Principles of AI Planning

12. Planning with State-Dependent Action Costs

Bernhard Nebel and Robert Mattmüller
December 16th, 2016
Background
We now know the basics of classical planning.

Where to go from here? Possible routes:

- Algorithms: techniques orthogonal to heuristic search (partial-order reduction, symmetry reduction, decompositions, ...)
  \[\Rightarrow\] later

- Algorithms: techniques other than heuristic search (SAT/SMT planning, ...)
  \[\Rightarrow\] beyond the scope of this course

- Settings beyond classical planning (nondeterminism, partial observability, numeric planning, ...)
  \[\Rightarrow\] later

- A slight extension to the expressiveness of classical planning tasks
  \[\Rightarrow\] this chapter
What are State-Dependent Action Costs?

Action costs:

- **Unit**
- **Constant**
- **State-dependent**

Cost of flying to London from the current location:

\[|x_{\text{current}}| + |y_{\text{current}}|.\]
What are State-Dependent Action Costs?

Action costs:  
- **unit**
- **constant**
- **state-dependent**

\[
\begin{align*}
\text{cost}(\text{fly}(\text{Madrid}, \text{London})) &= 1, \\
\text{cost}(\text{fly}(\text{Paris}, \text{London})) &= 1, \\
\text{cost}(\text{fly}(\text{Freiburg}, \text{London})) &= 1, \\
\text{cost}(\text{fly}(\text{Istanbul}, \text{London})) &= 1.
\end{align*}
\]
What are State-Dependent Action Costs?

Action costs: unit │ constant │ state-dependent

\[
\begin{align*}
\text{cost}(\text{fly}(\text{Madrid}, \text{London})) &= 14, & \text{cost}(\text{fly}(\text{Paris}, \text{London})) &= 5, \\
\text{cost}(\text{fly}(\text{Freiburg}, \text{London})) &= 10, & \text{cost}(\text{fly}(\text{Istanbul}, \text{London})) &= 32.
\end{align*}
\]
What are State-Dependent Action Costs?

Action costs:  

\[ \text{cost}(\text{flyTo}(\text{London})) = |x_{\text{London}} - x_{\text{current}}| + |y_{\text{London}} - y_{\text{current}}| = |x_{\text{current}}| + |y_{\text{current}}|. \]
Why Study State-Dependent Action Costs?

- **In classical planning**: actions have unit costs.
  - Each action $a$ costs 1.

- **Simple extension**: actions have constant costs.
  - Each action $a$ costs some $cost_a \in \mathbb{N}$.
  - Example: Flying between two cities costs amount proportional to distance.
  - Still easy to handle algorithmically, e.g. when computing $g$ and $h$ values.

- **Further extension**: actions have state-dependent costs.
  - Each action $a$ has cost function $cost_a : S \rightarrow \mathbb{N}$.
  - Example: Flying to a destination city costs amount proportional to distance, depending on the current city.
Why Study State-Dependent Action Costs?

- **Human perspective:**
  - “natural”, “elegant”, and “higher-level”
  - modeler-friendly $\leadsto$ less error-prone?

- **Machine perspective:**
  - more structured $\leadsto$ exploit structure in algorithms?
  - fewer redundancies, exponentially more compact

- **Language support:**
  - numeric PDDL, PDDL 3
  - RDDL, MDPs (state-dependent rewards!)

- **Applications:**
  - modeling preferences and soft goals
  - application domains such as PSR

*(Abbreviation: SDAC = state-dependent action costs)*
Handling State-Dependent Action Costs

Good news:

- Computing \( g \) values in forward search still easy.
  (When expanding state \( s \) with action \( a \), we know \( \text{cost}_a(s) \).)

Challenge:

- But what about SDAC-aware \( h \) values
  (relaxation heuristics, abstraction heuristics)?
- Or can we simply compile SDAC away?

This chapter:

- Proposed answers to these challenges.
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
A SAS$^+$ planning task with state-dependent action costs or SDAC planning task is a tuple $\Pi = \langle V, I, O, \gamma, (\text{cost}_a)_{a \in O} \rangle$ where $\langle V, I, O, \gamma \rangle$ is a (regular) SAS$^+$ planning task with state set $S$ and $\text{cost}_a : S \rightarrow \mathbb{N}$ is the cost function of $a$ for all $a \in O$.

**Assumption:** For each $a \in O$, the set of variables occurring in the precondition of $a$ is disjoint from the set of variables on which the cost function $\text{cost}_a$ depends.

(Question: Why is this assumption unproblematic?)

Definitions of plans etc. stay as before. A plan is **optimal** if it minimizes the sum of action costs from start to goal.

For the rest of this chapter, we consider the following running example.
Example (Household domain)

Actions:

\[
\begin{align*}
vacuumFloor &= \langle \top, \text{floorClean} \rangle \\
washDishes &= \langle \top, \text{dishesClean} \rangle \\
doHousework &= \langle \top, \text{floorClean} \land \text{dishesClean} \rangle
\end{align*}
\]

Cost functions:

\[
\begin{align*}
cost_{vacuumFloor} &= [\neg \text{floorClean}] \cdot 2 \\
cost_{washDishes} &= [\neg \text{dishesClean}] \cdot (1 + 2 \cdot [\neg \text{haveDishwasher}]) \\
cost_{doHousework} &= cost_{vacuumFloor} + cost_{washDishes}
\end{align*}
\]

(Question: How much can applying action washDishes cost?)
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

\[
\begin{align*}
\text{dishesClean, haveDishwasher:} & \ 0 \\
\text{dishesClean, } \neg \text{haveDishwasher:} & \ 0 \\
\neg \text{dishesClean, haveDishwasher:} & \ 1 \\
\neg \text{dishesClean, } \neg \text{haveDishwasher:} & \ 3 \\
\end{align*}
\]

\[
\begin{align*}
washDishes( dC, hD) & = \langle dC \wedge hD, dC \rangle, \quad \text{cost} = 0 \\
washDishes( dC, \neg hD) & = \langle dC \wedge \neg hD, dC \rangle, \quad \text{cost} = 0 \\
washDishes( \neg dC, hD) & = \langle \neg dC \wedge hD, dC \rangle, \quad \text{cost} = 1 \\
washDishes( \neg dC, \neg hD) & = \langle \neg dC \wedge \neg hD, dC \rangle, \quad \text{cost} = 3 \\
\end{align*}
\]
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? ⇝ Compilation II
State-Dependent Action Costs

