

Satisfiability as Abstract Interpretation

Leopold Haller
(joint work with Vijay D'Silva)



A Tale of Two Communities

AI
(1977)

*over-
approximate,
sound*

GAP

*under-
approximate,
precise*

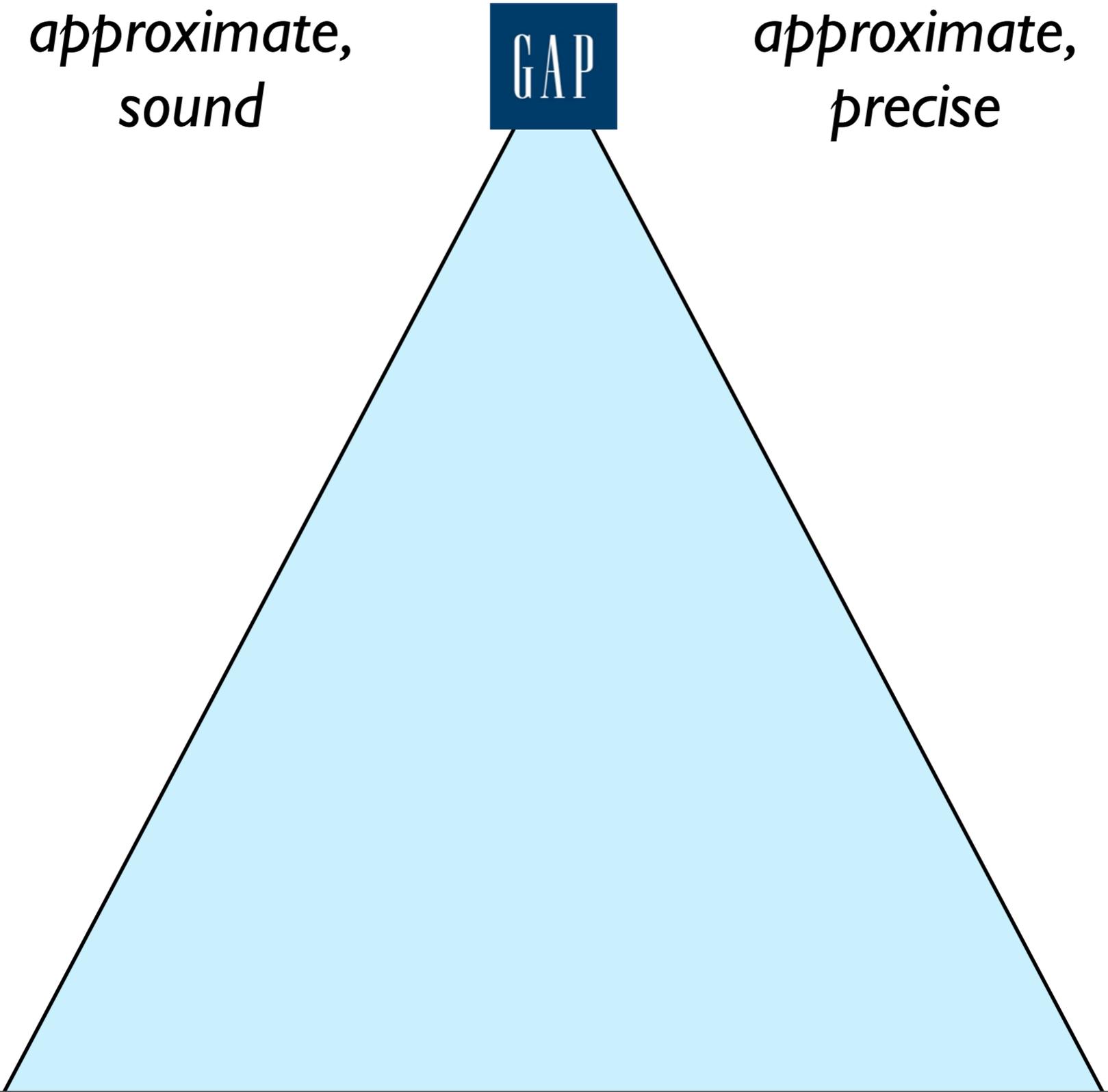
DP
(1960)

DPLL
(1962)

CDCL
(1996)

Learning.
Efficiency!

Εfficiency!



A Tale of Two Communities

AI
(1977)

*over-
approximate,
sound*

GAP

*under-
approximate,
precise*

DP
(1960)

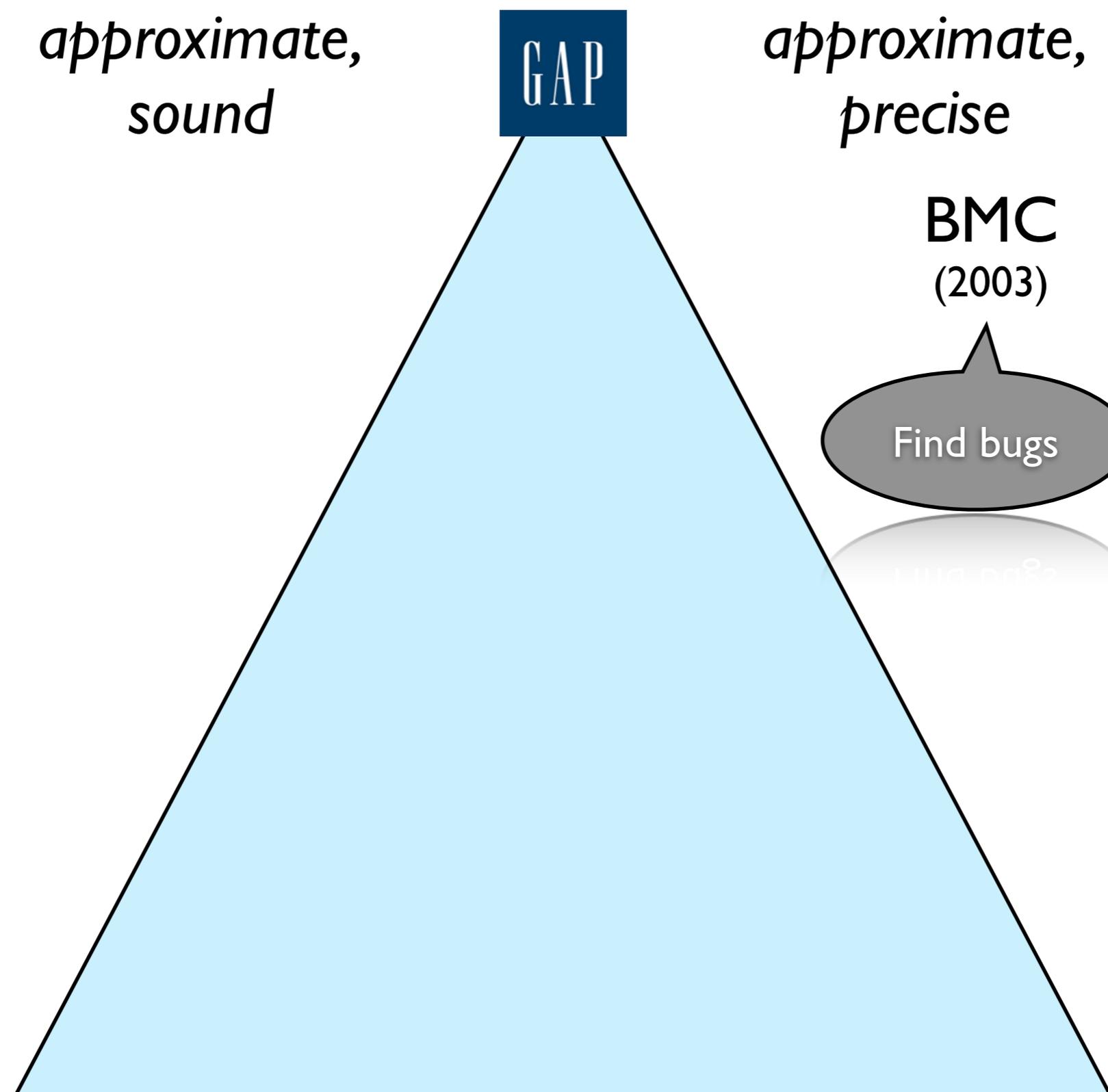
DPLL
(1962)

BMC
(2003)

Find bugs

CDCL
(1996)

Learning.
Efficiency!



A Tale of Two Communities

AI
(1977)

*over-
approximate,
sound*

GAP

*under-
approximate,
precise*

DP
(1960)

DPLL
(1962)

BMC
(2003)

CDCL
(1996)

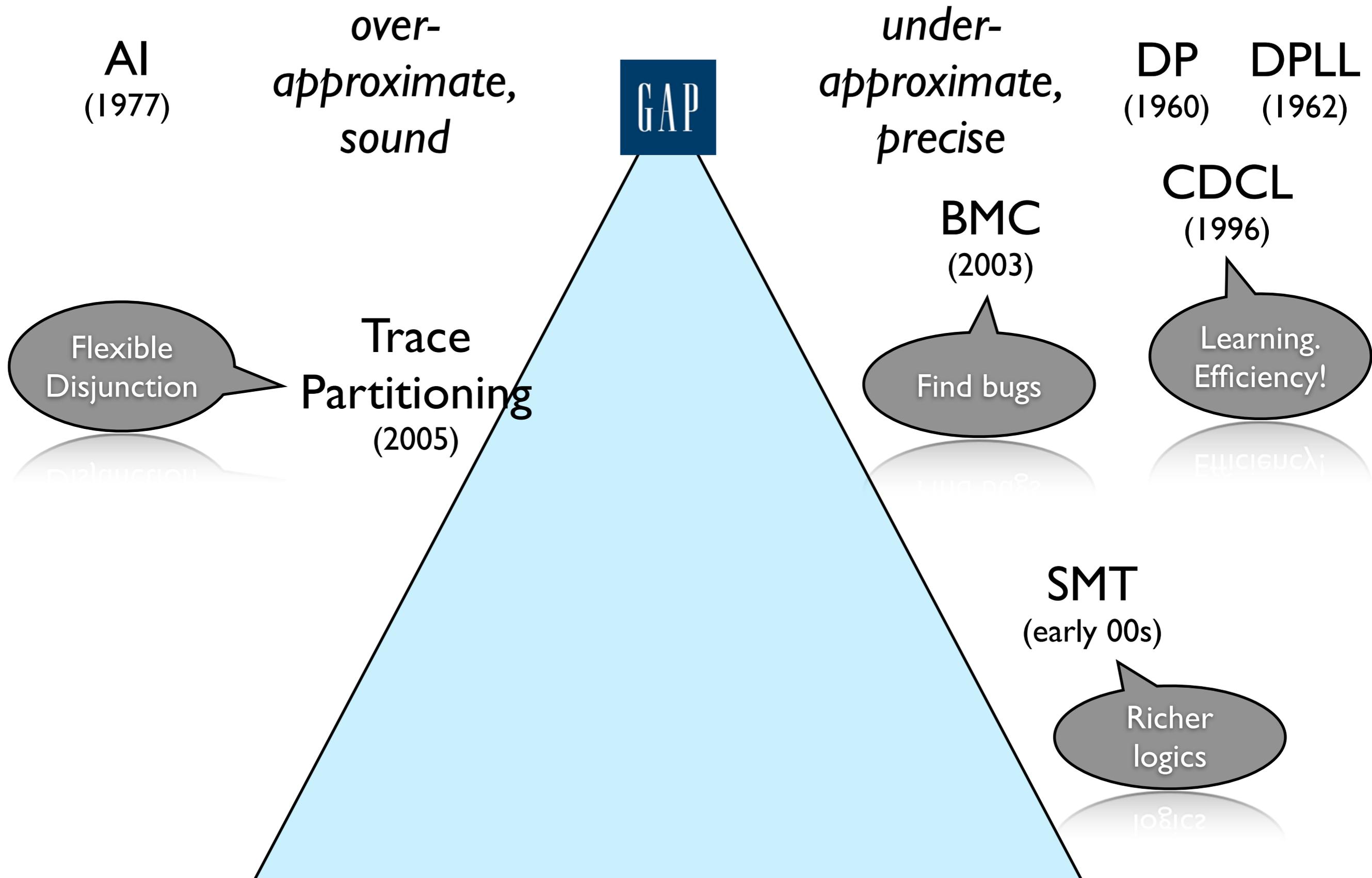
Find bugs

Learning.
Efficiency!

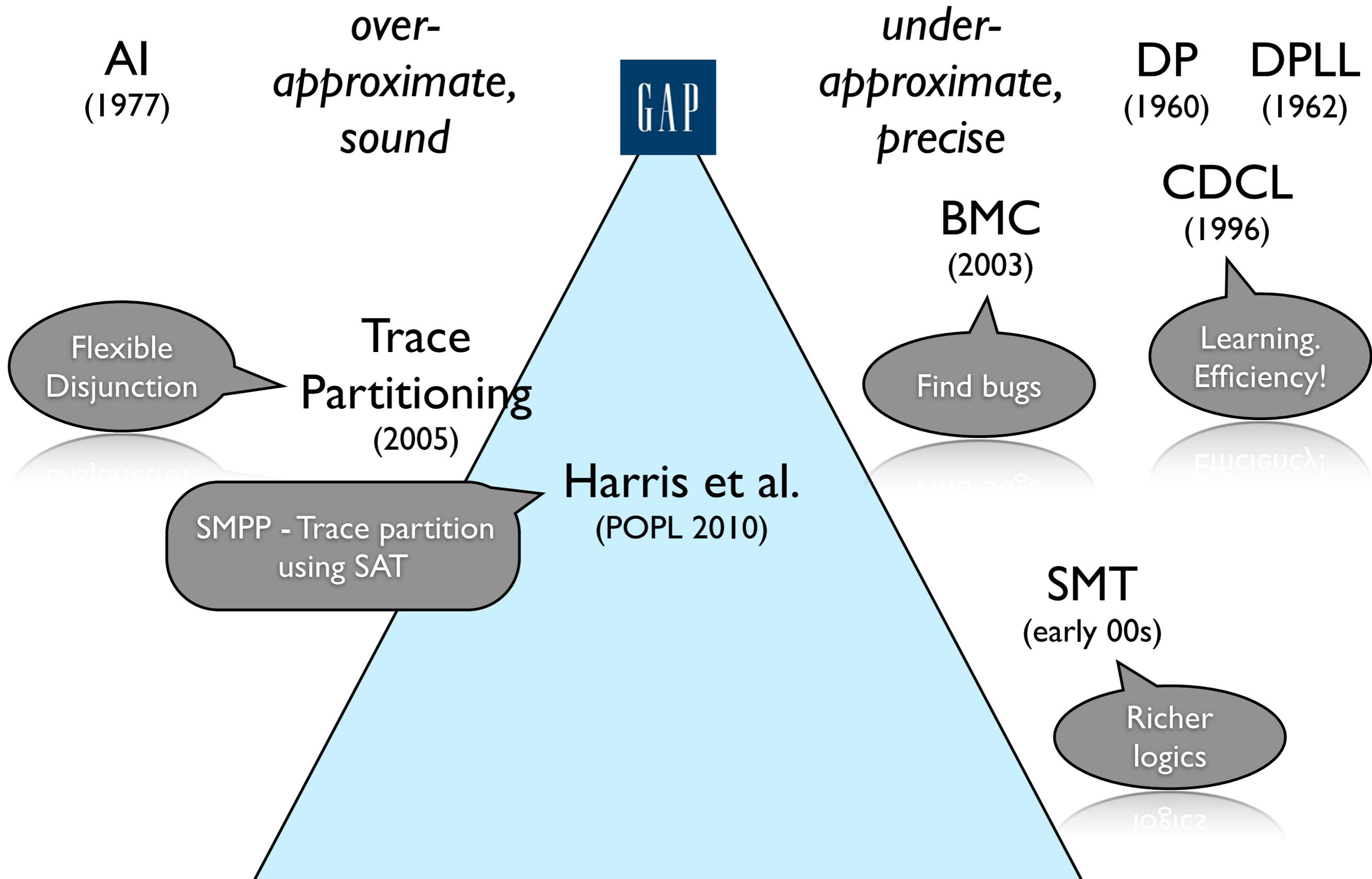
SMT
(early 00s)

Richer
logics

A Tale of Two Communities



A Tale of Two Communities



A Tale of Two Communities

AI
(1977)

*over-
approximate,
sound*

GAP

*under-
approximate,
precise*

DP
(1960)

DPLL
(1962)

CDCL
(1996)

BMC
(2003)

Trace
Partitioning
(2005)

Flexible
Disjunction

Find bugs

Learning.
Efficiency!

