Lecture *Hierarchical Planning*

Chapter:
Heuristics for (Hierarchical) Planning Problems

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Overview:

Recap on Search in Non-hierarchical Planning

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- With the right combination of algorithm and heuristic, we can also provide optimality guarantees.
- In classical planning, heuristics estimate the number of actions (or their costs) that need to be applied to reach a goal state.
- In POCL planning, heuristics could also estimate the number of required modifications (which, in addition to task insertion, may estimate the number of ordering constraints and causal links that need to be added).

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  - Search nodes get bigger and bigger. Thus, paradoxically, the problem gets *harder* the closer we approach a solution.

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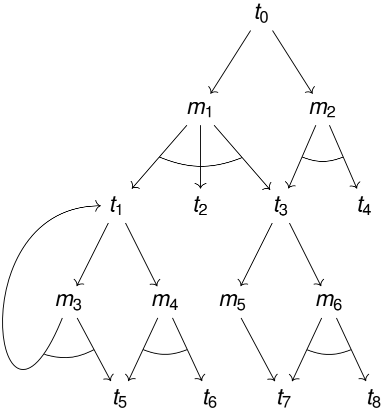
- Recap: the *decomposition tree (DT)* is the representation of the decompositional structure of a single task network.
- In contrast, the decomposition graph represents the planning *domain* (cf. introductory chapter).
- Due to possibly cyclic methods, DTs are in general no sub structures of TDGs.

Example

The Task Decomposition Graph (TDG) represents how tasks can be decomposed:



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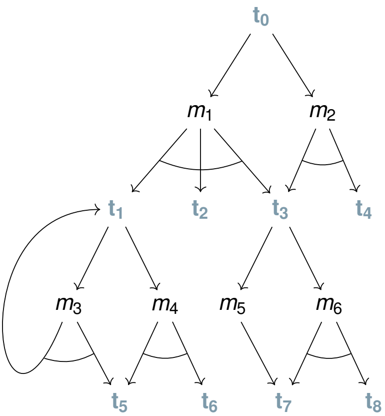

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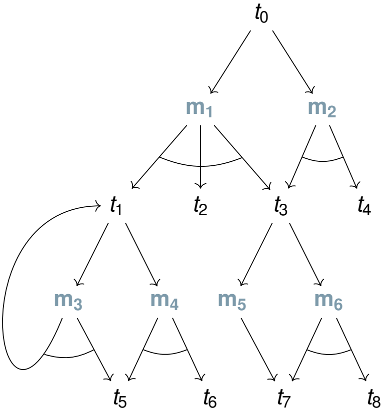

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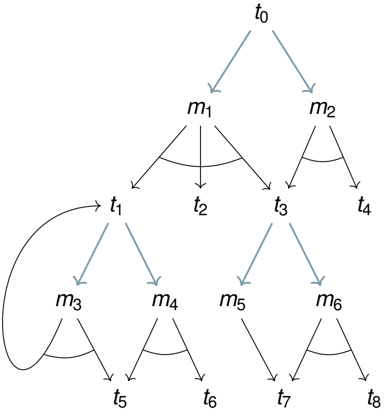

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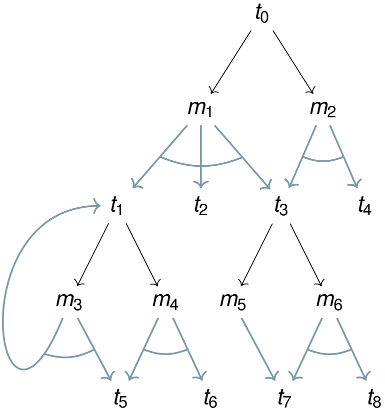

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- $Ground_{VC}(tn)$ denotes the set of all possible groundings of tn by also taking into account the variable constraints VC.

Formal Definition

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   Let $v_t \in V_T$ with $v_t = t(\bar{c})$ and $(t(\bar{\tau}), tn_m, VC_m) \in M$.
   Then, for all $v_m \in Ground_{VC_m \cup \{\bar{\tau} = \bar{c}\}}(tn_m)$ holds:
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4. **tightness**
   $\mathcal{G}$ is minimal, such that 1. to 3. hold.

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  - Lifted Model: Exponential time (due to the grounding).

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  - Repeat until every compound task (i.e., their groundings) is in the TDG.

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Note: *Technically*, any modification to the TDG will violate its definition. We still refer to the resulting structures as TDGs, though.

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Step 4: Restrict TDG:

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Step 5: Since the set of reachable primitive tasks may have changed, we can repeat all previous steps (possibly multiple times).
This step does usually not pay off empirically.

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- A classical *action landmark* is an action that is part of every solution.

Hierarchical Landmarks

- A hierarchical landmark is a task (primitive or compound) that occurs on any sequence of decompositions from the initial task (network) to any solution.
- A formal definition will be provided or has to be found in the exercises.

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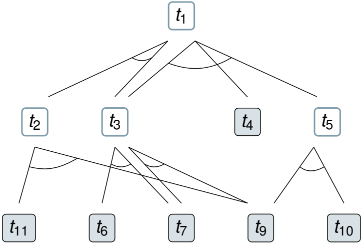
Hierarchical Landmarks (Membership)

- Is the problem semi-decidable?

$\rightarrow$ Exercise!

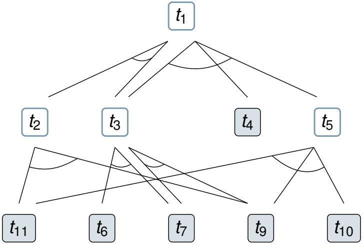
Landmark Computation

General idea: Compute the intersection of all partial plans that belong to the same compound task.



Landmark Computation, Improved

We can still do better than that, though...



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→ This allows to use *any* classical heuristic (or classical landmark technique!).

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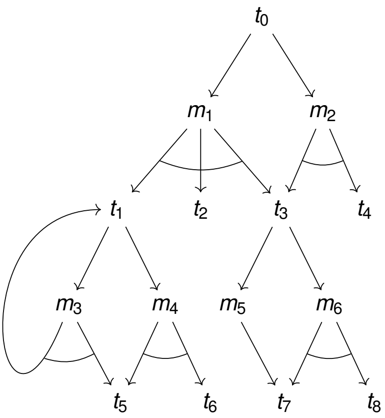
- But how..? We know that:
  - *all tasks within a method* need to be "accomplished" (applied or decomposed).
  - For each compound task, only one of its methods needs to be applied.
- Note: For convenience, we later write $t(\bar{\tau}) \in T$ as shorthand for $t(\bar{\tau}) = \alpha(t'), t' \in T$.

Overview



Exploit TDG for effort estimation.

Step 1:
Compute the TDG.

Step 2:
Compute TDG-based estimates $h_T(t)/h_M(t)$ for each task/method node in the TDG (*once* via preprocessing).

Step 3:
For search node (task network or partial plan) *tn* and its tasks T, compute $h(tn)$ based on the estimates for the $t \in T$.

- Via estimating the costs of missing actions → TDG-c.
- Via estimating the still required modifications → TDG-m.