Compilation II: “Purely Sequential Action Decomposition”

Example

Assume we own a dishwasher:

\[
\begin{align*}
    \text{cost}_{\text{doHousework}} &= 2 \cdot [\neg \text{floorClean}] + [\neg \text{dishesClean}] \\
    \text{floorClean}: 0 &\quad \text{dishesClean}: 0 \\
    \neg \text{floorClean}: 2 &\quad \neg \text{dishesClean}: 1
\end{align*}
\]

\[
\begin{align*}
    \text{doHousework}_1(\text{fC}) &= \langle \text{fC, fC} \rangle, \quad \text{cost} = 0 \\
    \text{doHousework}_1(\neg \text{fC}) &= \langle \neg \text{fC, fC} \rangle, \quad \text{cost} = 2 \\
    \text{doHousework}_2(\text{dC}) &= \langle \text{dC, dC} \rangle, \quad \text{cost} = 0 \\
    \text{doHousework}_2(\neg \text{dC}) &= \langle \neg \text{dC, dC} \rangle, \quad \text{cost} = 1
\end{align*}
\]
Compilation II

If costs are \textit{additively decomposable}:

- high-level actions $\approx$ \textit{macro actions}
- decompose into \textit{sequential micro actions}
State-Dependent Action Costs
Compilation II: “Purely Sequential Action Decomposition”

Properties:

✅ linear blow-up
❌ not always possible

● plan lengths not preserved

E.g., in a state where \( \neg fC \) and \( \neg dC \) hold, an application of

\[ \text{doHousework} \]

in the SDAC setting is replaced by an application of the action sequence

\[ \text{doHousework}_{1}(\neg fC), \text{doHousework}_{2}(\neg dC) \]

in the compiled setting.
Properties (ctd.):

- plan costs preserved
- blow-up in search space
  
  E.g., in a state where \( \neg fC \) and \( \neg dC \) hold, should we apply \( \text{doHousework}_1(\neg fC) \) or \( \text{doHousework}_2(\neg dC) \) first?

  \( \leadsto \) impose action ordering!

- attention: we should apply all partial effects at end!
  
  Otherwise, an effect of an earlier action in the compilation might affect the cost of a later action in the compilation.

**Question:** Can this always work (kind of)? \( \leadsto \) Compilation III
State-Dependent Action Costs
Compilation III: “EVMDD-Based Action Decomposition”

Example

\[ cost_{\text{doHousework}} = [\neg \text{floorClean}] \cdot 2 + 
\quad [\neg \text{dishesClean}] \cdot (1 + 2 \cdot [\neg \text{haveDishwasher}]) \]

Simplify right-hand part of diagram:

- Branch over single variable at a time.
- Exploit: \text{haveDishwasher} irrelevant if \text{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 (cf. theory of BDDs)

Properties:

- ✓ always possible
- ● worst-case exponential blow-up, but as good as it gets
- ● as with Compilation II: plan lengths not preserved, plan costs preserved
- ● as with Compilation II: action ordering, all effects at end!
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: 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”, well-behaved cases (Question: For example?)

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
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)

\[ \text{cost}_a = xy^2 + z + 2 \]

\[ \mathcal{D}_x = \mathcal{D}_z = \{0, 1\}, \quad \mathcal{D}_y = \{0, 1, 2\} \]

- Directed acyclic graph
- Dangling incoming edge
- Single terminal node 0
- Decision nodes with:
  - decision variables
  - edge label
  - edge weights
- We see: \( z \) independent from rest, \( y \) only matters if \( x \neq 0 \).
Example (EVMDD Evaluation)

\[ \text{cost}_a = xy^2 + z + 2 \]

\[ \mathcal{D}_x = \mathcal{D}_z = \{0, 1\}, \quad \mathcal{D}_y = \{0, 1, 2\} \]

\[ s = \{x \mapsto 1, \ y \mapsto 2, \ z \mapsto 0\} \]

\[ \text{cost}_a(s) = \]

\[ \text{cost}_a(s) = x \cdot y^2 + z + 2 \]
Example (EVMDD Evaluation)

\[ \text{cost}_a = xy^2 + z + 2 \]

\[ \mathcal{D}_x = \mathcal{D}_z = \{0, 1\}, \quad \mathcal{D}_y = \{0, 1, 2\} \]

\[ s = \{x \mapsto 1, \ y \mapsto 2, \ z \mapsto 0\} \]

\[ \text{cost}_a(s) = 2 + \]
Example (EVMDD Evaluation)

\[ \text{cost}_a = xy^2 + z + 2 \]

\( D_x = D_z = \{0, 1\}, \quad D_y = \{0, 1, 2\} \)

\( s = \{x \mapsto 1, \ y \mapsto 2, \ z \mapsto 0\} \)

\[ \text{cost}_a(s) = 2 + 0 + \]
EVMDDs
Edge-Valued Multi-Valued Decision Diagrams

Example (EVMDD Evaluation)

\[ \text{cost}_a = xy^2 + z + 2 \]

\[ \mathcal{D}_x = \mathcal{D}_z = \{0, 1\}, \quad \mathcal{D}_y = \{0, 1, 2\} \]

\[ s = \{x \mapsto 1, \ y \mapsto 2, \ z \mapsto 0\} \]

\[ \text{cost}_a(s) = 2 + 0 + 4 + \]
Example (EVMDD Evaluation)

\[ \text{cost}_a = xy^2 + z + 2 \quad \text{and} \quad D_x = D_z = \{0, 1\}, \quad D_y = \{0, 1, 2\} \]

\[ s = \{x \mapsto 1, \; y \mapsto 2, \; z \mapsto 0\} \]

\[ \text{cost}_a(s) = 2 + 0 + 4 + 0 = 6 \]
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 $\otimes \in \{+, -, \cdot, \ldots\}$, EVMDDs $\mathcal{E}_1, \mathcal{E}_2$. Compute EVMDD $\mathcal{E} = \mathcal{E}_1 \otimes \mathcal{E}_2$.

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

- **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
Compilation
Idea: each edge in the EVMDD becomes a new micro action with constant cost corresponding to the edge constraint, precondition that we are currently at its start EVMDD node, and effect that we are currently at its target EVMDD node.