Harris et al.
(POPL 2010)

SMPP - Trace partition
using SAT

Combine AD
and SMT

Cousot&Cousot&Mauborgne
(FOSSACS 2011)

SMT
(early 00s)

Richer
logics

A Tale of Two Communities

AI
(1977)

*over-
approximate,
sound*

GAP

*under-
approximate,
precise*

DP
(1960)

DPLL
(1962)

CDCL
(1996)

BMC
(2003)

Trace
Partitioning
(2005)

Flexible
Disjunction

Find bugs

Learning.
Efficiency!

Harris et al.
(POPL 2010)

SMPP - Trace partition
using SAT

SMT
(early 00s)

Combine AD
and SMT

Cousot&Cousot&Mauborgne
(FOSSACS 2011)

Richer
logics

Focus on path
using SMT

Monnieaux & Gonnord
(SAS 2011)

A Tale of Two Communities

DPLL (1962) CDCL (1996) solvers

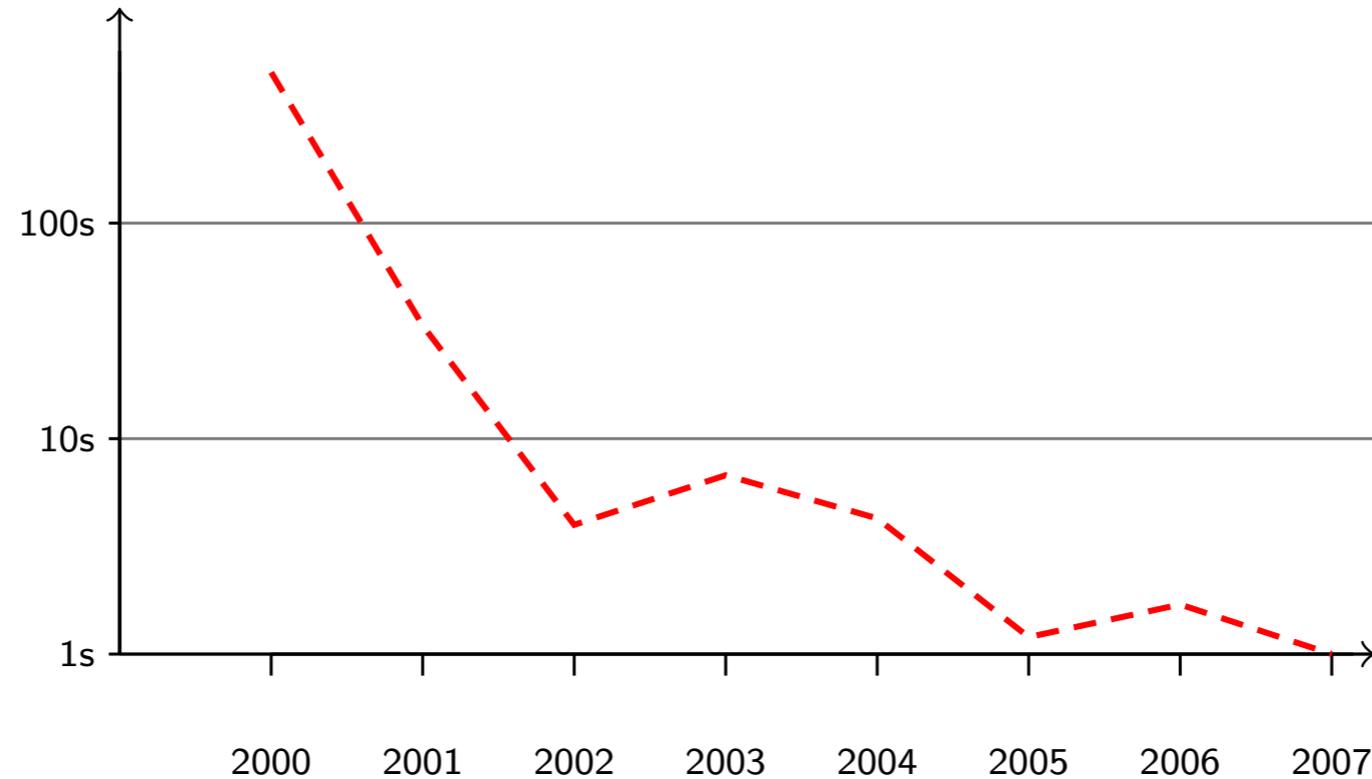
are

(proper) abstract interpreters

AI
(1977)

Why does this matter?

Why does this matter?

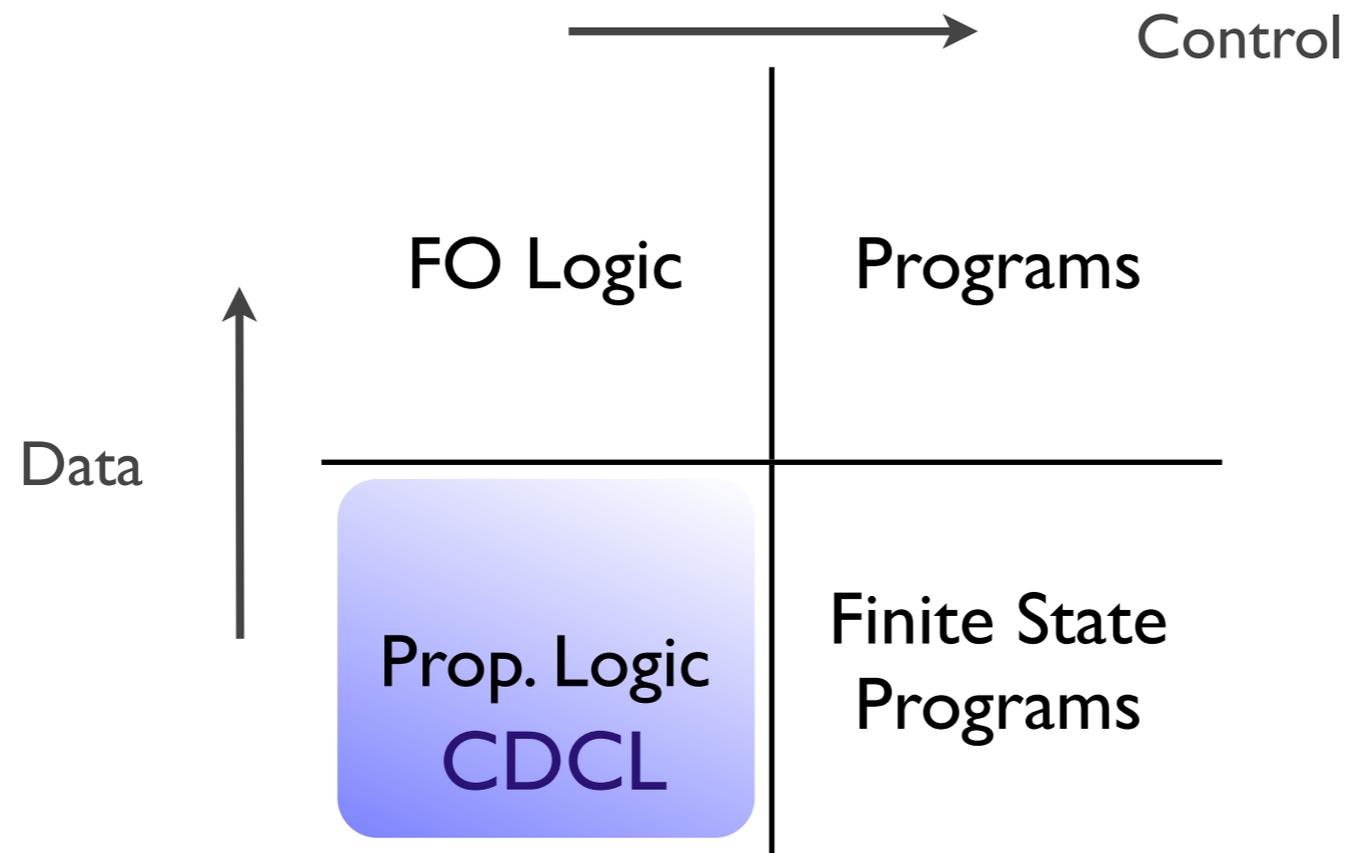


“ the practical success of SAT has come as a surprise to many in the computer science community. The combination of strong practical drivers and open competition in this experimental research effort created enough momentum to overcome the pessimism based on theory. Can we take these lessons to other problems and domains?”

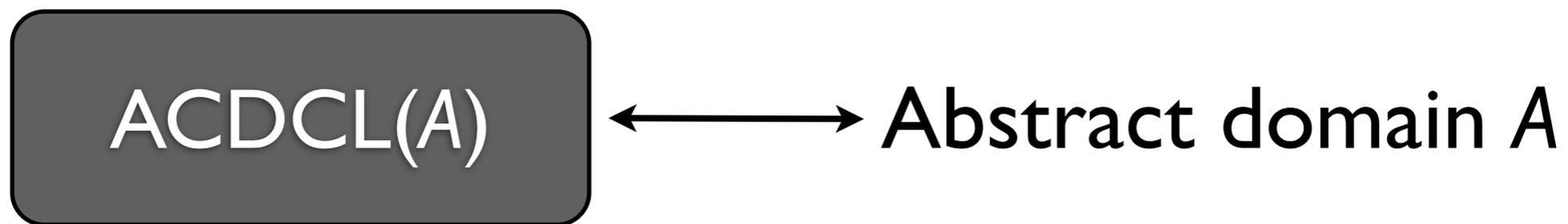
– Malik & Zhang, 2009

Why does this matter?

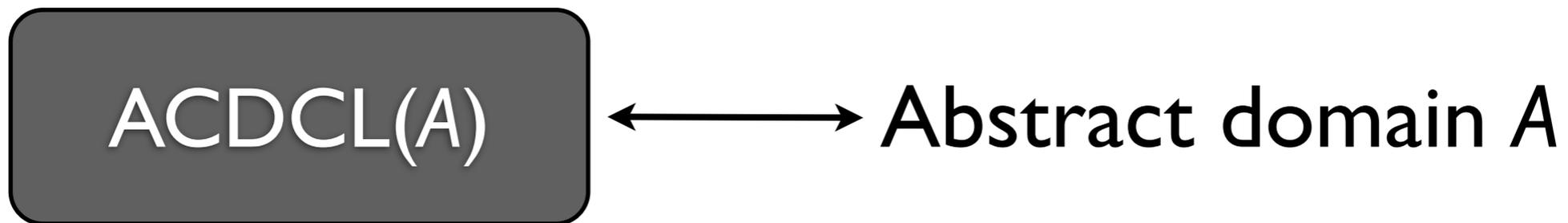
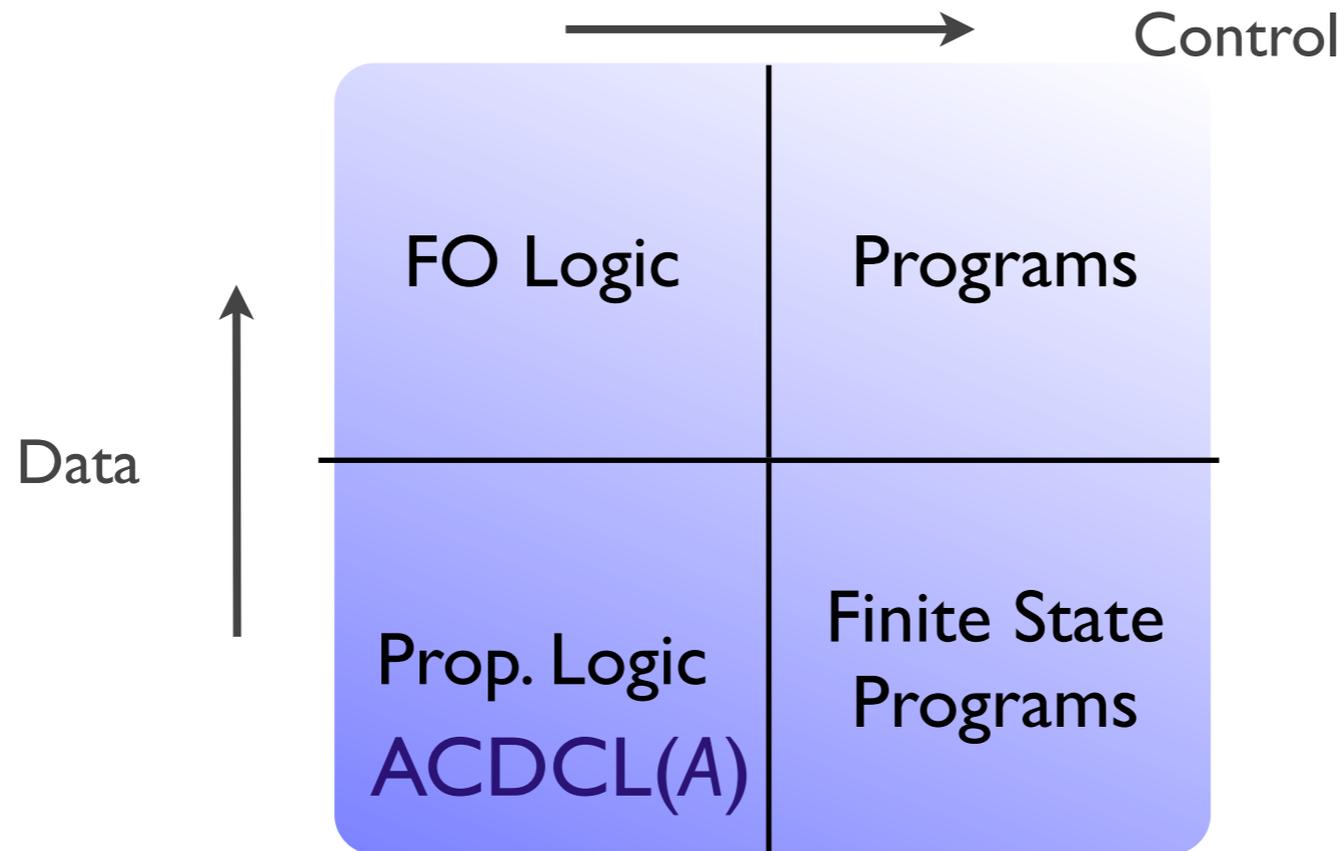
Why does this matter?