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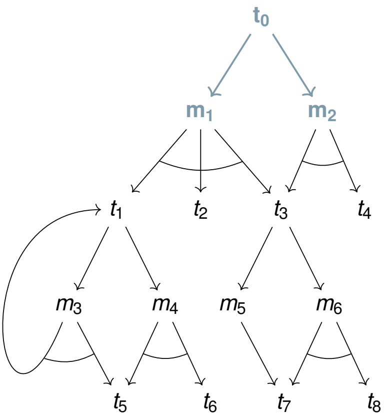
- The resulting heuristic will be admissible (trivial).

Illustration of TDG-c Computation



Example:

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

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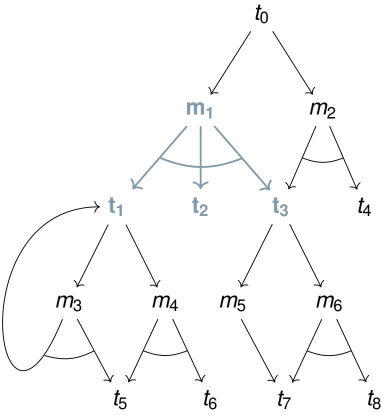
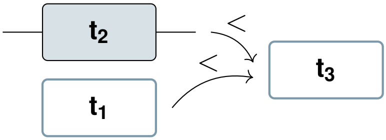


Example:

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



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

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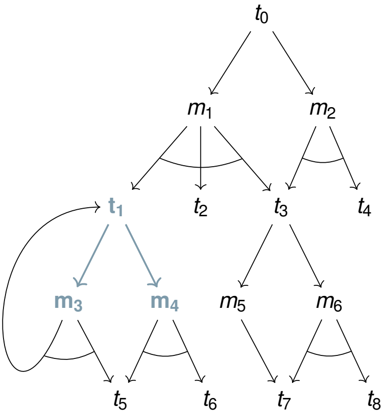

Example:

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

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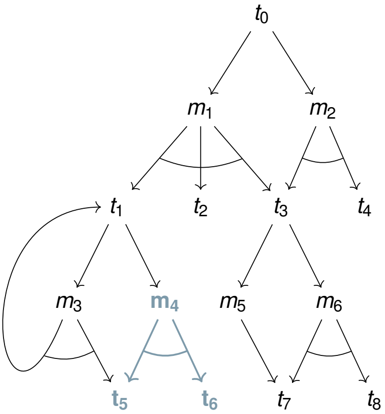
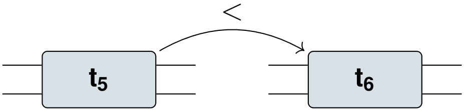


Example:

Method $m_4 = (t_1, tn)$ with task network tn:



$$h(m_4) = c(t_5) + c(t_6)$$

TDG-c Computation

Let $\mathcal{G} = \langle V_T, V_M, E_{T \to M}, E_{M \to T} \rangle$ be a TDG.
The TDG-c estimates of $\mathcal{G}$'s task nodes are given by:

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- The heuristic formulae were given for *lifted* planning and can be simplified for ground planning:

$$\sum_{\substack{t(\bar{\tau}) \in T \\ t(\bar{\tau}) \text{ abstract}}} \left(\min_{v_t \in Ground_{VC}(t(\bar{\tau}))} h_T(v_t) \right) \text{ becomes } \sum_{\substack{t(\bar{c}) \in T \\ t(\bar{c}) \text{ abstract}}} h_T(t(\bar{c})).$$

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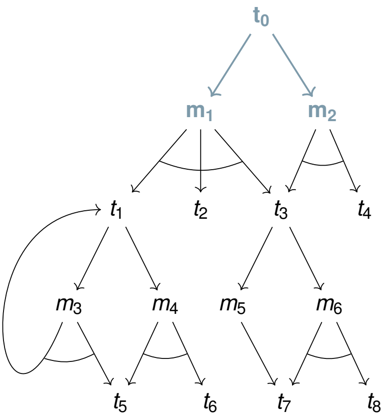
- We thus exploit the TDG to estimate how many *modifications* we require for certain tasks.
- The resulting heuristic will be *not be* admissible, but admissible in the number of required modifications (trivial). This means that any solution returned by A^* will have the property that no other solution can be created with fewer modifications. (This is not something we aim for, it's just a property we get.)

Illustration of TDG-m Computation – For Decomposition-based Search



Example:

$$h_T(t_0) = 1 + min\{h_M(m_1), h_M(m_2)\}$$

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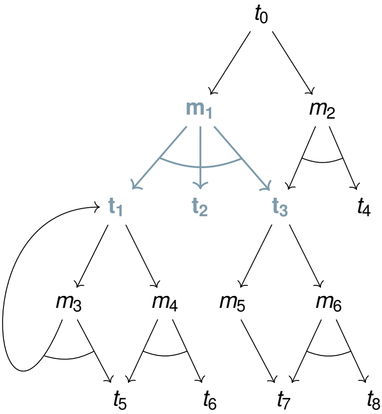
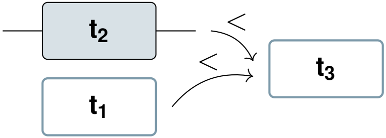


Example:

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



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

(Also subtract $|CL|$ in case we have a partial plan containing causal links.)

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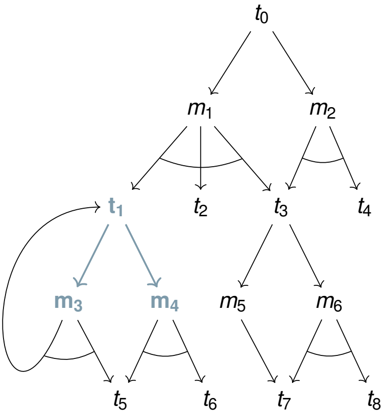

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$$h_T(t_1) = 1 + min\{h_M(m_3), h_M(m_4)\}$$

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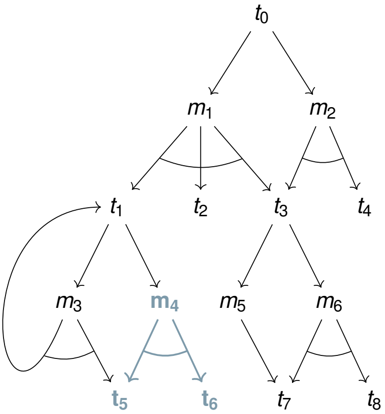

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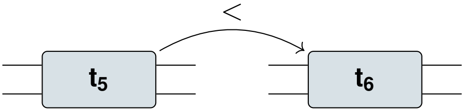

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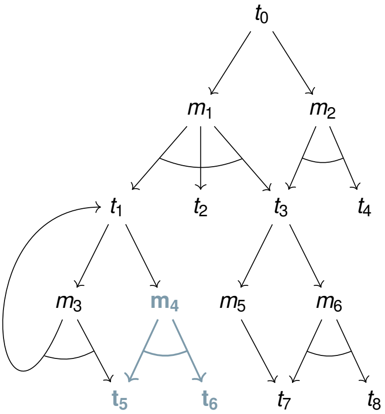

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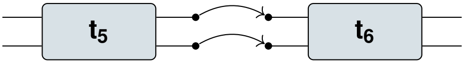

$$\begin{aligned} h_M(m_4) &= h_T(t_5) + h_T(t_6) - |CL| \\ &= |pre(t_5)| + |pre(t_6)| - 2 \\ &= 2 + 2 - 2 = 2 \end{aligned}$$

TDG-m Computation

Let $\mathcal{G} = \langle V_T, V_M, E_{T\to M}, E_{M\to T}\rangle$ be a TDG.
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progression-based: Ignore links and use 1 instead of $|pre(v_t)|$.