Example (EVMDD-based action compilation)

Let $a = \langle \chi, e \rangle$, $\text{cost}_a = xy^2 + z + 2$.

Auxiliary variables:

- One semaphore variable $\sigma$ 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).
Example (EVMDD-based action compilation, ctd.)

\[ a^\chi = \langle \chi \land \sigma = 0 \land \alpha = 0, \]
\[ \sigma := 1 \land \alpha := 1 \rangle, \quad \text{cost} = 2 \]
\[ a^{1,x=0} = \langle \alpha = 1 \land x = 0, \alpha := 3 \rangle, \quad \text{cost} = 0 \]
\[ a^{1,x=1} = \langle \alpha = 1 \land x = 1, \alpha := 2 \rangle, \quad \text{cost} = 0 \]
\[ a^{2,y=0} = \langle \alpha = 2 \land y = 0, \alpha := 3 \rangle, \quad \text{cost} = 0 \]
\[ a^{2,y=1} = \langle \alpha = 2 \land y = 1, \alpha := 3 \rangle, \quad \text{cost} = 1 \]
\[ a^{2,y=2} = \langle \alpha = 2 \land y = 2, \alpha := 3 \rangle, \quad \text{cost} = 4 \]
\[ a^{3,z=0} = \langle \alpha = 3 \land z = 0, \alpha := 4 \rangle, \quad \text{cost} = 0 \]
\[ a^{3,z=1} = \langle \alpha = 3 \land z = 1, \alpha := 4 \rangle, \quad \text{cost} = 1 \]
\[ a^e = \langle \alpha = 4, e \land \sigma := 0 \land \alpha := 0 \rangle, \quad \text{cost} = 0 \]
Definition (EVMDD-based action compilation)

Let \( \Pi = \langle V, I, O, \gamma, (cost_a)_{a \in O} \rangle \) be an SDAC planning task, and for each action \( a \in O \), let \( \mathcal{E}_a \) be an EVMDD that encodes the cost function \( cost_a \).

Let \( EAC(a) \) be the set of actions created from \( a \) using \( \mathcal{E}_a \) similar to the previous example. Then the EVMDD-based action compilation of \( \Pi \) using \( \mathcal{E}_a, a \in O \), is the task \( \Pi' = EAC(\Pi) = \langle V', I', O', \gamma' \rangle \), where

- \( V' = V \cup \{ \sigma \} \cup \{ \alpha_a | a \in O \} \),
- \( I' = I \cup \{ \sigma \mapsto 0 \} \cup \{ \alpha_a \mapsto 0 | a \in O \} \),
- \( O' = \bigcup_{a \in O} EAC(a) \), and
- \( \gamma' = \gamma \land (\sigma = 0) \land \bigwedge_{a \in O} (\alpha_a = 0) \).
EVMDD-Based Action Compilation

Let $\Pi$ be an SDAC task and $\Pi' = EAC(\Pi)$ its EVMDD-based action compilation (for appropriate EVMDDs $E_a$).

**Proposition**

$\Pi'$ has only state-independent costs.

**Proof.**

By construction.

**Proposition**

The size $\|\Pi'\|$ is in the order $O(\|\Pi\| \cdot \max_{a \in O} \|E_a\|)$, i.e. polynomial in the size of $\Pi$ and the largest used EVMDD.

**Proof.**

By construction.
Let $\Pi$ be an SDAC task and $\Pi' = EAC(\Pi)$ its EVMDD-based action compilation (for appropriate EVMDDs $E_a$).

**Proposition**

$\Pi$ and $\Pi'$ admit the same plans (up to replacement of actions by action sequences). Optimal plan costs are preserved.

**Proof.**

Let $\pi = a_1, \ldots, a_n$ be a plan for $\Pi$, and let $s_0, \ldots, s_n$ be the corresponding state sequence such that $a_i$ is applicable in $s_{i-1}$ and leads to $s_i$ for all $i = 1, \ldots, n$.

For each $i = 1, \ldots, n$, let $E_{a_i}$ be the EVMDD used to compile $a_i$. State $s_{i-1}$ determines a unique path through the EVMDD $E_{a_i}$, which uniquely corresponds to an action sequence $a_i^0, \ldots, a_i^{k_i}$ (for some $k_i \in \mathbb{N}$; including $a_i^\chi$ and $a_i^e$).
Proof (ctd.)

By construction, \( \text{cost}(a_i^0) + \cdots + \text{cost}(a_i^{k_i}) = \text{cost}_{a_i}(s_{i-1}) \).

Moreover, the sequence \( a_i^0, \ldots, a_i^{k_i} \) is applicable in \( s_{i-1} \cup \{ \sigma \mapsto 0 \} \cup \{ \alpha_a \mapsto 0 \, | \, a \in O \} \) and leads to \( s_i \cup \{ \sigma \mapsto 0 \} \cup \{ \alpha_a \mapsto 0 \, | \, a \in O \} \).

Therefore, by induction, \( \pi' = a_1^0, \ldots, a_1^{k_1}, \ldots, a_n^0, \ldots, a_n^{k_n} \) is applicable in \( s_0 \cup \{ \sigma \mapsto 0 \} \cup \{ \alpha_a \mapsto 0 \, | \, a \in O \} \) (and leads to a goal state). Moreover,

\[
\text{cost}(\pi') = \text{cost}(a_1^0) + \cdots + \text{cost}(a_1^{k_1}) + \cdots + \text{cost}(a_n^0) + \cdots + \text{cost}(a_n^{k_n}) = \\
\text{cost}_{a_1}(s_0) + \cdots + \text{cost}_{a_n}(s_{n-1}) = \text{cost}(\pi).
\]

Still to show: \( \Pi' \) admits no other plans. It suffices to see that the semaphore \( \sigma \) prohibits interleaving more than one EVMDD evaluation, and that each \( \alpha_a \) makes sure that the EVMDD for \( a \) is traversed in the unique correct order.
Example

Let \( \Pi = \langle V, I, O, \gamma \rangle \) with \( V = \{x, y, z, u\} \), \( D_x = D_z = \{0, 1\} \), \( D_y = D_u = \{0, 1, 2\} \), \( I = \{x \mapsto 1, y \mapsto 2, z \mapsto 0, u \mapsto 0\} \), \( O = \{a, b\} \), and \( \gamma = (u = 2) \) with

\[
\begin{align*}
  a &= \langle u = 0, u := 1 \rangle, & \text{cost}_a &= xy^2 + z + 2, \\
  b &= \langle u = 1, u := 2 \rangle, & \text{cost}_b &= z + 1.
\end{align*}
\]

Optimal plan for \( \Pi \):

\[ \pi = a, b \text{ with } \text{cost}(\pi) = 6 + 1 = 7. \]
EVMDD-Based Action Compilation

Example (Ctd.)

