

- 1 **Memoryless plans** map a state/an observation to an operator.

We use this definition of plans for **fully observable** problems only.

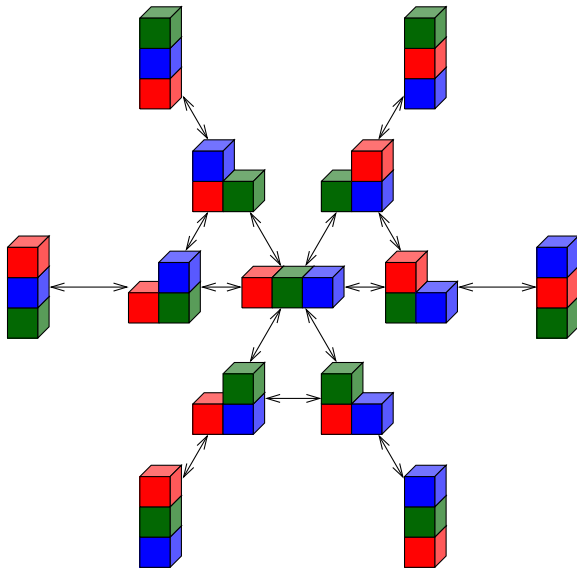
- 2 **Conditional plans** generalize memoryless plans.

They are needed for problems without full observability.

- The **state of the execution** of a conditional plan depends on **observations** on earlier execution steps.
- The state of the execution = a primitive form of memory.
- The operator to be executed depends on the state of the execution.

Memoryless plans

Example



AI Planning

Plans

Plans

Example
Definition

Images

Algorithms

Regression

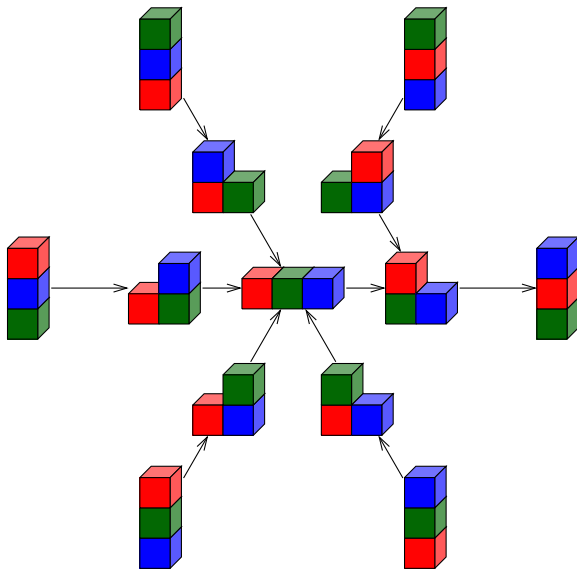
CPC
operators

CPC images

BDDs

Memoryless plans

Example



AI Planning

Plans

Plans

Example

Definition

Images

Algorithms

Regression

CPC

operators

CPC images

BDDs

Memoryless plans

Definition

Definition

Let S be the set of all states.

A **memoryless plan** is a partial function $\pi : S \rightarrow O$.

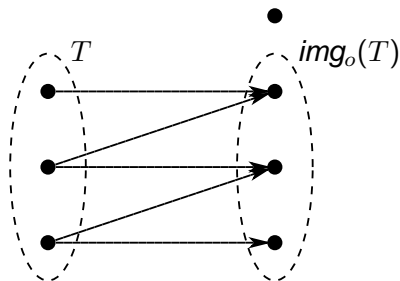
Execution of a memoryless plan

- 1 Determine the current state s (full observability!!!).
- 2 If $\pi(s)$ is not defined then terminate execution.
If the objective is to reach a goal state, then $\pi(s)$ is not defined if s is a goal state so that the execution terminates.
- 3 Execute action $\pi(s)$.
- 4 Goto step 1.

Images

Image

The **image** of a set T of states with respect to an operator o is the set of those states that can be reached by executing o in a state in T .



AI Planning

Plans

Plans

Images

Images

Preimages

Strong preimages

Algorithms

Regression

CPC

operators

CPC images

BDDs

Images

Formal definition

Definition (Image of a state)

$$img_o(s) = \{s' \in S \mid sos'\}$$

Definition (Image of a set of states)

$$img_o(T) = \bigcup_{s \in T} img_o(s)$$

AI Planning

Plans

Plans

Images

Images

Preimages

Strong preimages

Algorithms

Regression

CPC

operators

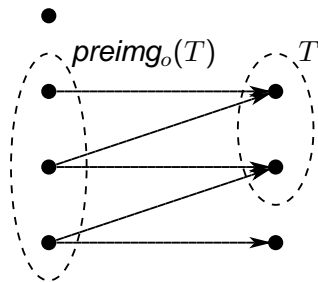
CPC images

BDDs

Preimages

Weak preimage

The **preimage** of a set T of states with respect to an operator o is the set of those states from which a state in T can be reached by executing o .



AI Planning

Plans

Plans

Images

Images

Preimages

Strong preimages

Algorithms

Regression

CPC
operators

CPC images

BDDs

Preimages

Formal definition

Definition (Weak preimage of a state)

$$\text{preimg}_o(s') = \{s \in S \mid sos'\}$$

Definition (Weak preimage of a set of states)

$$\text{preimg}_o(T) = \bigcup_{s \in T} \text{preimg}_o(s).$$

AI Planning

Plans

Plans

Images

Images

Preimages

Strong preimages

Algorithms

Regression

CPC

operators

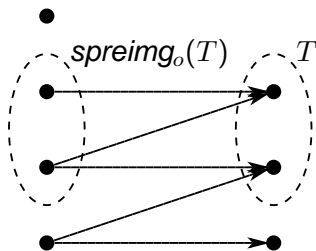
CPC images

BDDs

Strong preimages

Strong preimage

The **strong preimage** of a set T of states with respect to an operator o is the set of those states from which a state in T is always reached when executing o .



