Sequencing Operator Counts with State-Space Search

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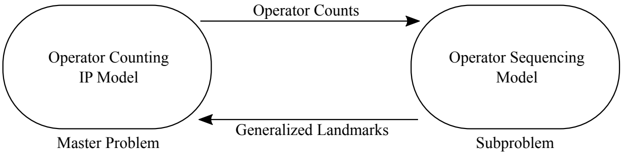

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- Otherwise, *OpSeq* uses **assumptions** to generate a constraint.

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- This approach generates smaller and more informed constraints;
- Improves from advancements in planning research.

Constraint Generation Rule

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$$L = \{\, [Y_o \geq \mathcal{C}(o) + 1] \mid \exists s \xrightarrow{o} s' : f(s') \leq f_{\max} \wedge \\ ((v_o \notin vars(s) \wedge c(o) > 0) \vee s(v_o) = 0)\}.$$

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Constraint Generation Strategy Example

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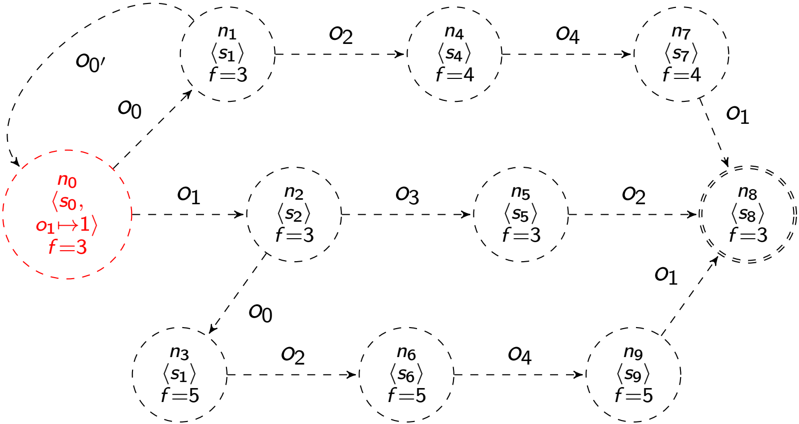

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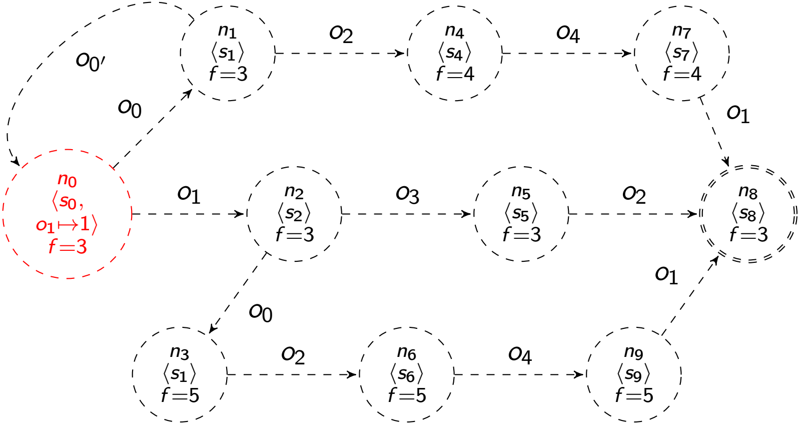

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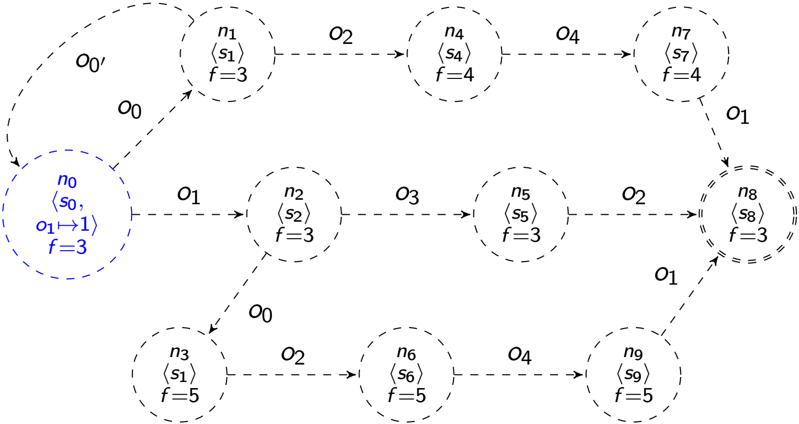

