

Planning and Optimization

D4. Operator Counting

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Operator-counting Framework

Reminder: Optimal Cost Partitioning for Landmarks

Variables

Occurrences_{*o*} for each operator *o*

Objective

Minimize $\sum_o \text{Occurrences}_o \cdot \text{cost}(o)$

Subject to

$$\sum_{o \in L} \text{Occurrences}_o \geq 1 \text{ for all landmarks } L$$

$$\text{Occurrences}_o \geq 0 \text{ for all operators } o$$

Numbers of operator occurrences in any plan satisfy constraints.
Minimizing the total plan cost gives an admissible estimate.

Can we apply this idea more generally?

Operator Counting

Operator-counting Constraints

- **linear constraints** whose variables denote **number of occurrences** of a given operator
- must be satisfied by every plan

Examples:

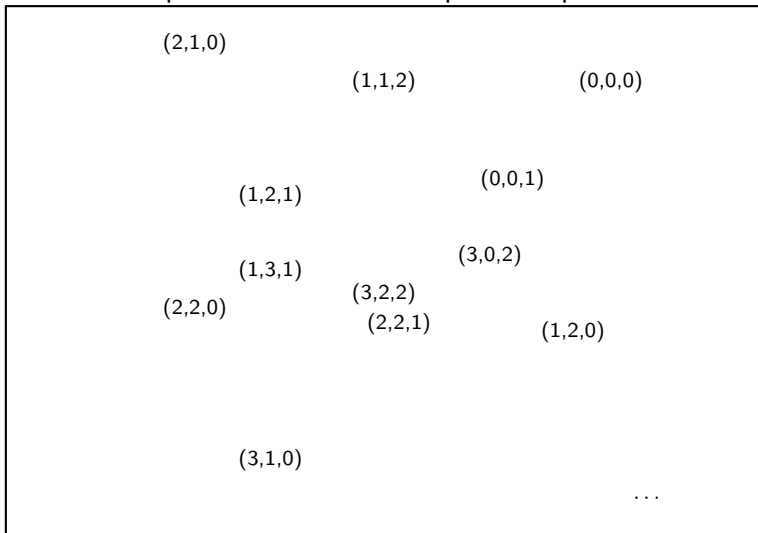
- $Y_{o_1} + Y_{o_2} \geq 1$ “must use o_1 or o_2 at least once”
- $Y_{o_1} - Y_{o_3} \leq 0$ “cannot use o_1 more often than o_3 ”

Motivation:

- declarative way to **represent knowledge** about solutions
- allows **reasoning about solutions** to derive heuristic estimates