AI Planning

Plans

Plans

Images

Images

Preimages

Strong preimages

Algorithms

Regression

CPC
operators

CPC images

BDDs

Strong preimages

Formal definition

Definition (Strong preimage of a set of states)

$$\text{spreimg}_o(T) = \{s \in S \mid s' \in T, sos', \text{img}_o(s) \subseteq T\}$$

AI Planning

Plans

Plans

Images

Images

Preimages

Strong preimages

Algorithms

Regression

CPC

operators

CPC images

BDDs

Algorithms for fully observable problems

1 Heuristic search (forward)

Nondeterministic planning can be viewed as AND-OR search.

OR nodes: Choice between operators

AND nodes: Nondeterministically reached state

Heuristic AND-OR search algorithms: AO*, ...

2 Dynamic programming (backward)

Idea Compute operator/distance/value for a state based on the operators/distances/values of its all successor states.

- 1 0 actions needed for goal states.
- 2 If states with i actions to goals are known, states with $\leq i + 1$ actions to goals can be easily identified.

Automatic reuse of already found plan suffixes.

AI Planning

Plans

Plans

Images

Algorithms

AND-OR search

Dynamic programming

Bwd-distances

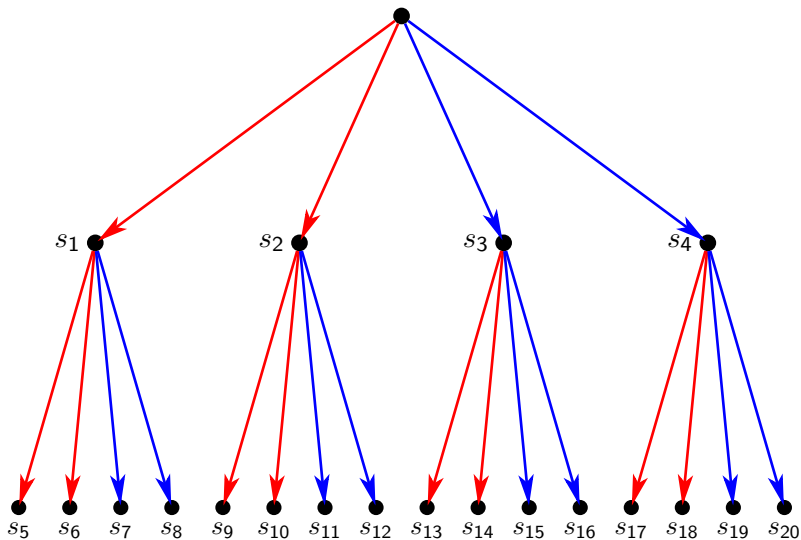
Regression

CPC operators

CPC images

BDDs

AND-OR search



AI Planning

Plans

Plans

Images

Algorithms

AND-OR search

Dynamic programming

Bwd-distances

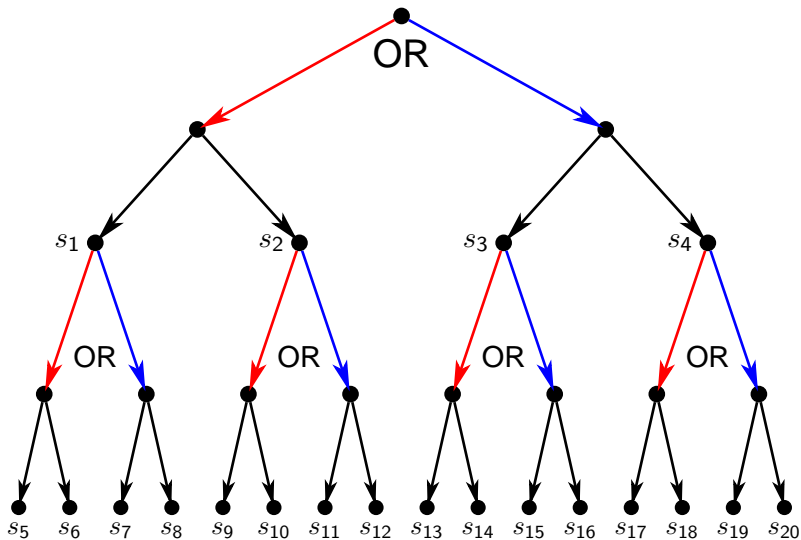
Regression

CPC operators

CPC images

BDDs

AND-OR search



AI Planning

Plans

Plans

Images

Algorithms

AND-OR search

Dynamic programming

Bwd-distances

Regression

CPC operators

CPC images

BDDs

Dynamic programming

Planning by dynamic programming

If for all successors of state s with respect to operator o a plan exists, assign operator o to s .

Base case $i = 0$: In goal states there is nothing to do.

Inductive case $i \geq 1$: If there is $o \in O$ such that for all $s' \in \text{img}_o(s)$ s' is a goal state or $\pi(s')$ was assigned on iteration $i - 1$, then assign $\pi(s) = o$.

Connection to distances

If s is assigned a value on iteration $i \geq 1$, then the **backward distance** of s is i .

The dynamic programming algorithm essentially computes the **backward distances** of states.

AI Planning

Plans

Plans

Images

Algorithms

AND-OR search

Dynamic programming

Bwd-distances

Regression

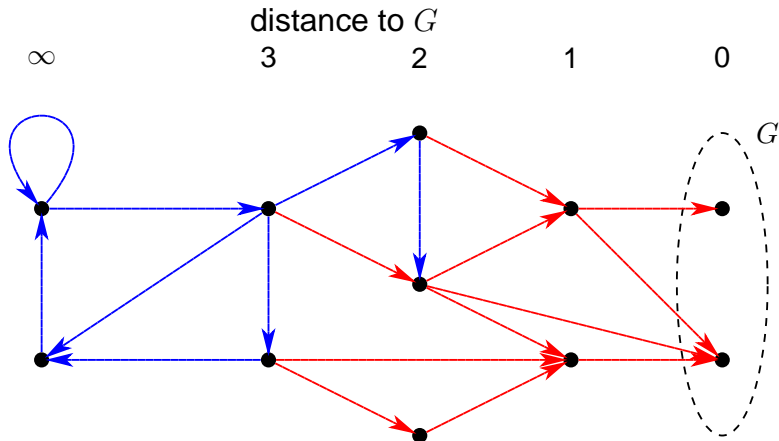
CPC operators

CPC images

BDDs

Backward distances

Example



AI Planning

Plans

Plans

Images

Algorithms

AND-OR search

Dynamic programming

Bwd-distances

Regression

CPC operators

CPC images

BDDs

Backward distances

Definition of distance sets

Definition

Let G be a set of states and O a set of operators. Define the **backward distance sets** D_i^{bwd} for G, O that consist of those states for which there is a guarantee of reaching a state in G with at most i operator applications.

