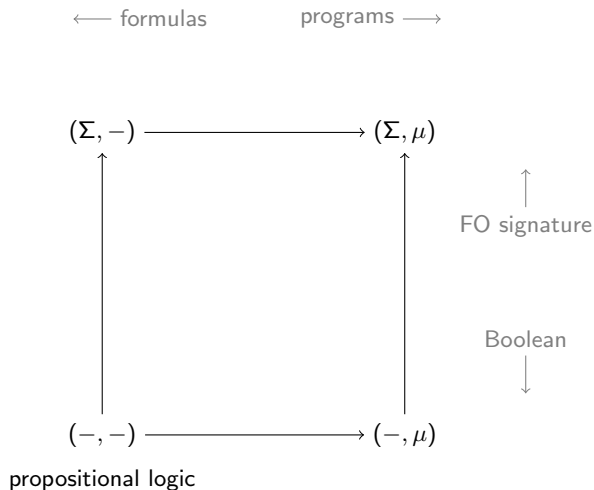


DPLL is Abstract Interpretation

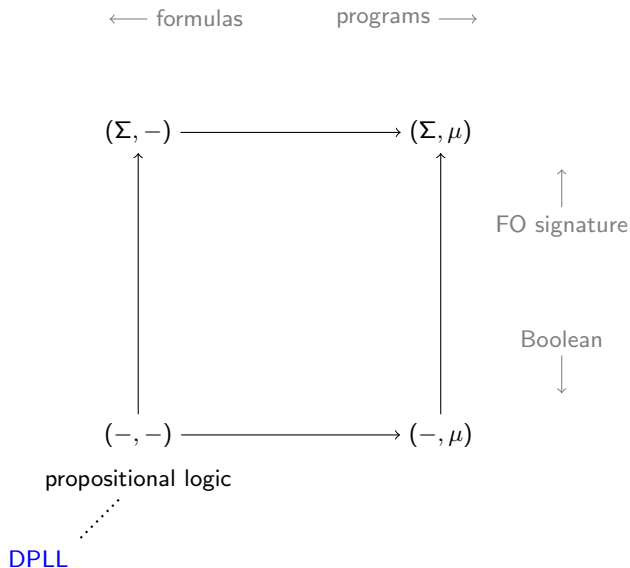
Leopold Haller
Vijay D'Silva



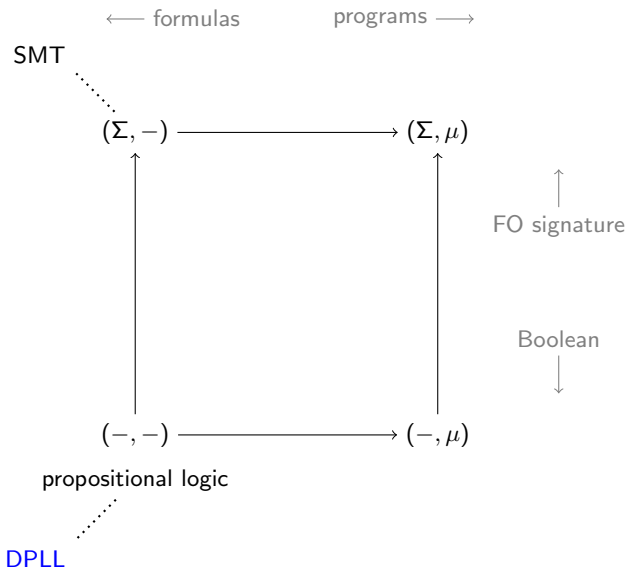
Analysing Logic and Programs



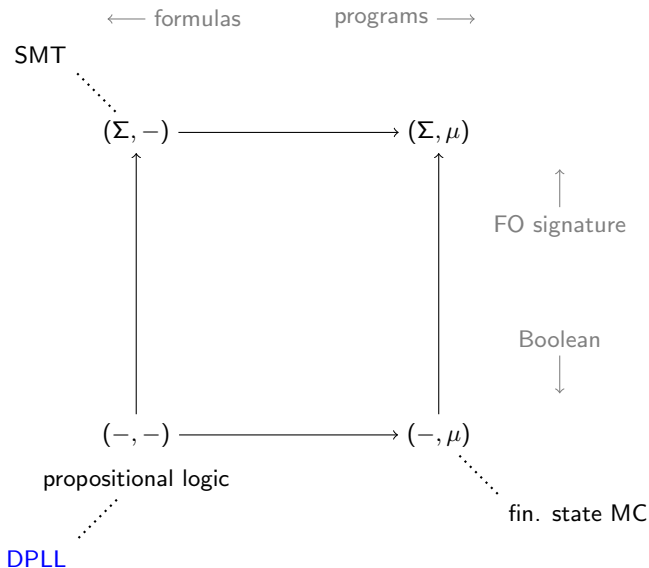
Analysing Logic and Programs



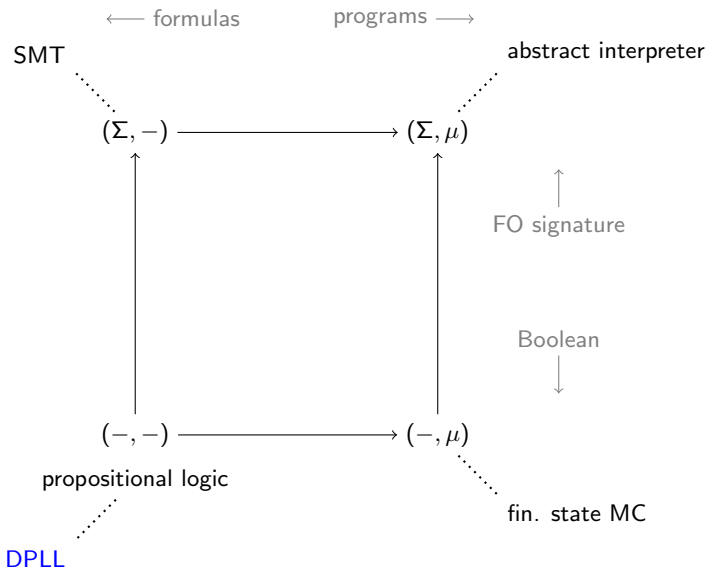
Analysing Logic and Programs



Analysing Logic and Programs



Analysing Logic and Programs

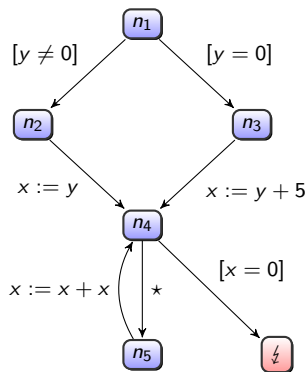


SAT Solvers are Efficient

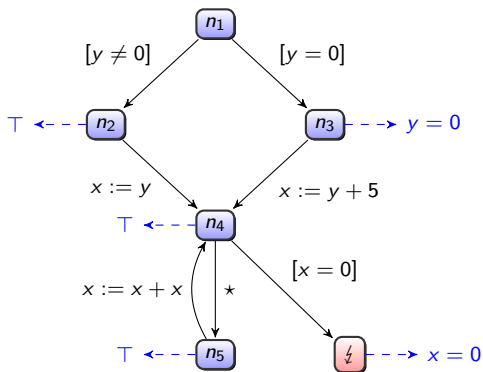


(Malik and Zhang 2009)

Prove the following program safe using the domain of intervals:

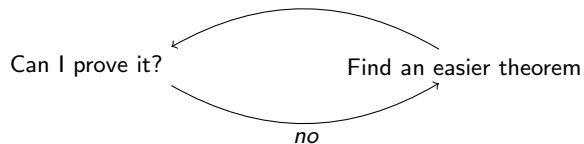


Prove the following program safe using the domain of intervals:



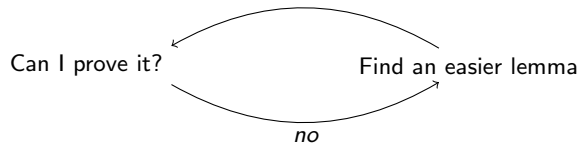
Flowchart for Proving a Theorem

Prove theorem T



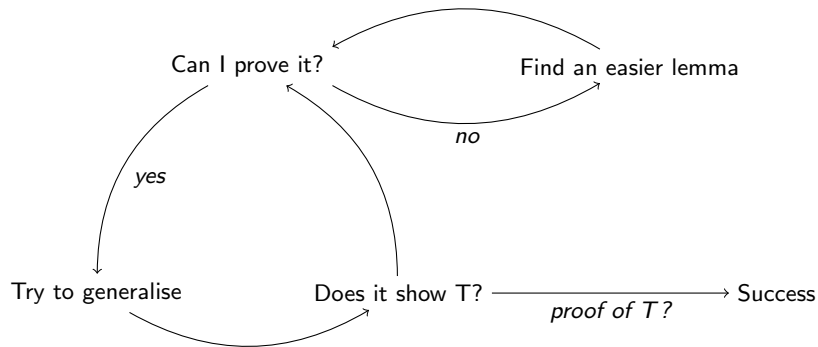
Flowchart for Proving a Theorem

Prove theorem T



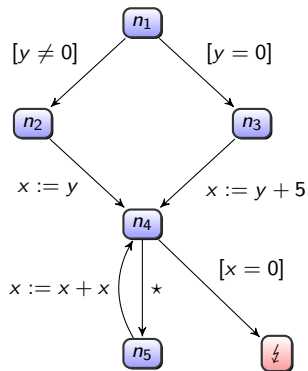
Flowchart for Proving a Theorem

Prove theorem T



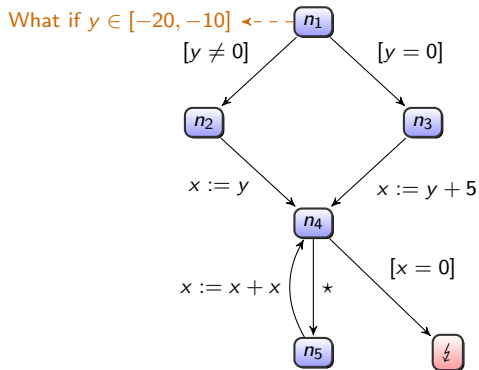
Refining the analysis

Let's try this on the program:



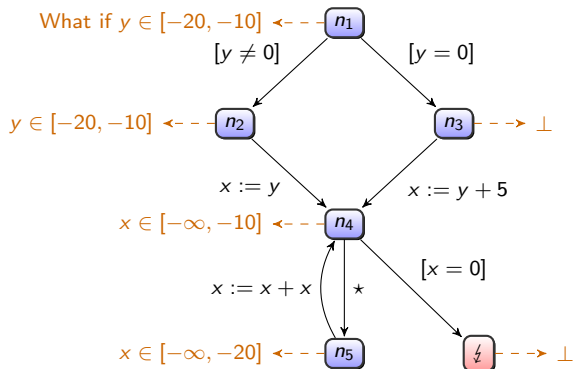
Refining the analysis

Let's try this on the program:



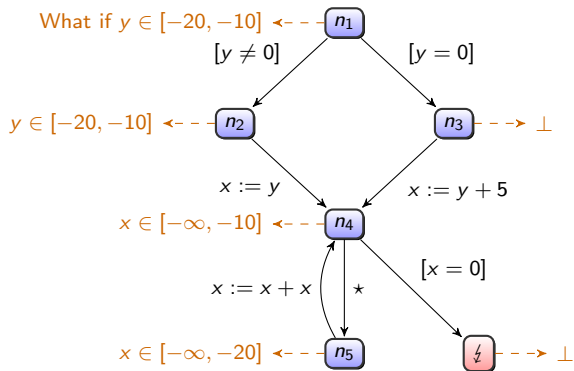
Refining the analysis

Let's try this on the program:



Refining the analysis

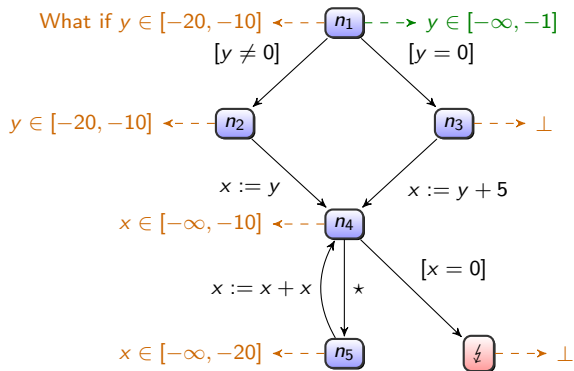
Let's try this on the program:



Analyse proof

Refining the analysis

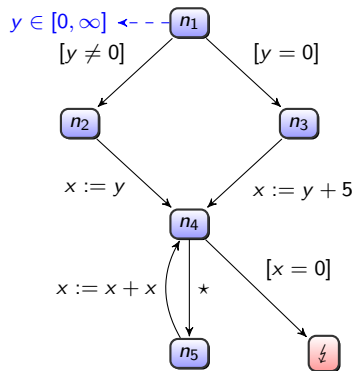
Let's try this on the program:



Analyse proof

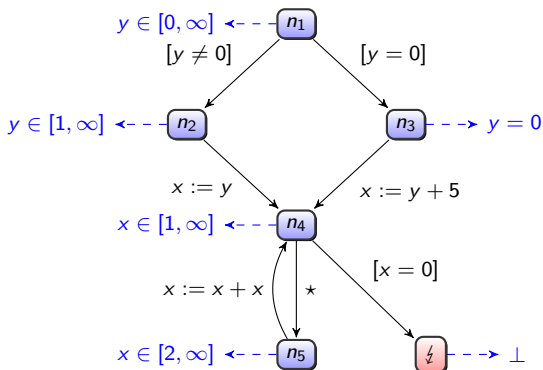
Refining the analysis

Let's try this on the program:



