Tutorial: An Introduction to Hierarchical Task Network (HTN) Planning

Pascal Bercher and Daniel Höller

Institute of Artificial Intelligence,
Ulm University, Germany

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Overview Part II

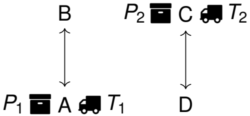
Solving HTN Planning Problems

- **Search-based Approaches**
  - Plan Space Search
  - Progression Search
- Compilation-based Approaches
  - Compilations to STRIPS/ADL
  - Compilations to SAT
- Heuristics for Heuristic Search
  - TDG-based Heuristics
  - Relaxed Composition Heuristics

Excursion

- Further Hierarchical Planning Formalisms

Example Domain



$deliver(p, l_2)$

$get\text{-}to(v, l_1)$ $\boxed{pick\text{-}up(v, l_1, p)}$ $get\text{-}to(v, l_2)$ $\boxed{drop(v, l_2, p)}$

$m\text{-}deliver(p, l_1, l_2, v)$

$get\text{-}to(v, l_2)$

$l_1 \neq l_2$

$\boxed{drive(v, l_1, l_2)}$

$m\text{-}direct(v, l_1, l_2)$

$get\text{-}to(v, l_2)$

$l_1 \neq l_2$

$get\text{-}to(v, l_1)$ $\boxed{drive(v, l_1, l_2)}$

$m\text{-}via(v, l_1, l_2)$

$get\text{-}to(v, l)$

$\boxed{no\text{-}op()}$

$m\text{-}noop(v, l)$

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  - *causal treat flaw* $t \lightning (t', c, t'')$: there is a causal link between t' and t'' protecting the condition c and the ordering constraints allow t to be ordered between t' and t'', i.e., $t' < t < t''$ – and c is a delete effect of t.

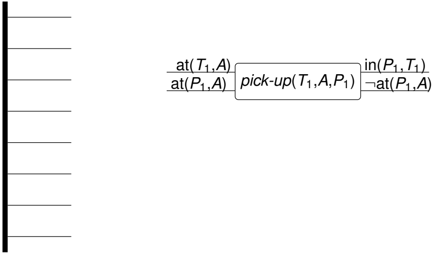
Flaws in Partial Plans

get-to(T_1,*B*)

Modifications for *compound task flaws*:

- Decompose the compound task (one modification for each method)

Flaws in Partial Plans



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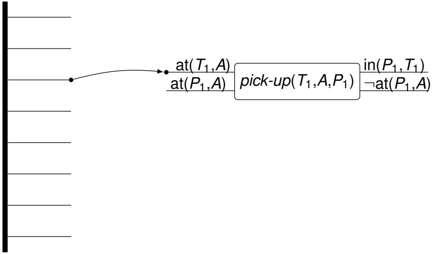

Modifications for *open precondition flaws*:

- Insert a causal link from existing plan step (one modification for each possible producer)

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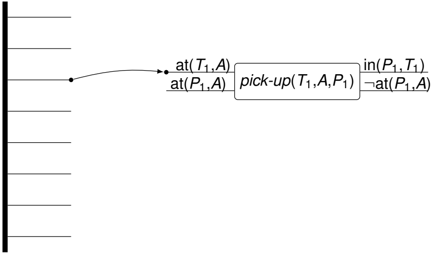

Modifications for *open precondition flaws*:

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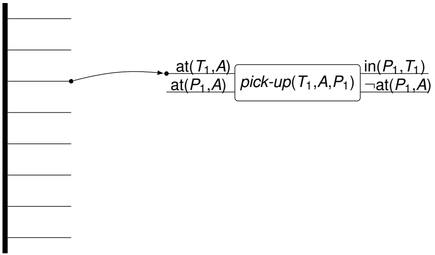
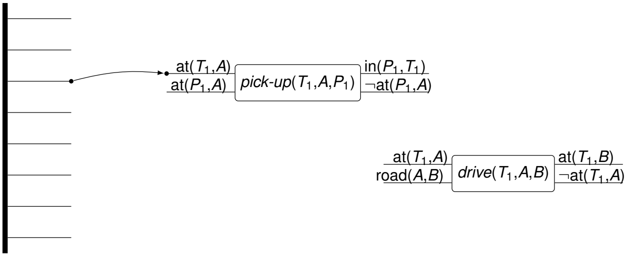


Modifications for *open precondition flaws*:

- Insert a causal link from existing plan step (one modification for each possible producer)
- Decompose a compound task if it has a sub task with a compatible effect (one modification for each method that has a compatible sub task)
- Insert a causal link from a newly inserted task (one modification for each possible producer) – only if task insertion is allowed!

Flaws in Partial Plans



Modifications for *causal threat flaws*:

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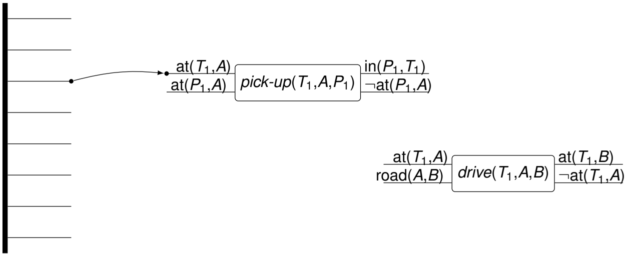

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- Move the threatening task before the producer of the threatened link, called *demotion* (not possible here)

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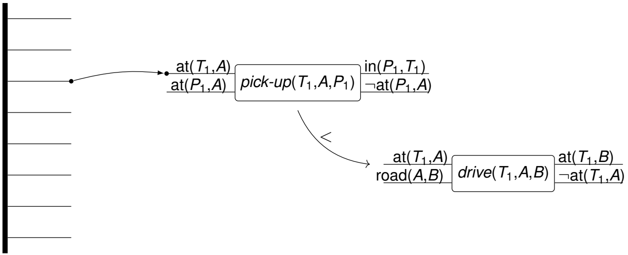

Modifications for *causal threat flaws*:

- Move the threatening task before the producer of the threatened link, called *demotion* (not possible here)
- Move the threatening task behind the consumer of the threatened link, called *promotion*

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- Search works both top-down (decomposition of compound tasks) as well as backwards (goal-directed causal link establishment)
- Search works in a two-step way:
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- Partial plans (as well as solutions) are only partially ordered, thus compactly representing many linearizations
- Search works both top-down (decomposition of compound tasks) as well as backwards (goal-directed causal link establishment)
- Search works in a two-step way:
  - Select a most-promising plan (via standard search strategies)
  - Then, select a flaw (this is *not(!)* a backtrack point) and branch over all possibilities to resolve it
- Follows the principle of least commitment

Standard Plan Space-based Algorithm

Input : $\mathit{fringe} = \{P_{\mathrm{init}}\}$
Output : A solution plan or `fail`.

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while fringe ≠ ∅ do
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- **FlawSel** selects (not a backtrack point!) a flaw according to a flaw selection strategy

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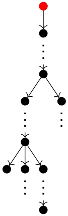

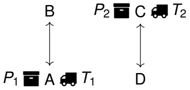

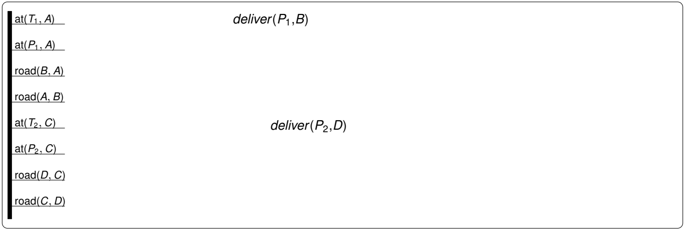

Flaws	**Modifications**

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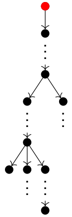

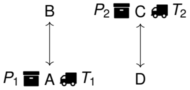

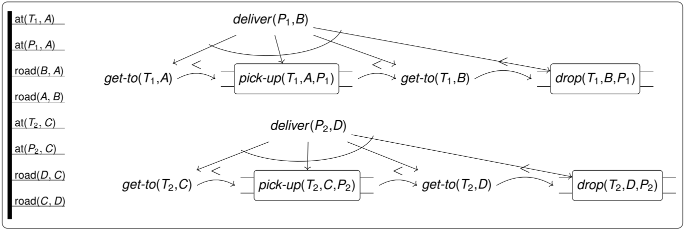

Flaws	**Modifications**
compound task: deliver(P_1, B)	decompose with *m-deliver*(P_1, A, B, T_1)
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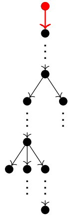

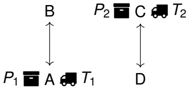

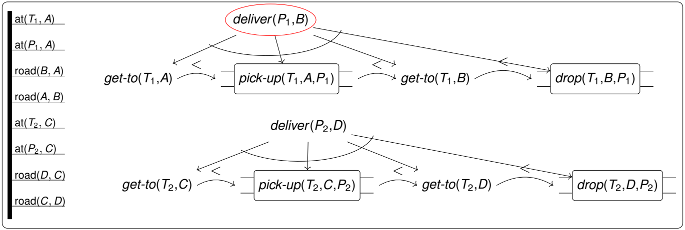

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compound task: deliver(P_2, D*)*	decompose with *m-deliver(* P_2, C, D, T_2*)*

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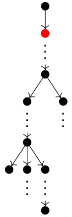

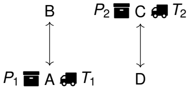

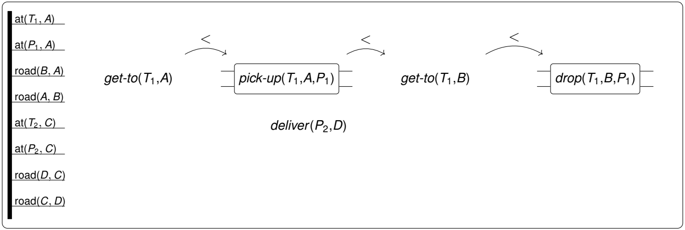

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compound task: deliver(P_2, D)	decompose with *m-deliver*(P_2, C, D, T_2)
compound task: get-to(T_1, A)	decompose with *m-direct*(T_1, B, A) decompose with *m-via*(T_1, B, A) decompose with *m-noop*(T_1, A)
open prec.: at(T_1, A) of *pick-up*(T_1, A, P_1)	insert causal link from *init* decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A) decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
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open prec.: at(T_1, B) of *drop*(T_1, B, P_1)	decompose *get-to*(T_1, B) with *m-direct*(T_1, A, B) decompose *get-to*(T_1, B) with *m-via*(T_1, A, B)
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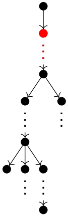

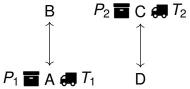

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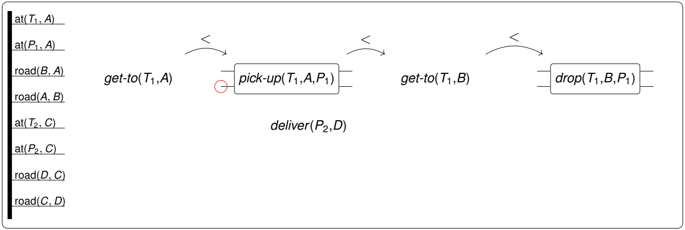

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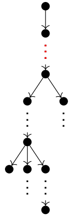
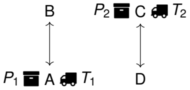
Standard Plan Space-based Algorithm





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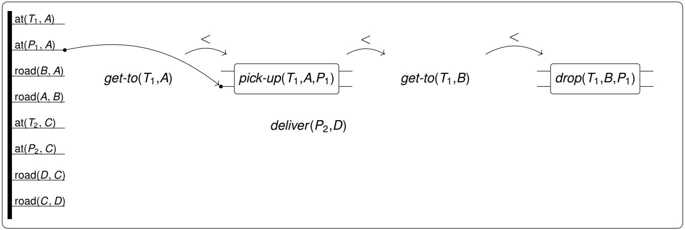

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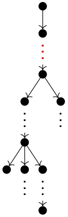
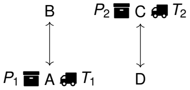
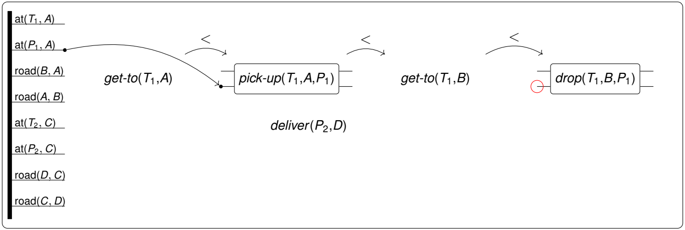
open prec.: in(P_1, T_1) of *drop(T_1, B, P_1)*	insert causal link from *pickup(T1, A, P1)*

Standard Plan Space-based Algorithm





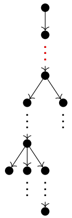


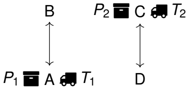
Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= ($*fringe* $\setminus \{P\})$
  $\cup$*Successors*(P, f)
return `fail`

Flaws	Modifications
compound task: deliver(P_2, D)	decompose with *m-deliver(P_2, C, D, T_2)*
compound task: get-to(T_1, A)	decompose with *m-direct(T_1, B, A)* decompose with *m-via(T_1, B, A)* decompose with *m-noop(T_1, A)*
open prec.: at(T_1, A) of *pick-up(T_1, A, P_1)*	insert causal link from *init* decompose *get-to(T_1, A)* with *m-direct(T_1, B, A)* decompose *get-to(T_1, A)* with *m-via(T_1, B, A)*
compound task: get-to(T_1, B)	decompose with *m-direct(T_1, A, B)* decompose with *m-via(T_1, A, B)* decompose with *m-noop(T_1, B)*
open prec.: at(T_1, B) of *drop(T_1, B, P_1)*	decompose *get-to(T_1, B)* with *m-direct(T_1, A, B)* decompose *get-to(T_1, B)* with *m-via(T_1, A, B)*
open prec.:* in(P_1, T_1) of *drop(T_1, B, P_1)	**insert causal link from *pickup($T1$, A, $P1$)***

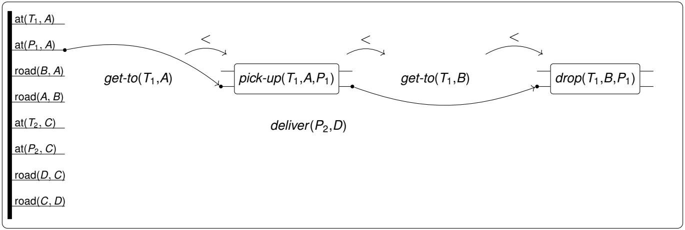
Standard Plan Space-based Algorithm





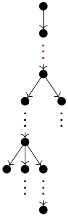
Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

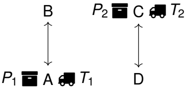
```
while fringe ≠ ∅ do
    P := PlanSel(fringe)
    F := FlawDet(P)
    if F = ∅ then return P
    f := FlawSel(F)
    fringe := (fringe \ {P})
              ∪Successors(P, f)
return fail
```



Flaws	Modifications
compound task: deliver(P_2, D)	decompose with *m-deliver(P_2, C, D, T_2)*
compound task: get-to(T_1, A)	decompose with *m-direct(T_1, B, A)*
	decompose with *m-via(T_1, B, A)*
	decompose with *m-noop(T_1, A)*
open prec.: at(T_1, A) of *pick-up(T_1, A, P_1)*	insert causal link from *init*
	decompose *get-to(T_1, A)* with *m-direct(T_1, B, A)*
	decompose *get-to(T_1, A)* with *m-via(T_1, B, A)*
compound task: get-to(T_1, B)	decompose with *m-direct(T_1, A, B)*
	decompose with *m-via(T_1, A, B)*
	decompose with *m-noop(T_1, B)*
open prec.: at(T_1, B) of *drop(T_1, B, P_1)*	decompose *get-to(T_1, B)* with *m-direct(T_1, A, B)*
	decompose *get-to(T_1, B)* with *m-via(T_1, A, B)*

Standard Plan Space-based Algorithm





Input : $fringe = \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

```
while fringe ≠ ∅ do
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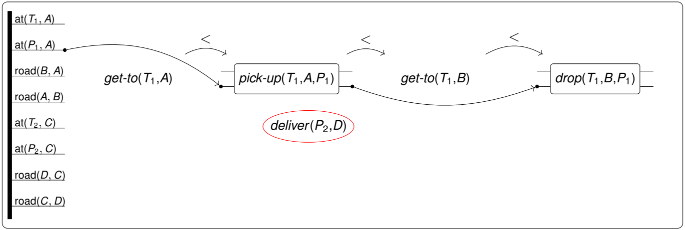
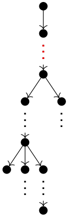
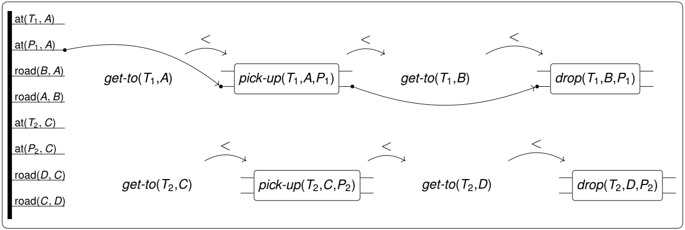
    F := FlawDet(P)
    if F = ∅ then return P
    f := FlawSel(F)
    fringe := (fringe \ {P})
              ∪Successors(P, f)
return fail
```

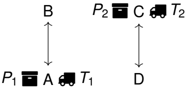


Flaws	**Modifications**
compound task: deliver(P_2, D)	**decompose with *m-deliver*(P_2, C, D, T_2)**
compound task: get-to(T_1, A)	decompose with *m-direct(T_1, B, A)* decompose with *m-via(T_1, B, A)* decompose with *m-noop(T_1, A)*
open prec.: at(T_1, A) of *pick-up(T_1, A, P_1)*	insert causal link from *init* decompose *get-to(T_1, A)* with *m-direct(T_1, B, A)* decompose *get-to(T_1, A)* with *m-via(T_1, B, A)*
compound task: get-to(T_1, B)	decompose with *m-direct(T_1, A, B)* decompose with *m-via(T_1, A, B)* decompose with *m-noop(T_1, B)*
open prec.: at(T_1, B) of *drop(T_1, B, P_1)*	decompose *get-to(T_1, B)* with *m-direct(T_1, A, B)* decompose *get-to(T_1, B)* with *m-via(T_1, A, B)*

Standard Plan Space-based Algorithm







Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

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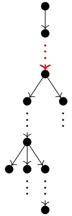
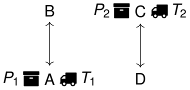
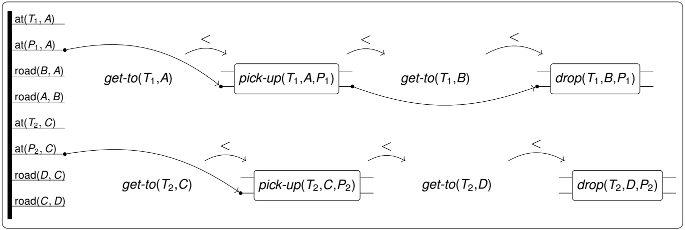
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= (\textit{fringe} \setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Flaws	**Modifications**
compound task: get-to(T_1, A)	decompose with *m-direct(T_1, B, A)*
	decompose with *m-via(T_1, B, A)*
	decompose with *m-noop(T_1, A)*
open prec.: at(T_1, A) of *pick-up(T_1, A, P_1)*	insert causal link from *init*
	decompose *get-to(T_1, A)* with *m-direct(T_1, B, A)*
	decompose *get-to(T_1, A)* with *m-via(T_1, B, A)*
compound task: get-to(T_1, B)	decompose with *m-direct(T_1, A, B)*
	decompose with *m-via(T_1, A, B)*
	decompose with *m-noop(T_1, B)*
open prec.: at(T_1, B) of *drop(T_1, B, P_1)*	decompose *get-to(T_1, B)* with *m-direct(T_1, A, B)*
	decompose *get-to(T_1, B)* with *m-via(T_1, A, B)*
...	...

Standard Plan Space-based Algorithm







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Output : A solution plan or `fail`.