$$D_0^{bwd} = G$$

$$D_i^{bwd} = D_{i-1}^{bwd} \cup \bigcup_{o \in O} \text{preimg}_o(D_{i-1}^{bwd}) \text{ for all } i \geq 1$$

AI Planning

Plans

Plans

Images

Algorithms

AND-OR search

Dynamic programming

Bwd-distances

Regression

CPC operators

CPC images

BDDs

Backward distances

Definition

Definition

Let G be a set of states and O a set of operators, and let $D_0^{bwd}, D_1^{bwd}, \dots$ be the backward distance sets for G and O . Then **the backward distance** from a state s to G is

$$\delta_G^{bwd}(s) = \begin{cases} 0 & \text{if } s \in G \\ i & \text{if } s \in D_i^{bwd} \setminus D_{i-1}^{bwd} \end{cases}$$

If $s \notin D_i^{bwd}$ for all $i \geq 0$ then $\delta_G^{bwd}(s) = \infty$.

AI Planning

Plans

Plans

Images

Algorithms

AND-OR search

Dynamic programming

Bwd-distances

Regression

CPC operators

CPC images

BDDs

Construction of a plan based on distances

AI Planning

Extraction of a plan from distance sets

- 1 Let $S' \subseteq S$ be those states having a finite backward distance.
- 2 Let s be a state with distance $i = \delta_G^{bwd}(s) \geq 1$.
- 3 Assign to $\pi(s)$ any operator $o \in O$ such that $img_o(s) \subseteq D_{i-1}^{bwd}$. Hence o decreases the backward distance by at least one.

The plan π solves the planning problem for $\langle S, I, O, G, P \rangle$ iff $I \subseteq S'$.

Plans

Plans

Images

Algorithms

AND-OR search

Dynamic programming

Bwd-distances

Regression

CPC operators

CPC images

BDDs

Making the algorithm a logic-based algorithm

- An algorithm that represents the states **explicitly** is feasible for transition systems with at most 10^6 or 10^7 states.
- For planning with bigger transition systems **structural properties** of the transition system have to be taken advantage of.
- Representing state sets as **propositional formulae** often allow taking advantage of the structural properties: a formula that represents a set of states or a transition relation that has certain regularities may be very small in comparison to the set or relation.

AI Planning

Plans

Plans

Images

Algorithms

Regression

Definition

CPC

operators

CPC images

BDDs

Making the algorithm a logic-based algorithm

- We use a formula ϕ as a **data structure** for representing the set $\{s \in S \mid s \models \phi\}$.
- We show that regression $regr_o^{nd}(\phi)$ for nondeterministic operators is one way of computing strong preimages.
- We present general techniques for computing images, preimages and strong preimages of sets of states represented as formulae.
- Many of the algorithms presented later in the lecture can be **lifted** to use a logic-based representation, thereby expanding their range of applicability to much bigger transition systems.

AI Planning

Plans

Plans

Images

Algorithms

Regression

Definition

CPC
operators

CPC images

BDDs

Regression for nondeterministic operators

Definition

We can easily generalize our regression operation for deterministic operators to **regression for nondeterministic operators** of a restricted syntactic form.

Definition (Regression for nondeterministic operators)

Let ϕ be a propositional formula and $o = \langle c, e_1 | \dots | e_n \rangle$ an operator where e_1, \dots, e_n are deterministic. Define

$$\text{regr}_o^{nd}(\phi) = \text{regr}_{\langle c, e_1 \rangle}(\phi) \wedge \dots \wedge \text{regr}_{\langle c, e_n \rangle}(\phi).$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

Definition

CPC
operators

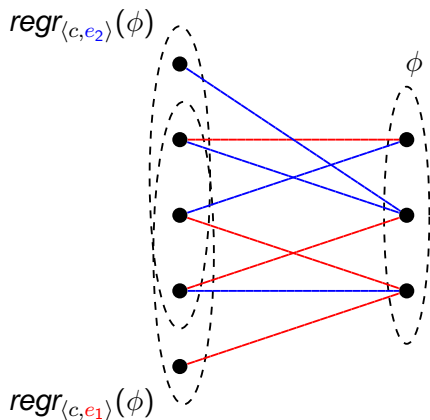
CPC images

BDDs

Regression for nondeterministic operators

Illustration

$$\text{regr}_{\langle c, (e_1|e_2) \rangle}(\phi) = \text{regr}_{\langle c, e_1 \rangle}(\phi) \wedge \text{regr}_{\langle c, e_2 \rangle}(\phi)$$



AI Planning

Plans

Plans

Images

Algorithms

Regression

Definition

CPC

operators

CPC images

BDDs

Regression for nondeterministic operators

Correctness

Theorem

Let ϕ be a formula over A , o an operator over A , and S the set of all states over A . Then

$$\{s \in S \mid s \models \text{regr}_o^{nd}(\phi)\} = \text{spreimg}_o(\{s \in S \mid s \models \phi\}).$$

Proof.