Compilation of $a$:

\[ a^\chi = \langle u = 0 \land \sigma = 0 \land \alpha_a = 0, \]
\[ \sigma := 1 \land \alpha_a := 1 \rangle, \quad \text{cost} = 2 \]

\[ a^{1.x=0} = \langle \alpha_a = 1 \land x = 0, \alpha_a := 3 \rangle, \quad \text{cost} = 0 \]

\[ a^{1.x=1} = \langle \alpha_a = 1 \land x = 1, \alpha_a := 2 \rangle, \quad \text{cost} = 0 \]

\[ a^{2.y=0} = \langle \alpha_a = 2 \land y = 0, \alpha_a := 3 \rangle, \quad \text{cost} = 0 \]

\[ a^{2.y=1} = \langle \alpha_a = 2 \land y = 1, \alpha_a := 3 \rangle, \quad \text{cost} = 1 \]

\[ a^{2.y=2} = \langle \alpha_a = 2 \land y = 2, \alpha_a := 3 \rangle, \quad \text{cost} = 4 \]

\[ a^{3.z=0} = \langle \alpha_a = 3 \land z = 0, \alpha_a := 4 \rangle, \quad \text{cost} = 0 \]

\[ a^{3.z=1} = \langle \alpha_a = 3 \land z = 1, \alpha_a := 4 \rangle, \quad \text{cost} = 1 \]

\[ a^e = \langle \alpha_a = 4, u := 1 \land \sigma := 0 \land \alpha_a := 0 \rangle, \quad \text{cost} = 0 \]
Example (Ctd.)

Compilation of \( b \):

\[
\begin{align*}
\alpha_{b} = 0 &\quad b^{x} = \langle u = 1 \land \sigma = 0 \land \alpha_{b} = 0, \\
\sigma := 1 \land \alpha_{b} := 1 \rangle, &\quad \text{cost} = 1 \\
\alpha_{b} = 1 &\quad b^{1,z=0} = \langle \alpha_{b} = 1 \land z = 0, \alpha_{b} := 2 \rangle, &\quad \text{cost} = 0 \\
\alpha_{b} = 1 &\quad b^{1,z=1} = \langle \alpha_{b} = 1 \land z = 1, \alpha_{b} := 2 \rangle, &\quad \text{cost} = 1 \\
\alpha_{b} = 2 &\quad b^{e} = \langle \alpha_{b} = 2, u := 2 \land \sigma := 0 \land \alpha_{b} := 0 \rangle, &\quad \text{cost} = 0
\end{align*}
\]
Example (Ctd.)

Compilation of $b$:

$$b^\chi = \langle u = 1 \land \sigma = 0 \land \alpha_b = 0,\rangle,$$
$$\sigma := 1 \land \alpha_b := 1 \rangle, \quad cost = 1$$

$$b^{1,z=0} = \langle \alpha_b = 1 \land z = 0, \alpha_b := 2 \rangle, \quad cost = 0$$

$$b^{1,z=1} = \langle \alpha_b = 1 \land z = 1, \alpha_b := 2 \rangle, \quad cost = 1$$

$$b^e = \langle \alpha_b = 2, u := 2 \land \sigma := 0 \land \alpha_b := 0 \rangle, \quad cost = 0$$

Optimal plan for $\Pi'$ (with $cost(\pi') = 6 + 1 = 7 = cost(\pi)$):

$$\pi' = a^\chi, a^{1,x=1}, a^{2,y=2}, a^{3,z=0}, a^e, b^\chi, b^{1,z=0}, b^e.$$

$cost = 2 + 0 + 4 + 0 + 0 = 6$  
$cost = 1 + 0 + 0 = 1$
Okay. We can compile SDAC away somewhat efficiently. Is this the end of the story?

No! Why not?

- **Tighter integration** of SDAC into planning process might be **beneficial**.
- Analysis of heuristics for SDAC might **improve our understanding**.

**Consequence:** Let’s study heuristics for SDAC in **uncompiled** setting.
Relaxations
We know: Delete-relaxation heuristics informative in classical planning.

Question: Are they also informative in SDAC planning?
Assume we want to compute the additive heuristic $h^{\text{add}}$ in a task with state-dependent action costs.

But what does an action $a$ cost in a relaxed state $s^+$?

And how to compute that cost?
Relaxed SAS$^+$ Tasks

Delete relaxation in SAS$^+$ tasks works as follows:

- Operators are already in effect normal form.
- We do not need to impose a positive normal form, because all conditions are conjunctions of facts, and facts are just variable-value pairs and hence always positive.
- Hence $a^+ = a$ for any operator $a$, and $\Pi^+ = \Pi$.
- For simplicity, we identify relaxed states $s^+$ with their on-sets $on(s^+)$. 
- Then, a relaxed state $s^+$ is a set of facts $(v, d)$ with $v \in V$ and $d \in D_v$ including at least one fact $(v, d)$ for each $v \in V$ (but possibly more than one, which is what makes it a relaxed state).
Relaxed SAS$^+$ Tasks

- A relaxed operator $a$ is applicable in a relaxed state $s^+$ if all precondition facts of $a$ are contained in $s^+$.
- Relaxed states accumulate facts reached so far.
- Applying a relaxed operator $a$ to a relaxed state $s^+$ adds to $s^+$ those facts made true by $a$.

**Example**

Relaxed operator $a^+ = \langle x = 2, y := 1 \land z := 0 \rangle$ is applicable in relaxed state $s^+ = \{(x, 0), (x, 2), (y, 0), (z, 1)\}$, because precondition $(x, 2) \in s^+$, and leads to successor $(s^+)' = s^+ \cup \{(y, 1), (z, 0)\}$.

