

Lagrangian Decomposition for Optimal Cost Partitioning

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Structure

In this presentation

- context: cost partitioning in classical planning
- Lagrangian decomposition
 - simplified, specialized, ignoring assumptions
 - see paper for details
- relation to cost partitioning
- subgradient optimization
- algorithm to compute optimal cost partitioning
without an LP solver

Lagrangian Decomposition

Starting with a Linear Program

Problem P

$$\text{Min } c \ x \ \text{s.t.}$$

$$A_1 \ x \geq b_1$$

...

$$A_k \ x \geq b_k$$

$$x \geq 0$$

Starting with a Linear Program

Problem P

$$\text{Min } c \ x \ \text{s.t.}$$

$$A_1 \ x \geq b_1$$

...

$$A_k \ x \geq b_k$$

$$x \geq 0$$

rewrite \rightarrow

Problem P

$$\text{Min } c \ x \ \text{s.t.}$$

$$A_i \ x_i \geq b_i \quad \forall i$$

$$x = x_i \quad \forall i$$

$$x, x_i \geq 0 \quad \forall i$$

Lagrangian Relaxation

Problem P

Min c x s.t.

$$A_i x_i \geq b_i \quad \forall i$$

$$x = x_i \quad \forall i$$

$$x, x_i \geq 0 \quad \forall i$$

Lagrangian Relaxation

Problem P

$$\text{Min } c \ x \ \text{s.t.}$$

$$A_i \ x_i \geq b_i \quad \forall i$$

$$x = x_i \quad \forall i$$

$$x, x_i \geq 0 \quad \forall i$$

relax \rightarrow

Problem $P(\lambda)$

$$\text{Min } c \ x + \sum_i \lambda_i (x_i - x) \ \text{s.t.}$$

$$A_i \ x_i \geq b_i \quad \forall i$$

$$x, x_i \geq 0 \quad \forall i$$

- Penalty term λ_i for violating $x = x_i$
called Lagrangian multiplier

Lagrangian Relaxation

Problem P

Min c x s.t.

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relax \rightarrow

Problem $P(\lambda)$

Min c $x + \sum_i \lambda_i (x_i - x)$ s.t.

$$A_i x_i \geq b_i \quad \forall i$$

$$x, x_i \geq 0 \quad \forall i$$

- Penalty term λ_i for violating $x = x_i$
called **Lagrangian multiplier**
- for every choice of λ : $\text{value}(P(\lambda)) \leq \text{value}(P)$
- **Lagrangian dual problem**: find λ that gives best lower bound
- best lower bound is perfect here: $\text{Max}_{\lambda} P(\lambda) = \text{value}(P)$

Lagrangian Decomposition

Problem $P(\lambda)$

$$\text{Min } c x + \sum_i \lambda_i (x_i - x) \text{ s.t.}$$

$$A_i x_i \geq b_i \quad \forall i$$

$$x, x_i \geq 0 \quad \forall i$$

$P(\lambda)$ decomposes into independent subproblems $P(\lambda) = \sum_i P_i(\lambda)$

Problem $P_0(\lambda)$

$$\text{Min } \left(c - \sum_i \lambda_i \right) x \text{ s.t.}$$

$$x \geq 0$$

Problem $P_i(\lambda)$

$$\text{Min } \lambda_i x_i \text{ s.t.}$$

$$A_i x_i \geq b_i$$

$$x_i \geq 0$$

A closer look at $P_0(\lambda)$

Problem $P_0(\lambda)$

$$\text{Min } \left(c - \sum_i \lambda_i \right) x \text{ s.t.}$$
$$x \geq 0$$

- if all objective coefficients non-negative: $\text{value}(P_0(\lambda)) = 0$
- otherwise $P_0(\lambda)$ is unbounded