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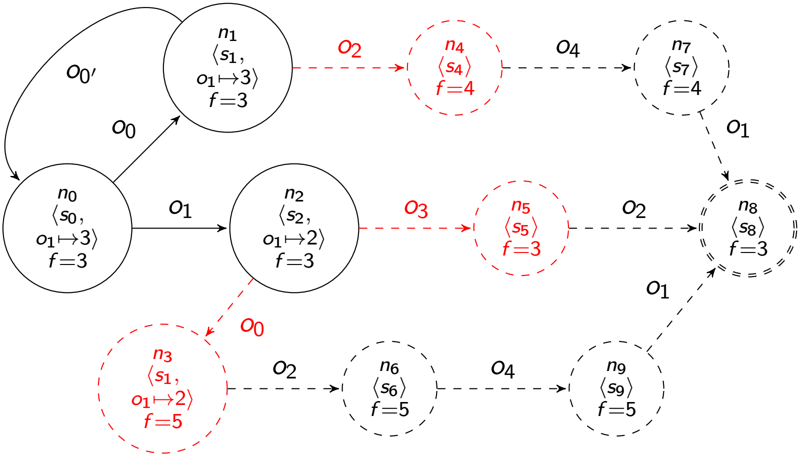

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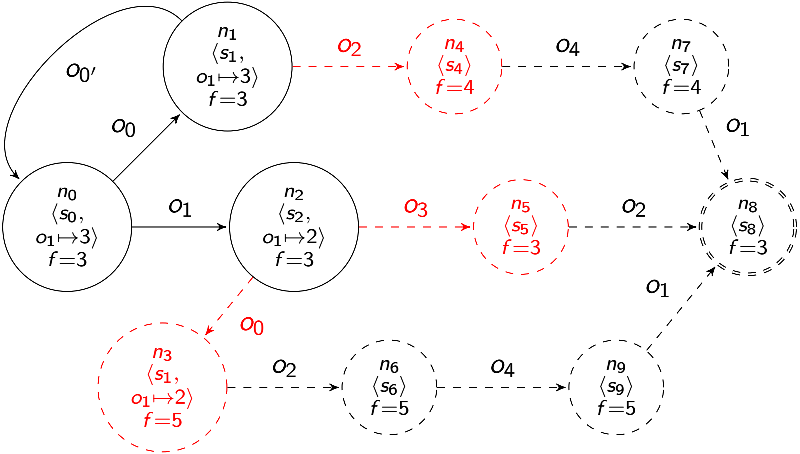

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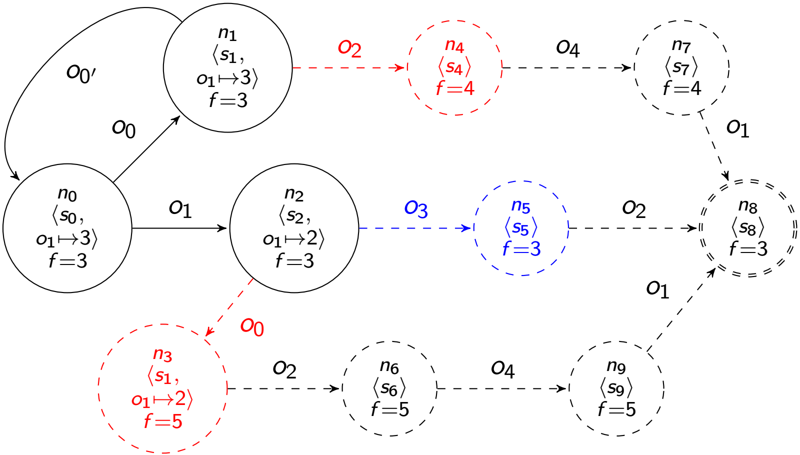

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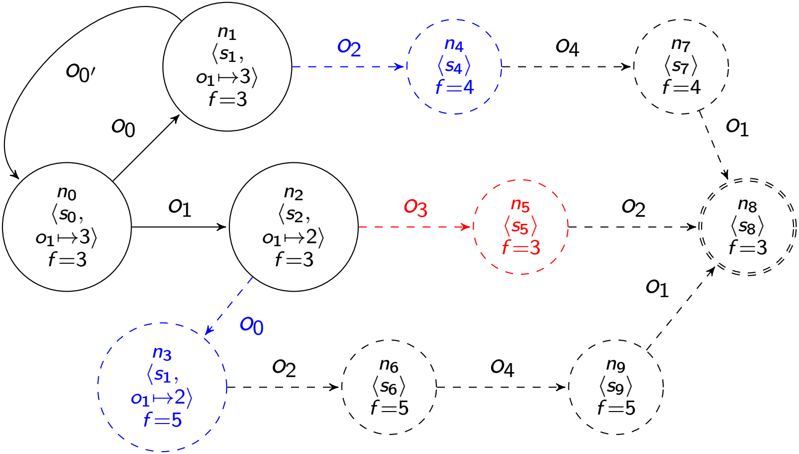

