Lifted Logic for Task Networks: TOHTN Planner Lilotane in the IPC 2020

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Abstract

We present our contribution to the International Planning Competition (IPC) 2020. Our planner Lilotane builds upon ideas established by Tree-REX and encodes a Totally Ordered Hierarchical Task Network (TOHTN) planning problem into incremental formulae of propositional logic (SAT). Lilotane, however, instantiates reductions and actions lazily and minimallistically without the need for full grounding, hence accelerating the planning process significantly. We discuss the results of the IPC and conclude that Lilotane, scoring second in the Total Order track, is an overall competitive system, what demonstrates the viability of our approach and its significance for future research.

Overview

In this report we present Lilotane (‘lı-tot-en, Lifted Logic for Task Networks), the first Satisfiability (SAT) based planner for Totally Ordered Hierarchical Task Network (TOHTN) problems that operates on a lifted planning problem. The design of Lilotane is heavily motivated by the observation that grounding an HTN planning problem (Ramoul et al. 2017; Behnke et al. 2020) induces an unavoidable worst-case combinatorial blowup with respect to the input size, and that this blowup can hinder SAT-based HTN planners to scale to larger problems even if they are logically of simple nature. Lilotane, by contrast, fully circumvents the stage of grounding and instead encodes a lifted problem representation into propositional logic.

The general planning procedure of our planner is similar to the planning pipeline known from its predecessor Tree-REX (Schreiber et al. 2019) as well as from totSAT (Behnke, Höller, and Biundo 2018):

1. The formal description of a planning problem $\Pi = (D, s_I, T)$, where $D$ is an HTN planning domain, $s_I$ is an initial state, and $T$ is a sequence of initial tasks, is parsed and preprocessed in some way.

2. Propositional logic clauses describing the problem’s upmost yet unencoded hierarchical layer $L_i$ are added, a fully expanded task network is assumed, and a SAT solver is run on the resulting formula.

3. If the solver finds a model, a plan is decoded from the satisfying assignment to the Boolean variables and returned. Otherwise, go to 2.

Algorithm 1: Lilotane Procedure (simplified)