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- To illustrate what this means: What heuristic do we get if the only abstract task can be decomposed into an empty task network (which will not work as solution due to a goal description or subsequent primitive tasks).
- However, the heuristic can still come up with even exponentially large heuristic values. (This is true although every task occurs just once in the TDG. Why?)

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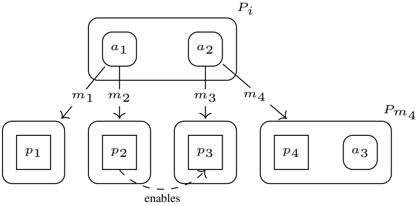

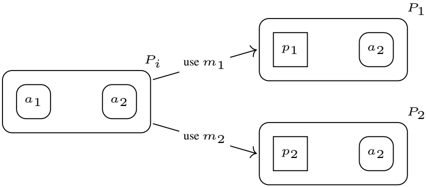

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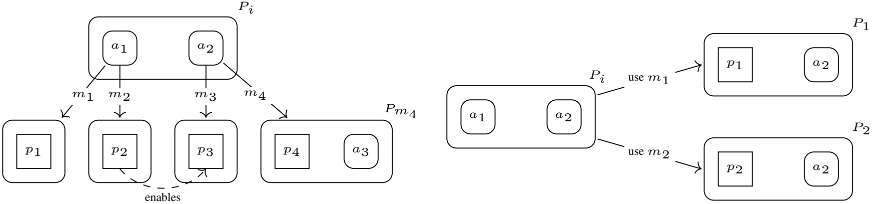

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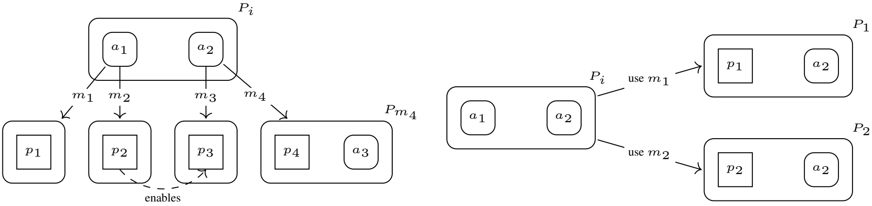

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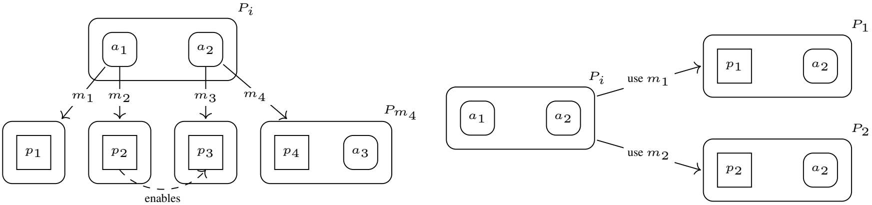

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- Then, we get $h_T(a_2) = i$. Let us now consider the heuristic values for P_1 and P_2 resulting from decomposing a_1 using m_1 or m_2, respectively.
- Without recomputation, we get $h(P_1) = h(P_2) = i$. With recomputation, we get $h(P_1) = j$ and $h(P_2) = i$, so we get improved heuristic accuracy due to updated reachability information in the TDG.

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- There are other cases, which are not yet handled, though. E.g., causal links might also limit the available actions.

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- Also, each progression allows a recomputation.

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- These equations are specific to decomposition-based planning. The latter is required because the method's primitive tasks were accounted by the heuristic, but are now covered by the cost value of the search node.

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  - In general, HTN problems do not have a goal description, so what's the classical problem's goal?
  - In classical planning, all actions can be applied, in hierarchical planning only those reachable from the initial task (network).

Classical Heuristics in HTN Planning

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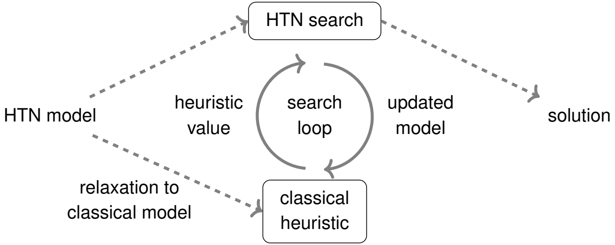
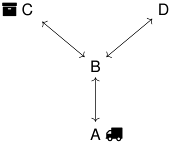
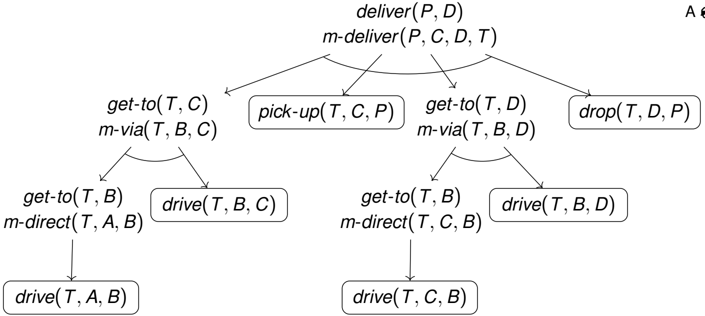
- It is *not* a preprocessing heuristic: Its “heuristics model” gets adapted for every search node. In that way, it corresponds the previous heuristics with enabled recomputation.



Simulating Composition



- Let's assume we want to "reconstruct" a decomposition tree via composition.



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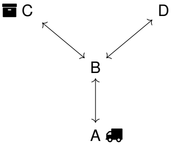

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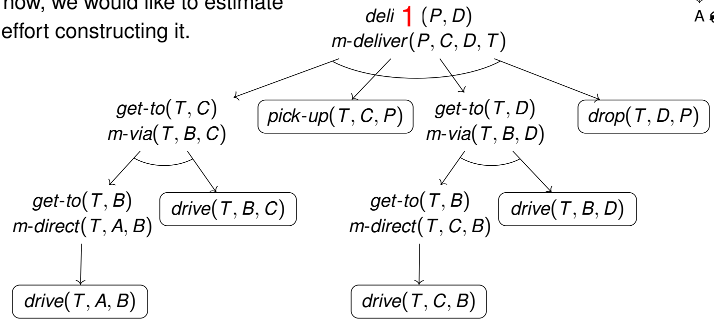

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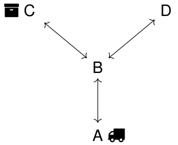

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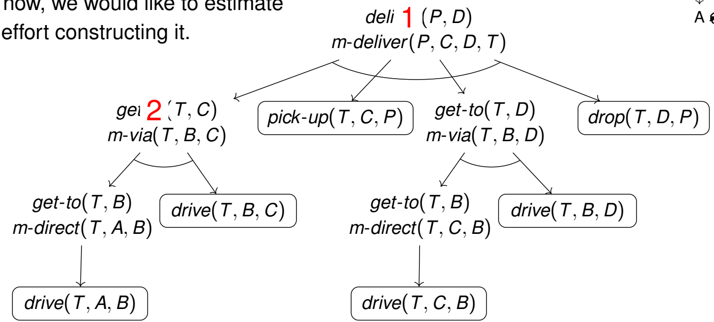

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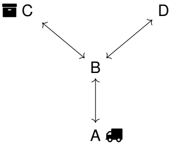

