

On State-Dominance Criteria in Fork-Decoupled Search

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Abstract

Fork-decoupled search is a recent approach to classical planning that exploits *fork* structures, where a single *center* component provides preconditions for several *leaf* components. The *decoupled states* in this search consist of a center state, along with a *price* for every leaf state. Given this, when does one decoupled state dominate another? Such *state-dominance* criteria can be used to prune dominated search states. Prior work has devised only a trivial criterion. We devise several more powerful criteria, show that they preserve optimality, and establish their interrelations. We show that they can yield exponential reductions. Experiments on IPC benchmarks attest to the possible practical benefits.

1 Introduction

Fork-decoupled search is a new approach to state-space decomposition in classical planning, recently introduced by Gnad and Hoffmann [2015]. The approach partitions the state variables into disjoint subsets, *factors*, like in factored planning (e.g. [Amir and Engelhardt, 2003; Kelareva *et al.*, 2007; Fabre *et al.*, 2010; Brafman and Domshlak, 2013]). While factored planning is traditionally designed to handle arbitrary cross-factor interactions, fork-decoupling assumes these interactions to take a fork structure [Katz and Domshlak, 2008; Katz and Keyder, 2012; Aghighi *et al.*, 2015], where a single *center* provides preconditions for several *leaves*. A simple pre-process can determine whether such a fork structure exists, and extract a corresponding factoring if so.

Fork factorings identify a form of “conditional independence” between the leaf factors: Given a fixed center path π^C , the *compliant* leaf moves – those leaf moves enabled by the preconditions supplied along π^C – can be selected independently for each leaf. The decoupled search thus searches only over center paths π^C . Each *decoupled state* in the search represents the compliant leaf moves in terms of a *pricing function*, mapping each leaf-factor state s^L to the cost of a cheapest π^C -compliant path achieving s^L . As Gnad and Hoffmann (henceforth: GH) show, this can exponentially reduce state space size. It may also cause exponential blow-ups though.

The worst-case exponential blow-ups result from irrelevant distinctions in pricing functions. One means to combat this,

and more generally to improve search, is *dominance pruning*, pruning a state s^F if a better state t^F has already been seen. But, given the complex structure of decoupled states, when is one “better” than another? GH employ the trivial criterion, where s^F and t^F must have the same center state and t^F needs to have cheaper prices than s^F for all leaf states. Here we introduce advanced methods, analyzing the structure of decoupled states to identify (and then, disregard) irrelevant distinctions. We devise several such methods, using different sources of information. We show that the methods preserve optimality, and we characterize their relative pruning power. We show that they can yield exponential search reductions. Experiments on International Planning Competition (IPC) benchmarks attest to the possible practical benefits.

The main text only outlines our proof arguments. The full proofs are in Appendix A.

2 Background

We use finite-domain state variables [Bäckström and Nebel, 1995; Helmert, 2006]. A *planning task* is a tuple $\Pi = \langle \mathcal{V}, \mathcal{A}, I, G \rangle$. \mathcal{V} is a set of *variables*, each associated with a finite domain $\mathcal{D}(v)$. I is the *initial state*. The *goal* G is a partial assignment to \mathcal{V} . \mathcal{A} is a finite set of *actions*, each a triple $\langle \text{pre}(a), \text{eff}(a), \text{cost}(a) \rangle$ of *precondition*, *effect*, and *cost*, where $\text{pre}(a)$ and $\text{eff}(a)$ are partial assignments to \mathcal{V} , and $\text{cost}(a) \in \mathbb{R}^{0+}$. For a partial assignment p , we denote with $\mathcal{V}(p) \subseteq \mathcal{V}$ the subset of variables on which p is defined. For $V \subseteq \mathcal{V}(p)$, we denote with $p[V]$ the assignment to V made by p . We identify (partial) variable assignments as sets of variable/value pairs, written as (var, val) . A *state* is a complete assignment to \mathcal{V} . Action a is *applicable* in state s if $\text{pre}(a) \subseteq s$. Applying a in s changes the value of all $v \in \mathcal{V}(\text{eff}(a))$ to $\text{eff}(a)[v]$, and leaves s unchanged elsewhere. We will sometimes write $s \xrightarrow{a} t$ for a transition from s to t with action a . A *plan* for Π is an action sequence π iteratively applicable in I which results in a state s_G where $G \subseteq s_G$. The plan is *optimal* if its summed-up cost, denoted $\text{cost}(\pi)$, is minimal among all plans for Π .

We next give a recap of GH’s definitions. A *fork factoring* \mathcal{F} is a partition of \mathcal{V} identifying a fork structure. Namely, (i) every action $a \in \mathcal{A}$ affects (touches in its effect) exactly one element (*factor*) of \mathcal{F} , which we denote $F(a)$. And (ii) there is a *center* $F^C \in \mathcal{F}$ s.t., for every $a \in \mathcal{A}$, $\mathcal{V}(\text{pre}(a)) \subseteq$

$F^C \cup F(a)$. We refer to the factors $F^L \in \mathcal{F}^L := \mathcal{F} \setminus \{F^C\}$ as *leaves*. We refer to actions affecting F^C as *center actions*, and to actions affecting a leaf as *leaf actions*. By construction (each action affects only one factor) these two kinds of actions are disjoint. Center actions are preconditioned only on F^C , leaf actions may be preconditioned on F^C and the leaf they affect. In brief: *the center provides preconditions for the leaves, and there are no other cross-factor interactions*.

As a running example, we use a Logistics-style planning task with a truck variable t , a package variable p , and n locations l_1, \dots, l_n . $I = \{(t, l_1), (p, l_1)\}$ and $G = \{(p, l_2)\}$. Action $\text{drive}(x, y)$ moves the truck from any location x to any other location y . The package can be loaded/unloaded at any location x with actions $\text{load}(x)/\text{unload}(x)$ respectively. Then $\mathcal{F} = \{\{t\}, \{p\}\}$ is a fork factoring where $\{t\}$ is the center and $\{p\}$ is the single leaf. If we have m packages p_i , we can set each $\{p_i\}$ as a leaf.

Not every task Π has a fork factoring. GH analyze Π 's causal graph (e.g. [Knoblock, 1994; Jonsson and Bäckström, 1995; Brafman and Domshlak, 2003; Helmert, 2006]) in a pre-process, identifying a fork factoring if one exists, else *abstaining* from solving Π . We follow this approach here. In what follows, we assume a fork factoring \mathcal{F} . Variable assignments to F^C are called *center states*, and for each $F^L \in \mathcal{F}^L$ assignments to F^L are *leaf states*. We denote by S^L the set of all leaf states, across $F^L \in \mathcal{F}^L$. For each leaf, s_I^L denotes the initial leaf state. For simplicity (wlog), we will assume that every leaf has a single goal leaf state, s_G^L .

Decoupled search searches over sequences of center actions π^C , called *center paths*, that are applicable to I . For each π^C , it maintains a compact representation of the *leaf paths* π^L that *comply* with π^C . A leaf path is a sequence of leaf actions applicable to I when ignoring preconditions on F^C . Intuitively, given the fork structure, a fixed center path determines what each leaf can do (independently of all other leaves, as they interact only via the center). This is captured by the notion of compliance: π^L complies with π^C if it uses only the center preconditions supplied along π^C , i.e., if π^L can be scheduled alongside π^C s.t. the combined action sequence is applicable in I . Decoupled search goes forward from I until it finds a center path π^C to a center goal state where every leaf has a π^C -compliant leaf path π^L to its goal leaf state. The global plan then results from augmenting π^C with the paths π^L .

In detail: A *decoupled state* s^F is given by a center path $cp(s^F)$. Its center state $cs(s^F)$ and *pricing function* $prices(s^F) : S^L \mapsto \mathbb{R}^{0+}$ are induced by $cp(s^F)$, as follows. $cs(s^F)$ is the outcome of applying $cp(s^F)$ to s_I^L . $prices(s^F)$ maps each leaf state s^L to the cost of a cheapest $cp(s^F)$ -compliant leaf path ending in s^L (or ∞ if no such path exists).¹ The *initial decoupled state* I^F has the empty center path $cp(I^F) = \langle \rangle$. A *goal decoupled state* s_G^F is one with a *goal center state* $cs(s_G^F) \supseteq G[F^C]$ and where, for every leaf factor $F^L \in \mathcal{F}^L$, its goal leaf state s_G^L has been reached, i.e., $prices(s_G^F)[s_G^L] < \infty$. The actions applicable in s^F are those center actions a where $\text{pre}(a) \subseteq cs(s^F)$. Applying a to s^F

¹Pricing functions can be maintained in time low-order polynomial in the size of the individual leaf state spaces. See GH for details.

results in t^F where $cp(t^F) := cp(s^F) \circ \langle a \rangle$, inducing $cs(t^F)$ and $prices(t^F)$ as above.

In the running example, $cs(I^F) = \{(t, l_1)\}$, $prices(I^F)[(p, l_1)] = 0$, $prices(I^F)[(p, t)] = 1$, and $prices(I^F)[(p, l_i)] = \infty$, for all $i \neq 1$. Observe that $prices(I^F)[(p, t)]$ represents the cost of a *possible* package move, not a move we have already committed to. The actions applicable to I^F are $\text{drive}(l_1, l_i)$. Applying any such action, in the outcome decoupled state s^F we have $prices(s^F)[(p, l_i)] = 2$, while all other prices remain the same. If we apply $\text{drive}(l_1, l_2)$, then s^F is a goal decoupled state. The global plan is then extracted from s^F by augmenting the center path $cp(s^F) = \langle \text{drive}(l_1, l_2) \rangle$ with the compliant goal leaf path $\langle \text{load}(l_1), \text{unload}(l_2) \rangle$.