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Input: $\Pi = (D, s_I, T)$
Result: Plan $\pi$
1 Preprocess $\Pi$;  // parsing, simplification
2 $H := \emptyset$;
3 $L_0 := \langle$ CreateInitialPosition$(T, s_I) \rangle$;
4 Encode($L_0$);  // encode first layer
5 $H := H \circ \langle L_0 \rangle$;
6 for $l = 0, 1, \ldots$ do
   // instantiate new layer
   $L_{l+1} := \emptyset$;
   $S := (s_I, \emptyset)$;  // reachable facts
   $x' := 0$;
   for $x = 0, \ldots, |L_l| - 1$ do
      // generate child positions of $P_{l,x}$
      $e_{l,x} := \max \{1, \max \{\subtasks(r) \mid r \in P_{l,x}\}\}$;
      for $z = 0, \ldots, e_{l,x} - 1$ do
         $P_{l+1,x'} :=$ Instantiate($P_{l,x}, z, S$);
         $L_{l+1} := L_{l+1} \circ \langle P_{l+1,x'} \rangle$;
         $S := S \cup \text{possibleFactChanges}(P_{l+1,x'})$;
         $x' := x' + 1$;
   end
   // encode new layer
   Encode($L_{l+1}$);
   // finalize layer, attempt to solve
   $H := H \circ L_{l+1}$;
   result := Solve($H$);
   if result is SAT then
      return Decode($H, \text{result}$);
   end
end
```

The main difference between previous approaches and Lilotane is that the latter avoids the complete grounding of the problem in step 1; instead we perform lazy instantiation of operators and methods in step 2, just in time for when they are needed. We avoid to instantiate all free arguments of an action or a reduction occurring at some place of the hierar-
of inserted operations (line 15). We can use these facts-col-
tive state (line 8) and adding any direct or indirect effects
that may possibly occur, beginning with the ini-

After receiving the lifted problem description from
pan-door parser, we instantiate the problem’s hierarchy from top
to bottom, i.e., we begin with an initial layer following from
the problem description (line 3) and then construct layer
+1 on the basis of layer . Each operation (i.e., action or re-
duction) at some position of layer can induce one or several
new positions at layer +1. Each such new position may
again feature a variety of different operations, as illustrated
in Fig. 1. Only one such operation at each position will be
chosen by a SAT solver for the final plan. This approach is
based on Tree-REX (Schreiber et al. 2019) where the same
layout of layers was used but its construction was based on
a problem’s full grounding. By contrast, we instantiate op-
erations just when needed to achieve some subtask, and we
preserve free arguments of methods instead of instantiating
them with all possible combinations of constants.

As we instantiate each layer in chronological order (“from
left to right”), we can maintain sets of positive and nega-
tive facts which may possibly occur, beginning with the ini-
tial state (line 8) and adding any direct or indirect effects
of inserted operations (line 15). We can use these fact col-
lections to discard any operations with a precondition that
turns out to be impossible to achieve in line 13. In line 15
we determine the possible effects of a given operation us-
ing a conservative overestimation which we compute by a
traversal of the (lifted) recursive children of a method. In ad-
dition, we logically infer new preconditions for a method by
recursively aggregating the preconditions and effects of its
possible children: This helps us to profit from the described
pruning methods even on domains which do not natively fea-
ture any method preconditions.

By allowing for free arguments to remain in an operation,
we significantly reduce the number of instantiated actions
and reductions. Consider an example task (navigate ?rover
?from ?to) which, according to its parent task
(investigate A), evaluates to (navigate ?rover
?from A). Performing a conventional instantiation we
receive tasks (navigate R1 B A), (navigate R1 C A), (navigate R1 D A),
(navigate R2 B A) and so on. Our algorithm avoids this blowup by instanti-
ating only one task: (navigate α β A). Thereby, α and
β are new symbols which did not occur in the problem be-
fore and which we call pseudo-constants. With our novel
SAT encoding we can let the solver decide which partic-
ular constant to substitute each pseudo-constant with. Our
instantiation algorithm introduces a pseudo-constant when-
ever the valid domain of a free variable is larger than one,
i.e., whenever there is a nontrivial choice to make regarding
the substitution.

We introduced several further techniques to increase per-
formance, such as (i) the sharing of pseudo-constants among
multiple operations and the notion of an operation dominat-
ing another operation if it represents a superset of ground
operations; (ii) the retroactive pruning of any subtree of op-
erations which turned out to be impossible to achieve; (iii)
the transformation of certain reductions into equivalent ac-
tions; and more.

Figure 1: Sketch of Lilotane’s instantiation procedure.
Above: Position at layer contains three operations (re-
ductions , and action ) with different possible chil-
dren. Below: New positions , , are appended to
layer by aggregating the respective possible children.

Encoding

The general structure of our propositional logic encoding is an adaptation of the Tree-REX encoding (Schreiber et al. 2019). The main difference is that we now must deal with ac-
tions, reductions, and facts containing pseudo-constants. We
now provide some central, slightly simplified clause defini-
tions for illustration purposes and refer to Schreiber (2021)
for the complete specification.

As in previous work we use one Boolean variable for each
occurring reduction, action, and fact per position per layer
of the problem. These variables are assigned regardless of
whether the object contains pseudo-constants or not. Also,
we have one variable representing whether position
at layer features a primitive operation, i.e., an
action and not a reduction.

In addition, we introduce global variables which corre-
spond to substituting some pseudo-constant with an actual
constant . For each pseudo-constant we add clauses

\[
\bigvee_{c \in \text{dom}(\kappa)} [\kappa/c] \land \bigwedge_{c_1 \neq c_2 \in \text{dom}(\kappa)} \neg[\kappa/c_1] \lor \neg[\kappa/c_2],
\]
i.e., exactly one of the possible substitutions of $\kappa$ with a constant from its possible domain, $\text{dom}(\kappa)$, must hold.

Next, we define the semantics of facts containing pseudo-constants, which we call pseudo-facts. Let $f_p$ be a pseudo-fact and for each of its pseudo-constants $\kappa$ let $c_\kappa$ be one of the possible constants to be substituted such that substituting each $\kappa$ with $c_\kappa$ leads to ground fact $f$.

$$\left( \bigwedge_{\kappa \in f_p} \left[ \kappa / c_\kappa \right] \right) \Rightarrow (\text{holds}(f_p, l, i) \iff \text{holds}(f, l, i))$$

In words, we enforce a pseudo-fact to be equivalent to the ground fact it corresponds to when performing particular substitutions. This rule does imply that we need to fully instantiate all potentially occurring facts at the respective position; yet, we claim that there are commonly much fewer ground facts than there are actions or reductions.

Frame axioms are encoded only for ground facts, as the meaning of pseudo-facts is well-defined by the previous sets of clauses. We add clauses as follows:

(i) If a fact $f$ changes its value, then either the position is non-primitive, or some action directly supports this fact change, or some pseudo-action indirectly supports the fact change. (ii) If fact $f$ changes its value and action $a$ from the indirect support is applied, then some set of substitutions must be active which unify some effect $f_p$ of $a$ with $f$.

Note that for (ii), in the general case a transformation of a Disjunctive Normal Form (DNF) into Conjunctive Normal Form (CNF) is required when $a$ features many different pseudo-facts as effects which can be unified to $f$. We use a simple compilation which builds a tree of literals and then obtains CNF clauses by traversing it.

Compared to a SAT encoding based on a ground representation, there are some subtle new edge cases to consider. For instance, we need to add further clauses which constrain the sets of possible substitution combinations (due to invariant preconditions which we do not encode directly), retroactively restrict the domain of a pseudo-constant to incorporate argument type restrictions of a child operation, and conditionally disable certain negative action effects if an equivalent fact also occurs as a positive effect in the action.

We consider our new encoding to be structurally more complex than that of Tree-REX but observed empirically that our approach not only significantly cuts the time spent for instantiation but also leads to much smaller formulae, often-times by orders of magnitude.

Technical Remarks
Our planner is written from scratch in C++ (i.e., we did not reuse any code from previous planners). In the competition version we use SAT solver Glucose (Audemard and Simon 2009) with kind permission of the authors: Empirically we found this solver to work best on the class of formulae generated by our approach. We build upon pandaPlparser (Behnke et al. 2020) for parsing planning problems specified in HDDL and for performing light preprocessing tasks on the problem’s lifted representation. Lilotane is free software licensed under the GNU General Public License (GPL) v3.0; additional legal constraints may apply depending on the licensing of the particular SAT solver.

Post-IPC Discussion
We now discuss the results of the International Planning Competition (IPC) 2020.

A large set of diverse benchmark problems from various authors was gathered for the IPC, what will certainly facilitate thorough evaluations of TOHTN planners in the future. Compared to most previous evaluations in TOHTN planning (Schreiber et al. 2019; Behnke, Höller, and Biundo 2018) we observed that the peak difficulty of problems has been increased substantially: Oftentimes a domain known from previous evaluations was extended by ten more instances, each of which larger than any previous instance. This means that a planner reaching a near-perfect score on some domain is generally a much stronger result than before.

Lilotane scored the second place in the Total Order track of the IPC 2020. It found a plan for 548 out of 892 instances in at least one out of ten repetitions and reached an IPC score of 11.6. Lilotane was outperformed by progression search planner HyperTensioN which reached a considerably better score of 13.51 and found a plan for 545 instances in at least one repetition. HyperTensioN solved 84% of its instances in less than a second. Lilotane only solved 41% of its instances in under a second and solved 84% in under one minute. Overall we observed that while the IPC score benefits the overall much faster execution times of HyperTensioN, Lilotane performed similar to HyperTensioN in terms of robustness and, unlike HyperTensioN, was able to solve some instance(s) on every single domain.

All further competitors scored significantly lower. In particular, Lilotane outperformed the only ground approach participating, PDDL4J, on all but four domains. HyperTensioN scored best on 15/24 domains and Lilotane scored best on 8/24 domains; only a single domain (Entertainment) was neither won by HyperTensioN nor by Lilotane.

Lilotane’s worst performances are on the domains Blockworld-HPDDL, Minecraft(-Player), and Multiarm-
Blockworld. We noticed that each of these domains leads to deep and large hierarchical task networks which favor greedy progression search planners over planners such as Lilotane which are required to instantiate the entire hierarchy with all possible alternatives up to the layer where a plan can be found. Furthermore, compiled universal quantifications in Blockworld-HPPDDL and Multiarm-Blockworld lead to many preconditions per operator which are comparably costly for our encoding.

By contrast, our planner excelled on domains such as Monroe (complex goal and task recognition problems on top of a disaster management domain, see Höller et al. 2018) and Woodworking. The latter domain encompasses large manufacturing and processing tasks and notably features a high number of arguments per operator and method. As our approach keeps free arguments lifted, it can handle this domain very well. We are also pleased to observe that Lilotane scored well on the Childsnack domain: This domain is a textbook example for a logically trivial domain which leads to huge ground representations. Hence, prior SAT-based approaches have considerable problems with this domain while our approach solves even large problems with relative ease.

Although the IPC was an agile competition where only run times were of interest, we also want to shed light on the length of the plans found by the best competitors (with respect to the number of actions in a plan). We found that Lilotane produced considerably shorter plans than the winner: We filtered out all 439 instances for which both Lilotane and HyperTensioN found a plan on some runs and then averaged the found plan length over all successful runs for each instance. On 264 instances Lilotane found shorter plans on average, on 77 instances the found plans are of equal average length and on 98 instances HyperTensioN found shorter plans on average. Summed up over all these instances, the number of actions reported by HyperTensioN corresponds to 229% of the number of actions reported by Lilotane. This significant difference in plan quality can be explained by the careful iterative deepening procedure of Lilotane: Any found plan length is bounded by the size of the layer where it was found, and Lilotane finds a plan on the very first layer where any plan can be found.

Conclusion and Outlook

We presented our submission to the IPC 2020 named Lilotane which is the first lifted SAT-based HTN planning system. Lilotane showed promising performance and convinced on a large and diverse set of benchmarks with respect to its robustness and the high-quality plans it finds. As such, the performance of Lilotane in the IPC 2020 demonstrates that SAT-based HTN planning without grounding is not only viable, but in fact a highly appealing approach if done carefully. We expect these results to open up new perspectives for SAT-based planning in related problem classes. We refer to a separate article (Schreiber 2021) which discusses the research at hand in more detail, provides proofs of correctness, and describes further improvements of Lilotane integrated after the planner submission deadline of the IPC.

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