Relaxed plans, dominance, monotonicity etc. as before. The above definition generalizes the one for propositional tasks.
Action Costs in Relaxed States

Example

Assume $s^+$ is the relaxed state with

$$s^+ = \{(x, 0), (x, 1), (y, 1), (y, 2), (z, 0)\}.$$

What should action $a$ with $cost_a = xy^2 + z + 2$ cost in $s^+$?
Idea: We should assume the cheapest way of applying $o^+$ in $s^+$ to guarantee admissibility of $h^+$.
(Allow at least the behavior of the unrelaxed setting at no higher cost.)

Example

\[
\begin{align*}
  x = 0, y = 1, z = 0 & \Rightarrow a \ [2] \\
  x = 0, y = 2, z = 0 & \Rightarrow a \ [2] \\
  x = 1, y = 1, z = 0 & \Rightarrow a \ [3] \\
  x = 1, y = 2, z = 0 & \Rightarrow a \ [6]
\end{align*}
\]
**Idea:** We should assume the *cheapest* way of applying $o^+$ in $s^+$ to guarantee admissibility of $h^+$. (Allow at least the behavior of the unrelaxed setting at no higher cost.)

**Example**

![Diagram](attachment:image.png)
Action Costs in Relaxed States

**Definition**

Let $V$ be a set of FDR variables, $s : V \rightarrow \bigcup_{v \in V} D_v$ an unrelaxed state over $V$, and $s^+ \subseteq \{(v, d) | v \in V, d \in D_v\}$ a relaxed state over $V$. We call $s$ consistent with $s^+$ if $\{(v, s(v)) | v \in V\} \subseteq s^+$.

**Definition**

Let $a \in O$ be an action with cost function $cost_a$, and $s^+$ a relaxed state. Then the **relaxed cost** of $a$ in $s^+$ is defined as

$$cost_a(s^+) = \min_{s \in S \text{ consistent with } s^+} cost_a(s).$$

(Question: How many states $s$ are consistent with $s^+$?)
Problem with this definition: There are generally exponentially many states $s$ consistent with $s^+$ to minimize over.

Central question: Can we still do this minimization efficiently?

Answer: Yes, at least efficiently in the size of an EVMDD encoding $cost_a$. 
Cost Computation for Relaxed States

Example

Relaxed state $s^+ = \{(x, 0), (x, 1), (y, 1), (y, 2), (z, 0)\}$.

- Computing $\text{cost}_{a}(s^+) = \text{minimizing over } \text{cost}_{a}(s) \text{ for all } s \text{ consistent with } s^+ = \text{minimizing over all start-end-paths in EVMDD following only edges consistent with } s^+$.

- Observation: Minimization over exponentially many paths can be replaced by top-sort traversal of EVMDD, minimizing over incoming arcs consistent with $s^+$ at all nodes!
Cost Computation for Relaxed States

Example

Relaxed state $s^+ = \{(x, 0), (x, 1), (y, 1), (y, 2), (z, 0)\}$.

- Computing $\text{cost}_a(s^+) =$ minimizing over $\text{cost}_a(s)$ for all $s$ consistent with $s^+ = \{(x, 0), (x, 1), (y, 1), (y, 2), (z, 0)\}$.

- Observation: Minimization over exponentially many paths can be replaced by top-sort traversal of EVMDD, minimizing over incoming arcs consistent with $s^+$ at all nodes!
Cost Computation for Relaxed States

Example

Relaxed state $s^+ = \{(x, 0), (x, 1), (y, 1), (y, 2), (z, 0)\}$.

Computing $cost_a(s^+) = \min_{s \in s^+} cost_a(s)$ for all $s$ consistent with $s^+$.

Observation: Minimization over exponentially many paths can be replaced by top-sort traversal of EVMDD, minimizing over incoming arcs consistent with $s^+$ at all nodes!
Cost Computation for Relaxed States

Example

Relaxed state $s^+ = \{(x, 0), (x, 1), (y, 1), (y, 2), (z, 0)\}$.

- Computing $cost_a(s^+) =$ minimizing over $cost_a(s)$ for all $s$ consistent with $s^+$ = minimizing over all start-end-paths in EVMDD following only edges consistent with $s^+$.

- Observation: Minimization over exponentially many paths can be replaced by top-sort traversal of EVMDD, minimizing over incoming arcs consistent with $s^+$ at all nodes!
Cost Computation for Relaxed States

Example

Relaxed state $s^+ = \{(x, 0), (x, 1), (y, 1), (y, 2), (z, 0)\}$.

- Computing $\text{cost}_a(s^+) = \min$ over $\text{cost}_a(s)$ for all $s$ consistent with $s^+ = \min$ over all start-end-paths in EVMDD following only edges consistent with $s^+$.

- Observation: Minimization over exponentially many paths can be replaced by top-sort traversal of EVMDD, minimizing over incoming arcs consistent with $s^+$ at all nodes!
Example

Relaxed state $s^+ = \{(x, 0), (x, 1), (y, 1), (y, 2), (z, 0)\}$.

- $\text{cost}_a(s^+) = 2$
- Cost-minimizing $s$ consistent with $s^+$: $s(x) = s(z) = 0$, $s(y) \in \{1, 2\}$. 
Theorem

A top-sort traversal of the EVMDD for $\text{cost}_a$, adding edge weights and minimizing over incoming arcs consistent with $s^+$ at all nodes, computes $\text{cost}_a(s^+)$ and takes time in the order of the size of the EVMDD.

Proof.

Homework?
Relaxation Heuristics

The following definition is equivalent to the RPG-based one.

**Definition (Classical additive heuristic \( h^{add} \))**

\[
\begin{align*}
    h^{add}(s) &= h^{add}_s(\text{GoalFacts}) \\
    h^{add}_s(\text{Facts}) &= \sum_{\text{fact} \in \text{Facts}} h^{add}_s(\text{fact}) \\
    h^{add}_s(\text{fact}) &= \begin{cases} 
    0 & \text{if } \text{fact} \in s \\
    \min_{\text{achiever } a \text{ of } \text{fact}} [h^{add}_s(\text{pre}(a)) + \text{cost}_a] & \text{otherwise}
    \end{cases}
\end{align*}
\]

**Question:** How to generalize \( h^{add} \) to SDAC?
Relaxations with SDAC

**Example**

\[
\begin{align*}
  a &= \langle \top, \ x = 1 \rangle & \text{cost}_a &= 2 - 2y \\
  b &= \langle \top, \ y = 1 \rangle & \text{cost}_b &= 1 \\
  s &= \{x \mapsto 0, y \mapsto 0\} & \\
  h_s^{add}(y = 1) &= 1 \\
  h_s^{add}(x = 1) &= ?
\end{align*}
\]
Relaxations with SDAC