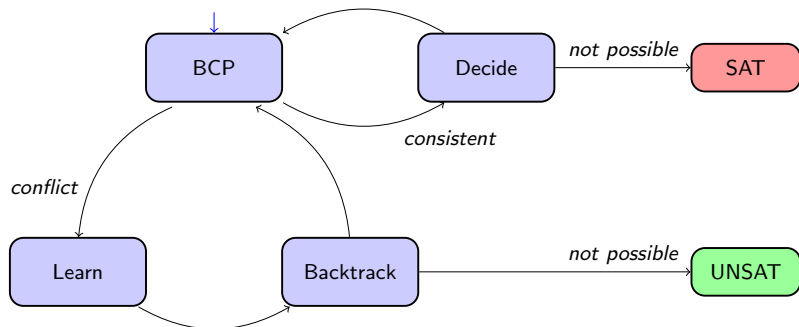
Refining the analysis

Let's try this on the program:



The Modern DPLL algorithm

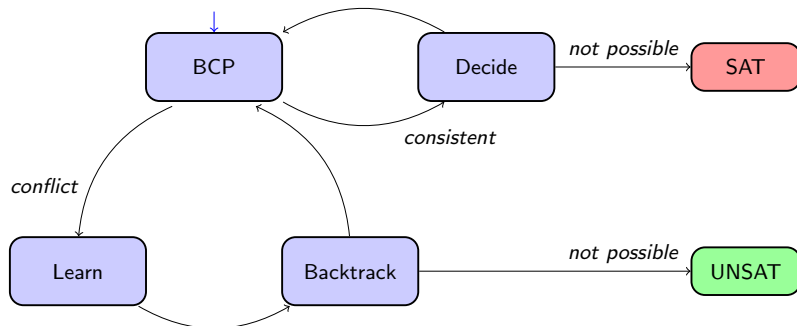
Decide **satisfiability** of propositional formula ϕ in **conjunctive normal form (CNF)**



Preliminaries

- Set of **variables** Var
- $v, \neg v$ are **literals** for $v \in \text{Var}$
- Disjunction of literals is a **clause** $v_1 \vee \neg v_2 \vee v_3$
- **CNF** formula is a conjunction of clauses

The Modern DPLL algorithm



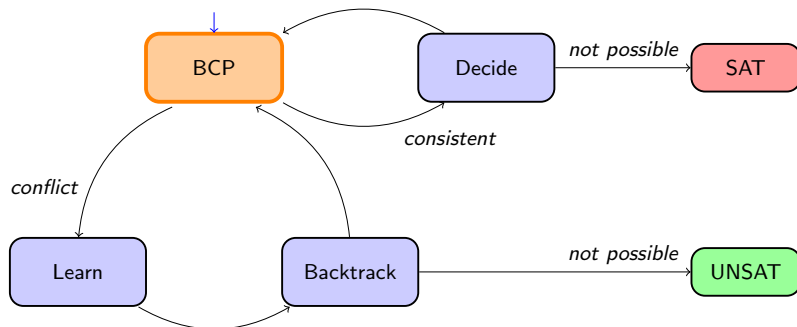
Partial assignments

SAT solver explores the space of **partial functions**:

$$\text{Var} \longrightarrow \{t, f\}$$

Uses **deduction** and **search** to find a satisfying assignment or exhaustively search space.

The Modern DPLL algorithm

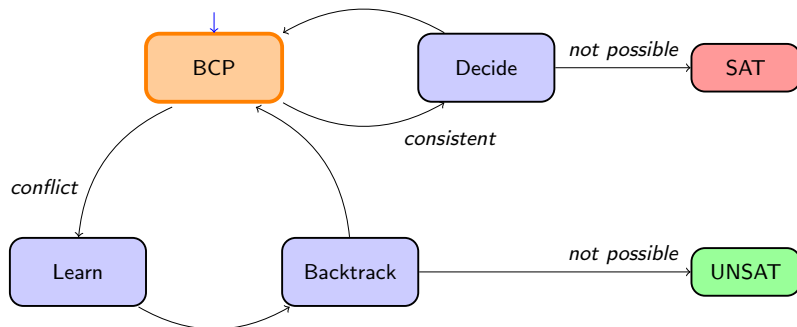


$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

BCP example

BCP: $\emptyset \rightarrow$

The Modern DPLL algorithm

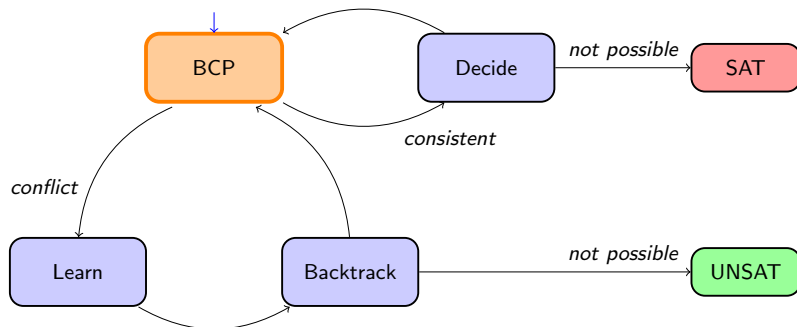


$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

BCP example

BCP: $\emptyset \rightarrow \{x \mapsto t\} \rightarrow$

The Modern DPLL algorithm

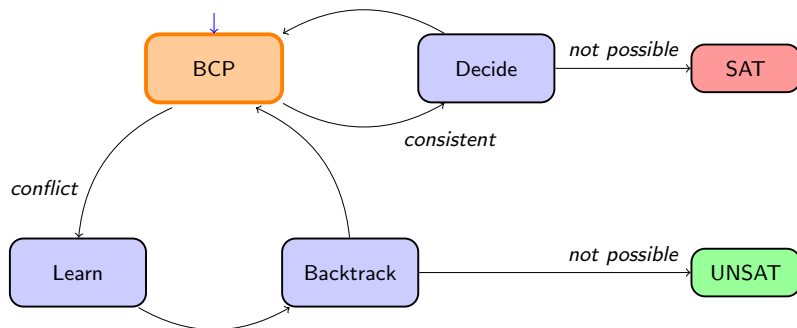


$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

BCP example

BCP: $\emptyset \rightarrow \{x \mapsto t\} \rightarrow \{x \mapsto t, y \mapsto f\}$

The Modern DPLL algorithm

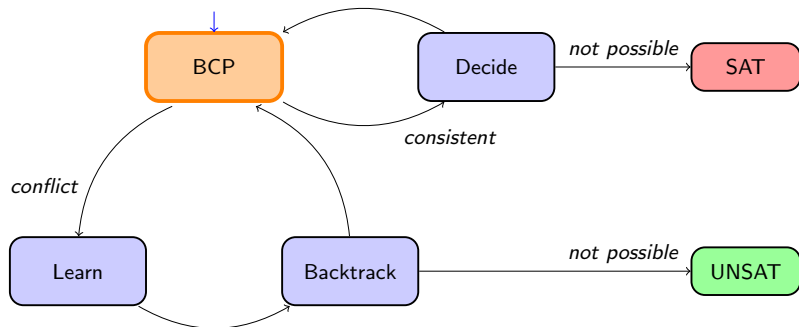


Unit rule

Deduction uses the unit rule:

$$\text{unit}(\rho, l_1 \vee \dots \vee l_i \dots \vee l_k) = \begin{cases} \text{conflict} & \text{all literals are contradicted by } \rho \\ \rho[l_i \mapsto t] & \text{all literals but } l_i \text{ contradicted } \rho \\ \rho & \text{otherwise} \end{cases}$$

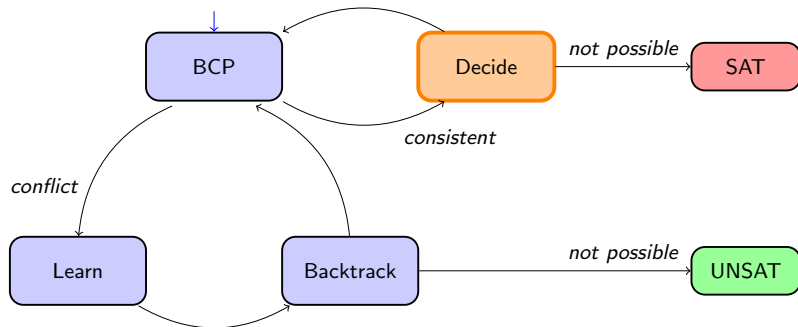
The Modern DPLL algorithm



Boolean Constraint Propagation

```
BCP( $\phi, \rho$ ) {  
  repeat  
     $\rho' \leftarrow \rho$ ;  
    for Clause  $c \in \phi$  do  $\rho \leftarrow \text{unit}(c, \rho)$ ;  
  until  $\rho = \rho'$  ;  
}
```

The Modern DPLL algorithm



$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

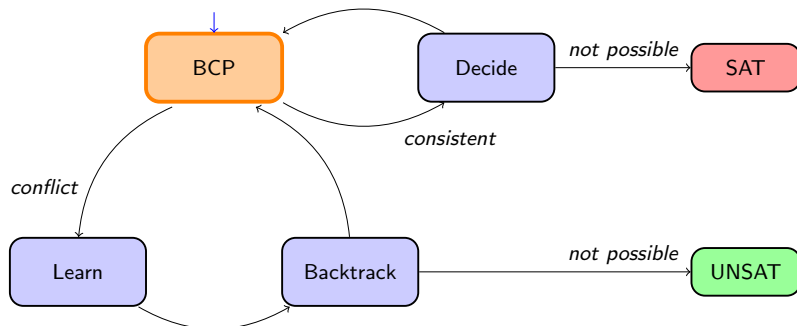
Decision

BCP: $\emptyset \rightarrow \{x \mapsto t\} \rightarrow \{x \mapsto t, y \mapsto f\} \rightarrow$

Add **assumption** to partial assignment:

Decision: $\{x \mapsto t, y \mapsto f, z \mapsto f\}$

The Modern DPLL algorithm



$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

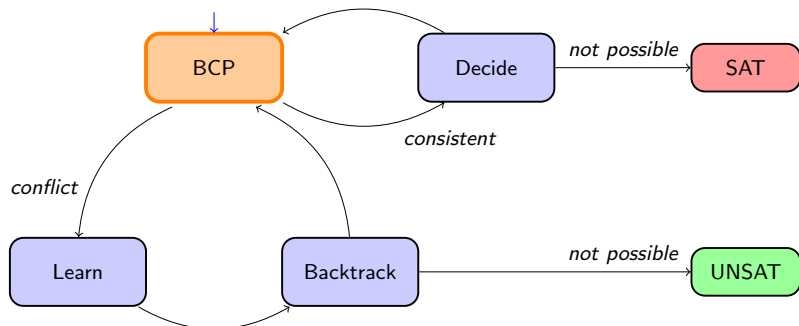
BCP

BCP: $\emptyset \rightarrow \{x \mapsto t\} \rightarrow \{x \mapsto t, y \mapsto f\} \rightarrow$

Decision: $\{x \mapsto t, y \mapsto f, z \mapsto f\} \rightarrow$

BCP:

The Modern DPLL algorithm



$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

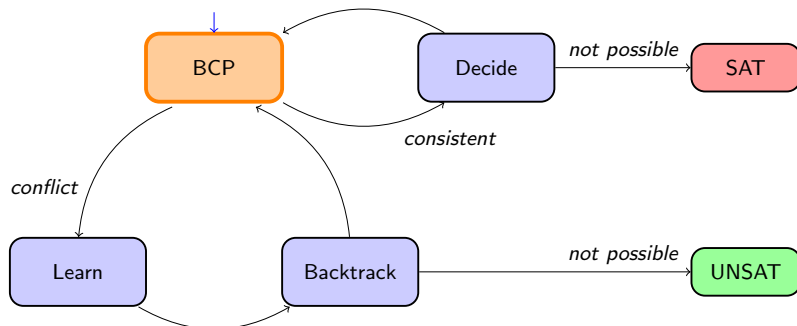
BCP

BCP: $\emptyset \rightarrow \{x \mapsto t\} \rightarrow \{x \mapsto t, y \mapsto f\} \rightarrow$

Decision: $\{x \mapsto t, y \mapsto f, z \mapsto f\} \rightarrow$

BCP: $\{x \mapsto t, y \mapsto f, z \mapsto f, w \mapsto f\}$

The Modern DPLL algorithm



$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

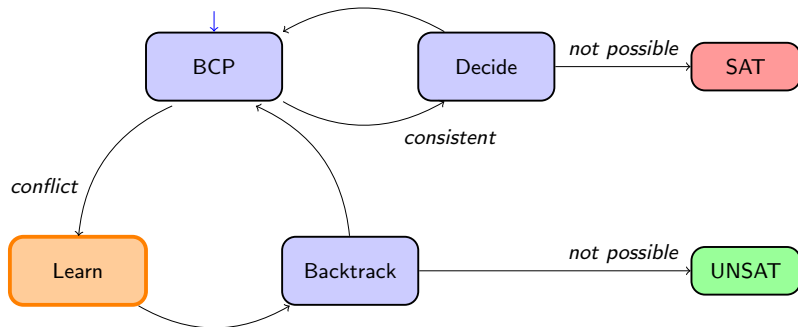
BCP

BCP: $\emptyset \rightarrow \{x \mapsto t\} \rightarrow \{x \mapsto t, y \mapsto f\} \rightarrow$

Decision: $\{x \mapsto t, y \mapsto f, z \mapsto f\} \rightarrow$

BCP: $\{x \mapsto t, y \mapsto f, z \mapsto f, w \mapsto f\} \rightarrow \text{conflict}$

The Modern DPLL algorithm



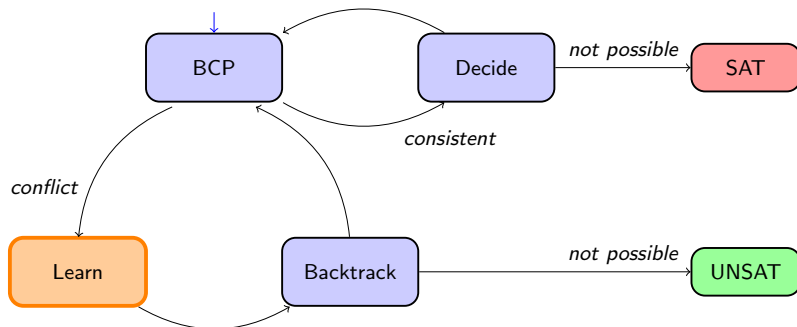
$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

