rule `logs-3` is the most interesting of the learned rules as it was surprisingly effective in optimizing the plans. Rule `logs-3` seems to be an overgeneralization of rule `triangle`, but precisely by not requiring that the nodes are `adjacent-in-critical-path`, it applies in a greater number of situations.

We compared the performance of the manual and learned rules on a set of logistics problems involving up to 50 packages. Each problem instance has the same number of packages, locations, and goals. There was a single truck and a single city. We tested four planners: `Initial`, the sequential circular-trip initial plan generator described above; `IPP`, which produces optimal plans; `PbR-Manual`, PbR with the manually-specified rules in Figure 11; and `PbR-Learned`, PbR with the learned rules of Figure 12.

```
(define-rule :name loop
  :if (:operators
        ((?n1 (drive-truck ?t ?l1 ?l2 ?c))
         (?n2 (drive-truck ?t ?l2 ?l1 ?c)))
       :links ((?n1 ?n2))
       :constraints
        ((adjacent-in-critical-path ?n1 ?n2)))
  :replace (:operators (?n1 ?n2))
  :with NIL)

(define-rule :name triangle
  :if (:operators
        ((?n1 (drive-truck ?t ?l1 ?l2 ?c))
         (?n2 (drive-truck ?t ?l2 ?l3 ?c)))
       :links ((?n1 ?n2))
       :constraints
        ((adjacent-in-critical-path ?n1 ?n2)))
  :replace (:operators (?n1 ?n2))
  :with (:operators
          ((?n3 (drive-truck ?t ?l1 ?l3 ?c)))))

(define-rule :name load-earlier
  :if (:operators
        ((?n1 (drive-truck ?t ?l1 ?l2 ?c))
         (?n2 (drive-truck ?t ?l3 ?l2 ?c))
         (?n3 (load-truck ?p ?t ?l2)))
       :links ((?n2 ?n3))
       :constraints
        ((adjacent-in-critical-path ?n2 ?n3)
         (before ?n1 ?n2)))
  :replace (:operators (?n3))
  :with (:operators ((?n4 (load-truck ?p ?t ?l2)))
         :links ((?n1 ?n4))))

(define-rule :name unload-later
  :if (:operators
        ((?n1 (drive-truck ?t ?l1 ?l2 ?c))
         (?n2 (unload-truck ?p ?t ?l2))
         (?n3 (drive-truck ?t ?l3 ?l2 ?c)))
       :links ((?n1 ?n2))
       :constraints
        ((adjacent-in-critical-path ?n1 ?n2)
         (before ?n2 ?n3)))
  :replace (:operators (?n2))
  :with (:operators ((?n4 (unload-truck ?p ?t ?l2)))
         :links ((?n3 ?n4))))
```

Figure 11: Manual Rewriting Rules (Logistics)

The performance results are shown in Figure 13. In these graphs each data point is the average of 20 problems for each given number of packages. All the problems were satisfiable. IPP could only solve problems up to 7 packages (it also solved 10 out of 20 for 8 packages, and 1 out of 20 for 9 packages, but these are not shown in the figure). Figure 13(a) shows the average planning time. Figure 13(b) shows the average cost for the 50 packages range. The results are similar to the previous experiments. Initial is efficient but highly suboptimal. PbR is able to considerably improve the cost of this plans and approach the optimal. Most interestingly, the learned rules in this domain achieve better quality plans than the manual ones. The reason is the more general nature of learned `logs-1` and `logs-3` rules compared to the manual `loop` and `triangle` rules.

```
(define-rule :name logs-1
  :if (:operators
        ((?n1 (drive-truck ?t ?l1 ?l2 ?c))
         (?n2 (drive-truck ?t ?l2 ?l1 ?c))))
  :replace (:operators ((?n1 ?n2)))
  :with NIL)

(define-rule :name logs-2
  :if (:operators
        ((?n1 (drive-truck ?t ?l1 ?l2 ?c))))
  :replace (:operators ((?n2)))
  :with (:operators
          ((?n2 (drive-truck ?t ?l3 ?l2 ?c)))))

(define-rule :name logs-3
  :if (:operators
        ((?n1 (drive-truck ?t ?l1 ?l2 ?c))
         (?n2 (drive-truck ?t ?l2 ?l3 ?c)))
      :links ((?n1 (at ?t ?l2) ?n2)))
  :replace (:operators ((?n1 ?n2)))
  :with (:operators
          ((?n3 (drive-truck ?t ?l1 ?l3 ?c)))))
```

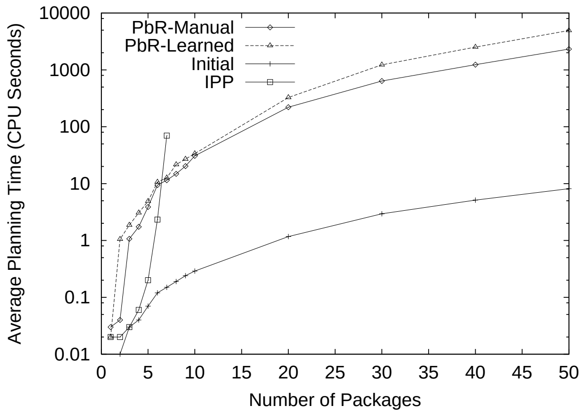
Figure 12: Learned Rewriting Rules (Logistics)

