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Transforming Partially Ordered Planning Problems into Totally Ordered Problems

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Declaration of Authorship:

Except where otherwise indicated, this report is my own original work.

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(Ying Xian Wu)

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Abstract

The refinement step of partially ordered HTN planning has in the worst case $k!$ possible solutions to search through when k plan steps should be ordered into a executable refinement. A large search space can be an advantage in case not enough is known about the domain to sensibly ensure a smaller search space will hold solutions, but also a disadvantage in the case that the search space is too large to efficiently search through. We attempt to linearize partially ordered HTN planning problems in order to reduce this disadvantage, while attempting to preserve at least one solution in the reduced search space. We test our techniques on the partially-ordered track of the bench-mark set of the IPC 2020. We use the Panda progression search planner on both linearised and partially-ordered problem. We find that in the majority of domains, the linearized problem can be solved faster. We also find that for the majority of problems, the linearized problem remains solvable.

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Introduction

1.1 Introduction to HTN Planning

I have no idea what to write here.

1.2 Motivation

1.2.1 Potential advantages and disadvantages of total vs. partial order

- pros of partial order:
 - plan recognition: independent goals can be described in parallel (Daniel should be able to write something about that)
 - partial order is more expressive (both in terms of plan existence and in terms of computational complexity) meaning that more problems can be expressed
 - Domain model might be more intuitive: if a task is independent of some others it might be counter-intuitive to demand a certain position of it (if artificially made totally ordered)
- pros of total order:
 - computational complexity is lower (fewer worst-case solving time)
 - we can exploit specialised algorithms as well as heuristics. Note that heuristic design is comparably easy for total-order problems due to the missing interaction between tasks.

1 Introduction

1.2.2 Further advantages from having a compilation of PO into TO plans

- We get another class of decidable partially ordered problems that's orthogonal to tail-recursive ones! (Because if the criterion 'matches', we know that the PO domain is equivalent to the resulting TO domain; the latter is decidable whereas the former is not.
- We can use more efficient algorithms and heuristics.

1.3 Contributions

Though the algorithm was implemented in the old PANDA-3 planner, and was used to produce many of the totally ordered domains in IPC benchmark, there does not exist empirical analysis of its performance, or specification of its formal properties. This paper provides both. It also investigates possible improvements to the original algorithm.

Background

2.1 Classical planning

A classical planning problem is defined as **Problem** = (D, S_I, S_G)

D is the domain of the problem, $S_I \in 2^F$ is the initial state and $S_G \in F$ is the goal.

Every fact $\in F$ included in S_G is true, and all other facts are false. This is the closed world assumption.

The domain $\mathbf{D} = (F, A)$. F is a finite set of facts, or propositional state variables. A is a finite set of actions. Every $a \in A$ is of type $2^F \times 2^F \times 2^F$, and of the format $\langle pre, add, del \rangle$. The preconditions, add, and delete effects, of an action a are referred to as $pre(a)$, $add(a)$, and $del(a)$ respectively. An action a is executable in a state s if its precondition pre holds in s , i.e. $pre \subseteq s$. If executable in s , its result is the successor state $s' = (s \setminus del) \cup add$, i.e., variables in $del(a)$ get removed and variables in $add(a)$ get added.

Solution: Solutions to a problem are action sequences executable in the initial state S_I that lead to a state s'' that satisfies all goals, i.e., $s'' \supseteq g$. Any such state s'' is called a goal state.

2.2 Partially Ordered Hierarchical Planning

Also known as Partially Ordered Hierarchical Task Network Planning or PO HTN planning for short.

Problem $= (D, S_I, T_I)$ is over some domain D , has an initial state S_I , which is a total assignment to F , and has a initial compound task T_I . Every fact $\in F$ included in S_I is true, and all other facts are false. This is the closed world assumption.

The domain $\mathbf{D} = (F, T_P, T_C, \delta, M)$.

1. F is the finite set of state variables, T_P is the finite set of primitive task names, T_C is the finite set of compound task names, and
2. δ is a mapping from primitive task name to action.
3. M is the finite set of decomposition methods. Each one maps a compound task name to a task network.
4. T_P is the set of all possible primitive task names
5. T_C is the set of all possible compound task names
6. δ maps actions to it's (preconditions, add, deletes) $\in 2^F \times 2^F \times 2^F$. This can alternatively be referred to as $prec(t), add(t), del(t)$ for $a \in F, t \in T_P$
7. M is a set of methods. If $m \in M$, m maps a compound task to a Task Network.

The **Task Network** $= (T, \prec, \alpha)$. T is a finite set of task identifiers (ids), \prec is a partial order over T , and α maps task ids $\in T$ to task names in T_C and T_P .

Task Decomposition A method $m = (c, tn_m)$ decomposes a task network $tn_1 = (T_1, \prec_1, \alpha_1)$ into a new task network tn_2 by replacing t (i.e. $tn_1 \rightarrow_{t,m} tn_2$), if and only if $t \in T_1$, $\alpha_1(t) = c$, and there exists a task network $tn' = (T', \prec' \alpha')$ with $tn' \cong tn_m$ and $T' \cap T = \emptyset$ and

$$tn_2 := ((T_1 \setminus \{t\}) \cup T', \prec_1 \cup \prec' \prec_X, \alpha_1 \cup \alpha') \quad (2.1)$$

$$\prec_X := \{(t_1, t_2) \in T_1 \times T' | (t_1, t) \in \prec_1\} \cup \quad (2.2)$$

$$\{(t_1, t_2) \in T' \times T_1 | (t, t_2) \in \prec_1\} \quad (2.3)$$

$$(2.4)$$

HTN Solution A solution to a problem is a task network $tn = (T, \prec, \alpha)$ if and only if

1. tn can be reached via decomposing tn_I
2. all tasks are primitive, $(\forall t \in T : \alpha(t) \in T_P)$
3. there exists a sequence $\langle t_1, t_2 \dots t_n \rangle$ of the task ids in T that agrees with \prec such that the application of that sequence $\langle \alpha(t_1), \alpha(t_2) \dots \alpha(t_n) \rangle$ in S_I is executable.