Example

\[ a = \langle \top, x = 1 \rangle \quad \text{cost}_a = 2 - 2y \]
\[ b = \langle \top, y = 1 \rangle \quad \text{cost}_b = 1 \]

\[ s = \{ x \mapsto 0, y \mapsto 0 \} \]
\[ h^\text{add}_s (y = 1) = 1 \]
\[ h^\text{add}_s (x = 1) = ? \]
Relaxations with SDAC

Example

\[ a = \langle \top, x=1 \rangle \quad \text{cost}_a = 2 - 2y \]
\[ b = \langle \top, y=1 \rangle \quad \text{cost}_b = 1 \]

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

\[ \begin{array}{c}
00 & \xrightarrow{a:2} & 10 \\
00 & \xrightarrow{b:1} & 01 & \xrightarrow{a:0} & 11 \\
\end{array} \]
\[ \Rightarrow \text{cheaper!} \]
(Here, we need the assumption that no variable occurs both in the cost function and the precondition of the same action):

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

\[
h^{add}_s(fact) = \begin{cases} 
0 & \text{if } fact \in s \\
\min_{\text{achiever } a \text{ of } fact} \left[h^{add}_s(pre(a)) + cost_a\right] & \text{otherwise}
\end{cases}
\]
Relaxations with SDAC

(Here, we need the assumption that no variable occurs both in the cost function and the precondition of the same action):

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

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

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

$S_a$: set of partial states over variables in cost function

$|S_a| \text{ exponential in number of variables in cost function}$
**Theorem**

Let \( \Pi \) be an SDAC planning task, let \( \Pi' \) be an EVMDD-based action compilation of \( \Pi \), and let \( s \) be a state of \( \Pi \). Then the classical \( h^{add} \) heuristic in \( \Pi' \) gives the same value for \( s \cup \{ \sigma \mapsto 0 \} \cup \{ \alpha_a \mapsto 0 \mid a \in O \} \) as the generalization of \( h^{add} \) to SDAC tasks defined above gives for \( s \) in \( \Pi \).

**Computing \( h^{add} \) for SDAC:**

- **Option 1:** Compute classical \( h^{add} \) on compiled task.
- **Option 2:** Compute \( Cost_s^a \) directly. How?
  - Plug EVMDDs as subgraphs into RPG
  - \( \sim \) efficient computation of \( h^{add} \)
Remark: We can use EVMDDs to compute $C_s^a$ and hence the generalized additive heuristic directly, by embedding them into the relaxed planning task.

We just briefly show the example, without going into too much detail.

Idea: Augment EVMDD with input nodes representing $h^{add}$ values from the previous RPG layer.

- Use augmented diagrams as RPG subgraphs.
- Allows efficient computation of $h^{add}$. 
Option 2: RPG Compilation

\[ cost_a = xy^2 + z + 2 \]
Option 2: RPG Compilation

- variable nodes become \(\lor\)-nodes
- weights become \(\land\)-nodes
Option 2: RPG Compilation

### Augment with input nodes

- **Input**: $x = 0, x = 1, y = 0, y = 1, y = 2, z = 0, z = 1$
- **0, Output**: $0, +0, +1, +4$
Option 2: RPG Compilation

Ensure complete evaluation
Option 2: Computing $Cost^S_a$

Input:
- $x=0$, $x=1$
- $y=0$, $y=1$, $y=2$
- $z=0$, $z=1$

Output:
- $0$

Diagram:
- Insert $h^{add}$ values

Expression:
$10 + 0 + 6 + \infty + 1 + 2 + 2$

$\forall x \in \{0, 1\}$
$\forall y \in \{0, 1, 2\}$
$\forall z \in \{0, 1\}$

December 16th, 2016 B. Nebel, R. Mattmüller – AI Planning 54 / 76
Option 2: Computing $Cost^S_a$

Evaluate nodes:

- $\wedge$: $\sum$(parents) + weight
- $\vee$: min(parents)
Option 2: Computing $Cost^S_a$

Evaluate nodes:
- $\land$: $\Sigma$(parents) + weight
- $\lor$: $\min$(parents)
Option 2: Computing $Cost^S_a$

Evaluate nodes:
- $\land$: $\Sigma$(parents) + weight
- $\lor$: min(parents)
Option 2: Computing $Cost^S_a$

Evaluate nodes:
- $\land$: $\Sigma$(parents) + weight
- $\lor$: min(parents)
Option 2: Computing $Cost_a^S$

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

Input

$x = 0$

$y = 0$, $y = 1$, $y = 2$

$z = 0$, $z = 1$

Output

$x = 0$, $x = 1$

$y = 0$, $y = 1$, $y = 2$

$z = 0$, $z = 1$
Option 2: Computing $Cost_a^S$

Evaluate nodes:
- $\land$: $\sum$(parents) + weight
- $\lor$: min(parents)
Option 2: Computing $Cost^S_a$

Evaluate nodes:
- $\land$: $\sum$(parents) + weight
- $\lor$: min(parents)
Option 2: Computing $\text{Cost}_a^S$

Evaluate nodes:
- $\land$: $\Sigma$(parents) + weight
- $\lor$: $\min$(parents)

Input

0, Output
Option 2: Computing $Cost^S_a$

Evaluate nodes:
- $\land$: $\sum$(parents) + weight
- $\lor$: min(parents)
Option 2: Computing $Cost^S_a$

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

![Diagram showing the computation of $Cost^S_a$ with values for $x$, $y$, and $z$.]
Option 2: Computing $Cost^S_a$

Costs $a$

\[
\begin{align*}
Cost^S_a &= \min_{\hat{s} \in S_a} [cost_a(\hat{s}) + h^{{add}}_s(\hat{s})] \\
\hat{s} &= \{x \mapsto 1, y \mapsto 2, z \mapsto 0\}
\end{align*}
\]

