State-Dependent Cost Partitionings for Cartesian Abstractions in Classical Planning

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September 28, 2016

KI 2016, Klagenfurt


The World of
Classical Planning

The World of **Classical Planning**

- Given:
  - Initial state
  - Goal
  - Actions
- Find: Plan from initial state to goal

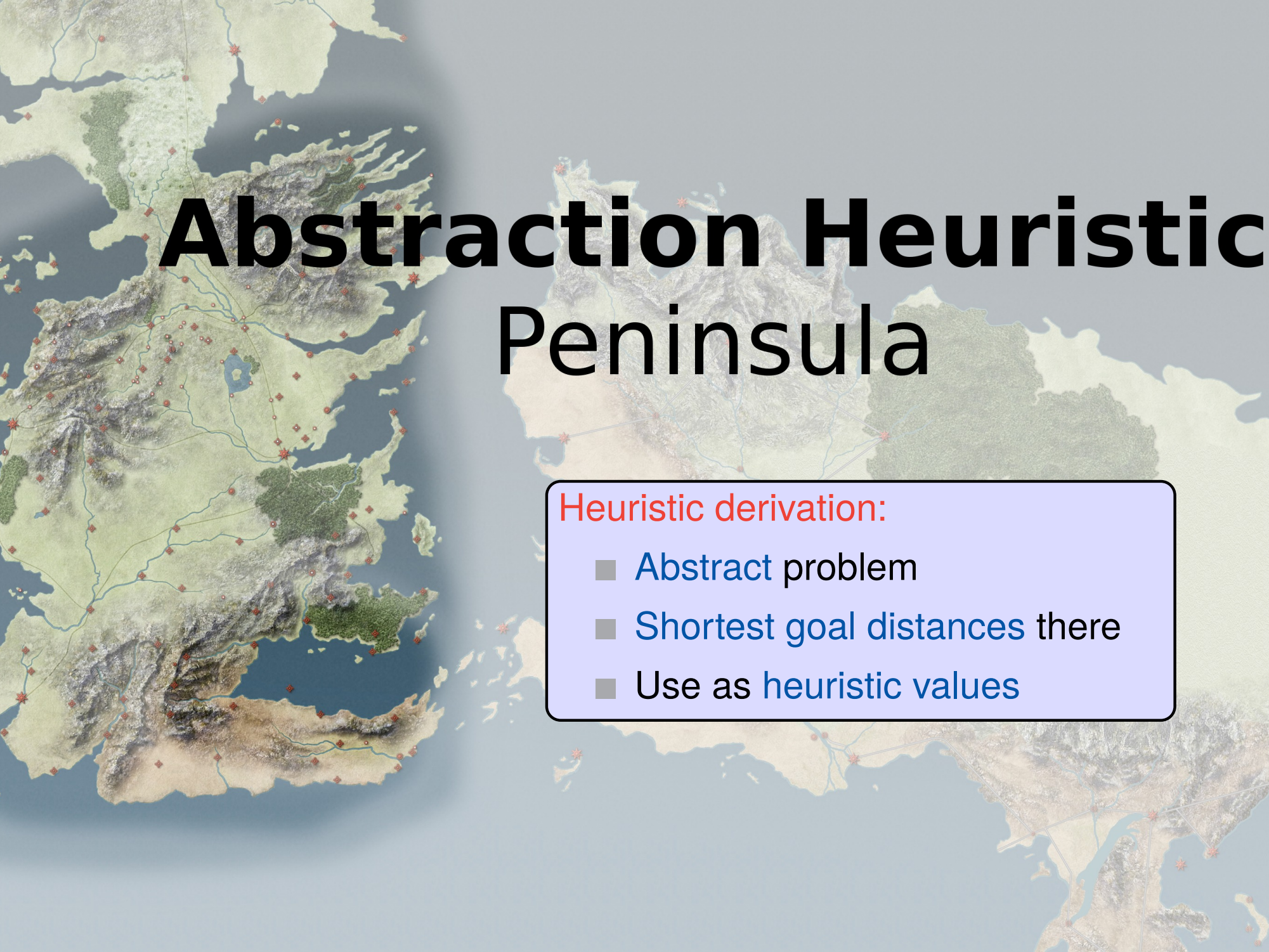

Planning as Heuristic
Search Continent

Planning as Heuristic Search Continent

Approach:

- State-space search for a plan
- Guided by a distance heuristic …
- …that is automatically derived


Abstraction Heuristic
Peninsula



Abstraction Heuristic
Peninsula

Heuristic derivation:

- Abstract problem
- Shortest goal distances there
- Use as heuristic values


Cost Partitioning
Bay

Cost Partitioning

Bay

- Challenge: single abstraction uninformative
- Solution: multiple abstractions

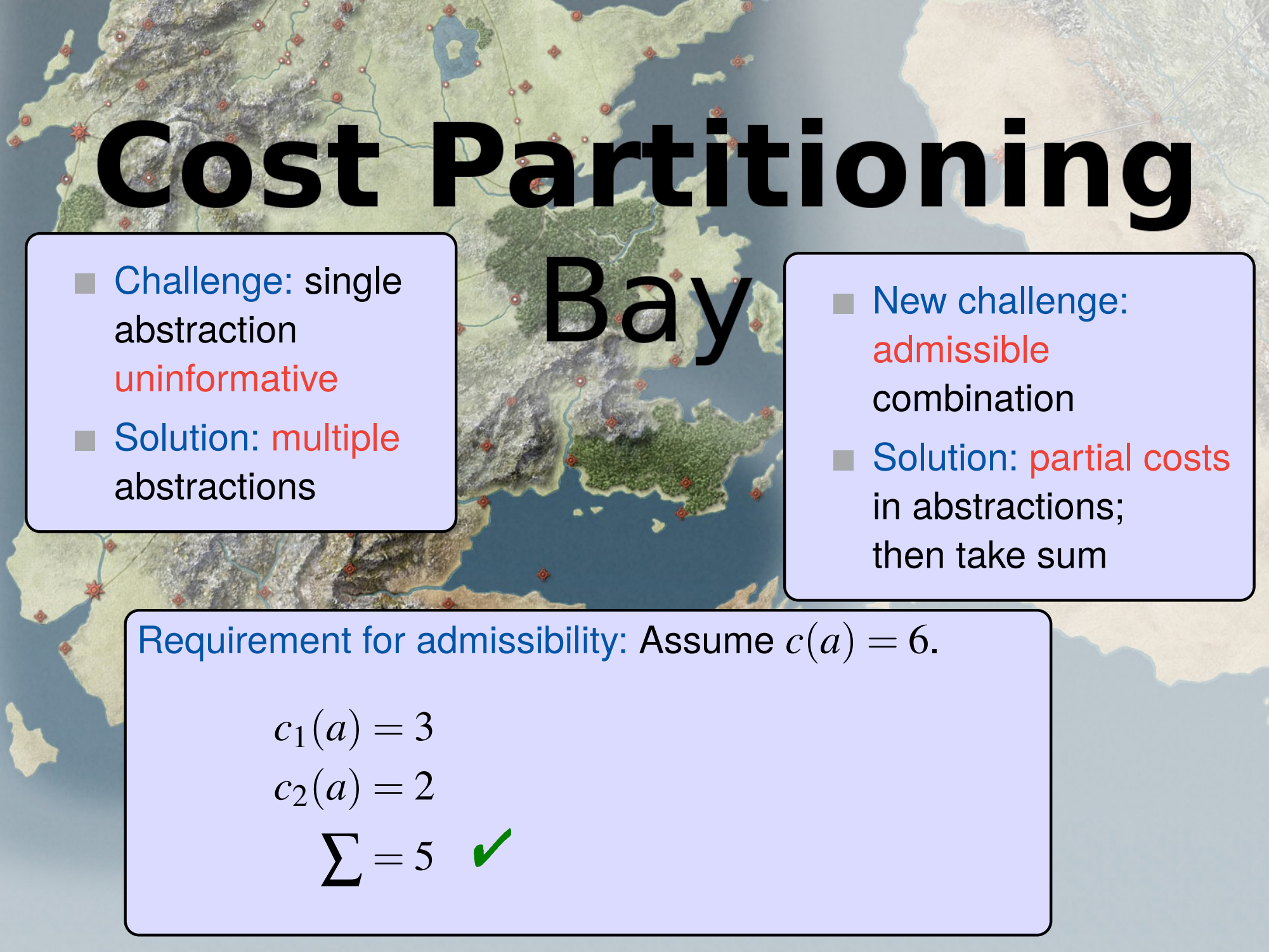
Cost Partitioning

Bay

- Challenge: single abstraction uninformative
- Solution: multiple abstractions

- New challenge: admissible combination
- Solution: partial costs in abstractions; then take sum

Cost Partitioning



- Challenge: single abstraction uninformative
- Solution: multiple abstractions

- New challenge: admissible combination
- Solution: partial costs in abstractions; then take sum

Requirement for admissibility: Assume $c(a) = 6$.