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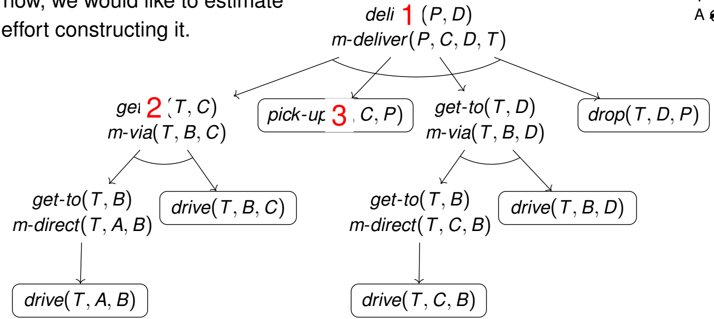

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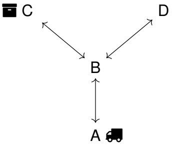
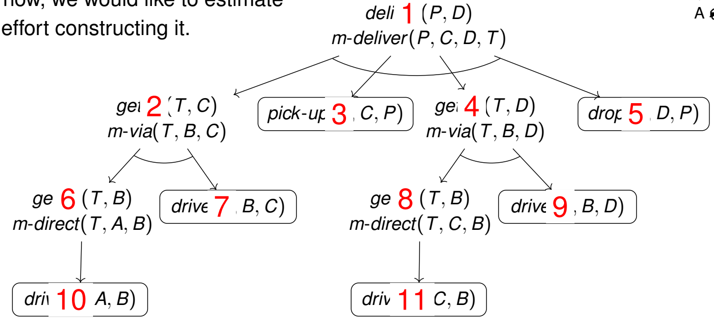
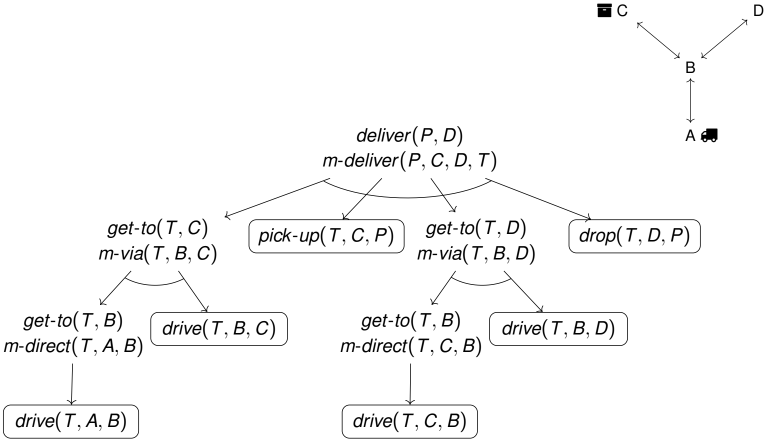
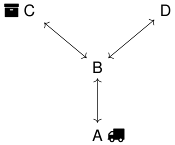




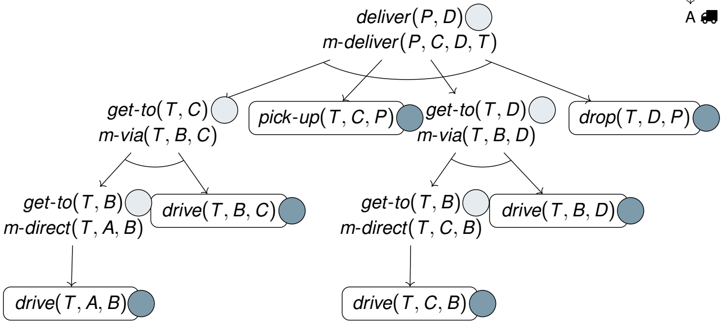
Simulating Composition



Simulating Composition

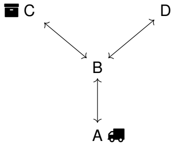


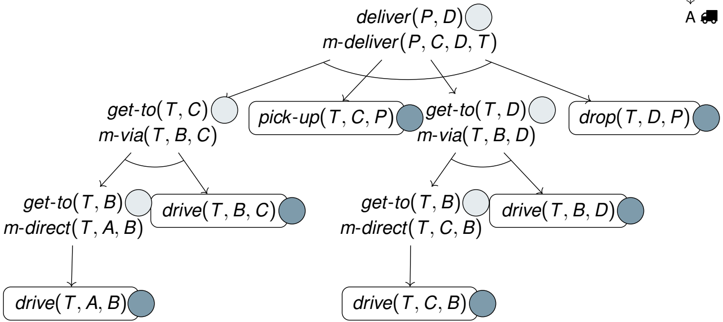
- Introduce new state features.

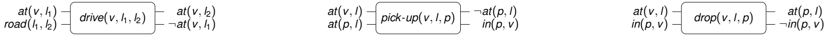


Simulating Composition

- Introduce new state features.

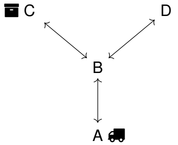


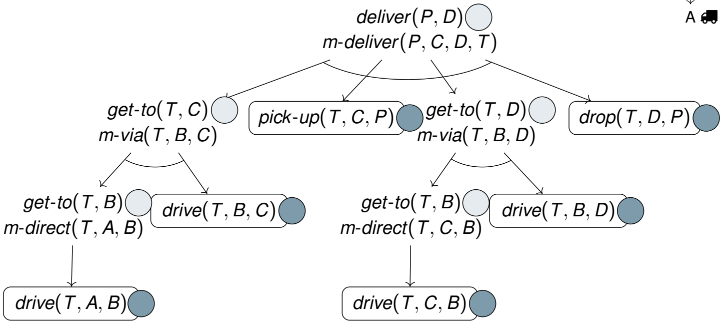


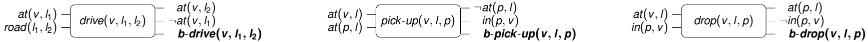


Simulating Composition

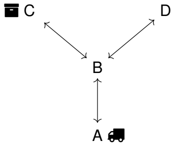
- Introduce new state features.
- Modify actions.







Simulating Composition



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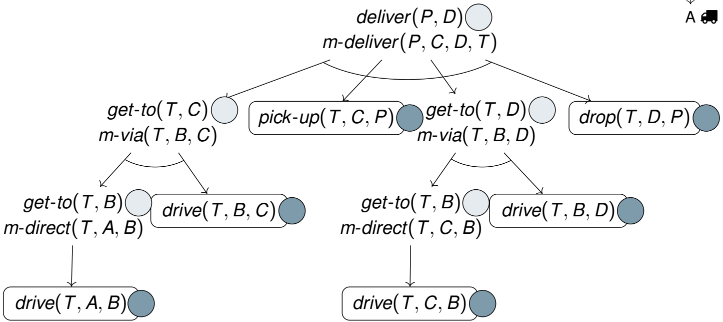
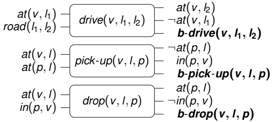
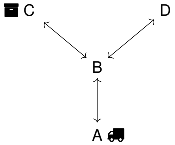
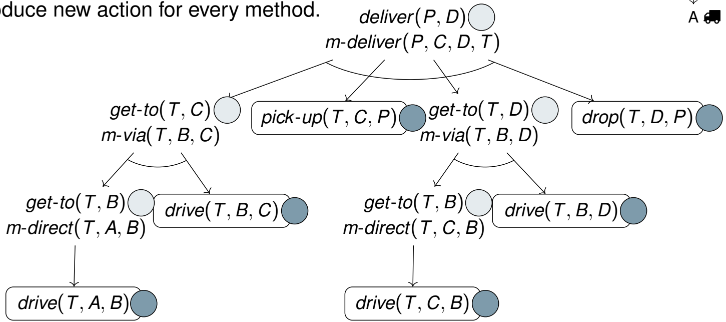


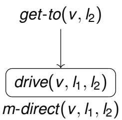


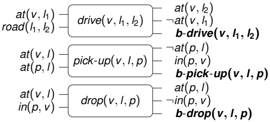
Simulating Composition



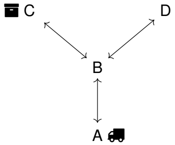
- Introduce new state features.
- Modify actions.
- Introduce new action for every method.