Cost $a = xy^2 + z + 2$

$\hat{s} = \{x \mapsto 1, y \mapsto 2, z \mapsto 0\}$
Option 2: Computing $Cost^S_a$

\[
Cost^S_a = \min \{ cost_a(\hat{s}) + h^\text{add}_s(\hat{s}) \} \\
\hat{s} \in S_a
\]

\[
cost_a = xy^2 + z + 2
\]

\[
\hat{s} = \{ x \mapsto 1, y \mapsto 2, z \mapsto 0 \}
\]

\[
\begin{align*}
\text{cost}_a(\hat{s}) &= 1 \cdot 2^2 + 0 + 2 = 6 \\
&= 2 + 0 + 4 + 0 \\
h^\text{add}_s(\hat{s}) &= 0 + 1 + 2 = 3
\end{align*}
\]
Option 2: Computing $\text{Cost}^S_a$

$\text{Cost}^S_a = \min \{\text{cost}_a(\hat{s}) + h^{\text{add}}_s(\hat{s})\}$

$\hat{s} \in S_a$

$\text{cost}_a = xy^2 + z + 2$

$\hat{s} = \{x \mapsto 1, y \mapsto 2, z \mapsto 0\}$

$\text{cost}_a(\hat{s}) = 1 \cdot 2^2 + 0 + 2 = 6$

$= 2 + 0 + 4 + 0$

$h^{\text{add}}_s(\hat{s}) = 0 + 1 + 2 = 3$

$\text{Cost}^S_a = 6 + 3 = 9$
Additive Heuristic

- Use above construction as subgraph of RPG in each layer, for each action (as operator subgraphs).
- Add AND nodes conjoining these subgraphs with operator precondition graphs.
- Link EVMDD outputs to next proposition layer.

Theorem

Let $\Pi$ be an SDAC planning task. Then the classical additive RPG evaluation of the RPG constructed using EVMDDs as above computes the generalized additive heuristic $h^{\text{add}}$ defined before.
Abstractions
Abstraction Heuristics for SDAC

Question: Why consider abstraction heuristics?

Answer:
- admissibility
- \(\leadsto\) optimality
Abstraction Heuristics for SDAC

Question: What are the abstract action costs?

Answer: For admissibility, abstract cost of action $a$ should be $\text{cost}_{a}(s_{\text{abs}}) = \min_{\text{concrete state } s} \text{cost}_{a}(s)$.

Problem: exponentially many states in minimization

Aim: Compute $\text{cost}_{a}(s_{\text{abs}})$ efficiently (given EVMDD for $\text{cost}_{a}(s)$).
Question: What are the abstract action costs?
Question: What are the abstract action costs?

Answer: For admissibility, abstract cost of $a$ should be

$$cost_a(s^{\text{abs}}) = \min_{\text{concrete state } s \text{ abstracted to } s^{\text{abs}}} cost_a(s).$$
Abstraction Heuristics for SDAC

Question: What are the abstract action costs?

Answer: For admissibility, abstract cost of action $a$ should be

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

Problem: exponentially many states in minimization

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

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

(Includes projections and domain abstractions.)

Definition (Cartesian abstraction)

A set of states $s_{\text{abs}}$ is Cartesian if it is of the form $D_1 \times \cdots \times D_n$, where $D_i \subseteq D_i$ 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.

$\Rightarrow$ exploit independence when computing abstract costs!
Cartesian Abstractions

We will see: possible if the abstraction is Cartesian or coarser. (Includes projections and domain abstractions.)

Definition (Cartesian abstraction)

A set of states $s^{\text{abs}}$ 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.

$\Rightarrow$ exploit independence when computing abstract costs!
Cartesian Abstractions

Example (Cartesian abstraction)

Cartesian abstraction over \(x, y\)

\[
\begin{array}{ccc}
\text{y = 0} & \text{y = 1} & \text{y = 2} \\
\text{x = 0} & \begin{array}{cc}
00 & 01 \\
10 & 11
\end{array} & 02 \\
\text{x = 1} & 10 & 11 & 12 \\
\text{x = 2} & 20 & 21 & 22
\end{array}
\]

Cost: \(x + y + 1\) (edges consistent with \(s_{abs}\))
Example (Cartesian abstraction)

Cartesian abstraction over \( x, y \)

Cost \( x + y + 1 \)
(edges consistent with \( s^{\text{abs}} \))

\[
\begin{array}{c|c|c}
  & y = 0 & y = 1 & y = 2 \\
  x = 0 & 00 & 01 & 02 \\
  x = 1 & 10 & 11 & 12 \\
  x = 2 & 20 & 21 & 22 \\
\end{array}
\]
Carousel Abstractions

Example (Cartesian abstraction)

Cartesian abstraction over $x$, $y$

Cost $x + y + 1$
(edges consistent with $s^{\text{abs}}$)

Cost

$\begin{align*}
\text{cost} &= 4 \\
\text{cost} &= 5
\end{align*}$

December 16th, 2016 B. Nebel, R. Mattmüller – AI Planning 60 / 76
Example (Cartesian abstraction)

Cartesian abstraction over $x, y$

Cost $x + y + 1$
(edges consistent with $s^{\text{abs}}$)

$$\begin{align*}
00 & \quad 01 & \quad 02 \\
10 & \quad 11 & \quad 12 \\
20 & \quad 21 & \quad 22
\end{align*}$$

$\begin{align*}
\text{cost} &= 4 \\
\text{cost} &= 5
\end{align*}$
Example (Cartesian abstraction)

Cartesian abstraction over $x, y$

Cost $x + y + 1$
(edges consistent with $S^{\text{abs}}$)

$y = 0$  $y = 1$  $y = 2$

$x = 0$

00  01  02

10  11  12

$x = 1$

$x = 2$

20  21  22

$cost = 4$  $cost = 5$

$min = 1$  $min = 3$
Example (Cartesian abstraction)

Cartesian abstraction over $x, y$

Cost $x + y + 1$
(edges consistent with $S^{abs}$)

$\begin{align*}
    y = 0 & \quad y = 1 & \quad y = 2 \\
    x = 0 & \quad \begin{array}{ll}
        00 & 01 \\
        10 & 11 \\
        20 & 21 \\
    \end{array} & \quad 02 \\
    x = 1 & \quad \begin{array}{ll}
        00 & 01 \\
        10 & 11 \\
        20 & 21 \\
    \end{array} & \quad 12 \\
    x = 2 & \quad \begin{array}{ll}
        00 & 01 \\
        10 & 11 \\
        20 & 21 \\
    \end{array} & \quad 22
\end{align*}$

$\begin{align*}
    cost = 4 & \quad cost = 5 \\
    min = 1 & \quad min = 3 & \quad min = 4
\end{align*}$
Cartesian Abstractions

Why does the topsort EVMDD traversal (cheapest path computation) correctly compute $cost_a(s^{abs})$?