$$c_1(a) = 3$$
$$c_2(a) = 2$$
$$\sum = 5 \quad \checkmark$$

Cost Partitioning

Bay

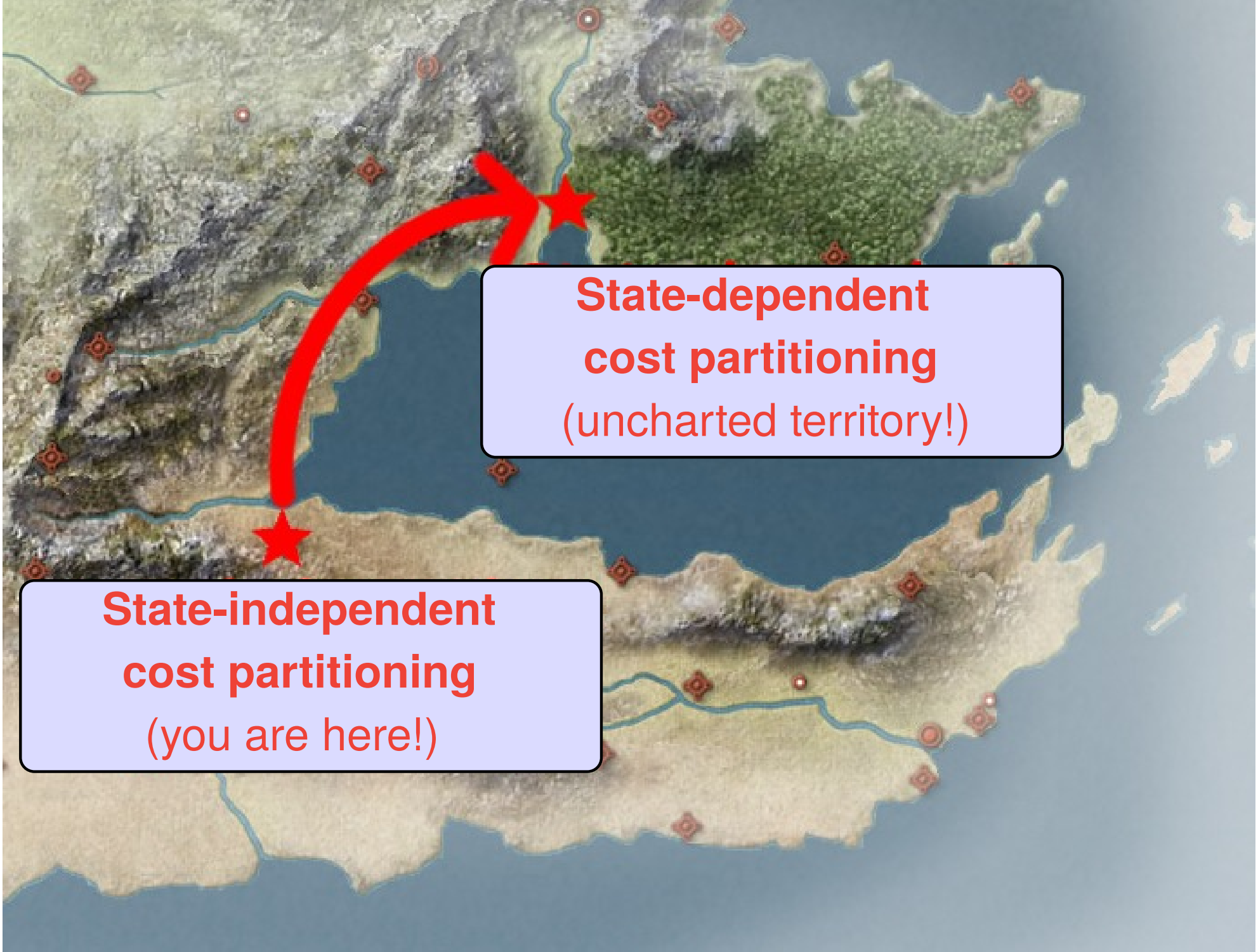
- Challenge: single abstraction uninformative
- Solution: multiple abstractions

- New challenge: admissible combination
- Solution: partial costs in abstractions; then take sum

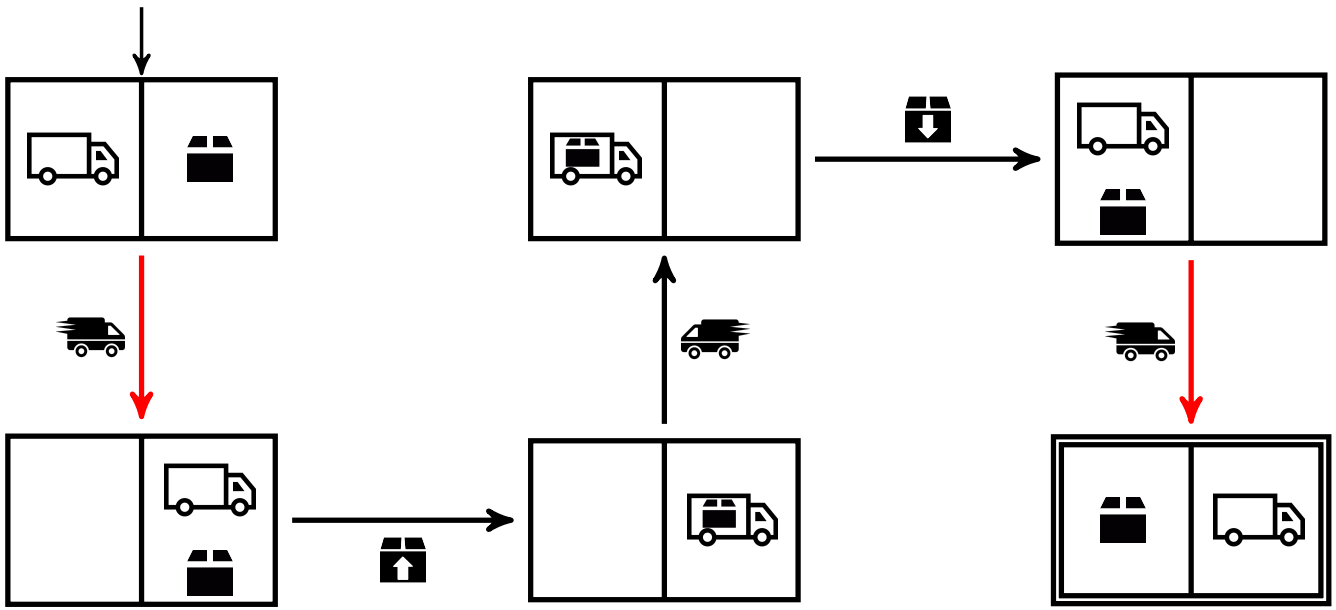
Requirement for admissibility: Assume $c(a) = 6$.

$c_1(a) = 3$
$c_2(a) = 2$
$\sum = 5$ ✔

$c_1(a) = 4$
$c_2(a) = 3$
$\sum = 7$ ✗


State-dependent
cost partitioning
(uncharted territory!)
State-independent
cost partitioning
(you are here!)

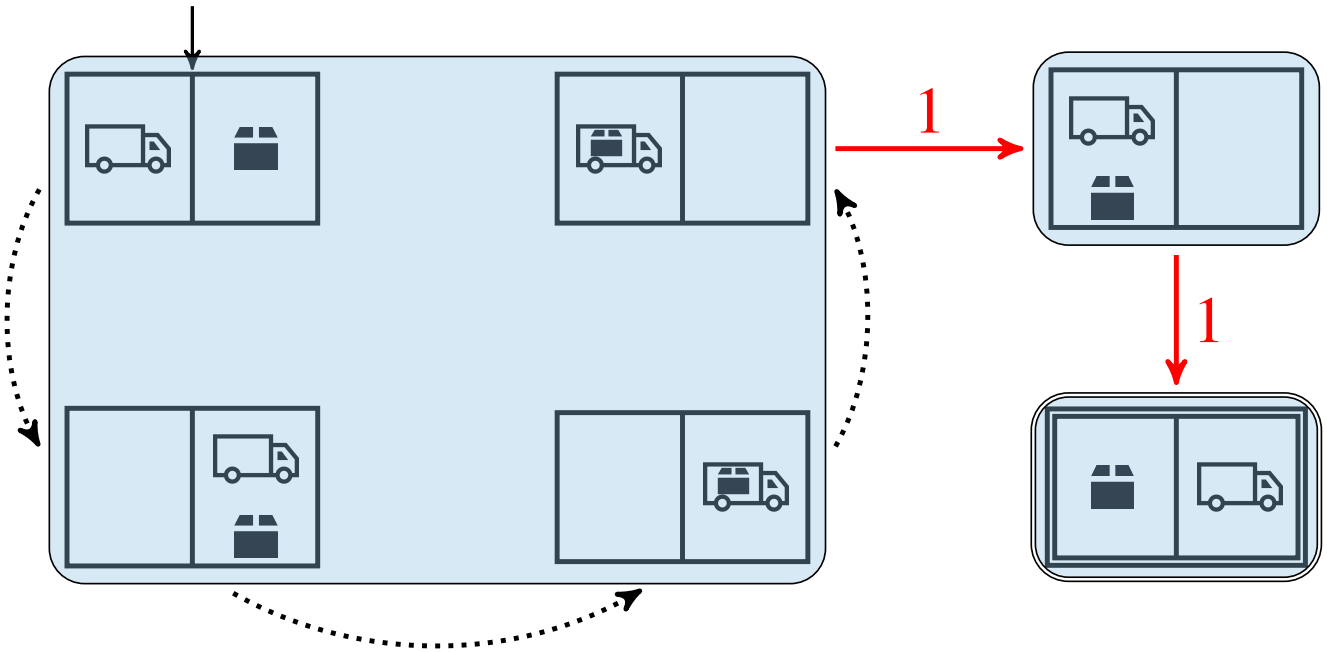
Running Example: Logistics Task



Cost of optimal plan: 5

Running Example: Logistics Task

Abstraction



Cost of abstract plan: 2

Cost Partitioning

A cost partitioning is a tuple $P = \langle c_1, \ldots, c_n \rangle$ where

- each $c_i : A \to \mathbb{R}$ is a cost function,
- sum of partial action costs bounded by original action cost

$$\sum_i c_i(a) \leq c(a) \qquad \text{for all } a \in A.$$

Theorem [Katz and Domshlak, 2010; Pommerening et al., 2015]

For admissible heuristics $h_1, \ldots, h_n$ and cost partitioning P, the cost partitioning heuristic $h^P(s) = \sum_i h_i(s, c_i)$ is admissible.