Learn

BCP: $\{x \mapsto t, y \mapsto f, z \mapsto f, w \mapsto f\} \rightarrow \text{conflict}$

Find reason for the conflict,

The Modern DPLL algorithm



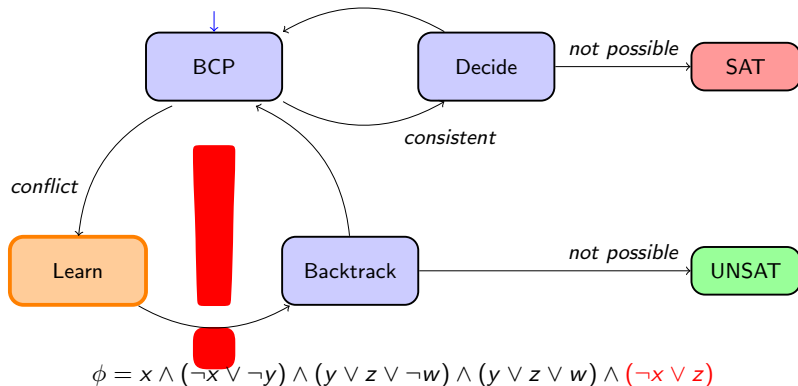
$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

Learn

BCP: $\{x \mapsto t, y \mapsto f, z \mapsto f, w \mapsto f\} \rightarrow \text{conflict}$

Find reason for the conflict, e.g., $x \wedge \neg z$ can never be true:

The Modern DPLL algorithm



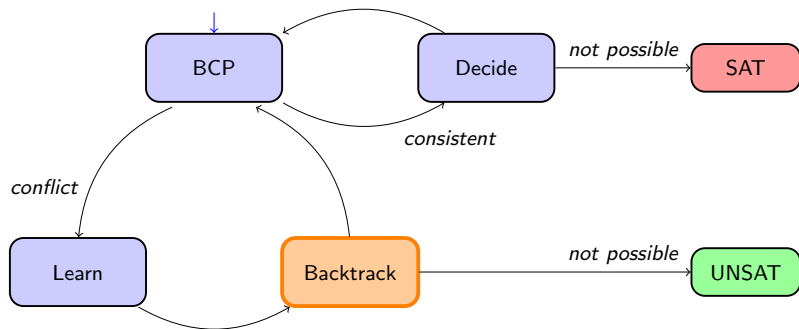
Learn

BCP: $\{x \mapsto t, y \mapsto f, z \mapsto f, w \mapsto f\} \rightarrow \text{conflict}$

Find reason for the conflict, e.g., $x \wedge \neg z$ can never be true:

Learn $\neg(x \wedge \neg z) = \neg x \vee z$.

The Modern DPLL algorithm



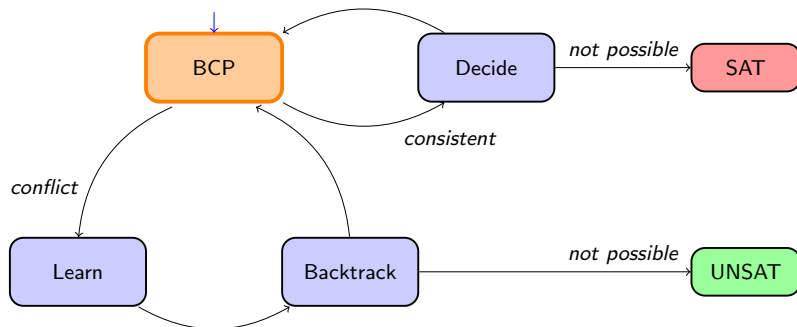
$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w) \wedge (\neg x \vee z)$$

Backtrack

Undo assumptions that contradict learned clause:

Backtrack: $\{x \mapsto t, y \mapsto t\}$

The Modern DPLL algorithm



$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w) \wedge (\neg x \vee z)$$

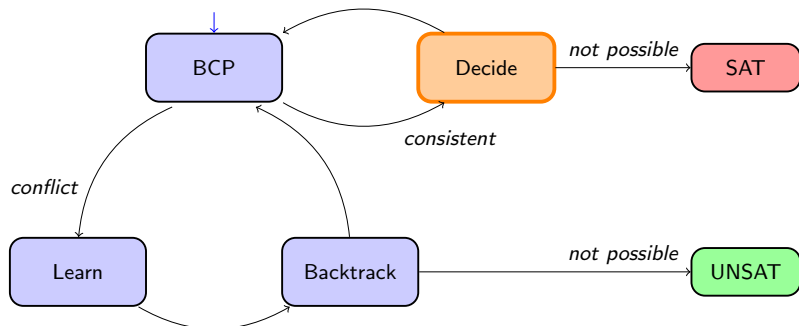
BCP

Backtrack: $\{x \mapsto t, y \mapsto t\} \rightarrow$

BCP automatically takes us to a new part of the search space:

BCP: $\{x \mapsto t, y \mapsto t, z \mapsto t\}$

The Modern DPLL algorithm

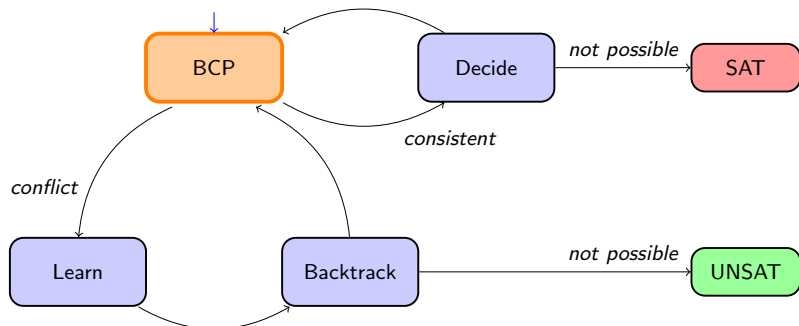


$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w) \wedge (\neg x \vee z)$$

Decide

Backtrack: $\{x \mapsto t, y \mapsto t\} \rightarrow$
BCP: $\{x \mapsto t, y \mapsto t, z \mapsto t\} \rightarrow$
Decide: $\{x \mapsto t, y \mapsto t, z \mapsto t, w \mapsto f\}$

The Modern DPLL algorithm

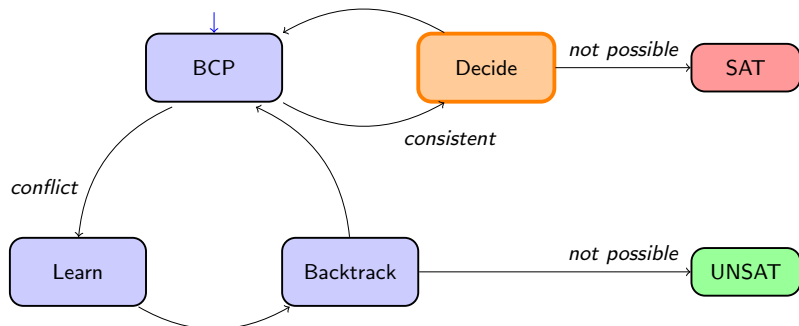


$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w) \wedge (\neg x \vee z)$$

Decide

Backtrack: $\{x \mapsto t, y \mapsto t\} \rightarrow$
BCP: $\{x \mapsto t, y \mapsto t, z \mapsto t\} \rightarrow$
Decide: $\{x \mapsto t, y \mapsto t, z \mapsto t, w \mapsto f\}$

The Modern DPLL algorithm

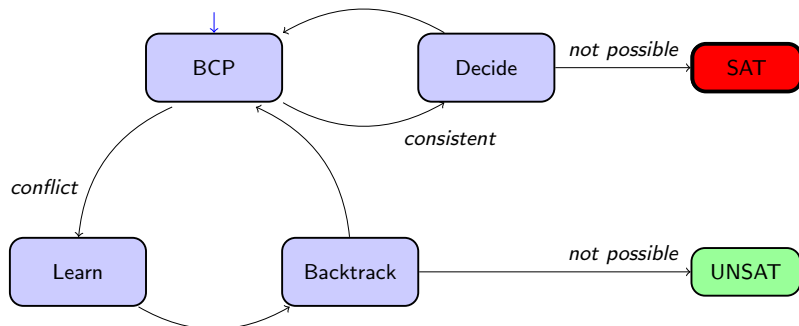


$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w) \wedge (\neg x \vee z)$$

Decide

Backtrack: $\{x \mapsto t, y \mapsto t\} \rightarrow$
BCP: $\{x \mapsto t, y \mapsto t, z \mapsto t\} \rightarrow$
Decide: $\{x \mapsto t, y \mapsto t, z \mapsto t, w \mapsto f\}$

The Modern DPLL algorithm



$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w) \wedge (\neg x \vee z)$$

Decide

Backtrack: $\{x \mapsto t, y \mapsto t\} \rightarrow$
BCP: $\{x \mapsto t, y \mapsto t, z \mapsto t\} \rightarrow$
Decide: $\{x \mapsto t, y \mapsto t, z \mapsto t, w \mapsto f\}$

```
bool v1, ..., vk;  
if( $\phi$ )  
    assert(0);  
// program safe iff  $\phi$  UNSAT
```


$$C = \langle \wp(\text{Var} \rightarrow \{\mathbf{t}, \mathbf{f}\}), \subseteq, \cap, \cup \rangle$$
$$\text{post}_{\phi}^C(X) = \{\varepsilon \in X \mid \phi \text{ is true under } \varepsilon\}$$

$$C = \langle \wp(\text{Var} \rightarrow \{t, f\}), \subseteq, \cap, \cup \rangle$$
$$\text{post}_{\phi}^C(X) = \{\varepsilon \in X \mid \phi \text{ is true under } \varepsilon\}$$

Examples

$$\text{post}_{a \wedge b}^C(\top) = \{\langle a \mapsto t, b \mapsto t \rangle\}$$

$$\text{post}_{a \vee \neg b}^C(\top) = \{\langle a \mapsto t, b \mapsto t \rangle, \langle a \mapsto t, b \mapsto f \rangle, \langle a \mapsto f, b \mapsto f \rangle\}$$

$$C = \langle \wp(\text{Var} \rightarrow \{t, f\}), \subseteq, \cap, \cup \rangle$$
$$\text{post}_{\phi}^C(X) = \{\varepsilon \in X \mid \phi \text{ is true under } \varepsilon\}$$

Examples

$$\text{post}_{a \wedge b}^C(\top) = \{\langle a \mapsto t, b \mapsto t \rangle\}$$

$$\text{post}_{a \vee \neg b}^C(\top) = \{\langle a \mapsto t, b \mapsto t \rangle, \langle a \mapsto t, b \mapsto f \rangle, \langle a \mapsto f, b \mapsto f \rangle\}$$

ϕ is satisfiable exactly if $\text{post}_{\phi}^C(\top) \neq \emptyset$.

DPLL datastructure

Partial assignment $\text{Var} \mapsto \{t, f\}$ and additional conflict states.

Each variable is:

unknown

true

false

conflicting

Abstraction and DPLL

DPLL operates over an abstract domain

$$\text{Var} \rightarrow \wp(\{t, f\}) = \text{Var} \longrightarrow \begin{array}{c} \top \\ / \quad \backslash \\ t \quad \quad f \\ \backslash \quad / \\ \perp \end{array}$$

$$A = \langle \text{Var} \rightarrow \wp(\{t, f\}), \sqsubseteq, \sqcap, \sqcup \rangle$$

$$C \xrightleftharpoons[\alpha]{\gamma} A$$

DPLL datastructure

Partial assignment $\text{Var} \mapsto \{t, f\}$ and additional conflict states.

