Planning with State-Dependent Action Costs

ICAPS 2016 Tutorial

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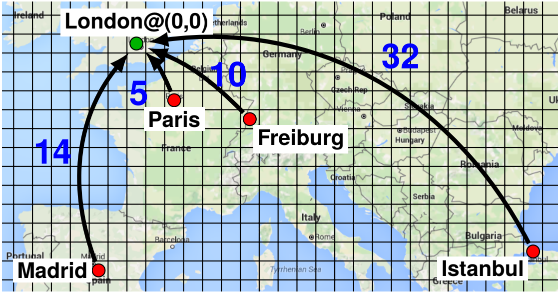
Part I

Theory

Section

Background

What are State-Dependent Action Costs?



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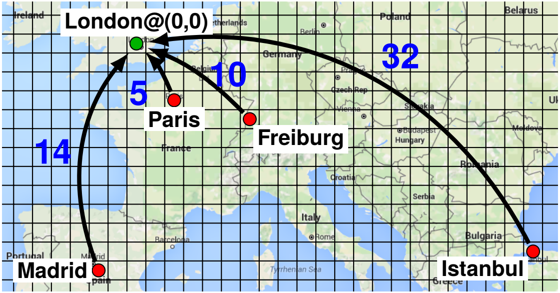
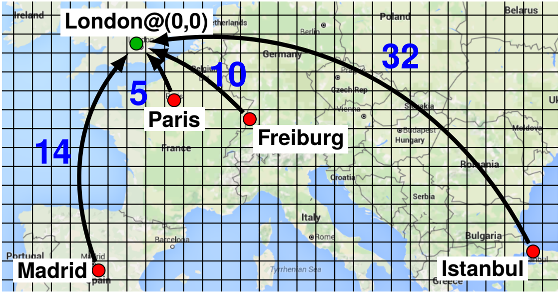
What are State-Dependent Action Costs?



Action costs: unit — constant — state-dependent

$$cost(fly(Madrid, London)) = 1, \quad cost(fly(Paris, London)) = 1,$$
$$cost(fly(Freiburg, London)) = 1, \quad cost(fly(Istanbul, London)) = 1.$$

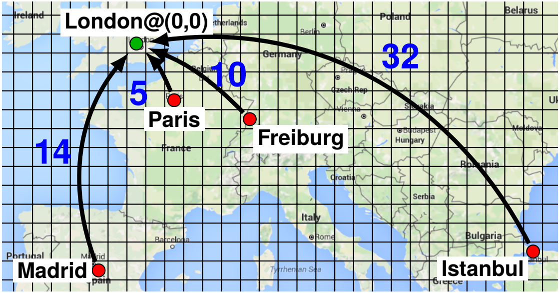
What are State-Dependent Action Costs?



Action costs: unit — constant — state-dependent

$$cost(fly(Madrid, London)) = 14, \quad cost(fly(Paris, London)) = 5,$$
$$cost(fly(Freiburg, London)) = 10, \quad cost(fly(Istanbul, London)) = 32.$$

What are State-Dependent Action Costs?



Action costs: unit — constant — state-dependent

$$cost(flyTo(London)) = |x_{\text{London}} - x_{\text{current}}| + |y_{\text{London}} - y_{\text{current}}|$$
$$= |x_{\text{current}}| + |y_{\text{current}}|.$$

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Why Study State-Dependent Action Costs?

- Human perspective:
  - "natural" and "elegant"
  - modeler-friendly $\rightsquigarrow$ less error-prone?
- Machine perspective:
  - more structured $\rightsquigarrow$ exploit in algorithms?
  - fewer redundancies, exponentially more compact
- Language support:
  - numeric PDDL, PDDL 3
  - RDDL, MDPs (state-dependent rewards!)
- Applications:
  - modeling preferences and soft goals
  - PSR domain

(Abbreviation: SDAC = state-dependent action costs)

Handling State-Dependent Action Costs

Good news:

- Computing g values in forward search still easy.

Challenge:

- But what about SDAC-aware h values?
- Or can we simply compile SDAC away?

This tutorial:

- Proposed answers to these challenges.

Handling State-Dependent Action Costs

Roadmap:

1. Look at compilations.
2. This leads to edge-valued multi-valued decision diagrams (EVMDDs) as data structure to represent cost functions.
3. Based on EVMDDs, formalize and discuss:
   - compilations
   - relaxation heuristics
   - abstraction heuristics

State-Dependent Action Costs

Running Example

Example (Household domain)

Actions:

$$\begin{aligned}\texttt{vacuumFloor} &= \langle \top, \texttt{floorClean} \rangle \\ \texttt{washDishes} &= \langle \top, \texttt{dishesClean} \rangle \\ \texttt{doHousework} &= \langle \top, \texttt{floorClean} \wedge \texttt{dishesClean} \rangle\end{aligned}$$

Cost functions:

$$\begin{aligned}\mathit{cost}_{\texttt{vacuumFloor}} &= [\neg\texttt{floorClean}] \cdot 2 \\ \mathit{cost}_{\texttt{washDishes}} &= [\neg\texttt{dishesClean}] \cdot (1 + 2 \cdot [\neg\texttt{haveDishwasher}]) \\ \mathit{cost}_{\texttt{doHousework}} &= \mathit{cost}_{\texttt{vacuumFloor}} + \mathit{cost}_{\texttt{washDishes}}\end{aligned}$$

State-Dependent Action Costs

Compilations

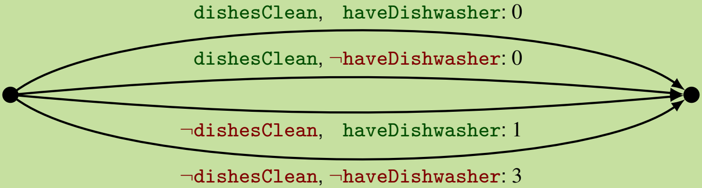
Different ways of compiling SDAC away:

- Compilation I: “Parallel Action Decomposition”
- Compilation II: “Purely Sequential Action Decomposition”
- Compilation III: “EVMDD-Based Action Decomposition”
  (combination of Compilations I and II)

State-Dependent Action Costs

Compilation I: “Parallel Action Decomposition”

Example



$$\begin{aligned}
\mathtt{washDishes}(\ \mathtt{dC}, \ \mathtt{hD}) &= \langle\ \mathtt{dC} \wedge \ \mathtt{hD}, \mathtt{dC}\rangle, \quad \mathit{cost} = 0\\
\mathtt{washDishes}(\ \mathtt{dC}, \neg\mathtt{hD}) &= \langle\ \mathtt{dC} \wedge \neg\mathtt{hD}, \mathtt{dC}\rangle, \quad \mathit{cost} = 0\\
\mathtt{washDishes}(\neg\mathtt{dC}, \ \mathtt{hD}) &= \langle\neg\mathtt{dC} \wedge \ \mathtt{hD}, \mathtt{dC}\rangle, \quad \mathit{cost} = 1\\
\mathtt{washDishes}(\neg\mathtt{dC}, \neg\mathtt{hD}) &= \langle\neg\mathtt{dC} \wedge \neg\mathtt{hD}, \mathtt{dC}\rangle, \quad \mathit{cost} = 3
\end{aligned}$$

State-Dependent Action Costs

Compilation I: “Parallel Action Decomposition”

Compilation I

Transform each action into multiple actions:

- one for each partial state relevant to cost function
- add partial state to precondition
- use cost for partial state as constant cost

Properties:

✓ always possible

✗ exponential blow-up

Question: Exponential blow-up avoidable? $\rightsquigarrow$ Compilation II

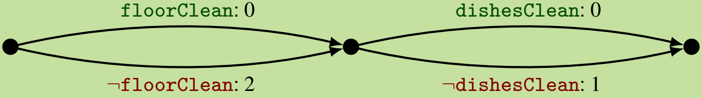
State-Dependent Action Costs

Compilation II: “Purely Sequential Action Decomposition”

Example

Assume we own a dishwasher:

$$cost_{\texttt{doHousework}} = 2 \cdot [\neg\texttt{floorClean}] + [\neg\texttt{dishesClean}]$$



$$\begin{aligned}
\texttt{doHousework}_1(\ \texttt{fC}) &= \langle\ \texttt{fC}, \texttt{fC}\rangle, & cost &= 0\\
\texttt{doHousework}_1(\neg\texttt{fC}) &= \langle\neg\texttt{fC}, \texttt{fC}\rangle, & cost &= 2\\
\texttt{doHousework}_2(\ \texttt{dC}) &= \langle\ \texttt{dC}, \texttt{dC}\rangle, & cost &= 0\\
\texttt{doHousework}_2(\neg\texttt{dC}) &= \langle\neg\texttt{dC}, \texttt{dC}\rangle, & cost &= 1
\end{aligned}$$

State-Dependent Action Costs

Compilation II: “Purely Sequential Action Decomposition”

Compilation II

If costs additively decomposable:

- high-level actions $\approx$ macro actions
- decompose into sequential micro actions

Properties:

- ✔ linear blow-up
- ✗ not always possible
- plan lengths not preserved, costs preserved
- blow-up in search space $\rightsquigarrow$ action ordering!
- attention: all partial effects at end!

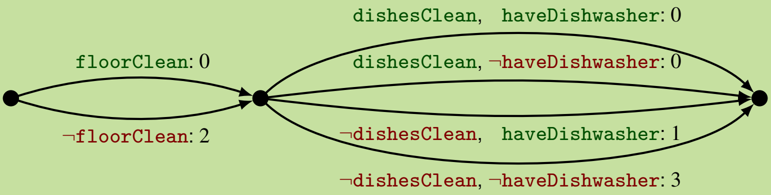
Question: Can this always work (kind of)? $\rightsquigarrow$ Compilation III

State-Dependent Action Costs

Compilation III: “EVMDD-Based Action Decomposition”

Example

$$\mathit{cost}_{\texttt{doHousework}} = [\neg\texttt{floorClean}]\cdot 2 + [\neg\texttt{dishesClean}]\cdot(1 + 2\cdot[\neg\texttt{haveDishwasher}])$$



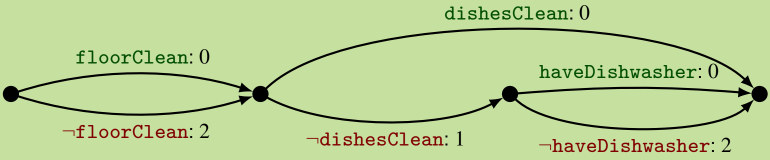
Simplify right-hand part of diagram:

- Branch over single variable at a time.
- Exploit: `haveDishwasher` irrelevant if `dishesClean` is true.

State-Dependent Action Costs

Compilation III: “EVMDD-Based Action Decomposition”

Example (ctd.)



Later:

- Compiled actions
- Auxiliary variables to enforce action ordering

State-Dependent Action Costs

Compilation III: “EVMDD-Based Action Decomposition”

Compilation III

- exploit as much additive decomposability as possible
- multiply out variable domains where inevitable
- Technicalities:
  - fix variable ordering
  - perform Shannon and isomorphism reduction

Properties:

✔ always possible

- worst-case exponential blow-up, but as good as it gets
- plan lengths not preserved, costs preserved
- as before: action ordering, all partial effects at end!

State-Dependent Action Costs

Compilation III: “EVMDD-Based Action Decomposition”

Compilation III provides optimal combination of sequential and parallel action decomposition, given fixed variable ordering.

Question: How to find such decompositions automatically?

Answer: Figure for Compilation III basically a reduced ordered edge-valued multi-valued decision diagram (EVMDD)!

[Lai et al., 1996; Ciardo and Siminiceanu, 2002]

EVMDDs

Edge-Valued Multi-Valued Decision Diagrams

EVMDDs:

- Decision diagrams for arithmetic functions
- Decision nodes with associated decision variables
- Edge weights: partial costs contributed by facts
- Size of EVMDD compact in many “typical” cases

Properties:

✔ satisfy all requirements for Compilation III,
even (almost) uniquely determined by them

✔ already have well-established theory and tool support

✔ detect and exhibit additive structure in arithmetic functions

EVMDDs

Edge-Valued Multi-Valued Decision Diagrams

Consequence:

- represent cost functions as EVMDDs
- exploit additive structure exhibited by them
- draw on theory and tool support for EVMDDs

Two perspectives on EVMDDs:

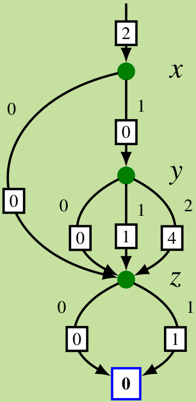
- graphs specifying how to decompose action costs
- data structures encoding action costs
  (used independently from compilations)

EVMDDs

Edge-Valued Multi-Valued Decision Diagrams

Example (EVMDD Evaluation)

$cost_a = xy^2 + z + 2$ $\mathcal{D}_x = \mathcal{D}_z = \{0,1\},\ \mathcal{D}_y = \{0,1,2\}$



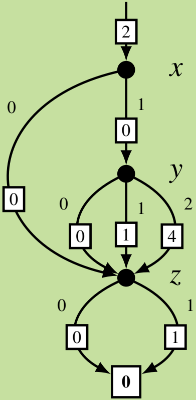
- Directed acyclic graph
- Dangling incoming edge
- Single terminal node **0**
- Decision nodes with:
  - decision variables
  - edge label
  - edge weights

EVMDDs

Edge-Valued Multi-Valued Decision Diagrams

Example (EVMDD Evaluation)

$\mathit{cost}_a = xy^2 + z + 2$ $\mathcal{D}_x = \mathcal{D}_z = \{0,1\},\ \mathcal{D}_y = \{0,1,2\}$



- $s = \{x \mapsto 1,\ y \mapsto 2,\ z \mapsto 0\}$
- $\mathit{cost}_a(s) =$

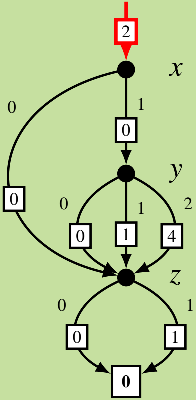
EVMDDs

Edge-Valued Multi-Valued Decision Diagrams

Background
State-Dependent Action Costs
Edge-Valued Multi-Valued Decision Diagrams
Compilation
Relaxations
Abstractions
Summary

Example (EVMDD Evaluation)

$cost_a = xy^2 + z + 2$ $\mathcal{D}_x = \mathcal{D}_z = \{0,1\},\ \mathcal{D}_y = \{0,1,2\}$



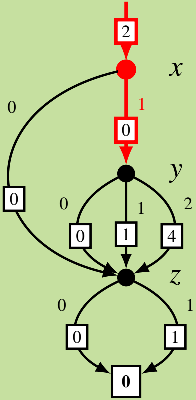
- $s = \{x \mapsto 1,\ y \mapsto 2,\ z \mapsto 0\}$
- $cost_a(s) = 2 +$