2.3 Totally Ordered Hierarchical Planning

Totally ordered hierarchical planning is the same as partially ordered planning in all respects except the task network. Both define a **Task Network** $= (T, \prec, \alpha)$. The difference is that \prec now specifies the order between task ids such that for every a, b , in T , there exists an ordering in \prec that (a, b) or (b, a) . In other words, the tasks are totally ordered.

Undecidable A decision problem is equivalent to a function that accepts (potentially infinite) inputs and returns a yes or no. The decision problem is undecidable if it can be proved that there exists no algorithm for the problem that always leads to a correct yes-or-no answer.

Partially ordered HTN planning is undecidable, while totally ordered HTN planning is decidable.

2.4 Further Definitions (may be required)

Task Decomposition Tree Given a planning problem P , then a decomposition tree $g = (T, E, \prec, \alpha, \beta)$ is a 5-tuple with the following properties. (T, E) is a tree with nodes T and directed edges E pointing towards the leafs. There is a strict partial order defined over the nodes, given by \prec . The nodes are labeled with task names by $\alpha : T \rightarrow C \cup O$. Additionally, $\beta : T \rightarrow M$ labels inner nodes with methods. $T(g)$ refers to the tasks of g , and $ch(g, t)$ refers to the direct children of $t \in T(g)$ in g .

Lifted Each object that exists in the world has a type from a pre-determined set of types defined by the domain. Methods apply to the set of object(s) that belong to a certain type.

Grounded A transition is ground if the parameters list only involves specific objects. Problems are grounded when all methods are grounded.

So to ground a problem: Let ω be a set of typed objects. The groundings of a transition schema a over ω is denoted by $\sigma(a, \omega)$ and corresponds to the set of all ground transitions obtained by substituting σ with a list of compatible objects taken from ω , and then substituting each occurrence of the variables which were in σ with the newly introduced objects.

Partial Order Causal Link Planning *POCL criterion*. A partial POCL plan $P = (PS, \prec, CL)$ is called POCL plan (also POCL solution) to a planning problem if and only if every precondition is supported by a causal link and there are no causal threats.

PO criterion. We refer to a partial POCL plan $P = (PS, \prec, CL)$ without causal links, i.e., $CL = \emptyset$, as a partial partially ordered (PO) plan. Due to the absence of causal links, the solution criteria are here defined directly by the desired property of every linearization being executable.

2 Background

i.e. A partial PO plan $P = (PS, \prec)$ is called PO plan (also PO solution) to a planning problem if and only if every linearization is executable in the initial state and results into a goal state. i.e. it has every necessary ordering.

Therefore a linearization exists if and only if a POCL solution exists.

Related Work

On the Efficient Inference of Preconditions and Effects of Compound Tasks in Partially Ordered HTN Planning Domains, Conny Olz (2022)

Algorithm, Formalisation, Benchmark

4.1 Algorithm 1

Domain (F, T_P, T_C, δ, M) and Problem $= (T_I, S_0, TN_G)$

Algorithm 1: Calculate all possible preconditions and effects for compound tasks

Function *GetPreEff*($F, T_P, T_C, \delta, M, visited$)

```

function for  $c \in T_C$  do
  if  $c \notin visited$  then
    for  $t \in \{t | m \in M \wedge m(c) = tn\}$  do
      for  $a \in F$  do
        if  $t \in T_P$  then
           $pre^*[v] = pre^*[v] \wedge Pre(t)$   $add^*[v] = add^*[v] \wedge Add(t)$ 
           $del^*[v] = del^*[v] \wedge Del(t)$ 
        else
           $visited.add(c)$  ;
          GetPreEff( $F, T_P, T_C, \delta, M, visited$ );
        end
      end
    end
  end
end
return  $pre^*, add^*, del^*$ ;
end

```

Algorithm 2: Calculation of linearized methods**Data:** $(F, T_P, T_C, \delta, M), pre^*, add^*, del^*$ **Result:** (F, T_P, T_C, δ, M) **for** $m \in M$ **do** $NS_m \leftarrow \emptyset$; **for** $a \in F$ **do** $NS_m = \{(t, t', 1) | (a \in add^*(t) \wedge a \in pre^*(t') \wedge t, t' \in tasks(m))\} \cup NS_m$; $NS_m = \{(t', t, 1) | (a \in add^*(t) \wedge a \in del^*(t') \wedge t, t' \in tasks(m))\} \cup NS_m$; $NS_m = \{(t', t, 1) | (a \in del^*(t) \wedge a \in pre^*(t') \wedge t, t' \in tasks(m))\} \cup NS_m$; $NS_m = \{(t, t', 1) | (a \in del^*(t) \wedge a \in add^*(t') \wedge t, t' \in tasks(m))\} \cup NS_m$; **end** directed graph $G = (tasks(m), E)$; $E \leftarrow \emptyset$; **for** $ordering \in \prec$ **do** $E = E \cup (ordering, 0)$ **end** **for** $(t, t', w) \in NS_m$ **do** $E = E \cup ((t, t'), w)$ **end** $BackEdges \leftarrow DFS(G)$; **for** $e \in BackEdges$ **do** **if** $weight(e) = 1$ **then** $E = E \setminus e$ **end** **if** $weight(e) = 0$ **then** $A, B = e$; $Path = Dijkstra(B, A)$; $randEdge = RANDOM(\{e \mid weight(e) = 0 \wedge e \in Path\})$; $E = E \setminus randEdge$ **end** **end** $\prec' = TopologicalSort(G)$; $m' = (tasks(m), \prec', \alpha(t))$; $M' = m' \cup M'$;**end**Return new domain = $(F, T_P, T_C, \delta, M')$

1. GetPreEff (time)= NumMethods * log(TDG height) * NumStateBits
2. Linearize (time) = order based on precondtions + (create graph + DFS + Dijkstra)*(as needed)
3. Let the method size be V, and the number of edges be E
4. Linearize = NumMethods * (NumStateBits + Method Size + Method Size +

$$(\text{orderings}) + (\text{Method Size})\log(\text{method Size}))$$

Therefore this algorithm is $O(?)$ time?