Let $o = \langle c, (e_1 \mid \dots \mid e_n) \rangle$.

$$\{s \in S \mid s \models \text{regr}_o^{nd}(\phi)\}$$

$$= \{s \in S \mid s \models \text{regr}_{\langle c, e_1 \rangle}(\phi) \wedge \dots \wedge \text{regr}_{\langle c, e_n \rangle}(\phi)\}$$

$$= \{s \in S \mid s \models \text{regr}_{\langle c, e_1 \rangle}(\phi), \dots, s \models \text{regr}_{\langle c, e_n \rangle}(\phi)\}$$

$$= \{s \in S \mid \text{app}_{\langle c, e_1 \rangle}(s) \models \phi, \dots, \text{app}_{\langle c, e_n \rangle}(s) \models \phi\}$$

$$= \{s \in S \mid s' \models \phi \text{ for all } s' \in \text{img}_o(s), \text{ there is } s' \models \phi \text{ with } sos'\}$$

$$= \text{spreimg}_o(\{s \in S \mid s \models \phi\})$$

3rd = is by properties of deterministic regression.

4th = is by $\text{img}_o(s) = \{\text{app}_{\langle c, e_1 \rangle}(s), \dots, \text{app}_{\langle c, e_n \rangle}(s)\}$. □

AI Planning

Plans

Plans

Images

Algorithms

Regression

Definition

CPC
operators

CPC images

BDDs

Regression for nondeterministic operators

Example

Example

Let $o = \langle d, (b|\neg c) \rangle$. Then

$$\begin{aligned} \text{regr}_o^{nd}(b \leftrightarrow c) &= \text{regr}_{\langle d, b \rangle}(b \leftrightarrow c) \wedge \text{regr}_{\langle d, \neg c \rangle}(b \leftrightarrow c) \\ &= (d \wedge (\top \leftrightarrow c)) \wedge (d \wedge (b \leftrightarrow \perp)) \\ &\equiv d \wedge c \wedge \neg b. \end{aligned}$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

Definition

CPC
operators

CPC images

BDDs

Backward distances with formulas

AI Planning

By using regression we can compute formulas that represent backward distance sets.

Definition

Let G be a formula and O a set of operators. The **backward distance sets** D_i^{bwd} for G, O are represented by the following formulae.

$$D_0^{bwd} = G$$

$$D_i^{bwd} = D_{i-1}^{bwd} \vee \bigvee_{o \in O} \text{regr}_o^{nd}(D_{i-1}^{bwd}) \text{ for all } i \geq 1$$

Plans

Plans

Images

Algorithms

Regression

Definition

CPC
operators

CPC images

BDDs

Backward distances with formulas

AI Planning

Definition

Let G be a formula and O a set of operators, and let $D_0^{bwd}, D_1^{bwd}, \dots$ be the formulae representing the backward distance sets for G and O . Then **the backward distance** from a state s to G is

$$\delta_G^{bwd}(s) = \begin{cases} 0 & \text{if } s \models G \\ i & \text{if } s \models D_i^{bwd} \wedge \neg D_{i-1}^{bwd} \end{cases}$$

If $s \not\models D_i^{bwd}$ for all $i \geq 0$ then $\delta_G^{bwd}(s) = \infty$.

Plans

Plans

Images

Algorithms

Regression

Definition

CPC

operators

CPC images

BDDs

General images and preimages with formulas

- The definition of regression covers only a subclass of nondeterministic operators.
- How to define strong preimages for all operators, and images and preimages?
- Now we apply a general idea:
 - 1 View operators/actions as binary relations.
 - 2 Represent these binary relations as formulae.
 - 3 Define relational operations for relations represented as formulae.

AI Planning

Plans

Plans

Images

Algorithms

Regression

Definition

CPC

operators

CPC images

BDDs

General images and preimages with formulas

Definition

Define the set of state variables possibly changed by e as

$$\text{changes}(a) = \{a\}$$

$$\text{changes}(\neg a) = \{a\}$$

$$\text{changes}(c \triangleright e) = \text{changes}(e)$$

$$\text{changes}(e_1 \wedge \dots \wedge e_n) = \text{changes}(e_1) \cup \dots \cup \text{changes}(e_n)$$

$$\text{changes}(e_1 | \dots | e_n) = \text{changes}(e_1) \cup \dots \cup \text{changes}(e_n)$$

Assumption

Let $e_1 \wedge \dots \wedge e_n$ occur in the effect of an operator. If e_1, \dots, e_n are not all deterministic then a and $\neg a$ may occur as an atomic effect in at most one of e_1, \dots, e_n .

This assumption rules out effects like $(a|b) \wedge (\neg a|c)$ that may make a simultaneously true and false.

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

BDDs

General images and preimages with formulas

AI Planning

In nondeterministic choices $e_1 | \dots | e_n$ the formula for each e_i has to express the changes for exactly the same set B of state variables.

Definition

$\tau_B^{nd}(e) = \tau_B(e)$ when e is deterministic

$$\tau_B^{nd}(e_1 | \dots | e_n) = \tau_B^{nd}(e_1) \vee \dots \vee \tau_B^{nd}(e_n)$$

$$\tau_B^{nd}(e_1 \wedge \dots \wedge e_n) = \tau_{B \setminus (B_2 \cup \dots \cup B_n)}^{nd}(e_1) \wedge \tau_{B_2}^{nd}(e_2) \wedge \dots \wedge \tau_{B_n}^{nd}(e_n)$$

where $B_i = \text{changes}(e_i)$ for $i \in \{2, \dots, n\}$

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

BDDs

General images and preimages with formulas

AI Planning

Example

We translate the effect

$$e = (a|(d \triangleright a)) \wedge (c|d)$$

into a propositional formula. The set of state variables is

$$A = \{a, b, c, d\}.$$

$$\begin{aligned}\tau_{\{a,b,c,d\}}^{nd}(e) &= \tau_{\{a,b\}}^{nd}(a|(d \triangleright a)) \wedge \tau_{\{c,d\}}^{nd}(c|d) \\ &= (\tau_{\{a,b\}}^{nd}(a) \vee \tau_{\{a,b\}}^{nd}(d \triangleright a)) \wedge (\tau_{\{c,d\}}^{nd}(c) \vee \tau_{\{c,d\}}^{nd}(d)) \\ &= ((a' \wedge (b \leftrightarrow b')) \vee (((a \vee d) \leftrightarrow a') \wedge (b \leftrightarrow b'))) \wedge \\ &\quad ((c' \wedge (d \leftrightarrow d')) \vee ((c \leftrightarrow c') \wedge d'))\end{aligned}$$

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

BDDs

General images and preimages with formulas

AI Planning

Definition

Let A be a set of state variables. Let $o = \langle c, e \rangle$ be an operator over A in normal form. Define $\tau_A^{nd}(o) = c \wedge \tau_A^{nd}(e)$.