EVMDDs

Edge-Valued Multi-Valued Decision Diagrams

Example (EVMDD Evaluation)

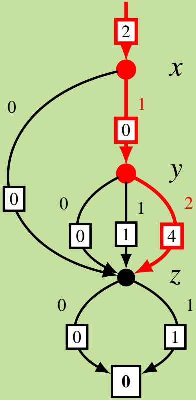
$\mathit{cost}_a = xy^2 + z + 2$ $\qquad \mathcal{D}_x = \mathcal{D}_z = \{0,1\},\ \mathcal{D}_y = \{0,1,2\}$



- $s = \{x \mapsto 1,\ y \mapsto 2,\ z \mapsto 0\}$
- $\mathit{cost}_a(s) = 2 + 0 +$

Example (EVMDD Evaluation)

$cost_a = xy^2 + z + 2$ $\mathcal{D}_x = \mathcal{D}_z = \{0,1\},\ \mathcal{D}_y = \{0,1,2\}$



- $s = \{x \mapsto 1,\ y \mapsto 2,\ z \mapsto 0\}$
- $cost_a(s) = 2 + 0 + 4 +$

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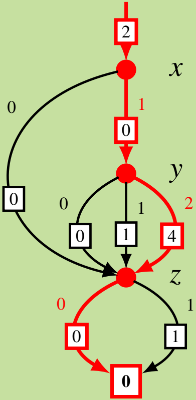
EVMDDs

Edge-Valued Multi-Valued Decision Diagrams

Example (EVMDD Evaluation)

$cost_a = xy^2 + z + 2$ $\qquad \mathcal{D}_x = \mathcal{D}_z = \{0,1\},\ \mathcal{D}_y = \{0,1,2\}$



- $s = \{x \mapsto 1,\ y \mapsto 2,\ z \mapsto 0\}$
- $cost_a(s) = 2 + 0 + 4 + 0 = 6$

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EVMDDs

Edge-Valued Multi-Valued Decision Diagrams

Properties of EVMDDs:

- ✔ Existence for finitely many finite-domain variables
- ✔ Uniqueness/canonicity if reduced and ordered
- ✔ Basic arithmetic operations supported

(Lai et al., 1996; Ciardo and Siminiceanu, 2002)

EVMDDs

Arithmetic operations on EVMDDs

Given arithmetic operator $\otimes \in \{+, -, \cdot, \dots\}$, EMVDDs $\mathcal{E}_1$, $\mathcal{E}_2$.
Compute EVMDD $\mathcal{E} = \mathcal{E}_1 \otimes \mathcal{E}_2$.

Implementation: procedure $\texttt{apply}(\otimes, \mathcal{E}_1, \mathcal{E}_2)$:

- Base case: single-node EVMDDs encoding constants
- Inductive case: apply $\otimes$ recursively:
  - push down edge weights
  - recursively apply $\otimes$ to corresponding children
  - pull up excess edge weights from children

Time complexity [Lai et al., 1996]:

- additive operations: product of input EVMDD sizes
- in general: exponential

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Section

Compilation

EVMDD-Based Action Compilation

Example (EVMDD-based action compilation)

Let $a = \langle \mathit{pre}, \mathit{eff} \rangle$, $\mathit{cost}_a = xy^2 + z + 2$.

Auxiliary variables:

- One semaphore variable σ with $\mathcal{D}_\sigma = \{0, 1\}$ for entire planning task.
- One auxiliary variable $\alpha = \alpha_a$ with $\mathcal{D}_{\alpha_a} = \{0, 1, 2, 3, 4\}$ for action a.

Replace a by new auxiliary actions (similarly for other actions).

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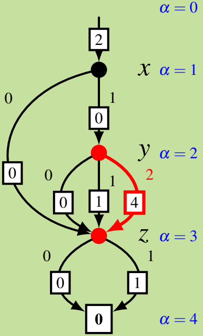
EVMDD-Based Action Compilation

Example (EVMDD-based action compilation, ctd.)



$$a^{\mathit{pre}} = \langle \mathit{pre} \wedge \sigma = 0 \wedge \alpha = 0,\quad \sigma = 1 \wedge \alpha = 1 \rangle, \qquad \mathit{cost} = 2$$

$$a^{1,x=0} = \langle \alpha = 1 \wedge x = 0,\ \alpha = 3 \rangle, \qquad \mathit{cost} = 0$$

$$a^{1,x=1} = \langle \alpha = 1 \wedge x = 1,\ \alpha = 2 \rangle, \qquad \mathit{cost} = 0$$

$$a^{2,y=0} = \langle \alpha = 2 \wedge y = 0,\ \alpha = 3 \rangle, \qquad \mathit{cost} = 0$$

$$a^{2,y=1} = \langle \alpha = 2 \wedge y = 1,\ \alpha = 3 \rangle, \qquad \mathit{cost} = 1$$

$$a^{2,y=2} = \langle \alpha = 2 \wedge y = 2,\ \alpha = 3 \rangle, \qquad \mathit{cost} = 4$$

$$a^{3,z=0} = \langle \alpha = 3 \wedge z = 0,\ \alpha = 4 \rangle, \qquad \mathit{cost} = 0$$

$$a^{3,z=1} = \langle \alpha = 3 \wedge z = 1,\ \alpha = 4 \rangle, \qquad \mathit{cost} = 1$$

$$a^{\mathit{eff}} = \langle \alpha = 4,\ \mathit{eff} \wedge \sigma = 0 \wedge \alpha = 0 \rangle, \qquad \mathit{cost} = 0$$

EVMDD-Based Action Compilation

Let Π be an SDAC-task and Π' the result of EVMDD-based action compilation applied to Π.

Proposition

Π' has only state-independent costs. □

Proposition

Size of Π' is polynomial in size of Π times size of largest EVMDD used in compilation. □

Proposition

Π and Π' admit the same plans (modulo replacement of actions by action sequences). Optimal plan costs are preserved. □

Section

Relaxations

Relaxation Heuristics

We know: Delete-relaxation heuristics informative in classical planning.

Question: Also informative in SDAC planning?

Relaxation Heuristics

Definition (Classical additive heuristic h^{add})

$$h_s^{add}(Facts) = \sum_{fact \in Facts} h_s^{add}(fact)$$

$$h_s^{add}(fact) = \begin{cases} 0 & \text{if } fact \in s \\ \min\limits_{\text{achiever } a \text{ of } fact} [h_s^{add}(pre(a)) + cost_a] & \text{otherwise} \end{cases}$$

Question: How to generalize h^{add} to SDAC?

Relaxations with SDAC

Example

$$a = \langle \top,\ x = 1 \rangle \qquad cost_a = 2 - 2y$$

$$b = \langle \top,\ y = 1 \rangle \qquad cost_b = 1$$

$$s = \{x \mapsto 0, y \mapsto 0\}$$

$$h_s^{add}(y = 1) = 1$$

$$h_s^{add}(x = 1) = ?$$

Relaxations with SDAC

Example

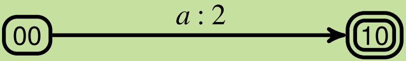
$$a = \langle \top,\ x{=}1 \rangle \qquad \mathit{cost}_a = 2 - 2y$$

$$b = \langle \top,\ y{=}1 \rangle \qquad \mathit{cost}_b = 1$$

$$s = \{x \mapsto 0, y \mapsto 0\}$$

$$h_s^{add}(y{=}1) = 1$$

$$h_s^{add}(x{=}1) = ?$$

- 

Relaxations with SDAC

Example

$$a = \langle \top,\ x{=}1 \rangle \qquad\qquad cost_a = 2 - 2y$$
$$b = \langle \top,\ y{=}1 \rangle \qquad\qquad cost_b = 1$$

$$s = \{x \mapsto 0, y \mapsto 0\}$$
$$h_s^{add}(y{=}1) = 1$$
$$h_s^{add}(x{=}1) = ?$$

- $00 \xrightarrow{a\,:\,2} 10$
- $00 \xrightarrow{b\,:\,1} 01 \xrightarrow{a\,:\,0} 11$ $\Rightarrow$ cheaper!