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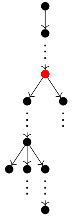
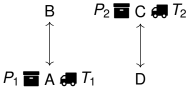
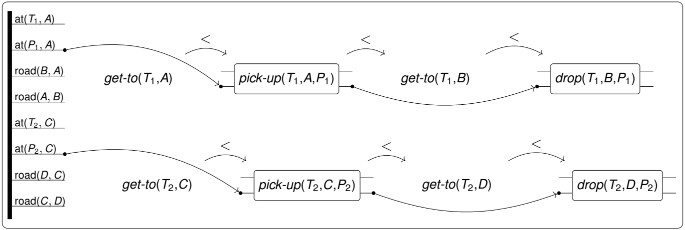
  $f :=$ **FlawSel**(F)
  fringe $:= ($*fringe* $\setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Flaws	Modifications
compound task: get-to(T_1, A)	decompose with *m-direct(T_1, B, A)*
	decompose with *m-via(T_1, B, A)*
	decompose with *m-noop(T_1, A)*
open prec.: at(T_1, A) of *pick-up(T_1, A, P_1)*	insert causal link from *init*
	decompose *get-to(T_1, A)* with *m-direct(T_1, B, A)*
	decompose *get-to(T_1, A)* with *m-via(T_1, B, A)*
compound task: get-to(T_1, B)	decompose with *m-direct(T_1, A, B)*
	decompose with *m-via(T_1, A, B)*
	decompose with *m-noop(T_1, B)*
open prec.: at(T_1, B) of *drop(T_1, B, P_1)*	decompose *get-to(T_1, B)* with *m-direct(T_1, A, B)*
	decompose *get-to(T_1, B)* with *m-via(T_1, A, B)*
...	...

Standard Plan Space-based Algorithm







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Output : A solution plan or `fail`.

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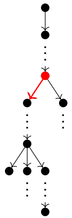
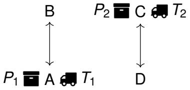
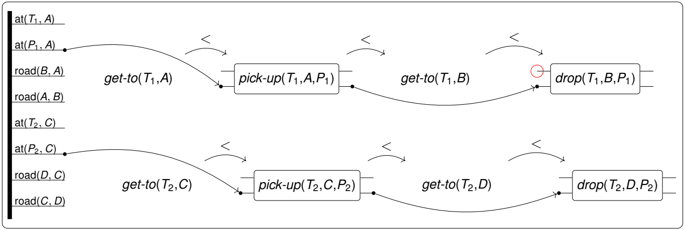
  fringe $:= ($*fringe* $\setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Flaws	Modifications
compound task: get-to(T_1, A)	decompose with *m-direct*(T_1, B, A) decompose with *m-via*(T_1, B, A) decompose with *m-noop*(T_1, A)
open prec.: at(T_1, A) of *pick-up*(T_1, A, P_1)	insert causal link from *init* decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A) decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
compound task: get-to(T_1, B)	decompose with *m-direct*(T_1, A, B) decompose with *m-via*(T_1, A, B) decompose with *m-noop*(T_1, B)
open prec.: at(T_1, B) of *drop*(T_1, B, P_1)	decompose *get-to*(T_1, B) with *m-direct*(T_1, A, B) decompose *get-to*(T_1, B) with *m-via*(T_1, A, B)
...	...

Standard Plan Space-based Algorithm





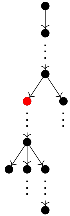


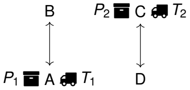
Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

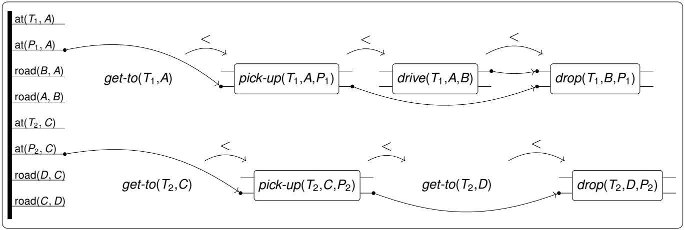
while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= (\textit{fringe} \setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Flaws	**Modifications**
compound task: get-to(T_1, *A*)	decompose with *m-direct*(T_1, *B*, *A*)
	decompose with *m-via*(T_1, *B*, *A*)
	decompose with *m-noop*(T_1, *A*)
open prec.: at(T_1, *A*) of *pick-up*(T_1, *A*, P_1)	insert causal link from *init*
	decompose *get-to*(T_1, *A*) with *m-direct*(T_1, *B*, *A*)
	decompose *get-to*(T_1, *A*) with *m-via*(T_1, *B*, *A*)
compound task: get-to(T_1, *B*)	decompose with *m-direct*(T_1, *A*, *B*)
	decompose with *m-via*(T_1, *A*, *B*)
	decompose with *m-noop*(T_1, *B*)
***open prec.:* at(T_1, *B*) of *drop*(T_1, *B*, P_1)**	**decompose *get-to*(T_1, *B*) with *m-direct*(T_1, *A*, *B*)**
	decompose *get-to*(T_1, *B*) with *m-via*(T_1, *A*, *B*)
...	...

Standard Plan Space-based Algorithm





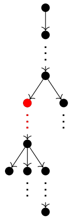


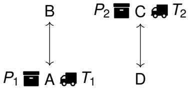
Flaws	**Modifications**
compound task: get-to(T_1, A)	decompose with *m-direct*(T_1, B, A)
	decompose with *m-via*(T_1, B, A)
	decompose with *m-noop*(T_1, A)
open prec.: at(T_1, A) of *pick-up*(T_1, A, P_1)	insert causal link from *init*
	decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A)
	decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
open prec.: at(T_1, A) of *drive*(T_1, A, B)	insert causal link from *init*
	decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A)
	decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
open prec.: road(A, B) of *drive*(T_1, A, B)	insert causal link from *init*
...	...

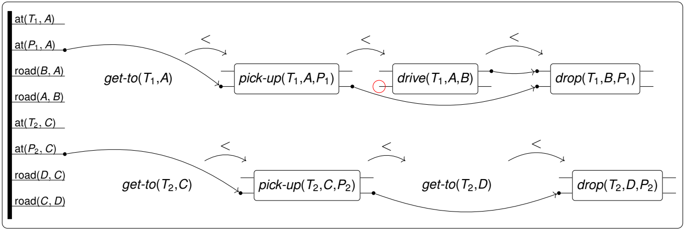
Input : $fringe = \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while $fringe \neq \emptyset$ **do**
  $P :=$ **PlanSel**($fringe$)
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  $fringe := (fringe \setminus \{P\})$
    $\cup Successors(P, f)$
return `fail`

Standard Plan Space-based Algorithm







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return `fail`

Flaws	**Modifications**
compound task: get-to(T_1, A)	decompose with *m-direct*(T_1, B, A)
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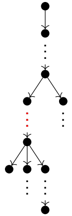
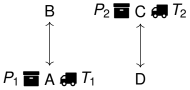
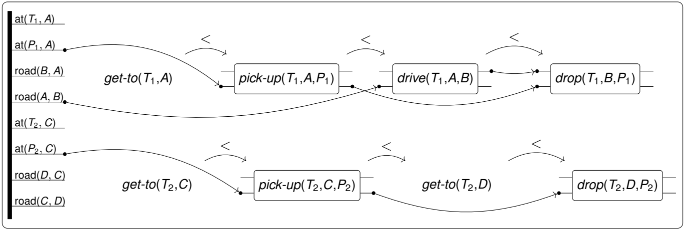
	decompose with *m-noop*(T_1, A)
open prec.: at(T_1, A) of *pick-up*(T_1, A, P_1)	insert causal link from *init*
	decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A)
	decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
open prec.: at(T_1, A) of *drive*(T_1, A, B)	insert causal link from *init*
	decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A)
	decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
***open prec.:* road(A, B) of *drive*(T_1, A, B)**	**insert causal link from *init***
...	...

Standard Plan Space-based Algorithm







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  fringe $:= (\textit{fringe} \setminus \{P\})$
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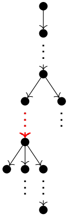
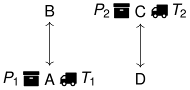
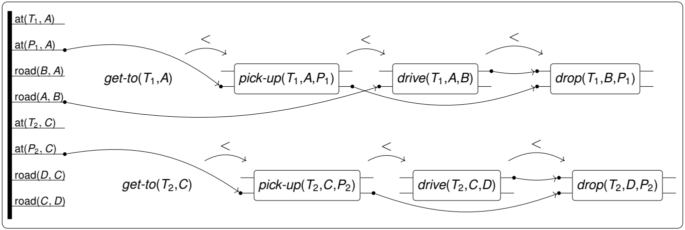
Flaws	Modifications
compound task: get-to(T_1, A)	decompose with *m-direct(T_1, B, A)*
	decompose with *m-via(T_1, B, A)*
	decompose with *m-noop(T_1, A)*
open prec.: at(T_1, A) of *pick-up(T_1, A, P_1)*	insert causal link from *init*
	decompose *get-to(T_1, A)* with *m-direct(T_1, B, A)*
	decompose *get-to(T_1, A)* with *m-via(T_1, B, A)*
open prec.: at(T_1, A) of *drive(T_1, A, B)*	insert causal link from *init*
	decompose *get-to(T_1, A)* with *m-direct(T_1, B, A)*
	decompose *get-to(T_1, A)* with *m-via(T_1, B, A)*
...	...

Standard Plan Space-based Algorithm





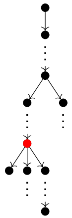


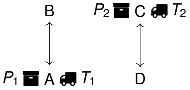
Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

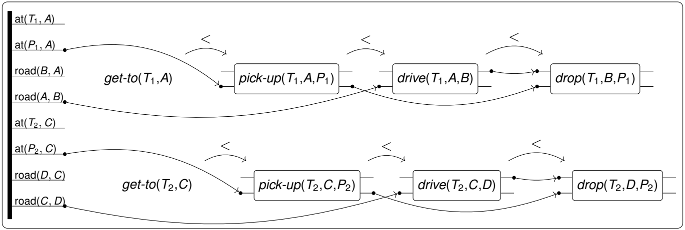
while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= ($*fringe* $\setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Flaws	**Modifications**
compound task: get-to(T_1, A)	decompose with *m-direct*(T_1, B, A)
	decompose with *m-via*(T_1, B, A)
	decompose with *m-noop*(T_1, A)
open prec.: at(T_1, A) of *pick-up*(T_1, A, P_1)	insert causal link from *init*
	decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A)
	decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
open prec.: at(T_1, A) of *drive*(T_1, A, B)	insert causal link from *init*
	decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A)
	decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
...	...

Standard Plan Space-based Algorithm





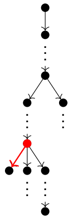


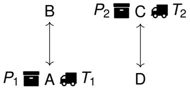
Flaws	**Modifications**
compound task: get-to(T_1, A)	decompose with *m-direct*(T_1, B, A)
	decompose with *m-via*(T_1, B, A)
	decompose with *m-noop*(T_1, A)
open prec.: at(T_1, A) of *pick-up*(T_1, A, P_1)	insert causal link from *init*
	decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A)
	decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
open prec.: at(T_1, A) of *drive*(T_1, A, B)	insert causal link from *init*
	decompose *get-to*(T_1, A) with *m-direct*(T_1, B, A)
	decompose *get-to*(T_1, A) with *m-via*(T_1, B, A)
...	...

Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= (\textit{fringe} \setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Standard Plan Space-based Algorithm





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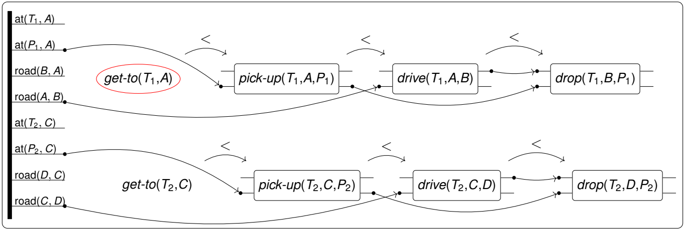
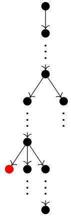
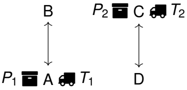
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= (\textit{fringe} \setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

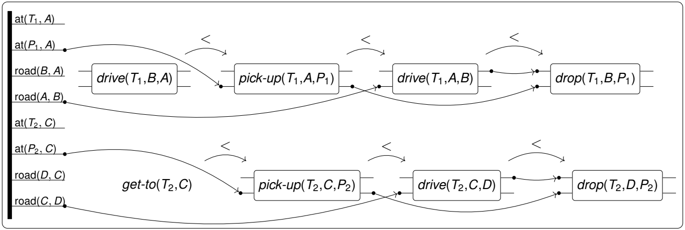


Flaws	Modifications
compound task: get-to(T_1, A***)***	**decompose with *m-direct(*** T_1, B, A***)***
	decompose with *m-via(*T_1, B, A*)*
	decompose with *m-noop(*T_1, A*)*
open prec.: at(T_1, A) of *pick-up(*T_1, A, P_1*)*	insert causal link from *init*
	decompose *get-to(*T_1, A*)* with *m-direct(*T_1, B, A*)*
	decompose *get-to(*T_1, A*)* with *m-via(*T_1, B, A*)*
open prec.: at(T_1, A) of *drive(*T_1, A, B*)*	insert causal link from *init*
	decompose *get-to(*T_1, A*)* with *m-direct(*T_1, B, A*)*
	decompose *get-to(*T_1, A*)* with *m-via(*T_1, B, A*)*
...	...

Standard Plan Space-based Algorithm





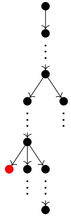


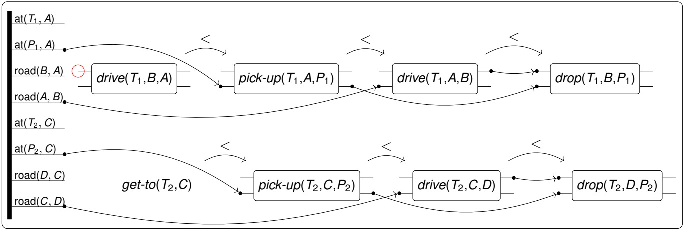
Flaws	Modifications
open prec: at(T_1, B) of *drive(T_1, B, A)*	—
open prec.: road(B, A) of *drive(T_1, B, A)*	insert causal link from *init*
open prec.: at(T_1, A) of *pick-up(T_1, A, P_1)*	insert causal link from *init* insert causal link from *drive(T_1, B, A)*
open prec.: at(T_1, A) of *drive(T_1, A, B)*	insert causal link from *init* insert causal link from *drive(T_1, B, A)*
...	...

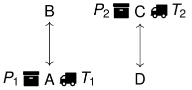
Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= ($*fringe* $\setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Standard Plan Space-based Algorithm







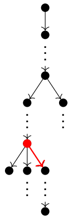
Flaws	**Modifications**
open prec:* at(T_1, B) of *drive(T_1, B, A)	**—**
open prec.: road(B, A) of *drive(T_1, B, A)*	insert causal link from *init*
open prec.: at(T_1, A) of *pick-up(T_1, A, P_1)*	insert causal link from *init* insert causal link from *drive(T_1, B, A)*
open prec.: at(T_1, A) of *drive(T_1, A, B)*	insert causal link from *init* insert causal link from *drive(T_1, B, A)*
...	...

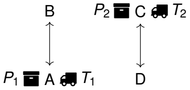
This partial plan can be discarded, because it has a flaw without modifications

Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= ($*fringe* $\setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Standard Plan Space-based Algorithm





Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
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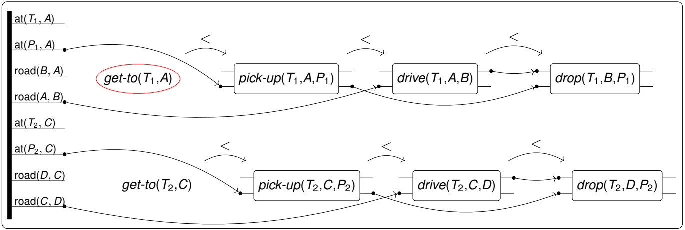
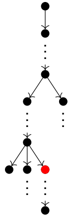
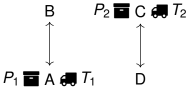
  $f :=$ **FlawSel**(F)
  fringe $:= (\textit{fringe} \setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

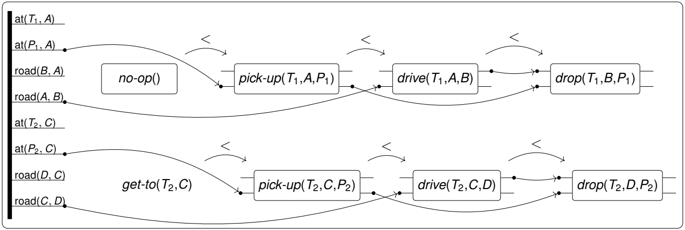


Flaws	Modifications
compound task: get-to(**T_1**, A)	decompose with *m-direct(*T_1*, B, A)*
	decompose with *m-via(*T_1*, B, A)*
	decompose with *m-noop(*T_1*, A)*
open prec.: at(T_1, A) of *pick-up(*T_1*, A, *P_1*)*	insert causal link from *init*
	decompose *get-to(*T_1*, A)* with *m-direct(*T_1*, B, A)*
	decompose *get-to(*T_1*, A)* with *m-via(*T_1*, B, A)*
open prec.: at(T_1, A) of *drive(*T_1*, A, B)*	insert causal link from *init*
	decompose *get-to(*T_1*, A)* with *m-direct(*T_1*, B, A)*
	decompose *get-to(*T_1*, A)* with *m-via(*T_1*, B, A)*
...	...

Standard Plan Space-based Algorithm







Flaws	**Modifications**
open prec.: at(T_1, A) of *pick-up(T_1, A, P_1)*	insert causal link from *init*
open prec.: at(T_1, A) of *drive(T_1, A, B)*	insert causal link from *init*
...	...

Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
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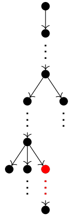
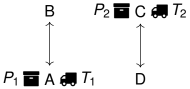
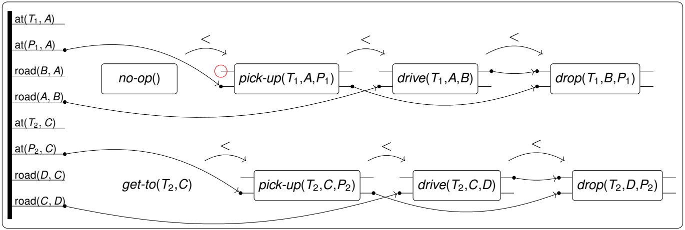
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= ($*fringe* $\setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Standard Plan Space-based Algorithm





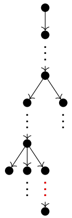


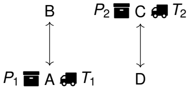
Flaws	Modifications
open prec.:* at(T_1, A) of *pick-up(T_1, A, P_1)	**insert causal link from *init***
open prec.: at(T_1, A) of *drive(T_1, A, B)*	insert causal link from *init*
...	...

Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
  $F :=$ *FlawDet*(P)
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:=$ (*fringe* $\setminus \{P\}$)
    $\cup$*Successors*(P, f)
return `fail`

Standard Plan Space-based Algorithm





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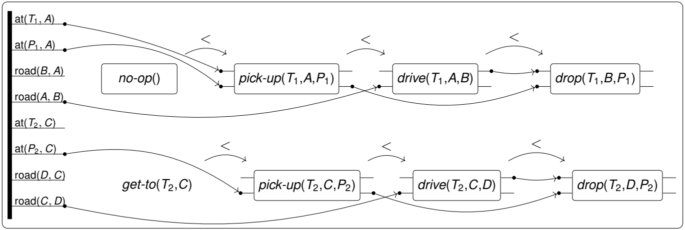
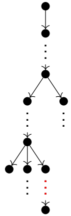
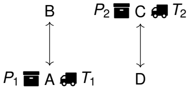
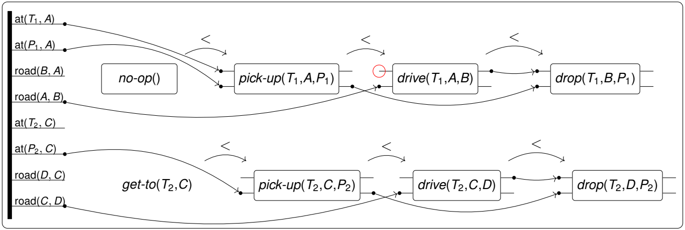


Flaws	**Modifications**
open prec.: at(T_1, A) of *drive(T_1, A, B)*	insert causal link from *init*
...	...

Standard Plan Space-based Algorithm







Flaws	**Modifications**
***open prec.:* at(T_1, A) of *drive*(T_1, A, B)**	**insert causal link from *init***
...	...

Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
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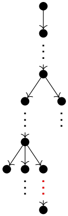
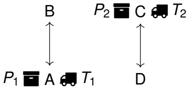
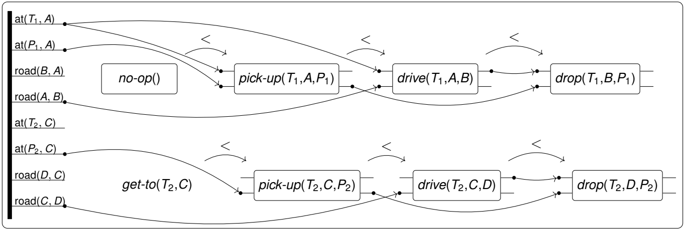
  fringe $:= (\textit{fringe} \setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Standard Plan Space-based Algorithm







Flaws	**Modifications**
...	...