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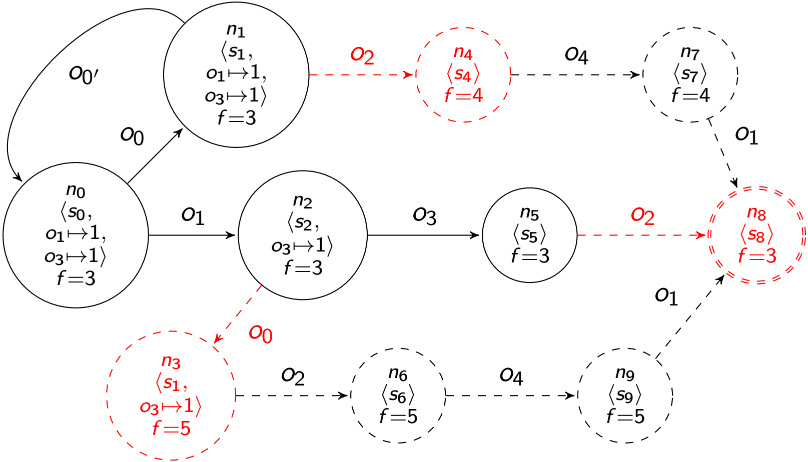

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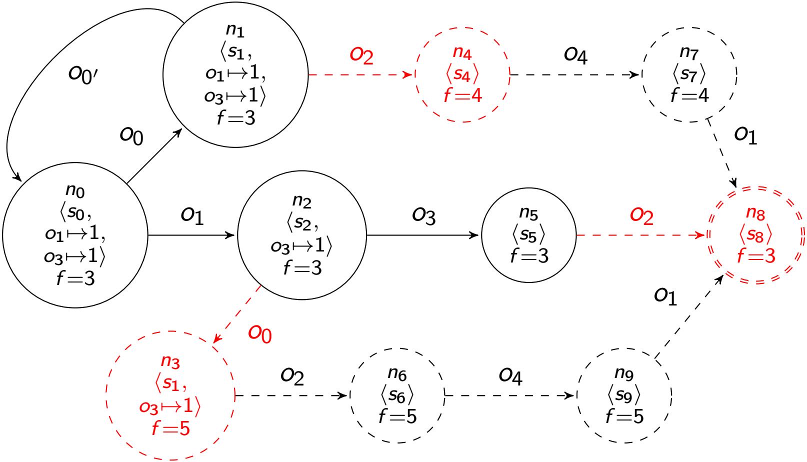

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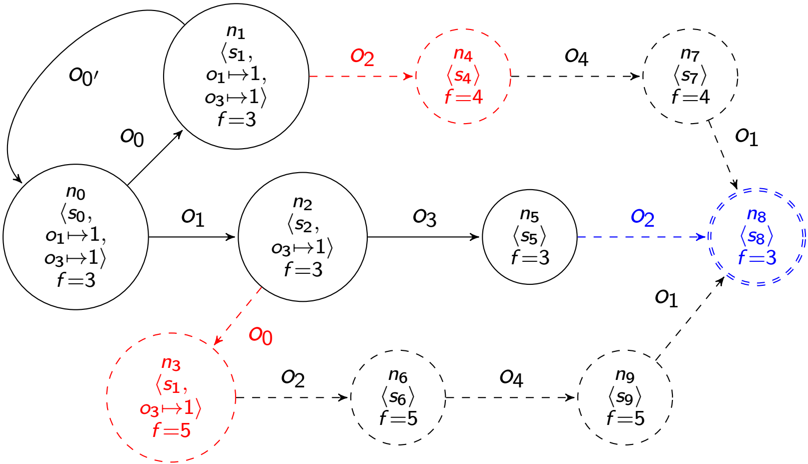

