LOLLIPOP: Generating and using proper plan and negative refinements for performance on online partial order planning

Paper ID#42

Abstract. The abstract! Infinite source of drama, confusion and *shameless* paper promotion. Stay tuned for more!

# Everything that starts with a # is purely commentary and WILL be removed

Introduction

Until the end of the 90s, Plan-Space Planning (PSP) was generally preferred by the automated planning community. Its early commitment, expressivity, and flexibility were clear advantages over State-Space Planning (SSP). However, more recently, drastic improvements in state search planning was made possible by advanced and efficient heuristics. This allowed those planners to scale up more efficiently than plan-space search ones, notably thanks to approaches like GraphPlan [1], fast-forward [2], LAMA [3] and Fast Downward Stone Soup [4]. This evolution led to a preference for performances upon other aspects of the problem of automated planning. Some of these aspects can be more easily addressed in Partial Order Planning (POP). For example POP, has can take advantage of least commitment [5] that offers more flexibility with a final plan that describes only the necessary order of the actions considered without forcing a particular sequence. POP has also been proven to be well suited for multi-agent planning [6] and temporal planning [7] . These advantages made UCPOP [8] one of the preferred POP planner of its time with works made to port some of its characteristics into state-based planning [9]. Related works already tried to explore new ideas to make POP into an attractive alternative to regular state-based planners like the appropriately named "Reviving partial order planning" [10] and VHPOP [11]. More recent efforts [12], [13] are trying to adapt the powerful heuristics from state-based planning to POP's approach. An interesting approach of these last efforts is found in [14] with meta-heuristics based on offline training on the domain. However, we clearly note that only a few papers lay the emphasis upon plan quality using POP [15], [16]. This work is the base of our project for an intelligent robotic system that can use plan and goal inference to help dependent persons to accomplish tasks. This project is based on the works of Ramirez et al. [17] on inverted planning for plan inference. This context led us to seek ways to improve POP with better refining techniques and resolver selection. Since we need to handle data derived from limited robotic sensors, we need a way for the planner to be able to be resilient to basic corruption on its input. Another aspect of this work lies in the fact that the final system will need to compute online planning with a feed of observational data. In order to achieve this we need a planner that can:

- repair and optimize existing plans,
- perform online planning efficiently
- retain performances on complex but medium sized problems.

Classical POP algorithms don't meet most of these criteria but can be enhanced to fit the first one. Usually, POP algorithms take a problem as an input and use a loop or a recursive function to refine the plan into a solution. We can simply expose the recursive function in order to be able to use our existing partial plan. This, however, causes multiples side effects if the input plan is suboptimal. *Our view* on the problem diverges from other works: PSP is a very different approach compared to SSP. It is usually more computationally expensive than modern state space planners but brings several advantages. We want to make the most of them instead of trying to change POP's fundamental nature. That view is at the core of our model: we use the refining and least commitment abilities of POP in order to improve online performances and quality. In order to achieve this, we start by computing a *proper plan* that is computed offline with the input of the domain. The explanation of the way this notion is defined and used can be found in section 2.1 of the present paper. Using existing partial plans as input leads to several issues, mainly with new flaw types that aren't treated in classical POP. This is why we focus the section 2.2 of our paper on plan quality and negative refinements. We, therefore, introduce new negative flaws and resolvers that aim to fix and optimise the plan: the *alternative* and the *orphan* flaws. Side effects of negative flaws and resolvers can lead to conflicts. In order to avoid them and enhance performances and quality, the algorithm needs resolver annd flaw selection mechanisms that are explained in the section 2.3 of our work. All these mechanisms are part of our aLternative Optimization with partiaL pLan Injection Partial Ordered Planning (LOLLIPOP) algorithm presented in details in section 2.4. We prove that the use of these new mechanisms leads to fewer iterations, a reduced branching factor and better quality than standard POP in section 3. Experimental results and benchmarks are presented and explained in the section 4 of this paper.

1 Partial Order Planning Preliminaries

While needing expressivity and simplicity in our domain definition we also need speed and flexibility for online planning on robots. Our framework is inspired by existing multi-purpose semantic tools such as RDF Turtle [18] and has an expressivity similar to PDDL 3.1 with object-fluents support [19]. This particular type of domain description was chosen because we intend to extend works on soft solving in order to handle corrupted data better in future papers. The next definitions are based on the ones exposed in [20].

Every planning paradigm needs a way to represent its fluents and

Figure 1 shows an example of a planning domain and problem that we will use as a guideline throughout the article.

Aller à la ligne

operators. Our planner is based on a rather classical domain definition with lifted operators and representing the fluents as propositional statements.

Definition 1 (Domain). *We define our planning domain as a tuple* $\Delta = \langle T, C, P, F, O \rangle$ *where*

- T *are the* ***types****,*
- C *is the set of* ***domain constants****,*
- P *is the set of* ***properties*** *with their arities and typing signatures,*
- F *represents the set of* ***fluents*** *defined as potential equations over the terms of the domain,*
- O *is the set of optionally parameterized* ***operators*** *with preconditions and effects.*

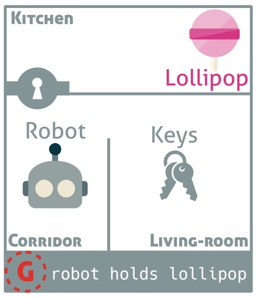
Along with a domain, every planner needs a problem description in order to work. For this, we use the classical problem representation with some special additions.