A *completion plan* for s^F consists of a center path π^C leading from s^F to some goal center state, augmented with goal leaf paths compliant with $cp(s^F) \circ \pi^C$. That is, we collect the postfix path for the center, and the complete path for each leaf. The *completion cost* of s^F , denoted $h^{F*}(s^F)$, is defined as the cost of a cheapest completion plan for s^F . By $d^{F*}(s^F)$, we denote the minimum, over all optimal completion plans π^F , of the number of center actions (decoupled-state transitions) in π^F .

3 Decoupled State Dominance

A binary relation \preceq over decoupled states is a *decoupled dominance relation* if $s^F \preceq t^F$ implies that $h^{F*}(s^F) \geq h^{F*}(t^F)$ and $d^{F*}(s^F) \geq d^{F*}(t^F)$. In *dominance pruning*, given such a relation \preceq , we prune a state s^F at generation time if we have already seen another state t^F (i.e., t^F is in the open or closed list) such that $s^F \preceq t^F$ and $g(s^F) \geq g(t^F)$. Intuitively, t^F dominates s^F if it has an at least equally good completion plan and center path. The center path condition is needed only in the presence of 0-cost actions, and ensures that the completion plan for t^F does not have to traverse s^F . If t^F can be reached with equal or better g -cost, pruning s^F preserves completeness and optimality of the search algorithm.

We derive practical decoupled dominance relations by efficiently testable sufficient criteria. The relations differ in terms of their pruning power. We capture their relative power with two simple terms of two simple notions. First, we say that \preceq' *subsumes* \preceq if $\preceq' \supseteq \preceq$, i.e., if \preceq' recognizes every occurrence of dominance recognized by \preceq . Second, we say that \preceq' is *exponentially separated* from \preceq if there exists a family of planning tasks in which the decoupled state space is exponential in the size of the input task under dominance pruning using \preceq and polynomial when using \preceq' .² We will devise several decoupled dominance relations, weaker and stronger ones. Weaker relations are useful in practice (only) when they cause less computational overhead.

Previous work only considered what we will refer to as the *basic* decoupled dominance relation, denoted \preceq_B .

Definition 1 (\preceq_B relation) \preceq_B is the relation over decoupled states defined by $s^F \preceq_B t^F$ iff $cs(s^F) = cs(t^F)$ and, for all $s^L \in S^L$, $prices(s^F)[s^L] \geq prices(t^F)[s^L]$.

²More precisely, as the pruning depends on the expansion order: in which this statement is true for any expansion order.

This method simply does a point-wise comparison between $\text{prices}(s^F)$ and $\text{prices}(t^F)$, whenever both have the same center state. Basic dominance pruning often helps to reduce search effort, but is unnecessarily restrictive in its insistence on *all* leaf prices being cheaper. This is inappropriate in cases where s^F has some irrelevant cheaper prices. It may, indeed, cause exponential blow-ups as, e.g., in our running example.

The standard state space in our running example is small, since $|\mathcal{V}| = 2$. Yet the decoupled state space has size exponential in the number n of locations. Through the leaf state prices, the decoupled states “remember” the locations visited by the truck in the past. For example, the decoupled state reached through the center sequence $\langle \text{drive}(l_1, l_3), \text{drive}(l_3, l_4) \rangle$ has finite prices for $(p, l_1), (p, t), (p, l_3)$, and (p, l_4) , and price ∞ elsewhere; while the decoupled state reached through the sequence $\langle \text{drive}(l_1, l_4) \rangle$ has finite prices for $(p, l_1), (p, t)$, and (p, l_4) . Intuitively, the difference between the two pricing functions does not matter, because, with initial location l_1 and goal location l_2 , the prices for $(p, l_i), i > 2$ are irrelevant. But without recognizing this fact, the decoupled state space enumerates (pricing functions corresponding to) every combination of visited locations.

It is remarkable here that the blow-up occurs in a simple Logistics task. This is a new insight. GH already pointed out the risk of blow-ups, but only in complex artificial examples. On IPC benchmarks, empirically the decoupled state space always is smaller than the standard one. Our insight here is that this is not because blow-ups don’t occur, but because the blow-ups (e.g. remembering truck histories) are hidden behind the gains (e.g. not enumerating combinations of package locations). Indeed, in the standard IPC Logistics benchmarks, the blow-up above occurs for all non-airport locations within every city, and these blow-ups multiply across cities. All our advanced dominance pruning methods get rid of this blow-up (though none guarantees to avoid blow-ups in general).

4 Frontier-Based Dominance

Our first dominance relation is based on the idea that differing prices on a leaf state s^L do not matter if “ s^L has no purpose”. In our running example, say that we are checking whether $s^F \preceq t^F$ and $\text{prices}(s^F)[(p, l_3)] = 2$ while $\text{prices}(t^F)[(p, l_3)] = \infty$, and thus $s^F \not\preceq_B t^F$. However, say that $\text{prices}(s^F)[(p, t)] = 1$. Then the cheaper price for (p, l_3) in s^F does not matter, because the only purpose of having the package at l_3 is to load it into the truck. Indeed, the only outgoing transition of the leaf state (p, l_3) leads to (p, t) .

We capture the relevant leaf states in s^F in terms of its *frontier*: those leaf states that are either themselves relevant (this applies only to the goal leaf state), or that can still contribute to achieving cheaper prices somewhere.

Definition 2 (Frontier) We define the frontier of a decoupled state s^F , $F(s^F) \subseteq S^L$ as $F(s^F) := \{s_G^L\} \cup \{s^L \mid \exists s^L \xrightarrow{a} t^L : \text{prices}(s^F)[s^L] + \text{cost}(a) < \text{prices}(s^F)[t^L]\}$.

We now obtain a decoupled dominance relation by comparing prices only on the frontier of s^F :

Definition 3 (\preceq_F relation) \preceq_F is the relation over decoupled states defined by $s^F \preceq_F t^F$ iff $\text{cs}(s^F) = \text{cs}(t^F)$ and, for all $s^L \in F(s^F)$, $\text{prices}(s^F)[s^L] \geq \text{prices}(t^F)[s^L]$.

Theorem 1 \preceq_F is a decoupled dominance relation.

Comparing the prices on the frontier is enough because, in any completion plan for s^F , if a compliant leaf path π^L decreases the price of the goal leaf state (e.g., from ∞ to some finite value), then π^L must pass through a frontier state s^L . Hence, in a completion plan for t^F , we can use the postfix behind s^L . This completion plan can only be better than that for s^F because $\text{prices}(s^F)[s^L] \geq \text{prices}(t^F)[s^L]$.

It is easy to see that \preceq_F is strictly better than \preceq_B :

Theorem 2 \preceq_F subsumes \preceq_B and is exponentially separated from it.

The first part of this claim is trivial as both relations are based on comparing prices, but \preceq_F does so on a subset of leaf states. A task family demonstrating the second part of the claim is our running example. The only leaf action applicable in any leaf state (p, l_i) is $\text{load}(l_i)$, leading to (p, t) . However, for any reachable s^F , we have $\text{prices}(s^F)[(p, t)] = 1$ because this price is already achieved in the initial state, and prices can only decrease. So the only possible frontier state, apart from (p, t) , is the goal (p, l_2) . But only two different prices are reachable for (p, l_2) , namely ∞ and 2. This shows the claim.

5 Effective-Price Dominance

Our next method appears orthogonal to frontier-based dominance at first sight, but turns out to subsume it. The method is based on replacing the prices in t^F , i.e., the dominating state in the comparison $s^F \preceq t^F$, with smaller *effective* prices, denoted $E\text{prices}(t^F)$. We then simply compare all such prices:

Definition 4 (\preceq_E relation) \preceq_E is the relation over decoupled states defined by $s^F \preceq_E t^F$ iff $\text{cs}(s^F) = \text{cs}(t^F)$ and, for all $s^L \in S^L$, $\text{prices}(s^F)[s^L] \geq E\text{prices}(t^F)[s^L]$.

The modified comparison is sound because the effective prices are designed to preserve $h^{F*}(t^F)$. Precisely: (*) For any center path π^C starting in t^F , and for any leaf state s_G^L of leaf F^L , if π_s^L is a π^C -compliant leaf path from s_I^L to s_G^L , then there exists a path π^L from s_I^L to s_G^L that complies with $\text{cp}(t^F) \circ \pi^C$ such that $\text{cost}(\pi^L) \leq E\text{prices}(t^F)[s^L] + \text{cost}(\pi_s^L)$. In other words, if $\text{prices}(t^F)[s^L] > E\text{prices}(t^F)[s^L]$, then any completion plan can be modified to use some other leaf state which does provide a total price of $E\text{prices}(t^F)[s^L] + \text{cost}(\pi_s^L)$ or less.

It turns out that this can be ensured with the following simple definition. We define $E\text{prices}(t^F)$ as the point-wise minimum pricing function p that satisfies:

$$p[s^L] = \begin{cases} \text{prices}(t^F)[s^L] & \text{if } s^L = s_G^L \\ \min\{\text{prices}(t^F)[s^L], \\ \max_{s^L \xrightarrow{a} t^L} (p[t^L] - \text{cost}(a))\} & \text{otherwise} \end{cases}$$

For each F^L , $E\text{prices}(t^F)$ can be computed by a simple backwards algorithm starting at the goal leaf state s_G^L . To illustrate the definition, consider any t^F in our running example. The price of (p, t) is 1, and its effective price also is 1 because its successor leaf state $s_G^L = (p, l_2)$ always has effective price ≥ 2 . For any irrelevant location $l_i, i > 2$, however, due to the transition to (p, t) whose effective price is 1, we get $E\text{prices}(t^F)[(p, l_i)] = 0$ regardless of what the actual price

of (p, l_i) in t^F is. The effective price 0 is sound because, in any completion plan for t^F starting with $\text{load}(l_i)$, we can use $\text{load}(l_1)$ instead to get (p, t) with price 1.