4.1.1 Solution preserving properties of Algorithm 1

Proposition 0. *Removes linearizations*

Proof. This algorithm linearises all the methods to be totally ordered. Since sub-tasks inherit the orderings of their parents, it's impossible to preserve a solution that requires the interleaving of sub-tasks if their respective parents that are already ordered with respect to each other. This proves that the algorithm will always remove some linearizations, assuming the original domain was not already totally ordered.

Consider the simple problem:

$$F = \{a, b, c, g\}$$

$$N_p = \{T_A, T_B, T_C, G\}$$

$$N_c = \{AB\}$$

$$\delta = \{(T_A, A), (T_B, B), (T_C, C)\}$$

$$M = (AB, \{\{4, 5\}, \{\}, \{(4, A), (5, B)\}\})$$

$$TN_{Init} = \{\{0, 1, 2\}, \{(0, 2), (1, 2)\}, \{(0, AB), (1, C), (2, G)\}\}$$

$$S_I = \langle a \rangle \quad A = \langle \text{pre } a, \text{del } a, \text{add } c \rangle$$

$$C = \langle \text{pre } c, \text{del } c, \text{add } b \rangle$$

$$B = \langle \text{pre } b, \text{del } b, \text{add } g \rangle$$

$$G = \langle \text{pre } g, , \rangle$$

The initial task network enforces that G is the last action. To make G executable it needs the variable g, which only B can add. To make B executable it needs the variable b, which only C can add. To make C executable it needs the variable c, which only A can add. A is executable in the initial state. Therefore, the only solution is A C B G. This is impossible to achieve by linearizing methods, since either AB before C or C before AB, both of which exclude the solution.

This proves that the algorithm can remove all solutions, so Algorithm 1 is not complete.

Proposition 1. *Soundness*

Proof. We do not modify the sub-tasks a method produces, just the ordering between them, so the set of plans from the totally ordered method is just a subset of the plans possible from the partially ordered one. Any solution to the linearized problem is then obviously a solution to the original problem.

Proposition 2. *If Algorithm 1 didn't have to cycle-break, at least one solution is preserved*

Proof. Assume that there exists a solution in the PO domain. Using the same decomposition in the linearised domain, we can produce a linearization (a_0, a_1, \dots, a_n) of those

actions in the PO solution. We then prove by induction over the sequence (a_0, \dots, a_n) that it is executable.

If (a_0, \dots, a_n) is not executable, that means there exists some action $a_k, 0 < k < n$ that is not executable in the corresponding state. However a_k must be executable in some linearization for $\{a_0, \dots, a_n\}$, as we assumed it was a PO solution. So there must exist an action $a_i, 0 < i < n$, that will add A. Actions a_0 and a_k must have a shared parent p in TDG. Then p has subtasks t_0 and t_k that are parents of a_0 and a_k respectively.

The linearization of this method would have drawn an ordering (t_i, t_k) due to the way the algorithm defines $prec^*, add^*$ etc. We are assuming that all methods linearized without conflict, so (t_i, t_k) should not be required. This safely enforces (a_k, a_0) ordering in the final TO plan, meaning a_0 is not the first action in the resulting total order imposed by the algorithm. Therefore if a_k 's precondition could be met by any action a_i , a_i would be ordered in front of it.

If a_i does not exist then a_k can never be executed for any linearization of $\{a_0, \dots, a_n\}$, contradicting the assumption that this was a PO solution. Since each action in the solution is executable, the entire sequence is executable linearization of actions produced by decomposition of initial task, i.e. the solution.

2.1 *Even if Algorithm 1 didn't have to cycle break, $\exists t.add^*(t)! = add(t) \vee del^*(t)! = del(t)$*

Proof. Suppose there exists a compound task t whose method 1 decomposes to an action a, with $add(a) = \{A\}$. Assume there is another method which decomposes to action b, with $add(b) = \{B\}$. Therefore $prec^*(t) = \{A, B\}$ but both A and B, will not be applied in every execution of t.

2.2 *If Algorithm 1 didn't have to cycle break, there may be t such that $prec^*(t)$*

Proof. Assume some compound task t' decomposes into at least two sub-tasks, $\{t_1, t_2\}$. Suppose that $a \in F, a \in add(t_1)$ and $a \in F, a \in prec(t_2)$. By the algorithm rules

- Add $\{(t, t') | (a \in add^*(t) \wedge a \in prec^*(t') \wedge t, t' \in tasks(m))\}$ to NS_m
- Add $\{(t', t) | (a \in add^*(t) \wedge a \in del^*(t') \wedge t, t' \in tasks(m))\}$ to NS_m
- Add $\{(t', t) | (a \in del^*(t) \wedge a \in prec^*(t') \wedge t, t' \in tasks(m))\}$ to NS_m
- Add $\{(t, t') | (a \in del^*(t) \wedge a \in add^*(t') \wedge t, t' \in tasks(m))\}$ to NS_m

We know that t_1 is ordered before t_2 . And by the previous proposition 2.1, we know that there does not exist a task t_3 such that $a \in del(t_3)$. Therefore, t_2 will always be executable regardless of what other tasks might do. However, $a \in prec^*(t')$ because $a \in prec^*(t_2)$. Therefore it's possible for preconditions to be erroneous, even if Algorithm 1 did not need to cycle break.