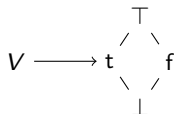
Each variable is:

unknown

true false

conflicting

Best Abstract Transformers over the Cartesian Abstraction



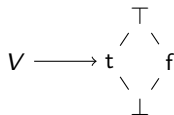
$$post_{\phi}^A(\top) = \perp \implies \phi \text{ is unsatisfiable}$$

Best abstract transformer for a clause $a \vee b$

We synthesize the transformer $post_{a \vee b}^A$ for the argument $(a \mapsto \mathbf{f}, b \mapsto \top)$:

$$post_{a \vee b}^A(\langle a \mapsto \mathbf{f}, b \mapsto \top \rangle) =$$

Best Abstract Transformers over the Cartesian Abstraction



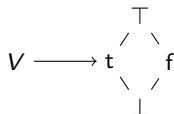
$$post_{\phi}^A(\top) = \perp \implies \phi \text{ is unsatisfiable}$$

Best abstract transformer for a clause $a \vee b$

We synthesize the transformer $post_{a \vee b}^A$ for the argument $(a \mapsto f, b \mapsto \top)$:

$$post_{a \vee b}^A(\langle a \mapsto f, b \mapsto \top \rangle) = \alpha \circ post_{a \vee b}^C \circ \gamma(\langle a \mapsto f, b \mapsto \top \rangle)$$

Best Abstract Transformers over the Cartesian Abstraction



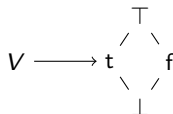
$$post_{\phi}^A(\top) = \perp \quad \Longrightarrow \quad \phi \text{ is unsatisfiable}$$

Best abstract transformer for a clause $a \vee b$

We synthesize the transformer $post_{a \vee b}^A$ for the argument $(a \mapsto f, b \mapsto \top)$:

$$\begin{aligned} post_{a \vee b}^A(\langle a \mapsto f, b \mapsto \top \rangle) &= \alpha \circ post_{a \vee b}^C \circ \gamma(\langle a \mapsto f, b \mapsto \top \rangle) \\ &= \alpha \circ post_{a \vee b}^C(\{\langle a : f, b : f \rangle, \langle a : f, b : \top \rangle\}) \end{aligned}$$

Best Abstract Transformers over the Cartesian Abstraction



$$post_{\phi}^A(\top) = \perp \quad \Longrightarrow \quad \phi \text{ is unsatisfiable}$$

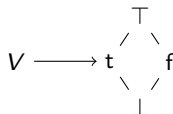
Best abstract transformer for a clause $a \vee b$

We synthesize the transformer $post_{a \vee b}^A$ for the argument $(a \mapsto f, b \mapsto \top)$:

$$\begin{aligned} post_{a \vee b}^A(\langle a \mapsto f, b \mapsto \top \rangle) &= \alpha \circ post_{a \vee b}^C \circ \gamma(\langle a \mapsto f, b \mapsto \top \rangle) \\ &= \alpha \circ post_{a \vee b}^C(\{\langle a : f, b : f \rangle, \langle a : f, b : \top \rangle\}) \\ &= \alpha(\{\langle a : f, b : \top \rangle\}) = \langle a \mapsto f, b \mapsto \top \rangle \end{aligned}$$

Best Abstract Transformers over the Cartesian Abstraction

DPLL operates over an abstract domain.
The unit rule is the best abstract transformer.



$$post_{\phi}^A(\top) = \perp \implies \phi \text{ is unsatisfiable}$$

Best abstract transformer for a clause $a \vee b$

We synthesize the transformer $post_{a \vee b}^A$ for the argument $(a \mapsto f, b \mapsto \top)$:

$$\begin{aligned} post_{a \vee b}^A(\langle a \mapsto f, b \mapsto \top \rangle) &= \alpha \circ post_{a \vee b}^C \circ \gamma(\langle a \mapsto f, b \mapsto \top \rangle) \\ &= \alpha \circ post_{a \vee b}^C(\{\langle a : f, b : f \rangle, \langle a : f, b : t \rangle\}) \\ &= \alpha(\{\langle a : f, b : t \rangle\}) = \langle a \mapsto f, b \mapsto t \rangle \end{aligned}$$

Literals:

$$post_v^A(a) = a \sqcap \langle v \mapsto t \rangle$$

$$post_{\neg v}^A(a) = a \sqcap \langle v \mapsto f \rangle$$

Disjunction and Conjunction:

$$post_{\phi \vee \psi}^A(a) = post_{\phi}^A(a) \sqcup post_{\psi}^A(a)$$

$$post_{\phi \wedge \psi}^A(a) = post_{\phi}^A(a) \sqcap post_{\psi}^A(a)$$

Literals:

$$post_v^A(a) = a \sqcap \langle v \mapsto t \rangle$$

$$post_{\neg v}^A(a) = a \sqcap \langle v \mapsto f \rangle$$

Disjunction and Conjunction:

$$post_{\phi \vee \psi}^A(a) = post_{\phi}^A(a) \sqcup post_{\psi}^A(a)$$

$$post_{\phi \wedge \psi}^A(a) = post_{\phi}^A(a) \sqcap post_{\psi}^A(a)$$

Imprecision example:

$$\phi = a \wedge (\neg a \vee b)$$

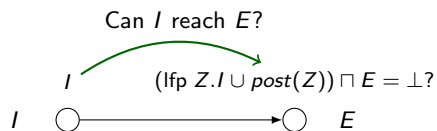
$$\begin{aligned} post_{\phi}^A(\top) &= post_a^A(\top) \sqcap post_{\neg a \vee b}^A(\top) \\ &= \langle a \mapsto t \rangle \sqcap (\langle a \mapsto f \rangle \sqcup \langle b \mapsto t \rangle) \\ &= \langle a \mapsto t \rangle \sqcap \top = \langle a \mapsto t \rangle \quad \rightarrow \text{analysis too imprecise} \end{aligned}$$

Refined Abstract Analyses through gfp Iteration

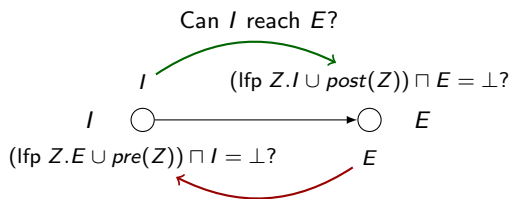
Can I reach E ?



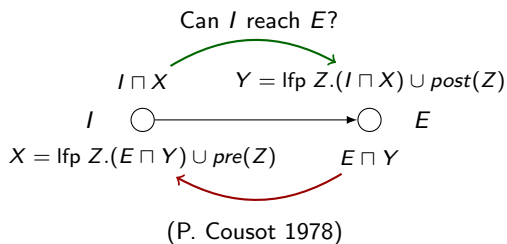
Refined Abstract Analyses through gfp Iteration



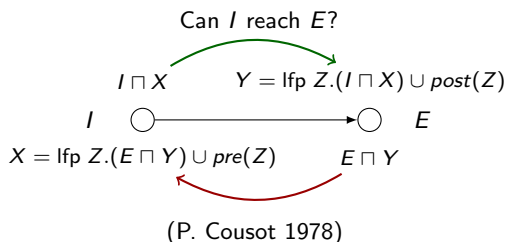
Refined Abstract Analyses through gfp Iteration



Refined Abstract Analyses through gfp Iteration



Refined Abstract Analyses through gfp Iteration

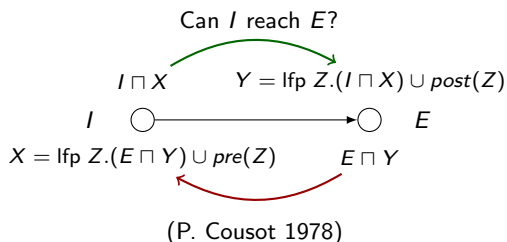


Iterating abstractions for increased precision

Iterate forward and backward analysis

$$\text{gfp}\langle X, Y \rangle. \quad \langle \text{lfp } Z.(E \sqcap Y) \sqcup \text{pre}(Z), \text{lfp } Z.(I \sqcap X) \sqcup \text{post}(Z) \rangle$$

Refined Abstract Analyses through gfp Iteration



Iterating abstractions for increased precision

Iterate forward and backward analysis

$$\text{gfp}\langle X, Y \rangle. \quad \langle \text{lfp } Z.(E \sqcap Y) \sqcup \text{pre}(Z), \text{lfp } Z.(I \sqcap X) \sqcup \text{post}(Z) \rangle$$

In propositional logic, it is the case that $\text{pre} = \text{post}$

$$\text{gfp}\langle X, Y \rangle. \quad \langle \text{post}_{\phi}^A(\top \sqcap Y), \text{post}_{\phi}^A(\top \sqcap X) \rangle$$

Fixed point semantics: $\text{gfp } \text{post}_{\phi}^A$

Fixed Point Semantics

Fixed point semantics example: $\phi = a \wedge (\neg a \vee b)$

$$post_{\phi}^A(\top) = \langle a \mapsto t \rangle \sqcap \top = \langle a \mapsto t \rangle$$

$$post_{\phi}^A(\langle a \mapsto t \rangle) = \langle a \mapsto t \rangle \sqcap (\perp \sqcup \langle a \mapsto t, b \mapsto t \rangle) = \langle a \mapsto t, b \mapsto t \rangle$$

Fixed Point Semantics

Fixed point semantics example: $\phi = a \wedge (\neg a \vee b)$

$$post_{\phi}^A(\top) = \langle a \mapsto t \rangle \sqcap \top = \langle a \mapsto t \rangle$$

$$post_{\phi}^A(\langle a \mapsto t \rangle) = \langle a \mapsto t \rangle \sqcap (\perp \sqcup \langle a \mapsto t, b \mapsto t \rangle) = \langle a \mapsto t, b \mapsto t \rangle$$

Boolean Constraint Propagation

```
BCP( $\phi, \rho$ ) {  
  repeat  
     $\rho' \leftarrow \rho$ ;  
    for Clause  $c \in \phi$  do  $\rho \leftarrow \text{unit}(c, \rho)$ ;  
  until  $\rho = \rho'$  ;  
}
```

Fixed Point Semantics

DPLL operates over an abstract domain.

The unit rule is the best abstract transformer.

BCP is the gfp semantics of the abstract transformer

Fixed point semantics example: $\phi = a \wedge (\neg a \vee b)$

$$\text{post}_{\phi}^A(\top) = \langle a \mapsto \text{t} \rangle \sqcap \top = \langle a \mapsto \text{t} \rangle$$

$$\text{post}_{\phi}^A(\langle a \mapsto \text{t} \rangle) = \langle a \mapsto \text{t} \rangle \sqcap (\perp \sqcup \langle a \mapsto \text{t}, b \mapsto \text{t} \rangle) = \langle a \mapsto \text{t}, b \mapsto \text{t} \rangle$$

Boolean Constraint Propagation

```
BCP( $\phi, \rho$ ) {  
  repeat  
     $\rho' \leftarrow \rho$ ;  
    for Clause  $c \in \phi$  do  $\rho \leftarrow \text{unit}(c, \rho)$ ;  
  until  $\rho = \rho'$  ;  
}
```

Example

$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

$$\text{gfp } \text{post}_{\phi}^A = \langle x \mapsto \text{t}, y \mapsto \text{f} \rangle \rightarrow \text{too imprecise}$$

Example

$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

$$\text{gfp } post_{\phi}^A = \langle x \mapsto t, y \mapsto f \rangle \rightarrow \text{too imprecise}$$

Trace partitioning (Mauborgne and Rival 2005)

Partition $\text{gfp } post_{\phi}^A(X)$ using transformers F and F'

①

$$\text{gfp } X.(post_{\phi}^A(X) \sqcap F(X)) \quad \rightarrow F(X) = post_{\neg z}^A(X)$$

②

$$\text{gfp } X.(post_{\phi}^A(X) \sqcap F'(X)) \quad \rightarrow F'(X) = post_{\neg x \vee z}^A(X)$$

Partitioning of gfp Semantics

DPLL operates over an abstract domain.

The unit rule is the best abstract transformer.

BCP is the gfp semantics of the abstract transformer

Decisions and learning are dynamic construction of trace partitionings

Example

$$\phi = x \wedge (\neg x \vee \neg y) \wedge (y \vee z \vee \neg w) \wedge (y \vee z \vee w)$$

$$\text{gfp } \text{post}_{\phi}^A = \langle x \mapsto \text{t}, y \mapsto \text{f} \rangle \rightarrow \text{too imprecise}$$

Trace partitioning (Mauborgne and Rival 2005)

Partition $\text{gfp } \text{post}_{\phi}^A(X)$ using transformers F and F'

1

$$\text{gfp } X.(\text{post}_{\phi}^A(X) \sqcap F(X)) \quad \rightarrow F(X) = \text{post}_{\neg z}^A(X)$$

2

$$\text{gfp } X.(\text{post}_{\phi}^A(X) \sqcap F'(X)) \quad \rightarrow F'(X) = \text{post}_{\neg x \vee z}^A(X)$$

DPLL is Abstract Interpretation

- 1 DPLL operates over an abstract domain
- 2 The unit rule is the best abstract transformer.
- 3 BCP is the gfp semantics of the abstract transformer
- 4 Decisions and learning are dynamic construction of trace partitionings

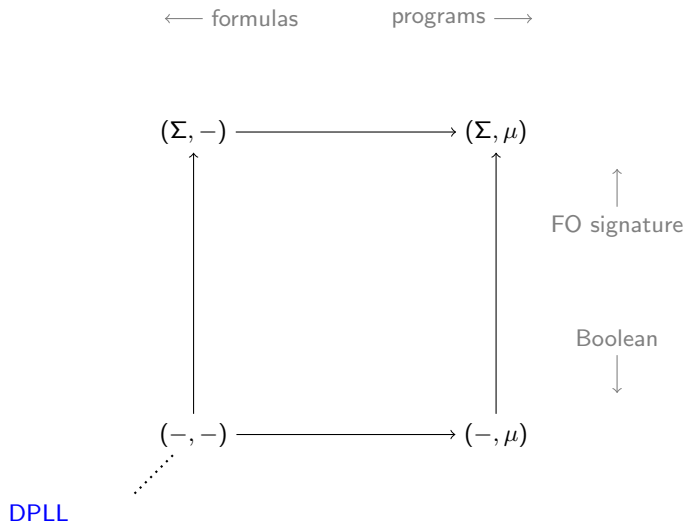
DPLL is Abstract Interpretation

- 1 DPLL operates over an abstract domain
- 2 The unit rule is the best abstract transformer.
- 3 BCP is the gfp semantics of the abstract transformer
- 4 Decisions and learning are dynamic construction of trace partitionings

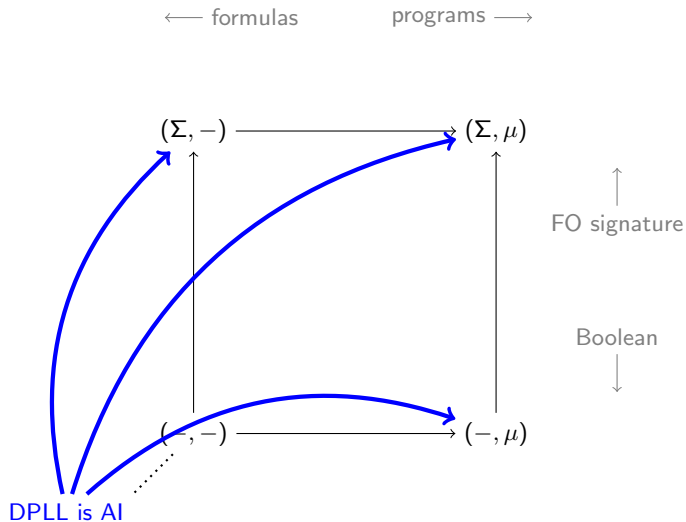
DPLL = AI + gfp semantics + dynamic trace partitioning

