Learning Plan Rewriting Rules

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Abstract

Considerable work has been done to automatically learn domain-specific knowledge to improve the performance of domain independent problem solving systems. However, most of this work has focussed on learning search control knowledge—knowledge that can be used by a problem solving system during search to improve its performance. An alternative approach to improving the performance of domain independent systems is by using *rewriting rules*. These are the rules that can be used by a problem solving system after generating an initial solution in order to transform it into a higher quality solution. This paper reviews various approaches that have been suggested for automatically learning rewriting rules, analyses them, and suggests novel algorithms for learning plan rewriting rules.

The ability to produce high quality plans is essential if AI planners are to be applied to the real world planning problems. Machine learning for planning suggests automatically learning domain specific information that can be used by the AI planners to produce high quality solutions. Considerable planning and learning research has been devoted to learning domain specific search control rules to improve planning performance (planning efficiency and plan quality). These rules improve planning performance by guiding a planner towards higher quality plans *during planing*. An alternative technique is *planning by rewriting* (Ambite & Knoblock 1997) that suggests first generating an initial plan using a planner and then using a set of rewrite-rules to transform it into a higher quality plan. However, automatically learning such rules has been a challenging problem. Previously, I designed a system called REWRITE (Upal 1999; 2000) that automatically learned plan rewrite rules by comparing two planning search trees (one search tree leading to a lower quality plan and the other search tree leading to a higher quality plan). However, REWRITE's performance with respect to planning efficiency was poor (Upal & Elio 2000) because it was unable to learn good rewrite rules. In (Upal 2000) we show that the problem lies with REWRITE's strategy of learning rules in one context (i.e., the context of search nodes) and then applying them in a different context (i.e., the context of the complete plans). (Upal 2000) also presents evidence to show that learning search control rules from search trees is a better option than learning rewrite rules by comparing planning traces.

Ambite *et al.* (Ambite, Knoblock, & Minton 2000) suggest a similar technique for learning rewrite rules. However, their system (called Pbr) learns by comparing two *completed solutions* to a planning problem; one of higher quality and other of lower quality. Pbr's learning component simply stores those steps of the better quality solution that are not present in the lower quality plan as *replacing* steps, and it stores those steps of the lower quality solution that are not present in the higher quality solution as the *to-be-replaced* steps and *to-be-replaced* constraints on the steps. Pbr also ranks its rules according to goodness. It prefers the rules that are smaller.

Next I present the background material on planning by rewriting followed by a review of the previously suggested algorithms and suggest new algorithms for learning plan rewriting rules.

Planning by Rewriting

The basic idea of rewriting can be traced back to the work on graph and number rewriting (Baadr & Nipkow 1998). The idea of using rewrite rules for AI planning was introduced by Ambite *et al.* (Ambite & Knoblock 1997) who referred to it as planning by rewriting.

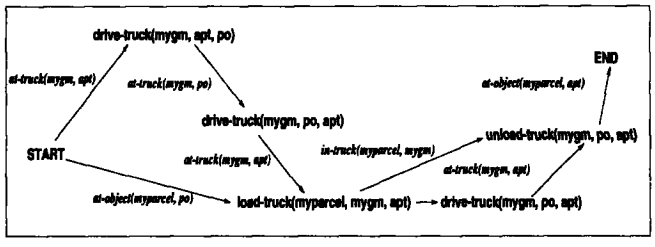
A planning by rewriting system consists of two component: a planning component for generating the initial plans, and a rewriting component that can rewrite these plans to transform them into higher quality plans. Since, by definition, planning by rewriting systems spend extra time in plan-rewriting, planning by rewriting can be expected to be useful in those planning domains in which generating suboptimal plans is significantly more efficient than generating optimal quality plans. Interestingly, many AI planning domains such as Blocksworld and the logistics transportation domain exhibit these properties (Ambite & Knoblock 1997).