Proposition 3. *When it does have to cycle break, it may preserve solutions*

Proof. As per proposition 2.1 and 2.2, not all of the preconditions and/or effects are always needed. Suppose the initial task network consisted of 2 sub-tasks, t_1, t_2 . If t_2 can decompose into an action a_1 such that $add(a_1) = A$, and an action a_2 such that

$del(a_2) = A$, and t_1 can decompose into an action a_3 with $prec(a_3) = A$ $t_2 = addA, delA$ and $t_1 = precA$. The rules $\{(addA, precA), (precA, delA)\}$ of Algorithm 1 require orderings $\{(t_2, t_2), (t_2, t_1), (t_1, t_2)\}$, i.e. Despite a cycle break being needed, this is obviously a solvable problem. Order t_2 before t_1 for this method. Then when solving decompose t_2 to a_1 and t_1 to a_3 - this creates a solution.

Proposition 4. *For some tasks it doesn't matter where they are executed*

Proof. Assume that some pair of tasks $(t_1), (t_2)$ has no ordering between them. Assume also that $t_1 t_2$ is ok but $(t_2)(t_1)$ is not, i.e. it matters where they are executed.

The required execution sequence implies that t_2 deletes some variable A t_1 relies on. But from the algorithm, that would mean that an ordering (t_1, t_2) was created, which contradicts the assumption that there is no ordering between them. Therefore $(t_2)(t_1)$ must also be ok.

Thus if some task t has no ordering from the algorithm, it can never matter where it is in relation to any other task. The algorithm will not order it specifically when $(\forall t' \in m, \forall a \in prec(t).a \notin add(t') \wedge a \notin del(t')) \wedge (\forall t' \in m, \forall a \in add(t).a \notin prec(t') \wedge a \notin del(t')) \wedge (\forall t' \in m, \forall a \in del(t).a \notin add(t') \wedge a \notin prec(t'))$ In other words, the variables that affect t , do not affect other tasks in that method.

4.2 Algorithm 2

Algorithm 3: Calculation of linearized methods

Data: $(F, T_P, T_C, \delta, M), pre^*, add^*, del^*$ **Result:** (F, T_P, T_C, δ, M) **for** $m \in M$ **do** $NS_m \leftarrow \emptyset$; **for** $a \in F$ **do** $NS_m = \{(t, t', 1) | (a \in add^*(t) \wedge a \in pre^*(t') \wedge t, t' \in tasks(m))\} \cup NS_m$; $NS_m = \{(t', t, 1) | (a \in add^*(t) \wedge a \in del^*(t') \wedge t, t' \in tasks(m))\} \cup NS_m$; $NS_m = \{(t', t, 1) | (a \in del^*(t) \wedge a \in pre^*(t') \wedge t, t' \in tasks(m))\} \cup NS_m$; $NS_m = \{(t, t', 1) | (a \in del^*(t) \wedge a \in add^*(t') \wedge t, t' \in tasks(m))\} \cup NS_m$; **end** directed graph $G = (tasks(m), E)$; $E \leftarrow \emptyset$; **for** $ordering \in \prec$ **do** $E = E \cup (ordering, 0)$ **end** **for** $(t, t', w) \in NS_m$ **do** $E = E \cup ((t, t'), w)$ **end** $BackEdges \leftarrow DFS(G)$; **if** $|BackEdges| > 0$ **then** $\prec' = TopologicalSort(G)$; $m' = (tasks(m), \prec', \alpha(t))$; $M' = m' \cup M'$; **else** $M' = m \cup M'$ **end****end**Return new domain = $(F, T_P, T_C, \delta, M')$

A possible option is to only linearize the methods which do not need cycle breaking.

4.2.1 Solution preserving properties of Algorithm 2

Proposition 5. *Algorithm 2 is sound**Proof.* Same as Proposition 1**Proposition 6.** *Does Algorithm 2 preserve at least one solution? When?**Proof.* ?

4.3 Algorithm 3

The definitions in Conny's paper assumes that there are no negative preconditions. Strict State-independent positive and negative effects:

$$eff_*^+ := (\bigcap_{s \in E(c)} \bigcap_{s' \in R_s(c)} s') \setminus (\bigcap_{s \in E(c)} s)$$

$$eff_*^- := \bigcap_{s \in E(c)} (F \setminus \bigcup_{s' \in R_s(c)} s')$$

if $E(c) \neq \emptyset$ otherwise $eff_*^{+/-}(c) := \text{undef}$

Strict Possible state-independent effects:

$$poss - eff_*^+ := \bigcup_{s \in E(c)} (\bigcup_{s' \in R_s(c)} s' \setminus s)$$

$$poss - eff_*^- := \bigcup_{s \in E(c)} ((\bigcup_{s' \in R_s(c)} (F \setminus s')) \cap s)$$

Relaxation: Define a new domain such that $A' = \{\emptyset, add, del\} | \{\emptyset, add, del\} \in A$. Using this new domain, define the relaxed guaranteed and relaxed possible effects $eff_*^{\emptyset+}$,

$$eff_*^{\emptyset-},$$

$$poss - eff_*^{\emptyset+},$$

$$poss - eff_*^{\emptyset-} \text{ as before.}$$

These effects will *definitely* happen, even if some methods cannot be linearised, Unlike Algorithm 1, this set of preconditions and effects have no false candidates in them. Unlike Algorithm 1, this set of preconditions and effects may be missing some State-independent

positive and negative effects.