Constraint encoded by $P_0(\lambda)$

$$\sum_i \lambda_i \leq c$$

Relation to Cost Partitioning

Summarizing Lagrangian Decomposition

Original Problem P

$$\text{Min } c \ x \ \text{s.t.}$$

$$A_i \ x \geq b_i \quad \forall i$$

$$x \geq 0$$

Lagrangian Dual Problem

$$\text{Max } \sum_i P_i(\lambda) \ \text{s.t.}$$

$$\sum_i \lambda_i \leq c$$

Subproblem $P_i(\lambda)$

$$\text{Min } \lambda_i \ x_i \ \text{s.t.}$$

$$A_i \ x_i \geq b_i$$

$$x_i \geq 0$$

Cost Partitioning of Operator-Counting Heuristics

Heuristic h

Min $cost$ x s.t.

$$A_i x \geq b_i \quad \forall i$$

$$x \geq 0$$

Optimal Cost Partitioning

Max $\sum_i h_i(cost_i)$ s.t.

$$\sum_i cost_i \leq cost$$

Heuristic $h_i(cost_i)$

Min $cost_i$ x_i s.t.

$$A_i x_i \geq b_i$$

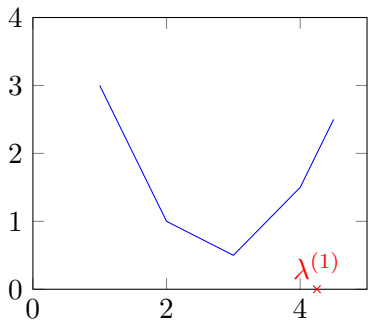
$$x_i \geq 0$$

How to Solve the Lagrangian Dual Problem

- Computing an optimal cost partitioning corresponds to solving the Lagrangian dual
- ... but how can we solve it?
- $P(\lambda)$ is concave and we want to maximize it
 \rightsquigarrow can use subgradient optimization

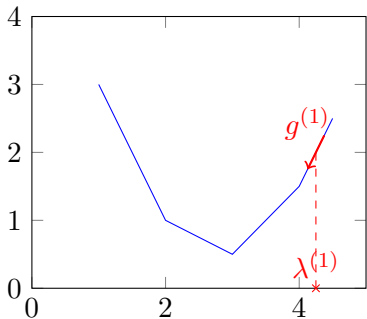
Subgradient Optimization

Subgradient Optimization



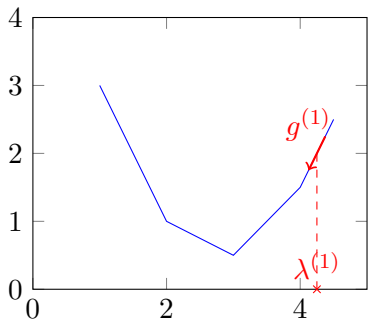
- choose point $\lambda^{(1)}$

Subgradient Optimization



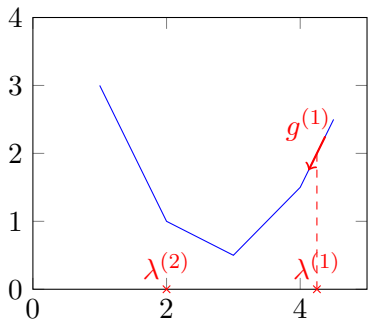
- choose point $\lambda^{(1)}$
- repeat for $t = 1, 2, \dots$
 - find subgradient $g^{(t)}$ at $\lambda^{(t)}$

Subgradient Optimization



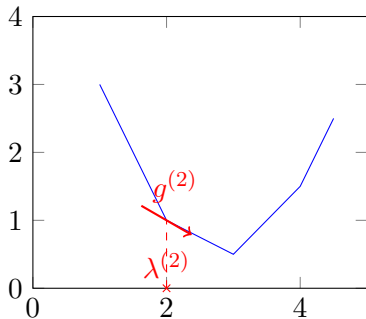
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 - compute step length $\eta(t)$