A rewrite rule consists of two *equivalent* sequences of actions such that one of them can be replaced by the

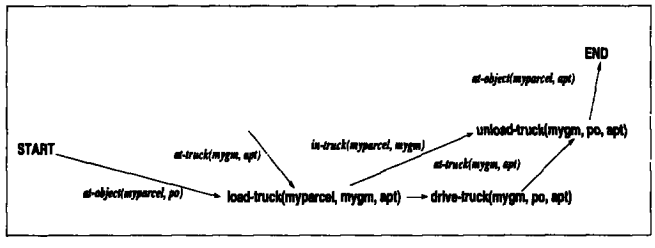
```
to-be-replaced:
   actions:  {drive-truck(Truck, From, To),
                    drive-truck(Truck, To, From)}
replacing:
   actions:  {}
```

Figure 1: A rewrite rule for the logistics transportation domain.

other. Figure 1 shows a rewrite rule from the logistics transportation domain consisting of two sequences of actions *replacing* and *to-be-replaced*. Given an initial suboptimal plan produced by the planning component, the task of the rewriting component is to delete the *to-be-replaced* sequence of actions from the initial plan and add the *replacing* sequence of actions to it. In order to better understand the rewriting process, it is useful to view a viable plan for a problem as a graph in which actions correspond to vertices and constraints on the actions (such as casual-link and the ordering constraints) correspond to the edges between the action. The rewriting process can be understood as deleting a subgraph and *replacing* it with another subgraph. Consider the



(a)



(b)

Figure 2: (a) An initial suboptimal plan from logistics transportation domain. (b) The rewritten plan.

graph shown in Figure 2(a) which corresponds to a suboptimal plan from the logistic transportation domain to which the rewrite rule of Figure 1 is applicable. Applying the rewrite rule to planning graph means deleting the subgraph corresponding to the *to-be-replaced* action vertices from the suboptimal plan and adding the *replacing* action vertices to the graph.

Good & Bad Rewrite Rules

Unfortunately, the new graph obtained by applying the rewrite rule may no longer corresponds to a viable plan. For instance, when the rewrite rule of Figure 1 is applied to planning graph of Figure 2(a) the subgoal *at-truck(mygm, apt)* becomes unresolved. Some re-planning has to be done to transform this incomplete plan into a complete plan again. Clearly, the more the replanning that is required the less efficient a planning by rewriting system will be. Hence, a rewrite rule learner must:

- learn rewrite rules that can be used efficiently by the plan rewriting process (i.e., the rules that require little replanning effort after their application), and
- use an efficient plan rewriting process.

For instance, consider the rules that consist of two action sequences that have exactly the same available effect set (the set of effects that actions in a subsequence can supply to the outside actions) and the same net precondition set (the set of unresolved goals that an action subsequence has). Using such rules will require minimal replanning effort because replanning is guaranteed to lead to complete plans without adding any new actions [1]. Unfortunately, such rules may be too specific to be used in a broad set of situations. In general, the bias for efficient replanning can be expected to favor over-specific rewrite rules.

Rewriting efficiency, however, is not the only criteria for determining the goodness of a plan rewriting process (in particular, for a rewriting module that is to be used as a part of a learning and planning system). From a machine learning perspective, a learning system must be able to learn general rules that are effective in leading to performance improvements in a broad set of situations. Hence a good rewrite rule learning system must:

- learn rewrite rules that are effectively applicable in a large number of situations, and
- use an effective rewriting process (i.e., its replanning component is able to successfully complete as many plans made incomplete by the rewrite rule application as possible).

For instance, consider a rewrite rule learner that generates rules by placing all subsets of the set of domain actions in its *to-be-replaced* and *replacing* action sequences. Such rules will guarantee generation of optimal quality plans. The problem is that many of these rules will be applicable in too broad a set of situations[2] but may only lead to performance improvements in a

[1] If we also assume that the *to-be-replaced* and the *replacing* actions are ordered then no replanning is required because the new plan can simply be obtained by substituting the *replacing* actions in place of the *to-be-replaced* actions.

[2] For instance, rules that have an empty set as a *to-be-replaced* action sequence will be applicable in every situation.

small subset of them. In general, the bias for large gains in the learning performance can be expected to favor over-general rewrite rules.

Finding the right balance between over-specific and over-general rewrite rules is a challenging machine learning problem. However, little work has been done to compare the consequences of different design decisions in the context of rewrite rules. Most of the work has focussed on finding a way to learn rewrite rules automatically. Ambite's Pbr (Ambite & Knoblock 1997) used a local search technique for rewriting. We implemented two versions of REWRITE called REWRITE-first and REWRITE-best using the first and the best rewriting strategies respectively (Upal & Elio 2000). The first rewriting strategy only performs one rewriting of an initial plan whereas the best rewriting strategy performs all possible rewritings to return the best quality plan found.