Definition 2 (Problem). *The planning problem is defined as a tuple* $\Pi = \langle \Delta, C_\Pi, I, G, p \rangle$ *where*

- Δ *is a planning domain,*
- C_Π *is the set of* ***problem constant*** *disjoint from* C*,*
- I *is the* ***initial state****,*
- G *is the* ***goal****,*
- p *is a given* ***partial plan****.*

The framework uses the *closed world assumption* in which all predicates and properties that aren't defined in the initial step are assumed false or don't have a value.

~~We want to introduce a problem in figure 1 that we will use to exemplify the presented notion.~~



```
go(?movable, ?room)
     ?movable is Movable, ?room is Room
     pre ?movable room != ?room,
         ?room locked false
     eff ?movable room ?room

grab(?graber, ?pickable)
     ?graber is Graber, ?pickable is Pickable
     pre ?graber holds nothing,
         ?graber room = ?pickable room
     eff ?graber holds ?pickable

unlock(?graber, ?room)
     ?graber is Graber, ?room is Room
     pre ?room locked, ?graber holds keys
     eff ?graber holds nothing,
         ?room locked false
```

Figure 1. Example domain and problem featuring a robot that aims to fetch a lollipop in a locked kitchen. The operator `go` is used for movable objects (such as the robot) to move to another room, the `grab` operator is used by grabbers to hold objects and the `unlock` operator is used to open a door when the robot holds the key.

In order to simplify this framework we need to introduce some differences from the classical representation. First ~~For example,~~ the partial plan is a part of the problem tuple as it is a needed input of the LOLLIPOP algorithm.

Definition 3 (Partial Plan). *We define a partial plan as a tuple* $\langle S, L, B \rangle$ *with* S *the set of* ***steps*** *(semi or fully instantiated operators also called* actions*),* L *the set of* ***causal links****, and* B *the set of* ***binding constraints****.*

~~In classical representations, a set of *ordering constraints* is also added. We propose to factorize this notion as being part of the causal links which~~ are always supported by an ordering constraint. The only case where bare ordering constraints are needed is in threats. We decided to represent them with "bare causal links". These are stored as causal links without bearing any fluents. This also eases implementation with

Second we factorize the set of ordering constraints, used in classical representation, as being part of the causal links. Indeed, causal links are …

the definition of the causal link giving only one graph of steps with a (possibly empty) list of fluents as a label as our main definition for a partial plan. That allows us to introduce the **precedence operator** noted $a_i \succ a_j$ with $a_i, a_j \in S$ iff there is a path of causal links that connects a_i with a_j with a_i being *anterior* to a_j. A specificity of Partial Order Planning is that it fixes flaws in a partial plan in order to refine it into a valid plan that is a solution to the given problem. In this section, we define the classical flaws in our framework.

Definition 4 (Subgoal). *A flaw in a partial plan, called subgoal is a missing causal link required to satisfy a precondition of a step. We can note a subgoal as:* $a_p \xrightarrow{s} a_n \notin L \mid \{a_p, a_n\} \subseteq S$ *with* a_n *called the* ***needer*** *and* a_p *an eventual* ***provider*** *of the fluent* s*. This fluent is called* open condition *or* ***proper fluent*** *of the subgoal.*

Definition 5 (Threat). *A flaw in a partial plan called threat consists of having an effect of a step that can be inserted between two actions with a causal link that is intolerant to said effect. We say that a step* a_b *is threatening a causal link* $a_p \xrightarrow{t} a_n$ *iff* $\neg t \in eff(a_b) \wedge a_p \succ a_b \succ a_n \models L$ *with* a_b *being the* ***breaker****,* a_n *the* needer *and* a_p *a* provider *of the* proper fluent t*.*

Flaws are fixed via the application of a resolver to the plan. A flaw can have several resolvers that match its needs.

Definition 6 (Resolvers). *A resolver is a potential causal link defined as a tuple* $r = \langle a_s, a_t, f \rangle$ *with :*

- $a_s, a_t \in S$ *being the source and target of the resolver,*
- f *being the considered fluent.*

For standard flaws, the resolvers are simple to find. For a *subgoal* the resolvers are a set of the potential causal links between a possible provider of the proper fluent and the needer. To solve a *threat* there is mainly two resolvers: a causal link between the needer and the breaker called **demotion** or a causal link between the breaker and the provider called **promotion**.

Once the resolver is applied, another important step is needed in order to be able to keep refining. The algorithm needs to take into account the **side effects** the application of the resolver had on the partial plan. The side effects ~~It searches the related flaws~~ of the elected resolver. ~~These related flaws~~ are searched by type.

Definition 7 (Side effects). *Flaws that arise because of the application of a resolver on the partial plan are called causal side effects or* related flaws*. They are caused by an action* a_t *called the* ***trouble maker*** *of a resolver. This action is the* source *of the resolver applied onto the plan.*

We can derive this definition for subgoals and threats:

- **Related Subgoals** are all the open conditions inserted with the *trouble maker*. The subgoals are often searched using the preconditions of the trouble maker and added when no causal links satisfy them.
- **Related Threats** are the causal links threatened by the insertion of the *trouble maker*. They are added when there is no path of causal links that prevent the action to interfere with the threatened causal link.