Subgradient Optimization



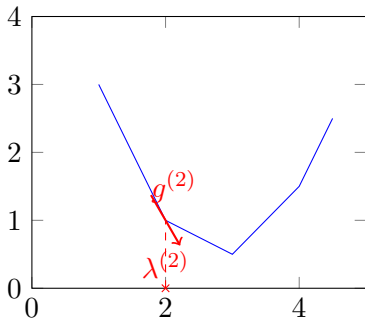
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- repeat for $t = 1, 2, \dots$
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 - compute **step length** $\eta^{(t)}$
 - set $\lambda^{(t+1)} = \lambda^{(t)} + \eta^{(t)}g^{(t)}$

Subgradient Optimization



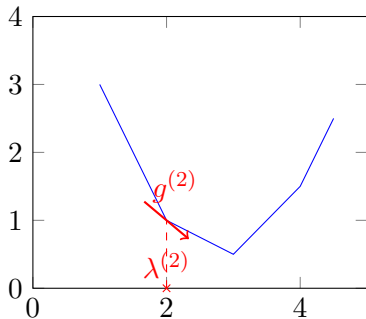
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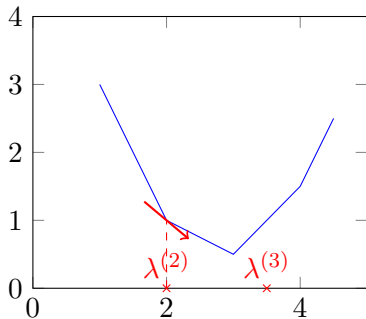
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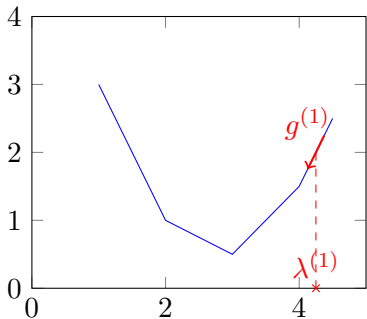
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Subgradient Optimization



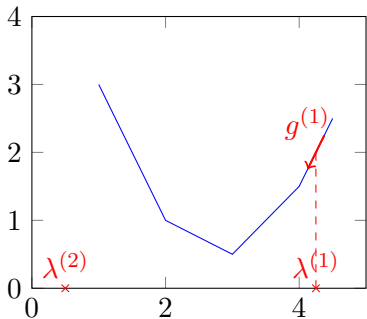
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Projected Subgradient Optimization



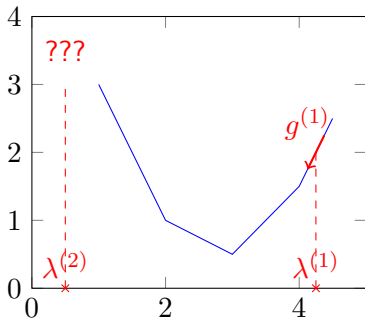
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Projected Subgradient Optimization



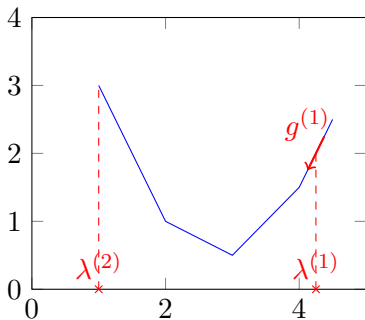
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Projected Subgradient Optimization



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Projected Subgradient Optimization



- choose point $\lambda^{(1)}$
- repeat for $t = 1, 2, \dots$
 - find subgradient $g^{(t)}$ at $\lambda^{(t)}$
 - compute step length $\eta(t)$
 - set $\lambda^{(t+1)} = \text{proj}((\lambda^{(t)} + \eta(t)g^{(t)})$

Application to Cost Partitioning over Abstractions

Subgradient Optimization for Cost Partitioning

Analogies in cost partitioning

- current point $\lambda^{(t)}$
- subgradient $g^{(t)}$
- projection

Subgradient Optimization for Cost Partitioning

Analogies in cost partitioning

- current point $\lambda^{(t)}$
 - current **cost functions** $cost_1, \dots, cost_k$
- subgradient $g^{(t)}$