- DPLL operates over an abstraction to compute a precise concrete result
- DPLL iteratively computes a minimal “error-preserving” transformer

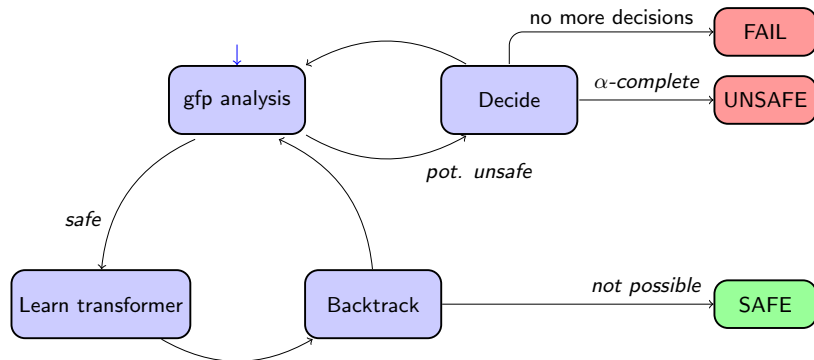
World Domination through Abstract Interpretation



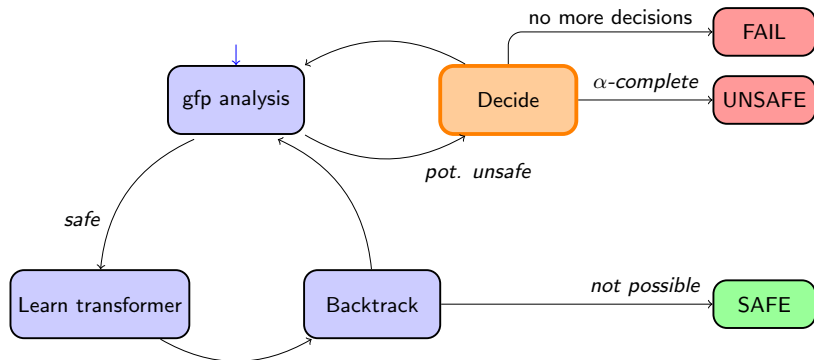
World Domination through Abstract Interpretation

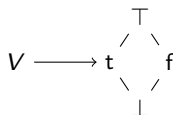


Generalising DPLL



Generalising DPLL





Complementable decompositions

Take $a = \langle x \mapsto t, y \mapsto f \rangle \in \text{Var} \rightarrow \wp(\{t, f\})$.

- Complement: $\neg a = \langle x \mapsto f \rangle \vee \langle y \mapsto t \rangle$
Not precisely expressible in $\text{Var} \rightarrow \wp(\{t, f\})$.
- Decomposition: $a = \langle x \mapsto t \rangle \sqcap \langle y \mapsto f \rangle$
Each element of the decomposition has a precise complement.

Decisions are made over complementable meet-irreducible elements.

Intervals

$a = \langle x \in [0, 10], y \in [-\infty, 0] \rangle$ has no precise complements

$$a = \underbrace{\langle x \geq 0 \rangle}_{\neg \langle x < 0 \rangle} \cap \underbrace{\langle x \leq 10 \rangle}_{\neg \langle x > 10 \rangle} \cap \underbrace{\langle y \leq 0 \rangle}_{\neg \langle y > 0 \rangle}$$

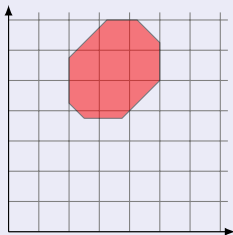
Decisions in Numeric Domains

Intervals

$a = \langle x \in [0, 10], y \in [-\infty, 0] \rangle$ has no precise complements

$$a = \underbrace{\langle x \geq 0 \rangle}_{\neg \langle x < 0 \rangle} \cap \underbrace{\langle x \leq 10 \rangle}_{\neg \langle x > 10 \rangle} \cap \underbrace{\langle y \leq 0 \rangle}_{\neg \langle y > 0 \rangle}$$

Octagons



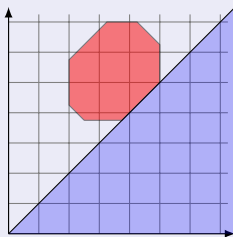
Decisions in Numeric Domains

Intervals

$a = \langle x \in [0, 10], y \in [-\infty, 0] \rangle$ has no precise complements

$$a = \underbrace{\langle x \geq 0 \rangle}_{\neg \langle x < 0 \rangle} \cap \underbrace{\langle x \leq 10 \rangle}_{\neg \langle x > 10 \rangle} \cap \underbrace{\langle y \leq 0 \rangle}_{\neg \langle y > 0 \rangle}$$

Octagons



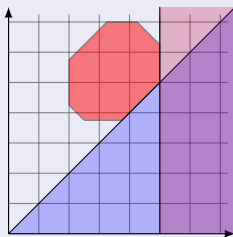
Decisions in Numeric Domains

Intervals

$a = \langle x \in [0, 10], y \in [-\infty, 0] \rangle$ has no precise complements

$$a = \underbrace{\langle x \geq 0 \rangle}_{\neg \langle x < 0 \rangle} \cap \underbrace{\langle x \leq 10 \rangle}_{\neg \langle x > 10 \rangle} \cap \underbrace{\langle y \leq 0 \rangle}_{\neg \langle y > 0 \rangle}$$

Octagons



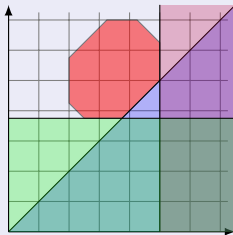
Decisions in Numeric Domains

Intervals

$a = \langle x \in [0, 10], y \in [-\infty, 0] \rangle$ has no precise complements

$$a = \underbrace{\langle x \geq 0 \rangle}_{\neg \langle x < 0 \rangle} \cap \underbrace{\langle x \leq 10 \rangle}_{\neg \langle x > 10 \rangle} \cap \underbrace{\langle y \leq 0 \rangle}_{\neg \langle y > 0 \rangle}$$

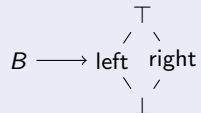
Octagons



Decisions in Trace Abstractions

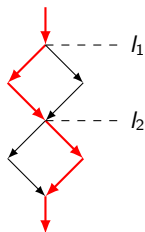
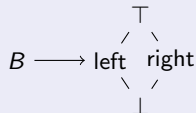
Control-flow abstraction

Set of control-flow branches B



Control-flow abstraction

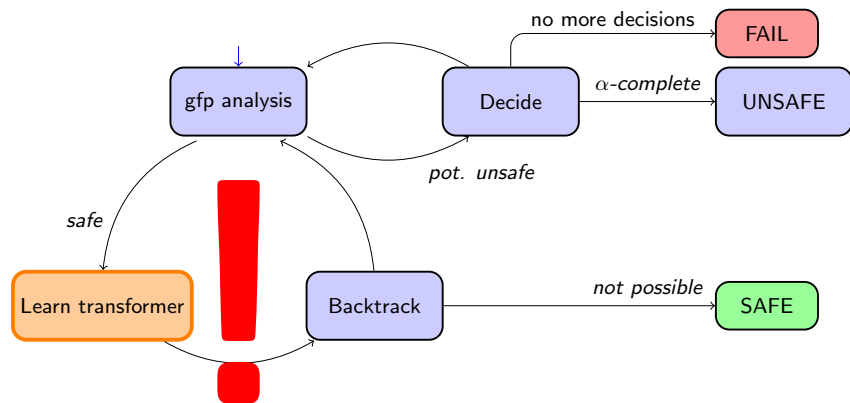
Set of control-flow branches B



Decomposition

$$\begin{aligned} a &= \langle l_1 \mapsto \text{left}, l_2 \mapsto \text{right} \rangle \\ &= \underbrace{\langle l_1 \mapsto \text{left} \rangle}_{\neg \langle l_1 \mapsto \text{right} \rangle} \sqcap \underbrace{\langle l_2 \mapsto \text{right} \rangle}_{\neg \langle l_2 \mapsto \text{left} \rangle} \end{aligned}$$

Generalising DPLL



DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$

DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$

DLO

 $\bar{1}$

DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

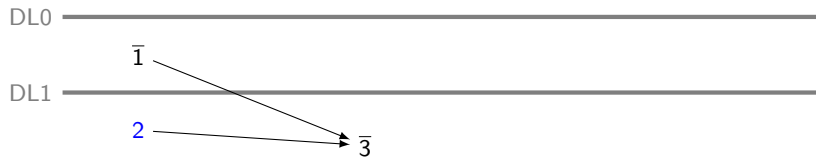
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$



DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

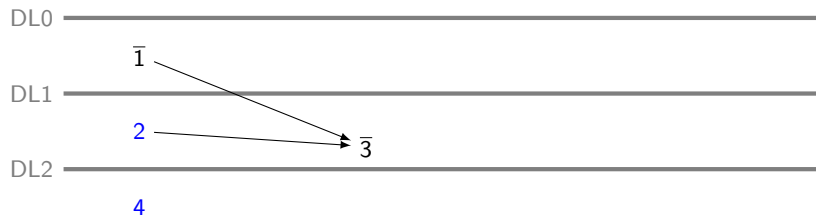
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$



DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

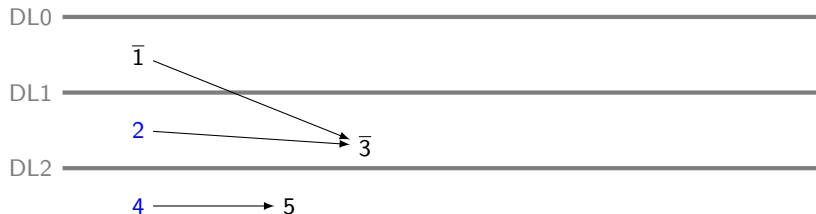
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$



DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

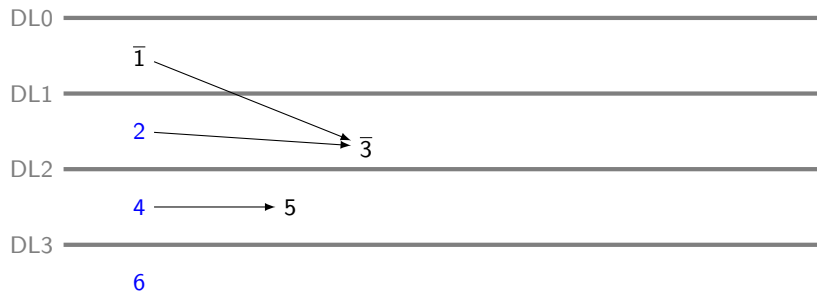
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$



DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

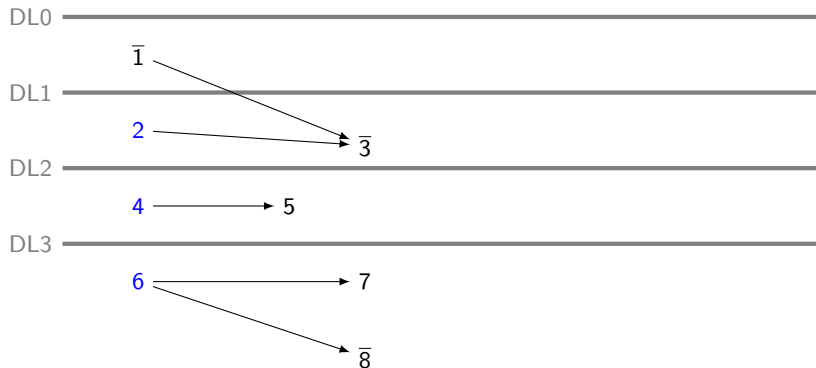
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$



DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

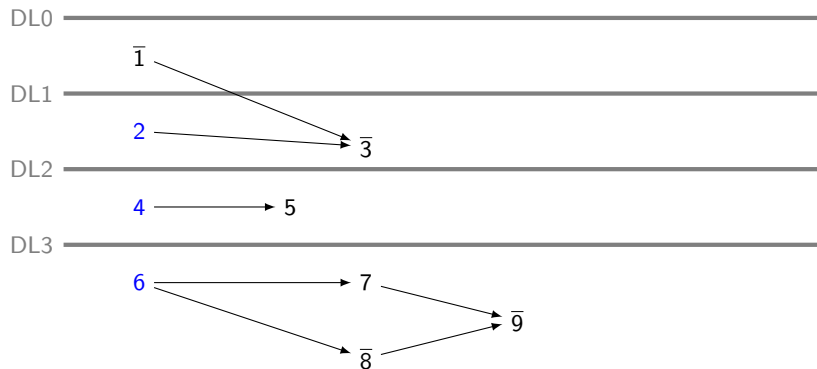
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$



DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

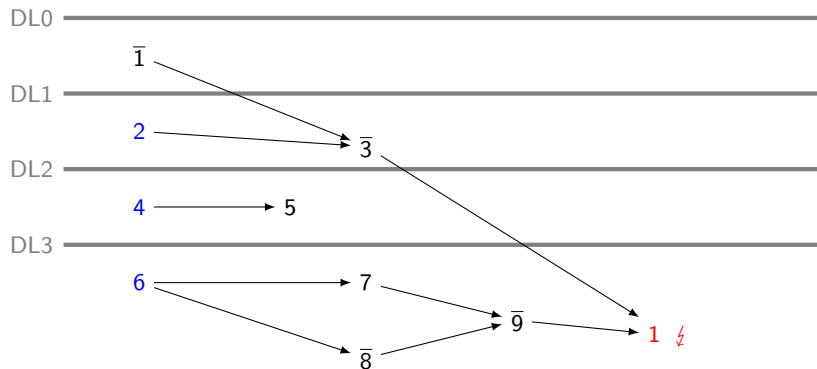
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$



DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

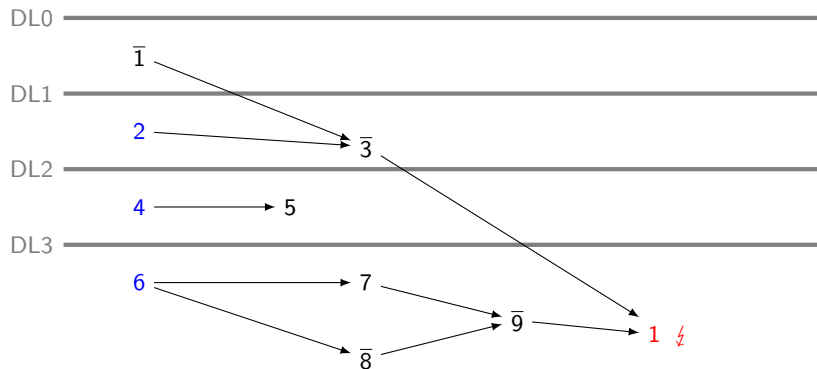
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$



DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$

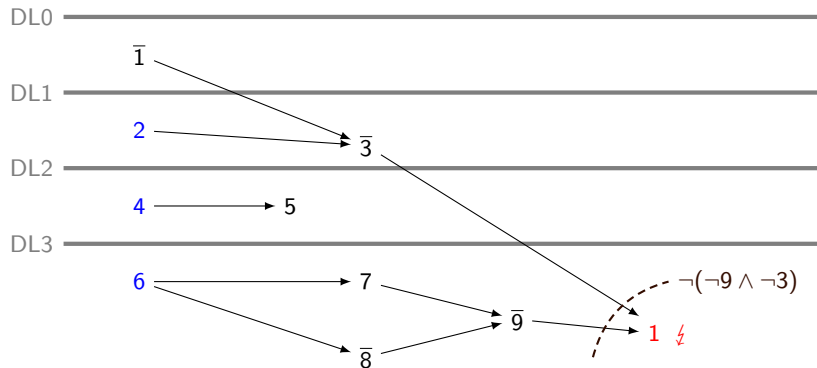


Every cut that disconnects the roots from the error is a reason

DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$

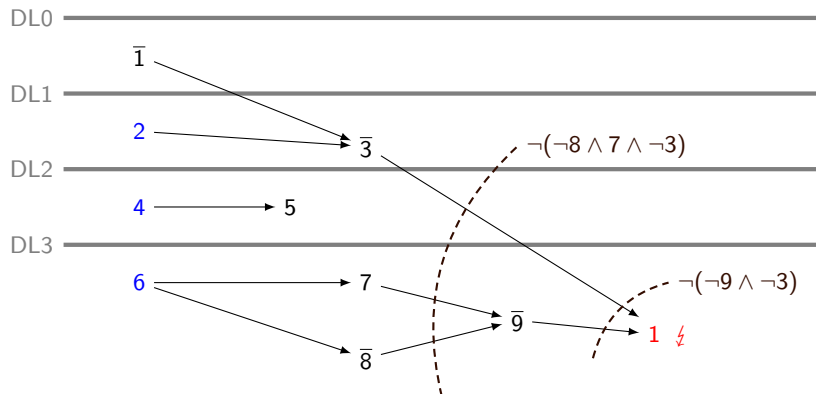


Every cut that disconnects the roots from the error is a reason

DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$

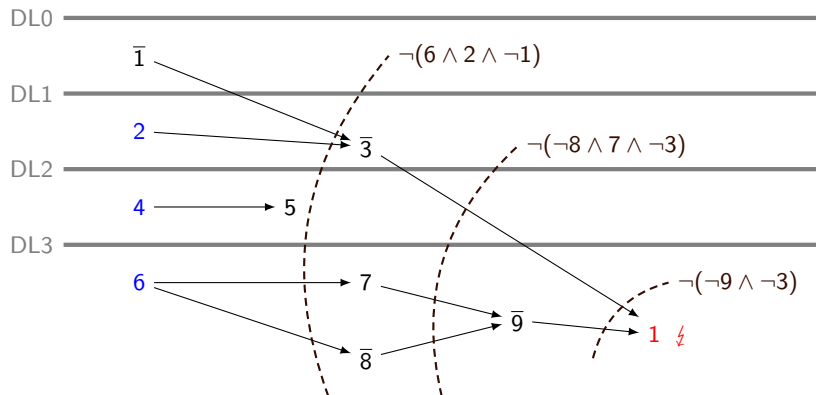


Every cut that disconnects the roots from the error is a reason

DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$

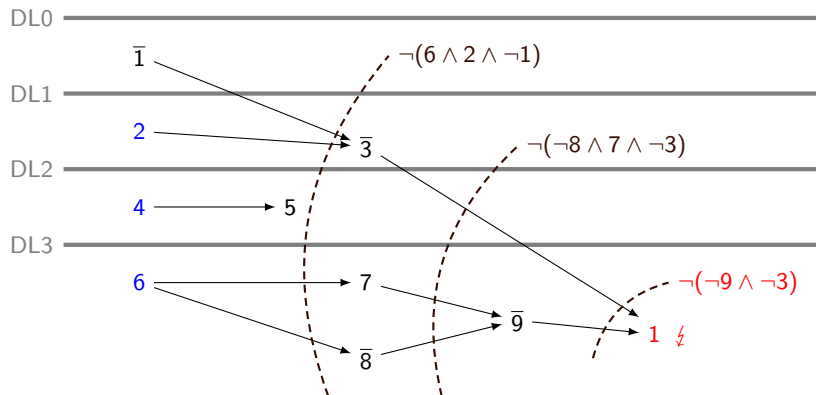


Every cut that disconnects the roots from the error is a reason

DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

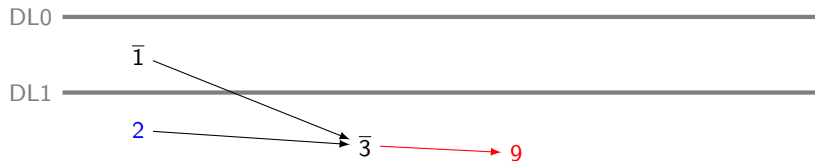
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1) \\ \wedge (9 \vee 3)$$



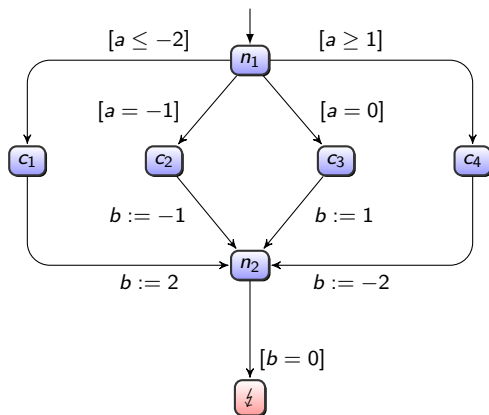
DPLL Learning Example

Learn deeper reason for a conflict using an **implication graph**

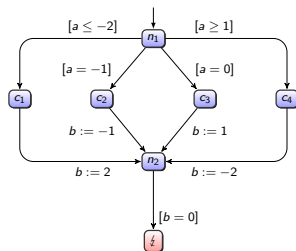
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1) \\ \wedge (9 \vee 3)$$



Putting it All Together: Simple Program Example

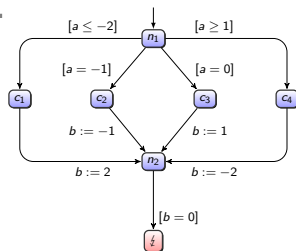


Abstract Implication Graph

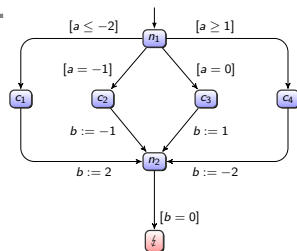
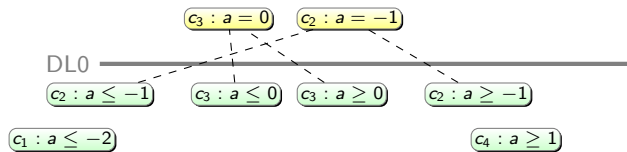


Abstract Implication Graph

DL0

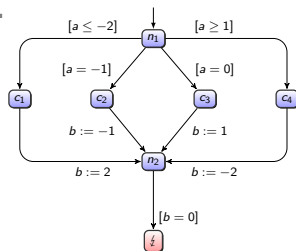
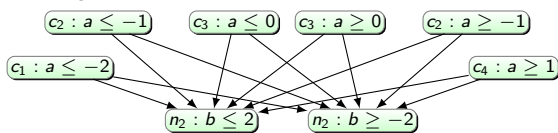


Abstract Implication Graph



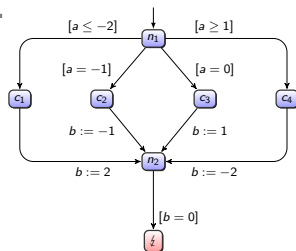
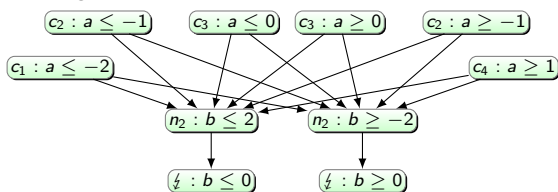
Abstract Implication Graph

DL0



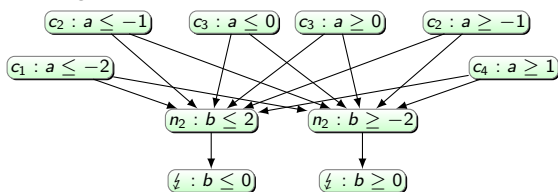
Abstract Implication Graph

DL0



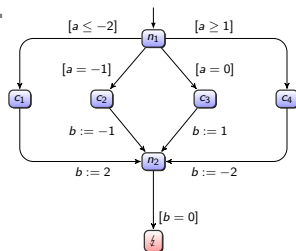
Abstract Implication Graph

DL0



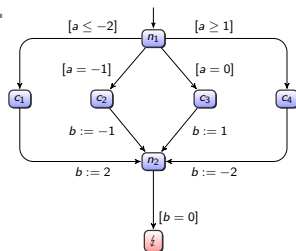
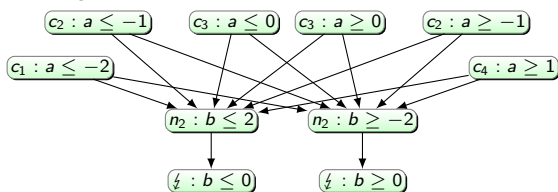
DL1

$n_1 : a \leq -42$

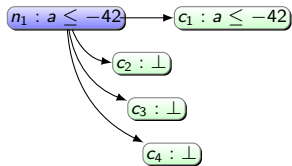


Abstract Implication Graph

DL0

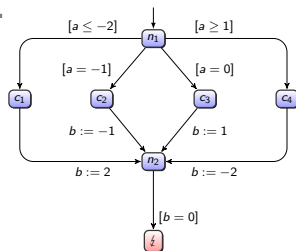
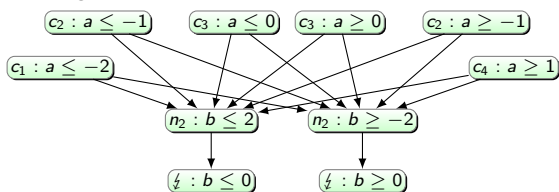


DL1

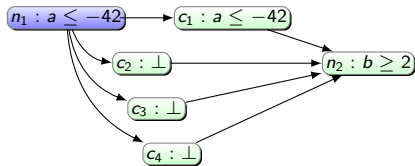


Abstract Implication Graph

DL0

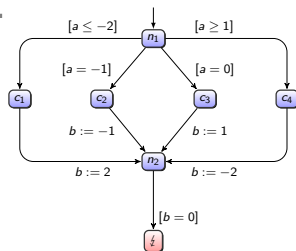
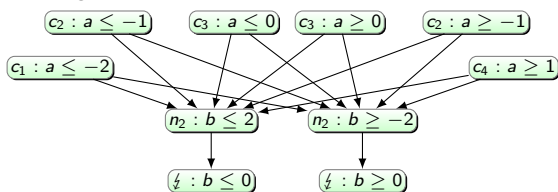


DL1

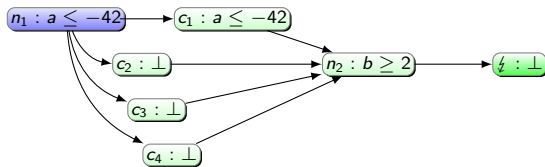


Abstract Implication Graph

DL0



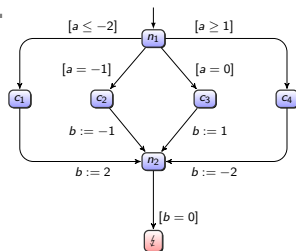
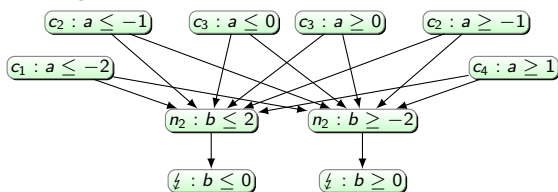
DL1



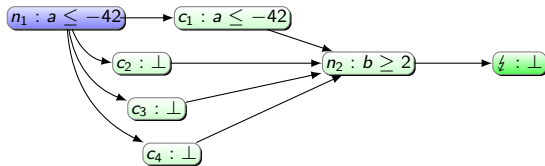
SAFE

Abstract Implication Graph

DL0



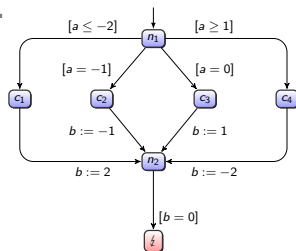
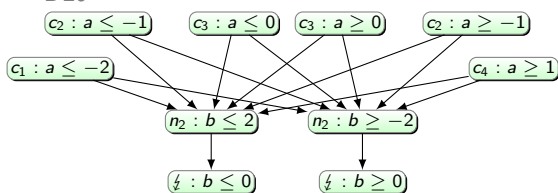
DL1



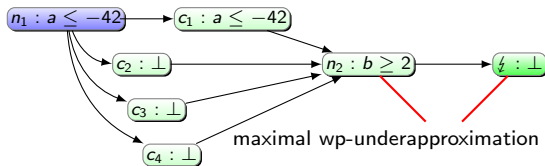
SAFE → Generalise!