Theorem 3 \preceq_E is a decoupled dominance relation.

To prove Theorem 3, observe that, whenever $s^F \preceq_E t^F$, given a completion plan for s^F , we can construct an equally good completion plan for t^F by using the same center path π^C , and, with (*) above, constructing equally good or cheaper compliant goal leaf paths. It remains to prove (*). Consider any t^F , center path π^C , leaf state s^L , and π^C -compliant goal leaf path π_s^L starting in s^L . In our example, e.g., say t^F is reached from I^F by applying $\text{drive}(l_1, l_3)$; that $\pi^C = \langle \text{drive}(l_3, l_2) \rangle$; that $s^L = (p, l_3)$; and that $\pi_s^L = \langle \text{load}(l_3), \text{unload}(l_2) \rangle$. Then, exists $\pi^L = \langle \text{load}(l_1), \text{unload}(l_2) \rangle$ that is compliant with $\text{cp}(t^F) \circ \pi^C$.

Formally, denote $\pi_s^L = \langle a_1, \dots, a_n \rangle$ and denote the leaf states it traverses by $s^L = s_0^L, \dots, s_n^L = s_G^L$. Observe that, as $E\text{prices}(t^F)[s_n^L] = \text{prices}(t^F)[s_n^L]$, π_s^L necessarily passes through a leaf state s_i^L whose effective and actual prices in t^F are identical. Let i be the smallest index for which that is so. Then, for all $j < i$, $E\text{prices}(t^F)[s_j^L] \neq \text{prices}(t^F)[s_j^L]$, and thus by the definition of effective prices we have that $E\text{prices}(t^F)[s_j^L] \geq E\text{prices}(t^F)[s_{j+1}^L] - \text{cost}(a_{j+1})$. Accumulating these inequalities, we get (***) $E\text{prices}(t^F)[s_0^L] \geq E\text{prices}(t^F)[s_i^L] - \sum_{j=1}^i \text{cost}(a_j)$. Consider now the path π^L from s_I^L to s_G^L constructed as the concatenation of: a cheapest $\text{cp}(t^F)$ -compliant path to s_i^L (in our example, $\langle \text{load}(l_1) \rangle$); with the postfix of π_s^L behind s_i^L (in our example, $\langle \text{unload}(l_2) \rangle$). Then $\text{cost}(\pi^L) = \text{prices}(t^F)[s_i^L] + \sum_{j=i+1}^n \text{cost}(a_j)$. As $E\text{prices}(t^F)[s_i^L] = \text{prices}(t^F)[s_i^L]$, we get $\text{cost}(\pi^L) = E\text{prices}(t^F)[s_i^L] + \sum_{j=i+1}^n \text{cost}(a_j)$. With (**), we get the desired property that $\text{cost}(\pi^L) \leq E\text{prices}(t^F)[s_0^L] + \sum_{j=1}^i \text{cost}(a_j) + \sum_{j=i+1}^n \text{cost}(a_j) = E\text{prices}(t^F)[s^L] + \text{cost}(\pi_s^L)$, concluding the proof.

Theorem 4 \preceq_E subsumes \preceq_F and is exponentially separated from it.

To prove the exponential separation, we extend our running example with a $\text{teleport}(l_i, l_j)$ action, for $i, j > 2$, that moves the package between irrelevant locations if the truck is at l_2 . Then, as long as l_2 and at least one such l_i have not been visited yet, all leaf states (p, l_i) for $i > 2$ with finite price are in the frontier, and \preceq_F suffers from the same blow-up as \preceq_B . The effective prices of (p, l_i) , however, remain 0 as before.

To see that \preceq_E subsumes \preceq_F , observe that the former can be viewed as a recursive version of the latter, when reformulating the frontier condition to “ $\exists s^L \xrightarrow{a} t^L : p[s^L] < p[t^L] - \text{cost}(a)$ ”. Formally, one can show that, if $E\text{prices}(t^F)[s^L] \leq \text{prices}(s^F)[s^L]$ holds for all frontier states $s^L \in F(s^F)$, then it also holds for all non-frontier states $s^L \notin F(s^F)$. This shows the claim as, for $s^F \preceq_F t^F$, we have $\text{prices}(s^F)[s^L] \geq \text{prices}(t^F)[s^L]$ on $s^L \in F(s^F)$, and thus $\text{prices}(s^F)[s^L] \geq E\text{prices}(t^F)[s^L]$ on these states.

Note that, with the above, to evaluate \preceq_E it suffices to compare the price of s^F vs. effective price of t^F on $F(s^F)$. This is equivalent to, but faster than, comparing all prices.

6 Simulation-Based Dominance

We use the concept of simulation relations [Milner, 1971; Gentilini et al., 2003] on leaf state spaces in order to identify leaf states t^L which can do everything that another leaf state s^L can do.³ In this situation, suppose that we are checking whether $s^F \preceq t^F$, and $\text{prices}(t^F)[s^L] > \text{prices}(s^F)[s^L]$, but $\text{prices}(t^F)[t^L] \leq \text{prices}(s^F)[s^L]$. Then t^F can still dominate s^F , because if a solution for s^F relies on s^L , then starting from t^F we can use t^L instead.⁴

Definition 5 (Leaf simulation) Let F^L be a leaf factor. A binary relation \preceq^L on F^L leaf states is a leaf simulation if: $s_G^L \not\preceq^L s^L$ for all $s^L \neq s_G^L$; and whenever $s_1^L \preceq^L t_1^L$, for every transition $s_1^L \xrightarrow{a} s_2^L$ either (i) $s_2^L \preceq^L t_1^L$ or (ii) there exists a transition $t_1^L \xrightarrow{a'} t_2^L$ s.t. $s_2^L \preceq^L t_2^L$, $\text{pre}[F^C](a') \subseteq \text{pre}[F^C](a)$, and $\text{cost}(a') \leq \text{cost}(a)$. We call \preceq^L the coarsest leaf simulation if, for every leaf-simulation \preceq' , we have $\preceq' \subseteq \preceq^L$.

This follows common notions, except for (i) which, intuitively, “allows t_1^L to stay where it is”, and except for allowing in (ii) different actions a' so long as they are at least as good in terms of center precondition and cost. The coarsest leaf simulation can be computed in time polynomial in the size of the leaf factor state space, as usual with simulation relations [Henzinger et al., 1995], and it has similar properties, such as being reflexive and transitive.

It is easy to see that, whenever $s^L \preceq^L t^L$, if a leaf path π_s^L starting in s^L complies with a center path π^C , then there exists a π^C -compliant leaf path π_t^L starting in t^L s.t. $\text{cost}(\pi_t^L) \leq \text{cost}(\pi_s^L)$.

Lemma 1 Let \preceq^L be a leaf simulation and π^C a center path. If $s^L \preceq^L t^L$ and there exists a path π_s^L from s^L to s_G^L compliant with π^C , then there exists a path π_t^L from t^L to s_G^L compliant with π^C such that $\text{cost}(\pi_t^L) \leq \text{cost}(\pi_s^L)$.

Consequently, we allow s^L to take a cheaper price from any leaf state that simulates it:

Definition 6 (\preceq_S Relation) The relation \preceq_S over decoupled states is defined by $s^F \preceq_S t^F$ iff $\text{cs}(s^F) = \text{cs}(t^F)$ and, for all $s^L \in S^L$, $\text{prices}(s^F)[s^L] \geq \min_{s^L \preceq^L t^L} \text{prices}(t^F)[t^L]$.

Theorem 5 \preceq_S is a decoupled dominance relation.

It is easy to see that this is strictly better than \preceq_B :

Theorem 6 \preceq_S subsumes \preceq_B and is exponentially separated from it.

³This is inspired by, but differs in scope and purpose from, the use of simulation relations on the state space for dominance pruning in standard search [Torralba and Hoffmann, 2015].

⁴Note that this is quite different from the recently proposed use of simulation relations on the state space for dominance pruning in standard search [Torralba and Hoffmann, 2015]. In that approach, the simulation is the dominance relation and the main difficulty is how to compute such a relation over the exponentially large state space. In our approach, the simulation relation is over small leaf state spaces, and it is a tool used towards defining a simulation relation over decoupled states.

The first part of this claim holds simply because \preceq^L is reflexive (and therefore $\min_{s^L \preceq^L t^L} \text{prices}(t^F)[t^L] \leq \text{prices}(t^F)[s^L]$). For the second part, we use again our running example. Leaf simulation captures that $(p, l_i) \preceq^L (p, t)$ for all $i > 2$, since (p, t) is the only successor of any (p, l_i) and naturally $(p, t) \preceq^L (p, t)$. So, \preceq_S reduces the price of such (p, l_i) to 1, avoiding the exponential blow-up.

Inspired by [Torralba and Kissmann, 2015], we also employ leaf simulation to discover superfluous leaf states and leaf actions. A transition $s^L \xrightarrow{a} t^L$ is superfluous if $t^L \preceq^L s^L$, or there exists another transition $s^L \xrightarrow{a'} u^L$ such that $t^L \preceq u^L$, $\text{pre}[F^C](a') \subseteq \text{pre}[F^C](a)$, and $\text{cost}(a') \leq \text{cost}(a)$. After removing such transitions, we run a reachability check on the leaf state space, removing unreachable leaf states. We subsequently remove leaf actions that do not induce any transition anymore. This reduces leaf state space size, and may sometimes improve the heuristic function due to the removal of some actions.

7 Method Interrelations and Combination

We have already established the relation of our methods relative to \preceq_B , as well as the relation between \preceq_E and \preceq_F . We next design a combination \preceq_{ES} of \preceq_E and \preceq_S , with their respective strengths, and we establish the remaining method interrelations. Figure 1 provides the overall picture.