Why does this matter?



Why does this matter?



Conflict Driven Clause Learning

Interpreting Logic

CDCL is Abstract Interpretation

ACDCL(A)

The CDCL Algorithm

Jargon Slide

Propositions

finite set V

Literal

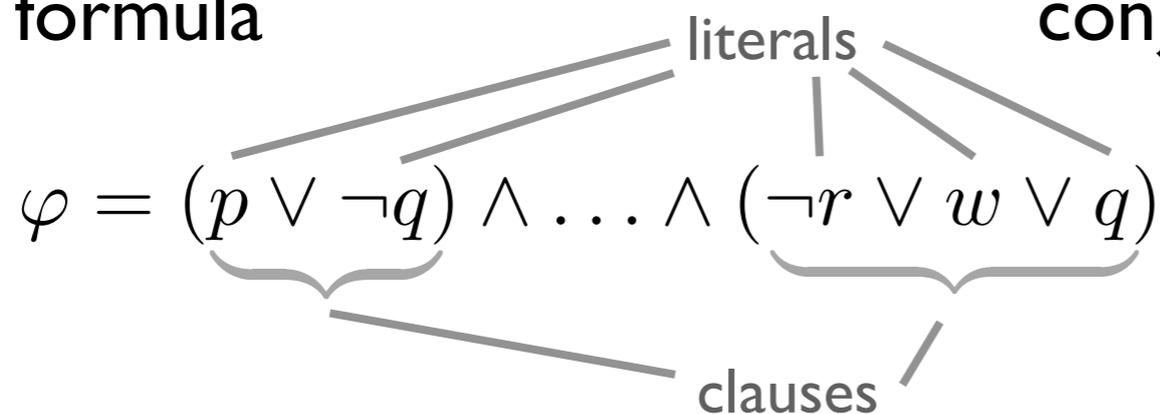
$p, \neg p \quad p \in V$

Clause

disjunction of literals

CNF formula

conjunction of clauses



Assignment

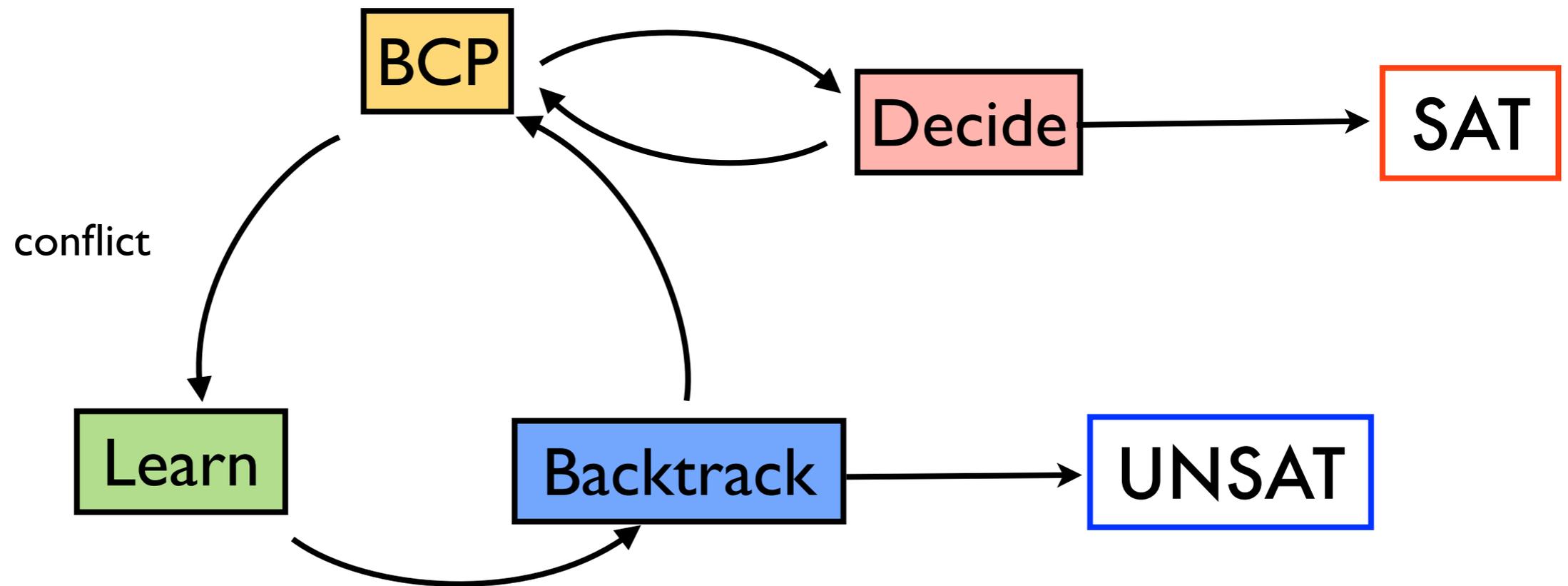
partial function $V \rightarrow \{t, f\}$

Satisfiability

Does there exist an assignment $V \rightarrow \{t, f\}$ such that φ is true?

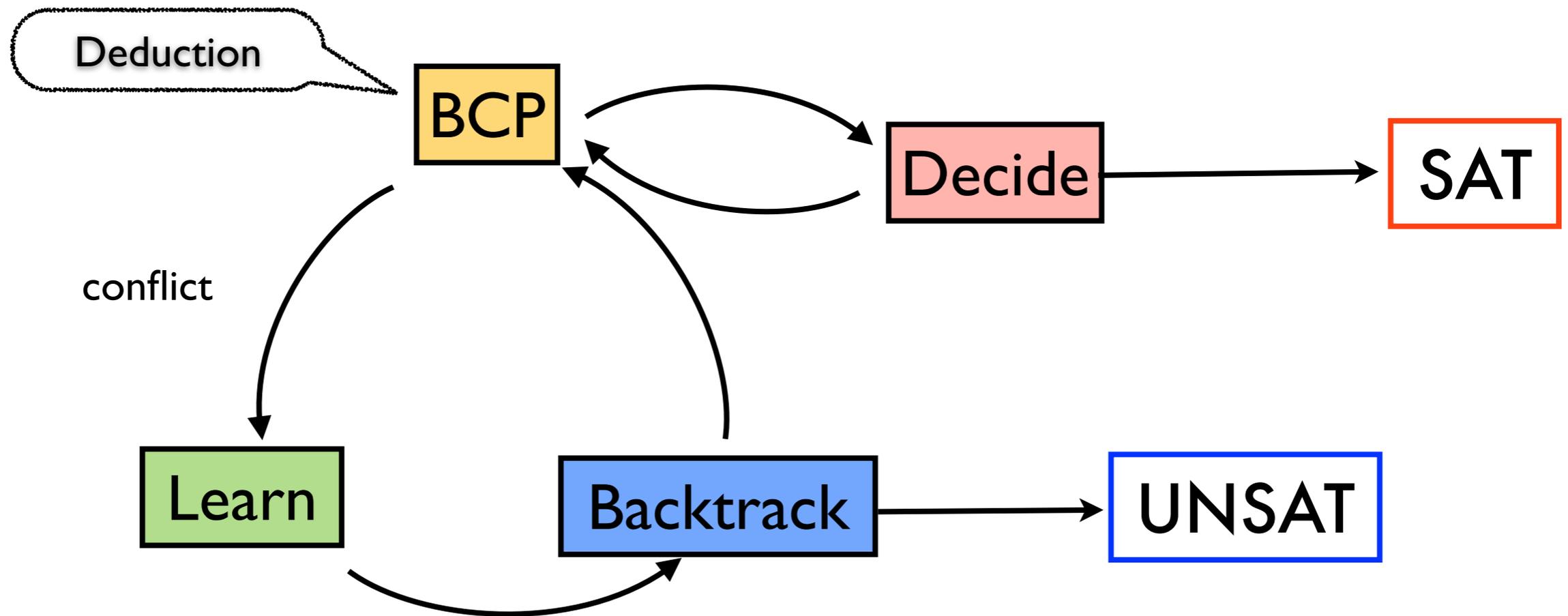
The CDCL Algorithm

Propositional CNF formula $\varphi = (p \vee \neg q) \wedge \dots \wedge (\neg r \wedge w \wedge q)$



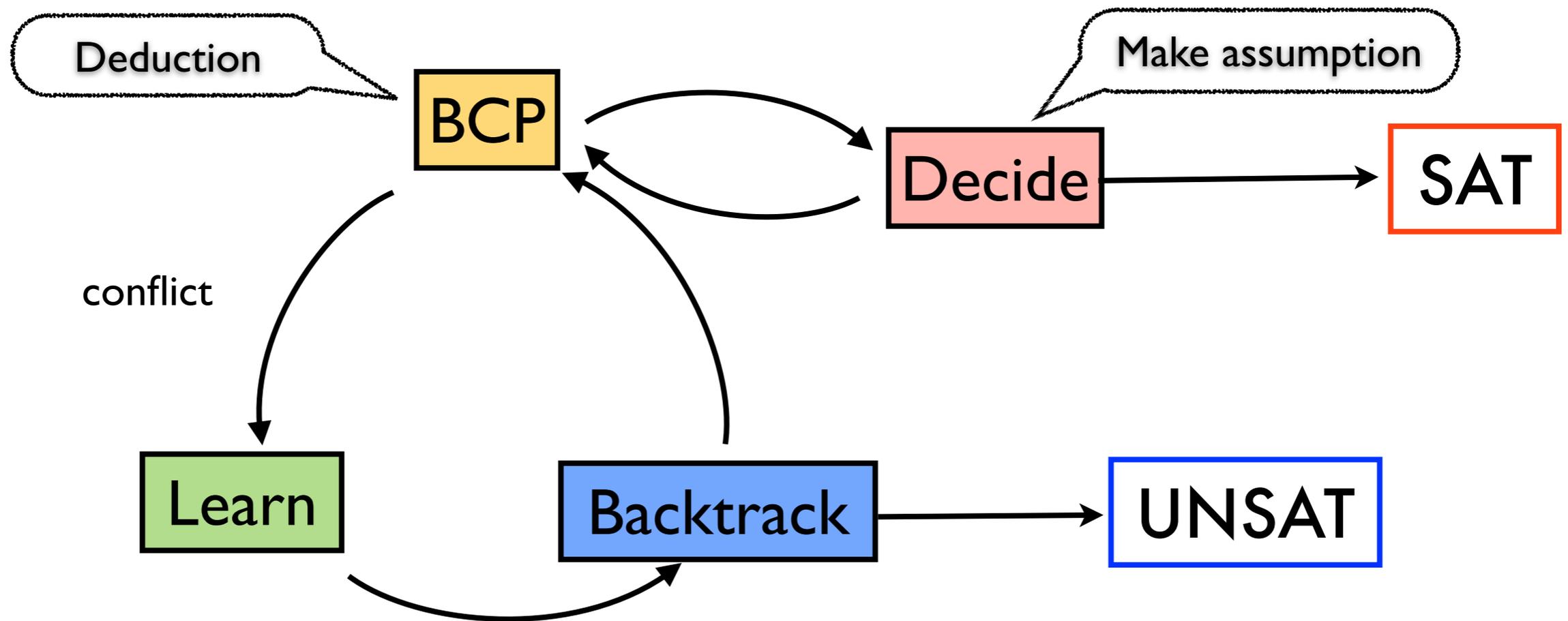
The CDCL Algorithm

Propositional CNF formula $\varphi = (p \vee \neg q) \wedge \dots \wedge (\neg r \wedge w \wedge q)$



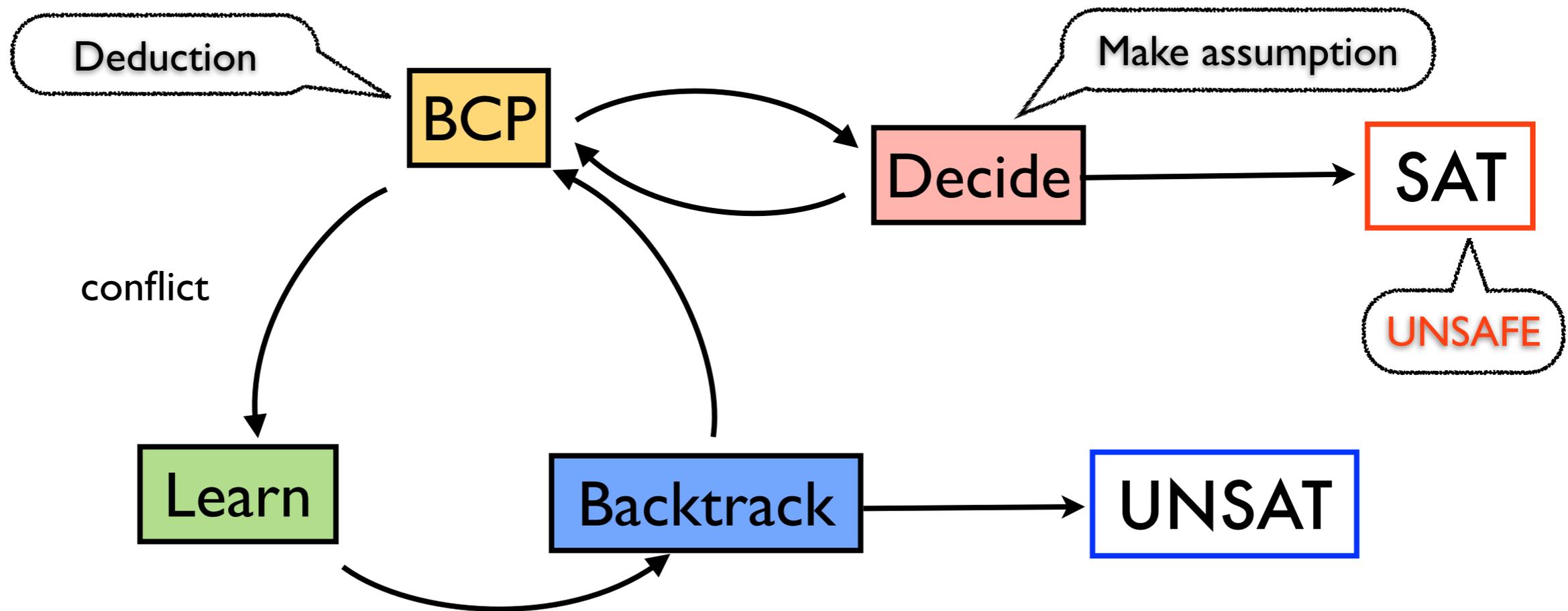
The CDCL Algorithm

Propositional CNF formula $\varphi = (p \vee \neg q) \wedge \dots \wedge (\neg r \wedge w \wedge q)$