Abstract Implication Graph

DL0



DL1

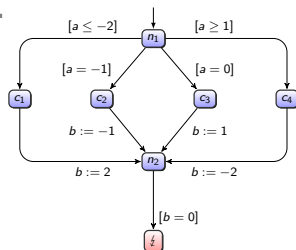
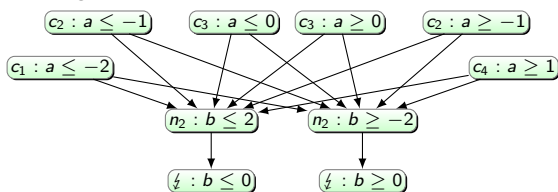


maximal wp-underapproximation transformer

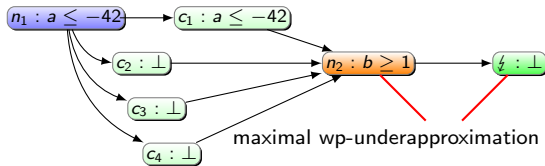
SAFE \rightarrow Generalise!

Abstract Implication Graph

DL0



DL1

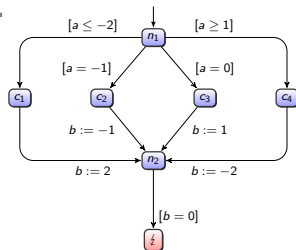
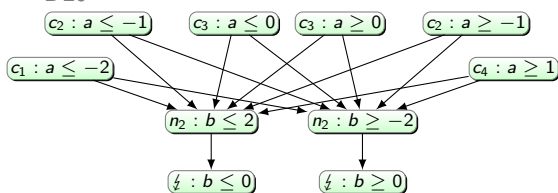


maximal wp-underapproximation transformer

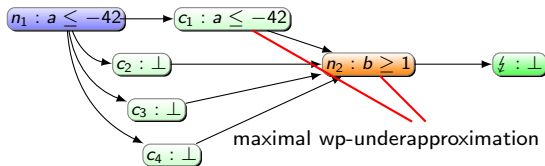
SAFE → Generalise!

Abstract Implication Graph

DL0



DL1

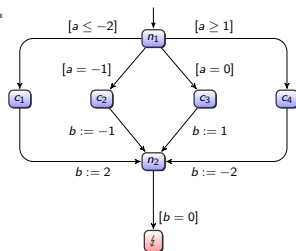
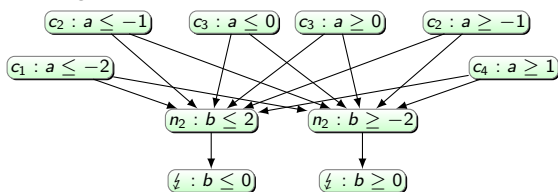


maximal wp-underapproximation transformer

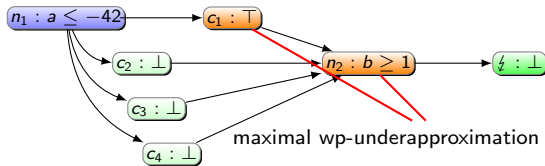
SAFE \rightarrow Generalise!

Abstract Implication Graph

DL0



DL1

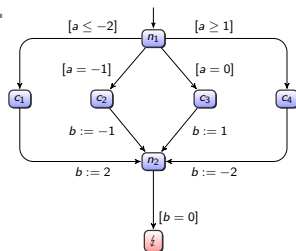
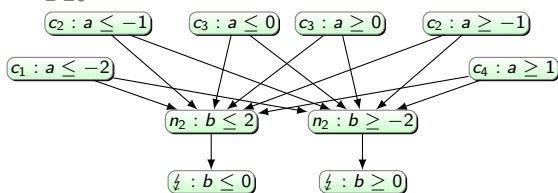


maximal wp-underapproximation transformer

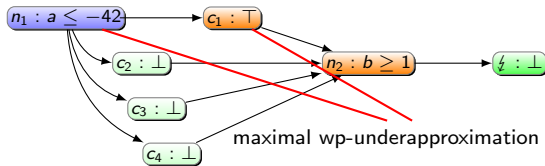
SAFE \rightarrow Generalise!

Abstract Implication Graph

DL0



DL1

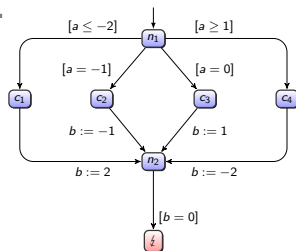
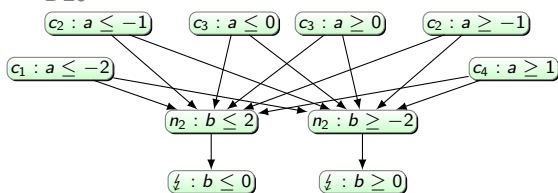


maximal wp-underapproximation transformer

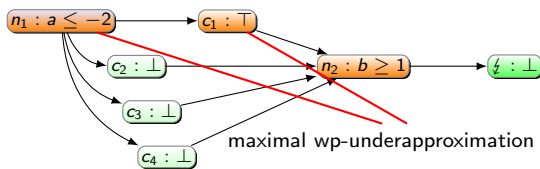
SAFE \rightarrow Generalise!

Abstract Implication Graph

DL0



DL1

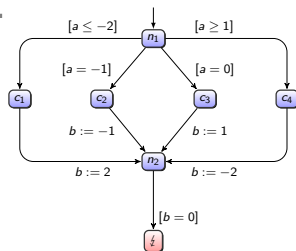
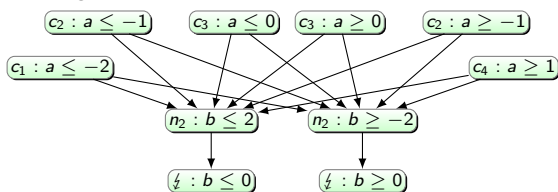


maximal wp-underapproximation transformer

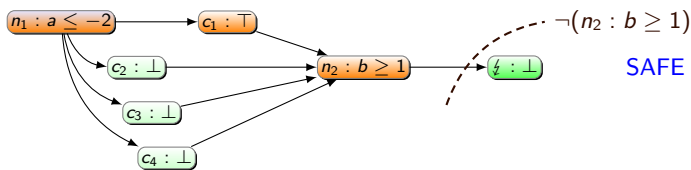
SAFE \rightarrow Generalise!

Abstract Implication Graph

DL0



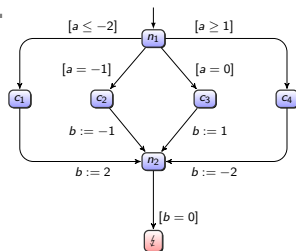
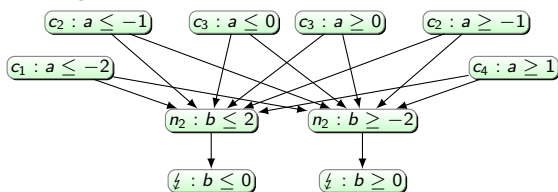
DL1



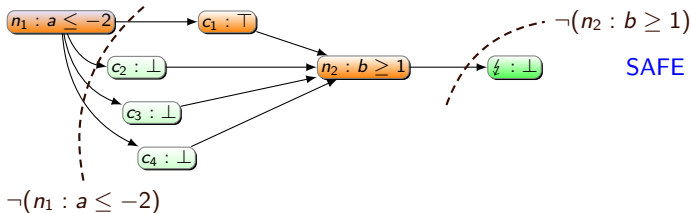
SAFE \rightarrow find cut

Abstract Implication Graph

DL0



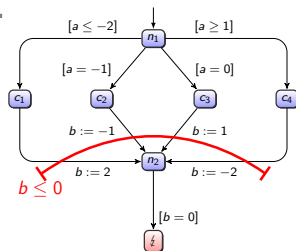
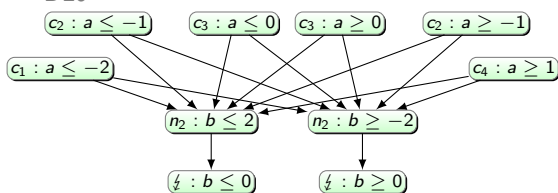
DL1



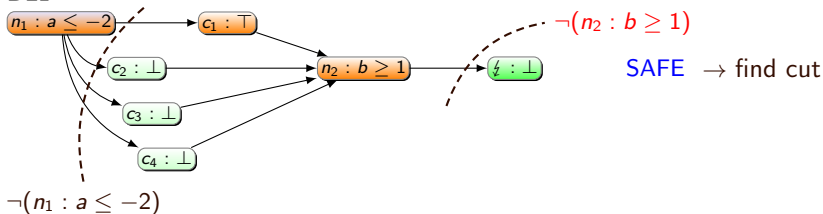
SAFE \rightarrow find cut

Abstract Implication Graph

DL0

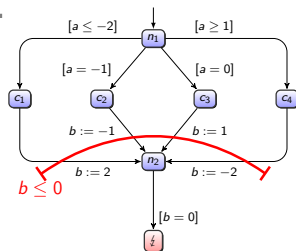
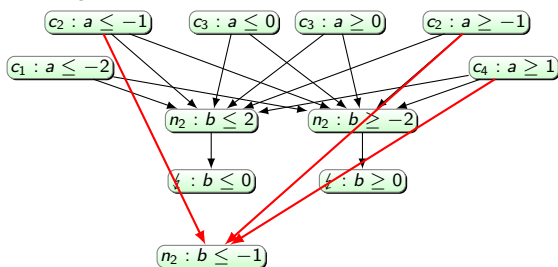


DL1

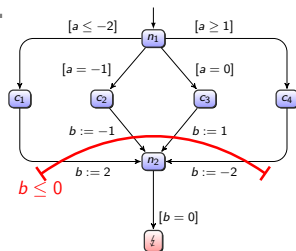
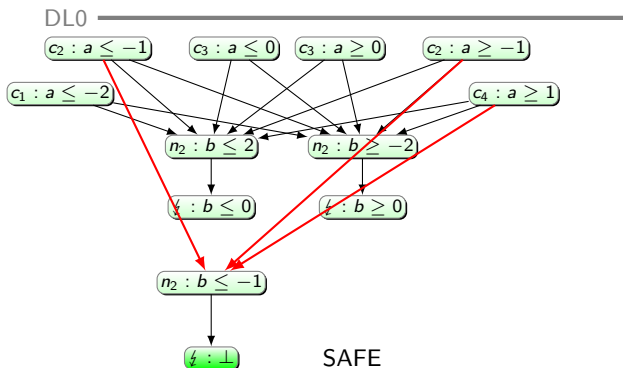