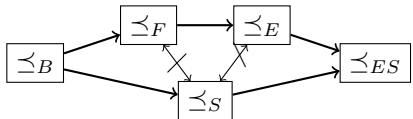


Figure 1: Summary of method interrelations. “ $A \rightarrow B$ ”: B subsumes A and is exponentially separated from it. “ $A \not\leftrightarrow B$ ”: A is exponentially separated from B and vice versa.

The combined relation \preceq_{ES} is obtained by modifying the effective prices underlying \preceq_E , enriching their definition with a leaf simulation, \preceq^L . We define $ESprices(t^F)$ as the point-wise minimum pricing function p that satisfies:

$$p[s^L] = \begin{cases} \text{prices}(t^F)[s^L] & \text{if } s^L = s_G^L \\ \min\{\min_{s^L \preceq^L t^L} \text{prices}(t^F)[t^L], \\ \max_{s^L \xrightarrow{a} t^L} (\text{p}[t^L] - \text{cost}(a))\} & \text{otherwise} \end{cases}$$

We integrate the information from a leaf simulation into the effective prices by allowing s^L to take cheaper prices from simulating states t^L . This amounts to substituting $\text{prices}(t^F)[s^L]$ with $\min_{s^L \preceq^L t^L} \text{prices}(t^F)[t^L]$ in the equation. We thus obtain, again, a decoupled dominance relation:

Definition 7 (\preceq_{ES} Relation) \preceq_{ES} is the relation over decoupled states defined by $s^F \preceq_{ES} t^F$ iff $cs(s^F) = cs(t^F)$ and, for all $s^L \in S^L$, $\text{prices}(s^F)[s^L] \geq ESpices(t^F)[s^L]$.

Theorem 7 \preceq_{ES} is a decoupled dominance relation.

Theorem 7 is shown by adapting the property (*) underlying the proof of Theorem 3. Say $\pi_s^L = \langle a_1, \dots, a_n \rangle$ is a π^C -compliant goal leaf path starting in s^L , traversing the leaf states $s^L = s_0^L, \dots, s_n^L = s_G^L$. Then, with

the same arguments as before, there exists i such that (a) $ESprices(t^F)[s_0^L] \geq ESpices(t^F)[s_i^L] - \sum_{j=1}^i \text{cost}(a_j)$, and (b) $ESprices(t^F)[s_i^L] = \min_{s_i^L \preceq^L t^L} \text{prices}(t^F)[t^L]$. We construct our desired path π^L from s_I^L to s_G^L by a cheapest $cp(t^F)$ -compliant path to a t^L minimizing the expression in (b), concatenated with a π^C -compliant goal leaf path π_t^L starting in t^L where $\text{cost}(\pi_t^L) \leq \text{cost}(\pi_s^L)$. Such π_t^L exists by the properties of leaf simulation, as in Theorem 5.

\preceq_{ES} subsumes each of its components. The exponential separations therefore follow directly from the individual ones:

Theorem 8 \preceq_{ES} subsumes \preceq_E and \preceq_S , and is exponentially separated from each of them.

One can also construct cases where \preceq_{ES} yields an exponentially stronger reduction than both \preceq_E and \preceq_S , i.e., where \preceq_{ES} is strictly more than the sum of its components. We complete our analysis by filling in the missing cases:

Theorem 9 \preceq_S is exponentially separated from \preceq_E , and therefore also from \preceq_F . \preceq_F , and therefore also \preceq_E , is exponentially separated from \preceq_S .

8 Experiments

We implemented our dominance pruning methods within the fork-decoupled search variant of FD [Helmert, 2006] by GH. Our baseline is GH’s basic pruning \preceq_B . For simplicity, we stick to the factoring strategy used by GH. This method greedily computes a factoring that maximizes the number of leaf factors. In case there are less than two leaves, the method abstains from solving a task. The rationale behind this is that the main advantage of decoupled search originates from not having to enumerate leaf state combinations across *multiple* leaf factors. Like GH, we show results on all IPC domains up to and including 2014 where the strategy does not abstain.

We focus on optimal planning, the main purpose of optimality-preserving pruning. We run a blind heuristic to identify the influence of different pruning methods per se, and we run LM-cut [Helmert and Domshlak, 2009] as a state-of-the-art heuristic. GH introduced two decoupled variants of A^* , ‘‘Fork-Decoupled’’ A^* and ‘‘Anytime Fork-Root’’ A^* , which to simplify terminology we will refer to as *Decoupled A^** (DA^*) and *Anytime Decoupled A^** (ADA^*). DA^* is a direct application of A^* to the decoupled state space. ADA^* orders the open list based on the heuristic estimate of remaining center-cost, uses the heuristic estimate of remaining global-cost for pruning against the best solution so far, and runs until the open list is empty. Both algorithms result in similar coverage, with moderate differences in some domains. Our techniques turn out to be more beneficial for ADA^* , which tends to have larger search spaces but less per-node runtime than DA^* . We show detailed data for ADA^* , and include data for baseline DA^* (with \preceq_B) for comparison. All experiments are run on a cluster of Intel E5-2660 machines running at 2.20 GHz, with time (memory) cut-offs of 30 minutes (4 GB).

Table 1 shows the number of instances solved, comparing to both baselines DA^* and ADA^* . Data for DA^* with the blind heuristic is not shown as it is identical to that for ADA^* . The main gain for blind search stems from Miconic (+9), and NoMystery (+3). When using LM-cut, the advantage over

| Domain | Expansions with Blind Heuristic: Improvement factor relative to \preceq_B | | | | | | | | Expansions with LM-cut: Improvement factor relative to \preceq_B | | | | | | | | | | | | | | | | | |
|-------------|---|----------|-------------|-------|------|----------|-------------|------|--|----------|-------------|-----|-------|----------|----------------|-----|------|------|-----|------|-------|------|--------|-------|------|--------|
| | # | $\sum D$ | \preceq_F | GM | max | $\sum D$ | \preceq_E | GM | max | $\sum D$ | \preceq_S | GM | max | $\sum D$ | \preceq_{ES} | GM | max | | | | | | | | | |
| Driverlog | 11 | 1.0 | 1.0 | 1.0 | 5.0 | 1.8 | 6.5 | 2.4 | 1.3 | 2.8 | 5.0 | 1.8 | 6.5 | 13 | 1.0 | 1.0 | 1.0 | 2.4 | 1.3 | 3.4 | 2.4 | 1.3 | 4.3 | | | |
| Logistics00 | 22 | 1.2 | 1.0 | 1.2 | 2.5 | 1.4 | 3.8 | 2.5 | 1.4 | 3.8 | 2.5 | 1.4 | 3.8 | 25 | 1.0 | 1.0 | 1.0 | 2.1 | 1.2 | 2.3 | 1.4 | 1.3 | 3.0 | | | |
| Logistics98 | 4 | 1.0 | 1.0 | 1.0 | 3.9 | 2.1 | 4.2 | 2.3 | 1.7 | 2.4 | 3.9 | 2.1 | 4.2 | 6 | 1.0 | 1.0 | 1.0 | 1.7 | 1.3 | 1.7 | 109.8 | 10.2 | 1245.2 | 134.7 | 10.8 | 1245.2 |
| Miconic | 36 | 3.3 | 1.7 | 5.2 | 3.3 | 1.7 | 5.2 | 3.3 | 1.7 | 5.2 | 3.3 | 1.7 | 5.2 | 135 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| NoMystery | 17 | 4.4 | 1.7 | 8.5 | 4.4 | 1.7 | 8.5 | 4.4 | 1.7 | 8.5 | 4.4 | 1.7 | 8.5 | 20 | 6.3 | 1.7 | 9.2 | 6.3 | 1.7 | 9.2 | 6.8 | 1.9 | 9.3 | 6.8 | 1.9 | 9.3 |
| TPP | 22 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.2 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.2 | 22 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| Zenotravel | 11 | 1.0 | 1.0 | 1.0 | 1.4 | 1.1 | 1.6 | 1.3 | 1.1 | 1.5 | 1.4 | 1.1 | 1.6 | 11 | 1.0 | 1.0 | 1.0 | 1.2 | 1.1 | 1.4 | 1.2 | 1.0 | 1.3 | 1.2 | 1.1 | 1.4 |
| Domain | Runtime with Blind Heuristic: Improvement factor relative to \preceq_B | | | | | | | | Runtime with LM-cut: Improvement factor relative to \preceq_B | | | | | | | | | | | | | | | | | |
| | # | $\sum D$ | \preceq_F | GM | max | $\sum D$ | \preceq_E | GM | max | $\sum D$ | \preceq_S | GM | max | $\sum D$ | \preceq_{ES} | GM | max | | | | | | | | | |
| Driverlog | 9 | 0.9 | 0.9 | 1.0 | 30.7 | 2.6 | 38.9 | 10.3 | 2.2 | 14.4 | 35.3 | 2.9 | 47.5 | 5 | 0.8 | 0.9 | 1.0 | 5.5 | 2.6 | 14.3 | 4.4 | 2.5 | 11.3 | 5.5 | 2.7 | 14.6 |
| Logistics00 | 7 | 1.4 | 1.3 | 1.5 | 6.4 | 5.9 | 15.2 | 8.4 | 8.3 | 22.5 | 7.5 | 7.0 | 19.7 | 9 | 0.9 | 0.9 | 0.9 | 3.8 | 1.5 | 4.6 | 2.7 | 3.7 | 6.4 | 4.1 | 3.5 | 5.0 |
| Logistics98 | 3 | 0.8 | 0.8 | 0.8 | 21.2 | 4.1 | 22.4 | 12.1 | 5.4 | 12.3 | 26.4 | 6.2 | 27.5 | 4 | 0.9 | 0.9 | 0.9 | 2.2 | 1.2 | 2.2 | 895.9 | 30.4 | 2643.9 | 750.2 | 26.2 | 2259.3 |
| Miconic | 19 | 24.0 | 10.0 | 53.9 | 24.3 | 9.0 | 47.9 | 22.6 | 8.6 | 45.7 | 23.5 | 8.8 | 47.0 | 81 | 0.9 | 1.0 | 1.2 | 1.0 | 0.9 | 1.1 | 1.0 | 1.0 | 1.2 | 0.9 | 0.9 | 1.0 |
| NoMystery | 9 | 47.3 | 5.6 | 157.1 | 36.2 | 4.1 | 118.8 | 64.2 | 7.4 | 210.2 | 53.7 | 6.0 | 182.7 | 12 | 13.3 | 3.0 | 21.0 | 12.6 | 2.9 | 22.4 | 16.2 | 3.8 | 28.9 | 14.6 | 3.6 | 26.0 |
| Pathways | 2 | 0.9 | 0.9 | 0.9 | 0.7 | 0.7 | 0.7 | 1.0 | 1.0 | 1.0 | 0.6 | 0.6 | 0.6 | 1 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 1.0 | 1.0 | 1.0 | 0.9 | 0.9 | 0.9 |
| Rovers | 2 | 0.8 | 0.8 | 0.8 | 0.5 | 0.5 | 0.6 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | 0.5 | 5 | 0.9 | 0.9 | 0.9 | 0.7 | 0.7 | 0.8 | 1.0 | 1.0 | 1.0 | 0.7 | 0.7 | 0.8 |
| Satellite | 3 | 0.9 | 0.9 | 1.0 | 0.6 | 0.7 | 0.9 | 1.0 | 1.0 | 1.0 | 0.5 | 0.6 | 0.8 | 4 | 1.0 | 1.0 | 1.0 | 0.9 | 0.8 | 0.9 | 1.0 | 1.0 | 1.0 | 0.9 | 0.8 | 0.9 |
| TPP | 13 | 0.8 | 0.8 | 1.0 | 0.0 | 0.1 | 0.3 | 0.1 | 0.3 | 0.8 | 0.0 | 0.1 | 0.3 | 11 | 0.8 | 0.8 | 1.0 | 0.1 | 0.2 | 0.4 | 0.1 | 0.4 | 0.8 | 0.1 | 0.1 | 0.3 |
| Woodwork08 | 2 | 1.5 | 1.2 | 1.5 | 0.7 | 0.8 | 1.0 | 1.5 | 0.3 | 1.5 | 1.0 | 0.3 | 1.0 | 8 | 1.0 | 1.0 | 1.1 | 1.0 | 1.0 | 1.0 | 1.2 | 0.9 | 1.7 | 1.1 | 0.8 | 1.4 |
| Woodwork11 | 1 | 1.5 | 1.5 | 1.5 | 0.7 | 0.7 | 0.7 | 1.5 | 1.5 | 1.5 | 1.0 | 1.0 | 1.0 | 5 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.3 | 1.2 | 1.3 | 1.3 | 1.2 | 1.3 |
| Zenotravel | 4 | 0.8 | 0.8 | 1.0 | 1.2 | 1.2 | 1.4 | 1.7 | 1.8 | 2.9 | 1.3 | 1.3 | 1.8 | 4 | 0.9 | 0.9 | 1.0 | 1.1 | 1.0 | 1.2 | 1.3 | 1.3 | 1.6 | 1.1 | 1.1 | 1.3 |