Our experiments with the two rewriting showed that if a rewrite rule learner is not selective with regards to size of its rewrite rule library then even the first rewriting strategy becomes too inefficient (Upal & Elio 2000). Ambite *et al.* (Ambite, Knoblock, & Minton 2000) suggest that a rewrite rule learner should prefer smaller rules because they are more likely to have a good balance of specificity and generality. However, we believe that this criteria is too simple because it does not take into account factors such as the gain in plan quality that is expected to be achieved as a result of applying the rule. We suggest a broader criteria for measuring the goodness of a rewrite rule:

1. gain in plan quality that is expected to be achieved as a result of a successful application of the rewrite rule.
2. Context similarity of the *to-be-replaced* actions sequence with the *replacing* action sequence. This can be measured by measuring the similarity between the precondition and the effect sets of the two actions sequences.
3. Simplicity of the rewrite rule. This can be measured by measuring the size of the rewrite rule. The smaller a rewrite rule the better it is expected to be.

Good & Bad Rewriting Processes

Similar to the conflict between over-general and over-specific rewrite rules, a conflict also exists between efficient and effective rewriting processes. For instance, consider the following two rewriting processes.

1. A rewriting process that uses a partial-order planner as a plan rewriting procedure.
2. A rewriting process that uses a simplified partial-order planner that can only use establishment to resolve open condition flaws as its replanning procedure.

Using the second rewriting algorithm the process of determining whether an incomplete plan can be rewritten or not can be performed more efficiently because it has strictly fewer number of choice points and hence a smaller search space to explore. However, such a replanning process would be unable to successfully replan (and hence improve plan quality of) a larger number of plans. Therefore, it will be less general than the first rewriting process.

Another variable in a rewriting system is the number of ways the initial plan can be rewritten. The reason is that a number of rules may be applicable to a plan. Application of each of these rules may lead to a number of different rewritten plans of different quality. This number can be as large as the number of ways of applying (i.e., instantiating) all the applicable rewrite rules. The benefit of applying all rewrite rules is that it allows evaluation of the entire neighborhood and hence the best quality plan can be obtained. However, searching the entire neighborhood can be inefficient. If we restrict the ways of rewriting a plan to the first feasible way of rewriting, then the rewrite algorithm becomes efficient. The drawback is that the rewriting system is not making use of all the learned knowledge and hence is not as effective as it can be.

In summary, the challenge for a rewrite rule learner is to learn plan rewriting rules that are:

- not too general or too specific, and are
- efficient, and
- effective.

Next section compares a number of rewriting rule learning algorithms with respect to the criteria of how efficiency and effectiveness.

Algorithms for Learning Rewrite Rules

Learning Through Static Domain Analysis

Recently, there has been a surge of interest in automatically learning domain specific rules by statically analyzing planning operators and/or the problem descriptions without solving the planning problems (Fox 2000). Even though most of this work has focussed on learning search control rules, such analysis can also be used to learn rewrite rules (for instance, by creating all possible combinations of domain actions in *to-be-replaced* and *replacing* actions). A number of improvements to this algorithm are possible. Figure 3 shows Algorithm 1 which is based on a number of heuristics that we have found to be useful for discovering good rewrite rules quickly.

Step 1 of the Algorithm 1 compares all domain actions with one another to find the ones that have an effect in common. If they do then it creates a rewrite rule with the more costly action as the *to-be-replaced* part of the rule and the less costly action as the *replacing* part of the rule and adds this rule to the set of rules found so far and tries to add an action to the chain by searching for an action that can supply a precondition of an action that is already in the chain. Every time it adds an action to a chain, it stores the chain with a higher quality plan in the *replacing* part of the

algorithm 1: (Domain-operator-set)
Set-of-Rules ⟵ {}
for all subsets $s_i = \{a_1, a_2\}$ of size 2 of
Domain-operator-set do
if a_1 and a_2 have an effect in common **then**
Set-of-Rules ⟵ Set-of-Rules
Rules ∪ find-rules($\{a_1\}$, $\{a_2\}$, Rulesize)
return Set-of-Rules

find-rules: (Chain1, Chain2, S)
if $S > 0$ then
S ⟵ $S - 1$
Set-of-Rules ⟵ Set-of-Rules ∪
{to-be-replaced=Chain1, replacing=Chain2}
Randomly pick-a-chain-to-expand-next
say Chain1
Newchain1 ⟵ expand(Chain1)
find-rules(Newchain1,Chain2, S)
return Set-of-Rules