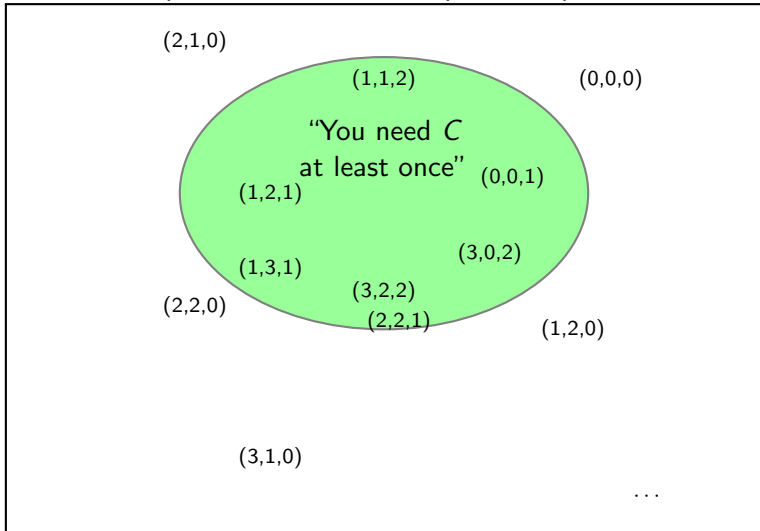
Operator Counting Heuristics

Operator occurrences in potential plans



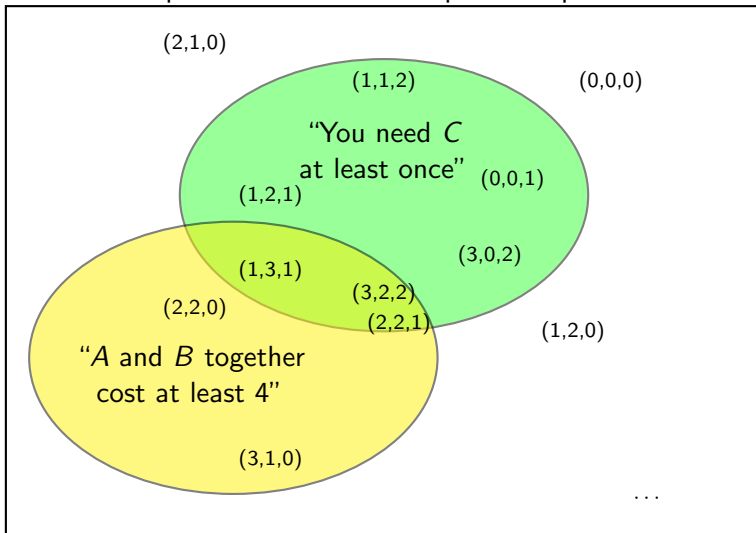
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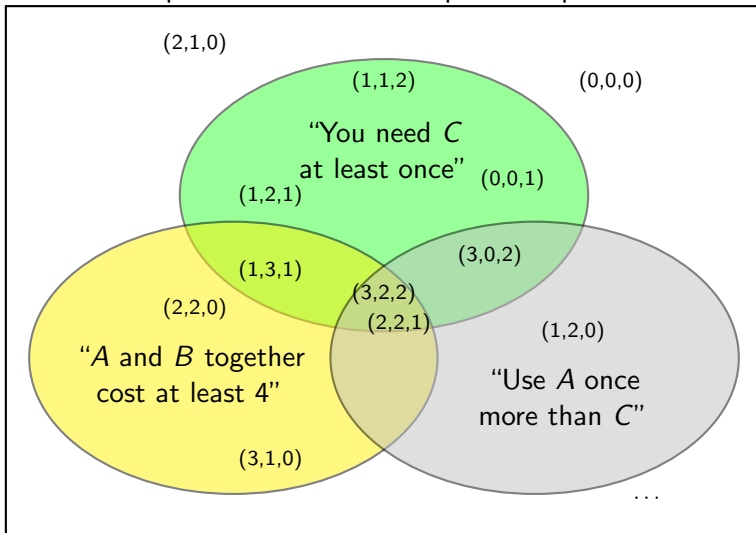
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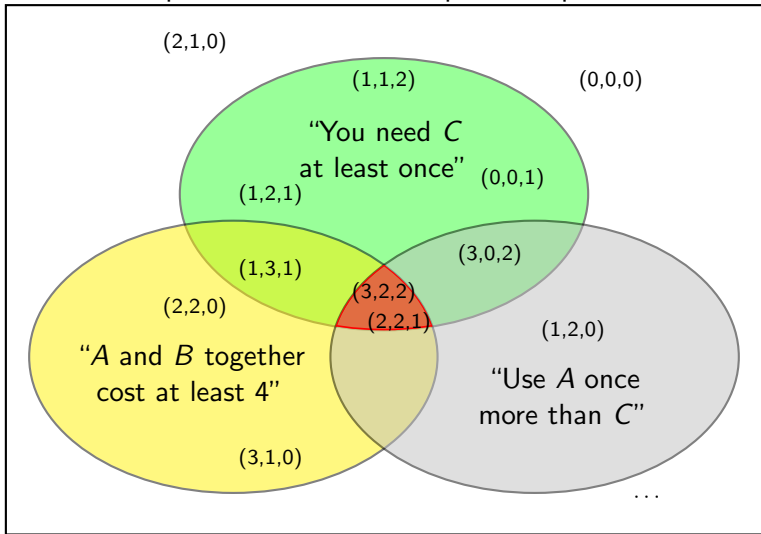
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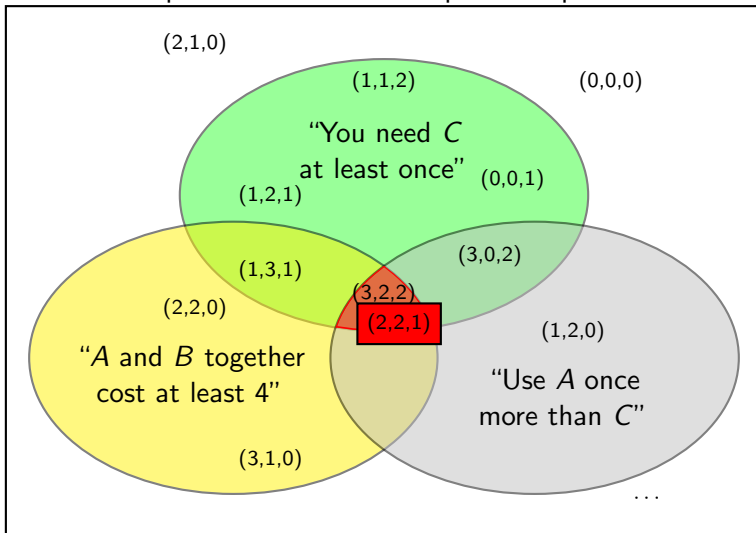
Operator Counting Heuristics