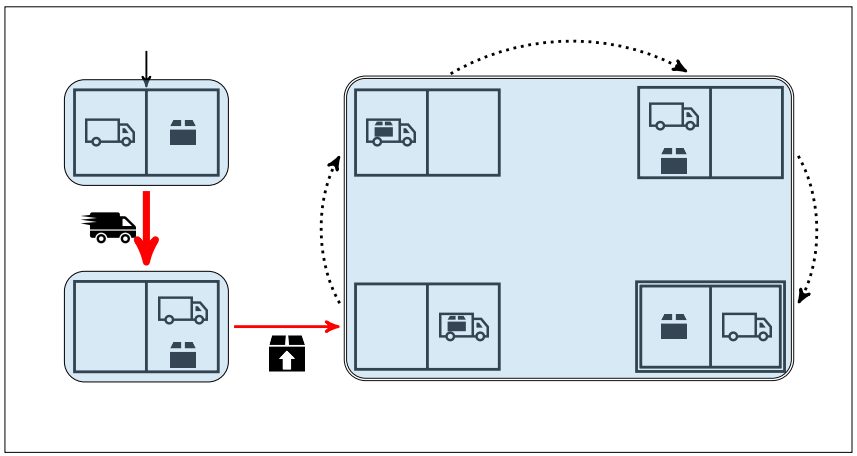
Optimal Cost Partitioning

An optimal cost partitioning for a state s is one which maximizes the heuristic estimate,

$$h^{ocp}(s) = \max_{P} \; h_P(s).$$

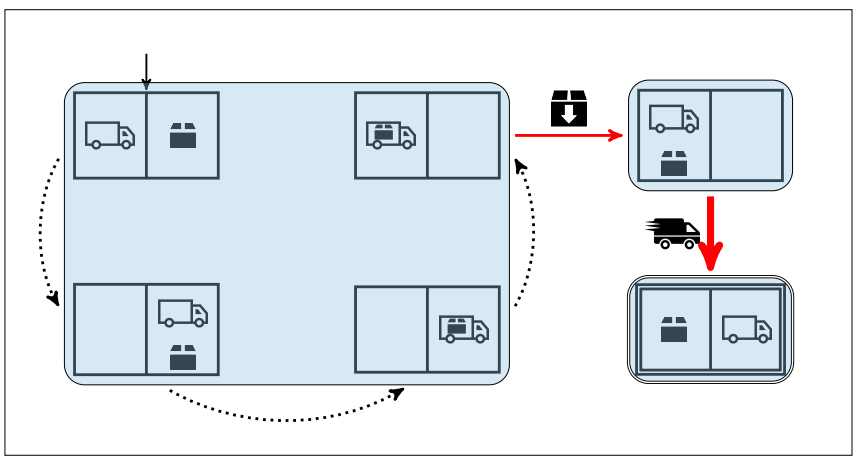
Running Example: Logistics Task

Optimal Cost Partitioning



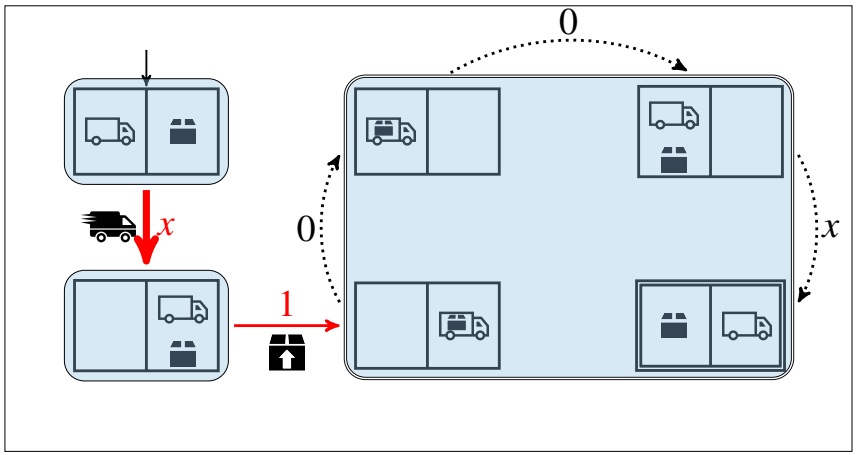
$$h_1(s_0) = c_1(\text{truck}) + c_1(\text{package})$$

$$h_2(s_0) = c_2(\text{package}) + c_2(\text{truck})$$



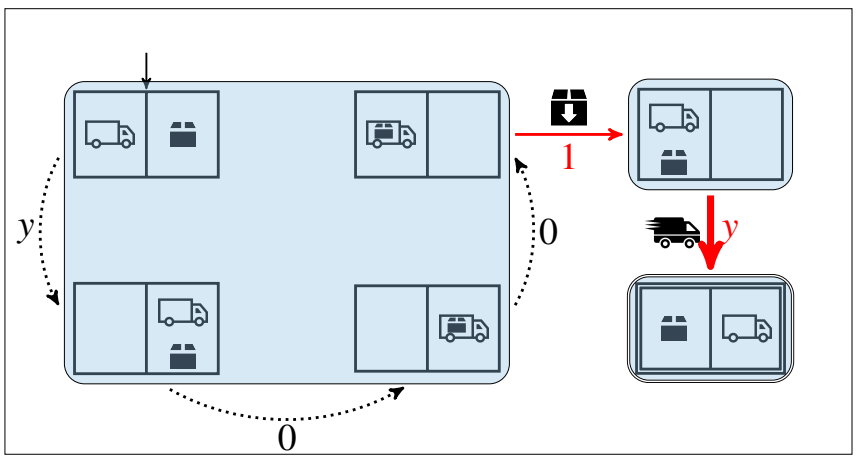
Running Example: Logistics Task

Optimal Cost Partitioning



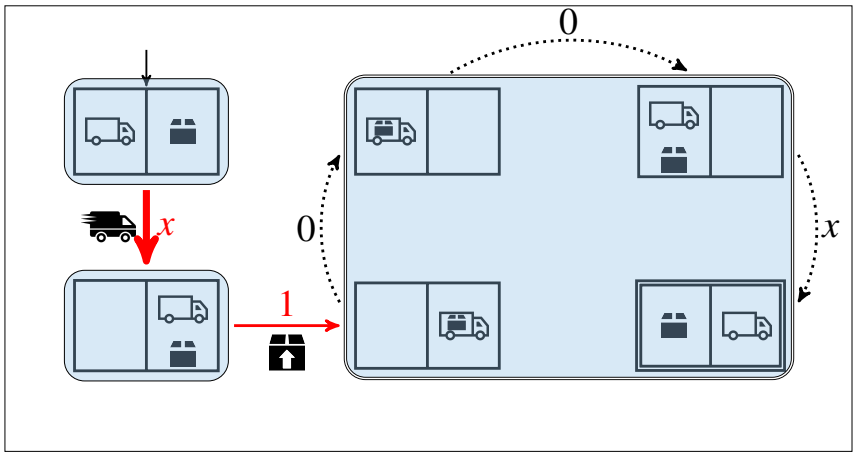
$$h_1(s_0) = c_1(\text{truck}) + c_1(\text{package})$$
$$h_2(s_0) = c_2(\text{package}) + c_2(\text{truck})$$

$$h^{ocp}(s_0) = 1 + c_1(\text{truck}) + c_2(\text{truck}) + 1$$
$$= 2 + x + y$$



Running Example: Logistics Task

Optimal Cost Partitioning



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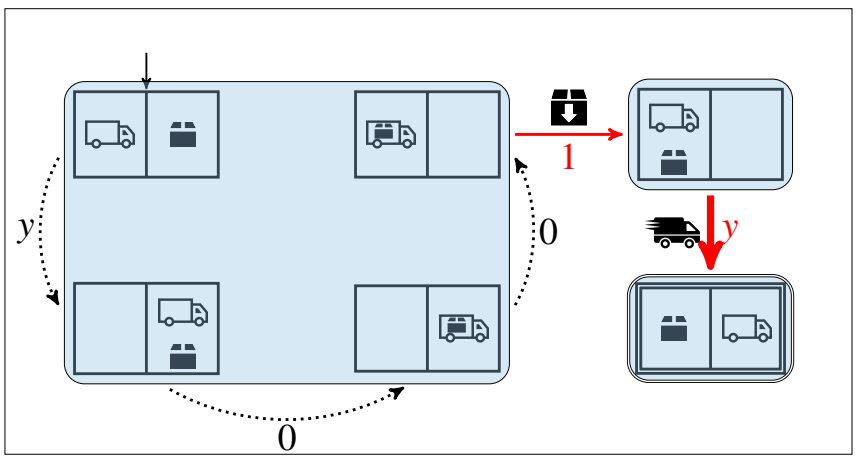
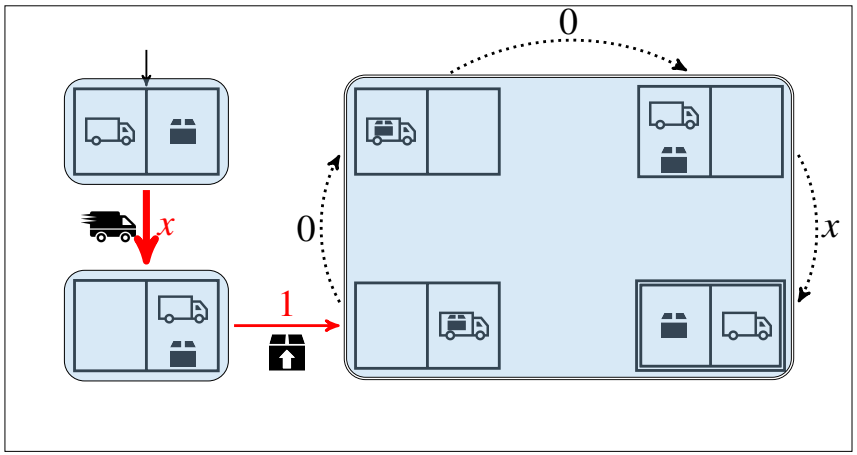