In the partial plan presented in figure 2, we consider that a resolver providing the fluent `robot holds key` is considered. This resolver will introduce the open conditions `robot holds nothing, key room _room, robot room _room` since it just introduced this instantiation of the `grab` operator in the partial plan. Each of these will trigger a related subgoal that will have this new `grab` operator as their needer. The potentially related threat of this resolver

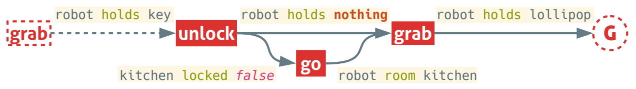


Figure 2. Example of a partial plan occurring during the computation of POP on the previous example domain illustrated by figure 1. The `grab` operator at the left is part of the currently considered resolver in POP's execution.

préciser différence entre full arrow et dotted arrow

is that the effect `robot holds key` might threaten the link between the existing `unlock` and `grab` steps but won't be considered since there are no way the new step can be inserted after `unlock`.

In classical POP, there is no need to search for side effects when fixing a threat or when simply adding a causal link between existing steps.

The classical POP algorithm is pretty straight forward: it starts with a simple partial plan and refines its *flaws* until they are all resolved to make the found plan a solution of the problem.

Algorithm 1 Classical Partial Order Planning

```
function POP(Queue of Flaws $a$, Problem $\Pi$)
    POPULATE($a$, $\Pi$)                          ▷ Populate agenda only on first call
    if $\Pi.G = \emptyset$ then                   ▷ Goal is empty, default solution is provided
        $\Pi.p.L \leftarrow (I \rightarrow G)$
    if $a = \emptyset$ then
        return Success                            ▷ Stop all recursion
    Flaw $f \leftarrow$ CHOOSE($a$)               ▷ Non deterministic choice
    Resolvers $R \leftarrow$ RESOLVERS($f$, $\Pi$)
    for all $r \in R$ do                          ▷ Non deterministic choice operator
        APPLY($r$, $\Pi.p$)                       ▷ Apply resolver to partial plan
        SideEffects $s \leftarrow$ SIDEEFFECT($r$)
        APPLY($s$, $a$)                           ▷ Side effects of the resolver
        if POP($a$, $\Pi$) = Success then         ▷ Refining recursively
            return Success
        REVERT($r$, $\Pi.p$)                      ▷ Failure, undo resolver insertion
        REVERT($s$, $a$)                          ▷ Failure, undo side effects application
    return Failure                                ▷ Revert to last non deterministic choice of resolver
```

The algorithm 1 is inspired by [21]. This POP implementation uses an agenda of flaws that is efficiently updated after each refinement of the plan. At each iteration, a flaw is selected and removed from the agenda (line 7). A resolver for this flaw is then selected and applied (line 10). If all resolvers cause failures, the algorithm backtracks to the last resolver selection to try another one. The algorithm terminates when no more resolver fits a flaw (`Failure`) or when all flaws have been fixed (`Success`).

This standard implementation has several limitations. First, it can easily make poor choices that will lead to excessive backtracking. It also can't undo redundant or nonoptimal links if they don't fail.

To illustrate these limitations, we use the example described in figure 1 where a robot must fetch a lollipop in a locked room. This problem is solvable by regular POP algorithms. However, we can have some cases where small changes in POP's inputs can cause a lot of unnecessary back-trackings. For example, if we add a new action called `dig_throught_wall` that has as effect to be in the desired room but that requires a hammer, the algorithm will simply need more backtracking. The effects could be worse if obtaining the hammer would require numerous steps (for example needing to build it). This problem can be solved most of the time using simple flaw selection mechanisms. However, this was never applied in the context of POP. The other limitation arises when the plan has been modified. This can arise in the context of the dynamical environments of online planning's application. Regular POP algorithms do not consider this issue as they do not take a partial plan as input. This can cause a variety of new problems that are related to planning corruption.

pelle :shover ?

In order to address these issues, we present a set of new mechanisms.

2 LOLLIPOP's Approach

introduction de l'approche/ce que tu vas présenter en 2/3 lignes

2.1 Proper Plan Generation and Injection

? quand on lit 2.1 on ne comprend pas le lien avec cette partie du titre

One of the main contributions of the present paper is our use of the concept of *proper plan*. First of all, we need to define this notion.

Definition 8 (Proper Plan)**.** *A proper plan O^P of a set of operators O is a labelled directed graph that binds two operators $o_1 \xrightarrow{f} o_2$ iff it exists at least a unifying fluent $f \in eff(o_1) \cap pre(o_2)$ between them.*

quelle est la différence entre proper plan et causal graph ? le préciser …

This definition was inspired by the notion of domain causal graph as explained in [20] and originally used as heuristic in [22]. A variation of this notion was used in [23] that builds the operator dependency graph of goals and uses precondition nodes instead of labels. A proper plan is, therefore, an *operator dependency graph* for a set of actions. This structure is very useful for getting information on the *shape of a problem*. This shape leads to an intuition based on the potential usefulness or hurtfulness of operators. Cycles in this graph denotes the dependencies of operators. We call *co-dependent* several operators that form a cycle. If the cycle is made of only one operator (self-loops), then it is called *auto-dependent*.