Relaxations with SDAC

Minimize over all situations where a is applicable.

Definition (Additive heuristic h^{add} for SDAC)

$$h_s^{\mathsf{add}}(fact) = \begin{cases} 0 & \text{if } fact \in s \\ \min\limits_{\text{achiever } a \text{ of } fact} [h_s^{\mathsf{add}}(pre(a)) + \mathit{cost}_a] & \text{otherwise} \end{cases}$$

Relaxations with SDAC

Minimize over all situations where a is applicable.

Definition (Additive heuristic h^{add} for SDAC)

$$h^{add}_s(fact) = \begin{cases} 0 & \text{if } fact \in s \\ \min_{\text{achiever } a \text{ of } fact} [h^{add}_s(pre(a)) + Cost^s_a] & \text{otherwise} \end{cases}$$

$$Cost^s_a = \min_{\hat{s} \in S_a} [cost_a(\hat{s}) + h^{add}_s(\hat{s})]$$

S_a: set of partial states over variables in cost function

$|S_a|$ exponential in number of variables in cost function

Relaxations with SDAC

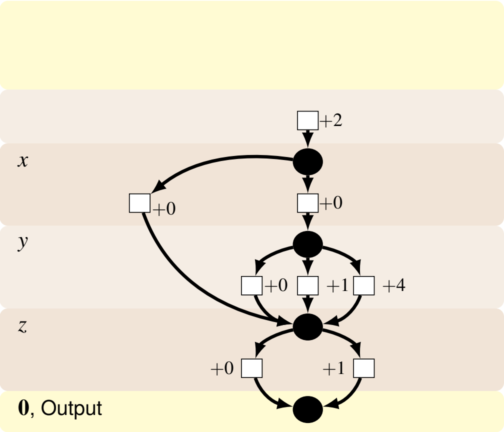
Properties of h^{add} for SDAC:

- Good: classical h^{add} on compiled task $=$ generalized h^{add} on SDAC-task
- Bad: exponential blow-up

Computing h^{add} for SDAC:

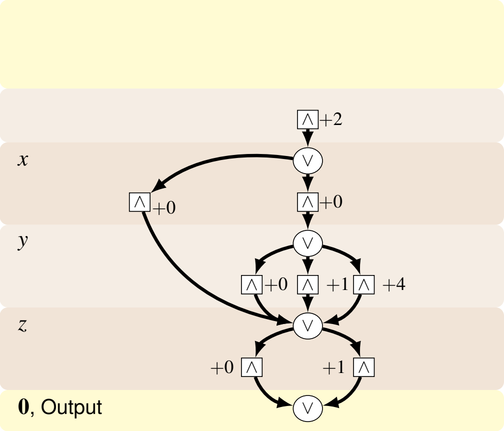
- Option 1: Compute classical h^{add} on compiled task.
- Option 2: Compute $Cost_a^s$ directly.
  - Plug EVMDDs as subgraphs into RPG
  - $\rightsquigarrow$ efficient computation of h^{add}

Option 2: RPG Compilation



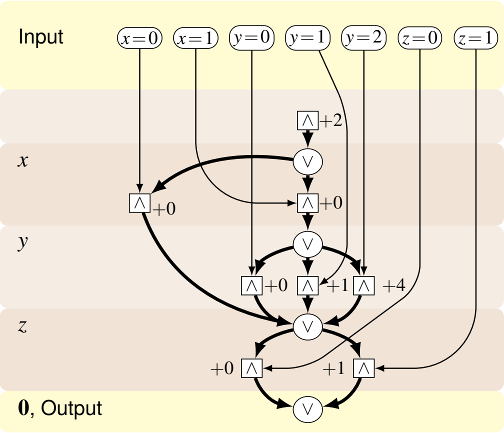
- $cost_a = xy^2 + z + 2$

Option 2: RPG Compilation



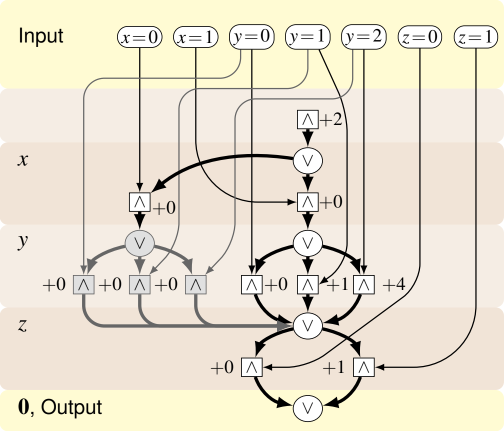
- variable nodes become $\vee$-nodes
- weights become $\wedge$-nodes

Option 2: RPG Compilation



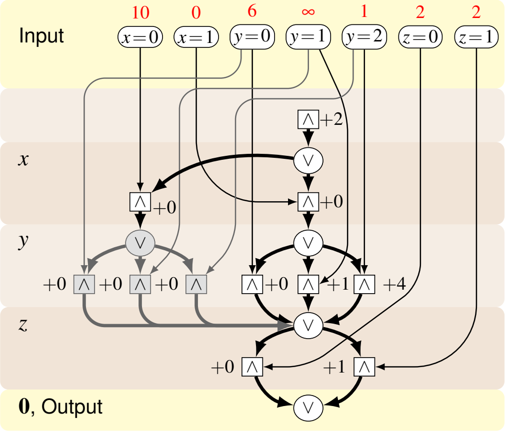
- Augment with input nodes

Option 2: RPG Compilation



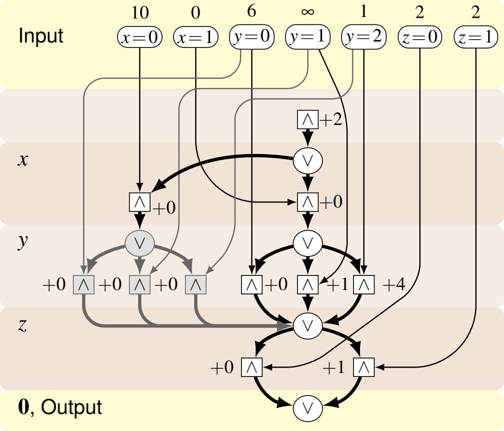
- Ensure complete evaluation

Option 2: Computing $Cost_a^s$



- Insert h^{add} values

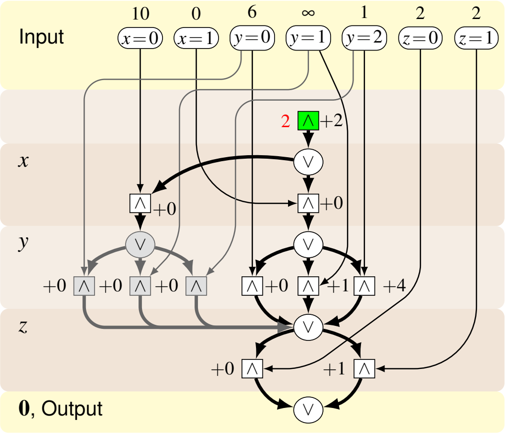
Option 2: Computing $Cost_a^s$



Evaluate nodes:

- $\wedge$: $\sum(\text{parents})$ + weight
- $\vee$: $\min(\text{parents})$

Option 2: Computing $Cost_a^s$



Evaluate nodes:

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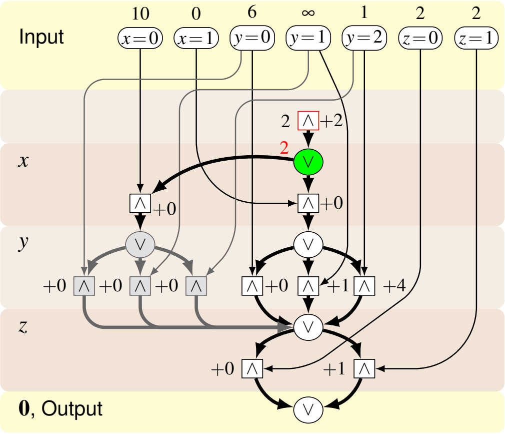

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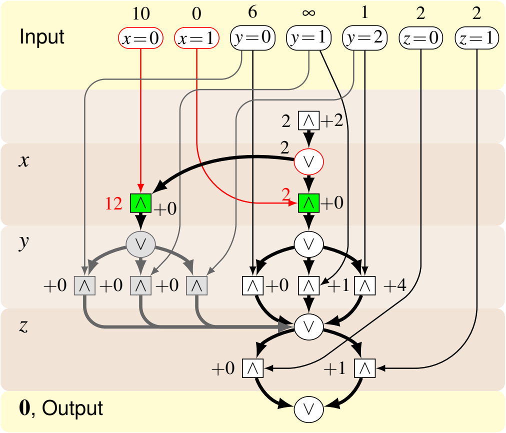

Evaluate nodes:

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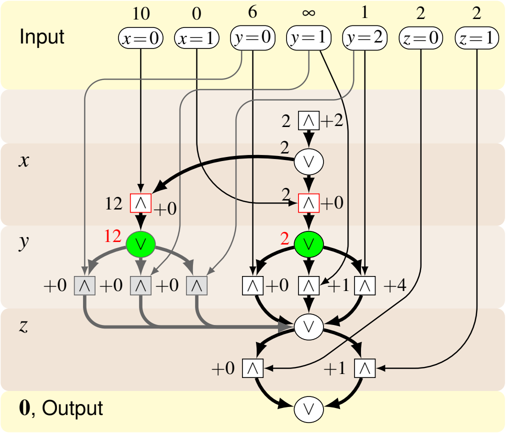

Evaluate nodes:

- $\wedge$: $\sum$(parents) + weight
- $\vee$: $\min$(parents)

Background
Compilation
Relaxations
Relaxed Planning Graph
Abstractions
Summary

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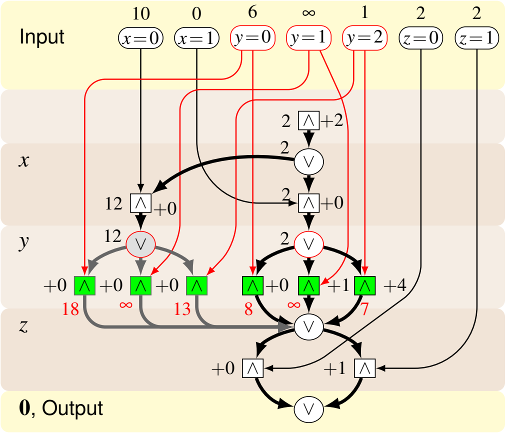
Option 2: Computing $Cost_a^s$



Evaluate nodes:

- $\wedge$: $\sum(\text{parents})$ + weight
- $\vee$: $\min(\text{parents})$

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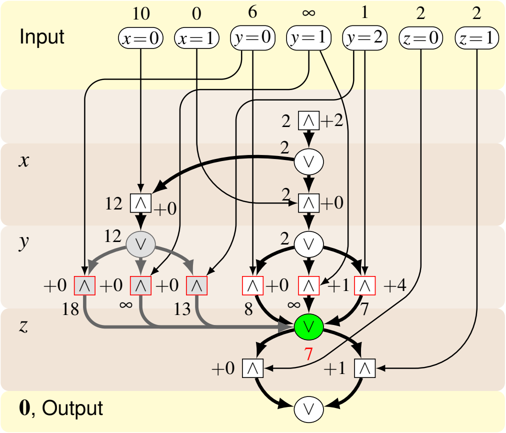

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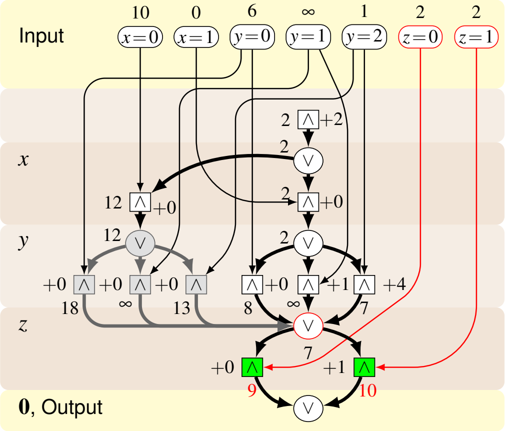

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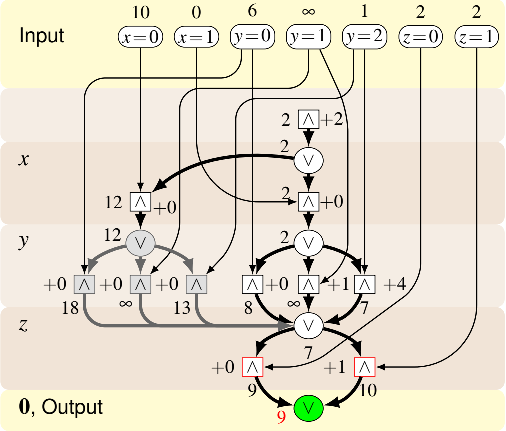

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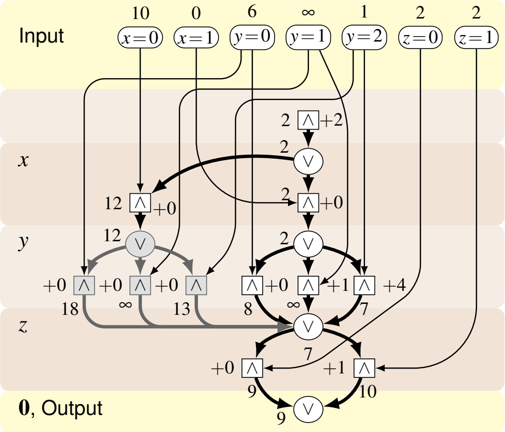
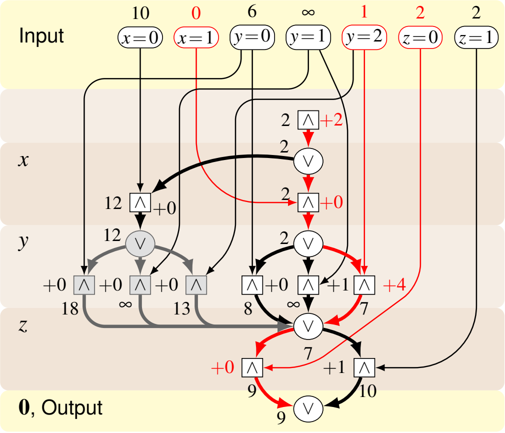