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Operator Counting Heuristics

Operator occurrences in potential plans



Operator-counting Constraint

Definition (Operator-counting Constraints)

Let Π be a planning task with operators O and let s be a state. Let \mathcal{Y} be the set of integer variables Y_o for each $o \in O$.

A linear inequality over \mathcal{Y} is called an **operator-counting constraint** for s if for every plan π for s setting each Y_o to the number of occurrences of o in π is a feasible variable assignment.

Operator-counting Heuristics

Definition (Operator-counting IP/LP Heuristic)

The operator-counting integer program IP_C for a set C of operator-counting constraints for state s is

$$\text{Minimize } \sum_{o \in O} Y_o \cdot \text{cost}(o) \text{ subject to}$$
$$C \text{ and } Y_o \geq 0 \text{ for all } o \in O,$$

where o is the set of operators.

The **IP heuristic** h_C^{IP} is the objective value of IP_C , the **LP heuristic** h_C^{LP} is the objective value of its LP-relaxation. If the LP/IP is infeasible, the heuristic estimate is ∞ .

Admissibility

Theorem (Operator-counting Heuristics are Admissible)

*The IP and the LP heuristic are **admissible**.*

Proof.

Let C be a set of operator-counting constraints for state s and π be an optimal plan for s . The number of operator occurrences of π are a feasible solution for C . As the IP/LP minimizes the total plan cost, the objective value cannot exceed the cost of π and is therefore an admissible estimate. □

Dominance

Theorem

Let C and C' be operator-counting constraints for s and let $C \subseteq C'$. Then $IP_C \leq IP_{C'}$ and $LP_C \leq LP_{C'}$.

Proof.

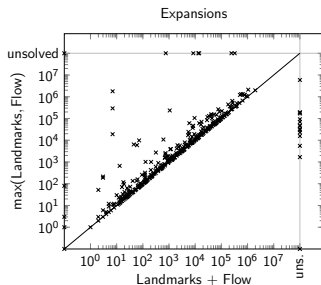
Every feasible solution of C' is also feasible for C . As the LP/IP is a minimization problem, the objective value subject to C can therefore not be larger than the one subject to C' . □

Adding more constraints can only improve the heuristic estimate.

Combining Heuristics

Combination of two heuristics

- Use both operator-counting constraints
- Combination always **dominates individual heuristics**
- **Positive interaction** between constraints



Combination often better than best individual heuristic

Constraints from Disjunctive Action Landmarks

Optimal cost partitioning for disjunctive action landmarks

- Use one landmark constraint per landmark

Landmark constraint for landmark L

$$\sum_{o \in L} Y_o \geq 1$$

Constraints from Flow Heuristic

Flow heuristic

- Use one flow constraint per atom

Flow Constraint for atom a

$$[a \in s] + \sum_{o \in O: a \in \text{eff}(o)} Y_o = [a \in \gamma] + \sum_{o \in O: a \in \text{pre}(o)} Y_o$$

Remark: Assumes transition normal form (not a limitation)

Constraints from Post-hoc Optimization Heuristic

Post-hoc optimization heuristic

- In chapter D3: X_o for cost incurred by operator o
- Replace each such variable with $Y_o \cdot cost(o)$ to fit the operator-counting framework.
- Use one post-hoc optimization constraint per sub-heuristic

Post-hoc optimization constraint for heuristic h

$$\sum_{o \text{ is relevant for } h} Y_o \cdot cost(o) \geq h(s)$$

Further Examples?