While building this proper plan, we need a **providing map** that indicates, for each fluent, the list of operators that can provide it. This associative table is easy to update and the list of provider can be sorted in order to drive resolver selection. A **needing map** is also built but isn't used in further mechanisms.

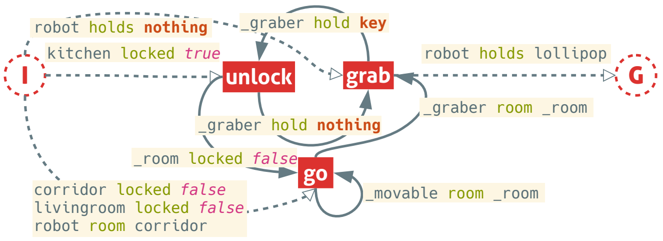


Figure 3. Diagram of the proper plan of example domain. In full arrows the proper plan as computed during domain compilation time and in dotted arrows the dependencies added to inject the initial and goal steps.

In the figure 3 we illustrate the application of this mechanism on our previous example. (Fig. 1) Continuous lines are the ~~base~~ *domain proper plan*. This particular proper plan, noted Δ^P, is built with the information ~~present in the domain.~~ provided by the planning domain

The generation of the proper plan is based upon the previous definition: It will explore the operators space and build a providing and needing map that gives the provided and needed fluents for each operator. Once done it will iterate on every precondition and search for a satisfying cause in order to add the causal link to the proper plan. The algorithm 2 details this procedure.

Applying the notion of proper plan for problems only needs the initial and goal steps added in the proper plan. In figure 3 we illustrate this insertion with our previous example using dotted lines.

~~A derived notion can be built from proper plan. We can make a "safe" version of this algorithm. The aim is to do a simple and fast backward~~

+ préciser pourquoi les cycles dans proper plan sont un problème

In order to build a safe proper plan without any cycles, we propose a safe proper plan generation algorithm detailed in Algo. 3. It does a simple and fast backward driven by the providing map. Therefore it can be tweaked with the powerful heuristics of state search plan.

ce n’est pas plutôt « si eff n’appartient pas » ?

préciser ce que add fait:
add o to the list of
operators providing eff

Algorithm 2 Proper plan generation and update algorithm

```
function ADDVERTEX(Operator $o$)
    CACHE($o$)                                  Update of the providing and needing map
    if binding then                             boolean that indicates if the binding was requested
        BIND($o$)
function CACHE(Operator $o$)
    for all $eff \in eff(o)$ do
        if $eff \in providing$ then             providing is the providing map
            ADD($providing, eff, o$)
    ...                                         Same operation with needing and preconditions
function BIND(Operator $o$)
    for all $pre \in pre(o)$ do
        if $pre \in providing$ then
            for all $p \in$ GET($providing, pre$) do
                Link $l \leftarrow$ GETEDGE($p, o$)       Create the link if needed
                $l \leftarrow l \cup \{pre\}$             Add the fluent as a cause
    ...                                         Same operation with needing and effects
```

~~chaining algorithm that can build a proper plan that does not contain cycles.~~

Algorithm 3 Safe proper plan generation algorithm

```
1  function SAFE(Problem $\Pi$)
2      Stack $open \leftarrow [\Pi.G]$
3      Stack $closed \leftarrow \emptyset$
4      while $open \neq \emptyset$ do
5          Operator $o \leftarrow$ POP($open$)            Remove o from open
6          PUSH($closed, o$)
7          for all $pre \in pre(o)$ do
8              Operators $p \leftarrow$ GETPROVIDING($\pi, pre$)
9              if $p = \emptyset$ then                si plusieurs operateurs provide pre,
10                 $\Pi.p.S \leftarrow \Pi.p.S \setminus \{p\}$   comment sont ils triés ?
11                 continue                    prendre le premier revient à faire quel choix ?
12             Operator $o' \leftarrow$ GETFIRST($p$)   (utilise utilité définie +loin?)
13             if $o' \in closed$ then
14                 continue
15             if $o' \notin \Pi.p.S$ then
16                 PUSH($open, o'$)
17             $\Pi.p.S \leftarrow \Pi.p.S \cup \{o'\}$
18             Link $l \leftarrow$ GETEDGE($o', o$)        Create the link if needed
19             $l \leftarrow l \cup \{pre\}$              Add the fluent as a cause
```

This algorithm is very useful since it is specifically used on goals. The result is a valid partial plan that can be used as input of POP algorithms. ~~The focus of this is that it is a simple backward search that is driven by the providing map and can, therefore, be tweaked with the powerful heuristics of state search plan.~~ Another interesting consequence is that most subgoals are quickly fixed. This allows POP to focus on the important and branching heavy decisions.