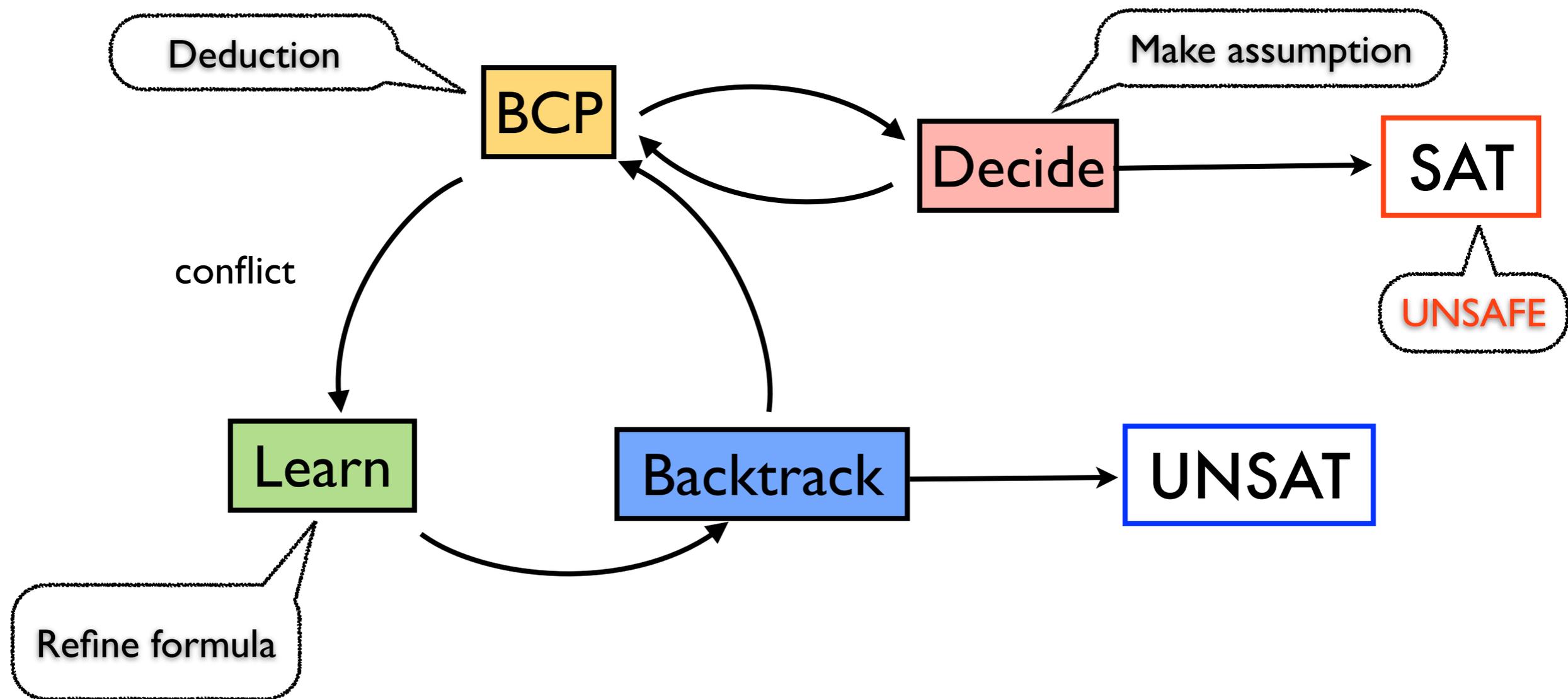
The CDCL Algorithm

Propositional CNF formula $\varphi = (p \vee \neg q) \wedge \dots \wedge (\neg r \wedge w \wedge q)$



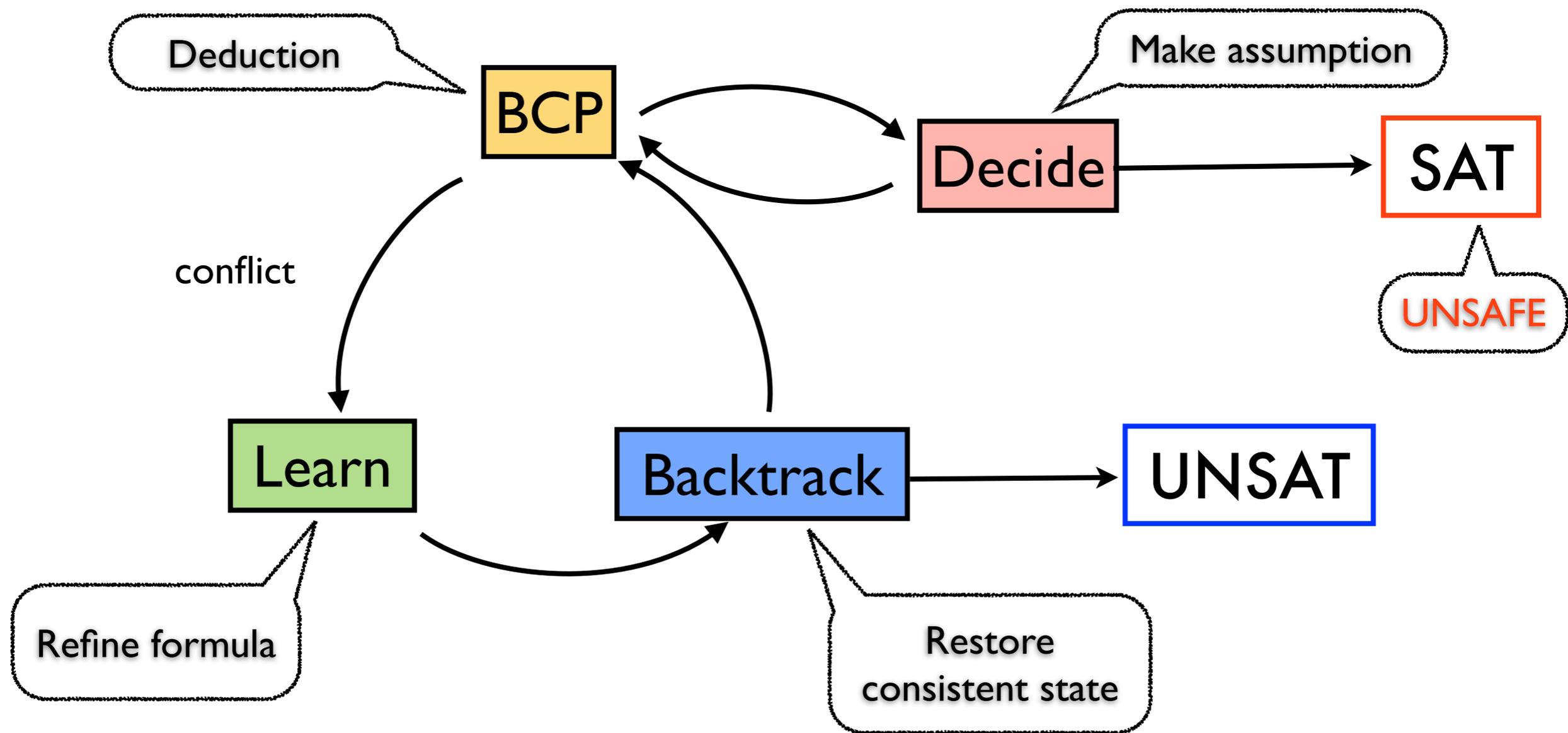
The CDCL Algorithm

Propositional CNF formula $\varphi = (p \vee \neg q) \wedge \dots \wedge (\neg r \wedge w \wedge q)$



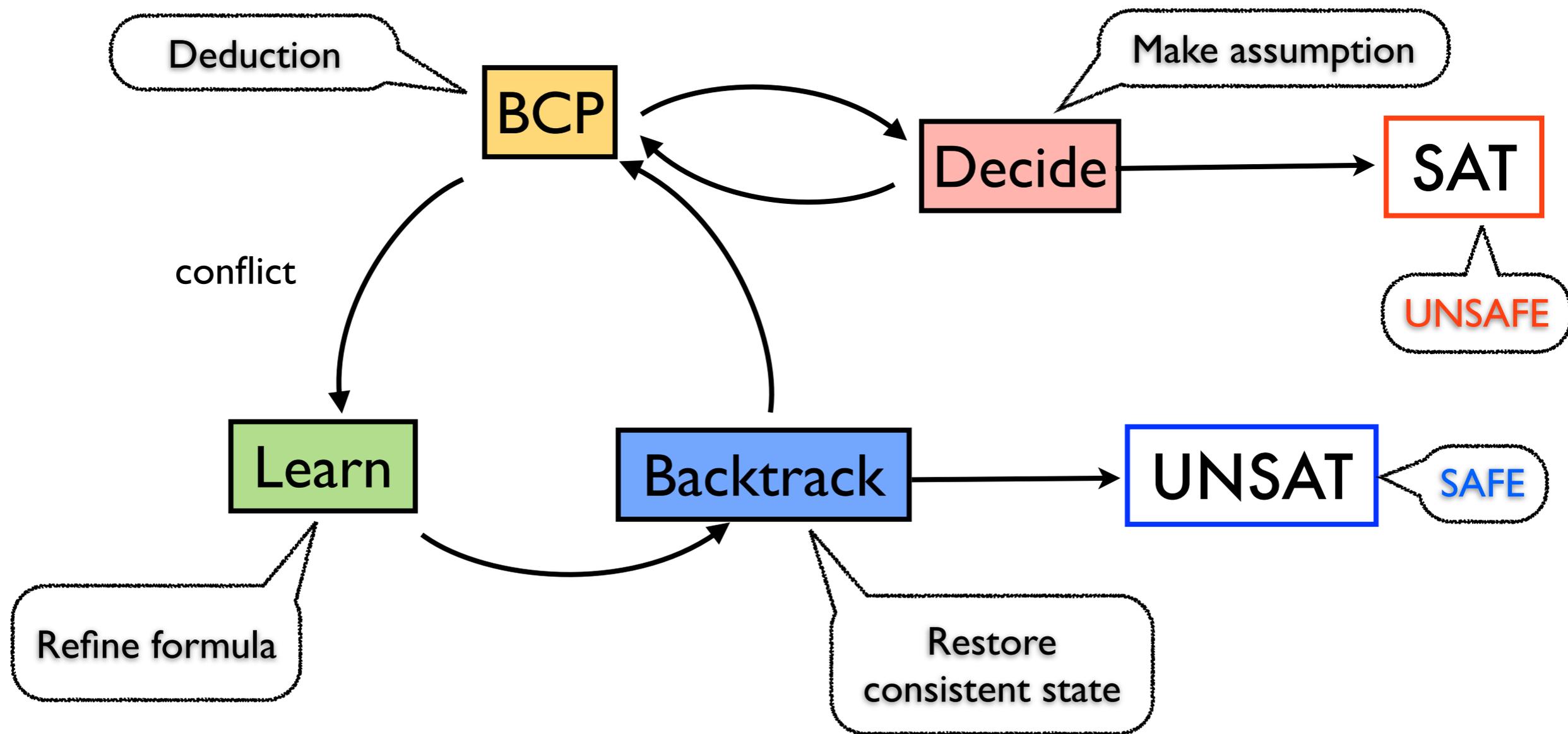
The CDCL Algorithm

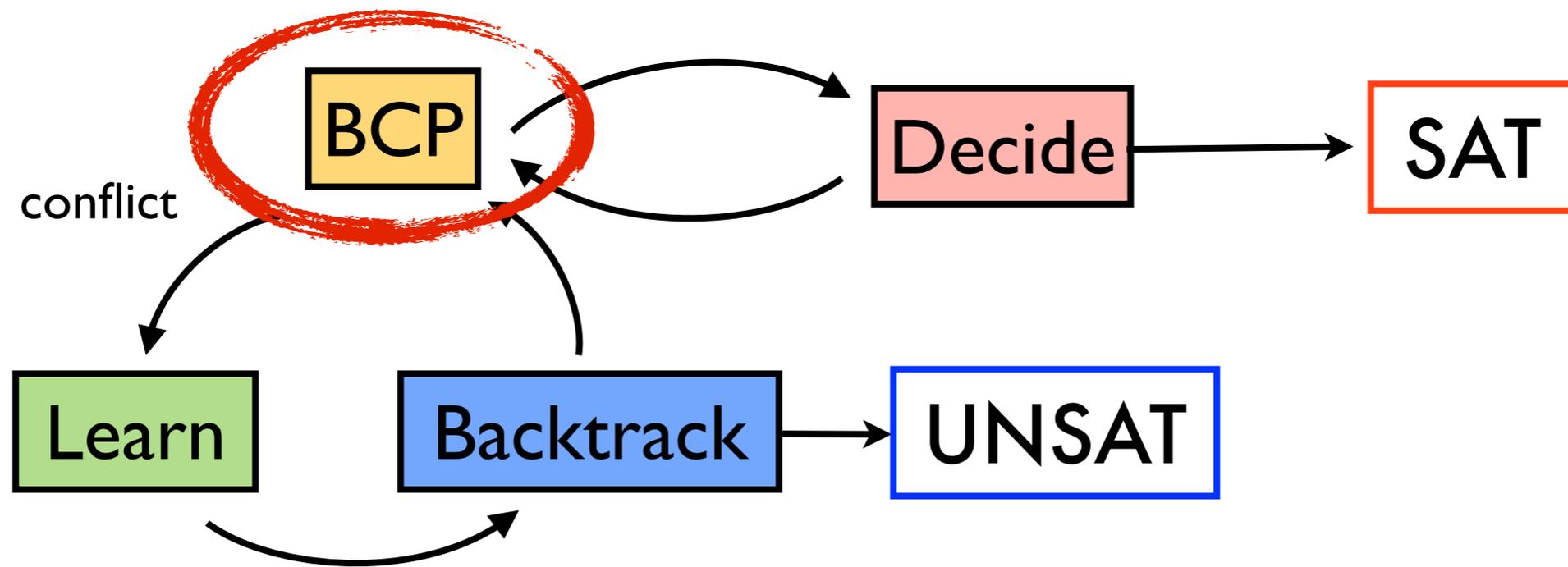
Propositional CNF formula $\varphi = (p \vee \neg q) \wedge \dots \wedge (\neg r \wedge w \wedge q)$