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

BDDs

Lemma

Let o be an operator. Then

$$\begin{aligned} & \{v \mid v \text{ is a valuation of } A \cup A', v \models \tau_A^{nd}(o)\} \\ &= \{s \cup s' [A'/A] \mid s, s' \in S, s' \in \text{img}_o(s)\}. \end{aligned}$$

Existential and universal abstraction

The most important operations performed on transition relations represented as propositional formulae are based on **existential abstraction** and **universal abstraction**.

Definition

Existential abstraction of a formula ϕ with respect to $a \in A$:

$$\exists a.\phi = \phi[\top/a] \vee \phi[\perp/a].$$

Universal abstraction is defined analogously by using conjunction instead of disjunction.

Definition

Universal abstraction of a formula ϕ with respect to $a \in A$:

$$\forall a.\phi = \phi[\top/a] \wedge \phi[\perp/a].$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

\exists -abstraction

Examples

Example

$$\begin{aligned} & \exists b.((a \rightarrow b) \wedge (b \rightarrow c)) \\ &= ((a \rightarrow \top) \wedge (\top \rightarrow c)) \vee ((a \rightarrow \perp) \wedge (\perp \rightarrow c)) \\ &\equiv c \vee \neg a \\ &\equiv a \rightarrow c \end{aligned}$$

$$\begin{aligned} \exists ab.(a \vee b) &= \exists b.(\top \vee b) \vee (\perp \vee b) \\ &= ((\top \vee \top) \vee (\perp \vee \top)) \vee ((\top \vee \perp) \vee (\perp \vee \perp)) \\ &= (\top \vee \top) \vee (\top \vee \perp) = \top \end{aligned}$$

Example

\exists -abstraction is also known as **forgetting**:

$$\begin{aligned} & \exists \text{mon} \exists \text{tue}((\text{mon} \vee \text{tue}) \wedge (\text{mon} \rightarrow \text{work}) \wedge (\text{tue} \rightarrow \text{work})) \\ &\equiv \exists \text{tue}((\text{work} \wedge (\text{tue} \rightarrow \text{work})) \vee (\text{tue} \wedge (\text{tue} \rightarrow \text{work}))) \equiv \text{work} \end{aligned}$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction
Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

\forall and \exists -abstraction in terms of truth-tables

Example

$\forall a$ and $\exists a$ correspond to **combining pairs of lines** with the same valuation for variables other than a .

Example

$$\exists c.(a \vee (b \wedge c)) \equiv a \vee b \quad \forall c.(a \vee (b \wedge c)) \equiv a$$

a	b	c	$a \vee (b \wedge c)$	a	b	$\exists c.(a \vee (b \wedge c))$	a	b	$\forall c.(a \vee (b \wedge c))$
0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	1	1	0	1	0
0	1	0	0	1	0	1	1	0	1
0	1	1	1	1	1	1	1	1	1
1	0	0	1						
1	0	1	1						
1	1	0	1						
1	1	1	1						

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Properties of abstraction operations

Definition

Existential and universal abstraction of ϕ with respect to a **set of atomic propositions** $B = \{b_1, \dots, b_n\}$ are

$$\begin{aligned}\exists B.\phi &= \exists b_1.(\exists b_2.(\dots \exists b_n.\phi \dots)) \\ \forall B.\phi &= \forall b_1.(\forall b_2.(\dots \forall b_n.\phi \dots)).\end{aligned}$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction
Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Properties of abstracted formulas

- 1 Let ϕ be a formula over A . Then $\exists A.\phi$ and $\forall A.\phi$ are formulae that consist of the constants \top and \perp and the logical connectives only.
- 2 The truth-values of these formulae are independent of the valuation of A , that is, their values are the same for all valuations.
- 3 $\exists A.\phi \equiv \top$ if and only if ϕ is satisfiable.
- 4 $\forall A.\phi \equiv \top$ if and only if ϕ is valid.

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Properties of \forall and \exists abstraction

Lemma

If ϕ is a formula over $A \cup A'$ and v a valuation of A then

- 1 $v \models \exists A'. \phi$ *iff* $v \cup v' \models \phi$ *for some valuation v' of A' .*
- 2 $v \models \forall A'. \phi$ *iff* $v \cup v' \models \phi$ *for all valuations v' of A' .*

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Size of abstracted formulae

- Abstracting one variable takes polynomial time in the size of the formula.
- Abstracting one variable **may double the formula size**.
- Abstracting n variables may increase size by factor 2^n .
- For making abstraction practical the formulae must be simplified, for example with equivalences like
 $\top \wedge \phi \equiv \phi$, $\perp \wedge \phi \equiv \perp$, $\top \vee \phi \equiv \top$, $\perp \vee \phi \equiv \phi$, $\neg \perp \equiv \top$,
and $\neg \top \equiv \perp$.

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Images by \exists -abstraction

Let

- $A = \{a_1, \dots, a_n\}$,
- $A' = \{a'_1, \dots, a'_n\}$,
- ϕ_1 be a formula on A representing a row vector $V_{1 \times 2^n}$ (equivalently, a set of valuations of A), and
- ϕ_2 a formula on $A \cup A'$ representing a matrix $M_{2^n \times 2^n}$ (equivalently, a binary relation on valuations of A).

The **product matrix** VM of size 1×2^n is represented by

$$\exists A. (\phi_1 \wedge \phi_2)$$

which is a formula on A' .