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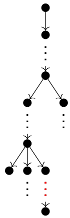
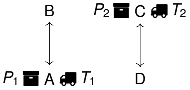
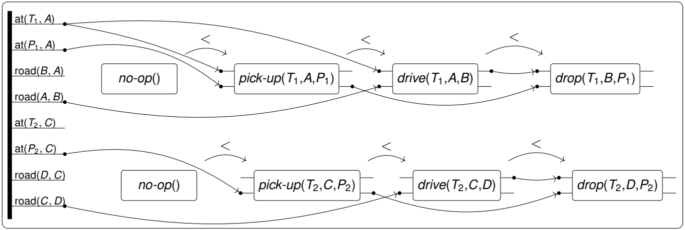
Standard Plan Space-based Algorithm





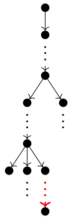


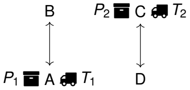
Flaws	**Modifications**
...	...

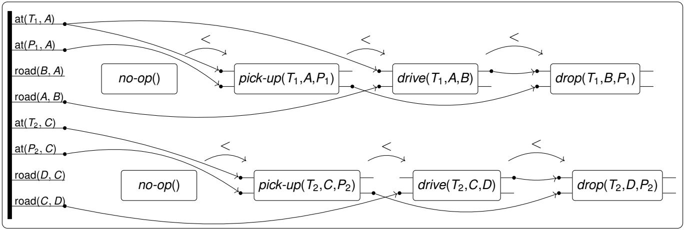
Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
  $F := \mathit{FlawDet}(P)$
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  $\mathit{fringe} := (\mathit{fringe} \setminus \{P\})$
    $\cup \mathit{Successors}(P, f)$
return `fail`

Standard Plan Space-based Algorithm







Flaws	**Modifications**
...	...

Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
  $P :=$ **PlanSel**(*fringe*)
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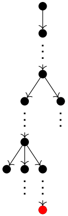
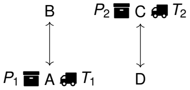
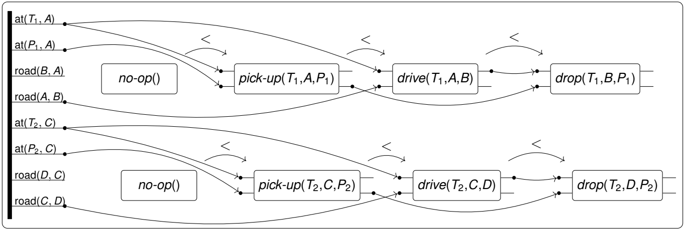
  if $F = \emptyset$ **then return** P
  $f :=$ **FlawSel**(F)
  fringe $:= (\textit{fringe} \setminus \{P\})$
    $\cup$*Successors*(P, f)
return `fail`

Standard Plan Space-based Algorithm







Flaws	**Modifications**

This partial plan has no flaws, so it is a solution and returned

Input : *fringe* $= \{P_{\text{init}}\}$
Output : A solution plan or `fail`.

while *fringe* $\neq \emptyset$ **do**
 $P :=$ **PlanSel**(*fringe*)
 $F :=$ *FlawDet*(P)
 if $F = \emptyset$ **then return** P
 $f :=$ **FlawSel**(F)
 fringe $:= ($*fringe* $\setminus \{P\})$
  $\cup$*Successors*(P, f)
return `fail`

Plan Space-based Search – Properties

- Plan Space-based search is **sound**

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- There is **no current state** during search (the initial state is never changed)
- Tasks are partially ordered and can be inserted anywhere in a partial plan

Overview Part II

Solving HTN Planning Problems

- **Search-based Approaches**
  - Plan Space Search
  - **Progression Search**
- Compilation-based Approaches
  - Compilations to STRIPS/ADL
  - Compilations to SAT
- Heuristics for Heuristic Search
  - TDG-based Heuristics
  - Relaxed Composition Heuristics

Excursion

- Further Hierarchical Planning Formalisms

Progression Search – Basic Characteristics

- Only those (primitive or compound) tasks in a task network that have **no predecessor** in the ordering relations are processed
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→ Search nodes contain the current task network **and** state

→ **Commitment** to the prefix of the solution during search

→ We are searching for an **empty** task network

Standard Progression Algorithm

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fringe ← {(s_I, tn_I, ())}
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    n ← fringe.poll()
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    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
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        else
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- **Action application** removes node and causes state transition

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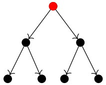

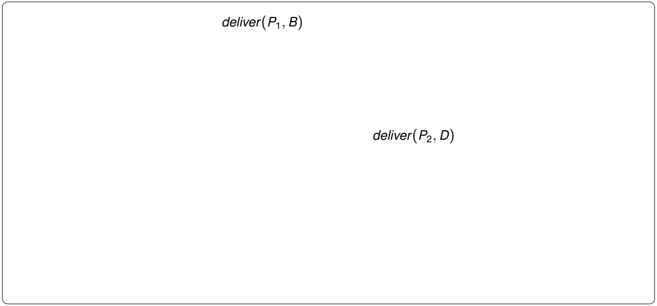

$\pi = ()$

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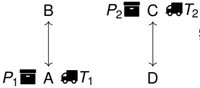

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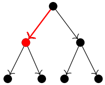

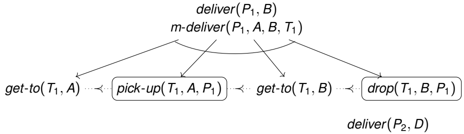

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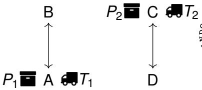

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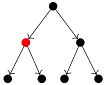

$get\text{-}to(T_1, A) \prec \boxed{pick\text{-}up(T_1, A, P_1)} \prec get\text{-}to(T_1, B) \prec \boxed{drop(T_1, B, P_1)}$

$deliver(P_2, D)$

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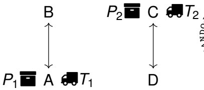

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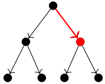

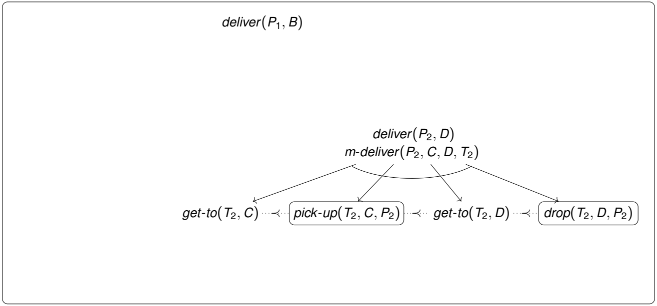

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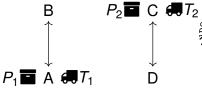

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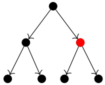

deliver(P_1, B)

get-to$(T_2, C) \prec \boxed{\textit{pick-up}(T_2, C, P_2)} \prec$ *get-to*$(T_2, D) \prec \boxed{\textit{drop}(T_2, D, P_2)}$

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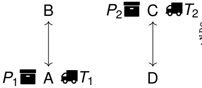
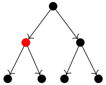


Standard Progression Algorithm



get-to(T_1, A) $\prec$ $\boxed{\textit{pick-up}(T_1, A, P_1)}$ $\prec$ *get-to*(T_1, B) $\prec$ $\boxed{\textit{drop}(T_1, B, P_1)}$

deliver(P_2, D)

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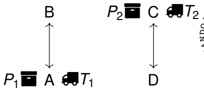

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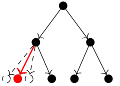

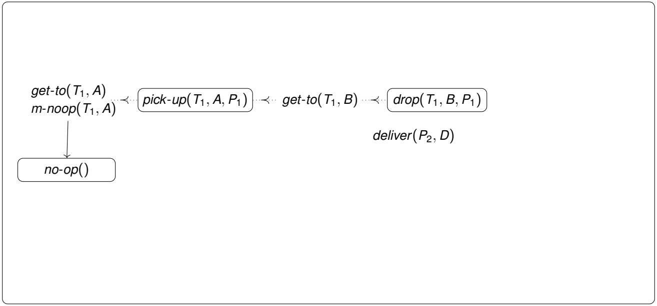

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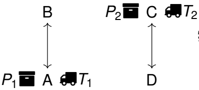

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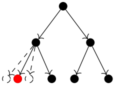

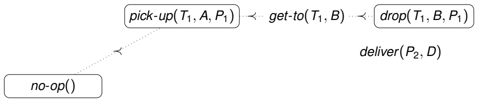

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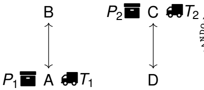

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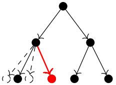

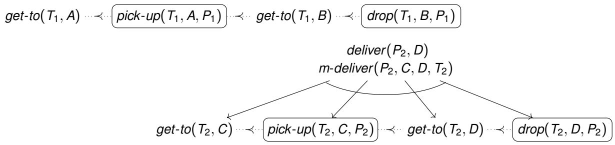

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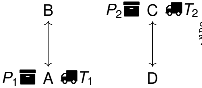

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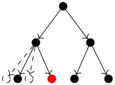

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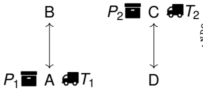

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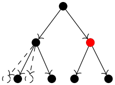

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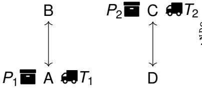

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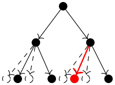

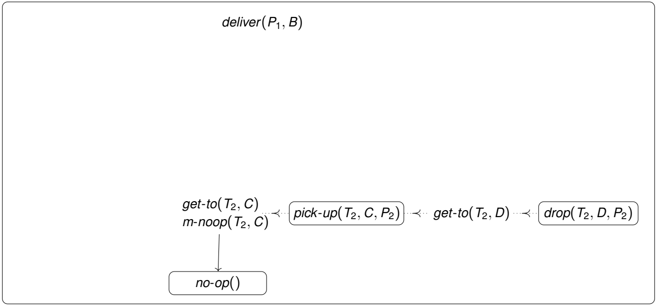

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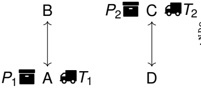

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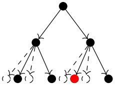

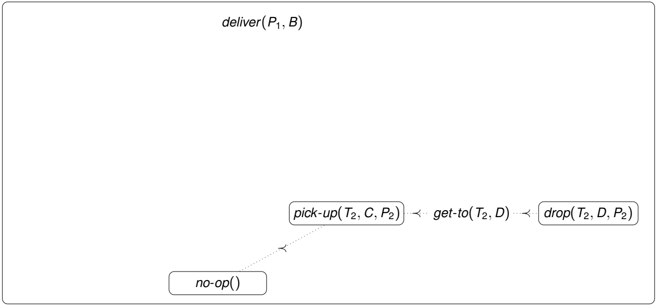

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        $n' \leftarrow n.decompose(t, m)$
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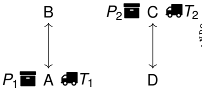
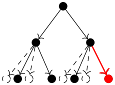
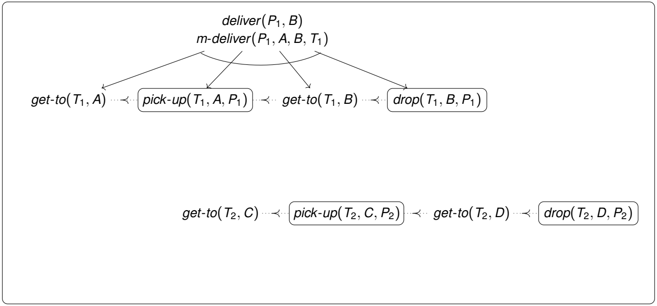


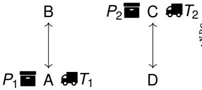
Standard Progression Algorithm



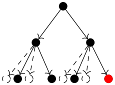
$fringe \leftarrow \{(s_I, tn_I, ())\}$
while $fringe \neq \emptyset$ **do**
  $n \leftarrow fringe.poll()$
  if $n.isgoal$ **then return** n
  $U \leftarrow n.unconstrainedNodes$
  for $t \in U$ **do**
    if $isPrimitive(t)$ **then**
      $n' \leftarrow n.apply(t)$
      $fringe.add(n')$
    else
      for $m \in t.methods$ **do**
        $n' \leftarrow n.decompose(t, m)$
        $fringe.add(n')$



$\pi = ()$



Standard Progression Algorithm

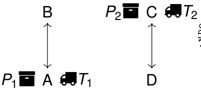


$get\text{-}to(T_1, A) \prec \boxed{pick\text{-}up(T_1, A, P_1)} \prec get\text{-}to(T_1, B) \prec \boxed{drop(T_1, B, P_1)}$

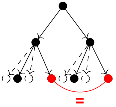
$get\text{-}to(T_2, C) \prec \boxed{pick\text{-}up(T_2, C, P_2)} \prec get\text{-}to(T_2, D) \prec \boxed{drop(T_2, D, P_2)}$

$$\pi = ()$$

```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n' ← n.apply(t)
            fringe.add(n')
        else
            for m ∈ t.methods do
                n' ← n.decompose(t, m)
                fringe.add(n')
```



Standard Progression Algorithm

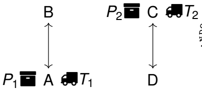


$get\text{-}to(T_1, A) \prec \boxed{pick\text{-}up(T_1, A, P_1)} \prec get\text{-}to(T_1, B) \prec \boxed{drop(T_1, B, P_1)}$

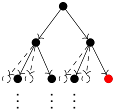
$get\text{-}to(T_2, C) \prec \boxed{pick\text{-}up(T_2, C, P_2)} \prec get\text{-}to(T_2, D) \prec \boxed{drop(T_2, D, P_2)}$

$$\pi = ()$$

```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n′ ← n.apply(t)
            fringe.add(n′)
        else
            for m ∈ t.methods do
                n′ ← n.decompose(t, m)
                fringe.add(n′)
```



Standard Progression Algorithm

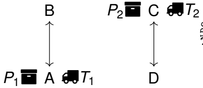


get-to$(T_1, A) \prec$ $\boxed{\textit{pick-up}(T_1, A, P_1)}$ $\prec$ *get-to*$(T_1, B) \prec$ $\boxed{\textit{drop}(T_1, B, P_1)}$

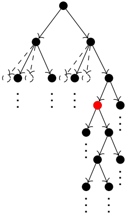
get-to$(T_2, C) \prec$ $\boxed{\textit{pick-up}(T_2, C, P_2)}$ $\prec$ *get-to*$(T_2, D) \prec$ $\boxed{\textit{drop}(T_2, D, P_2)}$

$\pi = ()$

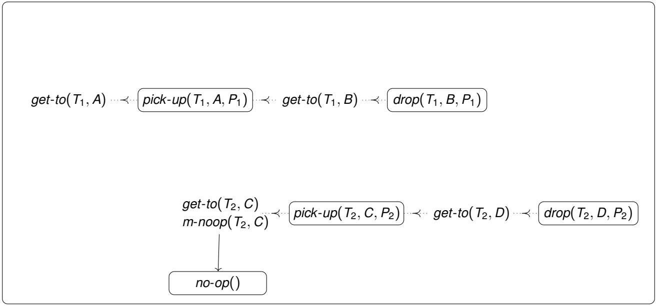
```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n′ ← n.apply(t)
            fringe.add(n′)
        else
            for m ∈ t.methods do
                n′ ← n.decompose(t, m)
                fringe.add(n′)
```



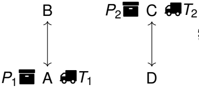
Standard Progression Algorithm



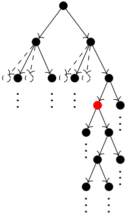
```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n′ ← n.apply(t)
            fringe.add(n′)
        else
            for m ∈ t.methods do
                n′ ← n.decompose(t, m)
                fringe.add(n′)
```



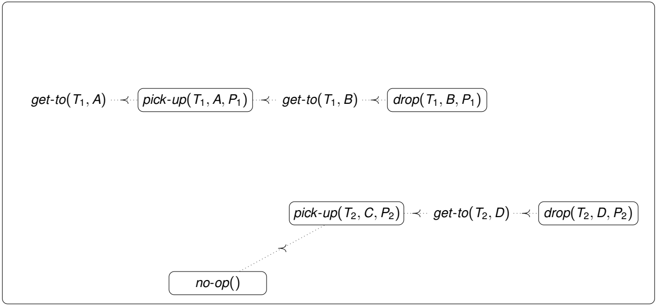
$$\pi = ()$$



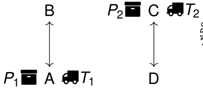
Standard Progression Algorithm



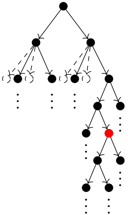
```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n' ← n.apply(t)
            fringe.add(n')
        else
            for m ∈ t.methods do
                n' ← n.decompose(t, m)
                fringe.add(n')
```



$$\pi = ()$$



Standard Progression Algorithm

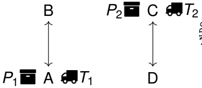


```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n′ ← n.apply(t)
            fringe.add(n′)
        else
            for m ∈ t.methods do
                n′ ← n.decompose(t, m)
                fringe.add(n′)
```

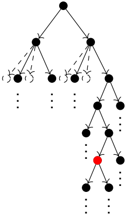
$\textit{get-to}(T_1, A) \prec \boxed{\textit{pick-up}(T_1, A, P_1)} \prec \textit{get-to}(T_1, B) \prec \boxed{\textit{drop}(T_1, B, P_1)}$

$\boxed{\textit{pick-up}(T_2, C, P_2)} \prec \textit{get-to}(T_2, D) \prec \boxed{\textit{drop}(T_2, D, P_2)}$

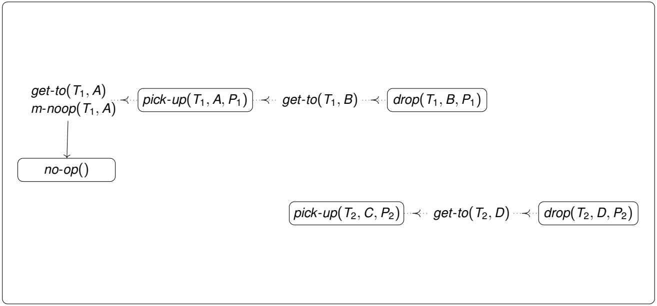
$\pi = (\textit{no-op}())$



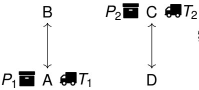
Standard Progression Algorithm



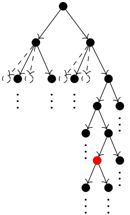
$fringe \leftarrow \{(s_I, tn_I, ())\}$
while $fringe \neq \emptyset$ **do**
  $n \leftarrow fringe.poll()$
  if $n.isgoal$ **then return** n
  $U \leftarrow n.unconstrainedNodes$
  for $t \in U$ **do**
    if $isPrimitive(t)$ **then**
      $n' \leftarrow n.apply(t)$
      $fringe.add(n')$
    else
      for $m \in t.methods$ **do**
        $n' \leftarrow n.decompose(t, m)$
        $fringe.add(n')$



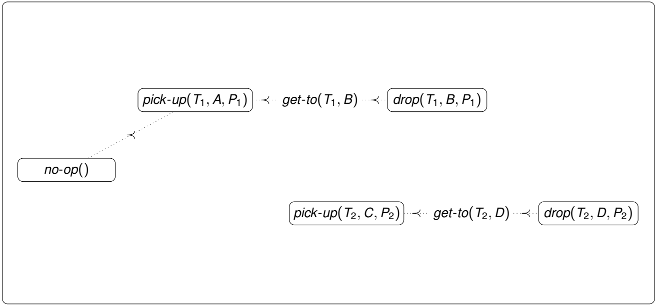
$\pi = (no\text{-}op())$



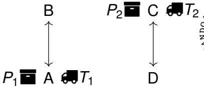
Standard Progression Algorithm



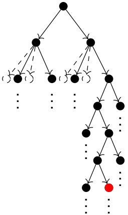
```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n' ← n.apply(t)
            fringe.add(n')
        else
            for m ∈ t.methods do
                n' ← n.decompose(t, m)
                fringe.add(n')
```



$$\pi = (\textit{no-op}())$$



Standard Progression Algorithm

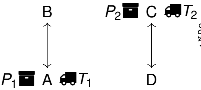


$fringe \leftarrow \{(s_I, tn_I, ())\}$
while $fringe \neq \emptyset$ **do**
  $n \leftarrow fringe.poll()$
  if $n.isgoal$ **then return** n
  $U \leftarrow n.unconstrainedNodes$
  for $t \in U$ **do**
    if $isPrimitive(t)$ **then**
      $n' \leftarrow n.apply(t)$
      $fringe.add(n')$
    else
      for $m \in t.methods$ **do**
        $n' \leftarrow n.decompose(t, m)$
        $fringe.add(n')$