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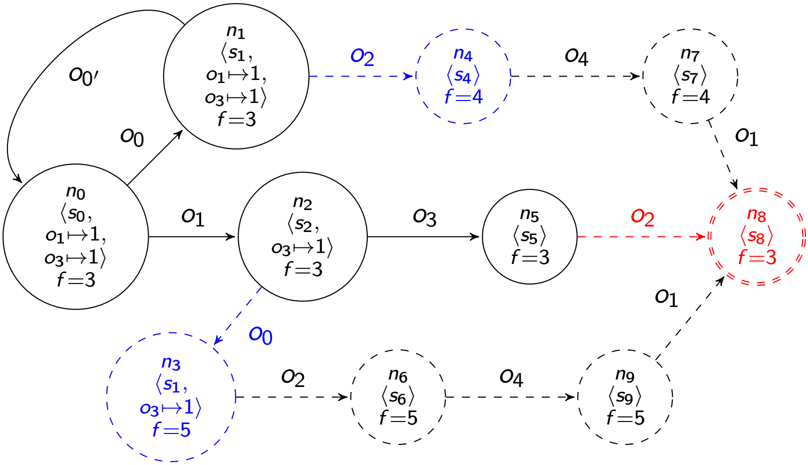

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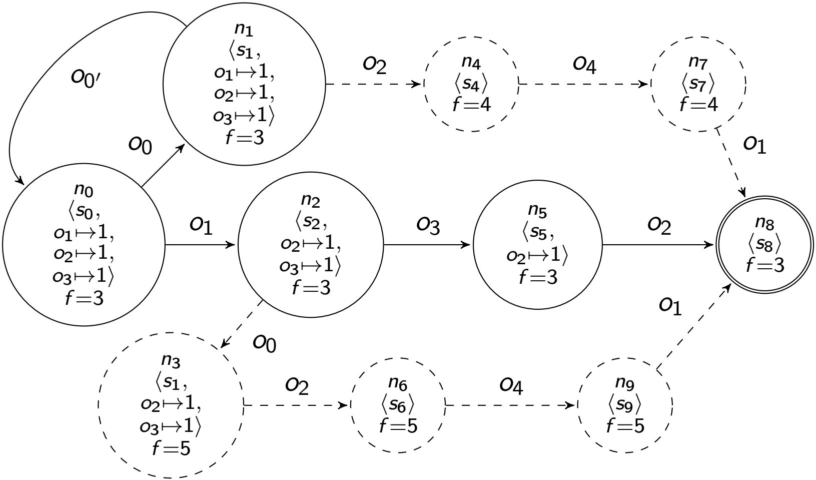

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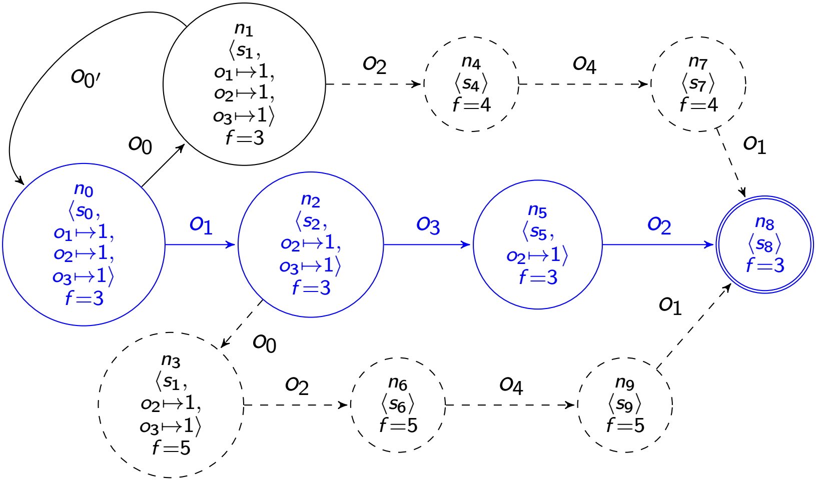

Plan: $\langle o_1, o_3, o_2 \rangle$.

Theorem

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Theorem 1. *For a solvable SAS^+ planning task Π, an operator counts $\mathcal{C}_s$ with an associated f-bound value f_{max}, such that OpSearch's modified A^* with an admissible heuristic function h cannot sequence $\mathcal{C}_s$, OpSearch always returns an admissible constraint to the master integer program.*

Results

OpSearch is Better than OpSeq

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OpSearch Improves with Better Heuristics

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As a more informed heuristic is used by *OpSearch*, **the number of subproblems solved, the memory usage and the size of the generated constraints decrease and the number of solved tasks increases**.

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- Also in *agile planning* to solve planning tasks for which informative heuristics are already known;
- Another practical application of our approach is for *diverse planning*, used for example by IBM, that aims to find several plans while guaranteeing diversity.

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- It is a novel research problem with great potential of development in both areas of *operations research* and *artificial intelligence*.

Thanks!

Wesley Luciano Kaizer
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References I

Davies, T. O., Pearce, A. R., Stuckey, P. J., and Lipovetzky, N. (2015).
Sequencing operator counts.
In *International Conference on Automated Planning and Scheduling*, pages 61–69.