??? As this proper plan is injected as input in POP it still needs refinements. The

2.2 Negative Refinements and Plan Optimization

The Classical POP algorithm works upon a principle of positive plan refinements. The two standard flaws (subgoals and threats) are fixed by *adding* steps, causal links, or variable binding constraints to the partial plan. In our case, it is important to be able to *remove* part of the plan that isn’t necessary for the solution. rappeler pourquoi

assume the input partial plan

Since we ~~are given a partial plan that~~ is quite complete, we need to define ? add new flaws to optimize and fix this plan. These flaws are called *negative* ~~since their resolvers differ from classical ones from their effects on the plan.~~ as their resolvers and their effects on the plan differ from classical ones.

Definition 9 (Alternative)**.** *An alternative is a negative flaw that occurs when it exists a better provider choice for a given link. An alternative to a causal link* $a_p \xrightarrow{f} a_n$ *is a provider* a_b *that have a better* utility value *than* a_p.

of an operator

The **utility value** is a measure of the usefulness at the heart of our ranking mechanism detailed in section 2.3. It uses the incoming and outgoing degree of the operator in ~~proper plans~~ the proper plan (il n’y en a qu’un?) to measure its usefulness.

It requires to choOse

Finding an alternative to an operator is computationally expensive. ~~The search needs to~~ search a better provider for every fluent needed by a step. In order to simplify that search, we select only the best provider for a given fluent and check if the one used is the same. If not we add the alternative as a flaw. This search is done only on updated steps for online planning. Indeed, the safe proper plan mechanism is guaranteed to only chose the best provider (algorithm 3 at line 12). Also subgoals won’t introduce new fixable alternative as they are guaranteed to select the best provider possible.

Definition 10 (Orphan)**.** *An orphan is a negative flaw that means that a step in the partial plan (other than the initial or goal step) is not participating in the plan. Formally,* a_o *is an orphan iff* $a_o \neq I \wedge a_o \neq G \wedge \left(p.d^+(a_o) = 0\right) \vee \forall l \in p.L^+(a_o), l = \emptyset$.

With $p.d^+(a_o)$ being the *outgoing degree* of a_o in the directed graph formed by p and $p.L^+(a_o)$ being the set of *outgoing causal links* of a_o in p. This last condition checks for *hanging orphans* that are bound with the goal with only bare causal links introduced by threat resolution.

The introduction of negative flaws requires to modify the reoslver definition (Def. 6)

~~With the introduction of negative flaws comes the modification of resolvers~~ to handle negative refinements.

~~We add onto the definition 6~~:

Definition 11 (Signed Resolvers)**.** *A signed resolver is a resolver with a notion of sign. We add to the resolver tuple* s *as the sign of the resolver in* $\{+, -\}$.

An alternative notation for the signed resolver is inspired by the causal link notation with simply the sign underneath :

$$r = a_s \xrightarrow[+/-]{f} a_t$$

The previously defined negative flaws have all their associated negative resolvers.

The solution to an alternative is a negative refinement that simply removes the targeted causal link. We ~~count on the fact~~ expect that this will cause a new subgoal as a side effect, that will prioritize its resolver by usefulness and then pick the most useful provider.

The resolver for orphans is the negative refinement that is meant to remove the targeted orphan ? action and its incoming causal link while tagging its providers as potential orphans.

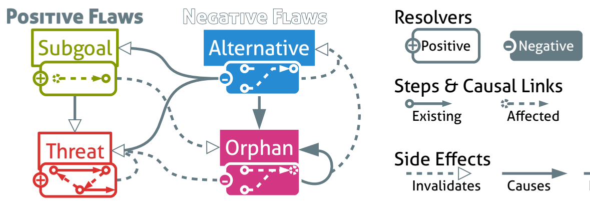


Figure 4. Schema representing flaws with their signs, resolvers and side effects relative to each other

the side effects mechanism also

The ~~standard mechanism of side effects~~ needs an upgrade since the new kind of flaws can easily interfere with one another. This is why we extend the ~~definition 7~~ with a notion of sign.

side effect defintion (Def. 7)

Definition 12 (Signed Side Effects)**.** *A signed side effect is either a regular* causal side effect *or an* invalidating side effect. *The sign of a side effect indicates if the related flaw needs to be added or removed from the agenda.*

The figure 4 illustrate s the extended notion of signed resolvers and side effects ~~of resolver application~~. When treating positive resolvers, nothing needs to change from the classical method. When dealing with negative resolvers, we need to search for additional subgoals and threats. In fact, negative refinements will most likely cause an increase in subgoals or threats since they remove causal links or steps. This deletion of causal links and steps can cause orphan flaws that need to be identified for removal.

In [24], an invalidating side effect is found as ... (donner le nom utilisé)
~~An **invalidating side effect** can be found in other works [24] with other names~~. In classical POP, it has been noticed that threats can disappear in some cases if subgoals or other threats were applied before them. In our formalism, we decide to gather under this notion every side effects that removes the need to consider a flaw. For example, orphans can be "saved" if a subgoal selects the orphan step. Alternatives can remove the need to compute further subgoal of a now orphan step as orphans simply remove the need to fix any flaws that concern the selected step.

These interactions between flaws are decisive in the validity and efficiency of the whole model, that is why we aim to drive flaw selection in a very rigorous manner.

2.3 Driving Flaws and Resolvers Selection

Resolvers and flaws selection are the keys to improving performances. Choosing a good resolver helps to reduce the branching factor that accounts for most of the time spent on running POP algorithms [25]. Flaw selection is also very important for efficiency, especially when considering negative flaws which can enter into conflict with other flaws.