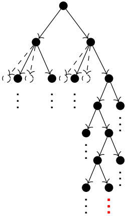
$\boxed{pick\text{-}up(T_1, A, P_1)} \prec get\text{-}to(T_1, B) \prec \boxed{drop(T_1, B, P_1)}$

$\boxed{pick\text{-}up(T_2, C, P_2)} \prec get\text{-}to(T_2, D) \prec \boxed{drop(T_2, D, P_2)}$

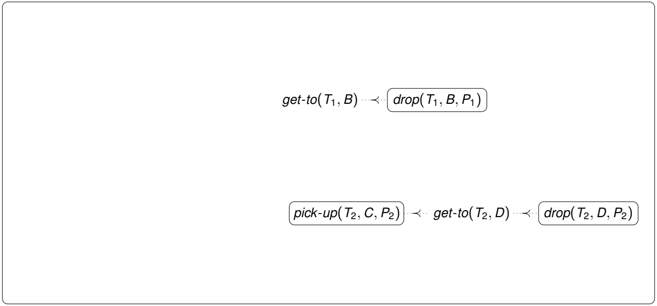
$$\pi = (no\text{-}op(), no\text{-}op())$$



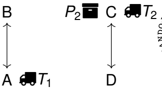
Standard Progression Algorithm



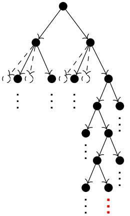
```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n' ← n.apply(t)
            fringe.add(n')
        else
            for m ∈ t.methods do
                n' ← n.decompose(t, m)
                fringe.add(n')
```



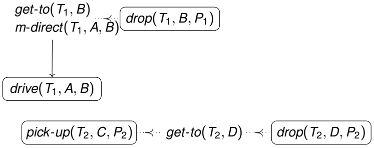
$$\pi = (\textit{no-op}(), \textit{no-op}(), \textit{pick-up}(T_1, A, P_1))$$



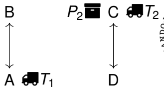
Standard Progression Algorithm



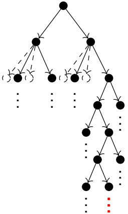
$fringe \leftarrow \{(s_I, tn_I, ())\}$
while $fringe \neq \emptyset$ **do**
    $n \leftarrow fringe.poll()$
    if $n.isgoal$ **then return** n
    $U \leftarrow n.unconstrainedNodes$
    for $t \in U$ **do**
        if $isPrimitive(t)$ **then**
            $n' \leftarrow n.apply(t)$
            $fringe.add(n')$
        else
            for $m \in t.methods$ **do**
                $n' \leftarrow n.decompose(t, m)$
                $fringe.add(n')$



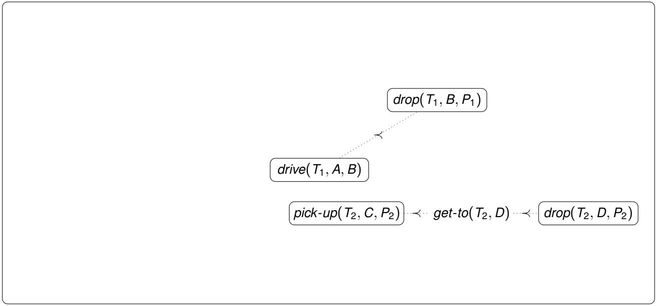
$$\pi = (no\text{-}op(), no\text{-}op(), pick\text{-}up(T_1, A, P_1))$$



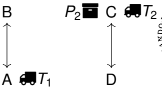
Standard Progression Algorithm



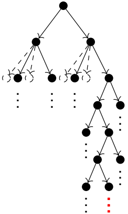
```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n' ← n.apply(t)
            fringe.add(n')
        else
            for m ∈ t.methods do
                n' ← n.decompose(t, m)
                fringe.add(n')
```



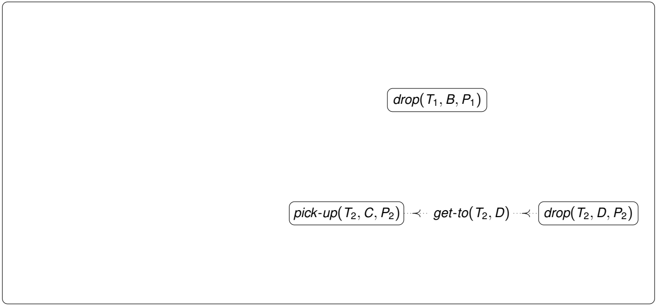
$$\pi = (no\text{-}op(), no\text{-}op(), pick\text{-}up(T_1, A, P_1))$$



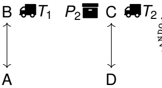
Standard Progression Algorithm



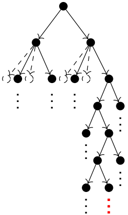
```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n′ ← n.apply(t)
            fringe.add(n′)
        else
            for m ∈ t.methods do
                n′ ← n.decompose(t, m)
                fringe.add(n′)
```



$$\pi = (no\text{-}op(), no\text{-}op(), pick\text{-}up(T_1, A, P_1), drive(T_1, A, B))$$

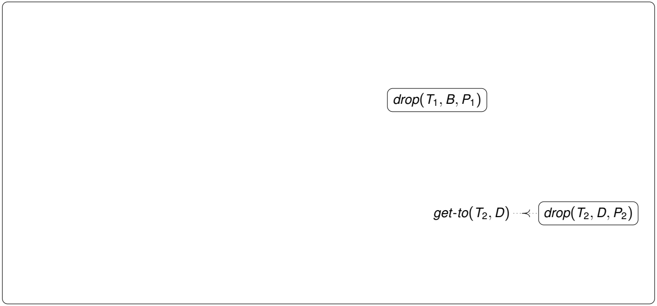


Standard Progression Algorithm

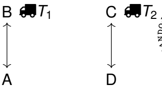


while *fringe* $\neq \emptyset$ **do**
- $n \leftarrow \mathit{fringe.poll}()$
- **if** *n.isgoal* **then return** n
- $U \leftarrow \mathit{n.unconstrainedNodes}$
- **for** $t \in U$ **do**
  - **if** $\mathit{isPrimitive}(t)$ **then**
    - $n' \leftarrow \mathit{n.apply}(t)$
    - $\mathit{fringe.add}(n')$
  - **else**
    - **for** $m \in \mathit{t.methods}$ **do**
      - $n' \leftarrow \mathit{n.decompose}(t, m)$
      - $\mathit{fringe.add}(n')$

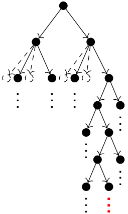
$\mathit{fringe} \leftarrow \{(s_I, tn_I, ())\}$



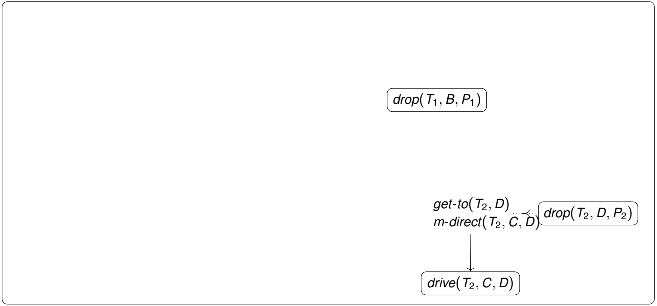
$$\pi = (\mathit{no\text{-}op}(), \mathit{no\text{-}op}(), \mathit{pick\text{-}up}(T_1, A, P_1), \mathit{drive}(T_1, A, B), \mathit{pick\text{-}up}(T_2, C, P_2))$$



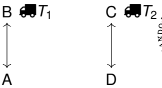
Standard Progression Algorithm



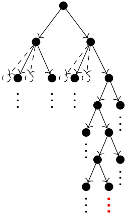
fringe $\leftarrow \{(s_I, tn_I, ())\}$
while *fringe* $\neq \emptyset$ **do**
  $n \leftarrow$ *fringe.poll*()
  if *n.isgoal* **then return** *n*
  $U \leftarrow$ *n.unconstrainedNodes*
  for $t \in U$ **do**
    if *isPrimitive*(t) **then**
      $n' \leftarrow$ *n.apply*(t)
      fringe.add(n')
    else
      for $m \in$ *t.methods* **do**
        $n' \leftarrow$ *n.decompose*(t, m)
        fringe.add(n')



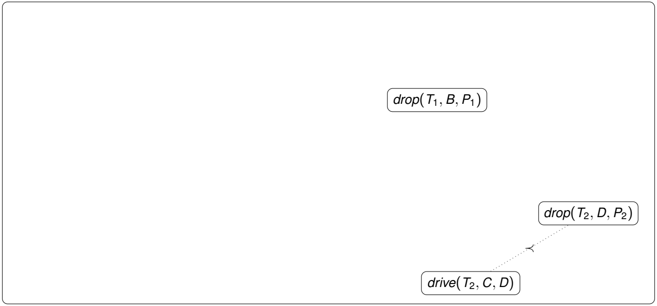
$$\pi = (no\text{-}op(), no\text{-}op(), pick\text{-}up(T_1, A, P_1), drive(T_1, A, B), pick\text{-}up(T_2, C, P_2))$$



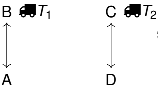
Standard Progression Algorithm



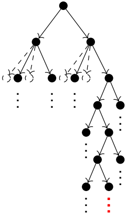
```
fringe ← {(s_I, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    U ← n.unconstrainedNodes
    for t ∈ U do
        if isPrimitive(t) then
            n′ ← n.apply(t)
            fringe.add(n′)
        else
            for m ∈ t.methods do
                n′ ← n.decompose(t, m)
                fringe.add(n′)
```



$\pi = (\textit{no-op}(), \textit{no-op}(), \textit{pick-up}(T_1, A, P_1), \textit{drive}(T_1, A, B), \textit{pick-up}(T_2, C, P_2))$



Standard Progression Algorithm



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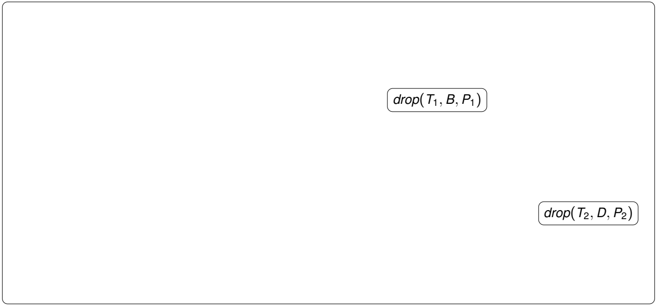

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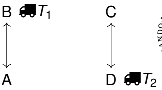

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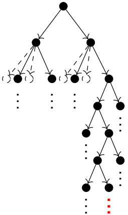

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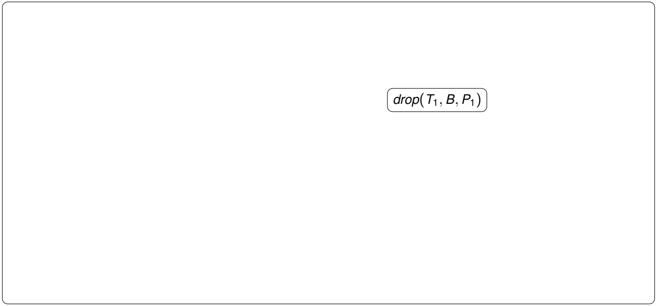
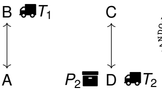
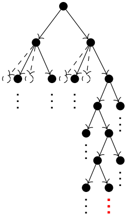


$\pi = (no\text{-}op(), no\text{-}op(), pick\text{-}up(T_1, A, P_1), drive(T_1, A, B), pick\text{-}up(T_2, C, P_2), drive(T_2, C, D), drop(T_2, D, P_2))$



Standard Progression Algorithm



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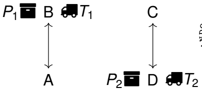
$\pi = (\textit{no-op}(), \textit{no-op}(), \textit{pick-up}(T_1, A, P_1), \textit{drive}(T_1, A, B), \textit{pick-up}(T_2, C, P_2), \textit{drive}(T_2, C, D), \textit{drop}(T_2, D, P_2), \textit{drop}(T_1, B, P_1))$



Progression Search – Properties

- Progression Search is **sound** . . .
- . . . and **complete**

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- It maintains the **current state** during search
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Progression Search – Properties

- Progression Search is **sound** . . .
- . . . and **complete**
- It maintains the **current state** during search
- This has been used to control search via state-based **preconditions** for **methods**
- It is also useful for calculating **heuristics**

Improving Progression Search

- Observation: In partially ordered models, standard progression search searches parts of the search space more than once

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- This is due to branching (i.e. a non-deterministic choice) over unconstrained **compound** tasks
- When processing actions, the algorithm **commits** to an ordering in the solution
- The decision which **task is decomposed** implies **no** commitment to the solution
- The decision which **method is used** implies commitment to the solution

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- This is due to branching (i.e. a non-deterministic choice) over unconstrained **compound** tasks
- When processing actions, the algorithm **commits** to an ordering in the solution
- The decision which **task is decomposed** implies **no** commitment to the solution
- The decision which **method is used** implies commitment to the solution

→ For selection of the compound task, no branching is needed, we can simply "pick" one and decompose it

→ The decision which method is used must be made via branching

Improved Progression Algorithm

```
fringe ← {(s_0, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    (U_C, U_P) ← n.unconstrainedNodes
    for t ∈ U_P do
        n' ← n.apply(t)
        fringe.add(n')
    t ← selectAbstractTask(U_C)
    for m ∈ t.methods do
        n' ← n.decompose(t, m)
        fringe.add(n')
```

- **Unconstrained tasks** are split into compound and primitive tasks

Improved Progression Algorithm

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```

- **Unconstrained tasks** are split into compound and primitive tasks
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$\textit{fringe} \leftarrow \{(s_0, tn_I, ())\}$
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    $n \leftarrow \textit{fringe.poll}()$
    if $\textit{n.isgoal}$ **then return** n
    $(U_C, U_P) \leftarrow \textit{n.unconstrainedNodes}$
    for $t \in U_P$ **do**
        $n' \leftarrow \textit{n.apply}(t)$
        $\textit{fringe.add}(n')$
    $t \leftarrow \textit{selectAbstractTask}(U_C)$
    for $m \in t.\textit{methods}$ **do**
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- **Unconstrained tasks** are split into compound and primitive tasks
- **Action application** is done via branching
- Only **one compound task** is processed

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while $fringe \neq \emptyset$ **do**
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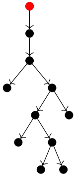
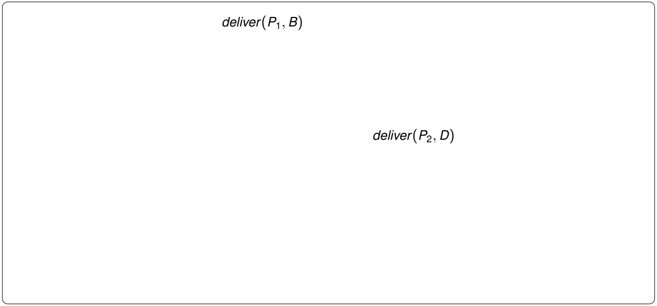
- **Unconstrained tasks** are split into compound and primitive tasks
- **Action application** is done via branching
- Only **one compound task** is processed
- **Method application** is done via branching

Improved Progression Algorithm





$\pi = ()$

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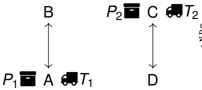
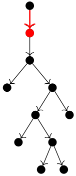
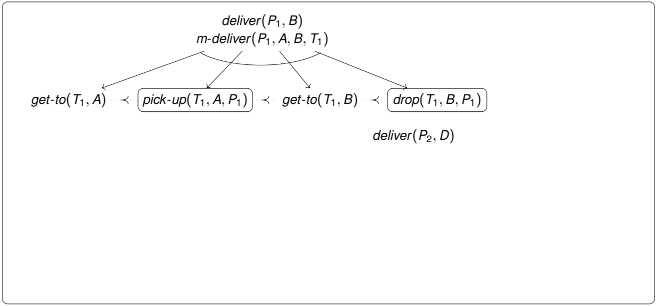


Improved Progression Algorithm





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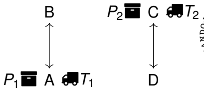
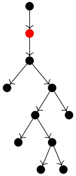


Improved Progression Algorithm



$$get\text{-}to(T_1, A) \prec \boxed{pick\text{-}up(T_1, A, P_1)} \prec get\text{-}to(T_1, B) \prec \boxed{drop(T_1, B, P_1)}$$

$$deliver(P_2, D)$$

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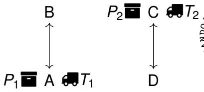
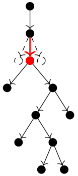
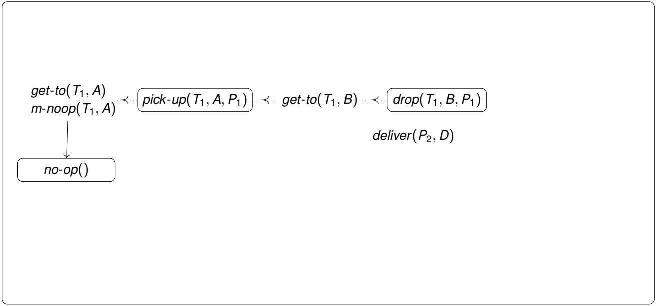


Improved Progression Algorithm





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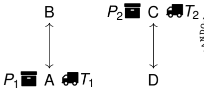
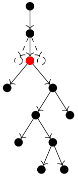
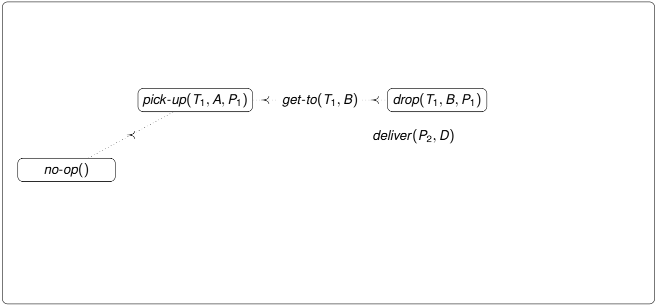


Improved Progression Algorithm





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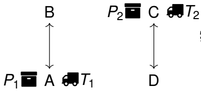
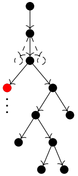
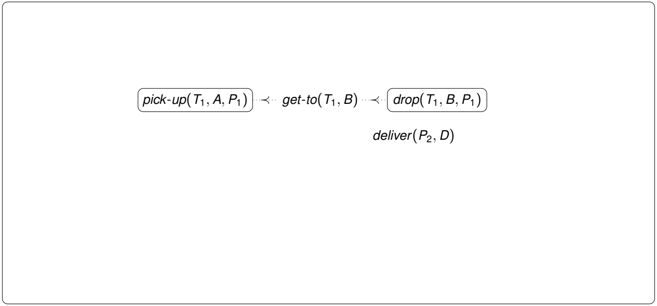


Improved Progression Algorithm





$\pi = (\textit{no-op}())$

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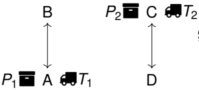

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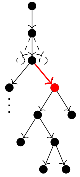

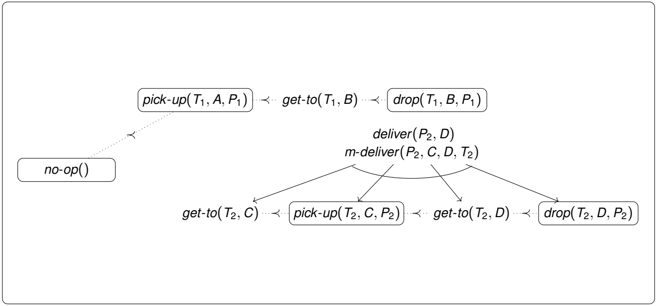

$$\pi = ()$$

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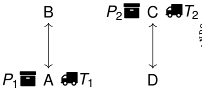
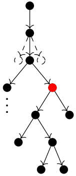
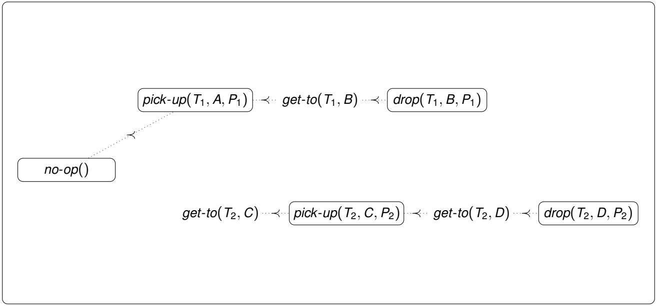


Improved Progression Algorithm





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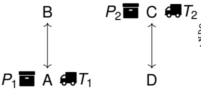
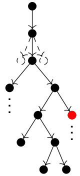
    fringe.add(n')