The CDCL Algorithm

Propositional CNF formula $\varphi = (p \vee \neg q) \wedge \dots \wedge (\neg r \wedge w \wedge q)$

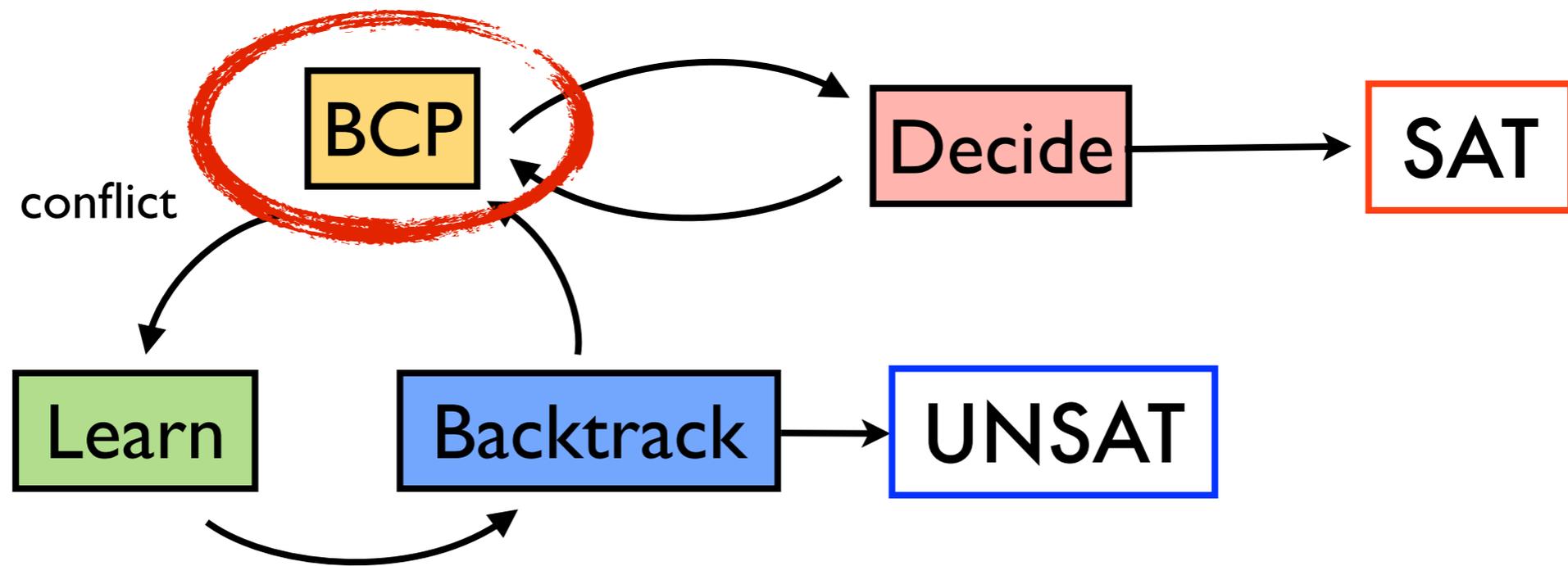




Boolean Constraint Propagation (BCP)

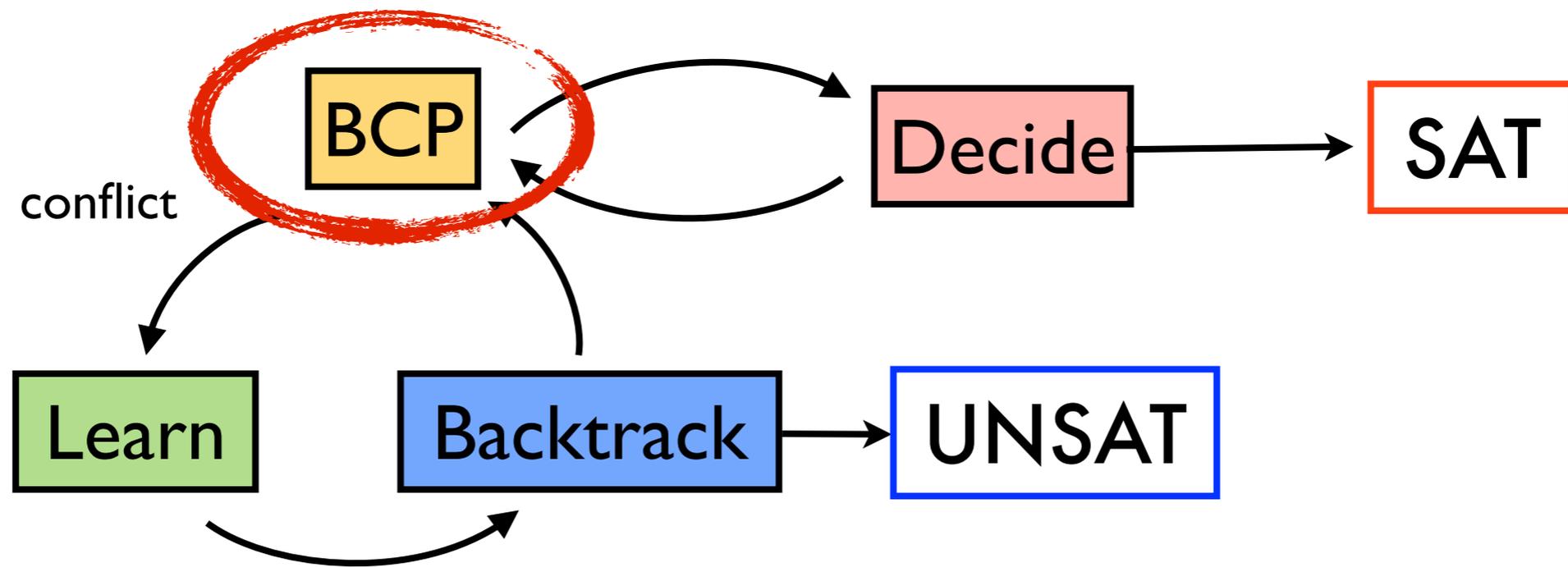
Operates over a partial function
(variable assignment)

$$V \rightarrow \{t, f\}$$



Boolean Constraint Propagation (BCP)

Unit Rule



Boolean Constraint Propagation (BCP)

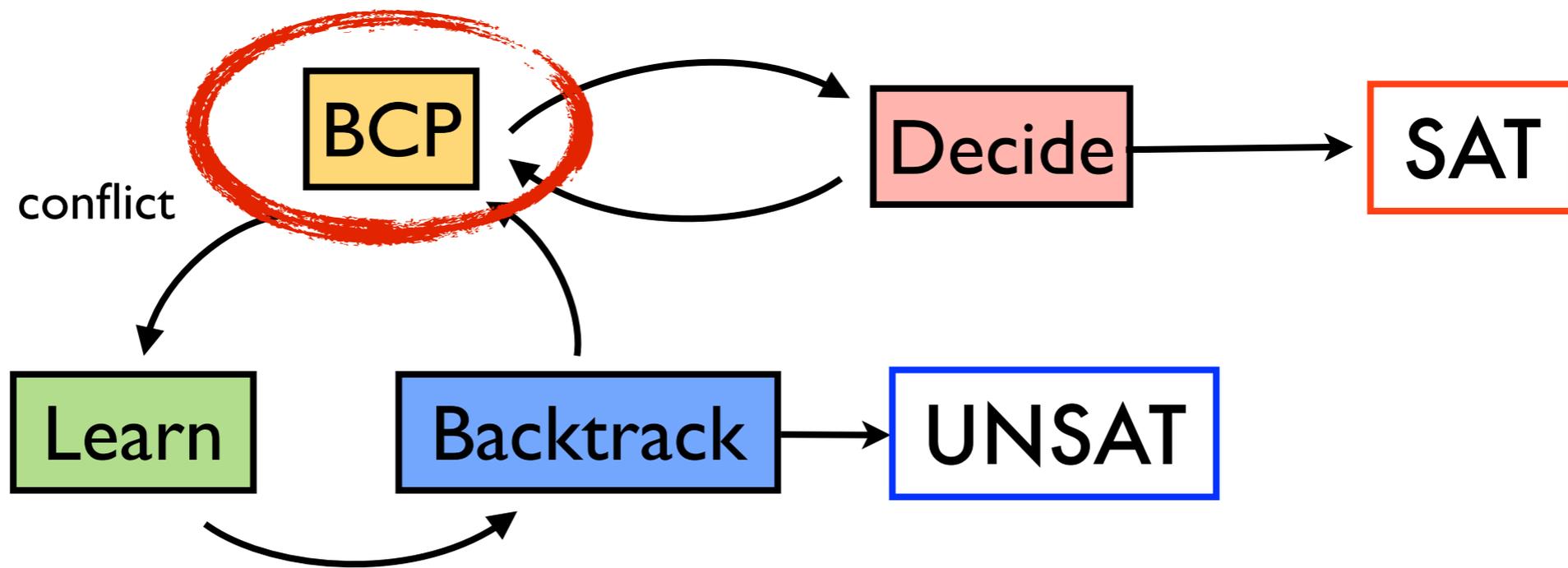
$$p \mapsto t$$

$$q \mapsto f$$

$$r \mapsto f$$

Unit Rule

$$\dots \wedge (\neg p \vee q \vee r \vee \neg w) \wedge \dots$$



Boolean Constraint Propagation (BCP)

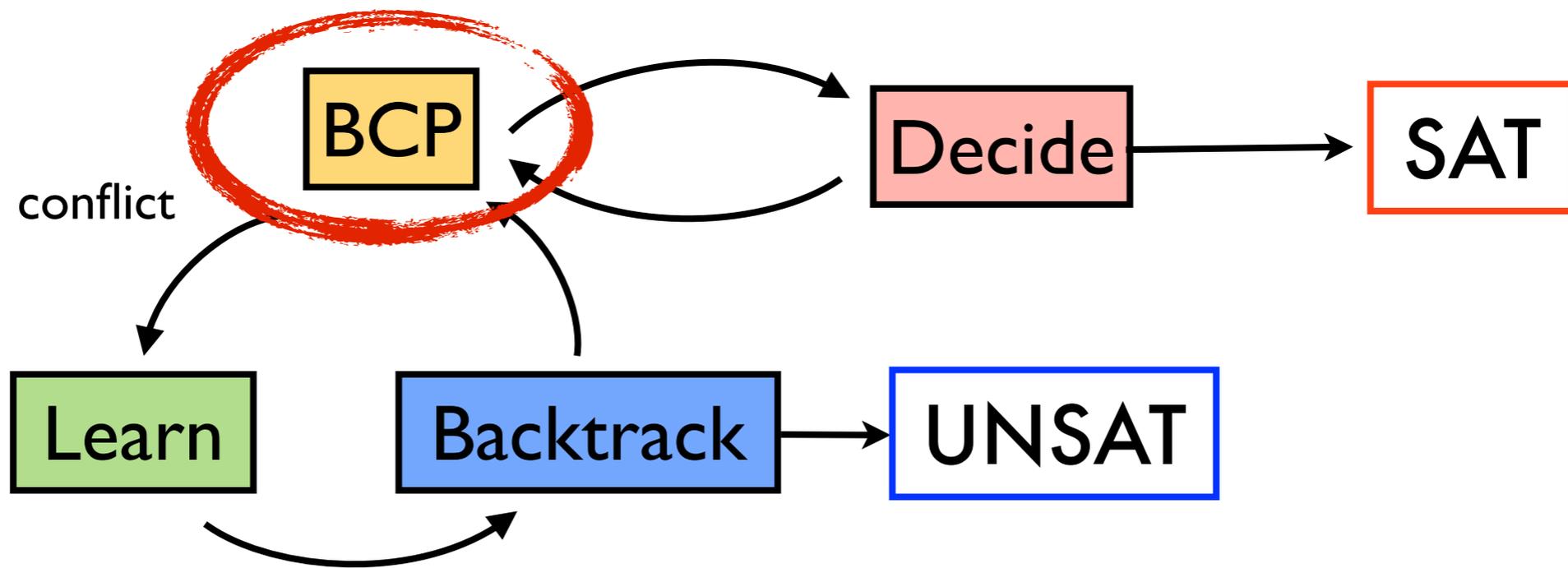
$$p \mapsto t$$

$$q \mapsto f$$

$$r \mapsto f$$

Unit Rule

$$\dots \wedge (\neg p \vee q \vee r \vee \neg w) \wedge \dots$$



Boolean Constraint Propagation (BCP)

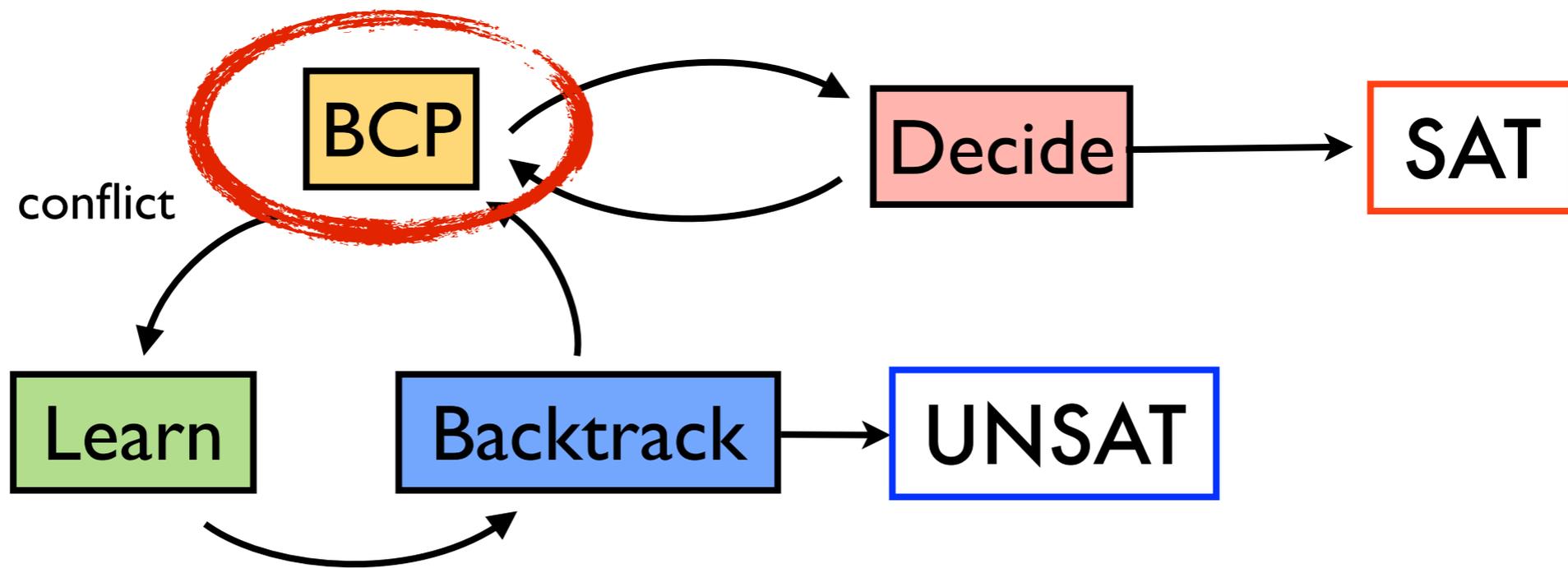
$$p \mapsto t$$

$$q \mapsto f$$

$$r \mapsto f$$

Unit Rule

$$\dots \wedge (\neg p \vee q \vee r \vee \neg w) \wedge \dots$$



Boolean Constraint Propagation (BCP)