Simulating Composition



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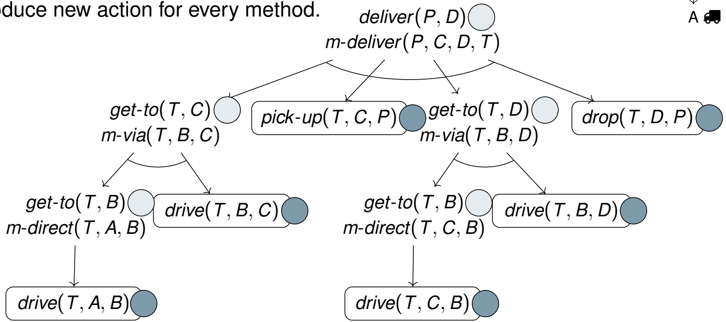
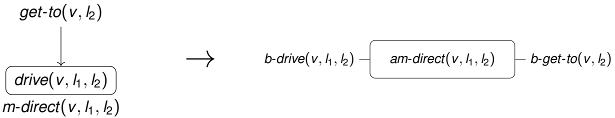
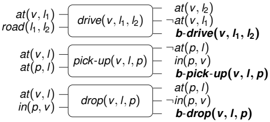
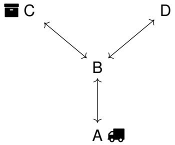
- Introduce new action for every method.



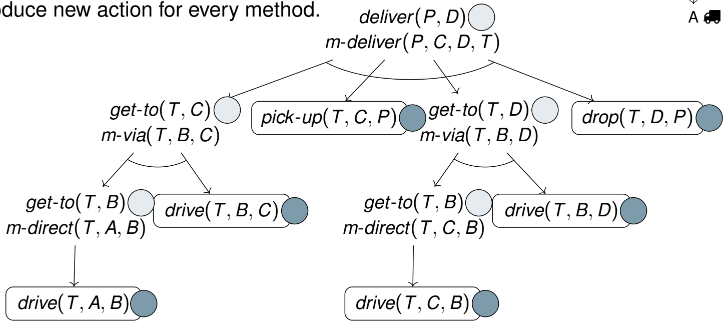


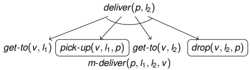


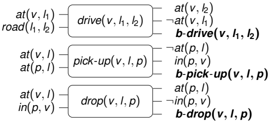
Simulating Composition



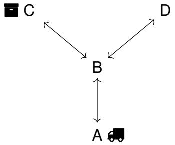
- Introduce new state features.
- Modify actions.
- Introduce new action for every method.



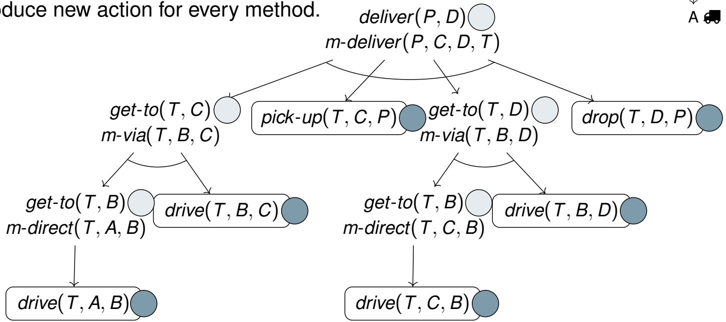


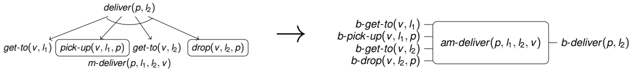


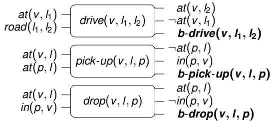
Simulating Composition



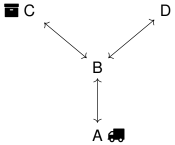
- Introduce new state features.
- Modify actions.
- Introduce new action for every method.







Simulating Composition



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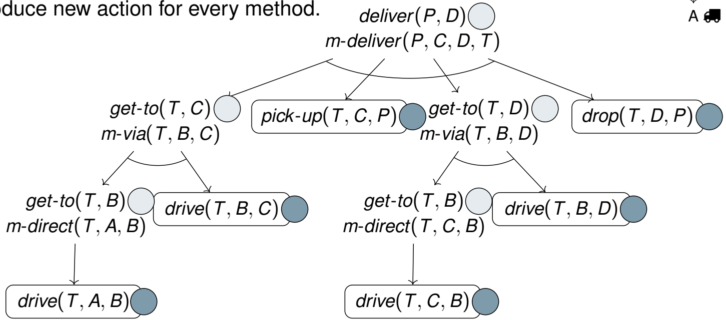
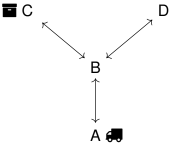
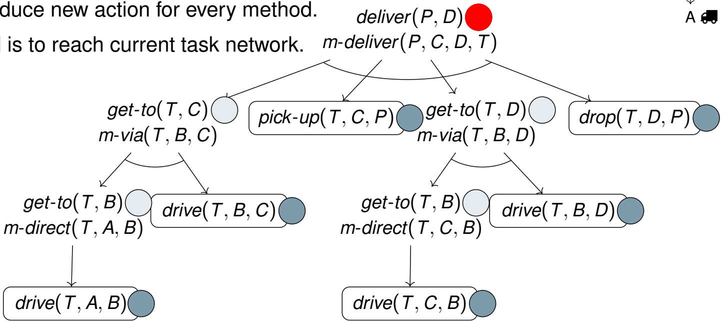
- Introduce new action for every method.



Simulating Composition

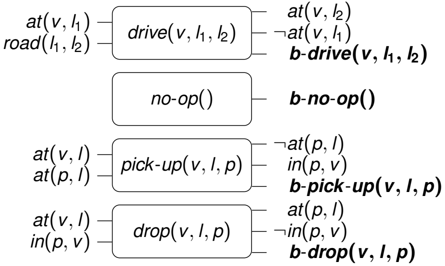


- Introduce new state features.
- Modify actions.
- Introduce new action for every method.
- Goal is to reach current task network.