Table 2: Improvement factor on commonly solved instances relative to \preceq_B , using ADA*. We show expansions up to last f -layer (top), and runtime (bottom), with the blind heuristic (left) and LM-cut (right). In the top part, some domains are skipped as all their factors are rounded to 1.0. In the bottom part, we only take into account the instances that are not trivially solved by all planners (< 0.1s). $\sum D$: Ratio over the per-domain sum. GM (max): geometric mean (maximum) of per-instance ratios.

| Domain | # | Blind Heuristic ADA* | | | | | LM-cut ADA* | | | | | |
|-------------|-----|----------------------|-------------|-------------|-------------|----------------|-------------|-------------|-------------|-------------|-------------|----------------|
| | | \preceq_B | \preceq_F | \preceq_E | \preceq_S | \preceq_{ES} | DA* | \preceq_B | \preceq_F | \preceq_E | \preceq_S | \preceq_{ES} |
| Driverlog | 20 | 11 | 11 | 11 | 11 | 11 | 13 | 13 | 13 | 13 | 13 | 13 |
| Logistics00 | 28 | 22 | 22 | 22 | 22 | 22 | 28 | 25 | 25 | 27 | 26 | 28 |
| Logistics98 | 35 | 4 | 4 | 5 | 5 | 5 | 6 | 6 | 6 | 6 | 6 | 6 |
| Miconic | 145 | 36 | 45 | 45 | 45 | 45 | 135 | 135 | 135 | 135 | 135 | 135 |
| NoMystery | 20 | 17 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| Pathways | 29 | 3 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 4 |
| Rovers | 40 | 7 | 6 | 7 | 6 | 7 | 9 | 9 | 9 | 9 | 9 | 9 |
| Satellite | 36 | 6 | 6 | 6 | 5 | 7 | 9 | 9 | 8 | 9 | 9 | 9 |
| TPP | 27 | 23 | 23 | 22 | 23 | 22 | 18 | 23 | 23 | 22 | 22 | 22 |
| Woodwork08 | 13 | 5 | 5 | 5 | 5 | 5 | 10 | 11 | 11 | 11 | 11 | 11 |
| Woodwork11 | 5 | 1 | 1 | 1 | 1 | 1 | 4 | 5 | 5 | 5 | 5 | 5 |
| Zenotravel | 20 | 11 | 11 | 12 | 12 | 12 | 13 | 11 | 11 | 12 | 12 | 13 |
| Σ | 418 | 146 | 157 | 158 | 160 | 157 | 267 | 271 | 271 | 272 | 272 | 275 |

Table 1: Coverage data.

\preceq_B is much smaller. We still gain +3 (+2) instances in Logistics00 (Zenotravel). In Satellite and TPP, we lose 1 instance in some configurations due to overhead at no search space reduction. \preceq_{ES} reliably removes the disadvantages of ADA* relative to DA*, and is best in the overall. We never strictly improve coverage over both baselines, though. As we shall see below, this is due to benchmark scaling, i.e., there are domains where runtime is improved over both baselines.

We next analyze the search space size reduction (top part of Table 2). In general, the blind heuristic has more margin of improvement except in Logistics98, where the improvement with LM-cut gets magnified due to the relevance analysis performed when enabling \preceq_S . In that domain, removing irrelevant leaf states and leaf actions renders LM-cut a lot stronger.⁵ Regarding the relative behavior of pruning tech-

⁵It may be surprising that, elsewhere, the improvements in Logistics are moderate, despite the inherent blow-up we explained earlier. This is because, in the commonly solved instances, the number of

niques, in two domains, namely Miconic and NoMystery, already the simplest technique (\preceq_F) gets the maximal improvement factor. In four domains, enabling effective-price pruning on top of frontier pruning results in additional pruning. Combining all techniques in \preceq_{ES} always inherits the strongest search space reduction of its components and in Logistics with LM-cut, it often is strictly better.

Consider now runtime, Table 2 bottom. One key observation is that, whenever the search space is reduced, the same holds for runtime, even for small search space reduction factors like, e.g., in Zenotravel. Remarkably, in some domains (e.g. Woodworking) where no search reduction is obtained, runtime decreases nevertheless for some simple methods such as \preceq_F . This is due to the cheaper dominance check – prices are compared only on *frontier* leaf states. There are also some bad cases, though, mainly in TPP, but also in Pathways, Rovers, and Satellite. These are also the domains in which coverage slightly decreases. What makes these domains special is the structure of their leaf state spaces. In Pathways, Rovers, and Satellite, all leaves are single variables with a single transition, $s_I^L \rightarrow s_G^L$, so there is no room for improvement. In TPP, the leaf state spaces are quite large (up to 5000 states), so our methods incur substantial overhead, but are unable to perform pruning. Presumably, this is because most of the leaf states can play a role in optimally reaching the goal.

Coming back to our previous observation that coverage is never improved over both baselines, the runtime analysis reveals an improvement over both baselines in several domains. ADA* with \preceq_S is faster than DA* with \preceq_B in all domains except Zenotravel, where the geomean per-instance runtime factor is 0.7. The other factors are: Driverlog 2.3; Logistics00 2.3; Logistics98 3.4; Miconic 2.7; NoMystery 3.2; Pathways

non-airport locations in each city is very small, mostly 1.

1.1; Rovers 2.1; Satellite 2.9; TPP 23.2; Woodworking08 1.4; and Woodworking11 2.0. In particular, in Driverlog, both Logistics domains, NoMystery, and Woodworking11, ADA* with \preceq_S improves runtime over both baselines.

Finally, consider the use of our pruning methods in DA*. For blind search, the numbers are almost identical to those for ADA* in Table 2, as DA* and ADA* differ mainly in their use of a (non-trivial) heuristic. With LM-cut, the pruning methods do not work as well for DA*. For example, for \preceq_S , the geomean per-instance runtime factors are: Driverlog 1.8; Logistics00 and Logistics98 2.5; NoMystery 2.0; TPP 0.9; Woodworking08 0.9; Woodworking11 1.3; Zenotravel 1.2; and 1.0 in the other domains. The picture is similar for the other pruning methods. The big runtime advantages observed with ADA* vanish, but the method also becomes less risky, i.e., the big runtime disadvantage in TPP vanishes as well. This makes sense since DA* searches less nodes (it has less potential for pruning) while spending more time on each node (making the dominance-checking overhead less pronounced).