Improved Progression Algorithm



$\boxed{pick\text{-}up(T_1, A, P_1)} \prec get\text{-}to(T_1, B) \prec \boxed{drop(T_1, B, P_1)}$

$get\text{-}to(T_2, C) \prec \boxed{pick\text{-}up(T_2, C, P_2)} \prec get\text{-}to(T_2, D) \prec \boxed{drop(T_2, D, P_2)}$

$\pi = (no\text{-}op())$

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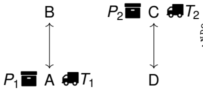
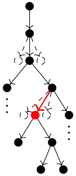
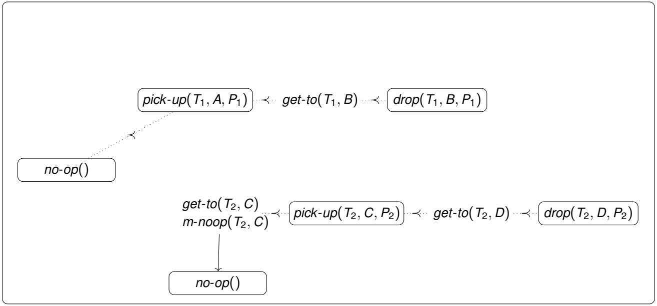
    $fringe.add(n')$
  $t \leftarrow selectAbstractTask(U_C)$
  for $m \in t.methods$ **do**
    $n' \leftarrow n.decompose(t, m)$
    $fringe.add(n')$



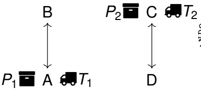
Improved Progression Algorithm



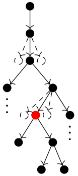


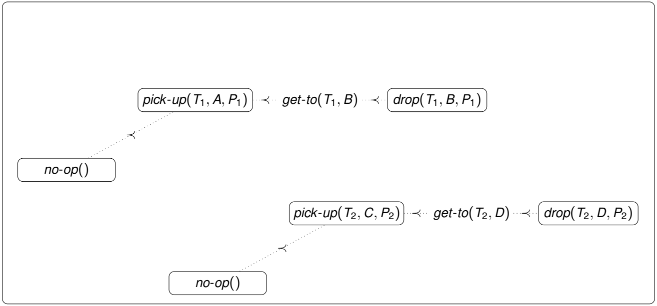
$\pi = ()$

```
fringe ← {(s_0, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    (U_C, U_P) ← n.unconstrainedNodes
    for t ∈ U_P do
        n' ← n.apply(t)
        fringe.add(n')
    t ← selectAbstractTask(U_C)
    for m ∈ t.methods do
        n' ← n.decompose(t, m)
        fringe.add(n')
```



Improved Progression Algorithm





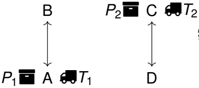
$\pi = ()$

```
fringe ← {(s_0, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    (U_C, U_P) ← n.unconstrainedNodes

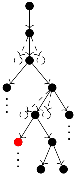
    for t ∈ U_P do
        n' ← n.apply(t)
        fringe.add(n')

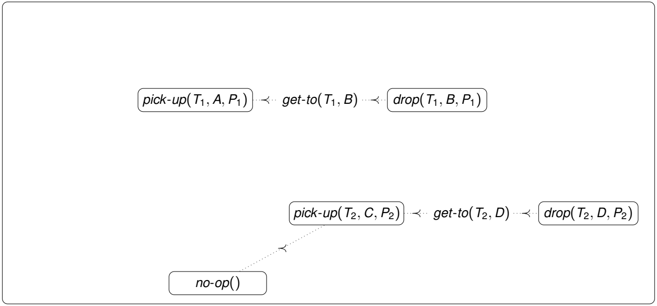
    t ← selectAbstractTask(U_C)

    for m ∈ t.methods do
        n' ← n.decompose(t, m)
        fringe.add(n')
```



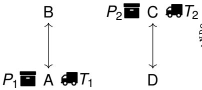
Improved Progression Algorithm



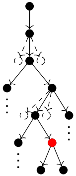


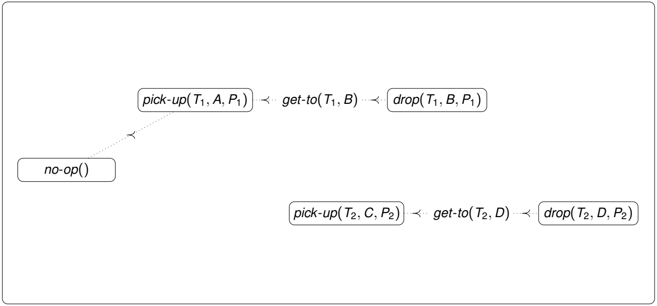
$\pi = (\mathit{no\text{-}op}())$

$\mathit{fringe} \leftarrow \{(s_0, tn_I, ())\}$
while $\mathit{fringe} \neq \emptyset$ **do**
  $n \leftarrow \mathit{fringe.poll}()$
  if $n.\mathit{isgoal}$ **then return** n
  $(U_C, U_P) \leftarrow n.\mathit{unconstrainedNodes}$
  for $t \in U_P$ **do**
    $n' \leftarrow n.\mathit{apply}(t)$
    $\mathit{fringe.add}(n')$
  $t \leftarrow \mathit{selectAbstractTask}(U_C)$
  for $m \in t.\mathit{methods}$ **do**
    $n' \leftarrow n.\mathit{decompose}(t, m)$
    $\mathit{fringe.add}(n')$



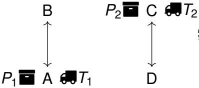
Improved Progression Algorithm



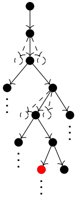


$\pi = (\textit{no-op}())$

$\textit{fringe} \leftarrow \{(s_0, tn_I, ())\}$
while $\textit{fringe} \neq \emptyset$ **do**
  $n \leftarrow \textit{fringe.poll}()$
  if $\textit{n.isgoal}$ **then return** n
  $(U_C, U_P) \leftarrow \textit{n.unconstrainedNodes}$
  for $t \in U_P$ **do**
    $n' \leftarrow \textit{n.apply}(t)$
    $\textit{fringe.add}(n')$
  $t \leftarrow \textit{selectAbstractTask}(U_C)$
  for $m \in \textit{t.methods}$ **do**
    $n' \leftarrow \textit{n.decompose}(t, m)$
    $\textit{fringe.add}(n')$



Improved Progression Algorithm

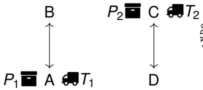


$pick\text{-}up(T_1, A, P_1) \prec get\text{-}to(T_1, B) \prec drop(T_1, B, P_1)$

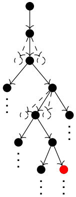
$pick\text{-}up(T_2, C, P_2) \prec get\text{-}to(T_2, D) \prec drop(T_2, D, P_2)$

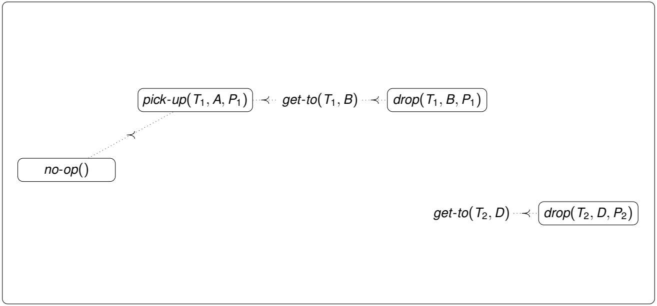
$$\pi = (no\text{-}op(), no\text{-}op())$$

$fringe \leftarrow \{(s_0, tn_I, ())\}$
while $fringe \neq \emptyset$ **do**
  $n \leftarrow fringe.poll()$
  if $n.isgoal$ **then return** n
  $(U_C, U_P) \leftarrow n.unconstrainedNodes$
  for $t \in U_P$ **do**
    $n' \leftarrow n.apply(t)$
    $fringe.add(n')$
  $t \leftarrow selectAbstractTask(U_C)$
  for $m \in t.methods$ **do**
    $n' \leftarrow n.decompose(t, m)$
    $fringe.add(n')$



Improved Progression Algorithm

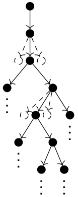


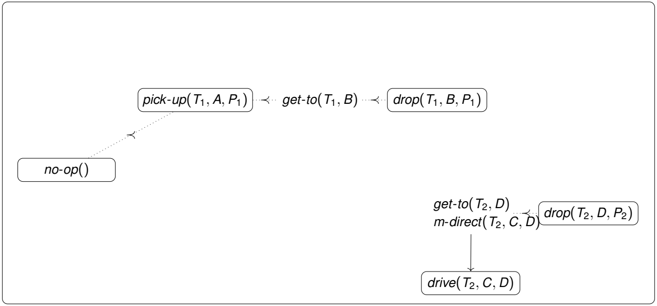


$$\pi = (\textit{no-op}(), \textit{pick-up}(T_2, C, P_2))$$

$\textit{fringe} \leftarrow \{(s_0, tn_I, ())\}$
while $\textit{fringe} \neq \emptyset$ **do**
  $n \leftarrow \textit{fringe.poll}()$
  if $n.\textit{isgoal}$ **then return** n
  $(U_C, U_P) \leftarrow n.\textit{unconstrainedNodes}$
  for $t \in U_P$ **do**
    $n' \leftarrow n.\textit{apply}(t)$
    $\textit{fringe.add}(n')$
  $t \leftarrow \textit{selectAbstractTask}(U_C)$
  for $m \in t.\textit{methods}$ **do**
    $n' \leftarrow n.\textit{decompose}(t, m)$
    $\textit{fringe.add}(n')$

Improved Progression Algorithm

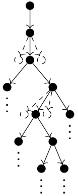


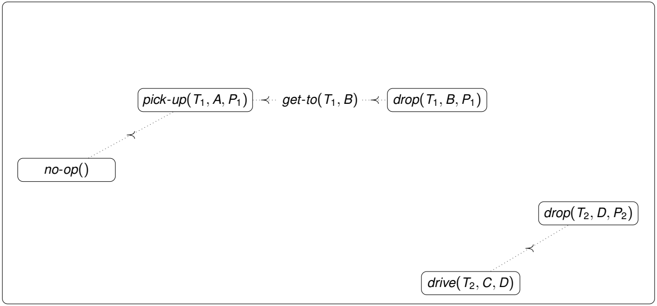



```
fringe ← {(s_0, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    (U_C, U_P) ← n.unconstrainedNodes
    for t ∈ U_P do
        n' ← n.apply(t)
        fringe.add(n')
    t ← selectAbstractTask(U_C)
    for m ∈ t.methods do
        n' ← n.decompose(t, m)
        fringe.add(n')
```

$$\pi = (\textit{no-op}(), \textit{pick-up}(T_2, C, P_2))$$

Improved Progression Algorithm

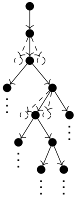


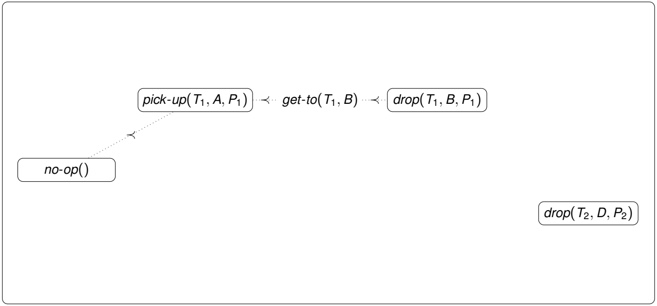


$$\pi = (\textit{no-op}(), \textit{pick-up}(T_2, C, P_2))$$

$\textit{fringe} \leftarrow \{(s_0, tn_I, ())\}$
while $\textit{fringe} \neq \emptyset$ **do**
  $n \leftarrow \textit{fringe.poll}()$
  if $n.\textit{isgoal}$ **then return** n
  $(U_C, U_P) \leftarrow n.\textit{unconstrainedNodes}$
  for $t \in U_P$ **do**
    $n' \leftarrow n.\textit{apply}(t)$
    $\textit{fringe.add}(n')$
  $t \leftarrow \textit{selectAbstractTask}(U_C)$
  for $m \in t.\textit{methods}$ **do**
    $n' \leftarrow n.\textit{decompose}(t, m)$
    $\textit{fringe.add}(n')$

Improved Progression Algorithm

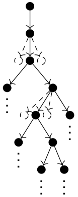


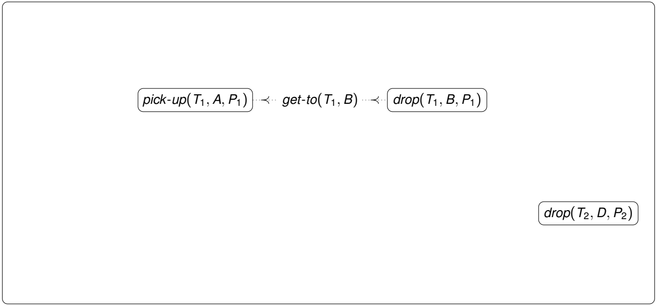


$fringe \leftarrow \{(s_0, tn_I, ())\}$
while $fringe \neq \emptyset$ **do**
  $n \leftarrow fringe.poll()$
  if $n.isgoal$ **then return** n
  $(U_C, U_P) \leftarrow n.unconstrainedNodes$
  for $t \in U_P$ **do**
    $n' \leftarrow n.apply(t)$
    $fringe.add(n')$
  $t \leftarrow selectAbstractTask(U_C)$
  for $m \in t.methods$ **do**
    $n' \leftarrow n.decompose(t, m)$
    $fringe.add(n')$

$$\pi = (no\text{-}op(), pick\text{-}up(T_2, C, P_2), drive(T_2, C, D))$$

Improved Progression Algorithm

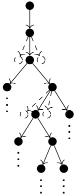




$$\pi = (\textit{no-op}(), \textit{pick-up}(T_2, C, P_2), \textit{drive}(T_2, C, D), \textit{no-op}())$$

$\textit{fringe} \leftarrow \{(s_0, tn_I, ())\}$
while $\textit{fringe} \neq \emptyset$ **do**
  $n \leftarrow \textit{fringe.poll}()$
  if $\textit{n.isgoal}$ **then return** n
  $(U_C, U_P) \leftarrow \textit{n.unconstrainedNodes}$
  for $t \in U_P$ **do**
    $n' \leftarrow \textit{n.apply}(t)$
    $\textit{fringe.add}(n')$
  $t \leftarrow \textit{selectAbstractTask}(U_C)$
  for $m \in t.\textit{methods}$ **do**
    $n' \leftarrow \textit{n.decompose}(t, m)$
    $\textit{fringe.add}(n')$

Improved Progression Algorithm

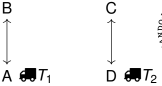


$$\text{get-to}(T_1, B) \prec \boxed{\text{drop}(T_1, B, P_1)}$$

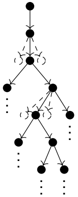
$$\boxed{\text{drop}(T_2, D, P_2)}$$

```
fringe ← {(s_0, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    (U_C, U_P) ← n.unconstrainedNodes
    for t ∈ U_P do
        n′ ← n.apply(t)
        fringe.add(n′)
    t ← selectAbstractTask(U_C)
    for m ∈ t.methods do
        n′ ← n.decompose(t, m)
        fringe.add(n′)
```

$$\pi = (\textit{no-op}(), \textit{pick-up}(T_2, C, P_2), \textit{drive}(T_2, C, D), \textit{no-op}(), \textit{pick-up}(T_1, A, P_1))$$



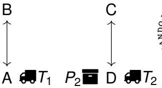
Improved Progression Algorithm



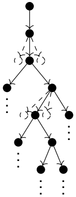
get-to$(T_1, B) \prec$ $\boxed{drop(T_1, B, P_1)}$

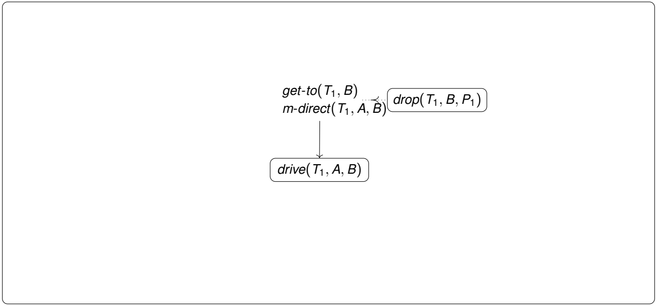
$$\pi = (\textit{no-op}(), \textit{pick-up}(T_2, C, P_2), \textit{drive}(T_2, C, D), \textit{no-op}(), \textit{pick-up}(T_1, A, P_1), \textit{drop}(T_2, D, P_2))$$

fringe $\leftarrow \{(s_0, tn_I, ())\}$
while *fringe* $\neq \emptyset$ **do**
    $n \leftarrow$ *fringe.poll*()
    if *n.isgoal* **then return** *n*
    $(U_C, U_P) \leftarrow$ *n.unconstrainedNodes*
    for $t \in U_P$ **do**
        $n' \leftarrow$ *n.apply*(t)
        fringe.add(n')
    $t \leftarrow$ *selectAbstractTask*(U_C)
    for $m \in t.methods$ **do**
        $n' \leftarrow$ *n.decompose*(t, m)
        fringe.add(n')



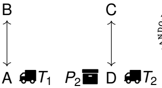
Improved Progression Algorithm



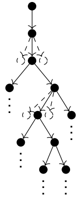


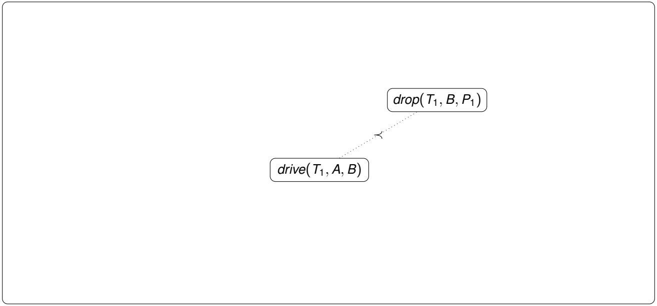
$fringe \leftarrow \{(s_0, tn_I, ())\}$
while $fringe \neq \emptyset$ **do**
  $n \leftarrow fringe.poll()$
  if $n.isgoal$ **then return** n
  $(U_C, U_P) \leftarrow n.unconstrainedNodes$
  for $t \in U_P$ **do**
    $n' \leftarrow n.apply(t)$
    $fringe.add(n')$
  $t \leftarrow selectAbstractTask(U_C)$
  for $m \in t.methods$ **do**
    $n' \leftarrow n.decompose(t, m)$
    $fringe.add(n')$

$\pi = (no\text{-}op(), pick\text{-}up(T_2, C, P_2), drive(T_2, C, D), no\text{-}op(), pick\text{-}up(T_1, A, P_1), drop(T_2, D, P_2))$



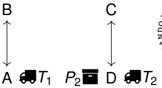
Improved Progression Algorithm



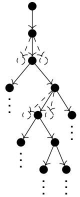


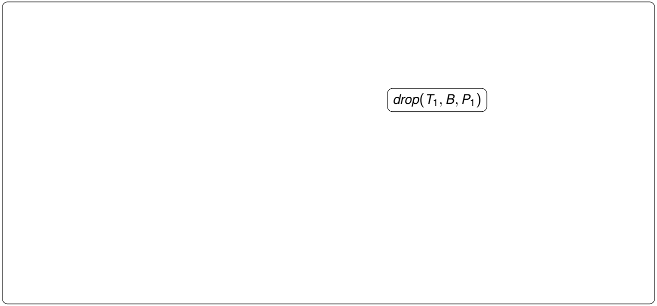
fringe $\leftarrow \{(s_0, tn_I, ())\}$
while *fringe* $\neq \emptyset$ **do**
  $n \leftarrow$ *fringe.poll*()
  if *n.isgoal* **then return** n
  $(U_C, U_P) \leftarrow$ *n.unconstrainedNodes*
  for $t \in U_P$ **do**
    $n' \leftarrow n.apply(t)$
    fringe.add(n')
  $t \leftarrow$ *selectAbstractTask*(U_C)
  for $m \in t.methods$ **do**
    $n' \leftarrow n.decompose(t, m)$
    fringe.add(n')

$$\pi = (\textit{no-op}(), \textit{pick-up}(T_2, C, P_2), \textit{drive}(T_2, C, D), \textit{no-op}(), \textit{pick-up}(T_1, A, P_1), \textit{drop}(T_2, D, P_2))$$



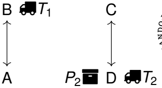
Improved Progression Algorithm



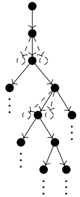



```
fringe ← {(s_0, tn_I, ())}
while fringe ≠ ∅ do
    n ← fringe.poll()
    if n.isgoal then return n
    (U_C, U_P) ← n.unconstrainedNodes
    for t ∈ U_P do
        n' ← n.apply(t)
        fringe.add(n')
    t ← selectAbstractTask(U_C)
    for m ∈ t.methods do
        n' ← n.decompose(t, m)
        fringe.add(n')
```

$$\pi = (\textit{no-op}(), \textit{pick-up}(T_2, C, P_2), \textit{drive}(T_2, C, D), \textit{no-op}(), \textit{pick-up}(T_1, A, P_1), \textit{drop}(T_2, D, P_2), \textit{drive}(T_1, A, B))$$

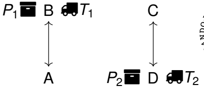


Improved Progression Algorithm



$fringe \leftarrow \{(s_0, tn_I, ())\}$
while $fringe \neq \emptyset$ **do**
  $n \leftarrow fringe.poll()$
  if $n.isgoal$ **then return** n
  $(U_C, U_P) \leftarrow n.unconstrainedNodes$
  for $t \in U_P$ **do**
    $n' \leftarrow n.apply(t)$
    $fringe.add(n')$
  $t \leftarrow selectAbstractTask(U_C)$
  for $m \in t.methods$ **do**
    $n' \leftarrow n.decompose(t, m)$
    $fringe.add(n')$

$$\pi = (\textit{no-op}(), \textit{pick-up}(T_2, C, P_2), \textit{drive}(T_2, C, D), \textit{no-op}(), \textit{pick-up}(T_1, A, P_1), \textit{drop}(T_2, D, P_2), \textit{drive}(T_1, A, B), \textit{drop}(T_1, B, P_1)))$$



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- It may **increase the progression bound** necessary to solve the problem (problematic for some planning systems)

Overview Part II

Solving HTN Planning Problems

- Search-based Approaches
  - Plan Space Search
  - Progression Search
- **Compilation-based Approaches**
  - **Compilations to STRIPS/ADL**
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Translating HTN Problems to STRIPS/ADL

The basic idea is quite simple:

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Approach:

- Add a **new part to the state** that represents the current task network
- **Simulate a progression search** on this part of the state
  - Adapt original actions with respect to applicability and to maintain the new state features
  - Add actions that simulate decomposition methods

HTN to STRIPS/ADL – Example

$\boxed{\textit{pick-up}(T_1, A, P_1)} \prec \textit{get-to}(T_1, B) \prec \boxed{\textit{drop}(T_1, B, P_1)}$

$\textit{deliver}(P_2, D)$

- Introduce id variables: $t_0, t_1, \ldots, t_b$
- Introduce new predicate for every task

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tasks: $\textit{ppick-up}(T_1, A, P_1, t_2)$,
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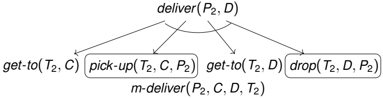

$\textit{m-deliver}(P_2, C, D, T_2, t_4, t_1, t_6, t_7)$

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- How many ids are sufficient?
  - Only computable for subclasses of HTN planning problems
  - Approach for general HTN planning problems:
    - Incrementally increase it like in SAT-based classical planning
    - But there is no upper bound, so only stop when a plan was found

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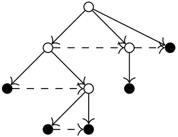
Challenges:

- How to represent **decomposition**?
- What is the best way to **bound** the problem?