maximize this subject to $x + y \leq 1$

Running Example: Logistics Task

Optimal Cost Partitioning



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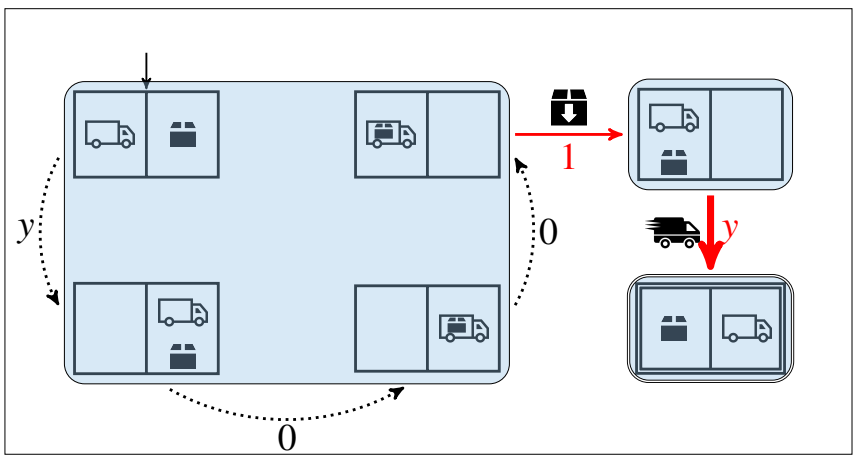
$$h^{ocp}(s_0) = 1 + c_1(\text{truck}) + c_2(\text{truck}) + 1$$
$$= 2 + x + y$$

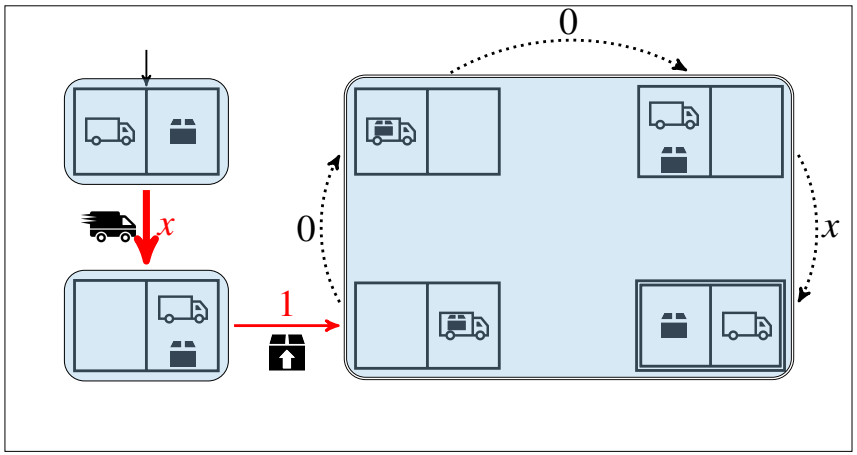


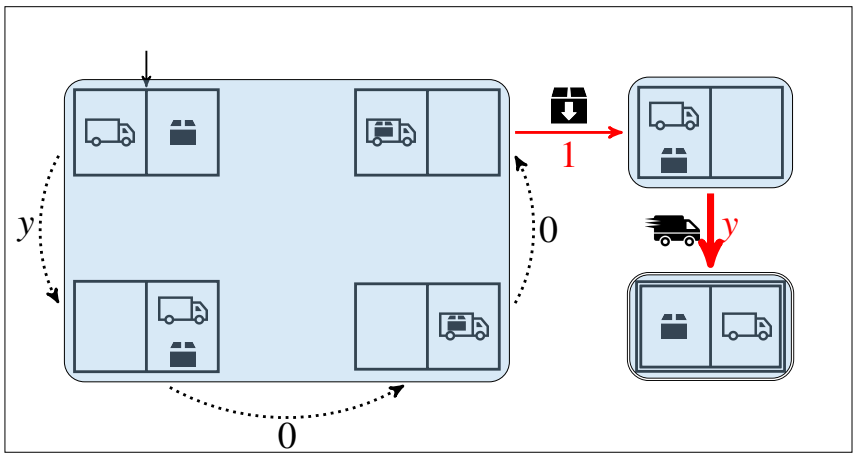
maximize this subject to $x + y \leq 1$

$$\Rightarrow \quad h^{ocp}(s_0) = 3$$

Running Example: Logistics Task

Optimal Cost Partitioning



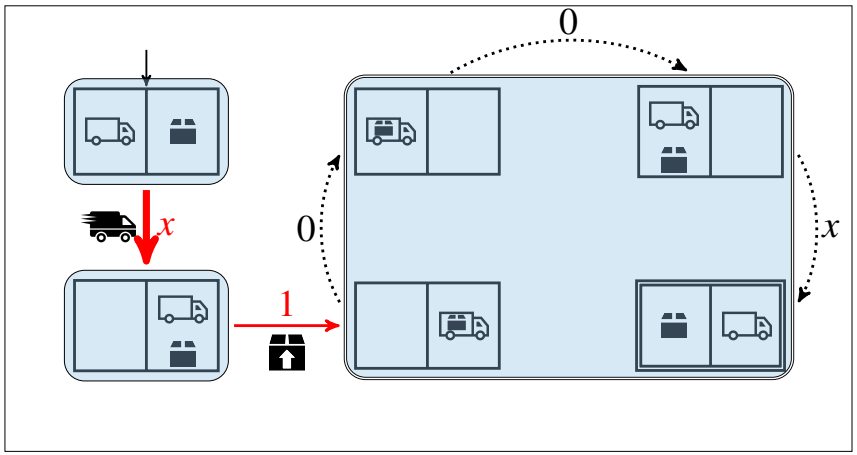


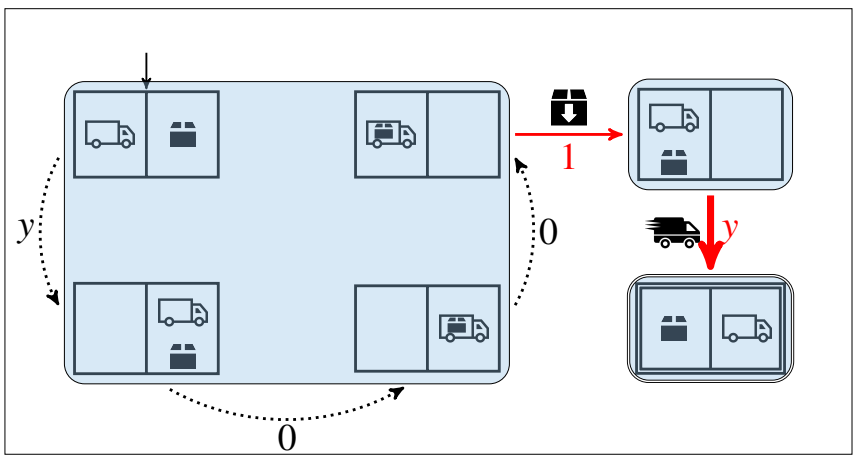
Problem: Action

- counted only once,
- but could be counted twice.

Running Example: Logistics Task

Optimal Cost Partitioning





Problem: Action

- counted only once,
- but could be counted twice.

Idea:

- Distinguish states in which action is applied.
  (= Assign partial costs state-wise.)
- If different, allow counting it both times.

State-Dependent Cost Partitioning

A state-dependent cost partitioning is a tuple $P = \langle c_1, \ldots, c_n \rangle$ where

- each $c_i : A \times S \to \mathbb{R}$ is a state-dependent cost function
- sum of partial action costs bounded by original action cost

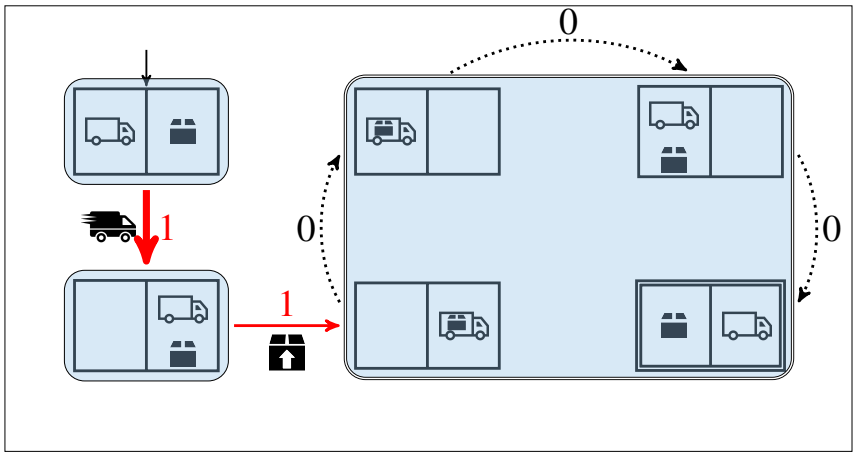
$$\sum_i c_i(a, s) \leq c(a) \qquad \text{for all } a \in A, s \in S.$$

Theorem

For admissible heuristics $h_1, \ldots, h_n$ and state-dependent cost partitioning P, the cost partitioning heuristic $h_P(s) = \sum_i h_i(s, c_i)$ is admissible.