Figure 3: Algorithm 1: Learning rewrite rules by static domain analysis.

rewrite rule and the chain with the lower quality in the *to-be-replaced* part of the rewrite rule. This process of expanding a chain by adding an action continues until a user provided depth limit *Rulesize* is reached.

Learning from Examples

The problem with static learning algorithms (such as Algorithm 1) is that they learn all possible rewrite rules, many of which may never be used in any possible example. The algorithms that use the training examples to learn from do not have this problem. Such algorithms can be divided into two types: those algorithms that use the completed solutions as their input, and those algorithms that use the solution traces (records of the two solutions) as their input to learn from. Unlike the traditional learning from examples algorithms (such as EBL) whose need only one example to learn from, learning to improve quality algorithms need two example solutions to learn from: one solution of higher quality and the other of lower quality.

By Comparing Planning Traces One way to learn from examples is by comparing two planning traces: the good and the bad planning trace. The good planning trace is the one that leads to a solution of higher quality and the bad planning trace is the one that leads to the solution of lower quality.

Given these two traces, the learning algorithm's first step is to retrace the bad planning-trace, looking for plan-refinement decisions that added a constraint that is not present in the good planning trace. We call such a decision point a *conflicting choice point*. Each conflicting choice point indicates a possible opportunity to

algorithm2(Higher quality plan H,
Lower quality plan L)
if *to-be-replaced=L, replacing=H* is
not in the set of rules **then** add it
else exit
for index1 = $|H|$ **downto** 1 **do**
for index2 = $|L|$ **downto** 1 do
for i = 1 **to** $|H|$ **do**
for j = 1 **to** $|L|$ **do**
$H \longleftarrow H \cup \{h_i\}$
$L \longleftarrow L \cup \{l_j\}$
add *to-be-replaced=L, replacing=H*
to Set-of-Rules
return Set-of-Rules

Figure 4: Algorithm 2: Learning plan rewriting rules by comparing two completed plans.

learn. For any conflicting choice point, there are two different plan-refinement decision sequences that can be applied to a partial plan: the one added by the bad trace, and by the good trace. The application of one set of plan-refinement decisions leads to a higher quality plan and the other to a lower quality plan. However, all of the *downstream* planning decisions may not be relevant to resolving the flaw at the conflicting choice point. The rest of the good trace and the rest of the bad trace are then examined, with the goal of labeling a subsequent plan-refinement decision q relevant if (a) there exists a causal-link $q \xrightarrow{c} p$ such that p is a relevant action, or (b) q binds an uninstantiated variable of a relevant open-condition.

Once both the good trace's relevant decisions and the bad trace's relevant decisions have been identified, Algorithm 2 computes (a) the actions that are added by the worse plan's relevant decision sequence. These become the action sequence to-be-replaced; (b) The actions that are added by the good trace's relevant decision sequence. These become the *replacing* action sequence; (c) The preconditions and effects of the *replacing* and the *to-be-replaced* action sequence. This information is then stored as a rewrite rule.

By Comparing Two Plans Rewrite rules can also be learned by comparing two completed plans (a higher and a lower quality one). Figure presents an algorithm for learning plan rewriting rules by comparing two completed plans. Given two plans for the same problem, it produces all subplans of these two plans and stores them as rewrite rules with the higher quality subplan being placed in the *replacing* part of the rewrite rule and the lower quality subplan in the *to-be-replaced* part of the rule.