Algorithm 4: Calculation of linearized methods

Data: (F, T_P, T_C, δ, M) ,
 $\text{eff}_*^{\emptyset+}, \text{eff}_*^{\emptyset-}, \text{poss} - \text{eff}_*^{\emptyset+}, \text{poss} - \text{eff}_*^{\emptyset-}$

Result: (F, T_P, T_C, δ, M)

for $m \in M$ **do**
 $NS_m \leftarrow \emptyset$;
 for $a \in F$ **do**
 $NS_m = \{(t, t', 1) | (a \in \text{add}^*(t) \wedge a \in \text{pre}^*(t') \wedge t, t' \in \text{tasks}(m))\} \cup NS_m$;
 $NS_m = \{(t', t, 1) | (a \in \text{add}^*(t) \wedge a \in \text{del}^*(t') \wedge t, t' \in \text{tasks}(m))\} \cup NS_m$;
 $NS_m = \{(t', t, 1) | (a \in \text{del}^*(t) \wedge a \in \text{pre}^*(t') \wedge t, t' \in \text{tasks}(m))\} \cup NS_m$;
 $NS_m = \{(t, t', 1) | (a \in \text{del}^*(t) \wedge a \in \text{add}^*(t') \wedge t, t' \in \text{tasks}(m))\} \cup NS_m$;
 Add edges between definite adds and definite deletes, weight = 1 ;
 Add edges between definite effects and possible preconditions, weight=2 ;
 Add edges between possible effects and possible preconditions, with
 weight=3 ;
 end
 directed graph $G = (\text{tasks}(m), E)$;
 $E \leftarrow \emptyset$;
 for $\text{ordering} \in \prec$ **do**
 $E = E \cup (\text{ordering}, 0)$
 end
 for $(t, t', w) \in NS_m$ **do**
 $E = E \cup ((t, t'), w)$
 end
 $\text{BackEdges} \leftarrow \text{DFS}(G)$;
 for $e \in \text{BackEdges}$ **do**
 if $\text{weight}(e) = 4$ **then**
 $E = E \setminus e$
 else
 $\text{weight}(e) = 3$
 end
 $A, B = e$;
 $\text{Path} = \text{Dijkstra}(B, A)$;
 $\text{randEdge} = \text{RANDOM}(\{e \mid \text{weight}(e) = 0 \wedge e \in \text{Path}\})$;
 $E = E \setminus \text{randEdge}$
 end
 $\prec' = \text{TopologicalSort}(G)$;
 $m' = (\text{tasks}(m), \prec', \alpha(t))$;
 $M' = m' \cup M'$;
end
 Return new domain = $(F, T_P, T_C, \delta, M')$

4.3.1 Solution preserving properties of Algorithm 3

Proposition 7. *Algorithm 3 is sound*

Proof. Same as Proposition 1

Proposition 8. *Does Algorithm 3 preserve at least one solution? When?*

Proof. ?

Evaluation

5.1 Empirical Evaluation

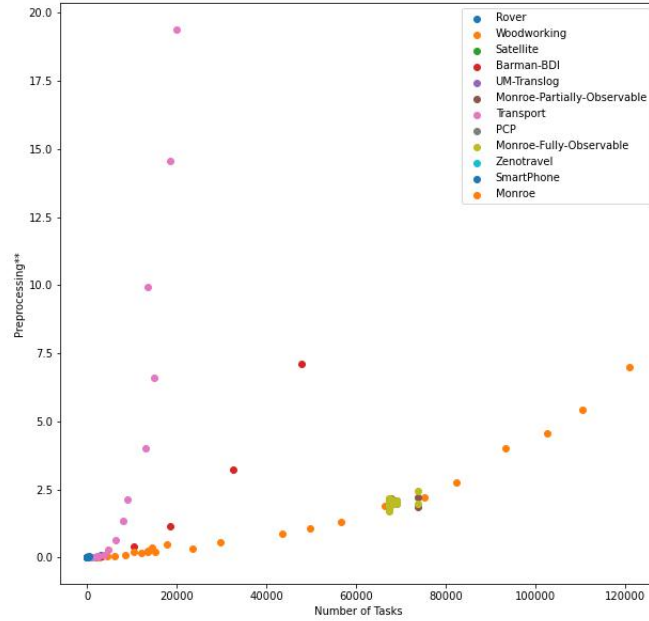
To prove that our technique is beneficial, we conduct a standard empirical evaluation on PO domains and compare the runtime of PO planners vs. transformation + TO planners

5.1.1 Hardware Setup

The following benchmark used 8GB RAM, Nectar cores, threads, processor, Nectar OS, and C++

Full Tables in Appendix. Plots/Tables of relevant properties, e.g.

5 Evaluation



1. None of the instances can be linearized.
2. Despite this, ?percent of linearized problems are solvable.
3. The additional processing time is within the same order of time as the time needed for grounding and a tiny fraction of the overall time \sim
4. We compare the ratio of (Grounding + Pre-processing time + TO solve time) to (Grounding + PO solve time), as those are the steps needed to solve the respective problems. The average solve time for the TO problem is ?? percent of the PO problem, for all problems.
5. Difference in reduction of total solving time influenced most by ? (e.g. domain, recursiveness of problem, percentage of linearizable methods, etc)

Concluding Remarks

If you wish, you may also name that section “*Conclusion and Future Work*”, though it might not be a perfect choice to have a section named “A & B” if it has subsections “A” and “B”. Also note that you don’t necessarily have to use these subsections; that also depends on how much content you have in each. (E.g., having a section header might be odd if it contains just three lines.)

6.1 Conclusion

This chapter usually summarizes the entire paper including the conclusions drawn, i.e., did the developed techniques work? Maybe add why or why not. Also note that every single scientific paper has such a section, so you can check out many examples, preferably at top-tier venues, e.g., by your supervisor(s).

6.2 Future Work

On top of that, you could discuss future work (and make clear why that is future work, i.e., by which observations did they get justified?).

Note that future work in scientific papers is often not mentioned at all or just in a very few sentences within the conclusion. That should not stop you from putting some effort in. This will (also) show the examiner(s)/supervisor(s) how well you understood the topic or how engaged you are.