Short answer: The exact same thing as with relaxed states, because relaxed states are Cartesian sets!

Longer answer:

1. For each Cartesian state $s^{abs}$ and each variable $v$, each value $d \in \mathcal{D}_v$ is either consistent with $s^{abs}$ or not.
2. This implies: at all decision nodes associated with variable $v$, some outgoing edges are enabled, others are disabled. This is independent from all other decision nodes.
3. This allows local minimizations over linearly many edges instead of global minimization over exponentially many paths in the EVMDD when computing minimum costs. $\leadsto$ polynomial in EVMDD size!
Cartesian Abstractions

Not Cartesian!

If abstraction not Cartesian: two variables can be
- independent in cost function ($\sim\sim$ compact EVMDD), but
- dependent in abstraction.

$\sim\sim$ cannot consider independent parts of EVMDD separately.
Cartesian Abstractions
Not Cartesian!

If abstraction not Cartesian: two variables can be

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

\(\leadsto\) cannot consider independent parts of EVMDD separately.

Example (Non-Cartesian abstraction)

\[\text{cost} : x + y + 1, \ \text{cost}(s^{\text{abs}}) = 2, \ \text{local minim.: } 1 \leadsto \text{underestimate!}\]
Wanted: principled way of computing Cartesian abstractions.

\[\rightarrow\] Counterexample-Guided Abstraction Refinement (CEGAR) (details omitted)
Practice
- **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](http://meddly.sourceforge.net)
EVMDD Libraries

**pyevmdd**

- **pyevmdd**: EVMDD library for Python
- **Authors**: RM and Florian Geißer
- **Language**: Python
- **License**: open source (GPLv3)
- **Disadvantages**:
  - restricted to EVMDDs
  - neither mature nor optimized
- **Purpose**: our EVMDD playground
- **Code**:
  [https://github.com/robertmattmueller/pyevmdd](https://github.com/robertmattmueller/pyevmdd)
- **Documentation**:
Usual way of representing costs in PDDL:

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

Custom syntax (non-standard PDDL):

- Besides :parameters, :precondition, and :effect, actions may have field
- :cost (<expression>)
Cost of move increases if ball color differs from room color

\[
\text{cost}(\text{move}) = \sum_{\text{room}} \sum_{\text{ball}} (\text{at}(\text{ball}, \text{room}) \land \text{red}(\text{ball}) \land \text{blue}(\text{room})) + \sum_{\text{room}} \sum_{\text{ball}} (\text{at}(\text{ball}, \text{room}) \land \text{blue}(\text{ball}) \land \text{red}(\text{room}))
\]
Colored Gripper

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

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

\[
\text{cost}(\text{move}) = \sum_{\text{ROOM}} \sum_{\text{BALL}} (\text{at}(\text{BALL, ROOM}) \land (\text{red}(\text{BALL})) \land (\text{blue}(\text{ROOM}))) \\
+ \sum_{\text{ROOM}} \sum_{\text{BALL}} (\text{at}(\text{BALL, ROOM}) \land (\text{blue}(\text{BALL})) \land (\text{red}(\text{ROOM})))
\]
EVMDD-Based Action Compilation

Idea: each edge in the EVMDD becomes a new micro action with constant cost corresponding to the edge constraint, precondition that we are currently at its start EVMDD node, and effect that we are currently at its target EVMDD node.

Example (EVMDD-based action compilation)

Let $a = \langle \chi, e \rangle$, $cost_a = xy^2 + z + 2$.

Auxiliary variables:

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

Replace $a$ by new auxiliary actions (similarly for other actions).
EVMDD-Based Action Compilation

Example (EVMDD-based action compilation, ctd.)

\[ a^x = \langle x \land \sigma = 0 \land \alpha = 0, \sigma := 1 \land \alpha := 1 \rangle, \quad \text{cost} = 2 \]

\[ a^{1,x=0} = \langle \alpha = 1 \land x = 0, \alpha := 3 \rangle, \quad \text{cost} = 0 \]

\[ a^{1,x=1} = \langle \alpha = 1 \land x = 1, \alpha := 2 \rangle, \quad \text{cost} = 0 \]

\[ a^{2,y=0} = \langle \alpha = 2 \land y = 0, \alpha := 3 \rangle, \quad \text{cost} = 0 \]

\[ a^{2,y=1} = \langle \alpha = 2 \land y = 1, \alpha := 3 \rangle, \quad \text{cost} = 1 \]

\[ a^{2,y=2} = \langle \alpha = 2 \land y = 2, \alpha := 3 \rangle, \quad \text{cost} = 4 \]

\[ a^{3,z=0} = \langle \alpha = 3 \land z = 0, \alpha := 4 \rangle, \quad \text{cost} = 0 \]

\[ a^{3,z=1} = \langle \alpha = 3 \land z = 1, \alpha := 4 \rangle, \quad \text{cost} = 1 \]

\[ a^e = \langle \alpha = 4, e \land \sigma := 0 \land \alpha := 0 \rangle, \quad \text{cost} = 0 \]
Disclaimer:
- Not completely functional
- Still some bugs

Uses pyevmdd

Language: Python

License: open source

Code: https://github.com/robertmattmueller/sdac-compiler
Summary
Summary:

- State-dependent actions costs practically relevant.
- EVMDDs exhibit and exploit structure in cost functions.
- Graph-based representations of arithmetic functions.
- Edge values express partial cost contributed by facts.
- Size of EVMDD is compact in many “typical” cases.
- Can be used to compile tasks with state-dependent costs to tasks with state-independent costs.
- Alternatively, can be embedded into the RPG to compute forward-cost heuristics directly.
- For $h^{add}$, both approaches give the same heuristic values.
- Abstraction heuristics can also be generalized to state-dependent action costs.
Future Work and Work in Progress:

- Investigation of other delete-relaxation heuristics for tasks with state-dependent action costs.
- Investigation of static and dynamic EVMDD variable orders.
- Application to cost partitioning, to planning with preferences, …
- Better integration of SDAC in PDDL.
- Tool support.
- Benchmarks.
References