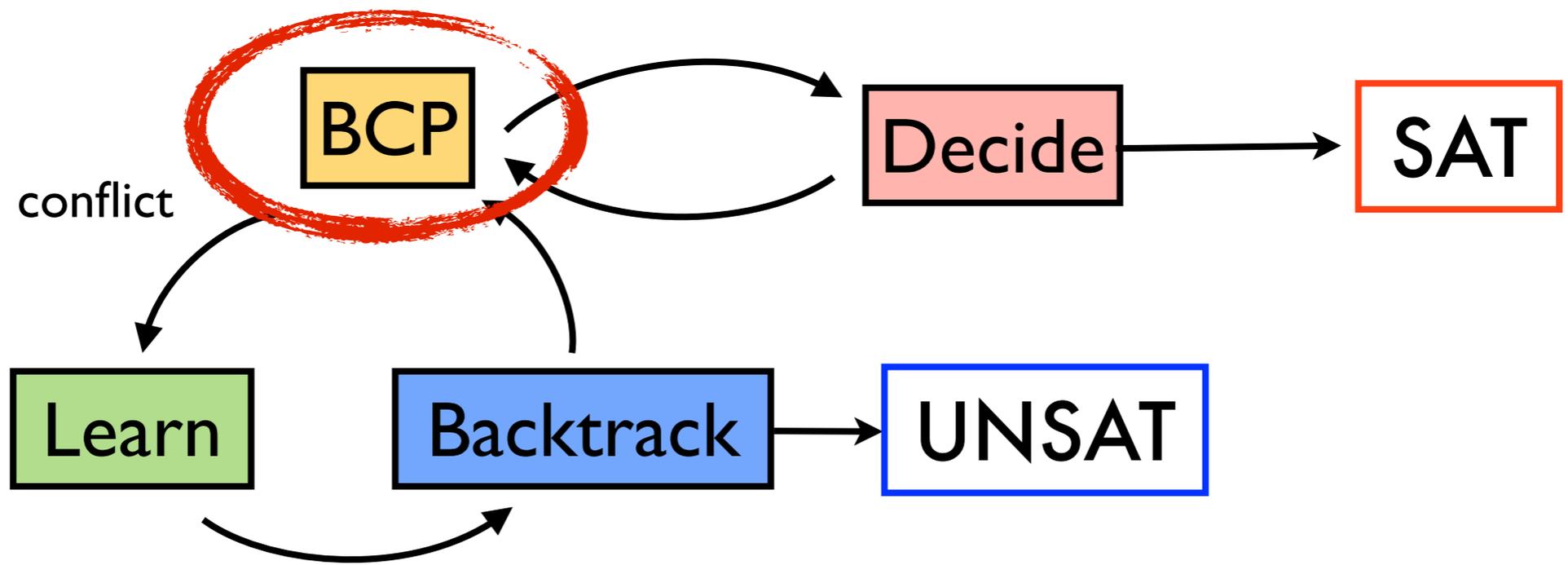
$$p \mapsto t$$

$$q \mapsto f$$

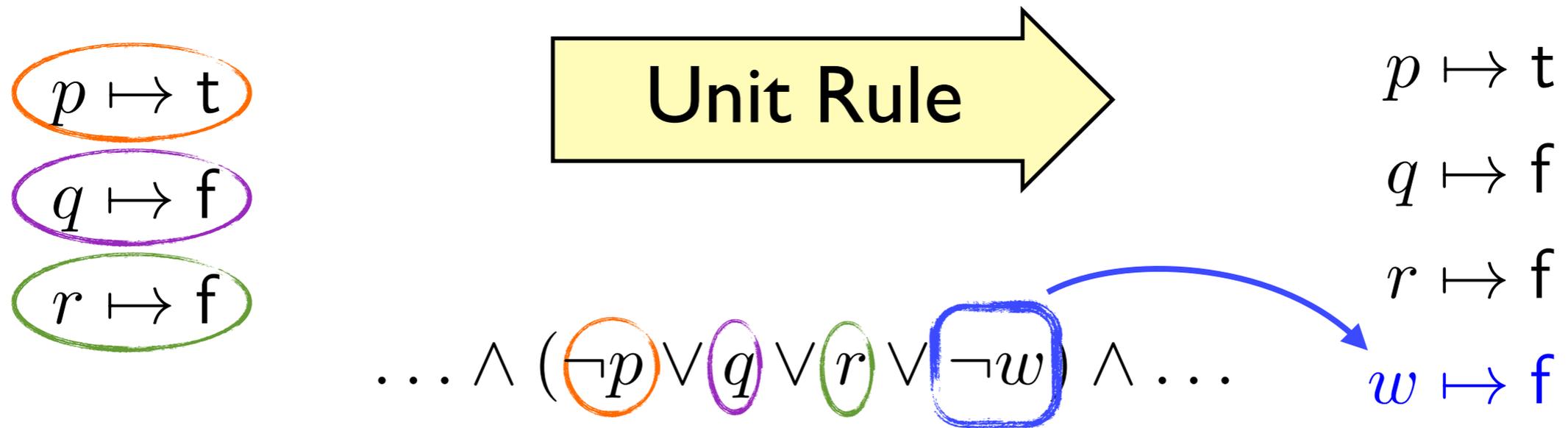
$$r \mapsto f$$

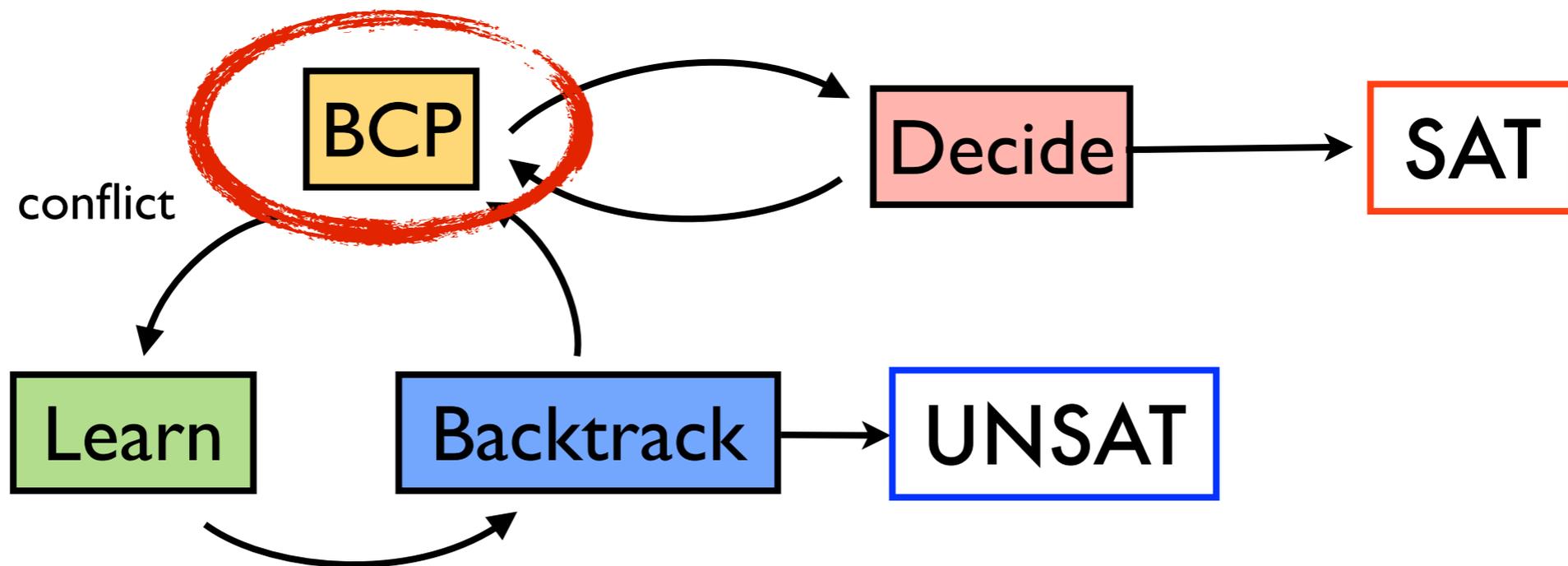
Unit Rule

$$\dots \wedge (\neg p \vee q \vee r \vee \neg w) \wedge \dots$$



Boolean Constraint Propagation (BCP)

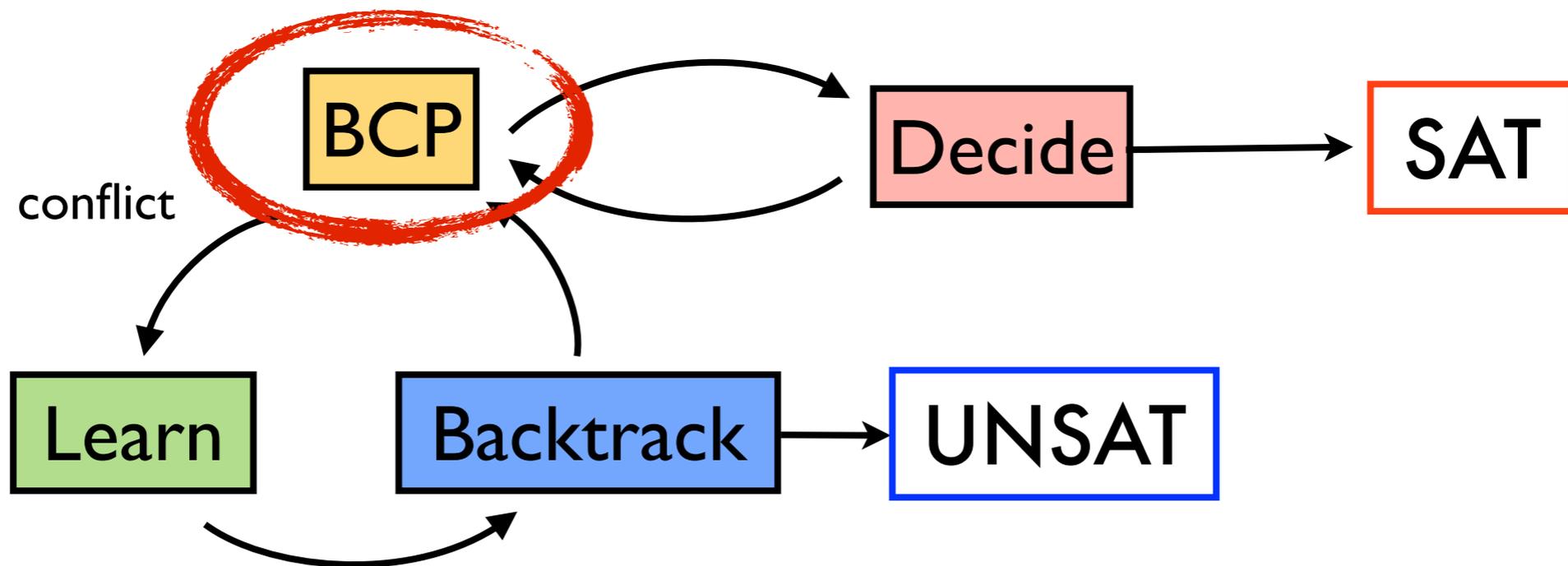




$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

Boolean Constraint Propagation (BCP)

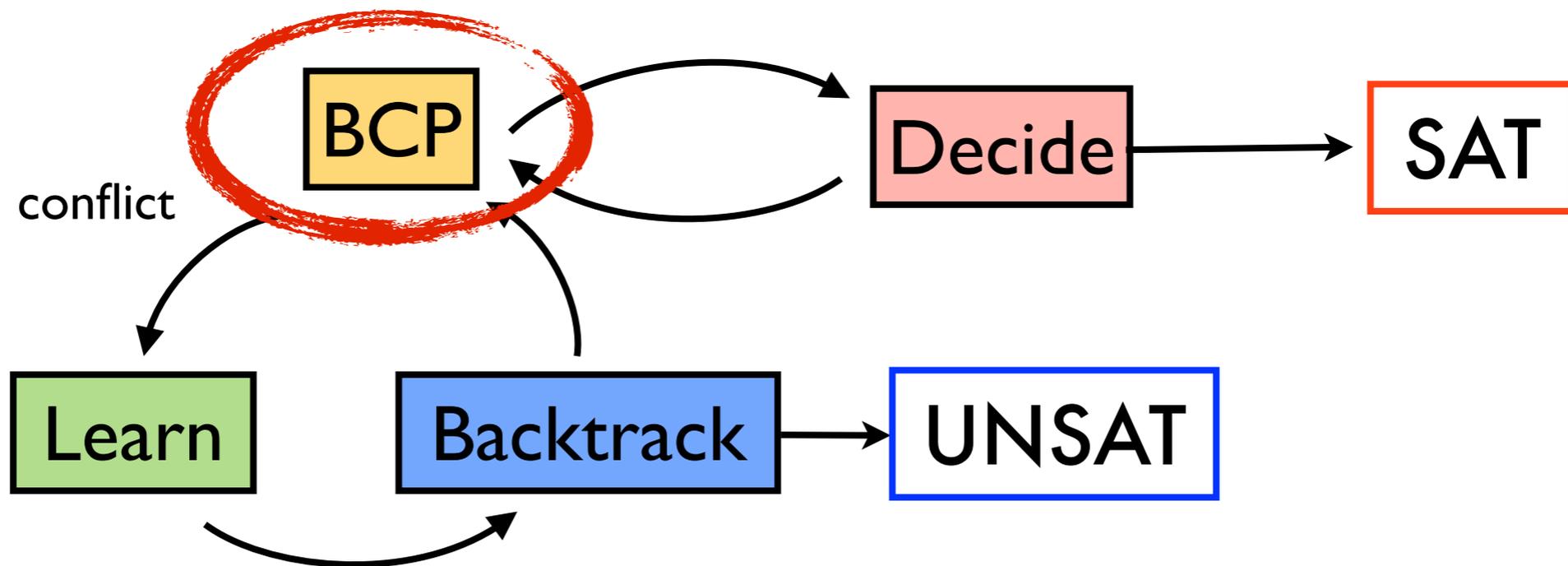
BCP = Exhaustive application of unit rule