To obtain a formula over A we have to rename the variables.

$$(\exists A. (\phi_1 \wedge \phi_2))[A/A']$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Images by \exists -abstraction

Example

Let $A = \{a, b\}$ be the state variables.

$$(1\ 0\ 1\ 0) \times \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix} = (0\ 1\ 0\ 1)$$

represents the image of $\{00, 10\}$ with respect to a relation.

$$\begin{aligned} & \exists a. \exists b. (\neg b \wedge (b \leftrightarrow \neg b')) \\ & \equiv \exists b. (\neg b \wedge (b \leftrightarrow \neg b')) \\ & \equiv (\neg \top \wedge (\top \leftrightarrow \neg b')) \vee (\neg \perp \wedge (\perp \leftrightarrow \neg b')) \\ & \equiv b' \end{aligned}$$

The formula b represents $\{01, 11\}$.

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Matrix multiplication by \exists -abstraction

Let

- $A = \{a_1, \dots, a_n\}$,
- $A' = \{a'_1, \dots, a'_n\}$,
- $A'' = \{a''_1, \dots, a''_n\}$,
- ϕ_1 be a formula on $A \cup A'$ representing matrix M_1 and
- ϕ_2 a formula on $A' \cup A''$ representing matrix M_2 .

The matrices M_1 and M_2 have size $2^n \times 2^n$.

The **product matrix** $M_1 M_2$ is represented by

$$\exists A'. (\phi_1 \wedge \phi_2)$$

which is a formula on $A \cup A''$.

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Matrix multiplication by \exists -abstraction

Example

Example

Let $\phi_1 = a \leftrightarrow \neg a'$ and $\phi_2 = a' \leftrightarrow a''$ represent two actions, reversing the truth-value of a and doing nothing. The sequential composition of these actions is

$$\begin{aligned}\exists a'. \phi_1 \wedge \phi_2 &= ((a \leftrightarrow \neg \top) \wedge (\top \leftrightarrow a'')) \vee ((a \leftrightarrow \neg \perp) \wedge (\perp \leftrightarrow a'')) \\ &\equiv ((a \leftrightarrow \perp) \wedge (\top \leftrightarrow a'')) \vee ((a \leftrightarrow \top) \wedge (\perp \leftrightarrow a'')) \\ &\equiv (\neg a \wedge a'') \vee (a \wedge \neg a'') \\ &\equiv a \leftrightarrow \neg a''.\end{aligned}$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Matrix multiplication

Multiply $(\neg a \leftrightarrow a') \wedge (\neg b \leftrightarrow b')$ and $(a' \leftrightarrow b'') \wedge (b' \leftrightarrow a'')$:

$$\begin{pmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} \times \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$$

This is

$$\begin{aligned} & \exists a'. \exists b'. (\neg a \leftrightarrow a') \wedge (\neg b \leftrightarrow b') \wedge (a' \leftrightarrow b'') \wedge (b' \leftrightarrow a'') \\ & \equiv (\neg a \leftrightarrow b'') \wedge (\neg b \leftrightarrow a''). \end{aligned}$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Images and preimages by formula manipulation

Define $s[A'/A] = \{\langle a', s(a) \rangle \mid a \in A\}$.

Lemma

Let ϕ be a formula on A and v a valuation of A . Then $v \models \phi$ iff $v[A'/A] \models \phi[A'/A]$.

Definition

Let o be an operator and ϕ a formula. Define

$$\begin{aligned}img_o(\phi) &= (\exists A. (\phi \wedge \tau_A^{nd}(o)))[A/A'] \\preimg_o(\phi) &= \exists A'. (\tau_A^{nd}(o) \wedge \phi[A'/A]) \\spreimg_o(\phi) &= \forall A'. (\tau_A^{nd}(o) \rightarrow \phi[A'/A]) \wedge \exists A'. \tau_A^{nd}(o).\end{aligned}$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Images by formula manipulation

Theorem

Let $T = \{s \in S \mid s \models \phi\}$. Then $\{s \in S \mid s \models \text{img}_o(\phi)\} = \{s \in S \mid s \models (\exists A. (\phi \wedge \tau_A^{nd}(o))) [A/A']\} = \text{img}_o(T)$.

Proof.

$s' \models (\exists A. (\phi \wedge \tau_A^{nd}(o))) [A/A']$
iff $s' [A'/A] \models \exists A. (\phi \wedge \tau_A^{nd}(o))$
iff there is valuation s of A s.t. $(s \cup s' [A'/A]) \models \phi \wedge \tau_A^{nd}(o)$
iff there is valuation s of A s.t. $s \models \phi$ and $(s \cup s' [A'/A]) \models \tau_A^{nd}(o)$
iff there is $s \in T$ s.t. $(s \cup s' [A'/A]) \models \tau_A^{nd}(o)$
iff there is $s \in T$ s.t. $s' \in \text{img}_o(s)$
iff $s' \in \text{img}_o(T)$.



AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Preimages by formula manipulation

Theorem

Let $T = \{s \in S \mid s \models \phi\}$. Then $\{s \in S \mid s \models \text{preimg}_o(\phi)\} = \{s \in S \mid s \models \exists A'. (\tau_A^{nd}(o) \wedge \phi[A'/A])\} = \text{preimg}_o(T)$.

Proof.

$s \models \exists A'. (\tau_A^{nd}(o) \wedge \phi[A'/A])$

iff there is $s'_0 : A' \rightarrow \{0, 1\}$ s.t. $(s \cup s'_0) \models \tau_A^{nd}(o) \wedge \phi[A'/A]$

iff there is $s'_0 : A' \rightarrow \{0, 1\}$ s.t. $s'_0 \models \phi[A'/A]$ and $(s \cup s'_0) \models \tau_A^{nd}(o)$

iff there is $s' : A \rightarrow \{0, 1\}$ s.t. $s' \models \phi$ and $(s \cup s'_0) \models \tau_A^{nd}(o)$

iff there is $s' \in T$ s.t. $(s \cup s'[A'/A]) \models \tau_A^{nd}(o)$

iff there is $s' \in T$ s.t. $s' \in \text{img}_o(s)$

iff there is $s' \in T$ s.t. $s \in \text{preimg}_o(s')$

iff $s \in \text{preimg}_o(T)$.