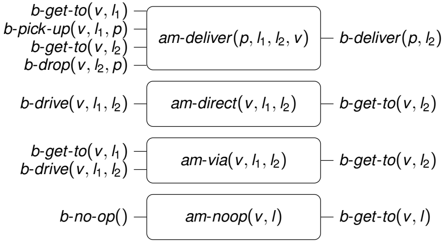


Simulating Composition – Resulting Model

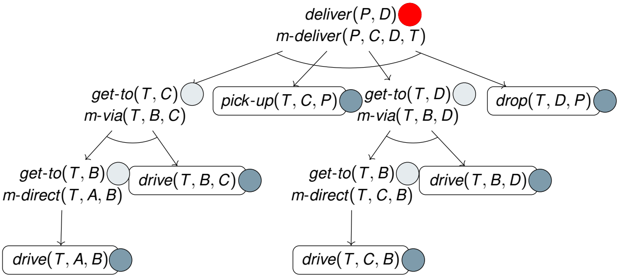
Altered action encodings:

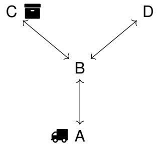


New actions encoding methods:



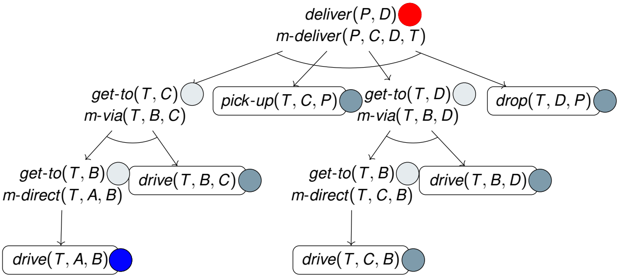
Unrelaxed Planning in the Transformed Model

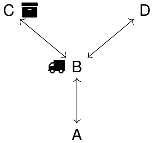


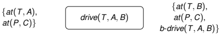


$\{at(T, A),$
$at(P, C)\}$

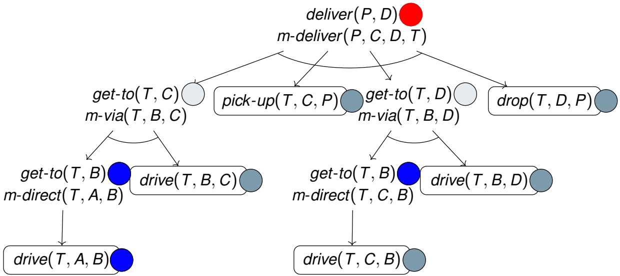
Unrelaxed Planning in the Transformed Model

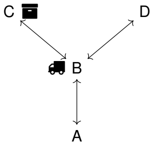


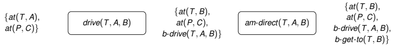




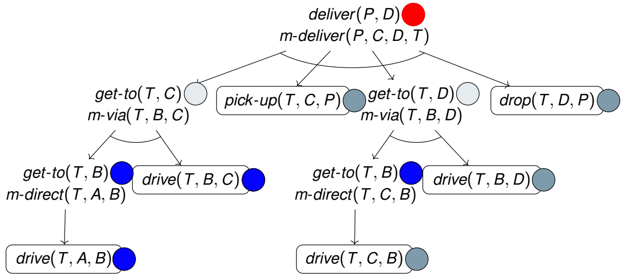
Unrelaxed Planning in the Transformed Model

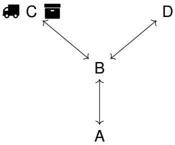


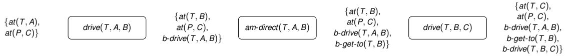




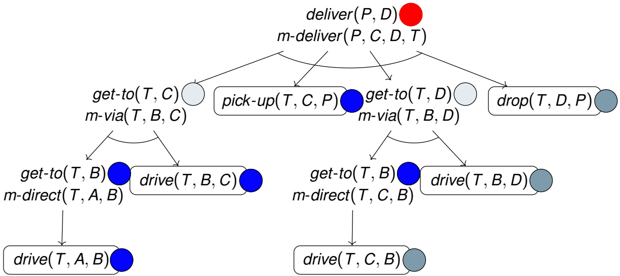
Unrelaxed Planning in the Transformed Model

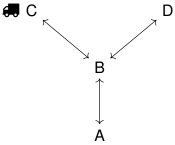


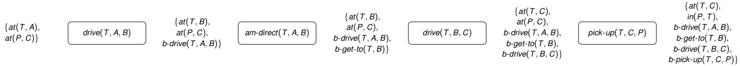




Unrelaxed Planning in the Transformed Model







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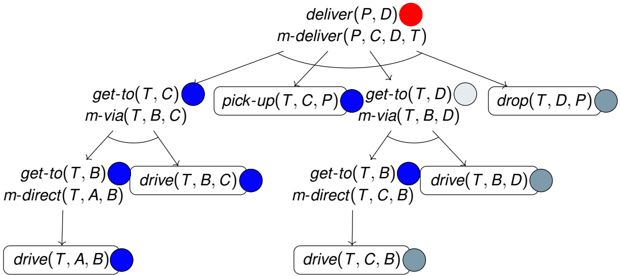
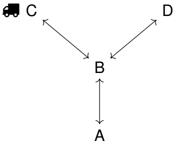
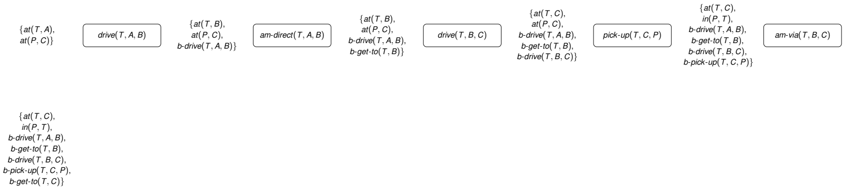
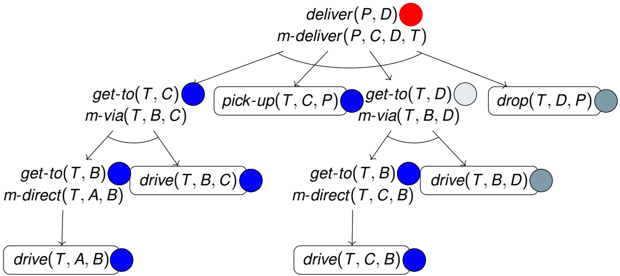
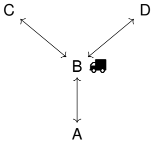


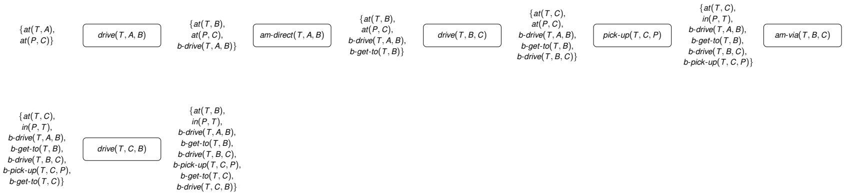




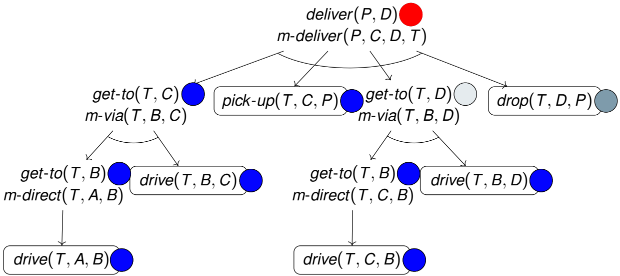
Unrelaxed Planning in the Transformed Model