- projection

Subgradient Optimization for Cost Partitioning

Analogies in cost partitioning

- current point $\lambda^{(t)}$
 - current **cost functions** $cost_1, \dots, cost_k$
- subgradient $g^{(t)}$
 - **optimal solutions of subproblems** $P_i(\lambda^{(t)})$
 - if subproblems are abstraction heuristics:
shortest paths in abstractions
- projection

Subgradient Optimization for Cost Partitioning

Analogies in cost partitioning

- current point $\lambda^{(t)}$
 - current **cost functions** $cost_1, \dots, cost_k$
- subgradient $g^{(t)}$
 - **optimal solutions of subproblems** $P_i(\lambda^{(t)})$
 - if subproblems are abstraction heuristics:
shortest paths in abstractions
- projection
 - project arbitrary set of cost functions to cost partitioning

Subgradient Optimization for Cost Partitioning

Anytime algorithm

- choose any cost partitioning $cost^{(1)}$
- repeat for $t = 1, 2 \dots$
 - for each abstraction i
 - find optimal solution π^* under $cost_i^{(t)}$
 - set $cost_i^{(t+1)}(o) = cost_i^{(t)}(o) + \eta(t)occurrences(o, \pi^*)$
 - project $cost^{(t+1)}$ to a cost partitioning