Appendix: All Results For Algorithms

A.1 Algorithm 1

A.1.1 Algorithm 1 pre-processing performance

* Percentage of number of linearised methods / number of methods with 2 or more subtasks

** All time in seconds

*** Average number of tasks per method, excluding the initial task network

A Appendix: All Results For Algorithms

Rover						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
396	2.24823	424	35.2727	0.049	0.004175	
2258	2.18431	2589	25.1229	0.1288	0.037174	
1484	2.20161	1866	39.6364	0.1101	0.023642	
460	2.32727	441	25.3776	0.0283	0.006185	
65	2.34694	50	35.1351	0.0119	0.001148	
59	2.35556	46	40.625	0.0112	0.001594	
1202	2.22602	1377	33.114	0.0767	0.029776	
382	2.37709	359	30.303	0.0235	0.006008	
561	2.28114	595	32.2115	0.0363	0.009243	
626	2.30711	662	33.6323	0.0422	0.008775	
89	2.47143	71	44.0	0.0132	0.001044	
595	2.19498	678	34.4262	0.0364	0.010964	
494	2.30469	513	32.7684	0.0292	0.013627	
245	2.22321	225	24.1379	0.0177	0.02508	
152	2.26016	124	21.5686	0.0141	0.004343	
414	2.3222	420	33.5593	0.0255	0.006752	
707	2.26154	716	22.7941	0.0367	0.010028	
243	2.42857	218	33.5443	0.0187	0.002684	
81	2.46667	61	40.0	0.0124	0.00088	

Recursive: False

Woodworking						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
1005	1.16356	1450	0.0	0.045	0.004655	
29804	1.02155	129218	0.0	1.4686	0.562532	
2748	1.11924	5620	0.0	0.0975	0.016805	
896	1.13949	1528	0.0	0.0444	0.00505	
93209	1.01596	485051	0.0	5.5487	4.02608	
12	1.0	9	0.0	0.013	5.5e-05	
75238	1.01763	373234	0.0	4.0672	2.19396	
56590	1.02022	258945	0.0	2.8876	1.29956	
21	1.0	15	0.0	0.0179	0.000101	
82285	1.01898	390298	0.0	4.5634	2.7429	
16	1.54545	12	0.0	0.0137	8.8e-05	
964	1.1419	1798	0.0	0.0547	0.006413	
23568	1.03312	84962	0.0	1.1152	0.331937	
1629	1.13057	2988	0.0	0.0644	0.00987	
15266	1.02848	57717	0.0	0.7028	0.210608	
32	1.12121	34	0.0	0.0143	0.000138	
4386	1.11759	9594	0.0	0.152	0.035009	
6167	1.06607	14167	0.0	0.2109	0.04804	
66431	1.01987	306499	0.0	3.4698	1.87959	
146	1.11111	199	0.0	0.019	0.000637	
721	1.24538	1191	0.0	0.0378	0.004715	
102683	1.01772	512099	0.0	5.9302	4.55552	
36	1.10811	38	0.0	0.0149	0.000148	
110366	1.01926	521261	0.0	7.7864	5.41724	
1267	1.22291	2087	0.0	0.057	0.008655	
120819	1.01804	592235	0.0	6.9148	6.97687	
43515	1.02161	196969	0.0	2.4068	0.891157	
254	1.11599	320	0.0	0.0233	0.001087	
49650	1.02036	230394	0.0	2.477	1.07154	

Recursive: False

A Appendix: All Results For Algorithms

Satellite						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
29	2.16667	37	53.125	0.01	0.000293	
128	2.27027	260	37.5	0.0081	0.002181	
10	2.33333	10	57.1429	0.0045	9.8e-05	
17	2.55	21	50.0	0.0044	0.000223	
32	2.18919	38	56.25	0.0053	0.000301	
88	2.22388	135	46.9565	0.0068	0.001072	
22	2.60714	29	48.0	0.0048	0.000327	
58	2.1875	81	54.9296	0.0061	0.000598	
55	2.24176	92	41.5584	0.0056	0.000872	
66	2.64286	99	50.5747	0.0064	0.001052	
76	2.7395	120	49.5413	0.0068	0.001529	
55	2.17808	74	54.6875	0.006	0.000559	
139	2.39801	202	53.2967	0.0091	0.001877	
98	2.27273	155	42.4	0.0087	0.001523	
40	2.55172	59	50.0	0.0052	0.000595	
44	2.63492	64	50.0	0.0058	0.000685	
24	2.14286	29	56.0	0.0047	0.000207	
17	2.55	21	50.0	0.0048	0.000222	
36	2.0	45	50.0	0.005	0.000288	
63	2.19512	83	54.9296	0.0064	0.000621	
66	2.20225	90	55.1282	0.0066	0.000683	
34	2.2	46	52.5	0.0051	0.000346	
131	2.75943	213	50.5102	0.0094	0.002685	
31	2.55	41	51.4286	0.0059	0.000431	

Recursive: False

Barman-BDI						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
1419	2.46201	1146	27.7451	0.0561	0.019318	
32612	2.52212	26972	22.9102	1.2605	3.24646	
18408	2.51788	15184	23.4252	0.6573	1.16557	
1125	2.45215	910	27.599	0.0446	0.017246	
165	2.32283	128	36.6337	0.0182	0.001367	
300	2.38723	236	34.3434	0.021	0.002747	
10434	2.51241	8586	23.929	0.3766	0.422801	
649	2.42747	518	30.4444	0.0346	0.006654	
2597	2.4759	2117	25.7727	0.0814	0.042462	
3060	2.49415	2480	26.899	0.0924	0.057508	
393	2.40909	309	33.9695	0.0239	0.003794	
3250	2.49112	2648	25.8966	0.0994	0.059478	
1484	2.475	1201	27.5349	0.0505	0.019722	
580	2.43573	460	31.9095	0.0298	0.006146	
559	2.42568	445	31.1688	0.0287	0.005748	
782	2.4464	626	29.8725	0.0364	0.008496	
1871	2.48379	1512	27.6549	0.0641	0.027674	
628	2.41833	503	29.7483	0.0333	0.006294	
444	2.39601	352	32.0	0.0256	0.004284	