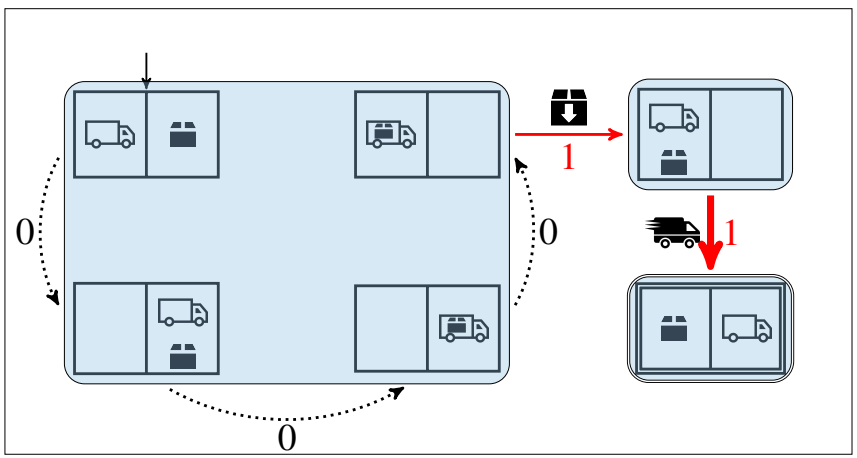
Running Example: Logistics Task

Optimal State-Dependent Cost Partitioning



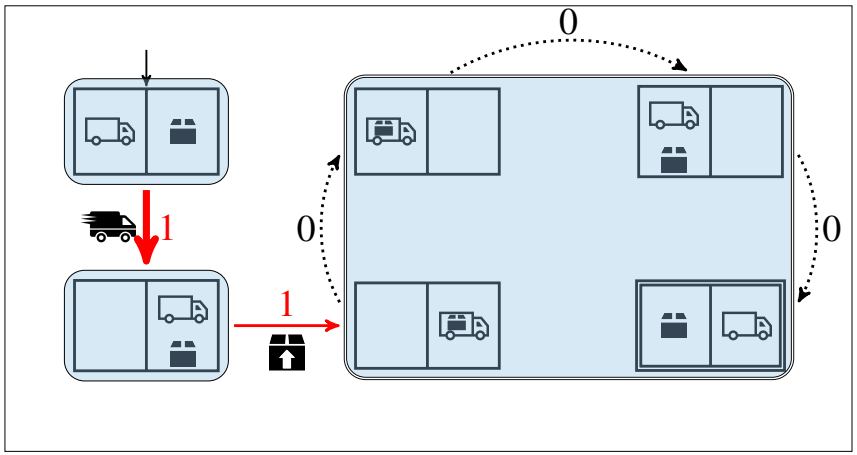
$$c_1(\text{truck}, s_0) = 1$$
$$c_1(\text{truck}, s') = 0 \quad (s' \neq s_0)$$

$$c_2(\text{truck}, s) = 1 - c_1(\text{truck}, s)$$
for all s



Running Example: Logistics Task

Optimal State-Dependent Cost Partitioning



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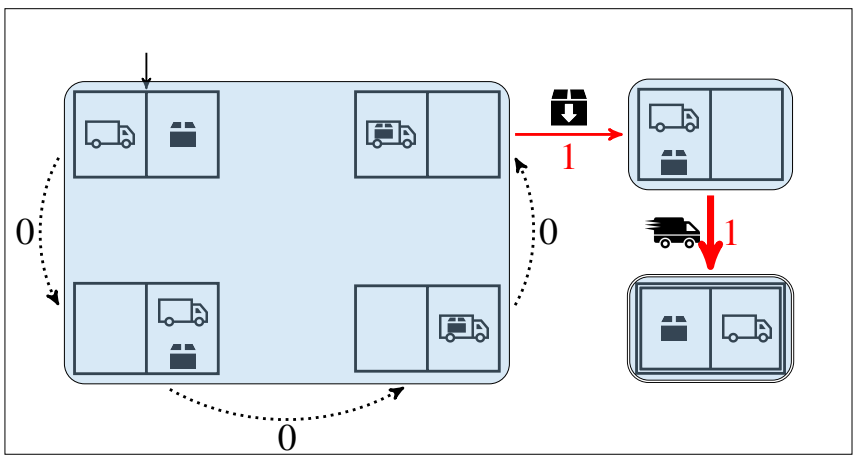
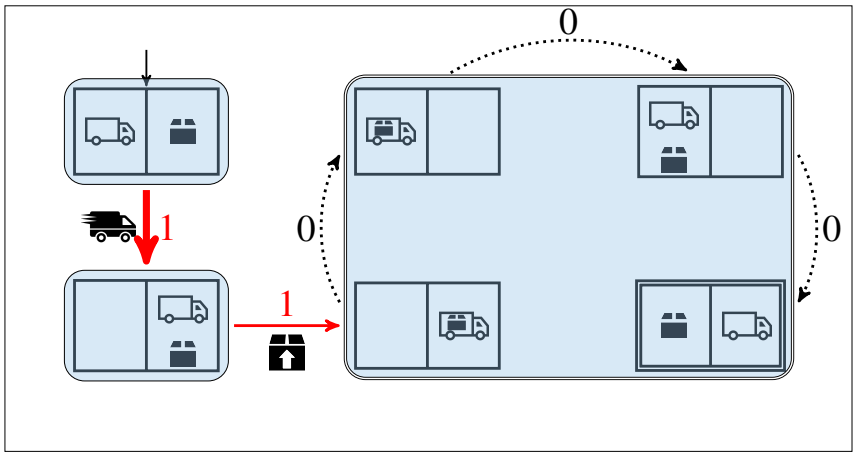
for all s

$$\Rightarrow \quad h^{\text{ocp-dep}}(s_0) = 1 + 1 + 1 + 1 = 4$$



Running Example: Logistics Task

Optimal State-Dependent Cost Partitioning



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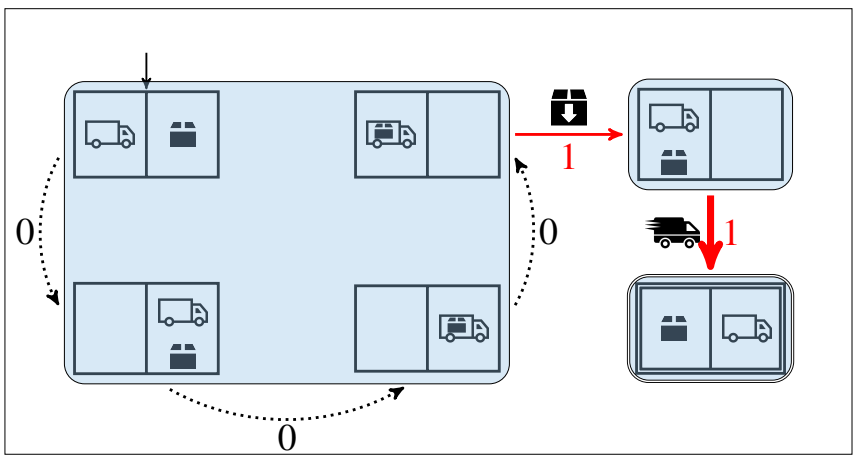


$$\Rightarrow \quad h^{\text{ocp-dep}}(s_0) = 1 + 1 + 1 + 1 = 4$$
$$> 3 = h^{\text{ocp}}(s_0).$$

Saturated Cost Partitioning

State-Independent or State-Dependent

Problem: Optimal state-dependent cost partitioning too expensive to compute (exponential).

Remedy: Consider saturated cost-partitioning as an alternative.

Idea: In current abstraction, leave as much remaining costs for subsequent abstractions as possible without making current abstraction less informative.

Details: See IJCAI 2016 paper [KPSGM16].