$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

Boolean Constraint Propagation (BCP)

BCP = Exhaustive application of unit rule

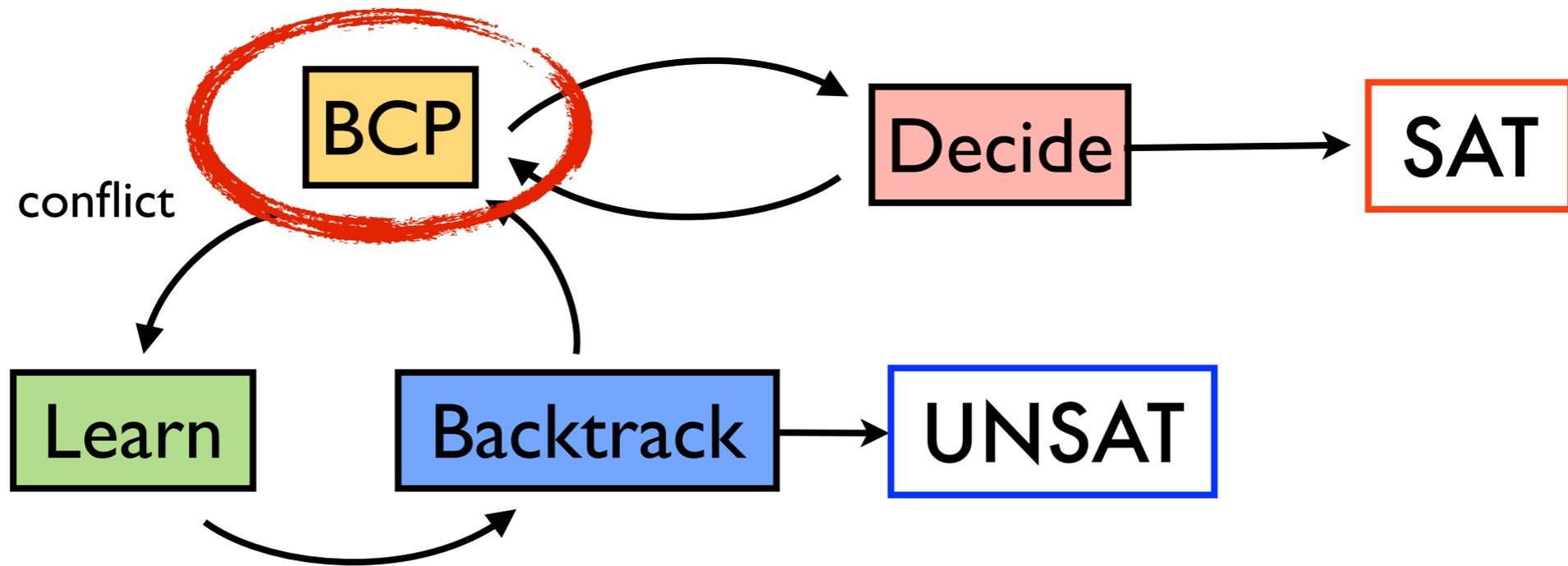


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

Boolean Constraint Propagation (BCP)

BCP = Exhaustive application of unit rule

$$\longrightarrow p \mapsto t$$

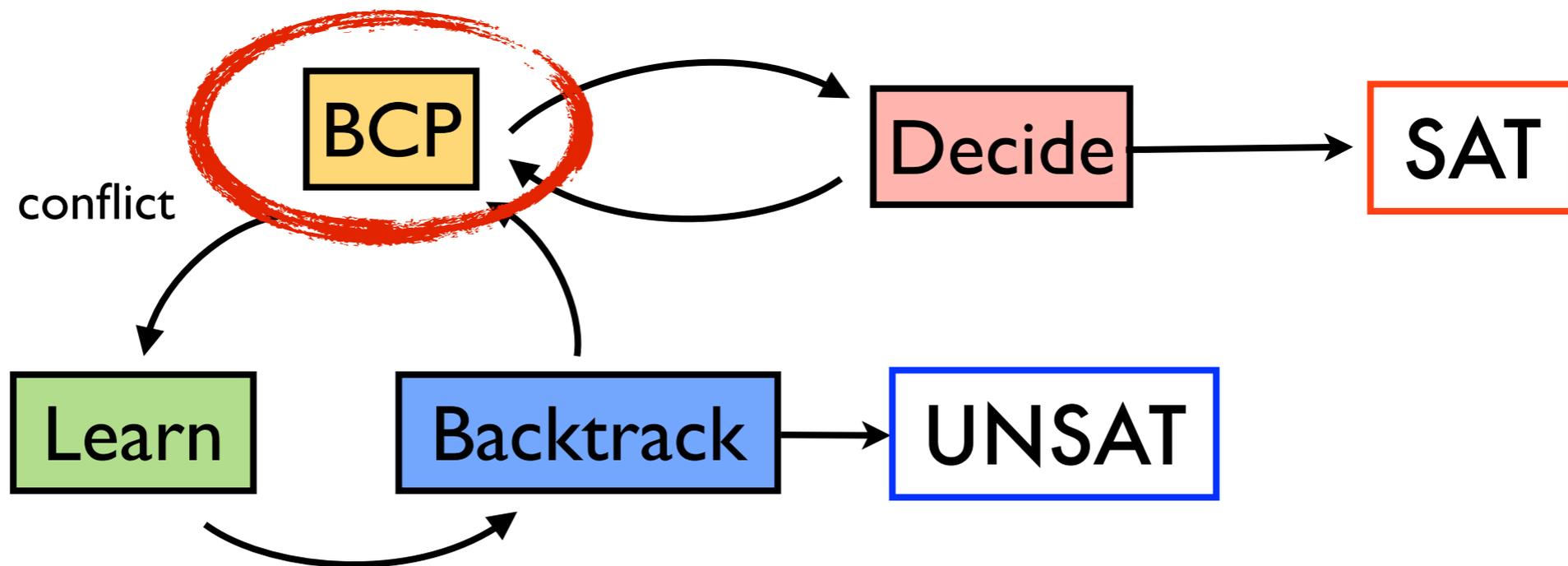


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

Boolean Constraint Propagation (BCP)

BCP = Exhaustive application of unit rule

$$\longrightarrow p \mapsto t$$

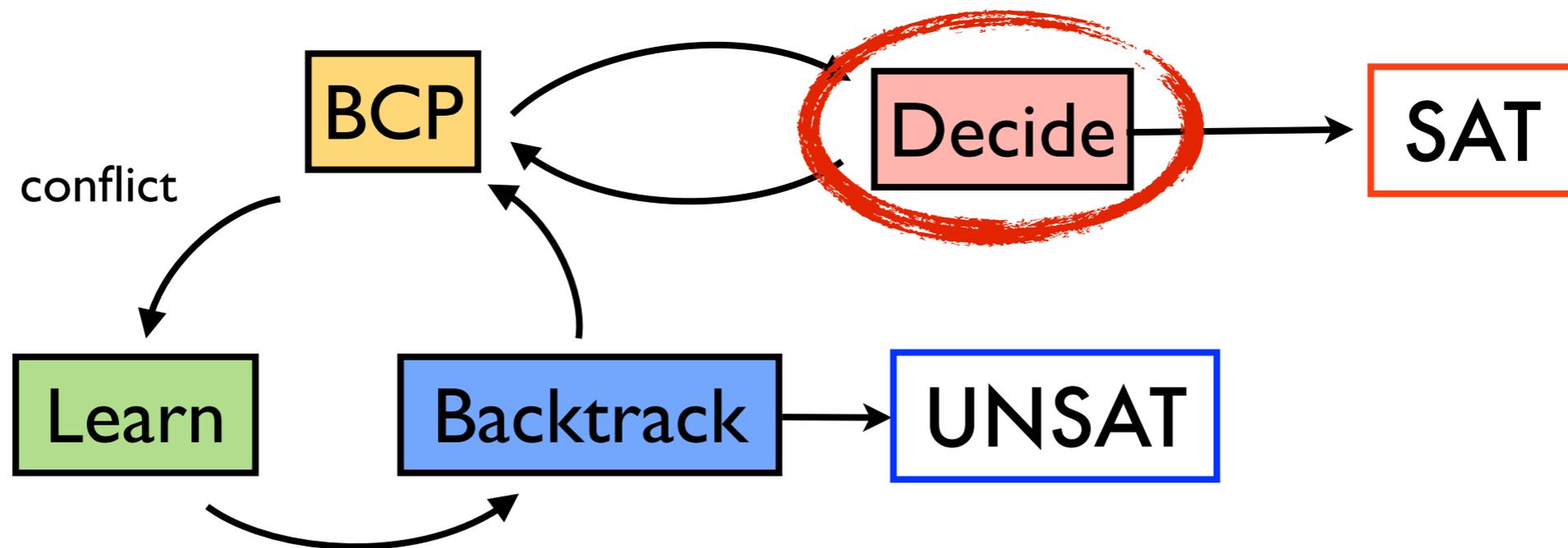


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

Boolean Constraint Propagation (BCP)

BCP = Exhaustive application of unit rule

$$\begin{array}{l} \longrightarrow p \mapsto t \\ \longrightarrow p \mapsto t \\ \qquad \qquad q \mapsto f \end{array}$$

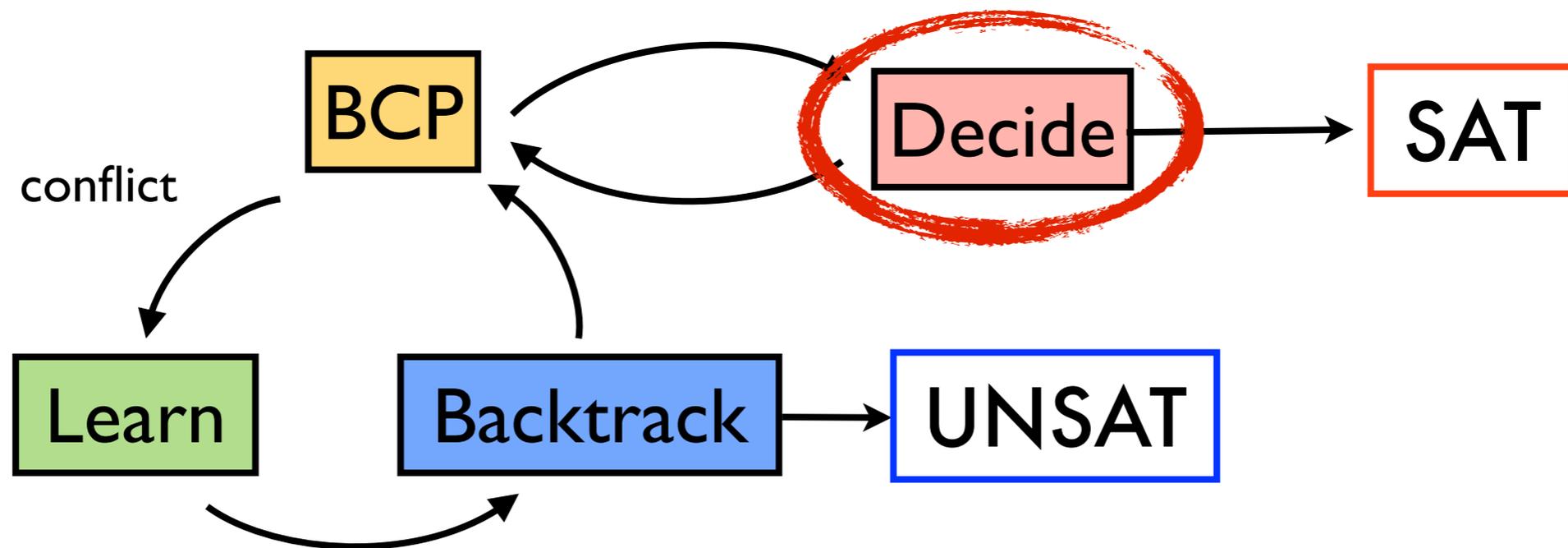


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

Decisions

$$p \mapsto t$$

$$q \mapsto f$$



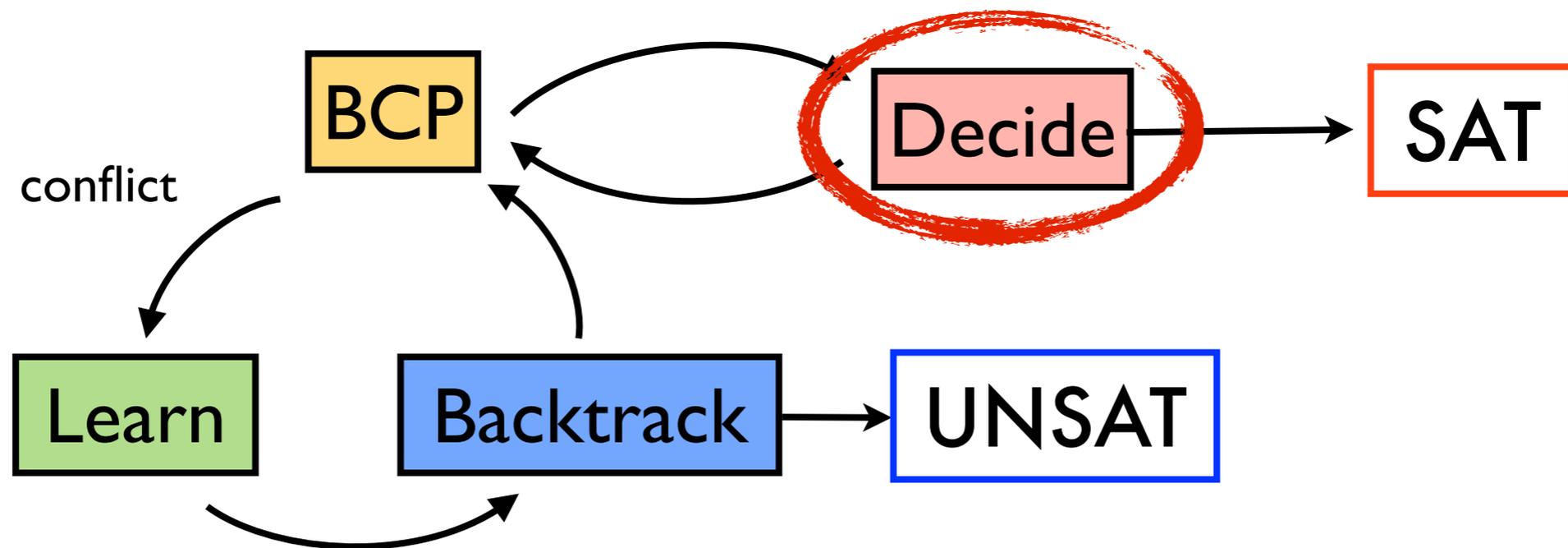
$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