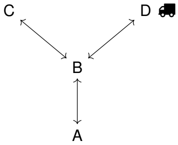


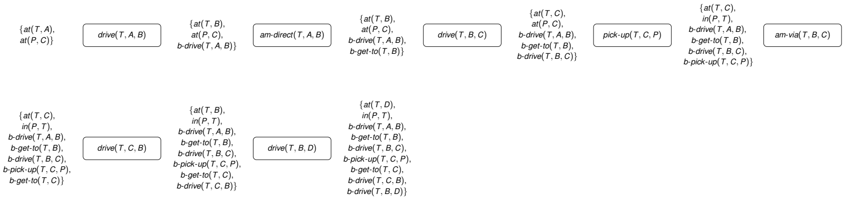




Unrelaxed Planning in the Transformed Model







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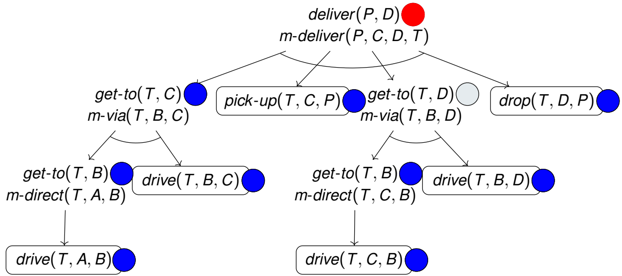
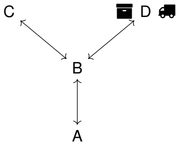
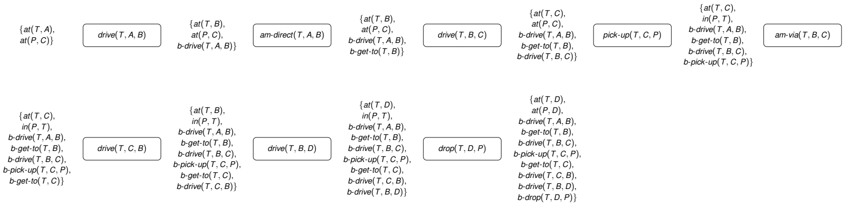
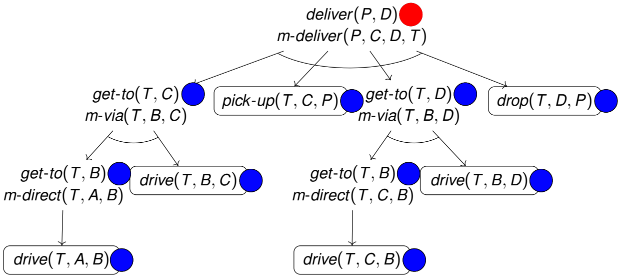
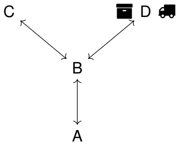


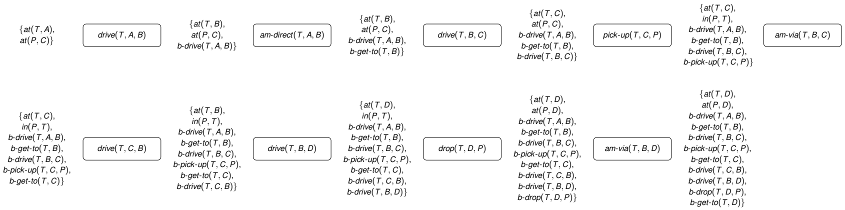




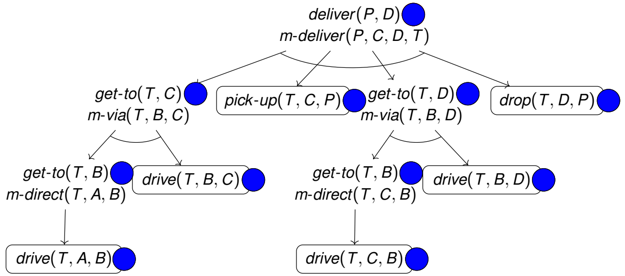
Unrelaxed Planning in the Transformed Model

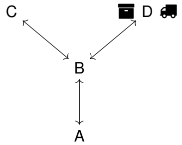


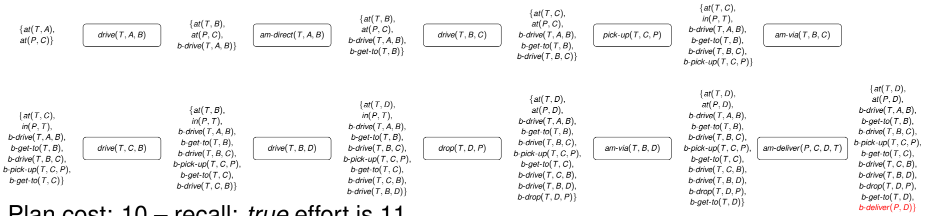




Unrelaxed Planning in the Transformed Model

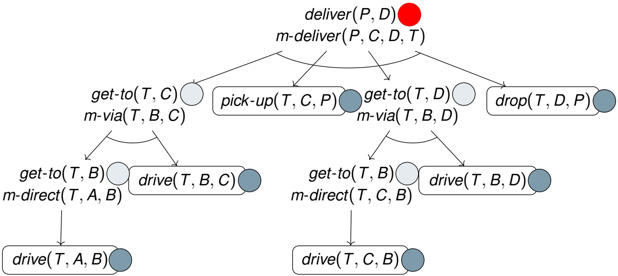


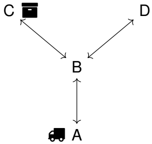




Plan cost: 10 – recall: *true* effort is 11.

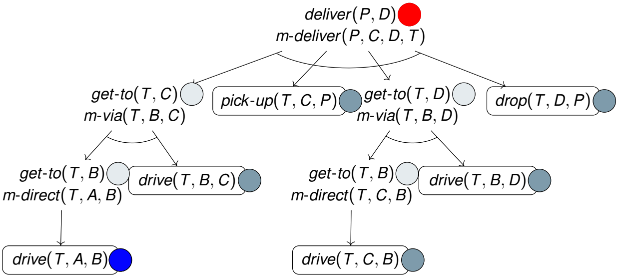
Relaxed Planning in the Transformed Model (Heuristic Computation)

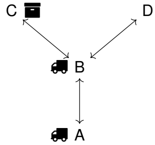


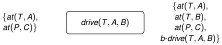


{at(T, A),
at(P, C)}

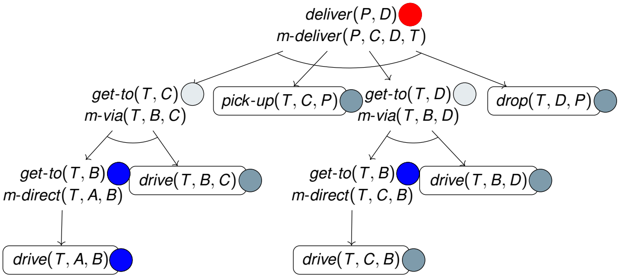
Relaxed Planning in the Transformed Model (Heuristic Computation)