Representing Decomposition

- We have already seen a structure to represent decomposition: **Decomposition Trees** (in the proof for TIHTN problems)



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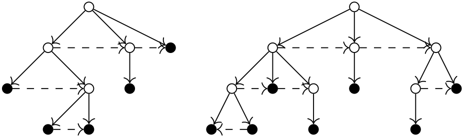

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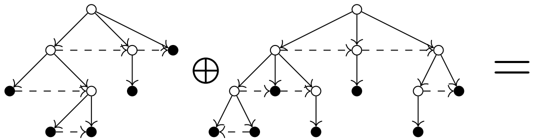

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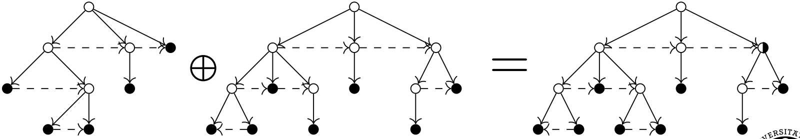

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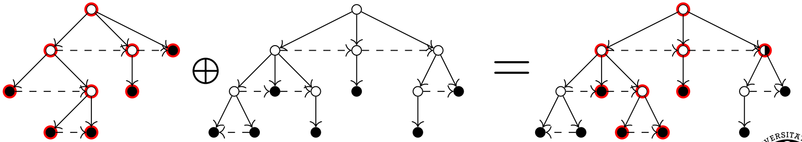

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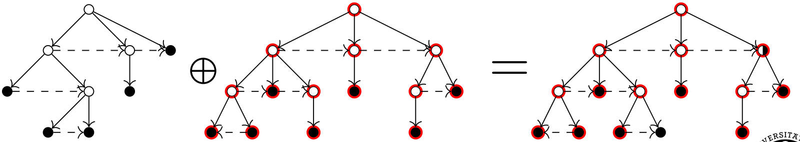

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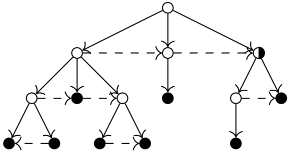

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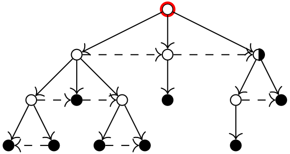

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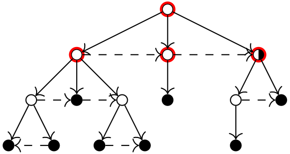

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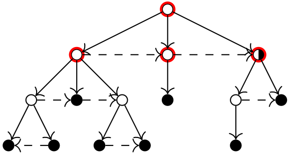

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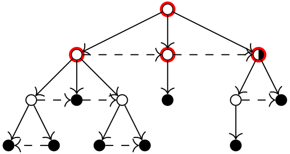

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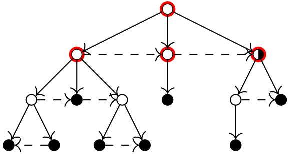

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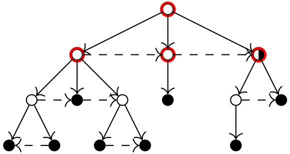

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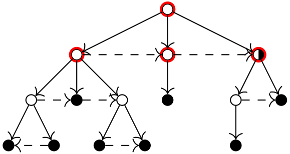

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- Current work tries greedily to put as few tasks as possible to each child

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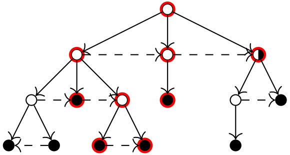
- A PDT contains **every** Decomposition Tree of height $\leq K$ as a sub-**graph**



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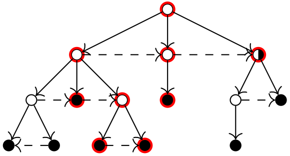

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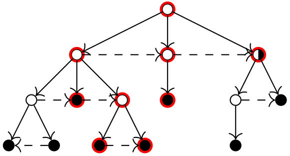

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→ To be used for the selection of a search node (task network/partial plan) out of the fringe

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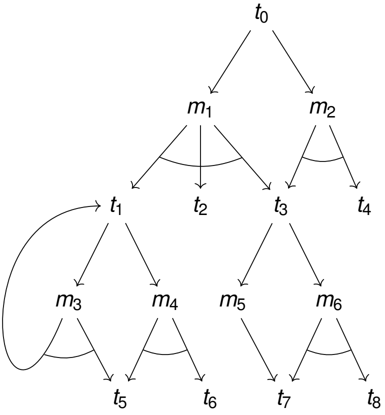
We introduce the Task Decomposition Graph (TDG) – which bases upon task insertion and delete relaxation – as a means to represent the task hierarchy.

TDG-based Heuristics

A TDG represents the decomposition structure:



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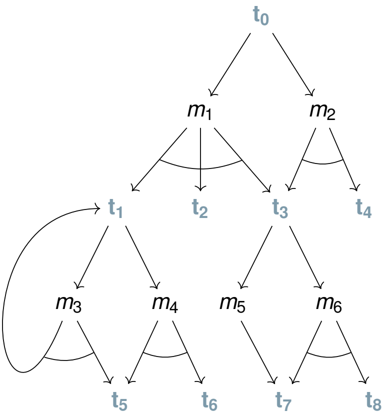

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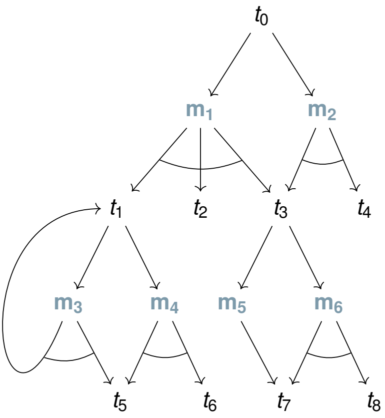

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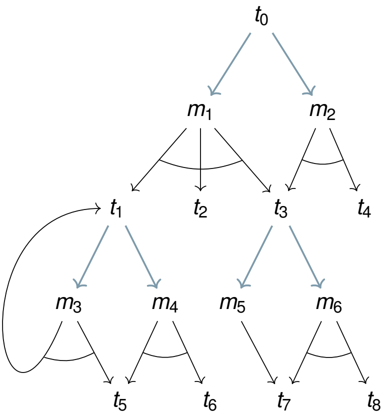

A TDG is a (possibly cyclic) bipartite graph $\mathcal{G} = \langle N_T, N_M, E_{(T,M)}, E_{(M,T)} \rangle$ with

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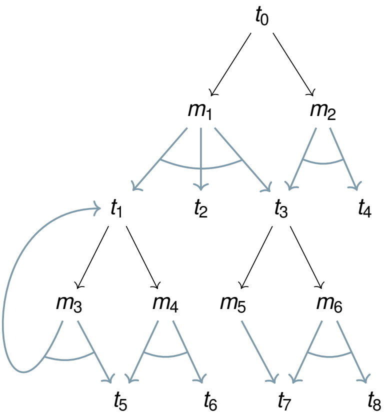

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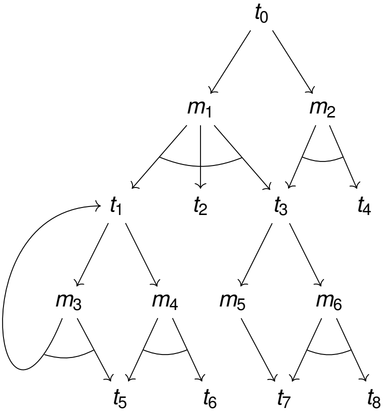

How to use the TDG to calculate an heuristic estimate?

Step 1:
Calculate the TDG in a preprocessing step.

Step 2:
Calculate heuristic $h(t)$ for each task t in TDG (still via preprocessing).

Step 3:
For a search node (partial plan) P and its task identifiers T, calculate $h(P) := \sum_{t \in T} h(t)$.

Cost-aware heuristic TDG-c

Let $\langle N_T, N_M, E_{T\to M}, E_{M\to T}\rangle$ be a TDG.

The estimates of the TDG are defined as follows:

$$h_T(n_t) := \begin{cases} cost(n_t) & \text{if } n_t \text{ primitive} \\ \min\limits_{(n_t,n_m)\in E_{T\to M}} h_M(n_m) & \text{else} \end{cases}$$

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For a given partial plan $P = (T, \prec, \alpha, CL)$, i.e, a search node, its heuristic is $h(P) := \sum_{t\in T} h(t)$ to estimate the cost of the cheapest reachable plan.

Cost-aware heuristic TDG-c (Example)

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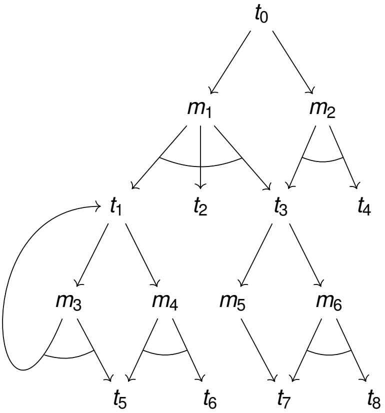

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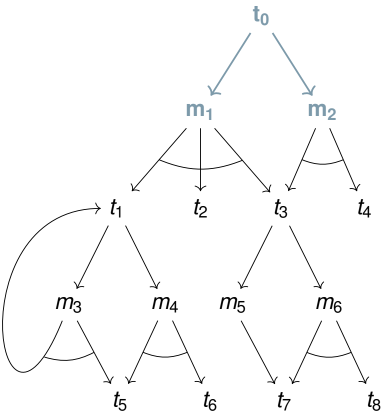

Example:

$$h_T(t_0) = min\{h_M(m_1), h_M(m_2)\}$$

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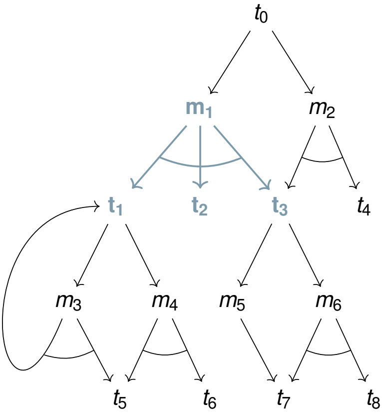
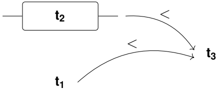


Example:

Method $m_1 = (t_0, tn)$ with task network tn:



$$h_M(m_1) = \sum_{t_i \in \{t_1, t_2, t_3\}} h_T(t_i)$$
$$= h_T(t_1) + cost(t_2) + h_T(t_3)$$

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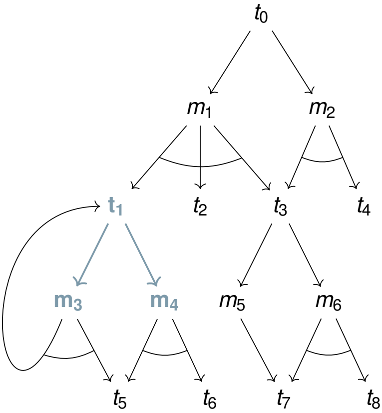

Example:

$$h_T(t_1) = min\{h_M(m_3), h_M(m_4)\}$$

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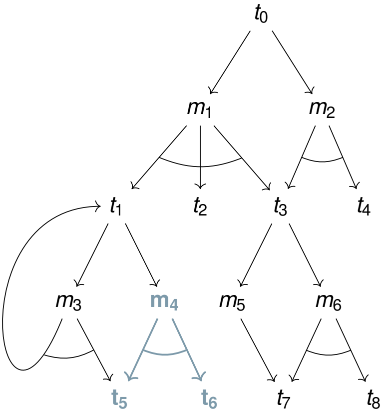

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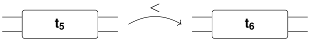

$$
\begin{aligned}
h_M(m_4) &= \sum_{t_i \in \{t_5, t_6\}} h_T(t_i) \\
&= h_T(t_5) + h_T(t_6) \\
&= cost(t_5) + cost(t_6)
\end{aligned}
$$

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Summary

TDG-c and TDG-m are admissible estimates of:

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- Both rely on task insertion and delete relaxation (for the construction process of the TDG)
- Only tasks within the the TDG account for the heuristic estimate, so task insertion is not reflected within the estimates ($\rightarrow$ room for improvement; but this guarantees admissibility)

Overview Part II

Solving HTN Planning Problems

- Search-based Approaches
  - Plan Space Search
  - Progression Search
- Compilation-based Approaches
  - Compilations to STRIPS/ADL
  - Compilations to SAT
- **Heuristics for Heuristic Search**
  - TDG-based Heuristics
  - **Relaxed Composition Heuristics**

Excursion

- Further Hierarchical Planning Formalisms

Classical Heuristics in HTN Planning

- We have seen two search-based approaches that can be instantiated as **heuristic search**
- We need to **sort** the fringe (according to what?)
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  - Which actions are reachable?
  - What is the objective, the “goal”?
    $\rightarrow$ usually no state-based goal given

Classical Heuristics in HTN Planning

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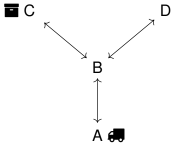
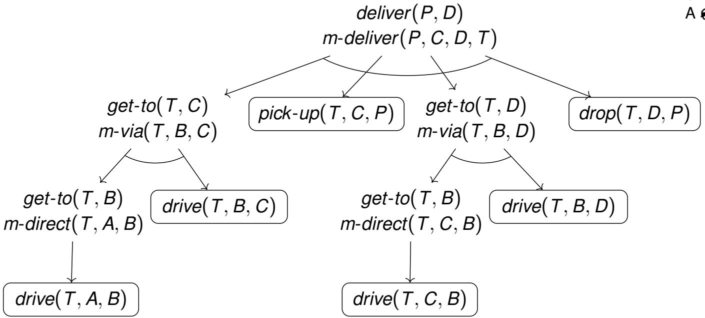
3. Use heuristic value in HTN planning
   - The fringe of the HTN planning system is sorted according to the heuristic value

Simulating Composition





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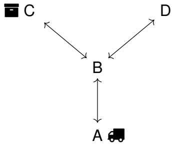

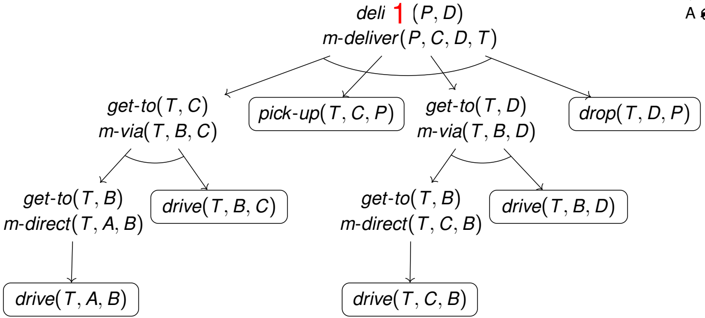

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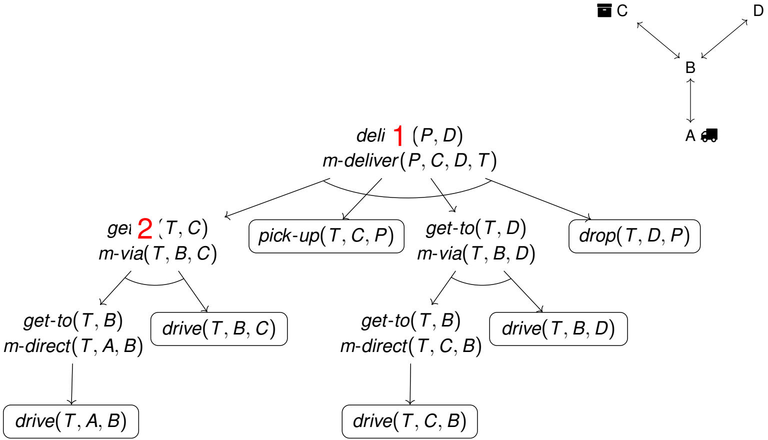

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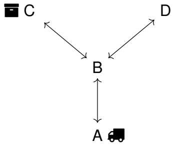

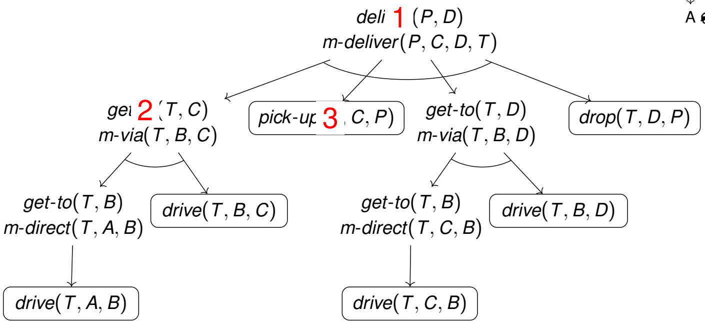

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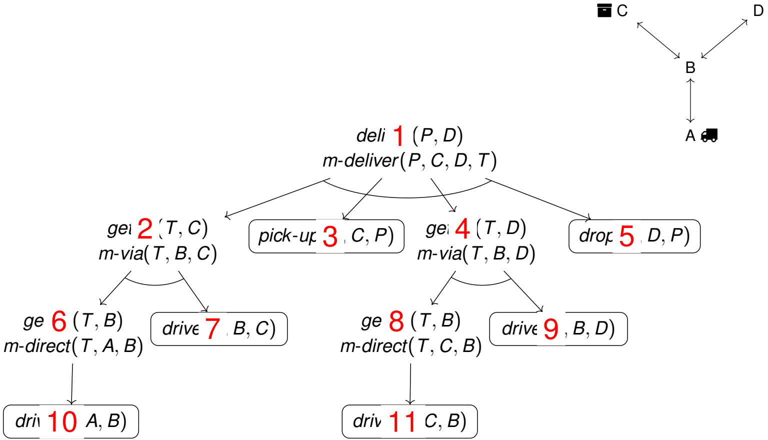

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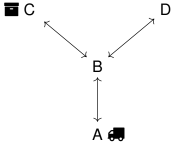