- $Cost_a^s = \min_{\hat{s} \in S_a} [cost_a(\hat{s}) + h_s^{add}(\hat{s})]$

Option 2: Computing $Cost_a^s$



- $Cost_a^s = \min_{\hat{s} \in S_a} [cost_a(\hat{s}) + h_s^{add}(\hat{s})]$
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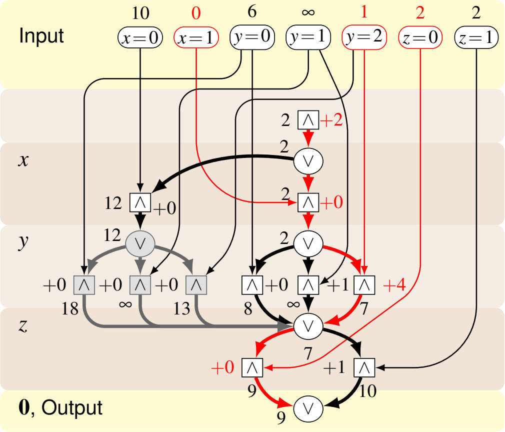

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- $cost_a = xy^2 + z + 2$
- $\hat{s} = \{x \mapsto 1, y \mapsto 2, z \mapsto 0\}$
- $cost_a(\hat{s}) = 1 \cdot 2^2 + 0 + 2 = 6$

  $= 2 + 0 + 4 + 0$
- $h_s^{add}(\hat{s}) = 0 + 1 + 2 = 3$

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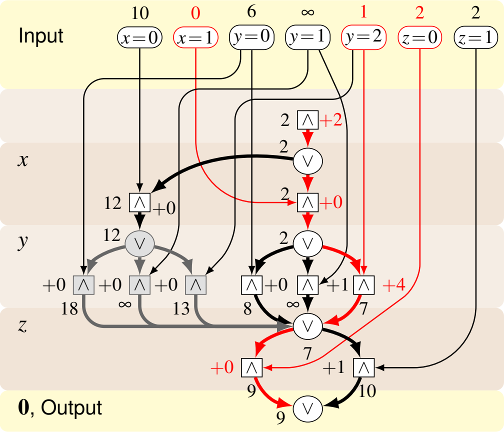

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- $cost_a(\hat{s}) = 1 \cdot 2^2 + 0 + 2 = 6$

  $= 2 + 0 + 4 + 0$
- $h_s^{add}(\hat{s}) = 0 + 1 + 2 = 3$
- $Cost_a^s = 6 + 3 = 9$

Additive Heuristic

RPG compilation:

- RPG subgraph in each layer for each action
- Connect subgraphs with precondition graphs
- Link outputs to next proposition layer

- Good: classical h^{add} on compiled task $=$
  generalized h^{add} on SDAC-task $=$
  cost value computed using RPG compilation

Section

Abstractions

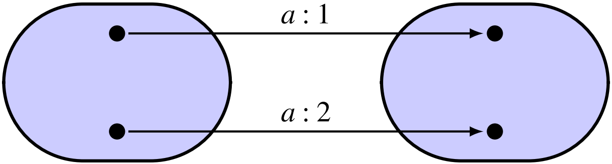
Abstraction Heuristics

Question: Why consider abstraction heuristics?

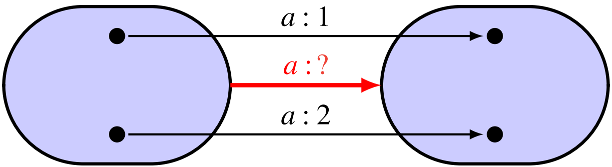
Answer:

- admissibility
- $\rightsquigarrow$ optimality

Abstraction Heuristics



Abstraction Heuristics



Question: What are the abstract action costs?

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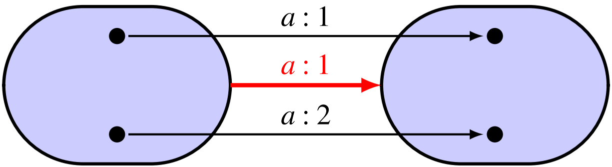
Abstraction Heuristics

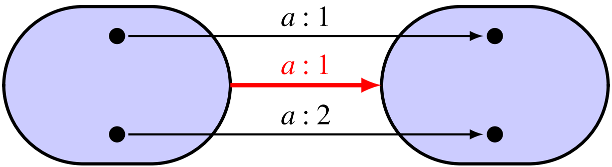


Question: What are the abstract action costs?

Answer: For admissibility, abstract cost of a should be

$$cost_a(s^{\text{abs}}) = \min_{\substack{\text{concrete state } s \\ \text{abstracted to } s^{\text{abs}}}} cost_a(s).$$

Abstraction Heuristics



Question: What are the abstract action costs?

Answer: For admissibility, abstract cost of a should be

$$\mathit{cost}_a(s^{\text{abs}}) = \min_{\substack{\text{concrete state } s \\ \text{abstracted to } s^{\text{abs}}}} \mathit{cost}_a(s).$$

Problem: exponentially many states in minimization

Aim: Compute $\mathit{cost}_a(s^{\text{abs}})$ efficiently (given EVMDD for $\mathit{cost}_a(s)$).

Cartesian Abstractions

We will see: possible if the abstraction is Cartesian or coarser.

(Includes projections and domain abstractions.)

Cartesian Abstractions

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(Includes projections and domain abstractions.)

Definition (Cartesian abstraction)

A set of states s^{abs} is Cartesian if it is of the form

$$D_1 \times \cdots \times D_n,$$

where $D_i \subseteq \mathcal{D}_i$ for all $i = 1, \ldots, n$.

An abstraction is Cartesian if all abstract states are Cartesian sets.

[Seipp and Helmert, 2013]

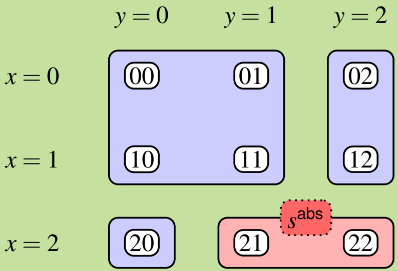
Intuition: Variables are abstracted independently.

$\rightsquigarrow$ exploit independence when computing abstract costs!