Recursive: False

A Appendix: All Results For Algorithms

UM-Translog						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
8	0.0	1	0.0	0.0188	0.000111	
12	0.0	1	0.0	0.016	0.000217	
11	7.5	3	0.0	0.016	0.000185	
12	0.0	1	0.0	0.0161	0.00024	
14	0.0	1	0.0	0.0162	0.000583	
12	3.5	3	0.0	0.0221	0.00026	
20	14.5	3	0.0	0.0221	0.001484	
10	7.5	3	0.0	0.0161	0.000186	
8	0.0	1	0.0	0.0165	0.000198	
22	0.0	1	0.0	0.0183	0.001156	
8	0.0	1	0.0	0.0174	0.000162	
8	0.0	1	0.0	0.017	0.000167	
14	0.0	1	0.0	0.0167	0.000537	
10	0.0	1	0.0	0.0168	0.000198	
14	7.5	3	0.0	0.0168	0.000551	
24	17.5	3	0.0	0.0191	0.001745	
10	0.0	1	0.0	0.0212	0.00023	
10	0.0	1	0.0	0.0173	0.000195	
8	0.0	1	0.0	0.0168	0.00017	
21	0.0	1	0.0	0.0174	0.000967	
8	0.0	1	0.0	0.0171	0.0002	
Recursive: False						

Monroe-Partially-Observable						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
67418	2.21429	55016	68.1127	2.0101	1.9434	
68890	2.21431	56051	68.0574	2.225	2.07487	
67422	2.2142	55020	68.1127	2.039	2.01091	
67433	2.2142	55029	67.8145	2.1308	2.00445	
73827	2.19955	60547	68.0642	2.1147	1.8394	
67430	2.21402	55028	68.1127	2.1293	2.03887	
67429	2.21408	55027	68.1134	2.7032	2.05474	
67812	2.21714	55315	67.682	2.1563	2.18095	
67811	2.21707	55314	67.9555	2.107	2.13088	
67428	2.21407	55026	68.1127	2.0435	1.89057	
68884	2.21444	56045	68.0574	2.1099	1.95732	
67425	2.21417	55023	68.1134	2.0865	1.90319	
67418	2.21429	55016	68.1127	2.0806	1.98215	
67801	2.21729	55304	67.9758	2.0694	2.11927	
73821	2.19967	60541	68.0642	2.2321	2.20587	
67425	2.21438	55021	68.1086	2.0549	1.84788	
67428	2.21407	55026	68.1127	2.0925	1.85908	
67422	2.2142	55020	68.1127	2.016	1.90154	
67433	2.21407	55031	67.8186	2.0786	1.87328	
67425	2.21438	55021	68.1086	2.0699	1.97273	
67801	2.21729	55304	67.9758	2.1719	2.01427	
67429	2.21415	55027	68.1127	2.1738	2.08523	
67443	2.21377	55041	68.1134	2.3989	1.95702	

Recursive: False

A Appendix: All Results For Algorithms

Transport						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
8062	1.38812	9073	0.0	0.2104	1.34733	
6386	1.37436	6826	0.0	0.1462	0.637496	
3673	1.38752	4135	0.0	0.0918	0.100144	
12969	1.40114	15377	0.0	0.3408	3.99726	
13421	1.36337	13761	0.0	0.3683	9.91777	
511	1.43529	511	0.0	0.016	0.004958	
129	1.43077	131	0.0	0.0077	0.000732	
402	1.36	401	0.0	0.0142	0.003512	
381	1.375	401	0.0	0.0143	0.003101	
116	1.20792	102	0.0	0.0093	0.032754	
19	1.53333	16	0.0	0.0055	0.000315	
45	1.3	41	0.0	0.0058	0.000963	
4763	1.38814	5365	0.0	0.1162	0.285897	
340	1.37288	355	0.0	0.0125	0.002433	
14939	1.40585	18057	0.0	0.4223	6.58352	
104	1.2551	99	0.0	0.0072	0.010046	
2286	1.36952	2396	0.0	0.052	0.050062	
175	1.42857	169	0.0	0.0084	0.001073	
18581	1.36651	19291	0.0	0.5784	14.5498	
397	1.43704	406	0.0	0.0128	0.00289	
235	1.42982	229	0.0	0.0115	0.001958	
1473	1.37047	1545	0.0	0.0348	0.023913	
44	1.31707	42	0.0	0.0052	0.000912	
1416	1.4306	1406	0.0	0.0323	0.027404	
605	1.36967	634	0.0	0.0176	0.004384	
1161	1.43952	1241	0.0	0.0273	0.011946	
2649	1.3913	3037	0.0	0.0639	0.037584	
204	1.42857	197	0.0	0.0085	0.001312	
20001	1.36381	20561	0.0	0.5632	19.3826	
363	1.38824	341	0.0	0.0132	0.008704	
9038	1.38179	9920	0.0	0.2186	2.12052	
115	1.42593	109	0.0	0.0068	0.000621	
71	1.30769	66	0.0	0.0055	0.005033	
81	1.23288	74	0.0	0.0067	0.005131	
103	1.21111	91	0.0	0.0074	0.018213	
144	1.42647	137	0.0	0.0074	0.000798	
79	1.28986	70	0.0	0.0066	0.010016	
68	1.24194	63	0.0	0.0068	0.002338	
309	1.39205	353	0.0	0.0118	0.001922	