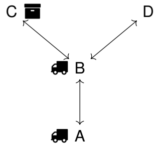


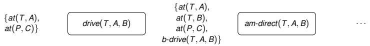




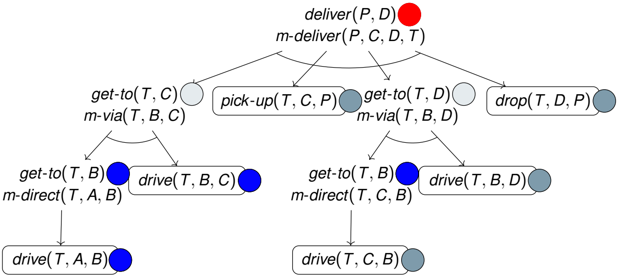
Relaxed Planning in the Transformed Model (Heuristic Computation)

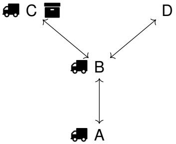


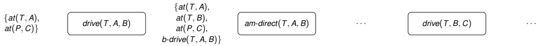




Relaxed Planning in the Transformed Model (Heuristic Computation)







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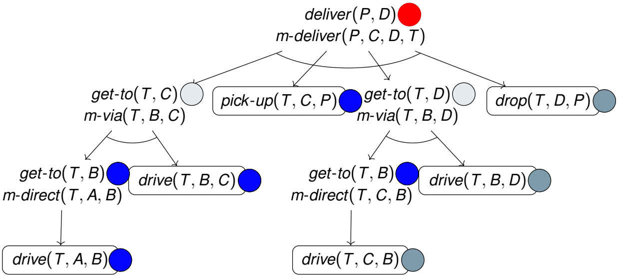

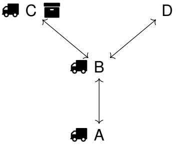

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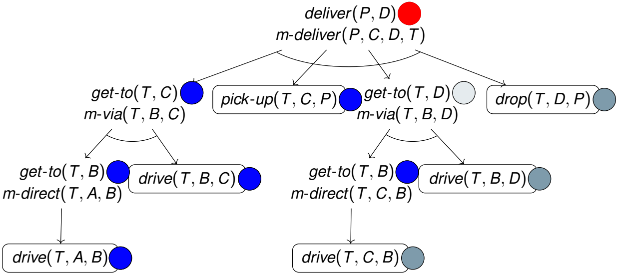

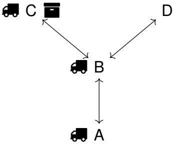

{*at*(*T*, *A*), *at*(*P*, *C*)} — *drive*(*T*, *A*, *B*) — {*at*(*T*, *A*), *at*(*T*, *B*), *at*(*P*, *C*), *b-drive*(*T*, *A*, *B*)} — *am-direct*(*T*, *A*, *B*) — … — *drive*(*T*, *B*, *C*) — … — *pick-up*(*T*, *C*, *P*) — … — *am-via*(*T*, *B*, *C*)

…

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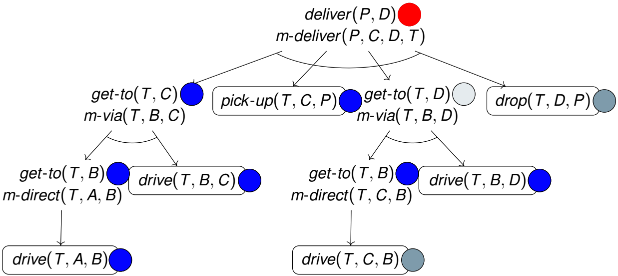

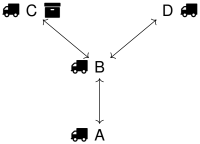

{$at(T, A)$, $at(P, C)$} | $drive(T, A, B)$ | {$at(T, A)$, $at(T, B)$, $at(P, C)$, $b\text{-}drive(T, A, B)$} | $am\text{-}direct(T, A, B)$ | … | $drive(T, B, C)$ | … | $pick\text{-}up(T, C, P)$ | … | $am\text{-}via(T, B, C)$

… | $drive(T, B, D)$ | …

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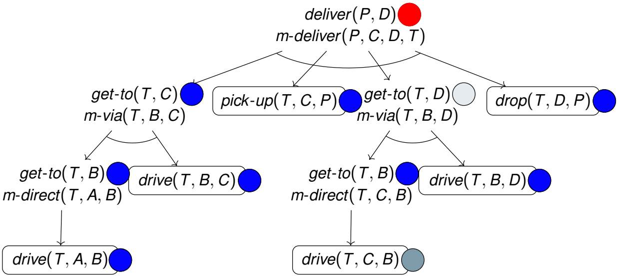

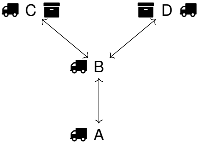

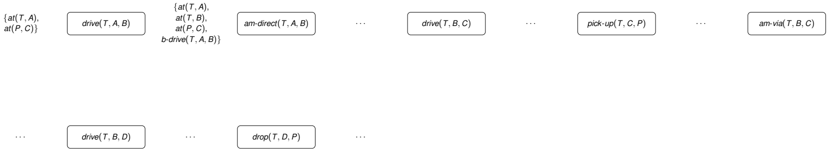

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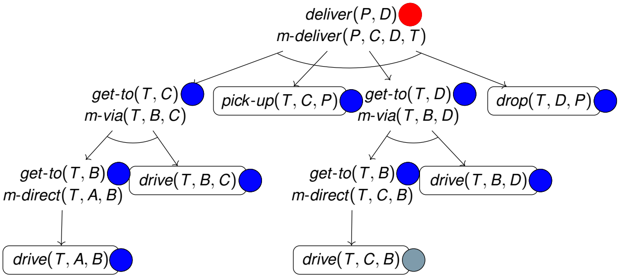

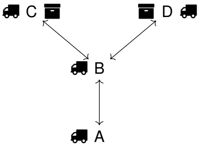

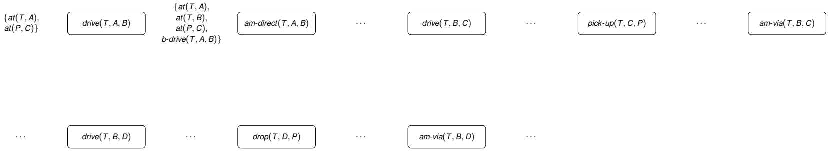

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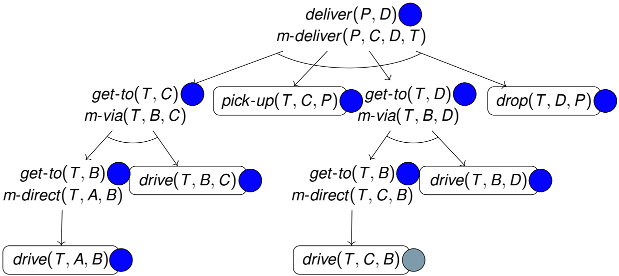

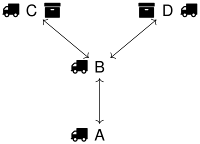

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Plan cost: 9 – recall: *true* effort is 11 and unrelaxed plan cost is 10.

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  - Admissibility (only if costs are chosen as above).

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  - Many classical heuristics compute heuristic values that are polynomial in the the input. The TDG heuristics can come up with exponential heuristic values.

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- We can also exploit *classical* heuristics for hierarchical planning by a relaxing problem transformation.