Cartesian Abstractions

Example (Cartesian abstraction)

Cartesian abstraction over x, y



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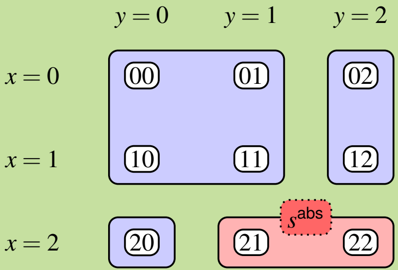
Cartesian Abstractions

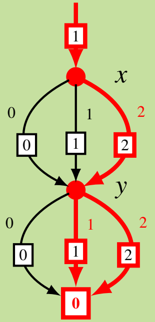
Example (Cartesian abstraction)

Cartesian abstraction over x, y

Cost $x + y + 1$

(edges consistent with s^{abs})





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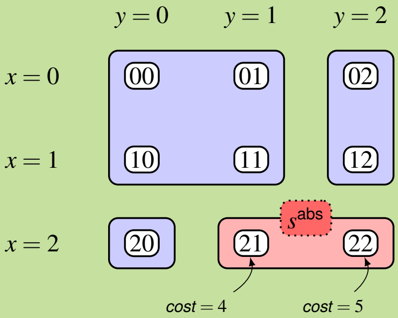

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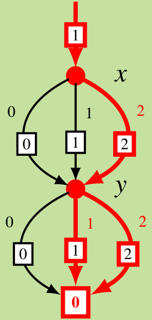

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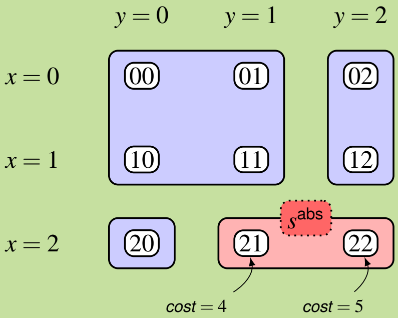

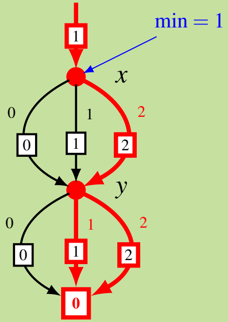

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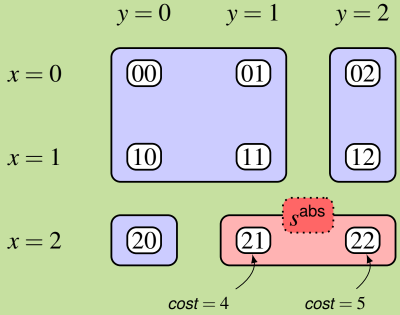

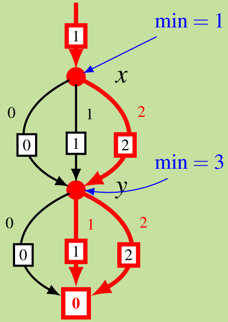

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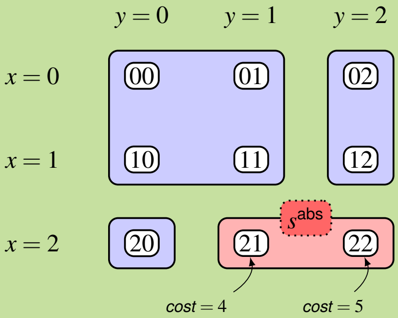

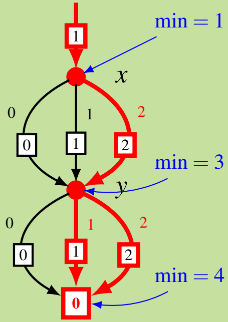

Cartesian Abstractions

What happens here? *or:*

Why does the topsort EVMDD traversal correctly compute $cost_a(s^{\text{abs}})$?

1. For each Cartesian state s^{abs} and each variable x, each value $d \in \mathcal{D}_x$ is either consistent with s^{abs} or not.
2. This implies: at all decision nodes associated with variable x, some outgoing edges are enabled, others are disabled.

   This is independent from all other decision nodes/variables.
3. This allows local minimizations over linearly many edges instead of global minimization over exponentially many paths in the EVMDD when computing minimum costs.

$\rightsquigarrow$ polynomial in EVMDD size!

Cartesian Abstractions

Not Cartesian!

If abstraction not Cartesian: two variables can be

- independent in cost function ($\rightsquigarrow$ compact EVMDD), but
- dependent in abstraction.

$\rightsquigarrow$ cannot consider independent parts of the EVMDD separately.

Cartesian Abstractions

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If abstraction not Cartesian: two variables can be

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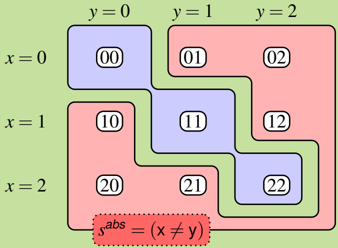
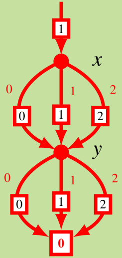
Example (Non-Cartesian abstraction)

cost : $x + y + 1$, *cost*$(s^{\text{abs}}) = 2$, local minim.: $1 \rightsquigarrow$ underestimate!





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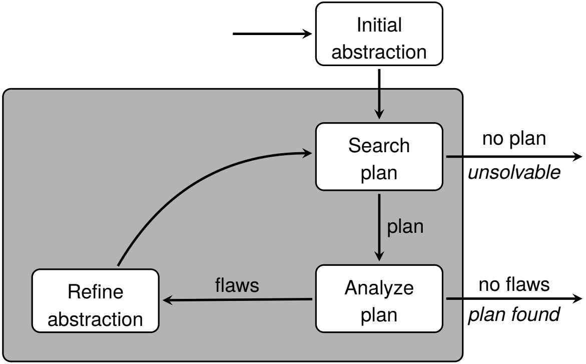
Counterexample-Guided Abstraction Refinement

Wanted: principled way of computing Cartesian abstractions.

⇝ Counterexample-Guided Abstraction Refinement (CEGAR)



Counterexample-Guided Abstraction Refinement

Possible flaws in abstract plan:

1. Concrete state does not fit abstract state (concrete and abstract traces diverge)
2. Action not applicable in concrete state
3. Trace completed, but goal not reached

Counterexample-Guided Abstraction Refinement

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Here, we need to consider a further type of flaw:

4. Cost-mismatch flaw: Action more costly in concrete state than in abstract state

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Here, we need to consider a further type of flaw:

4. Cost-mismatch flaw: Action more costly in concrete state than in abstract state

$\rightsquigarrow$ resolve cost-mismatch flaws with additional refinement.

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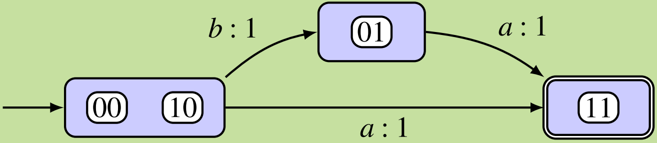
Counterexample-Guided Abstraction Refinement

Example (Cost-mismatch flaw)

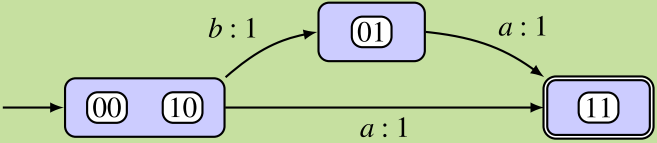


$$a = \langle \top, \quad x \wedge y \rangle, \quad \mathit{cost}_a = 2x + 1 \qquad s_0 = 10$$
$$b = \langle \top, \neg x \wedge y \rangle, \quad \mathit{cost}_b = 1 \qquad s_\star = x \wedge y$$

Background
Compilation
Relaxations
Abstractions
Cartesian Abstractions
Counterexample-Guided Abstraction Refinement
Summary

Counterexample-Guided Abstraction Refinement

Example (Cost-mismatch flaw)



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- Optimal abstract plan: $\langle a \rangle$ (abstract cost 1)

Counterexample-Guided Abstraction Refinement

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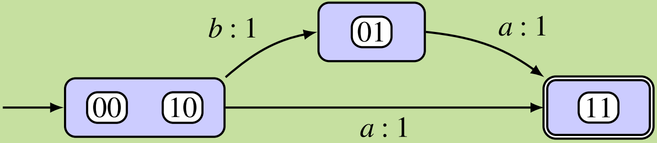