Above we define $s' = s'_0[A'/A]$ (and hence $s'_0 = s'[A'/A]$.) □

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Strong preimages by formula manipulation

Theorem

Let $T = \{s \in S \mid s \models \phi\}$. Then

$$\{s \in S \mid s \models \mathbf{spreimg}_o(\phi)\} = \{s \in S \mid s \models \forall A'. (\tau_A^{nd}(o) \rightarrow \phi[A'/A]) \wedge \exists A'. \tau_A^{nd}(o)\} = \mathbf{spreimg}_o(T).$$

Proof.

See the lecture notes. □

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Strong preimages vs. regression

Corollary

Let $o = \langle c, (e_1 | \dots | e_n) \rangle$ be an operator such that all e_i are deterministic. The formula $\text{spreimg}_o(\phi)$ is logically equivalent to $\text{regr}_o^{\text{nd}}(\phi)$.

Proof.

$$\{s \in S \mid s \models \text{regr}_o(\phi)\} = \text{spreimg}_o(\{s \in S \mid s \models \phi\}) = \{s \in S \mid s \models \text{spreimg}_o(\phi)\}. \quad \square$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Summary of matrix/logic/relational operations

matrices	formulas	state sets
vector $V_{1 \times n}$	formula on A	set
matrix $M_{n \times n}$	formula on $A \cup A'$	relation
$V_{1 \times n} + V'_{1 \times n}$	$\phi_1 \vee \phi_2$	union
	$\phi_1 \wedge \phi_2$	intersection
$V_{1 \times n} \times M_{n \times n}$	$(\exists A. (\phi \wedge \tau_A^{nd}(o)))[A/A']$	$img_o(T)$
$M_{n \times n} \times V_{n \times 1}$	$\exists A'. (\tau_A^{nd}(o) \wedge \phi[A'/A])$	$preimg_o(T)$
	$\forall A'. (\tau_A^{nd}(o) \rightarrow \phi[A'/A]) \wedge \exists A'. \tau_A^{nd}(o)$	$spreimg_o(T)$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Images and preimages of sets of operators

The union of images of ϕ with respect to all operators $o \in O$ is

$$\bigvee_{o \in O} \text{img}_o(\phi).$$

This can be computed more directly by using the disjunction $\bigvee_{o \in O} \tau_A(o)$ of the transition formulae:

$$\exists A. (\phi \wedge (\bigvee_{o \in O} \tau_A(o))) [A/A'].$$

Same works for preimages.

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Image computation vs. planning by satisfiability

- We tested plan existence by testing satisfiability of

$$\iota^0 \wedge \mathcal{R}_1(A^0, A^1) \wedge \dots \wedge \mathcal{R}_1(A^{t-1}, A^t) \wedge G^t$$

where $\mathcal{R}_1(A, A') = \bigvee_{o \in O} \tau_A(o)$.

- \exists -abstracting $A^0 \cup \dots \cup A^{t-1}$ yields

$$\exists A^{t-1}. (\dots \exists A^0. (\iota^0 \wedge \mathcal{R}_1(A^0, A^1)) \wedge \dots \wedge \mathcal{R}_1(A^{t-1}, A^t) \wedge G^t).$$

- This is equivalent to conjoining the t -fold image of ι

$$\bigvee_{o \in O} \text{img}_o(\dots \bigvee_{o \in O} \text{img}_o(\iota) \dots)$$

with G to test goal reachability in t steps.

We can do the same with preimages starting from G .

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Image computation vs. planning by satisfiability

- We tested plan existence by testing satisfiability of

$$\iota^0 \wedge \mathcal{R}_1(A^0, A^1) \wedge \dots \wedge \mathcal{R}_1(A^{t-1}, A^t) \wedge G^t$$

where $\mathcal{R}_1(A, A') = \bigvee_{o \in O} \tau_A(o)$.

- \exists -abstracting $A^0 \cup \dots \cup A^{t-1}$ yields

$$\exists A^{t-1}. (\dots \exists A^0. (\iota^0 \wedge \mathcal{R}_1(A^0, A^1)) \wedge \dots \wedge \mathcal{R}_1(A^{t-1}, A^t) \wedge G^t).$$

- This is equivalent to conjoining the t -fold image of ι

$$\bigvee_{o \in O} \text{img}_o(\dots \bigvee_{o \in O} \text{img}_o(\iota) \dots)$$

with G to test goal reachability in t steps.

We can do the same with preimages starting from G .

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

\exists/\forall -abstraction

Images

Preimages

Strong preimages

Summary

vs. SAT

BDDs

Shannon expansion

Definition

3-place connective **if-then-else** is defined by

$$\text{ite}(a, \phi_1, \phi_2) = (a \wedge \phi_1) \vee (\neg a \wedge \phi_2)$$

where a is a proposition.

Definition

Shannon expansion of a formula ϕ with respect to $a \in A$ is

$$\phi \equiv (a \wedge \phi[\top/a]) \vee (\neg a \wedge \phi[\perp/a]) = \text{ite}(a, \phi[\top/a], \phi[\perp/a])$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

BDDs

Binary decision diagrams

Example

By repeated application of Shannon expansion any propositional formula can be transformed to an equivalent formula containing no other connectives than *ite* and propositional variables only in the first position of *ite*.

Example

$$\begin{aligned} & (a \vee b) \wedge (b \vee c) \\ \equiv & \text{ite}(a, (\top \vee b) \wedge (b \vee c), (\perp \vee b) \wedge (b \vee c)) \\ \equiv & \text{ite}(a, b \vee c, b) \\ \equiv & \text{ite}(a, \text{ite}(b, \top \vee c, \perp \vee c), \text{ite}(b, \top, \perp)) \\ \equiv & \text{ite}(a, \text{ite}(b, \top, c), \text{ite}(b, \top, \perp)) \\ \equiv & \text{ite}(a, \text{ite}(b, \top, \text{ite}(c, \top, \perp)), \text{ite}(b, \top, \perp)) \end{aligned}$$

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

BDDs

Binary decision diagrams

Canonicity

AI Planning

Transformation to ordered BDDs

- 1 Fix an ordering a_1, \dots, a_n on all propositional variables.
- 2 Apply Shannon expansion to all variables in this order.
- 3 Represent the resulting formulae as directed acyclic graphs (DAG) so that shared subformulae occur only once.