It is possible to make this algorithm more efficient by heuristically generating certain subplans and not all of them. One such heuristic suggested by Ambite *et al.* (Ambite, Knoblock, & Minton 2000) is to remove only

Plan 1

1- START
2- drive-truck(mygm, apt, po)
3- drive-truck(mygm, po, apt)
4- load-truck(myparcel, mygm, apt)
5- drive-truck(mygm, apt, po)
6- unload-truck(myparcel, mygm, po)
7- END

Plan 2

1- START 2- load-truck(myparcel, mygm, apt)
3- drive-truck(mygm, apt, po)
4- unload-truck(myparcel, mygm, po)
5- END

Figure 5: Two plans for the same logistics planning problem.

the *identical* actions from the two plans. The problem with such a strategy is defining and identifying identical actions. One possibility is to perform a simple syntactic matching to identify identical actions without considering the context in which they are being applied. It is easy to come up with counterexamples in which this heuristic does not lead to good rewrite rules. The main reason being that sometimes syntactically similar ground actions are not in fact identical. For instance consider the two plans showed in Figure . A simple syntactic matching may match action 3 from Plan 2 with action 1 from Plan 1 even though the two actions are different.

Since the average number of actions in the simple training examples tends to be fairly small for most benchmark problems, Algorithm 2 can be run on them without any heuristics. This is certainly true if the learning system is to be trained on 2-3 goal problems. Ambite *et al.* argue that training a rewrite rule learner on simple problems is a good strategy because good rules tend to be small and can be discovered from 2-3 goal problems (Ambite, Knoblock, & Minton 2000).

Limiting the number of rules

Increasing number of learned rules is well known to be a major problem for the learning for planning systems (Minton 1989). Our experience with REWRITE shows that the number of rewrite rules learned by it was very large and as the number of rules increased, REWRITE's performance suffered. Hence a mechanism is needed to limit the number of rules learned. One suggestion is to perform a rule utility analysis along the lines suggested by (Minton 1989). Here we discuss some other technique for limiting the number or rewrite rules that can be used to weed out bad rewrite rules earlier than done by the utility analysis.

One idea is to use the goodness criteria to rank all the rewrite rules in the *Set-of-Rules* and remember a user specified number *Numrules* of these of these rules. Another idea suggested by Ambite (Ambite, Knoblock, & Minton 2000) is to run the system on various orderings of subsets of various sizes of the Set of rules and remember the smallest subset of rules that cover all the examples. However, in some situations no subset of rules may be able to cover all examples. Therefore, a more general form of this idea would be to prefer that subset that leads to the largest improvements in planning performance over the given examples. The two ideas can also be combined so that if more than one subset leads to optimal performance improvements then prefer the subset that has higher quality rewrite rules according to the goodness criteria.

Conclusion & Future Work

This paper has presented an analysis of rewrite rule learning algorithms and outlined a number of design issues involved in designing rewrite rule learning systems as well planning by rewriting systems in general. More work is needed to analyze the benefits and costs of various design choices. We are currently working on carefully designing empirical experiments to study these tradeoffs.

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References

Ambite, J., and Knoblock, C. 1997. Planning by rewriting: Efficiently generating high-quality plans. In *Proceedings of the Fourteenth National Conference on Artificial Intelligence.* Menlo Park, CA: AAAI Press.

Ambite, J.; Knoblock, C.; and Minton, S. 2000. Learning plan rewriting rules. In *Proceedings of the Fifth International Conference on Artificial Intelligence Planning Systems.* Menlo Park, CA: AAAI Press.

Baadr, F., and Nipkow, T. 1998. *Term Rewriting and All That.* Cambridge: Cambridge University Press.

Fox, M., ed. 2000. *Notes of the AIPS-00 Workshop on Analysing and Exploiting Domain Knowledge for Efficient Planning.*

Minton, S. 1989. Expalantion-based learning. *Artificial Intelligence* 40:63–118.

Upal, M. A., and Elio, R. 2000. Learning rewrite rules vs search control rules to improve plan quality. In *Proceedings of Canadian Artificial Intelligence Conference*, 240–253. New York: Springer Verlag.

Upal, M. A. 1999. Learning rewrite rules to improve plan quality. In *Proceedings of Sixteenth National Conference on Artificial Intelligence.* Menlo Park, CA: AAAI Press.

Upal, M. A. 2000. Learning to improve quality of the plans produced by partial-order planners. Technical report, PhD Thesis, University of Alberta.