Recursive: False

PCP						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
13	3.66667	13	0.0	0.0051	0.000401	
15	3.875	17	0.0	0.0051	0.00056	
13	3.66667	13	0.0	0.0049	0.000446	
15	3.16667	13	0.0	0.0052	0.00028	
15	4.5	17	0.0	0.0057	0.000935	
13	3.83333	13	0.0	0.0048	0.000576	
13	3.83333	13	0.0	0.005	0.000466	
13	3.66667	13	0.0	0.0049	0.000404	
17	3.125	17	0.0	0.0052	0.000377	
11	3.0	9	0.0	0.0044	0.000177	
11	3.5	9	0.0	0.0044	0.000277	
11	4.0	9	0.0	0.0046	0.000415	
11	4.5	9	0.0	0.0101	0.000928	
11	5.0	9	0.0	0.0045	0.00096	
11	3.5	9	0.0	0.0045	0.000274	
13	3.16667	13	0.0	0.0052	0.000282	
Recursive: False						

A Appendix: All Results For Algorithms

Monroe-Fully-Observable						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
67418	2.21429	55016	68.1127	1.9754	1.88009	
68890	2.21431	56051	68.0574	2.1289	1.98078	
67422	2.2142	55020	68.1127	2.0137	2.16721	
67435	2.21416	55031	67.8145	2.144	2.076	
73827	2.19955	60547	68.0642	2.1169	1.96254	
67436	2.21389	55034	67.8186	2.0457	1.70454	
67433	2.21399	55031	68.1134	2.145	1.75014	
67818	2.21701	55321	67.682	2.3581	2.08889	
67811	2.21707	55314	67.9555	2.143	2.06021	
67428	2.21407	55026	68.1127	2.1133	2.05435	
68884	2.21444	56045	68.0574	2.1945	2.07282	
67425	2.21417	55023	68.1134	2.1373	1.98499	
67418	2.21429	55016	68.1127	2.5008	2.08575	
67801	2.21729	55304	67.9758	2.4429	2.13274	
73821	2.19967	60541	68.0642	3.5701	2.43004	
67425	2.21438	55021	68.1086	2.252	2.13456	
67430	2.21402	55028	67.8186	2.1134	1.9436	
67422	2.2142	55020	68.1127	2.0775	1.89634	
67439	2.21393	55037	67.8186	2.1591	2.0417	
67425	2.21438	55021	68.1086	2.1023	1.99735	
67801	2.21729	55304	67.9758	2.0668	1.9264	
67429	2.21415	55027	68.1127	2.1173	1.91552	
67451	2.2136	55049	68.1134	2.297	2.05399	
67427	2.2142	55025	68.1127	2.2347	2.17898	

Recursive: False

Zenotravel						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
485	2.01786	449	48.8998	0.0262	0.002971	
123	2.02913	104	44.2105	0.011	0.000698	
97	2.05263	77	46.3768	0.0138	0.0006	
281	2.09244	239	46.9484	0.017	0.00185	

Recursive: False

SmartPhone						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
10	1.5	3	0.0	0.0279	0.000249	
74	1.18421	77	40.0	0.0279	0.003691	
26	2.27273	12	0.0	0.0247	0.000326	
281	1.05831	344	62.5	0.034	0.03811	
22	1.125	25	50.0	0.0243	0.000192	
23	1.375	9	0.0	0.025	0.001222	

Recursive: False

Monroe						
Tasks	avg***	Methods	Linearizable Methods % *	Grounding**	Preprocessing**	
10303	1.80762	13973	75.0408	0.9821	0.197555	
13609	1.87757	14132	65.5856	0.8972	0.218261	
13609	1.87757	14132	65.5856	0.9332	0.26452	
17739	2.08939	27207	68.4257	1.2638	0.488081	
14373	1.97155	23727	78.7107	1.0089	0.357765	
12092	1.84136	12684	68.3509	0.9201	0.184313	

Recursive: False

A.1.2 Solving Performance

			Rover	
Tasks	time to solve PO	time to solve TO		
396	203.617	0.168		
460	187.619	4.077		
65	0.236	0.057		
59	0.111	0.055		
1202	380.662	5.17		
382	155.551	0.6		
561	148.941	0.191		
626	204.075	4.275		
89	0.134	0.058		
595	202.559	0.403		
494	179.874	24.747		
245	125.468	0.257		
152	134.515	0.152		
414	201.005	0.204		
707	261.94	47.815		

We use the partially ordered track in the IPC 2020 benchmark.

A Appendix: All Results For Algorithms

A.2 Algorithm 2

A.3 Algorithm 3

Appendix: Explanation on Page Borders

What you find here is an explanation of why the border width keeps flipping from left to right – which you might have spotted and wondered why that’s the case.

Firstly, that is *intended* and thus correct, so there is no reason to worry about this. The reason is that this document is configured as a two-sided book, which means:

- We assume the document will be printed out,
- that this will be done in a two-sided mode (i.e., the document will be printed on both sides of each page), and
- that the bookbinding will be in the middle, just like in every book.

When you open the book, there are three borders of equal size n . This however requires that even pages have a border of n on their left and $\frac{n}{2}$ on their right, and odd pages have a border of $\frac{n}{2}$ on their left and n on their right. This is illustrated in Figure B.1.

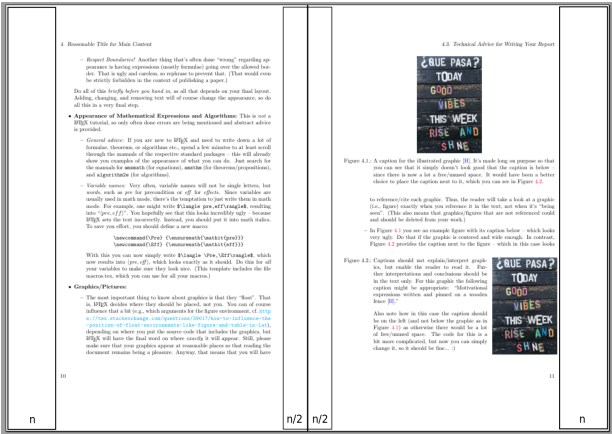


Figure B.1: Illustration showing why page borders flip.

Bibliography