- The definition of operator-counting constraints can be extended to groups of constraints and auxiliary variables.
- With this extended definition we could also cover
 - optimal cost partitioning for abstractions, and
 - the perfect relaxation heuristic h^+ .

Connection to Cost Partitioning

Operator-counting Heuristics and General Cost Partitioning

Theorem

Combining *operator-counting heuristics* in one LP
is equivalent to
computing their *optimal general cost partitioning* (gOCP).

Proof idea: The linear programs are each others duals.

Use the Theorem to Combine Heuristics

- Easy way to **compute cost partitioning** of heuristics
 - LP can be **more compact** (variable elimination)
 - No need for one variable per operator and subproblem
- Even **better combination** of heuristics with **IP heuristic**
 - Considers that operator cannot be used 1.5 times
 - But computation is **no longer polynomial**

Use the Theorem to Analyze Heuristics

Analyze operator counting heuristics

- 1 **Group linear constraints** into sets of operator-counting constraints
- 2 Figure out what heuristic is computed with just **one such set**
- 3 Your original operator-counting heuristic computes the optimal general cost partition of those component heuristics

Use the Theorem to Analyze Heuristics

Analyze operator counting heuristics

Example: flow heuristic

- 1 **Group linear constraints** into sets of operator-counting constraints
- 2 Figure out what heuristic is computed with just **one such set**
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Use the Theorem to Analyze Heuristics

Analyze operator counting heuristics

Example: flow heuristic

- 1 **Group linear constraints** into sets of operator-counting constraints
 - One group of flow constraints per variable
- 2 Figure out what heuristic is computed with just **one such set**
- 3 Your original operator-counting heuristic computes the optimal general cost partition of those component heuristics

Use the Theorem to Analyze Heuristics

Analyze operator counting heuristics

Example: flow heuristic

- ① **Group linear constraints** into sets of operator-counting constraints
 - One group of flow constraints per variable
- ② Figure out what heuristic is computed with just **one such set**
 - Minimizing total cost while respecting flow in projection to one variable
 - Shortest path in projection
- ③ Your original operator-counting heuristic computes the optimal general cost partition of those component heuristics

Use the Theorem to Analyze Heuristics

Analyze operator counting heuristics

Example: flow heuristic

- 1 **Group linear constraints** into sets of operator-counting constraints
 - One group of flow constraints per variable
- 2 Figure out what heuristic is computed with just **one such set**
 - Minimizing total cost while respecting flow in projection to one variable
 - Shortest path in projection
- 3 Your original operator-counting heuristic computes the optimal general cost partition of those component heuristics
 - Flow heuristic = $gOCP(\text{atomic projection heuristics})$

Other Examples

What about the rest of our examples?

- Landmark constraints
 - gOCP(individual landmark heuristics)
- Post-hoc optimization heuristic
 - gOCP(heuristics that spend a minimum cost on relevant ops)
 - Also: cost partitioning over atomic projection heuristics
 - Operator costs not independent
 - Scale with one factor per projection

Summary

Summary

- Many heuristics can be formulated in terms of **operator-counting constraints**.
- The operator-counting heuristic framework allows to **combine the constraints** and to reason on the entire encoded declarative knowledge.
- The heuristic estimate for the combined constraints **can be better than the one of the best ingredient heuristic** but never worse.
- The combination into one operator-counting heuristic corresponds to the computation of the **optimal general cost partitioning for the ingredient heuristics**.

Literature (1)

References on the operator-counting framework:



Blai Bonet.

An Admissible Heuristic for SAS+ Planning Obtained from the State Equation.

Proc. IJCAI 2013, pp. 2268–2274, 2013.

Suggests combination of flow constraints and landmark constraints.



Tatsuya Imai and Alex Fukunaga.

A Practical, Integer-linear Programming Model for the Delete-relaxation in Cost-optimal Planning.

Proc. ECAI 2014, pp. 459–464, 2014.

IP formulation of h^+ .

Literature (2)



Florian Pommerening, Gabriele Röger, Malte Helmert and Blai Bonet.

LP-based Heuristics for Cost-optimal Planning.

Proc. ICAPS 2014, pp. 226–234, 2014.

Systematic introduction of operator-counting framework.



Florian Pommerening, Malte Helmert, Gabriele Röger and Jendrik Seipp.

From Non-Negative to General Operator Cost Partitioning.

Proc. AAAI 2015, pp. 3335–3341, 2015.

Relation to general cost partitioning.