9 Conclusion

Dominance pruning methods can be quite useful for decoupled search. Our analysis of such methods is fairly complete, although of course other variants may be thinkable. More pressingly, the question remains whether there exist duplicate checking methods guaranteeing to avoid all blow-ups.

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A Proofs

Theorem 1 \preceq_F is a decoupled dominance relation.

Proof: Whenever $s^F \preceq_F t^F$ and a completion plan for s^F exists, we can construct an at least as good completion plan for t^F . Consider any completion plan for s^F consisting of a center path π^C , and a goal leaf path π^L for each leaf starting in s_I^L compliant with $cp(s^F) \circ \pi^C$. As $s^F \preceq_F t^F$ implies that $cs(s^F) = cs(t^F)$, π^C is applicable to t^F as well.

Denote $\pi^L = \langle a_1, \dots, a_n \rangle$ and denote the leaf states it traverses by $s_I^L = s_0^L, \dots, s_n^L = s_G^L$. Let s_i^L be the last state visited by π^L such that $prices(s^F)[s_i^L] = \sum_{j=1}^i \text{cost}(a_j)$. Such state must exist because the price of the initial state is always 0, $prices(s^F)[s_0^L] = 0$. s_i^L is the last state in which its price corresponds to the price obtained by π^L so $\langle a_{i+1}, \dots, a_n \rangle$ must be compliant with π^C .

It follows that $s_i^L \in F(s^F)$. This is trivially true if $s_i^L = s_n^L$ since the goal state always belongs to the frontier. If $s_i^L \neq s_n^L$ then $prices(s^F)[s_i^L] + \text{cost}(a_{i+1}) < prices(s^F)[s_{i+1}^L]$, which implies $s_i^L \in F(s^F)$. Since $s^F \preceq_F t^F$, it follows that $prices(t^F)[s_i^L] \leq prices(s^F)[s_i^L]$.

Consider the path π_t^L from s_I^L to s_G^L constructed as the concatenation of: a cheapest $cp(t^F)$ -compliant path to s_i^L with the postfix of π^L behind s_i^L . Then $\text{cost}(\pi_t^L) = prices(t^F)[s_i^L] + \sum_{j=i+1}^n \text{cost}(a_j) \leq \text{cost}(\pi^L)$. Since the first part of the plan up to s_i^L is compliant with $cp(t^F)$ and the rest is compliant with π^C , π_t^L is compliant with $cp(t^F) \circ \pi^C$ as desired. \square

Theorem 2 \preceq_F subsumes \preceq_B and is exponentially separated from it.

Proof: Subsumption is guaranteed as both relations are based on comparing the same pricing functions, but \preceq_F does so on a subset of leaf states. The exponential separation is shown

by our running example, in which decoupled search with \preceq_B incurs an exponential blow-up, as explained before.

Note that the price of (p, l_1) and (p, t) are always 0 and 1, respectively. Since the only leaf action applicable from (p, l_i) is $load(p, l_i)$ and the price of (p, t) is always lower than that of (p, l_i) for $i > 1$, $(p, l_i) \notin F(s^F), i > 2$ for any s^F . Hence, when using \preceq_F , there are at most 2 different decoupled states for every center state, depending on whether the price of (p, l_2) is 2 or ∞ . Therefore, the decoupled state space with \preceq_F has size linear in n instead of exponential. \square

Theorem 3 \preceq_E is a decoupled dominance relation.

Proof: Whenever $s^F \preceq_E t^F$ and a completion plan for s^F exists, we can construct an at least as good completion plan for t^F . Consider any completion plan for s^F consisting of a center path π^C , and a goal leaf path π^L for each leaf starting in s_I^L compliant with $cp(s^F) \circ \pi^C$. As $s^F \preceq_E t^F$ implies that $cs(s^F) = cs(t^F)$, π^C is applicable to t^F as well. Let s^L be a leaf state traversed by π^L such that the prefix of π^L up to s^L is compliant with $cp(s^F)$ and the suffix of π^L starting in s^L , π_s^L , is compliant with π^C . Denote $\pi_s^L = \langle a_1, \dots, a_n \rangle$ and denote the leaf states it traverses by $s^L = s_0^L, \dots, s_n^L = s_G^L$.

Let s_i^L be the first state visited by π_s^L such that $Eprices(t^F)[s_i^L] = prices(t^F)[s_i^L]$. Such state exists by definition since $Eprices(t^F)[s_n^L] = prices(t^F)[s_n^L]$. Then, for all $j < i$, $Eprices(t^F)[s_j^L] \neq prices(t^F)[s_j^L]$, and thus by the definition of effective prices we have that $Eprices(t^F)[s_j^L] \geq Eprices(t^F)[s_{j+1}^L] - \text{cost}(a_{j+1})$. Accumulating these inequalities, we get (*) $Eprices(t^F)[s_0^L] \geq Eprices(t^F)[s_i^L] - \sum_{j=1}^i \text{cost}(a_j)$.

Consider now the path π_t^L from s_I^L to s_G^L constructed as the concatenation of: a cheapest $cp(t^F)$ -compliant path to s_i^L with the postfix of π_s^L behind s_i^L . Then $\text{cost}(\pi_t^L) = prices(t^F)[s_i^L] + \sum_{j=i+1}^n \text{cost}(a_j)$. As $Eprices(t^F)[s_i^L] = prices(t^F)[s_i^L]$, we get $\text{cost}(\pi_t^L) = Eprices(t^F)[s_i^L] + \sum_{j=i+1}^n \text{cost}(a_j)$. With (*), we get the desired property that:

$$\begin{aligned} & \text{cost}(\pi_t^L) \\ & \leq Eprices(t^F)[s^L] + \sum_{j=1}^i \text{cost}(a_j) + \sum_{j=i+1}^n \text{cost}(a_j) \\ & = Eprices(t^F)[s^L] + \text{cost}(\pi_s^L) \\ & \leq prices(s^F)[s^L] + \text{cost}(\pi_s^L) \\ & = \text{cost}(\pi^L) \end{aligned}$$

\square

Theorem 4 \preceq_E subsumes \preceq_F and is exponentially separated from it.

Proof: To prove that \preceq_E subsumes \preceq_F , we show that if $Eprices(t^F)[s^L] \leq prices(s^F)[s^L]$ for all $s^L \in F(s^F)$, then it also holds for all $s^L \notin F(s^F)$.

Consider any $s^L \notin F(s^F)$. Let $R^L \subseteq F(s^F)$ be the set of leaf states in the frontier of s^F reachable from s^L through a path that does not traverse any other state in $F(s^F)$. Note that, since $s_G^L \in F(s^F)$, any path from s^L to s_G^L necessarily passes through some $r^L \in R^L$. Let r^L be $\text{argmax}_{t^L \in R^L} Eprices(t^F)[t^L] - \text{cost}(s^L, t^L)$ where $\text{cost}(s^L, t^L)$ is the cost of the optimal path from s^L to t^L .

First we show that $Eprices(t^F)[s^L] \leq Eprices(t^F)[r^L] - \text{cost}(s^L, r^L)$. By definition, $Eprices(t^F)[s^L] \leq \max_{s^L \xrightarrow{a} t^L} (Eprices(t^F)[t^L] - \text{cost}(a))$. Let s_1^L be any t^L that maximizes such expression. If $s_1^L \in R^L$ then $Eprices(t^F)[s^L] \leq Eprices(t^F)[s_1^L] - \text{cost}(s^L, s_1^L) \leq Eprices(t^F)[r^L] - \text{cost}(s^L, r^L)$ and we are done. If $s_1^L \notin R^L$ then we can compose the definition to obtain, $Eprices(t^F)[s^L] \leq Eprices(t^F)[s_1^L] - \text{cost}(a) \leq \max_{s_1^L \xrightarrow{a} s_2^L} (Eprices(t^F)[s_2^L] - \text{cost}(a))$. By repeating the same argument we have that at least one state $u^L \in R^L$. This is clear if there are no 0-cost actions because $Eprices(t^F)[s_i^L] < Eprices(t^F)[s_{i+1}^L]$ so the $Eprices(t^F)$ monotonically increases during this chain and there can be no cycles.

If there are 0-cost actions, there may be a 0-cost cycle, so we must prove that even in that case, there exists yet another state u^L outside the cycle such that $Eprices(t^F)[s^L] \leq Eprices(t^F)[u^L] - \text{cost}(s^L, u^L)$. Consider the set of states, S_s^L for which there is a 0-cost cycle such that $S_s^L \cap R^L = \emptyset$ and all the states in S_s^L have the same $Eprices(t^F)$. Let C be a constant such that $Eprices(t^F)[s_i^L] = C$ for all $s_i^L \in S_s^L$. Then, there exists $t^L \notin S_s^L$ such that $s_i^L \xrightarrow{a} t^L$, $Eprices(t^F)[s_i^L] \leq Eprices(t^F)[t^L] - \text{cost}(a)$ for some $s_i^L \in S_s^L$. Otherwise, $Eprices(t^F)[s_i^L] = C'$ for all $s_i^L \in S_s^L$ and some $C' < C$ would satisfy the equation for which $Eprices$ is defined to be the minimum point-wise that satisfies it.