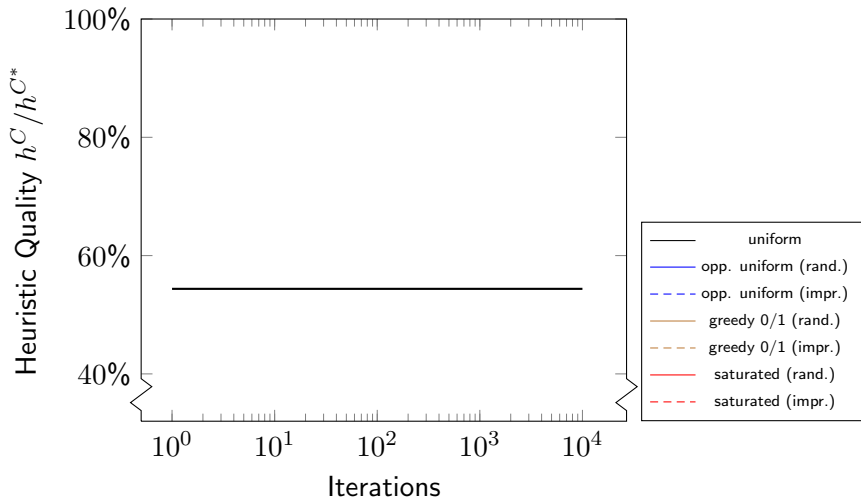
Experiments

Experiment Setup

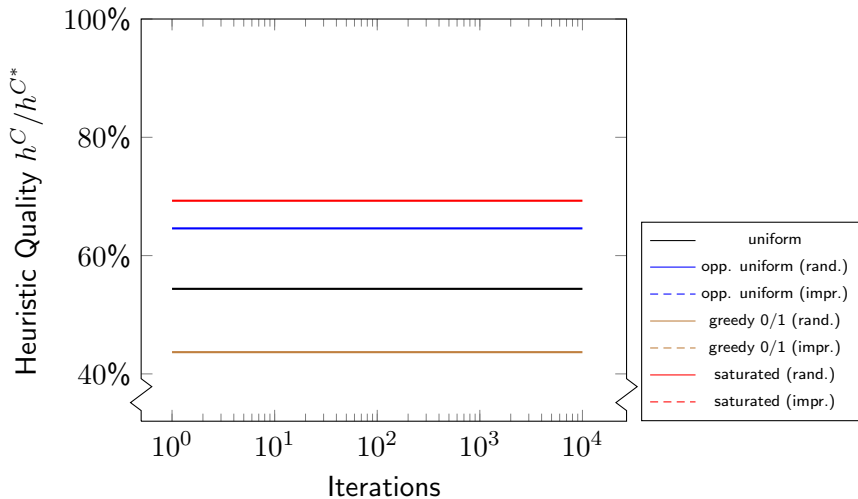
Experiment setup

- IPC instances from optimal tracks (1998–2018)
- projections to all interesting patterns up to size 2 (and 3)
- non-negative cost partitioning
 - no good way to project to general cost partitioning
- 300 s time limit, 2 GB memory limit
- heuristic values of initial states
- seeded with different cost partitioning methods
 - uniform
 - opportunistic uniform (random/improved order)
 - greedy zero-one (random/improved order)
 - saturated (random/improved order)