Related Work

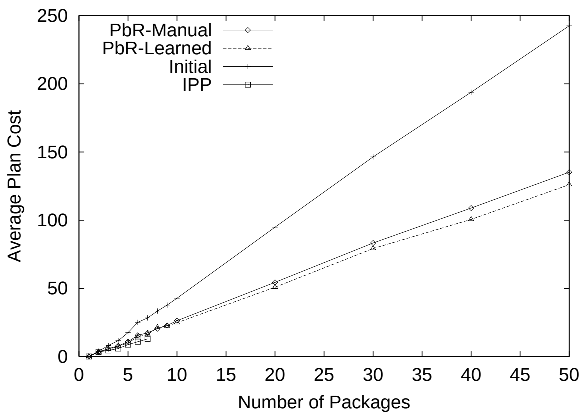
The most closely related work is that of learning search control rules for planning and scheduling. In a sense, our plan rewriting rules can be seen as "a posteriori" search control. Instead of trying to find search control that would steer the planner during generation towards the optimal plan and away from fruitless search, our approach is to generate fast a suboptimal initial plan, and then optimize it, after the fact, by means of the rewriting rules.

Explanation-Based Learning (EBL) has been used to improve the efficiency of planning (Minton 1988; Kambhampati, Katukam, & Qu 1996). Our rule generalization algorithm has some elements from EBL, but it compares two complete plans, with the aid of the operator specification, as opposed to problem-solving traces. Similarly to EBL search control rules, our learned plan rewriting rules also suffer from the utility problem (Minton 1988).

PbR addresses both planning efficiency and plan quality. Some systems also learn search control that addresses both these concerns (Estlin & Mooney 1997; Borrajo & Veloso 1997; Pérez 1996). However, from the reported experimental results on that work, PbR seems to be significantly more scalable.



(a) Average Planning Time



(b) Average Plan Cost

Figure 13: Performance (Logistics)

Search control can also be learned by analyzing the operator specification without using any examples (Etzioni 1993). Similar methods could be applied to PbR. For example, we could systematically generate rewriting rules that replace a set of operators by another set that achieves similar effects. Then, test the rules empirically and select those of highest utility.

In scheduling, several learning techniques have been successfully applied to obtain search control for iterative repair. Zweben et al. (Zweben *et al.* 1992) used an extension of EBL to learn the utility of the repairs, selecting when to apply a more-informed versus less-informed repair. Zhang and Dietterich (Zhang & Dietterich 1995) used a reinforcement learning approach to select repair strategies for the same problem. Both system learn how to select the repairs to improve the efficiency of search, but they do not learn the repairs themselves as in our work.

Conclusions and Future Work

Despite the advantages of Planning by Rewriting in terms of scalability, consideration of plan quality, and anytime behavior, the designer has to provide additional inputs to the system not required by other domain-independent approaches, namely, an initial plan generator, a set of plan rewriting rules, and a search strategy. In this paper, we have addressed the most demanding of these inputs, the generation of the rewriting rules. We have presented an approach to learning plan rewriting rules, tailored to a given planning domain and initial plan generator, by comparing initial and optimal plans. Our experiments show that this algorithm learns rules competitive with those specified by domain experts. Moreover, it proposed some useful rules not considered by the experts, and in some cases the learned rules achieved better quality plans than the manual rules.

A limitation of our algorithm is the size of training plans. In some domains some useful rules can only be learned from fairly large plans. For example, in the `logistics-strips` domain, rules that exchange packages among two trucks or two planes can only be learned from plans with several trucks, planes, and packages, but such plans near 100 steps and are very hard for current optimal planners. Interestingly this domain is actually composed of two (isomorphic) subdomains: truck transportation within a city and plane transportation between cities. Perhaps techniques similar to (Knoblock, Minton, & Etzioni 1991) can partition the domain and learn rules on more focused (and thus smaller) problems.

We plan to explore the issue of context in proposing rewriting rules more extensively. The algorithm for proposing ground rules we presented is one point in a continuum from fully-specified to partially-specified rules. Fully-specified rules provide all the context in which the differences between an initial plan and an optimal plan occur. That is, a fully-specified rule includes in addition to each node n in the plan difference all other nodes to which n is linked and the edges among n and such nodes. However not all such differences may be actually relevant for the transformation that the rewriting rule must capture, so a partially specified rule would be more appropriate. In machine learning terms, the issue is that of overfitting versus overgeneralization of the learned rule. The bias of our algorithm towards more partially-specified rules is the reason that it did not learn rules like the `load-earlier` and `unload-later` of Figure 11. In that logistics domain the optimal and initial plans always have the same `load-truck` and `unload-truck` operations, thus those operators do not appear in the plan difference, only edges that connect to those appear, but they are discarded while generating the partially-specified rule.

We plan to study the issue of rule utility more carefully. A simple extension of our algorithm for selecting rules would include a utility evaluation phase in which parameters such as the cost of matching, the number of successful matches and successful rewritings, and the cost improvement provided by a rule would be measured on a population of training problems and only rules above a certain utility threshold would be used in the rewriting process.

We intend to fully automate the additional inputs that PbR requires. For the initial plan generator, we are considering modifications of the ASP planner (Bonet, Loerincs, & Geffner 1997). The main idea of ASP is to use a relaxation of the planning problem (ignore negated effects) to guide classical heuristic search. We believe that ASP's relaxation heuristic coupled with search strategies that strive for efficiency instead of optimality, can yield a domain-independent solution for initial plan generation.

We also plan to develop a system that can automatically learn the optimal planner configuration for a given domain and problem distribution in a manner analogous to Minton's Multi-TAC system (Minton 1996). Our system would perform a search in the configuration space of the PbR planner proposing candidate sets of rewriting rules and different search methods. By testing each proposed configuration against a training set of simple problems, the system would hill-climb in the configuration space in order to achieve the most useful combination of rewriting rules and search strategy.

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