Theorem

Let ϕ_1 and ϕ_2 be two ordered BDDs obtained by using the same variable ordering. Then $\phi_1 \equiv \phi_2$ if and only if ϕ_1 and ϕ_2 are isomorphic (the same DAG.)

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

BDDs

Binary decision diagrams: example

$$(a \vee b) \wedge (b \vee c)$$

1

0

AI Planning

Plans

Plans

Images

Algorithms

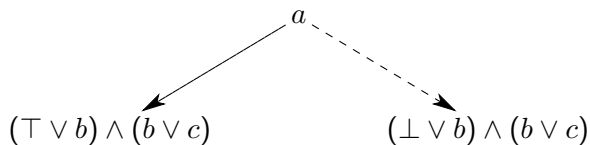
Regression

CPC
operators

CPC images

BDDs

Binary decision diagrams: example



1

0

AI Planning

Plans

Plans

Images

Algorithms

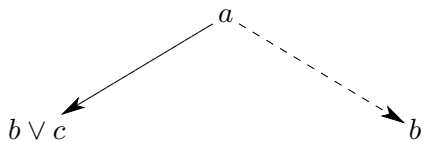
Regression

CPC
operators

CPC images

BDDs

Binary decision diagrams: example



1

0

AI Planning

Plans

Plans

Images

Algorithms

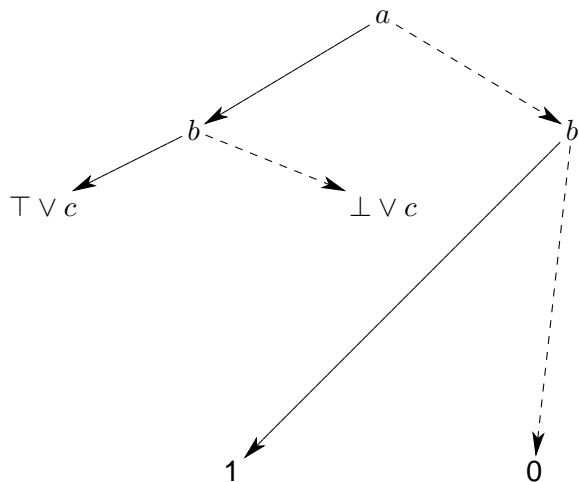
Regression

CPC
operators

CPC images

BDDs

Binary decision diagrams: example



AI Planning

Plans

Plans

Images

Algorithms

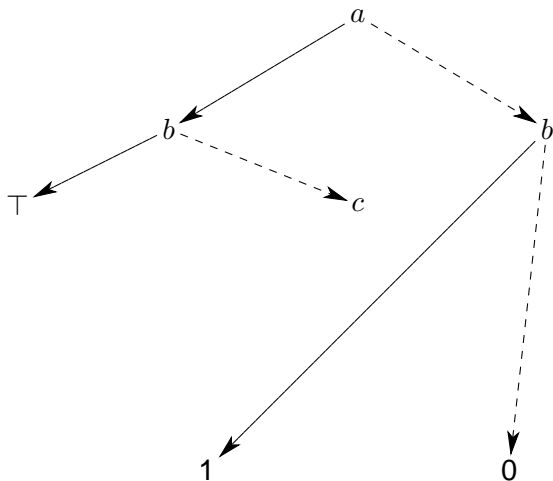
Regression

CPC
operators

CPC images

BDDs

Binary decision diagrams: example



AI Planning

Plans

Plans

Images

Algorithms

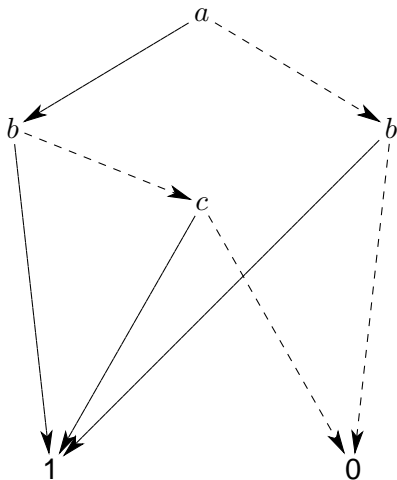
Regression

CPC
operators

CPC images

BDDs

Binary decision diagrams: example



AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

BDDs

Satisfiability algorithms vs. BDDs

Comparison: formula size, runtime

technique	size of $\mathcal{R}_1(P, P')$	runtime for plan length n
satisfiability	not a problem	exponential in n
BDDs	major problem	less dependent on n

Comparison: resource consumption

technique	critical resource
satisfiability	runtime
BDDs	memory

Comparison: application domain

technique	types of problems
satisfiability	lots of state variables, short plans
BDDs	few state variables, long plans

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC
operators

CPC images

BDDs

Properties of CPC normal forms

Trade-offs between different CPC normal forms

Normal forms that allow faster reasoning are more expensive to construct from an arbitrary propositional formula and may be much bigger.

Properties of different normal forms

	\vee	\wedge	\neg	$\phi \in \text{TAUT?}$	$\phi \in \text{SAT?}$	$\phi \equiv \phi'?$
circuits	poly	poly	poly	co-NP-hard	NP-hard	co-NP-hard
formulae	poly	poly	poly	co-NP-hard	NP-hard	co-NP-hard
DNF	poly	exp	exp	co-NP-hard	in P	co-NP-hard
CNF	exp	poly	exp	in P	NP-hard	co-NP-hard
BDD	exp	exp	poly	in P	in P	in P

For BDDs one \vee/\wedge is polynomial time/size (size is doubled) but repeated \vee/\wedge lead to exponential size.

AI Planning

Plans

Plans

Images

Algorithms

Regression

CPC operators

CPC images

BDDs