Finally, since $s^L \notin F(s^F)$, $\text{prices}(s^F)[s^L] \geq \text{prices}(s^F)[t^L] - \text{cost}(a)$ for all $s^L \xrightarrow{a} t^L$. Since all states in the path from s^L to any $r^L \in R^L$ do not belong to $F(s^F)$, we have the inequality $\text{prices}(s^F)[s^L] \geq \text{prices}(s^F)[r^L] - \text{cost}(s^L, r^L)$. Combining the previous inequalities we get:

$$\begin{aligned} & Eprices(t^F)[s^L] \\ & \leq Eprices(t^F)[r^L] - \text{cost}(s^L, r^L) \\ & \leq \text{prices}(s^F)[r^L] - \text{cost}(s^L, r^L) \\ & \leq \text{prices}(s^F)[s^L] \end{aligned}$$

For the exponential separation, consider the planning task of our running example with an additional teleport device that allows to teleport the package between any two locations that are not the goal. Hence, we have a new center variable *tel-activated* with domain $\{F, T\}$, initially set to F and two new actions *activate-teleport* that sets *tel-activated* to T and *teleport-package*(l_i, l_j) for $i, j \neq 2$ that has (*tel-activated*, T) and (p, l_i) as preconditions and (p, l_j) as effect. The cost of *activate-teleport* is n and all other actions have cost 1.

In this example, decoupled search with \preceq_F expands an exponential number of states with $(\text{tel-activated}, F)$ since for all reached (p, l_i) with $i > 2$, $(p, l_i) \in F(s^F)$ as long as any (p, l_i) is still not reached. When using \preceq_E , $\text{prices}(I^F)[(p, t)] = 1$ in every state, so $Eprices(s^F)[(p, l_i)] = 0$. Therefore, the state space is linear in the number of locations. \square

Lemma 1 Let \preceq^L be a leaf simulation and π^C a center path. If $s^L \preceq^L t^L$ and there exists a path π_s^L from s^L to s_G^L compliant with π^C , then there exists a path π_t^L from t^L to s_G^L compliant with π^C such that $\text{cost}(\pi_t^L) \leq \text{cost}(\pi_s^L)$.

Proof: Assume without loss of generality that π_s^L is a shortest optimal path compliant with π^C . Proof by induction on $|\pi_s^L|$. Base case, $|\pi_s^L| = 0$. Then, $s^L = s_G^L$ and $t^L = s_G^L$ because $s_G^L \not\preceq^L t^L$ for any $t^L \neq s_G^L$. Thus, $\pi_s^L = \pi_t^L = \langle \rangle$.

Inductive case. Let $s^L \xrightarrow{a_s^L} s_2^L$ be the first transition in π_s^L . Since $s^L \preceq^L t^L$, either (i) $s_2^L \preceq^L t^L$ or (ii) exists $t^L \xrightarrow{a_t^L} t_2^L$ such that a_t^L dominates a_s^L and $s_2^L \preceq t_2^L$. If (i) holds then the claim follows by induction since it must exist π_t^L with $\text{cost}(\pi_t^L) \leq \text{cost}(\pi_{s_2}^L)$ where $\pi_{s_2}^L$ is a shortest optimal π^C -compliant plan from s_2^L and necessarily $\text{cost}(\pi_{s_2}^L) \leq \text{cost}(\pi_s^L)$ and $\pi_{s_2}^L$ is shorter than π_s^L .

If (ii) holds, by induction we know that the claim holds for s_2^L and t_2^L , so exists a plan $\pi_{t_2}^L$. Thus, $\text{cost}(\pi_t^L) = \text{cost}(\pi_{t_2}^L) + c(a_t^L) \leq c(\pi_{s_2}^L) + c(a_s^L) \leq \text{cost}(\pi_{s_2}^L) + c(a_s^L) = c(\pi_s^L)$. Moreover, since π_s^L is compliant with π^C and $\text{pre}^C(a_t^L) \subseteq \text{pre}^C(a_s^L)$, π_t^L is also compliant with π^C . \square

Theorem 5 \preceq_S is a decoupled dominance relation.

Proof: Whenever $s^F \preceq_S t^F$ and a completion plan for s^F exists, we can construct an at least as good completion plan for t^F . Consider any completion plan for s^F consisting of a center path π^C , and a goal leaf path π^L for each leaf starting in s_I^L compliant with $cp(s^F) \circ \pi^C$. As $s^F \preceq_S t^F$ implies that $cs(s^F) = cs(t^F)$, π^C is applicable to t^F as well. Let s^L be a leaf state traversed by π^L such that the prefix of π^L up to s^L is compliant with $cp(s^F)$ and the suffix of π^L starting in s^L , π_s^L , is compliant with π^C . Denote $\pi_s^L = \langle a_1, \dots, a_n \rangle$ and denote the leaf states it traverses by $s^L = s_0^L, \dots, s_n^L = s_G^L$.

Since $s^F \preceq_S t^F$, $\min_{s^L \preceq^L t^L} \text{prices}(t^F)[t^L] \leq \text{prices}(s^F)[s^L]$. Then, exists t^L such that $s^L \preceq^L t^L$ and $\text{prices}(t^F)[t^L] \leq \text{prices}(s^F)[s^L]$. By Lemma 1, exists a π^C -compliant leaf plan π_t^L from t^L to s_G^L such that $\text{cost}(\pi_t^L) \leq \text{cost}(\pi_s^L)$. Consider now the path π_2^L from s_I^L to s_G^L constructed as the concatenation of: a cheapest $cp(t^F)$ -compliant path to t^L and π_t^L . By definition, π_2^L is compliant with $cp(t^F) \circ \pi^C$. Then, $\text{cost}(\pi_2^L) = \text{prices}(t^F)[t^L] + \text{cost}(\pi_t^L) \leq \text{prices}(s^F)[s^L] + \text{cost}(\pi_s^L) = \text{cost}(\pi^L)$. \square

Theorem 6 \preceq_S subsumes \preceq_B and is exponentially separated from it.

Proof: The subsumption holds simply because \preceq^L is reflexive, so $\min_{s^L \preceq^L t^L} \text{prices}(t^F)[t^L] \leq \text{prices}(t^F)[s^L]$.

To show the exponential separation, we use again our running example. Leaf simulation captures that $(p, l_i) \preceq^L (p, t)$ for all $i \neq 2$. As $\text{prices}(I^F)[(p, t)] = 1$, $\text{prices}(s^F)[(p, l_i)] = 1$ for $i > 2$ in any decoupled state. Therefore, the size of the decoupled state space when using \preceq_S is linear in the number of locations. \square

Theorem 7 \preceq_{ES} is a decoupled dominance relation.

Proof: Whenever $s^F \preceq_{ES} t^F$ and a completion plan for s^F exists, we can construct an at least as good completion plan for t^F . Consider any completion plan for s^F consisting of a

center path π^C , and a goal leaf path π^L for each leaf starting in s_I^L compliant with $cp(s^F) \circ \pi^C$. As $s^F \preceq_{ES} t^F$ implies that $cs(s^F) = cs(t^F)$, π^C is applicable to t^F as well. Let s^L be a leaf state traversed by π^L such that the prefix of π^L up to s^L is compliant with $cp(s^F)$ and the suffix of π^L starting in s^L , π_s^L , is compliant with π^C . Denote $\pi_s^L = \langle a_1, \dots, a_n \rangle$ and denote the leaf states it traverses by $s^L = s_0^L, \dots, s_n^L = s_G^L$.

By the same arguments as in the proof of Theorem 3, there exists i such that (a) $ESprices(t^F)[s_0^L] \geq ESprices(t^F)[s_i^L] - \sum_{j=1}^i \text{cost}(a_j)$, and (b) $ESprices(t^F)[s_i^L] = \min_{s^L \preceq^L t^L} prices(t^F)[t^L]$.

Hence, there exists t^L such that $prices(t^F)[t^L] \leq prices(s^F)[s^L] + \sum_{j=1}^i \text{cost}(a_j)$. Also, by Lemma 1, exists a π^C -compliant leaf plan, π_t^L , from t^L to s_G^L such that $\text{cost}(\pi_t^L) \leq \sum_{j=i+1}^n \text{cost}(a_j)$.

We construct our desired path π_2^L from s_I^L to s_G^L by a cheapest $cp(t^F)$ -compliant path to t^L , concatenated with π_t^L . In summary:

$$\begin{aligned} & \text{cost}(\pi_2^L) \\ &= prices(t^F)[t^L] + \text{cost}(\pi_t^L) \\ &\leq prices(s^F)[s_i^L] + \text{cost}(\pi_t^L) \\ &\leq prices(s^F)[s^L] + \sum_{j=1}^i \text{cost}(a_j) + \text{cost}(\pi_t^L) \\ &\leq prices(s^F)[s^L] + \text{cost}(\pi_s^L) \\ &= \text{cost}(\pi^L) \end{aligned} \quad \square$$

Theorem 8 \preceq_{ES} subsumes \preceq_E and \preceq_S , and is exponentially separated from each of them.

Proof: By definition, $ESprices(s^F)[s^L] \leq Eprices(s^F)[s^L]$ and $ESprices(s^F)[s^L] \leq \min_{s^L \preceq^L t^L} prices(t^F)[t^L]$ so subsumption follows.

To prove the exponential separation, consider the following planning task, in which we have a single center variable c (see Figure 2a) with domain c_0, c_{n+1} , and c_i^A, c_i^B for $i \in [1, \dots, n]$, arranged such that we can move from c_0 to c_1^X , from c_n^X to c_{n+1} , and from each c_i^X to each c_{i+1}^Y ($X, Y \in \{A, B\}$). The initial value is c_0 . We have a single leaf variable l with values l_0, l_{n+1} , and $l_i^A, l_i^B, l_i^{A2}, l_i^{B2}$ for $i \in [1, \dots, n]$ with initial value l_0 and goal value l_{n+1} . The transitions of the leaf l are depicted in Figure 2b. l has transitions from l_0 to l_1^X under center precondition c_1^X , from l_i^{X2} to l_{n+1} under center precondition c_{n+1} , from each l_i^X to l_{i+1}^X under center precondition c_i^X , and from each l_i^{X2} to each l_{i+1}^X and l_{i+1}^Y under center precondition c_i^X and c_i^Y , respectively ($X, Y \in \{A, B\}, X \neq Y$).