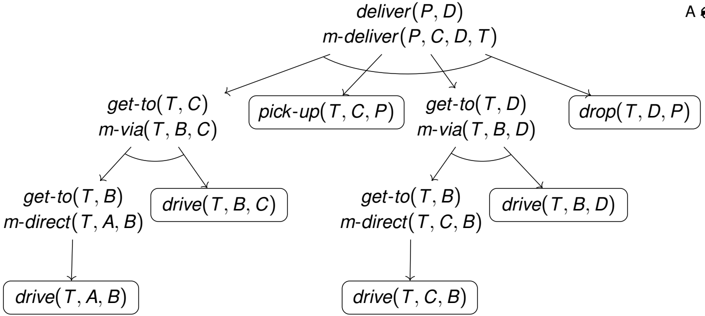

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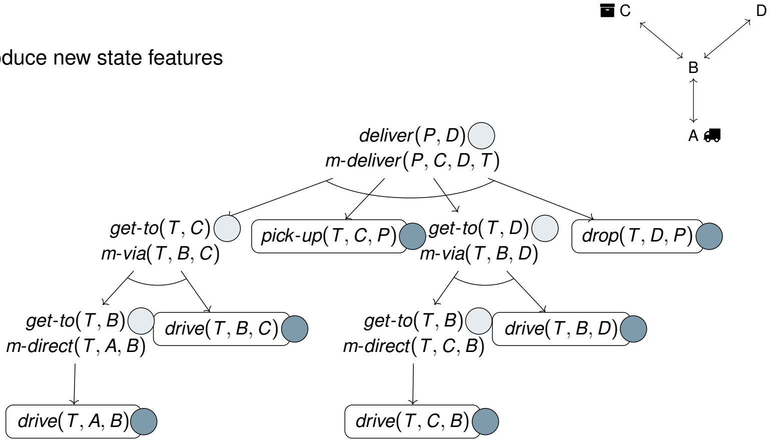

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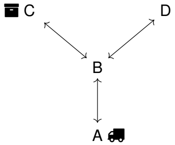

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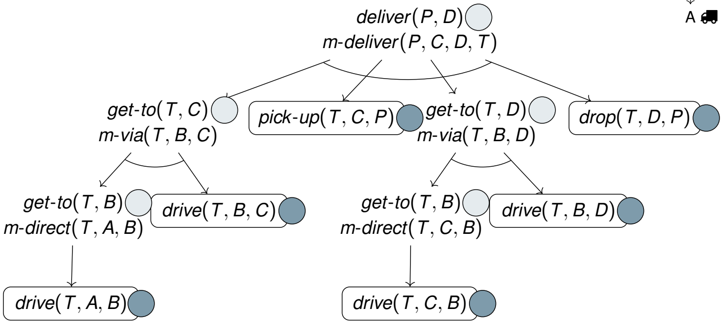

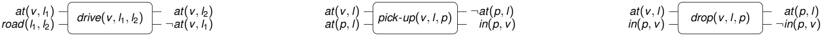

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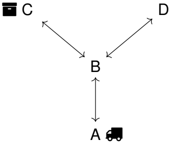

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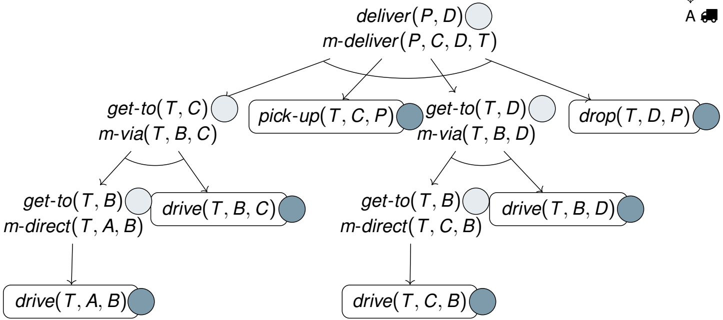

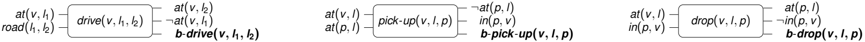

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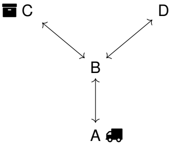

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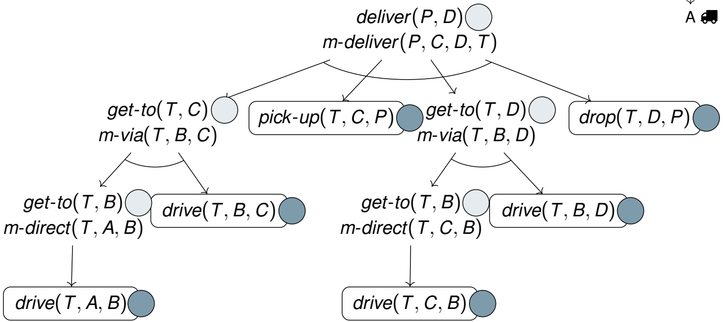

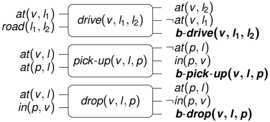

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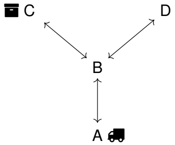

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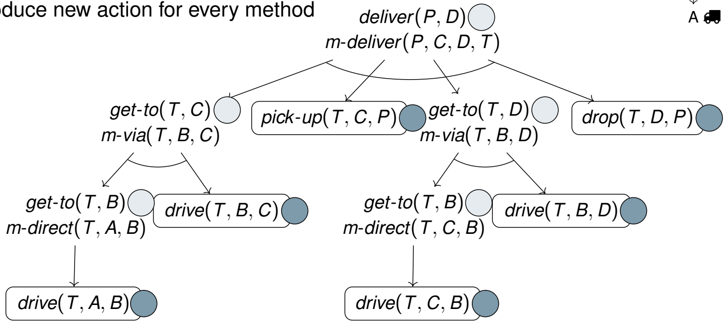

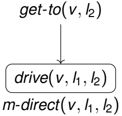

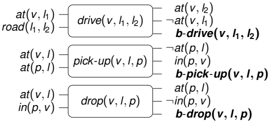

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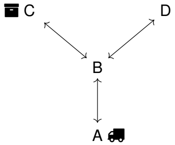

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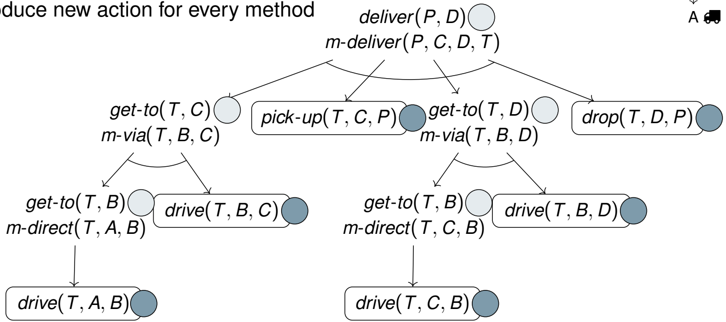

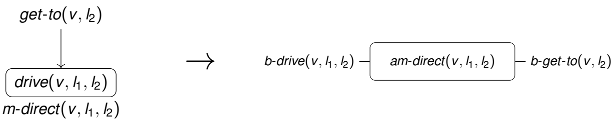

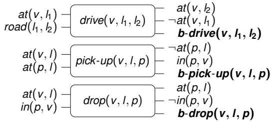

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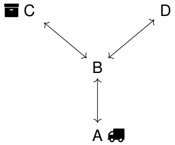

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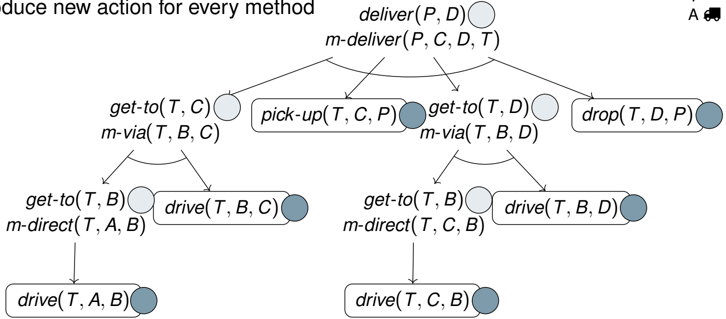

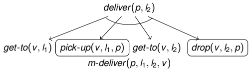

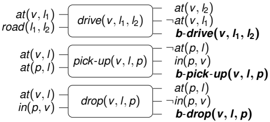

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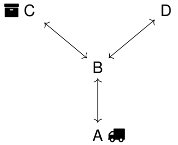

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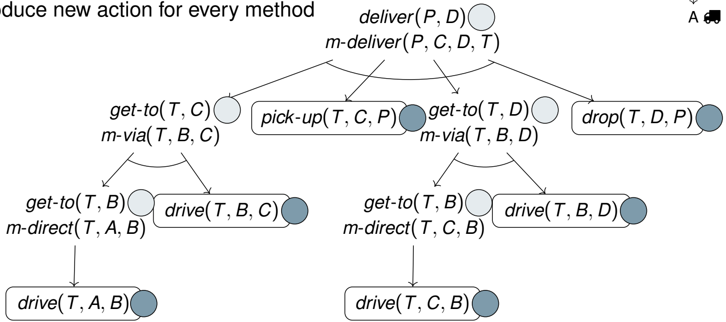
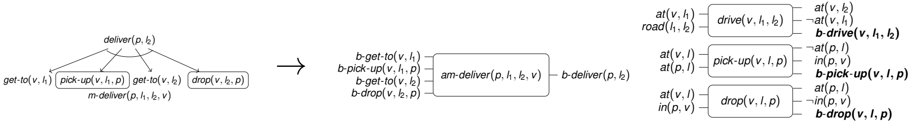
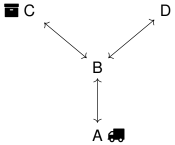
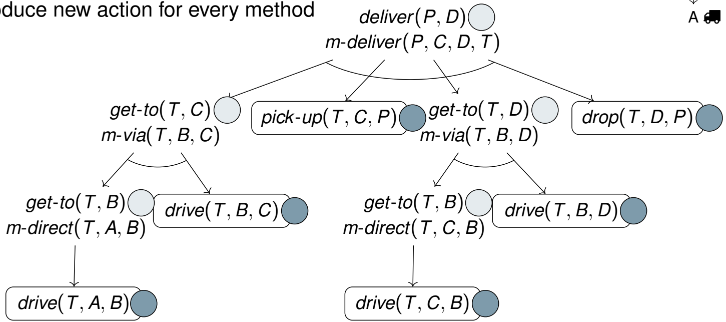




Simulating Composition

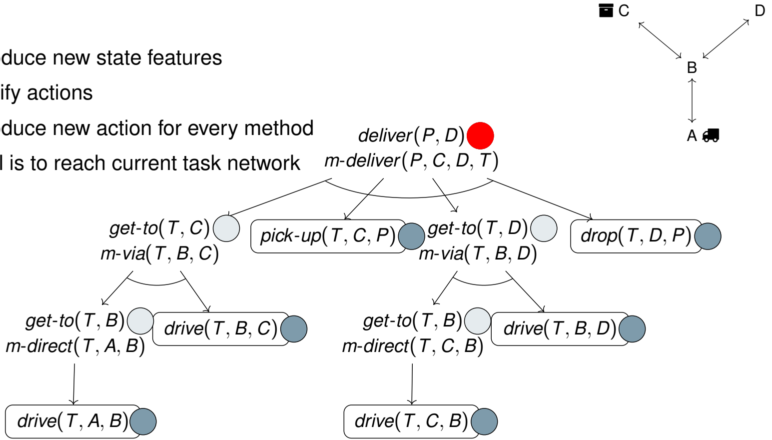


- Introduce new state features
- Modify actions
- Introduce new action for every method

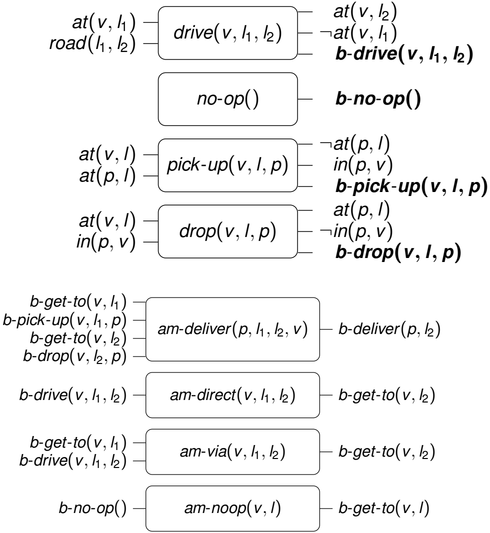


Simulating Composition

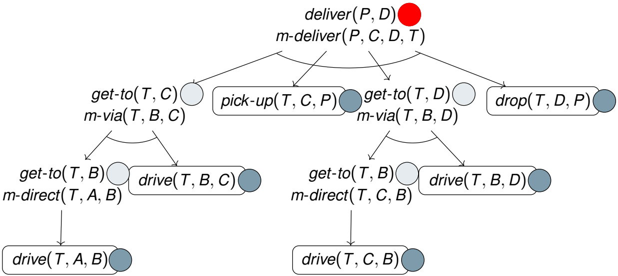
- Introduce new state features
- Modify actions
- Introduce new action for every method
- Goal is to reach current task network

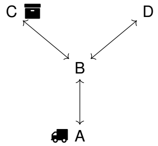


Simulating Composition – Resulting Model



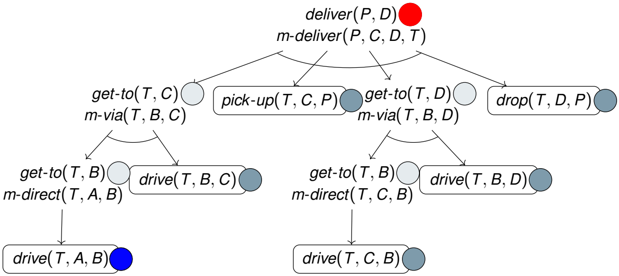
Planning in the Transformed Model

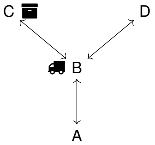




$\{at(T, A),$
$at(P, C)\}$

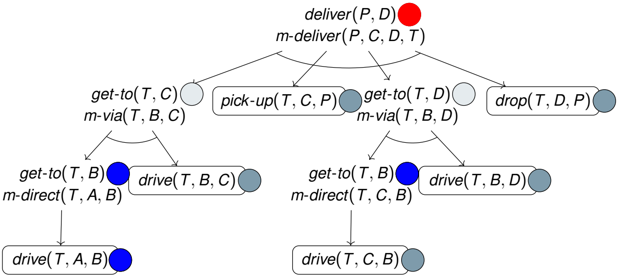
Planning in the Transformed Model

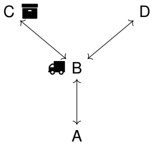


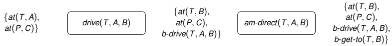


$\{at(T, A), at(P, C)\}$ *drive*(T, A, B) $\{at(T, B), at(P, C), b\text{-}drive(T, A, B)\}$

Planning in the Transformed Model







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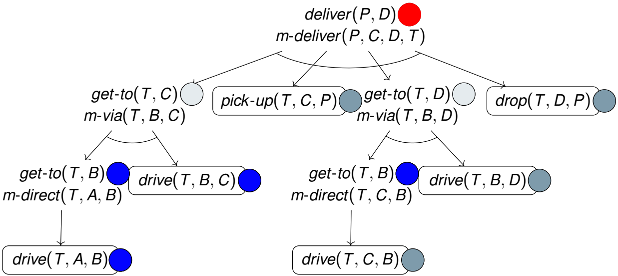

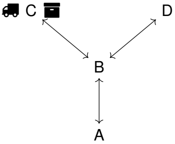

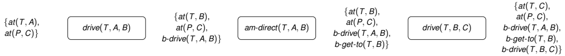

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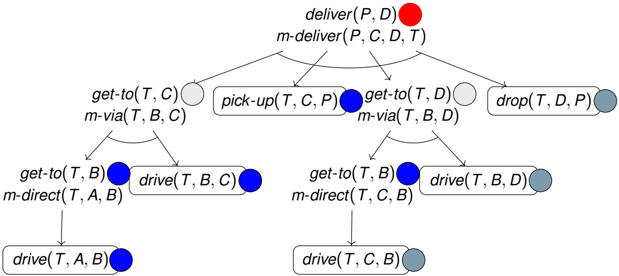

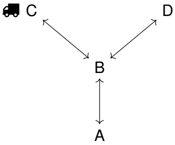

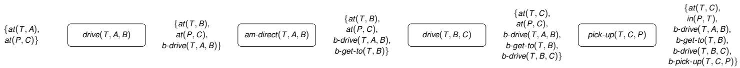

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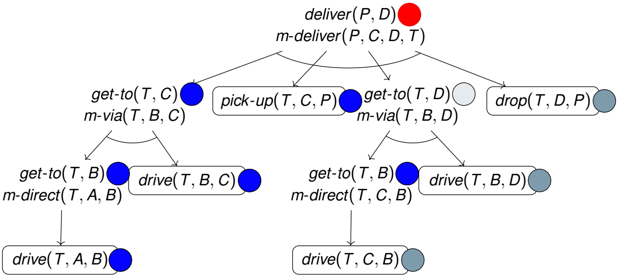
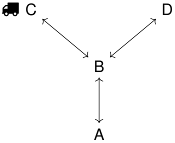
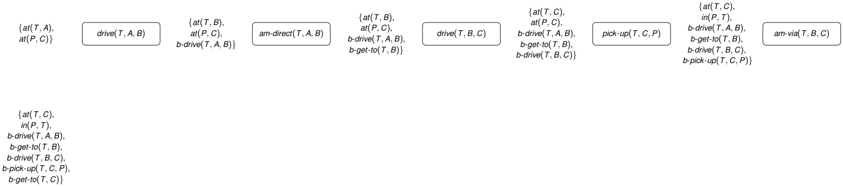
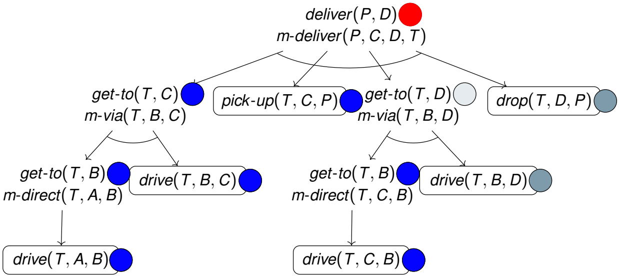
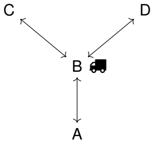