Flaws conflicts happen when two flaws of opposite sign target the same element of the partial plan. This can happen for example if an orphan removes a step needed by a subgoal or when a threat tries to add a promoting link against an alternative. The use of side effects will prevent most of these occurrences in the agenda but a base ordering will increase the general efficiency of the algorithm.

Based on the figure 4, we create a base ordering of flaws by type. This order takes into account the number of flaw types affected by causal side effects.

1. **Alternatives** will cut causal links that have a better provider. It is necessary to identify them early since they will add at least another subgoal to be fixed as a related flaw.
2. **Subgoals** are the flaws that cause most of the branching factor in POP algorithms. This is why we need to make sure that all open conditions are fixed before proceeding on finer refinements.
3. **Orphans** remove unneeded branches of the plan. However, these branches can be found out to be necessary for the plan in order to meet a subgoal. Since a branch can contain numerous actions, it is preferable to let the orphan in the plan until they are no longer needed. Also, threats concerning orphans are invalidated if the orphan is resolved first.
4. **Threats** occur quite often in the computation. They cost a lot of processing power since they need to check is there are no paths that fix the flaw already. Numerous threats are generated without need of intervention [24]. That is why we prioritize all related subgoals and orphans before threats because they can add causal links or remove threatening actions that will fix the threat.

Resolvers also need to be ordered, especially for the subgoal flaw. Ordering resolvers for a subgoal is the same operation as chosing a provider. Therefore, the problem becomes "how to rank operators ?". The most relevant information on an operator is its usefulness and hurtfulness. These indicate how much an operator will help and how much it may cause branching after selection.

Definition 13 (Degree of an operator)**.** *Degrees are a measurement of the usefulness of an operator. The notion is derived from the incoming and outgoing degree of a node in a graph.*

We note $p.d^+(o)$ and $p.d^-(o)$ respectively the outgoing and incoming degree of an operator in a plan p. These represent the number of causal links that goes out or toward the operator. We call proper degree of an operator $o.d^+ = |eff(o)|$ and $o.d^- = |pre(o)|$ the number of preconditions and effects that reflects its intrinsic usefulness.

There are several ways to use the degrees as indicators. *Utility values* increases with every d^+, since this reflects a positive participation in the plan, and decreases it with every d^- since actions with higher incoming degrees are harder to satisfy. The utility value bounds are useful when selecting special operators. For example, a user specified constraint could be layed upon an operator to ensure it is only selected as a last resort. This operator will be affected with the minimum value for the utility value. More comonly, the maximum value is used for initial and goal step to ensure their selection.

Our ranking mechanism includes several computation steps. The first step is the computation of the **base scores** noted $Z_0(o) = \langle o^+, o^- \rangle$. It is a tuple that contains two components : a positive score that acts as a participation measurement and a negative score that represent the dependencies of the operator. For each component of the score we consider a *sub score array* noted $S_z(o^\pm)$. We define them as follows :

- $S_z(o^+)$ containing only $\Delta^P.d^+(o)$, the positive degree of o in the domain proper plan. This will give a measurement of the predicted usefulness of the operator.
- $S_z(o^-)$ containing the following subscores :
  1. $o.d^-$ the proper negative degree of o. Having more preconditions can lead to a potentially higher need for subgoals.
  2. $\sum_{c \in C_{\Delta^P}(o)} |c|$ with $C_{\Delta^P}(o)$ being the set of cycles where o participates in the domain proper plan. If an action is co-dependant it may lead to dead end when searching for precondition as it will form a cycle.
  3. $|SC(o)|$ with $SC(o)$ is the set of self-cycle o participates in. This is usually symptomatic of a *toxic operator*. Having an operator behaving this way can lead to problems in the operator instanciation.
  4. $\left|pre(o) \setminus \Delta^P.L^-(o)\right|$ with $\Delta^P.L^-(o)$ being the set of incoming edges of o in the proper plan of the domain. This represent the number of open conditions in the domain proper plan. This is symptomatic of action that can't be satisfied without a compliant initial step.

A parameter is reserved for each subscore. It is noted $P_n^\pm$ with n being the index of the subgoal in the list. The final formula for the score is then defined as : $o^\pm = \sum_{n=1}^{|S_z(o^\pm)|} P_n^\pm S_z^n(o^\pm)$

Once this score is computed, the ranking mechanism starts the second phase, it computes the **realization scores** that are potential scores that are realized once the problem is specified. It first searches the *inapplicable operators* that are all operators in the domain proper plan that have a precondition that isn't satisfied with a causal link. Then it searches the *eager operators* that provides fluents with no corresponding causal link (as they are not needed). These operators are stored in relation with their inapplicable or eager fluents.

The third phase starts with the beginning of the solving algorithm, once the problem has been provided. It computes the *effective realization scores* based on the initial and goal step. It will add P_1^+ to o^+ for each realized eager operators (if the goal contains the related fluent) and subtract P_4^- from o^- for each inapplicable operators realized by the initial step.

From there, we have the **final scores** that are used in the ultimate phase. In this phase, the scores are combined into a single number to rank the operators. In order to respect the criteria of having a bounded value for the *utility value* we use the following formula : $r_o = o^+\alpha^{-o^-}$. This ensures that the value is positive with 0 as a minimum bound and $+\infty$ for a maximum. The initial and goal steps have their utility value set to the upper bound in order to ensure their selection over other steps.