Theoretical Results

Dominance and Incomparability

OPT-DEP

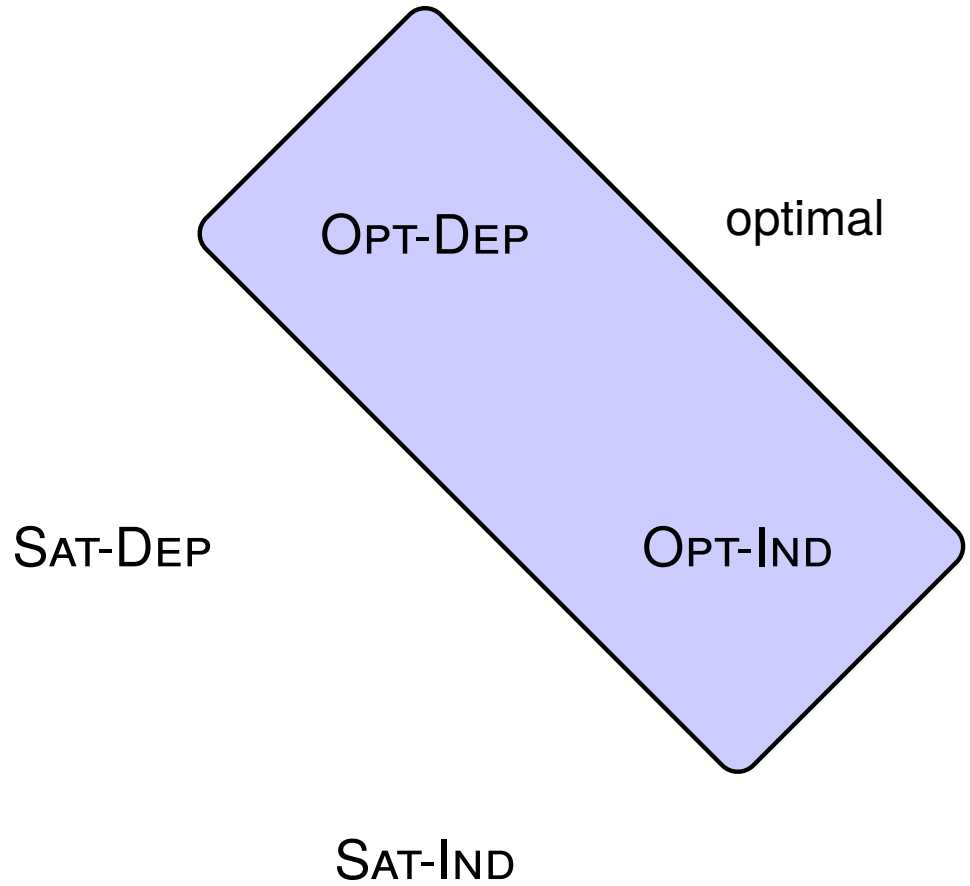
SAT-DEP

OPT-IND

SAT-IND

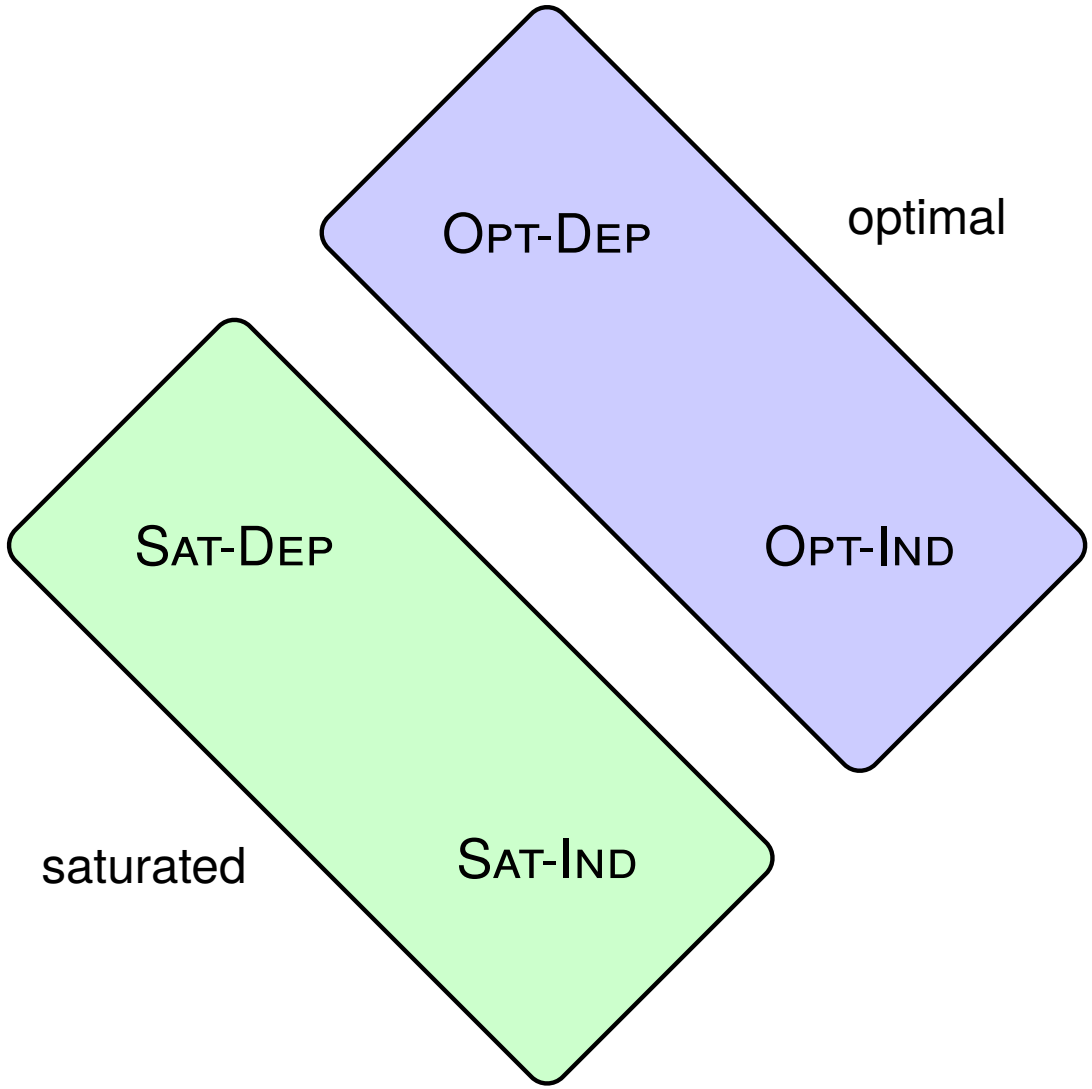
Theoretical Results

Dominance and Incomparability



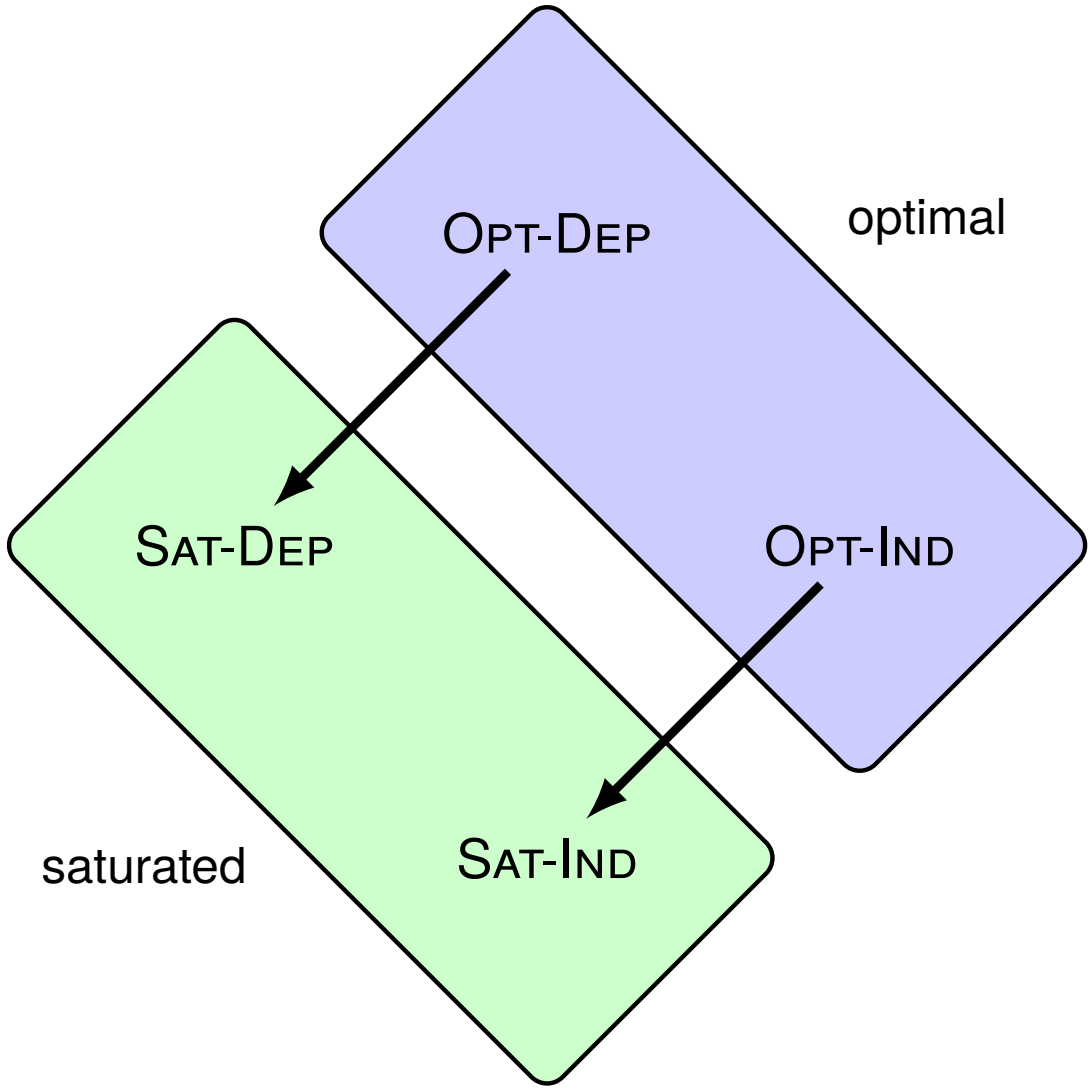
Theoretical Results

Dominance and Incomparability



Theoretical Results

Dominance and Incomparability



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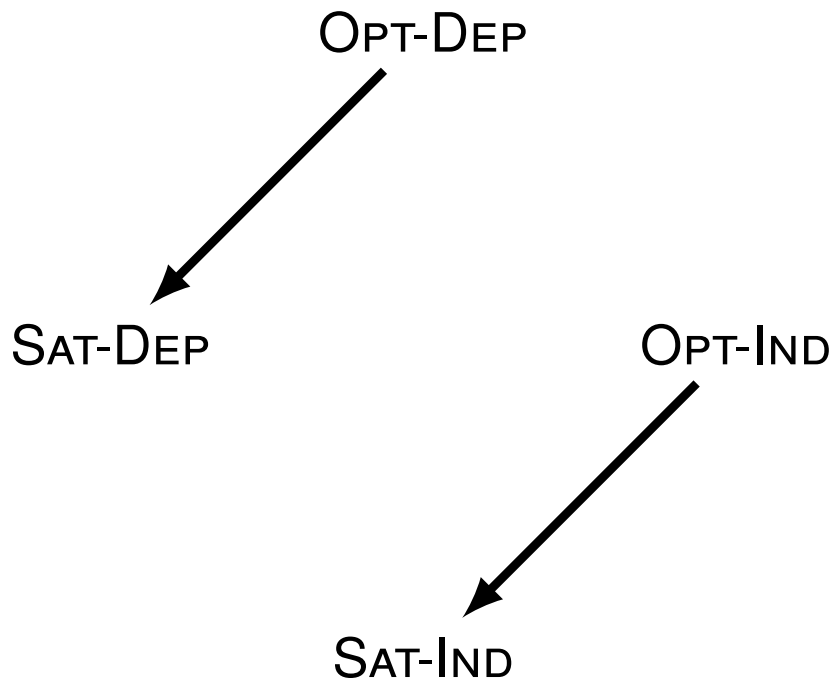