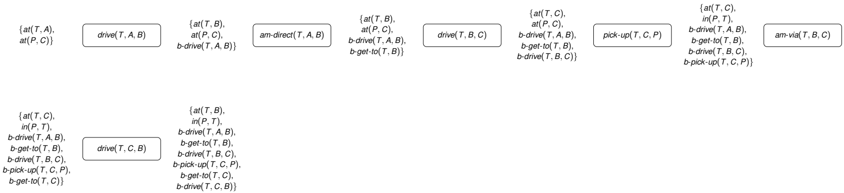




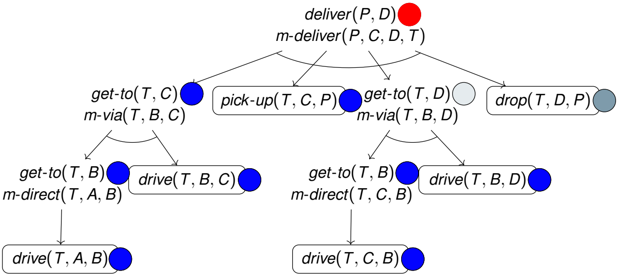
Planning in the Transformed Model

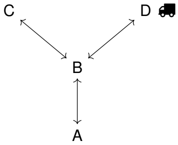


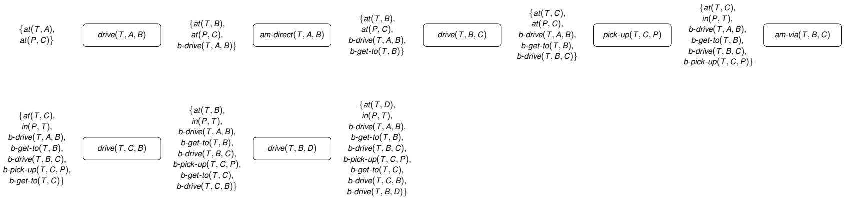




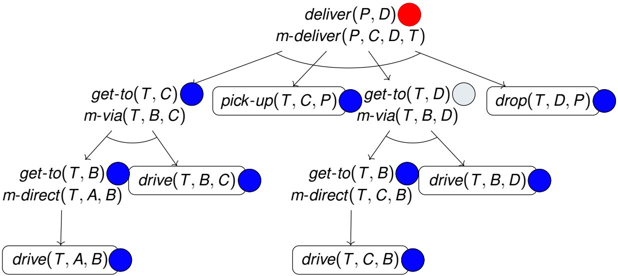
Planning in the Transformed Model

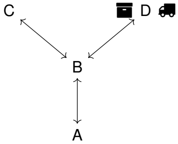


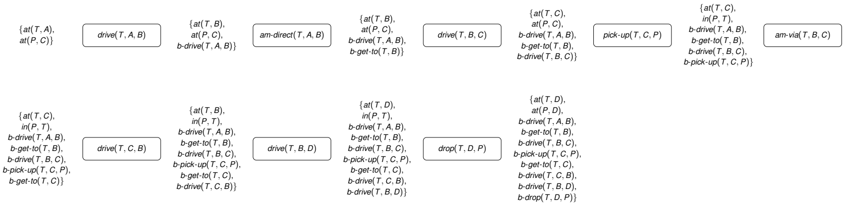




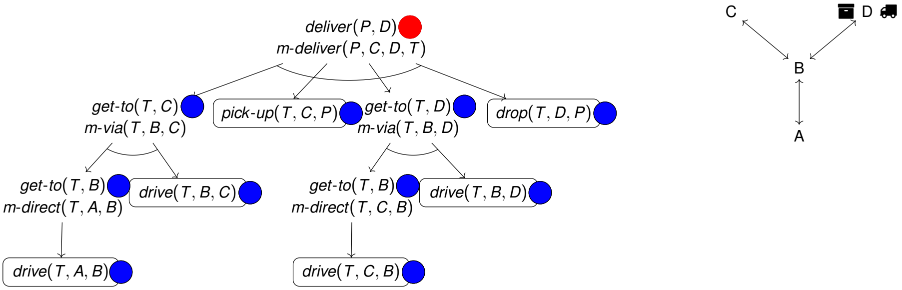
Planning in the Transformed Model







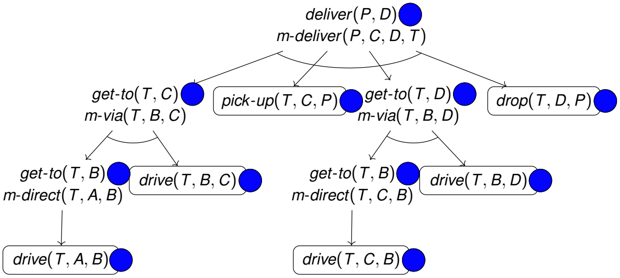
Planning in the Transformed Model

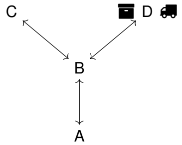


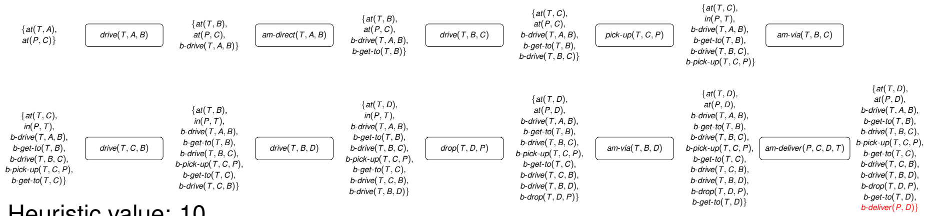
$\{at(T,A), at(P,C)\}$ | $drive(T,A,B)$ | $\{at(T,B), at(P,C), b\text{-}drive(T,A,B)\}$ | $am\text{-}direct(T,A,B)$ | $\{at(T,B), at(P,C), b\text{-}drive(T,A,B), b\text{-}get\text{-}to(T,B)\}$ | $drive(T,B,C)$ | $\{at(T,C), at(P,C), b\text{-}drive(T,A,B), b\text{-}get\text{-}to(T,B), b\text{-}drive(T,B,C)\}$ | $pick\text{-}up(T,C,P)$ | $\{at(T,C), in(P,T), b\text{-}drive(T,A,B), b\text{-}get\text{-}to(T,B), b\text{-}drive(T,B,C), b\text{-}pick\text{-}up(T,C,P)\}$ | $am\text{-}via(T,B,C)$

$\{at(T,C), in(P,T), b\text{-}drive(T,A,B), b\text{-}get\text{-}to(T,B), b\text{-}drive(T,B,C), b\text{-}pick\text{-}up(T,C,P), b\text{-}get\text{-}to(T,C)\}$ | $drive(T,C,B)$ | $\{at(T,B), in(P,T), b\text{-}drive(T,A,B), b\text{-}get\text{-}to(T,B), b\text{-}drive(T,B,C), b\text{-}pick\text{-}up(T,C,P), b\text{-}get\text{-}to(T,C), b\text{-}drive(T,C,B)\}$ | $drive(T,B,D)$ | $\{at(T,D), in(P,T), b\text{-}drive(T,A,B), b\text{-}get\text{-}to(T,B), b\text{-}drive(T,B,C), b\text{-}pick\text{-}up(T,C,P), b\text{-}get\text{-}to(T,C), b\text{-}drive(T,C,B), b\text{-}drive(T,B,D)\}$ | $drop(T,D,P)$ | $\{at(T,D), at(P,D), b\text{-}drive(T,A,B), b\text{-}get\text{-}to(T,B), b\text{-}drive(T,B,C), b\text{-}pick\text{-}up(T,C,P), b\text{-}get\text{-}to(T,C), b\text{-}drive(T,C,B), b\text{-}drive(T,B,D), b\text{-}drop(T,D,P)\}$ | $am\text{-}via(T,B,D)$ | $\{at(T,D), at(P,D), b\text{-}drive(T,A,B), b\text{-}get\text{-}to(T,B), b\text{-}drive(T,B,C), b\text{-}pick\text{-}up(T,C,P), b\text{-}get\text{-}to(T,C), b\text{-}drive(T,C,B), b\text{-}drive(T,B,D), b\text{-}drop(T,D,P), b\text{-}get\text{-}to(T,D)\}$

Planning in the Transformed Model

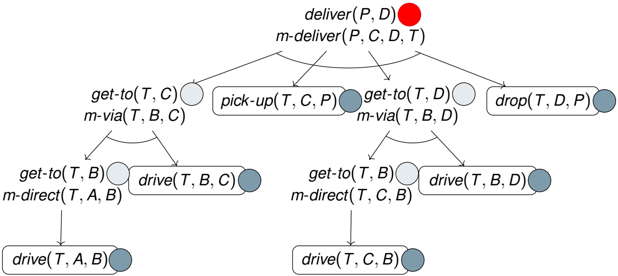


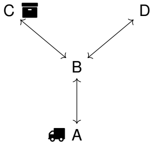




Heuristic value: 10

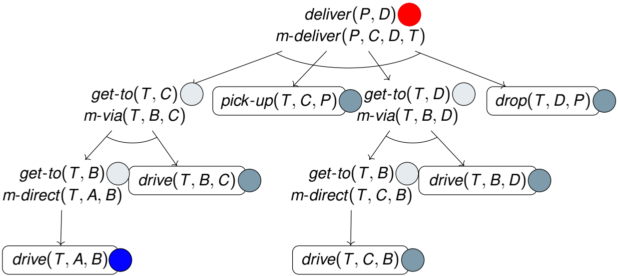
Heuristic Calculation (Delete Relaxed)

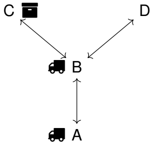


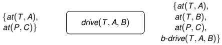


$\{at(T, A),$
$at(P, C)\}$

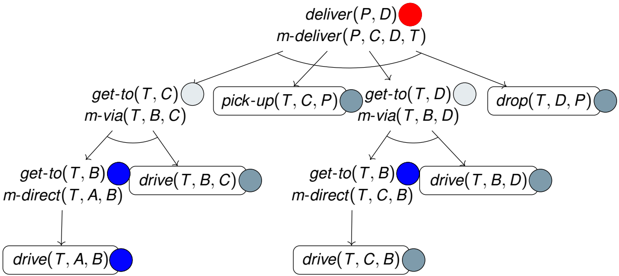
Heuristic Calculation (Delete Relaxed)

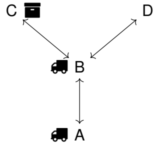






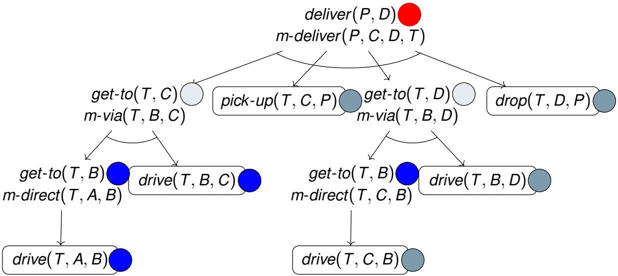
Heuristic Calculation (Delete Relaxed)

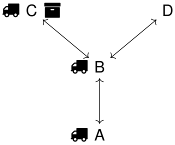


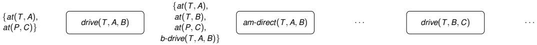


{*at*(*T*, *A*), *at*(*P*, *C*)} | *drive*(*T*, *A*, *B*) | {*at*(*T*, *A*), *at*(*T*, *B*), *at*(*P*, *C*), *b-drive*(*T*, *A*, *B*)} | *am-direct*(*T*, *A*, *B*) | ...

Heuristic Calculation (Delete Relaxed)







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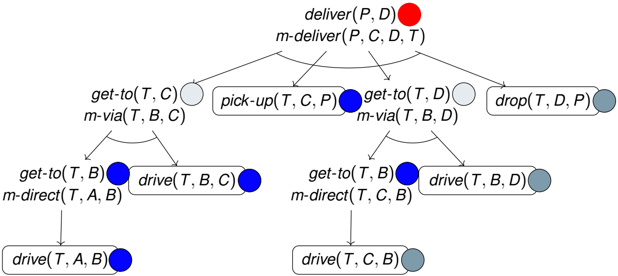

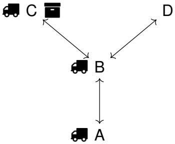

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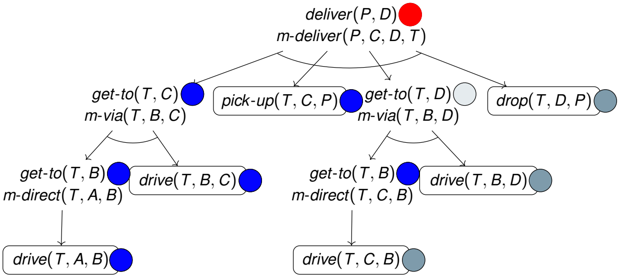
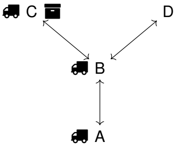


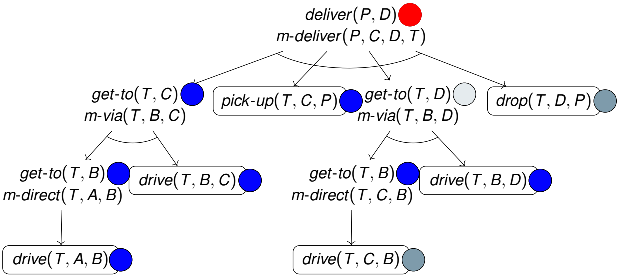


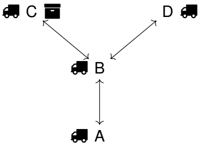
$\{at(T, A), at(P, C)\}$ | *drive*(T, A, B) | $\{at(T, A), at(T, B), at(P, C), b\text{-}drive(T, A, B)\}$ | *am-direct*(T, A, B) | … | *drive*(T, B, C) | … | *pick-up*(T, C, P) | … | *am-via*(T, B, C)

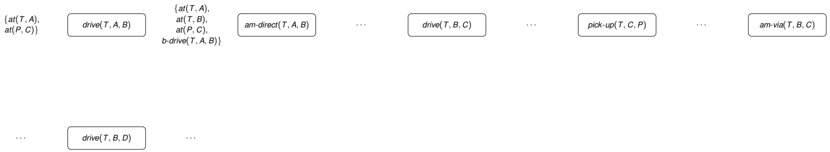
…

Using Classical Heuristics to Guide HTN Search

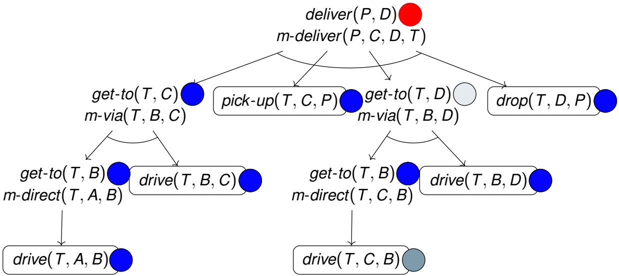
Heuristic Calculation (Delete Relaxed)

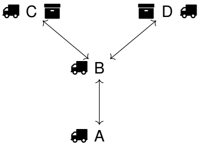




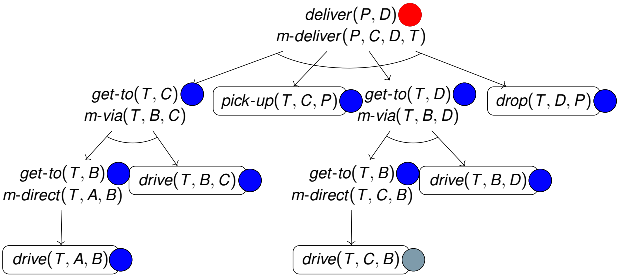


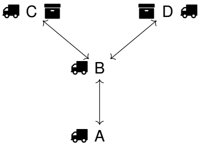
Heuristic Calculation (Delete Relaxed)





Heuristic Calculation (Delete Relaxed)



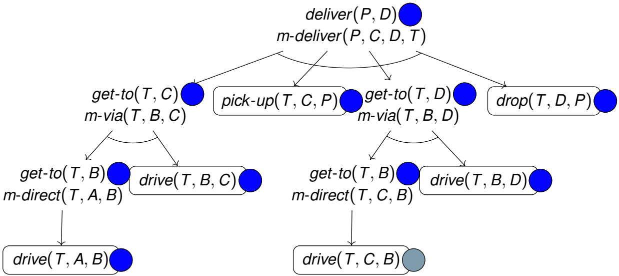


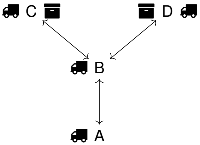
{*at*(*T*, *A*), *at*(*P*, *C*)} | *drive*(*T*, *A*, *B*) | {*at*(*T*, *A*), *at*(*T*, *B*), *at*(*P*, *C*), *b-drive*(*T*, *A*, *B*)} | *am-direct*(*T*, *A*, *B*) | ... | *drive*(*T*, *B*, *C*) | ... | *pick-up*(*T*, *C*, *P*) | ... | *am-via*(*T*, *B*, *C*)

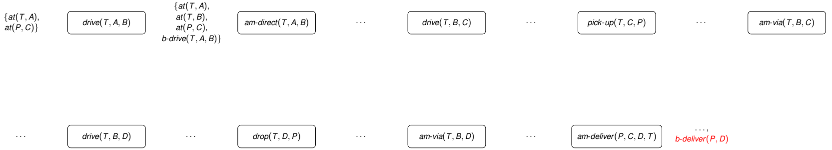
... | *drive*(*T*, *B*, *D*) | ... | *drop*(*T*, *D*, *P*) | ... | *am-via*(*T*, *B*, *D*) | ...

Using Classical Heuristics to Guide HTN Search

Heuristic Calculation (Delete Relaxed)







Using delete-relaxed classical heuristic: 9

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- ✓ Combines it with information on state-based executability
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  - Task insertion (e.g. to fulfill preconditions)
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- Heuristic function is allowed to do
  - Task sharing (every task must be proceeded only once)
  - Task insertion (e.g. to fulfill preconditions)
  - HTN ordering relations are relaxed
- Heuristic function may only insert tasks that lie within the decomposition hierarchy (not given here)

Computational Aspects

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→ **Efficient update** of the “heuristic model” possible

→ Classical heuristic combined with the encoding should be able to **deal with changed goal efficiently**

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- Perfect classical heuristic on the transformation has **less or equal costs**
- When the used classical heuristic has one of the following properties, the resulting HTN heuristic has it too:
  - Safety
  - Goal-awareness
  - Admissibility

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- Comparison to "HTN to STRIPS/ADL translation"
  - This transformation is a relaxation (set of solutions changes)
  - It is smaller
  - It is easier to compute

Overview Part II

Solving HTN Planning Problems

- Search-based Approaches
  - Plan Space Search
  - Progression Search
- Compilation-based Approaches
  - Compilations to STRIPS/ADL
  - Compilations to SAT
- Heuristics for Heuristic Search
  - TDG-based Heuristics
  - Relaxed Composition Heuristics

Excursion

- **Further Hierarchical Planning Formalisms**

Overview of Hierarchical Planning Variants

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- Hybrid planning (i.e., HTN + POCL Planning)
- Decompositional planning (i.e., hybrid without initial plan)
- GTN planning (decompose goals, not tasks)

Problem Definition

In *HTN planning with task insertion*, *TIHTN planning*, tasks may be added arbitrarily to task networks (not just via decomposition):

Let $\mathcal{P}^{\star} = (V, P, \delta, C, M, s_I, c_I)$ be a **TIHTN planning problem**.

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Let $\mathcal{P}^\star = (V, P, \delta, C, M, s_I, c_I)$ be a **TIHTN planning problem**.

Then, a task network *tn* is a solution if and only if:

- There is a sequence of decomposition methods $\overline{m}$ **and task insertions** that transforms c_I into *tn*,
- *tn* contains only primitive tasks, and
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- Task insertion makes the problem computationally easier (can be exploited for heuristics)

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Then, a task network *tn* is a solution if and only if:

- There is a sequence of decomposition methods $\overline{m}$ and **task mergings** that transform c_I into *tn* **(two tasks can be merged if they are identical and not ordered with respect to another)**,
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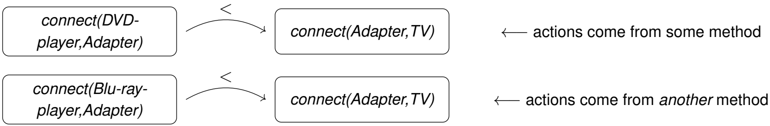
Benefits of allowing task sharing:

- Allows to eliminate duplicates that might just be modeling artifacts



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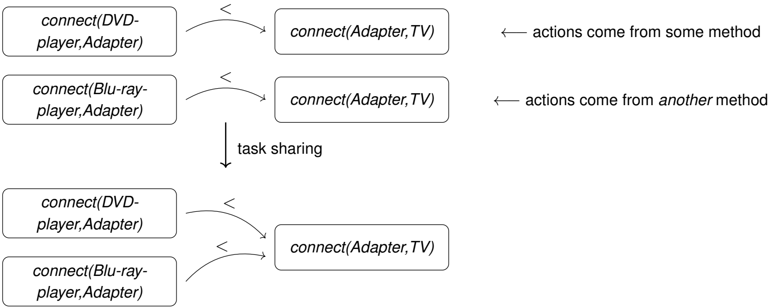

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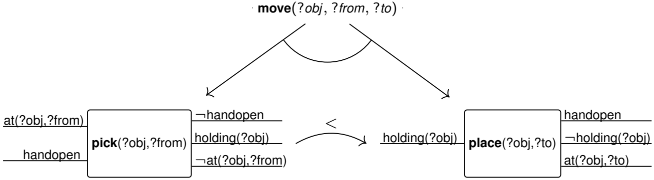

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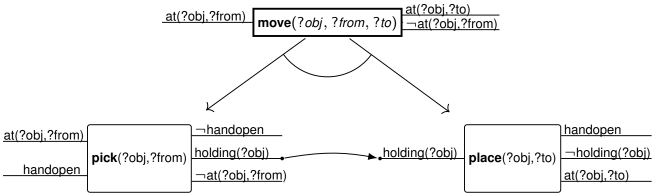

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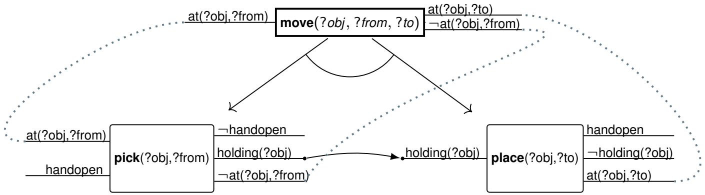

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- Plan explanation and visualization becomes more natural

Problem Definition

Decompositional planning is defined just as hybrid planning with task insertion – with the exception that there is no initial partial plan.

Motivation

Benefits of decompositional planning:

- Everything like in hybrid planning, except:

  lower expressivity (identical to non-hierarchical, classical planning), because the hierarchy does not induce constraints

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Benefits of HGN planning?

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- The application of state-based heuristics is more directly applicable than in HTN planning
- In some domains, defining a hierarchy on state features might be easier than defining a hierarchy on tasks

Thank You for Your Attention!

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Are there questions?