Choosing to compute the resolver selection at operator level has some interesting consequences on the performances. Indeed, this computation is much lighter than approaches with heuristics on plan space [14] as it reduce the overhead caused by real time computation of heuristics on complex data. In order to reduce this overhead more, the algorithm sorts the providing associative array in order to easily retrieve the best operator for each fluent. This means that the evaluation of the heuristic is done only once for each operator. This reduce the overhead and allows for faster results on smaller plans.

2.4 LOLLIPOP Algorithm

The LOLLIPOP algorithm uses the same refinement algorithm as described algorithm 1. The differences resides in the changes made on the notions of resolvers and side effects. The line 10 will apply negative resolvers if the selected flaw is negative. Also the line 11 will search for both sign of side effects. Another change resides in the initialization of the solving mechanism and the domain.

The algorithm 4 contains several parts. The first one is the code that is computed during the domain compilation time. It will prepare the rankings and the properplan and its caching mechanisms. It will also use strongly connected component detection algorithm to detect cycles. These cycles are be used during the base score computation. We added a detection of illegal fluents and operators in our domain initialization. Illegal operators are either inconsistent or toxic.

Definition 14 (Inconsistent operators)**.** *An operator a is contradictory if and only if*

$$\exists f\{f, \neg f\} \in eff(o) \vee \{f, \neg f\} \in pre(o)$$

Definition 15 (Toxic operators)**.** *Toxic operators have effects that are already in their preconditions or empty effects. They are defined as:*

$$o | pre(o) \cap eff(o) \neq \emptyset \vee eff(o) = \emptyset$$

Toxic actions can damage a plan as well as make the execution of POP algorithm longer than necessary. This is fixed by removing the toxic fluents ($pre(a) \nsubseteq eff(a)$) and by updating the effects with $eff(a) = eff(a) \setminus pre(a)$. If the effects become empty, the operator is removed from the domain.

The second part of the algorithm is done during the solving initialization. We start by realizing the scores, then we add the initial and goal step in the providing map by cahing them. Once the ranking mechanism is ready we sort the providing map. With the ordered providing map the algorithm runs the fast generation of the safe proper plan for the problem's goal.

Algorithm 4 LOLLIPOP initialisation mechanisms

```
function DOMAININIT(Operators $O$)
    ProperPlan $P$
    Ranking $R$
    for all Operator $o \in O$ do
        if ISILLEGAL($o$) then                      Remove toxic and useless fluents
            $O \leftarrow O \setminus \{o\}$                          If entirely toxic or useless
            continue
        $P$.ADDVERTEX($o$)                         Add, cache and bind all operators
    Cycles $C \leftarrow$ STRONGLYCONNECTEDCOMPONENT($P$)  Using DFS
    $R.Z \leftarrow$ BASESCORES($O$, $P$)
    $R.I \leftarrow$ INAPPLIABLES($P$)
    $R.E \leftarrow$ EAGERS($P$)
function LOLLIPOPINIT(Problem $\Pi$)
    REALIZE($\Pi.\Delta.R$, $\Pi$)                           Realize the scores
    CACHE($\Pi.\Delta.P$, $\Pi.I$)                  Cache initial step in providing ...
    CACHE($\Pi.\Delta.P$, $\Pi.G$)                            ... as well as goal step
    SORT($\Pi.\Delta.P.providing$, $\Pi.\Delta.R$)              Sort the providing map
    if $\Pi.p.L = \emptyset$ then
        SAFE($\Pi$)    Computing the safe proper plan if the plan is empty
    POPULATE($a$, $\Pi$)                           populate agenda with first flaws
function POPULATE(Agenda $a$, Problem $\Pi$)
    for all Update $u \in \Pi.U$ do                  Updates due to online planning
        Fluents $F \leftarrow eff(u.new) \setminus eff(u.old)$             Added effects
        for all Fluent $f \in F$ do
            for all Operator $o \in$ BETTER($\Pi.\Delta.P.providing$, $f$, $o$) do
                for all Link $l \in \Pi.P.L^+(o)$ do
                    if $f \in l$ then
                        ADDALTERNATIVE($a$, $f$, $o$, $\rightarrow(l)$, $\Pi$)
                                                 With $\rightarrow(l)$ the target of $l$
        $F \leftarrow eff(u.old) \setminus eff(u.new)$                    Removed effects
        for all Fluent $f \in F$ do
            for all Link $l \in \Pi.P.L^+(u.new)$ do
                if ISLIAR($l$) then
                    $\Pi.L \leftarrow \Pi.L \setminus \{l\}$
                    ADDORPHANS($a$, $u.new$, $\Pi$)
        ...  Same with removed preconditions and incomming liar links
    for all Operator $o \in \Pi.p.S$ do
        ADDSUBGOALS($a$, $o$, $\Pi$)
        ADDTHREATS($a$, $o$, $\Pi$)
```

The last part of this initialization is the agenda population. During this step, we perform a search of alternatives based on the list of updated fluents. A big problem with online updates is that the plan can become outdated relative to the domain. Some links might not be relevant for the operators that are replaced.