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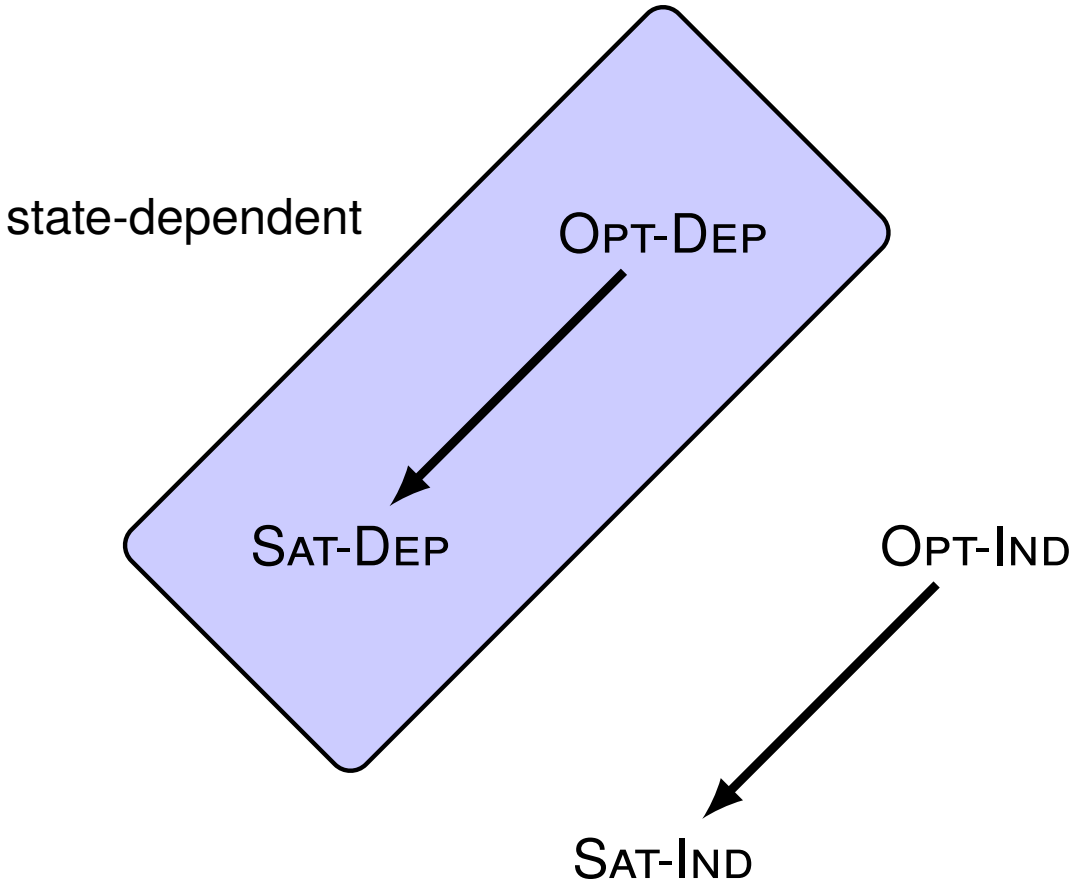

Theoretical Results

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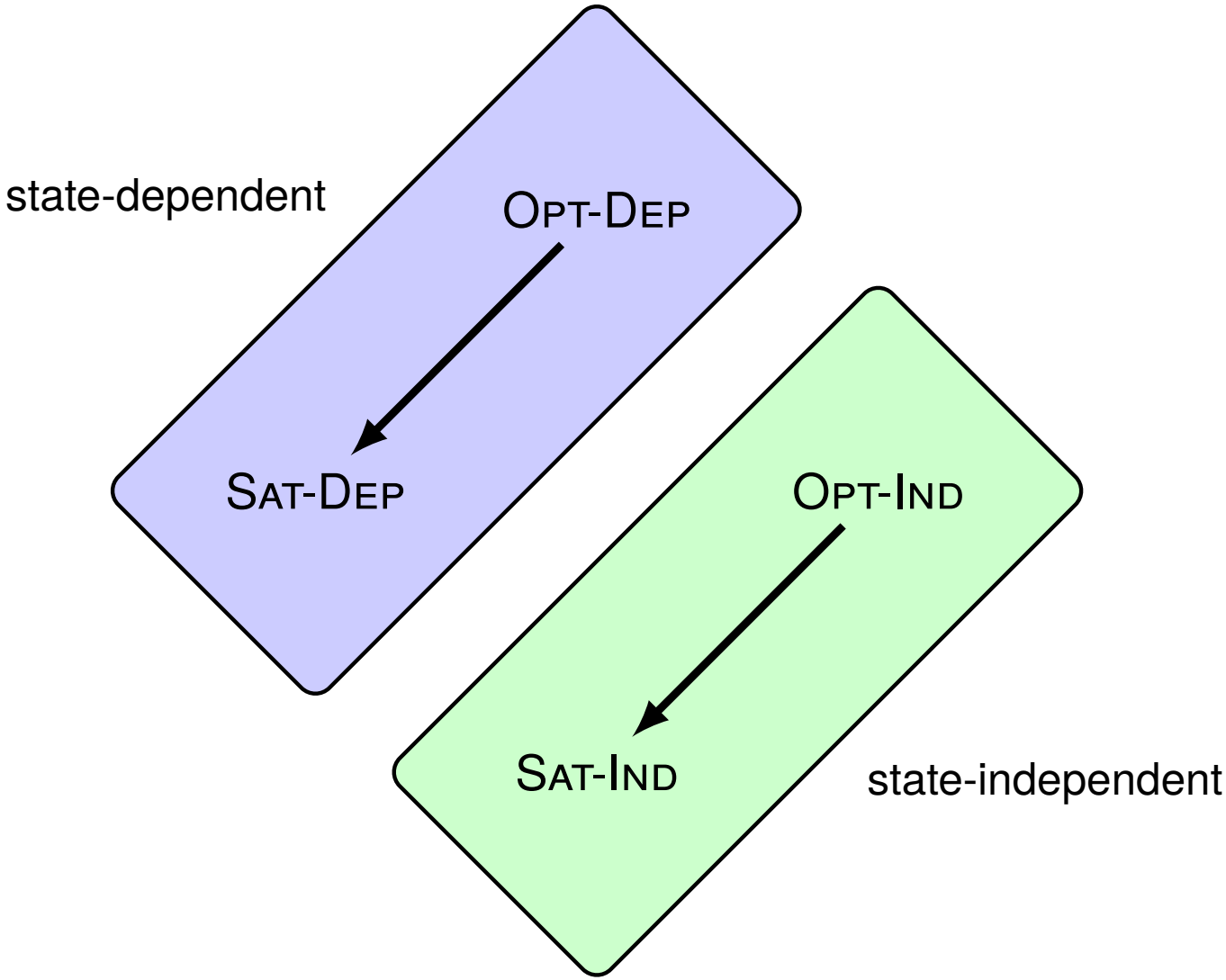

Theoretical Results

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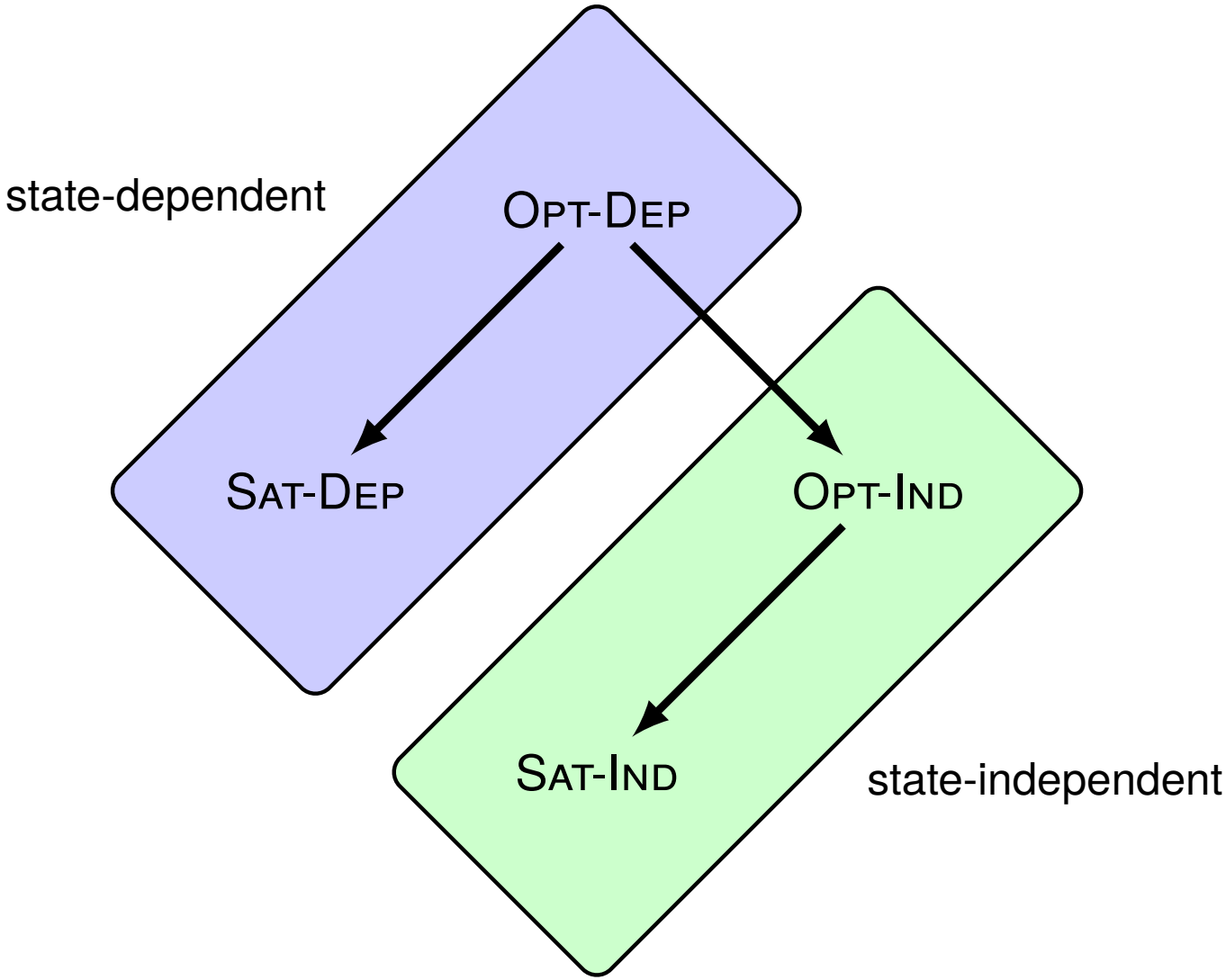