In this example, each of the separated techniques expands an exponential number of states in n :

- With \preceq_B , at each step in the center path, one of the two paths, A or B is chosen. Hence, the pricing function “remembers” which one of the two paths were taken and there is an exponential number of combinations.
- \preceq_F and \preceq_E ignore the prices of l_i^X because they do not belong to the frontier. However, they still remember whether l_i^{A2} or l_i^{B2} has been reached. \preceq_E helps

whenever l_n is reached but those states have the largest g -value (equal to $n+1$) so cannot prune any other state.

- \preceq_S finds the following leaf-simulation relation:

$$\begin{aligned} \preceq^L = & \{(l_i^X, l_j^{Y2}), (l_i^{X2}, l_j^{Y2}) \text{ for all } i \leq j, X, Y \in A, B\} \\ & \cup \{(x, x), (x, l_n) \text{ for all } x \in S^L\} \end{aligned}$$

In summary, according to \preceq^L states of the form l_i^{A2}, l_i^{B2} are equivalent and they simulate all previous states. However, nothing is found for states l_i^A and l_i^B .

Therefore, decoupled search with \preceq_S expands the same states than with \preceq_B . The main reason is that, even though it finds the equivalence between l_i^{A2} and l_i^{B2} , depending which path was used, either l_i^A or l_i^B will have a lower price.

For example, consider the states s^F and t^F reached from the initial decoupled state by applying the center actions $c_0 \rightarrow c_1^A$ and $c_0 \rightarrow c_1^B$, respectively. Then, $prices[s^F](l_1^A) = 1$ and $prices[s^F](l_1^{A2}) = 2$, $prices[t^F](l_1^B) = 1$ and $prices[t^F](l_1^{B2}) = 2$. The initial state has price 0 and other leaf states ∞ . In this case, $s \not\preceq_S t$ (nor $t \not\preceq_S s$) because $prices(s^F)[l_1^A] = 1 < \min_{s^L \preceq^L t^L} prices(t^F)[t^L] = 2$.

Finally, by using \preceq_{ES} , the decoupled state space is polynomial in n . Since $l_i^{A2} \preceq^L l_i^{B2}$ and $l_i^{B2} \preceq^L l_i^{A2}$, $ESprices(t^F)[l_i^{A2}] = ESprices(t^F)[l_i^{B2}]$. Hence, since the only transitions from l_i^A and l_i^B go to l_i^{A2} and l_i^{B2} , $ESprices(t^F)[l_i^A] = ESprices(t^F)[l_i^B] = ESprices(t^F)[l_i^{A2}] - 1$. Therefore, the number of different states according to \preceq_{ES} is polynomial in n . \square

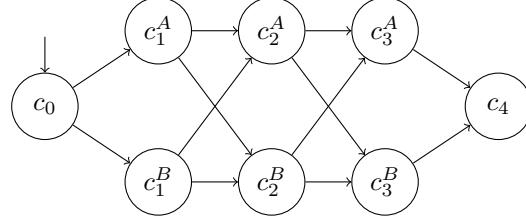
Theorem 9 \preceq_S is exponentially separated from \preceq_E , and therefore also from \preceq_F . \preceq_F , and therefore also \preceq_E , is exponentially separated from \preceq_S .

Proof: First, we prove that \preceq_F can be exponentially better than \preceq_S . Consider the following planning task, in which we have a single center variable c (see Figure 3a) with domain c_1, \dots, c_n , and c_i^A, c_i^B for $i \in [1, \dots, n-1]$, arranged such that we can move from c_i to c_i^X , and from c_i^X to c_{i+1} ($X \in \{A, B\}$). The initial value is c_1 .

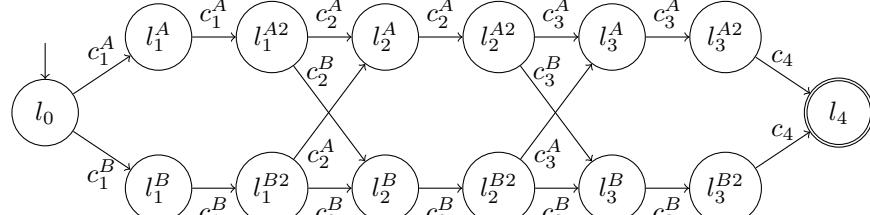
We have a single leaf variable l with values l_0, \dots, l_n , and $l_i^A, l_i^B, l_i^{A2}, l_i^{B2}$ for $i \in [1, \dots, n-1]$ with initial value l_0 and goal value l_n . The transitions are depicted in Figure 3b:

- From l_0 to l_1^X under center precondition c_1^X for $X \in \{A, B\}$.
- From l_{n-1}^{X2} to l_n under center precondition c_n^X for $X \in \{A, B\}$.
- From each l_i^X to l_i^{Y2} under center precondition c_i^X for $i \in [1, \dots, n-1]$, and $X, Y \in \{A, B\}$.
- From each l_i^{X2} to l_{i+1}^X under center precondition c_{i+1}^X (for $i \in [1, \dots, n-1]$ and $X \in \{A, B\}$).

In this example, the coarsest simulation relation consist only of $s^L \preceq^L s_G^L$ for all s^L . $a_i \not\preceq b_i$ because the center preconditions of their transitions are different. Note that



(a) Center factor



(b) Leaf factor

Figure 2: Illustrative example in which \preceq_{ES} is exponentially better than $\preceq_S + \preceq_E$ for $n = 3$

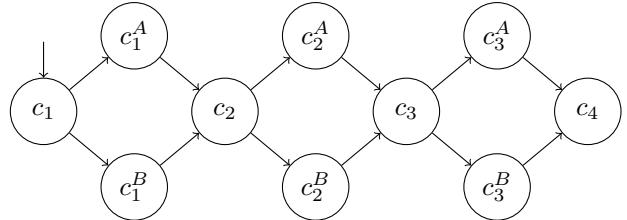
$l_i^A \not\preceq l_i^{A2}$ because $l_i^A \xrightarrow{c_i^A} l_{i+1}^{B2}$ and l_i^{A2} does not have any outgoing transition labeled with c_i^A . l_i^{A2} and l_i^{B2} are always reached at the same time, either via l_i^A or l_i^B . The pricing function remembers whether l_i^A or l_i^B was used and, hence, there are an exponential number of decoupled states with the same center state, even when using \preceq_S pruning.

However, every time l_i^A or l_i^B are reached, the center precondition c_i^A or c_i^B must be satisfied. Both l_i^{A2} and l_i^{B2} have always a price of $\text{prices}(s^F)[l_i^{A2}] = \text{prices}(s^F)[l_i^{B2}] \leq \text{prices}(s^F)[l_i^X] + 1$ for $X \in \{A, B\}$. Therefore, $l_i^A, l_i^B \notin F(\text{prices}(s^F))$ for all s^F and i . Since $\text{prices}(s^F)[l_i^{A2}] = \text{prices}(s^F)[l_i^{B2}]$, there are only a polynomial number of decoupled states when using dominance pruning with \preceq_F .

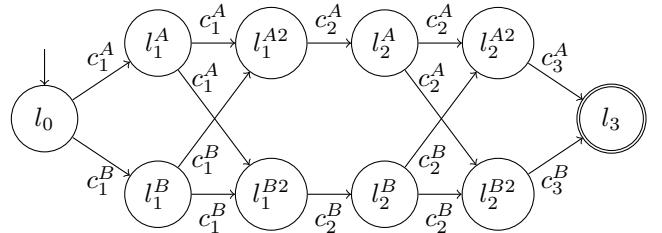
Next, we show that decoupled search with \preceq_S can be exponentially better than decoupled search with \preceq_E . Consider a planning task with the same center variable as our previous example. We have a single leaf variable l with values l_0, \dots, l_n , with initial value l_0 and goal value l_n . The transitions of the leaf l are depicted in Figure 3c. l has transitions from l_0 to l_1 without any center precondition, from l_0 to l_i under center precondition c_i^A for $i \in [2, n-1]$ and from l_i to l_n under center precondition c_n for $i \in [1, n-1]$.

In this example, decoupled search with \preceq_B expands an exponential number of states with the same center state because the pricing function remembers whether c_i^A was traversed or not for each $i \in [2, \dots, n-1]$. Both \preceq_F and \preceq_E cannot reduce the size of the decoupled state space in this example, because l_n is only reached under center precondition c_n , so $l_i \in F(s^F)$ for all $0 < i < n$ and $cs(s^F) \neq c_n$.

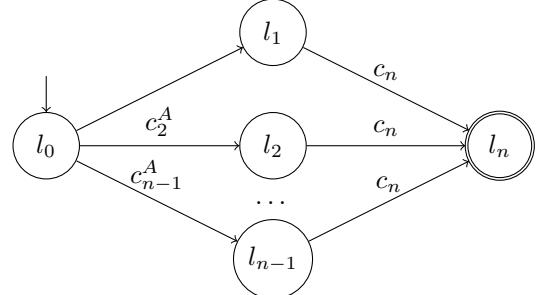
However, since all l_i for $i \in [1, n-1]$ have the same outgoing transitions, $l_i \preceq^L l_1$ for all $i \in [0, n-1]$. As the transition from l_0 to l_1 has no center precondition, $\text{prices}(s^F)[l_1] = 1$ for any s^F . Therefore, $\min_{l_i \preceq^L l_1} \text{prices}(s^F)[l_i] = 1$ for $i \in [1, n-1]$. Hence, the number of different decoupled states with \preceq_S is polynomial in n . \square



(a) Center factor



(b) Leaf factor where \preceq_F is exponentially better than \preceq_S .



(c) Leaf factor where \preceq_S is exponentially better than \preceq_E .

Figure 3: Exponential separations example for $n = 3$.