Abstract Implication Graph

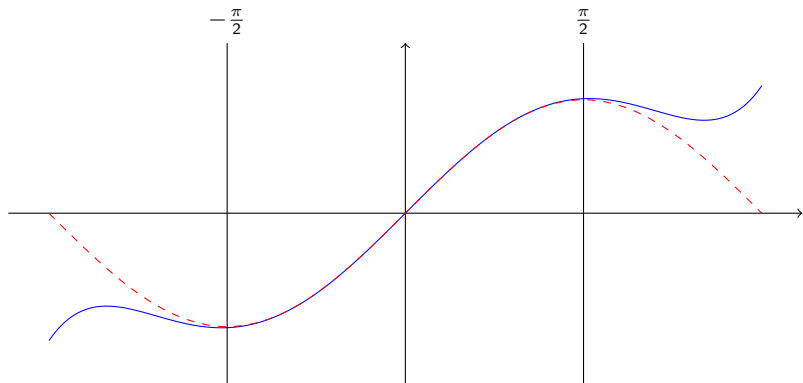
DL0



Abstract Implication Graph

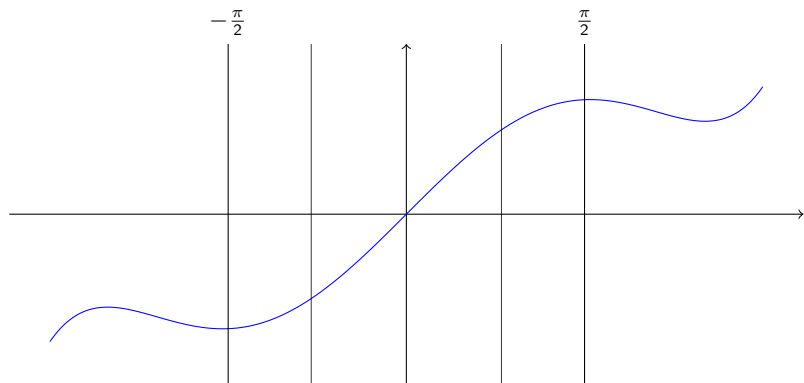


Property-dependent Trace Partitioning



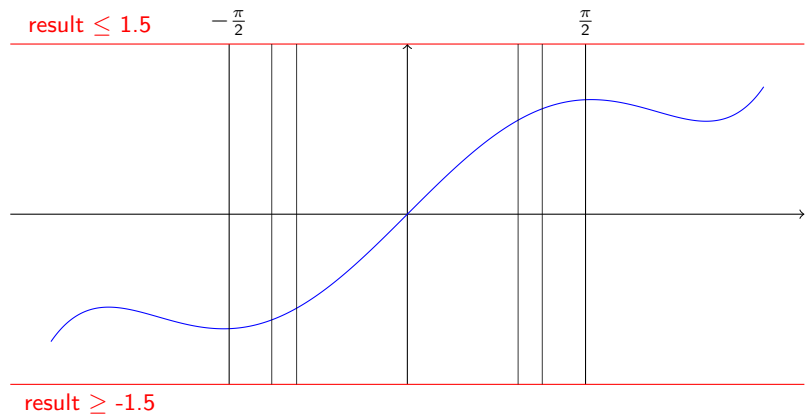
Property-dependent Trace Partitioning

result ≤ 2.0

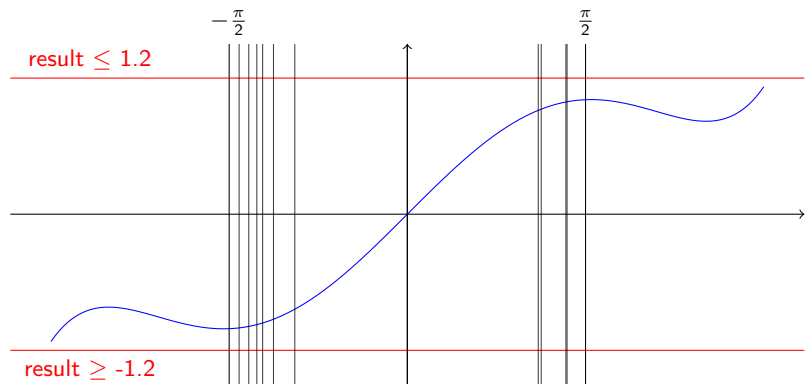


result ≥ -2.0

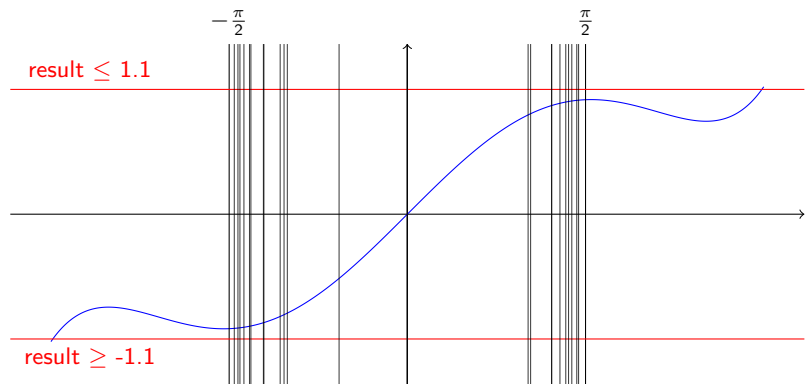
Property-dependent Trace Partitioning



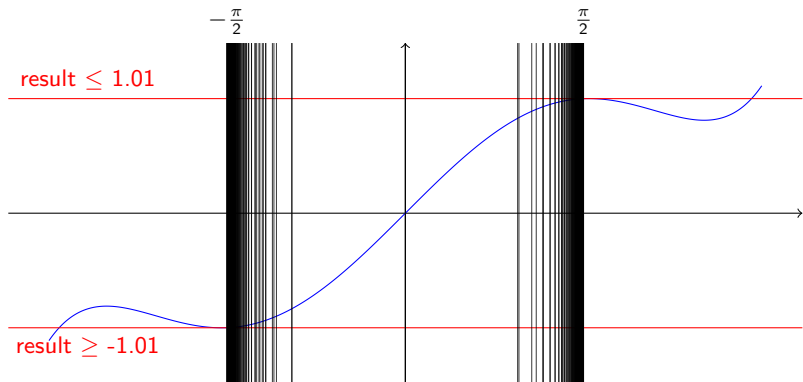
Property-dependent Trace Partitioning



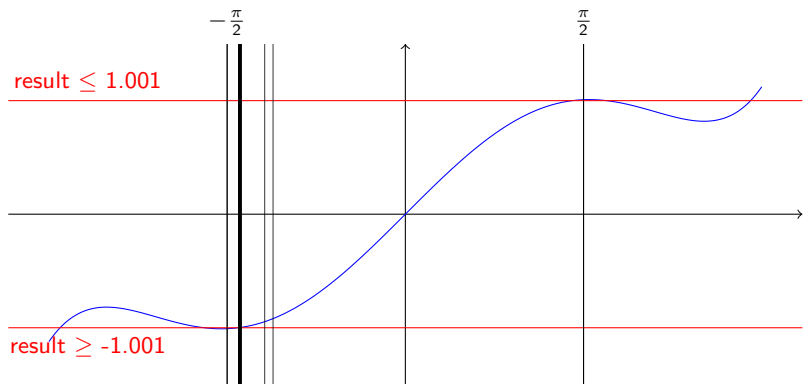
Property-dependent Trace Partitioning



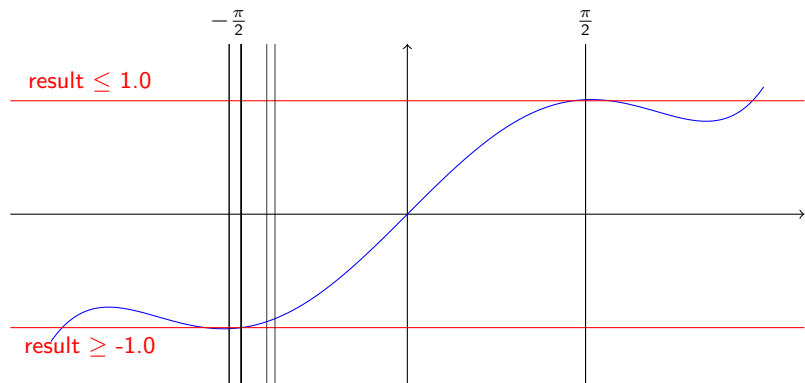
Property-dependent Trace Partitioning



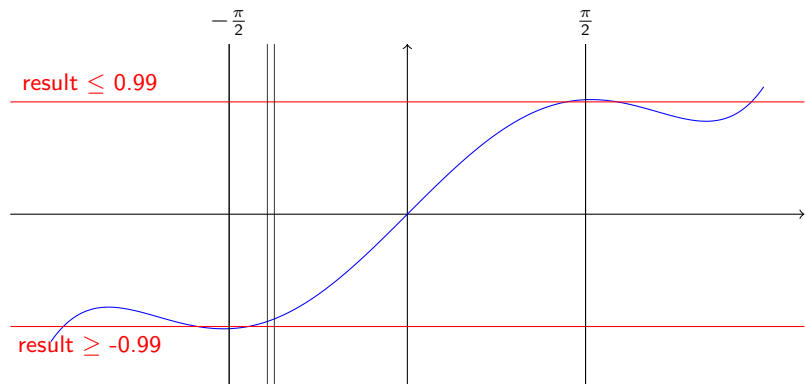
Property-dependent Trace Partitioning



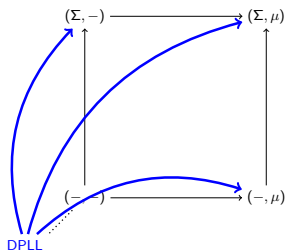
Property-dependent Trace Partitioning



Property-dependent Trace Partitioning



Conclusion



- A DPLL solver ...
 - ▶ is an abstract interpreter over the Cartesian Boolean abstraction
 - ▶ AI + gfp-iteration + dynamic trace partitioning
 - ▶ iteratively computes a minimal property-preserving abstract transformer

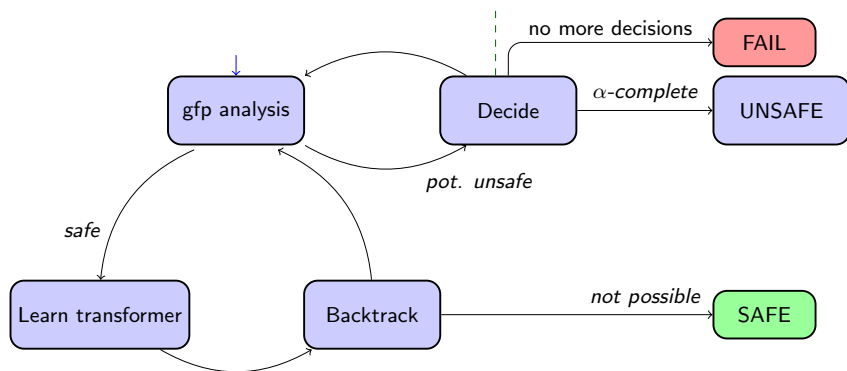
- We can simply change the domain to lift DPLL to richer logics and programs

Thank you for your attention

Appendix

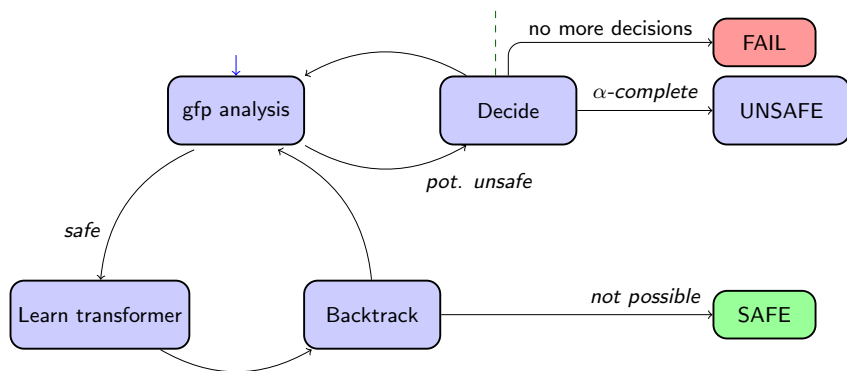
Generalising DPLL

Decision elements = complementable meet-irreducibles



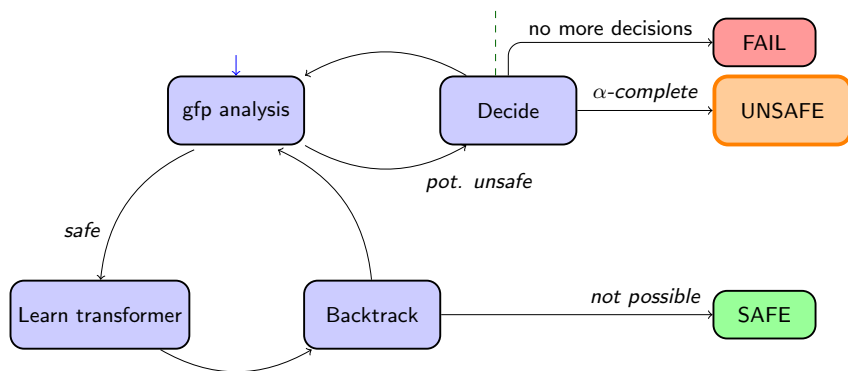
Generalising DPLL

Decision elements = complementable meet-irreducibles



Generalising DPLL

Decision elements = complementable meet-irreducibles



Satisfying assignments

DPLL constructs restricted transformers. When can we stop?

$$\phi = (a \vee b) \wedge (\neg b \vee c)$$

$$r = \langle a \mapsto \mathbf{t}, c \mapsto \mathbf{t} \rangle$$

Satisfying assignments

DPLL constructs restricted transformers. When can we stop?

$$\phi = (a \vee b) \wedge (\neg b \vee c)$$

$$r = \langle a \mapsto t, c \mapsto t \rangle$$

Construct **restricted transformer**

$$\widehat{F}_r(X) = \text{post}_\phi^A(X \sqcap r)$$

$$\alpha\text{-completeness: } \widehat{F}_r \circ \alpha = \alpha \circ F_r$$

$$\gamma\text{-completeness: } \gamma \circ \widehat{F}_r = F_r \circ \gamma$$

Satisfying assignments

DPLL constructs restricted transformers. When can we stop?

$$\phi = (a \vee b) \wedge (\neg b \vee c)$$

$$r = \langle a \mapsto \text{t}, c \mapsto \text{t} \rangle$$

Construct **restricted transformer**

$$\widehat{F}_r(X) = \text{post}_\phi^A(X \sqcap r)$$

$$\alpha\text{-completeness: } \widehat{F}_r \circ \alpha = \alpha \circ F_r$$

$$\gamma\text{-completeness: } \gamma \circ \widehat{F}_r = F_r \circ \gamma$$

\widehat{F}_r is a **sufficient to show SAT** $\iff \widehat{F}_r$ is α -complete and $\widehat{F}_r(\top) \sqcap \perp$

Satisfying assignments

DPLL constructs restricted transformers. When can we stop?

$$\phi = (a \vee b) \wedge (\neg b \vee c)$$

$$r = \langle a \mapsto t, c \mapsto t \rangle$$

Construct **restricted transformer**

$$\widehat{F}_r(X) = \text{post}_\phi^A(X \sqcap r)$$

$$\alpha\text{-completeness: } \widehat{F}_r \circ \alpha = \alpha \circ F_r$$

$$\gamma\text{-completeness: } \gamma \circ \widehat{F}_r = F_r \circ \gamma$$

\widehat{F}_r is a **sufficient to show SAT** $\iff \widehat{F}_r$ is α -complete and $\widehat{F}_r(\top) \sqsubset \perp$

\widehat{F}_r is **witness to SAT assignments** $\iff \widehat{F}_r$ is γ -complete and $\widehat{F}_r(\top) \sqsubset \perp$

Interval counter-example

When can we stop refining in a program?

Interval counter-example

When can we stop refining in a program?

```
int x, y; x = y; assert(x != 0);
```

$\langle y = 0 \rangle$

Let \hat{F} be the transformer from the **initial state** to the **error location**.

Interval counter-example

When can we stop refining in a program?

```
int x, y; x = y; assert(x != 0);
```

$\langle y = 0 \rangle$

Let \widehat{F} be the transformer from the **initial state** to the **error location**.

Witness for counter-example:

$$\widehat{F}_{\langle y=0 \rangle}(X) = \widehat{F}(X \sqcap \langle y = 0 \rangle)$$

$$\widehat{F}_{\langle y=0 \rangle} \text{ is } \gamma\text{-complete and } \widehat{F}_{\langle y=0 \rangle}(\top) \sqsupset \perp$$