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Counterexample-Guided Abstraction Refinement

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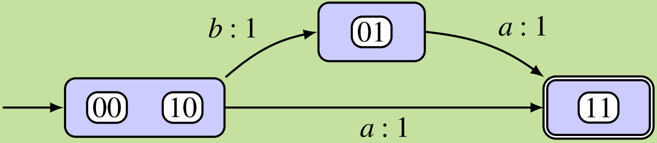

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- Optimal abstract plan: $\langle a \rangle$ (abstract cost 1)
- This is also a concrete plan (concrete cost 3)
- But optimal concrete plan: $\langle b, a \rangle$ (concr. and abstract cost 2)

Section

Summary

Summary

Summary: EVMDDs

- compact representation of cost functions
- exhibit additive structure

Recall: motivating challenges

- compiling SDAC away $\rightsquigarrow$ solved!
  - EVMDD-based action compilation
  - preserves h^{add} and h^{abs}
- SDAC-aware h values $\rightsquigarrow$ possible!
  - h^{add}
  - RPG embedding
  - Cartesian abstraction heuristics

Future Work

Future Work:

- Other delete-relaxation heuristics such as h^{FF}
- Static and dynamic EVMDD variable orders

Part II

Practice

Section

Libraries

EVMDD Libraries

MEDDLY

- MEDDLY: Multi-terminal and Edge-valued
  Decision Diagram LibrarY
- Authors: Junaid Babar and Andrew Miner
- Language: C++
- License: open source (LGPLv3)
- Advantages:
  - many different types of decision diagrams
  - mature and efficient
- Disadvantages:
  - documentation
- Code: `http://meddly.sourceforge.net`

EVMDD Libraries

pyevmdd

- pyevmdd: EVMDD library for Python
- Authors: RM and FG
- Language: Python
- License: open source (GPLv3)
- Disadvantages:
  - restricted to EVMDDs
  - neither mature nor optimized
- Purpose: our EVMDD playground
- Code: `https://github.com/robertmattmueller/pyevmdd`
- Documentation: `http://pyevmdd.readthedocs.io/en/latest/`

Section

PDDL

PDDL Representation

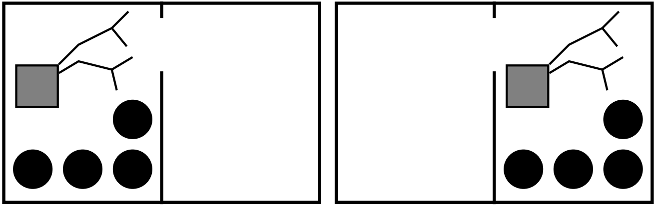
Usual way of representing costs in PDDL:

- effects `(increase (total-cost) (<expression>))`
- metric `(minimize (total-cost))`

Custom syntax:

- Besides `:parameters`, `:precondition`, and `:effect`, actions may have field
- `:cost (<expression>)`

Gripper

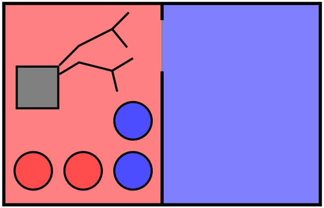


initial state goal state

Libraries

PDDL

Colored Gripper



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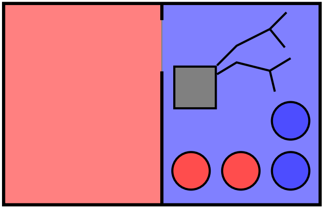
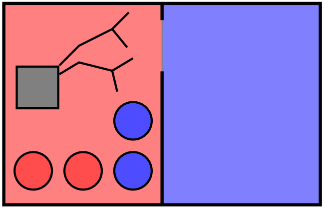


goal state

- Colored rooms and balls
- Cost of move increases if ball color differs from its room color
- Goal did not change!

Colored Gripper



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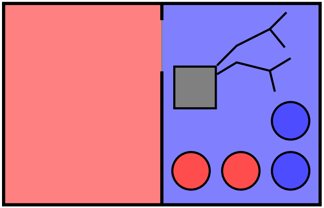

goal state

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- Cost of move increases if ball color differs from its room color
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$$cost(move) = \sum_{\text{ROOM}} \sum_{\text{BALL}} (at(\text{BALL}, \text{ROOM}) \wedge (red(\text{BALL})) \wedge (blue(\text{ROOM}))$$
$$+ \sum_{\text{ROOM}} \sum_{\text{BALL}} (at(\text{BALL}, \text{ROOM}) \wedge (blue(\text{BALL})) \wedge (red(\text{ROOM}))$$

EVMDD-Based Action Compilation

Example (EVMDD-based action compilation)

Let $a = \langle \mathit{pre}, \mathit{eff} \rangle$, $\mathit{cost}_a = xy^2 + z + 2$.

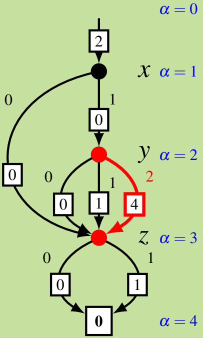
Auxiliary variables:

- One semaphore variable σ with $\mathcal{D}_\sigma = \{0, 1\}$ for entire planning task.
- One auxiliary variable $\alpha = \alpha_a$ with $\mathcal{D}_{\alpha_a} = \{0, 1, 2, 3, 4\}$ for action a.

Replace a by new auxiliary actions (similarly for other actions).

EVMDD-Based Action Compilation

Example (EVMDD-based action compilation, ctd.)



$$
\begin{aligned}
a^{pre} &= \langle pre \wedge \sigma = 0 \wedge \alpha = 0, \\
&\qquad \sigma = 1 \wedge \alpha = 1\rangle, && cost = 2 \\
a^{1,x=0} &= \langle \alpha = 1 \wedge x = 0,\ \alpha = 3\rangle, && cost = 0 \\
a^{1,x=1} &= \langle \alpha = 1 \wedge x = 1,\ \alpha = 2\rangle, && cost = 0 \\
a^{2,y=0} &= \langle \alpha = 2 \wedge y = 0,\ \alpha = 3\rangle, && cost = 0 \\
a^{2,y=1} &= \langle \alpha = 2 \wedge y = 1,\ \alpha = 3\rangle, && cost = 1 \\
a^{2,y=2} &= \langle \alpha = 2 \wedge y = 2,\ \alpha = 3\rangle, && cost = 4 \\
a^{3,z=0} &= \langle \alpha = 3 \wedge z = 0,\ \alpha = 4\rangle, && cost = 0 \\
a^{3,z=1} &= \langle \alpha = 3 \wedge z = 1,\ \alpha = 4\rangle, && cost = 1 \\
a^{eff} &= \langle \alpha = 4,\ eff \wedge \sigma = 0 \wedge \alpha = 0\rangle, && cost = 0
\end{aligned}
$$

EVMDD-Based Action Compilation Tool

- Disclaimer:
  - Not completely functional
  - Still some bugs
- Uses pyevmdd
- Language: Python
- License: open source
- Code: `https://github.com/robertmattmueller/sdac-compiler`

Part III

Acknowledgements

Acknowledgements

Acknowledgements:

- Christian Muise, for taking the time to get our compiler running in the cloud.
- Erik Wacker, for working on the compiler.
- Thomas Keller, for doing all the reasearch behind this tutorial with us.

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Part IV

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