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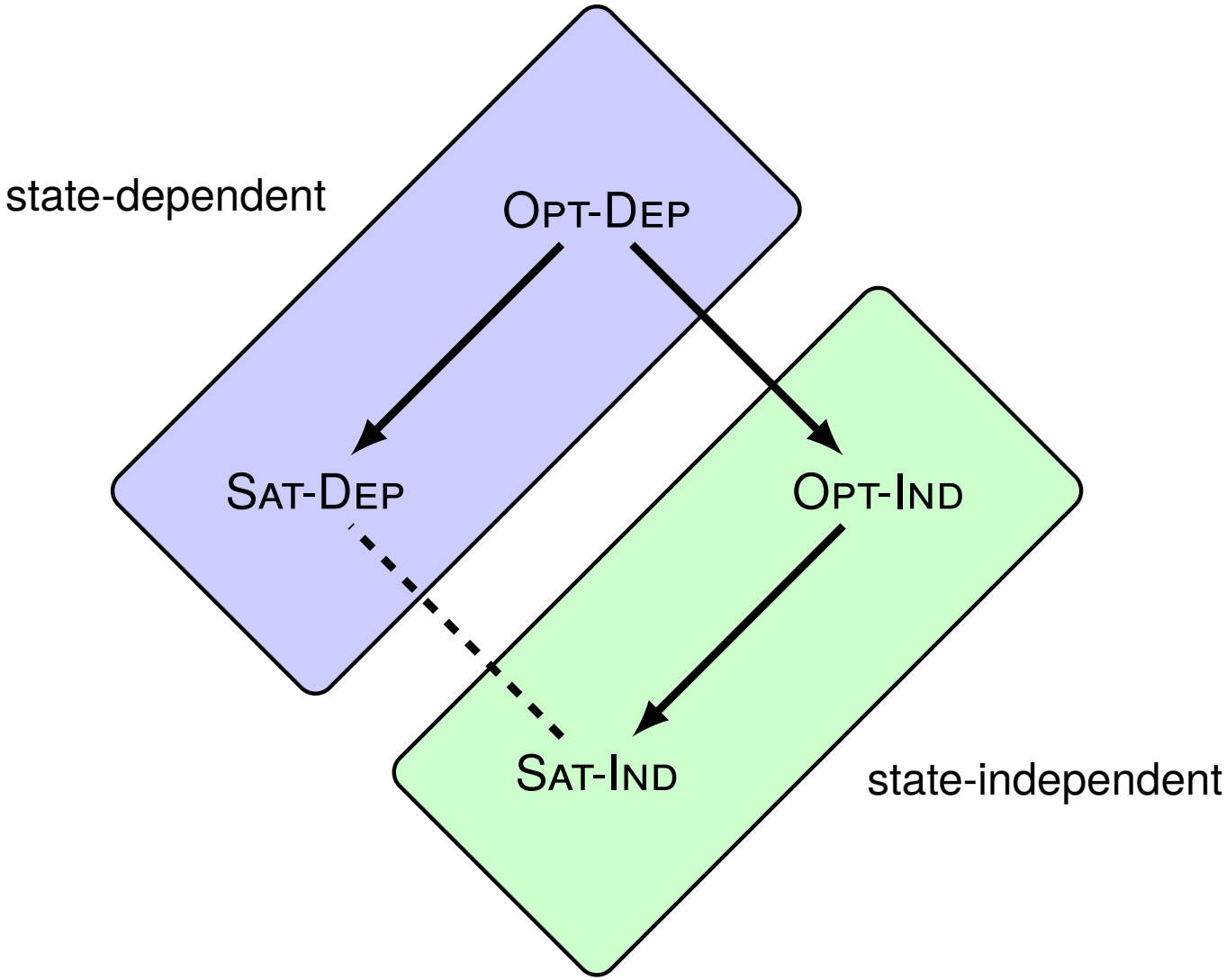

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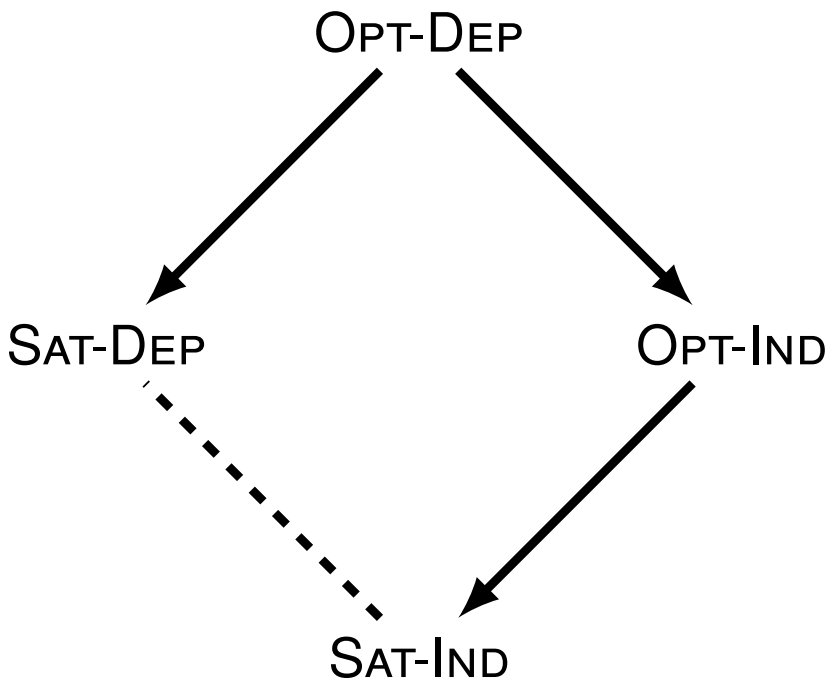

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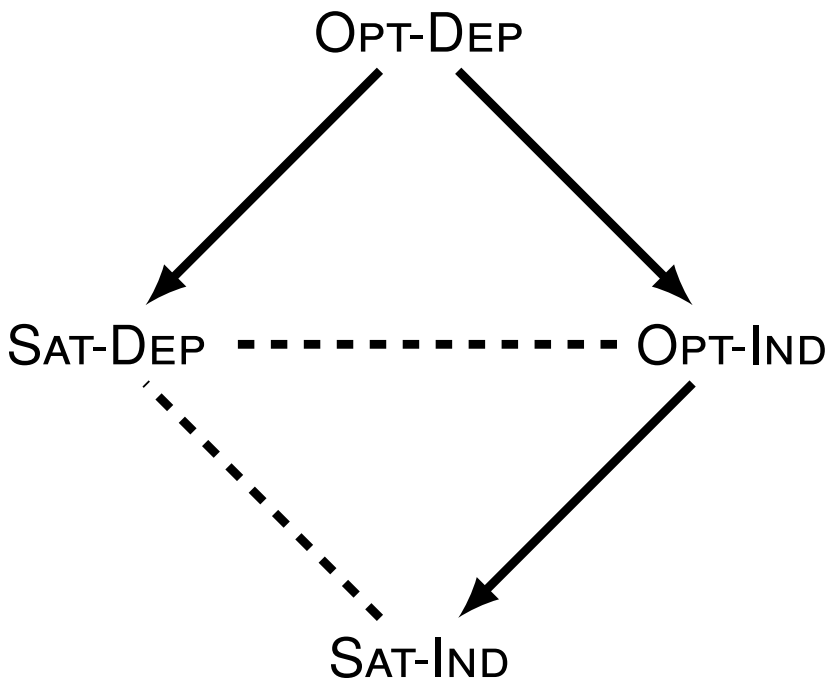

Conclusion

- State-dependent more fine-grained than state-independent cost partitioning.
- Complete classification of dominance among $\{\textsc{Opt}, \textsc{Sat}\} \times \{\textsc{Dep}, \textsc{Ind}\}$.
- Only preliminary empirical results.

Appendix

Empirical Results

Preliminary but promising.

- Opt-Dep really too expensive.
- Though theoretically incomparable,
  Sat-Dep often more accurate than Sat-Ind.
- Conjecture:
  Sat-Dep and Opt-Ind have potential to complement each other.