Definition 16 (Liar links)**.** *A liar link is a link that doesn't hold a fluent in the preconditions or effect of its source and target. We can note:*

$$a_i \xrightarrow{f} a_j | f \notin eff(a_i) \cap pre(a_j)$$

A liar link can be created by the removal of an effect or preconditions during online updates (with the causal link still remaining).

We call lies, fluents that are held by links without being in the connected operators. To resolve the problem we remove all lies. We delete the link altogether if it doesn't bear any fluent as a result of this operation. This removal triggers the addition of orphan flaws.

While keeping tabs on the updated operators is very important for LOLLIPOP to be able to solve online planning problems, another mechanism is used in order to ensure that LOLLIPOP is able to give a result if the problem is solvable. User provided plans have their steps tagged. This tag is used on failure. If the failure has backtracked to a user provided step, then it is removed and replaced by subgoals that represents each of its participation in the plan. This mechanism loops until every user provided steps have been removed.

3 Analysis

As proved in [8], the classical POP algorithm is *sound* and *complete*. In order to prove that these properties applies to LOLLIPOP, we need to introduce some hypothesis :

- updated operators are known.
- user provided steps are known.
- user provided plans doesn't contain illegal artifacts. This includes toxic or inconsistent actions, lying links and cycles.

An important property of the partial plan is its validity. A partial plan is **valid** iff it is *fully suported* and *contains no cycles*.

This property is taken from the original proof. We present it again for convinience.
Definition 17 (Full Support)**.** *A partial plan p is fully supported if each of its steps $o \in p.S$ is. A step is fully supported if each of its preconditions $f \in pre(o)$ is supported. A precondition is fully supported if it exists a causal link l that provides it. We can note :*

$$fs(P) \equiv \begin{array}{l} \forall o \in p.S \forall f \in pre(o) \exists l \in p.L^{-}(o) : \\ (f \in l \wedge \nexists t \in p.S(l_{\rightarrow} \succ t \succ o \wedge \neg f \in eff(t))) \end{array}$$

3.1 Proof of soundness

Soundness of LOLLIPOP. We first define an invariant property needed for the proof : $\forall s \in SG(p)\,(p \models s) \implies p \models \Pi$ with $SG(p)$ being the set of subgoals in the partial plan p.

We can use the definition of partial plan validity to state that $\forall f \in pre(\Pi.G)\,(fs(f)) \wedge \forall o \in \Pi.L^{-}_{\rightarrow}(G) \forall pre \in pre(o)\,(fs(pre) \wedge C_p(o) = \emptyset) \implies p \models \Pi$. This means that p is a solution if all preconditions of G are satisfied. We can satisfy these precondition using operators iff their precondition are all satisfied and if no other operator threatens their suporting links.

Since the invariant property is proven with POP and regular flaw selection, we need to consider the effect of the added mechanisms of LOLLIPOP. Since the new refinements of LOLLIPOP are negative, they don't add new links. Therefore, $\forall f \in F(p) \forall r \in r(f) : C_p(f.n) = C_{f(p)}(f.n)$ with $F(p)$ being the set of flaws in the partial plan p, $f.n$ being the needer of the flaw and $f(p)$ being the result partial plan after application of the flaw. Said otherwise, an iteration of LOLLIPOP won't add cycle inside a partial plan.

Lemma : if no loop in input, no loop in output.

Lemma : all remaining open condition in an input plan are satisfied.

Lemma : negative refinements conserve validity

Alternative always replace the removed link with a subgoal = equiv backtracking with all resolvers remaining => solvable

Orphan : no path exists between an orphan and the goal, removing them does not remove satisfaction of preconditions.

$\forall \pi \in \Pi_L, \pi.p$ is valid.

□

3.2 Proof of Completeness

A plan is fully supported if all steps are fully suported and they are when each of their pre is and a pre is supported if at least a causal link provides it.

Plans made by Lollipop are fully supported since the validity is recorded with causal links in the alg.

Old proof : POP is complete

Lemma : If the input plan is valid, lollipop returns a valid plan.

Since alternative and orphans conserve validity and no subgoal or threats exists (unless alternative introduce them but POP is complete) then the result is valid.

Lemma : if the plan is incomplete.

Cf POP

Lemma : if the plan is empty.

We want to add to the original proof a trivial case that was omited : $pre(G) = \emptyset$. In this case the line 4 of the algorithm 1 will return a valid plan.

Cf POP

Lemma : if the user plan leads to a dead end

PROBLEM : ex if 9+3 is in the plan, subgoal will fail and problem will fail.

SOLUTION : On failure, needer of the last flaw is deleted if it wasn't added by LOLLIPOP. They are deleted only once (until the input plan acts like an empty plan).

In this case, the backtracking is preserved and all possibilities are explored as in POP.

4 Experimental Results

#TODO Things we want to know:

- Is Lollipop faster than POP ? In which cases?
- Is the lollipop competitive in small problems?
- Measure the increase in quality
- Plot the selection time and every other indicator are taken in [25]

Conclusion

#TODO Things we want to discuss:

- Discussion of results and properties
- Summary of improvements
- Introducing soft solving and online planning.
- Online planning
- plan recognition and constrained planning

Conclusion

#TODO

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