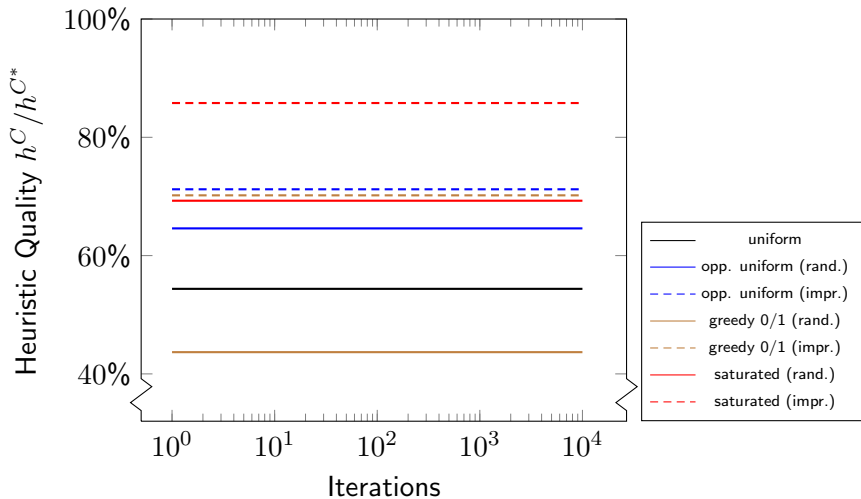
Heuristic Quality



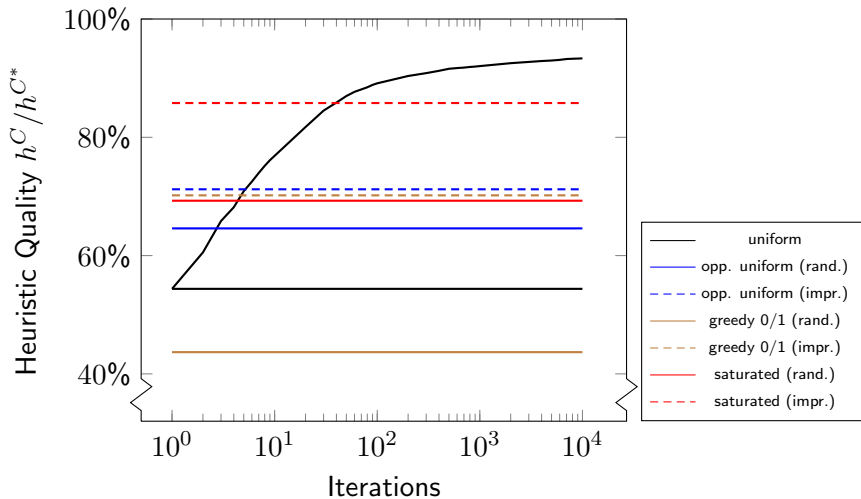
Heuristic Quality



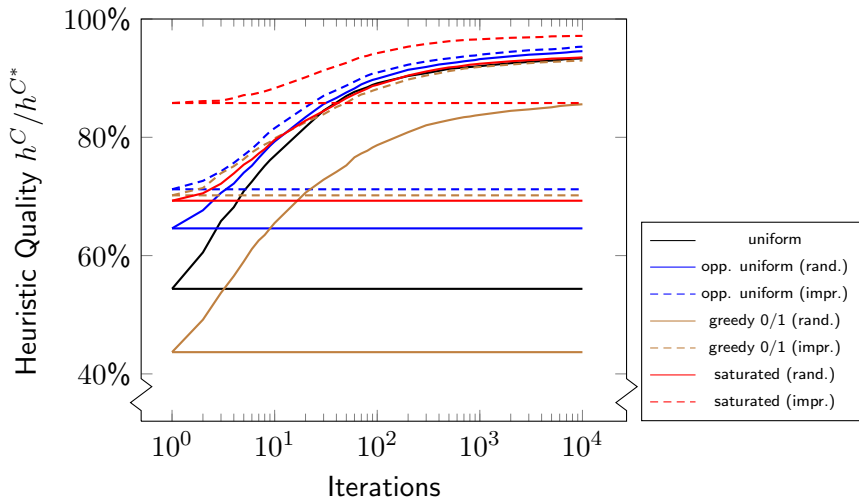
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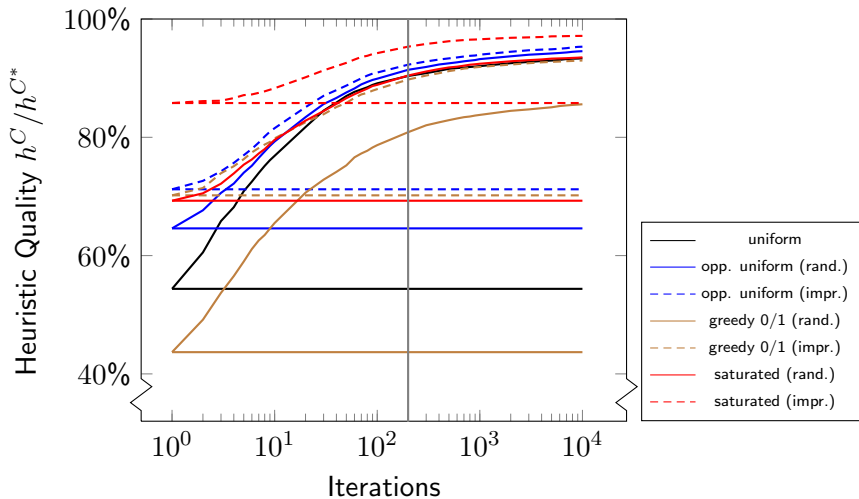
Heuristic Quality



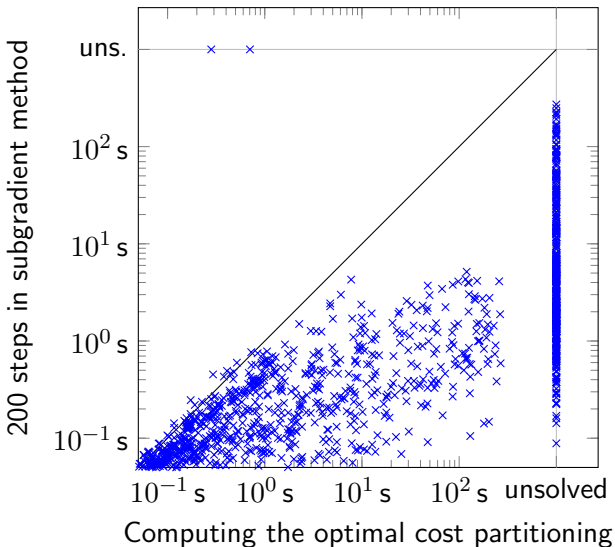
Heuristic Quality



Heuristic Quality



Runtime



Conclusion

Conclusion

Contributions to Cost Partitioning

- new interpretation as Lagrangian decomposition
- interesting relation to subgradient optimization
- anytime algorithm for suboptimal cost partitioning

Future Work

- techniques from subgradient optimization
 - better stopping conditions
 - dynamic step length functions
 - improved updates
- open questions
 - projection for general cost partitioning
 - consider highly different operator costs