Decisions

Pick an unassigned variable and assign a truth value

$$p \mapsto t$$

$$q \mapsto f$$



$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

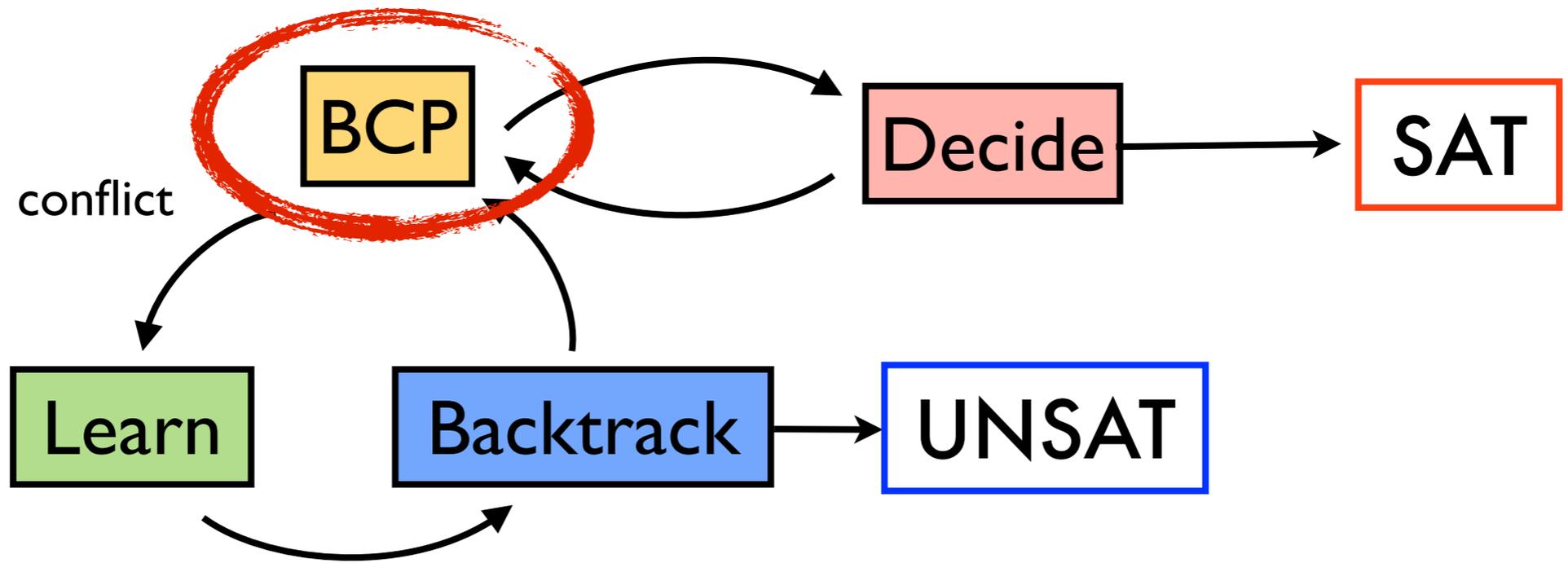
Decisions

Pick an unassigned variable and assign a truth value

$$\begin{array}{l} p \mapsto t \\ q \mapsto f \end{array}$$



$$\begin{array}{l} p \mapsto t \\ q \mapsto f \\ r \mapsto f \end{array}$$

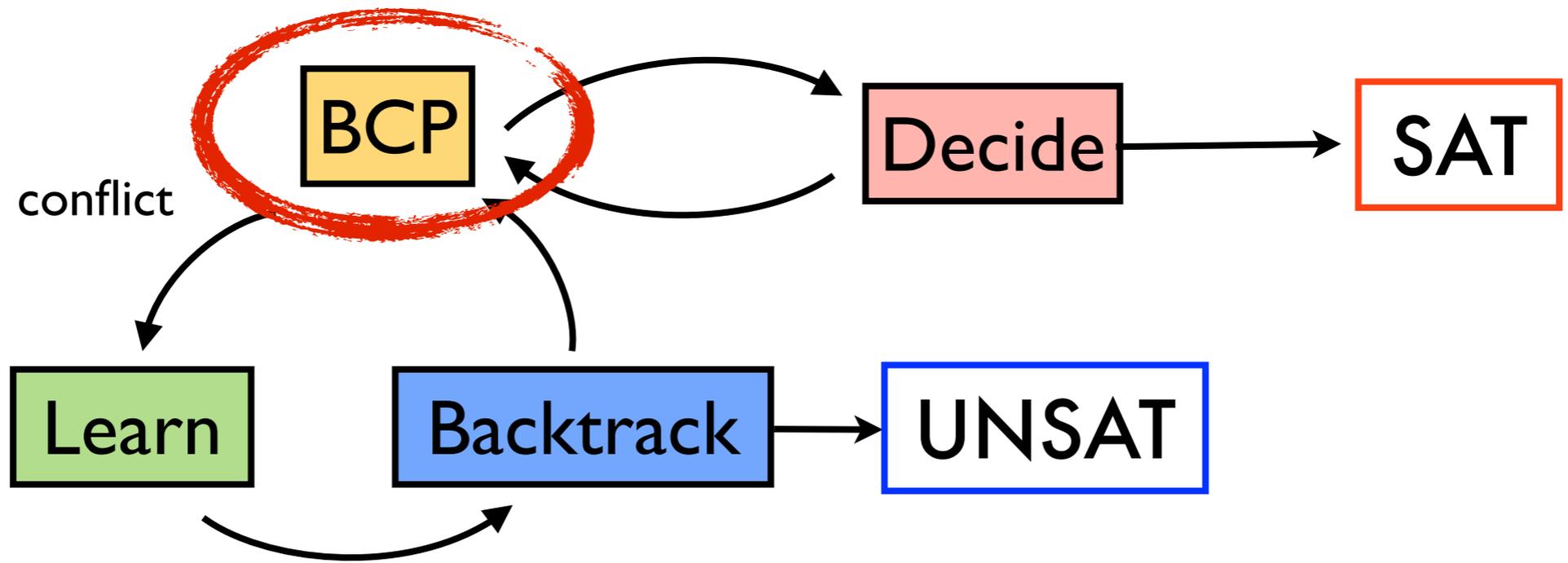


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

$$p \mapsto \text{t}$$

$$q \mapsto \text{f}$$

$$r \mapsto \text{f}$$

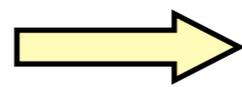


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

$p \mapsto t$

$q \mapsto f$

$r \mapsto f$

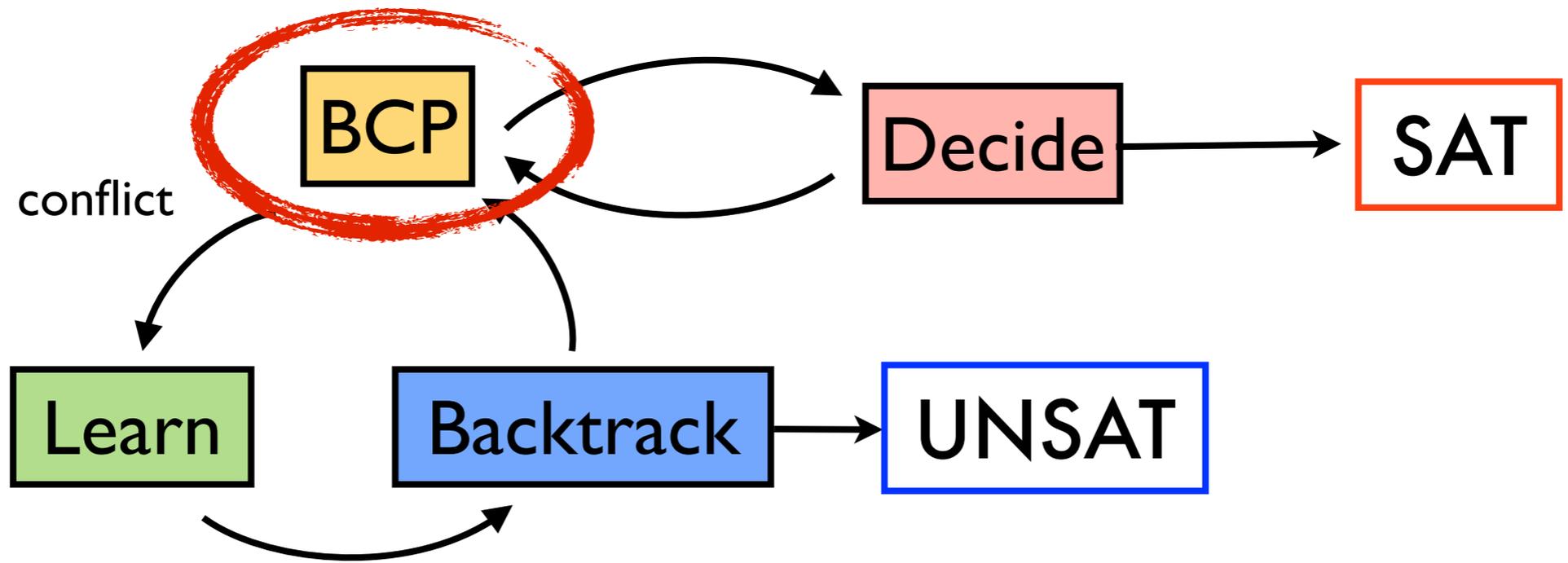


$p \mapsto t$

$q \mapsto f$

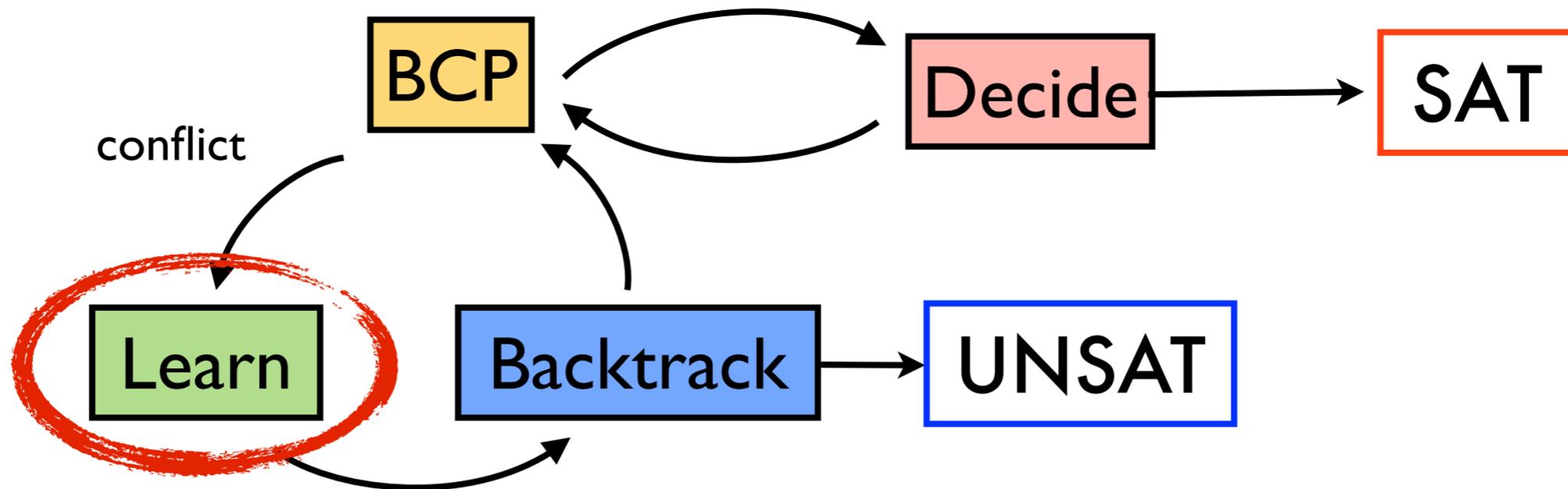
$r \mapsto f$

$w \mapsto f$

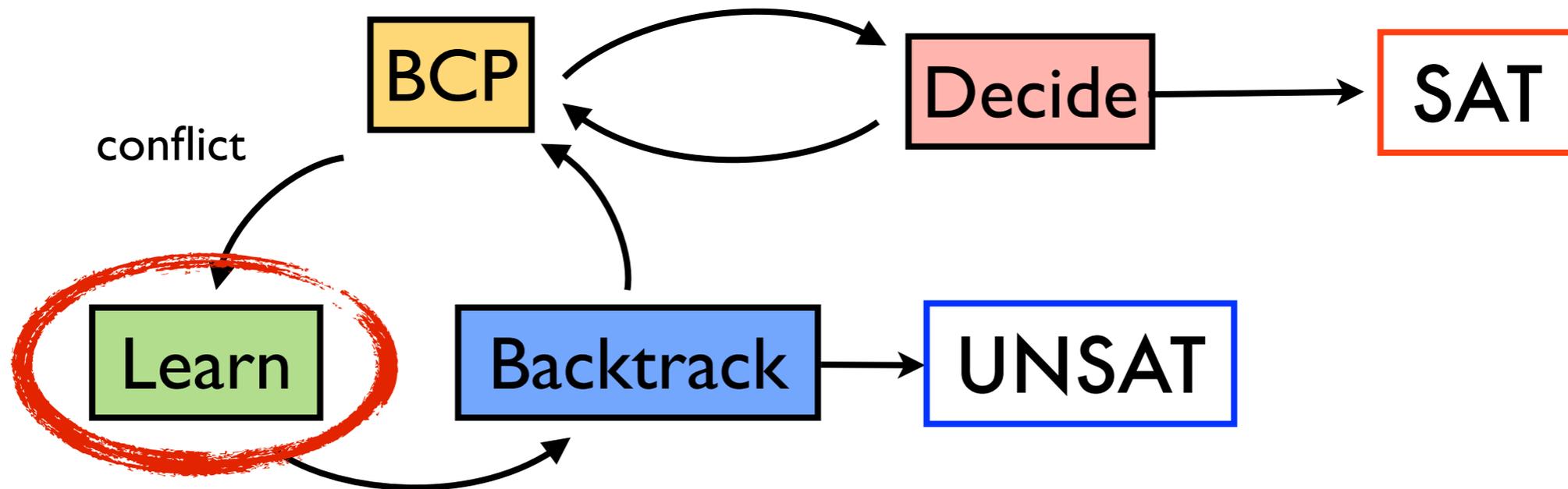


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

$p \mapsto t$		$p \mapsto t$		
$q \mapsto f$	→	$q \mapsto f$	→	conflict
$r \mapsto f$		$r \mapsto f$		
		$w \mapsto f$		



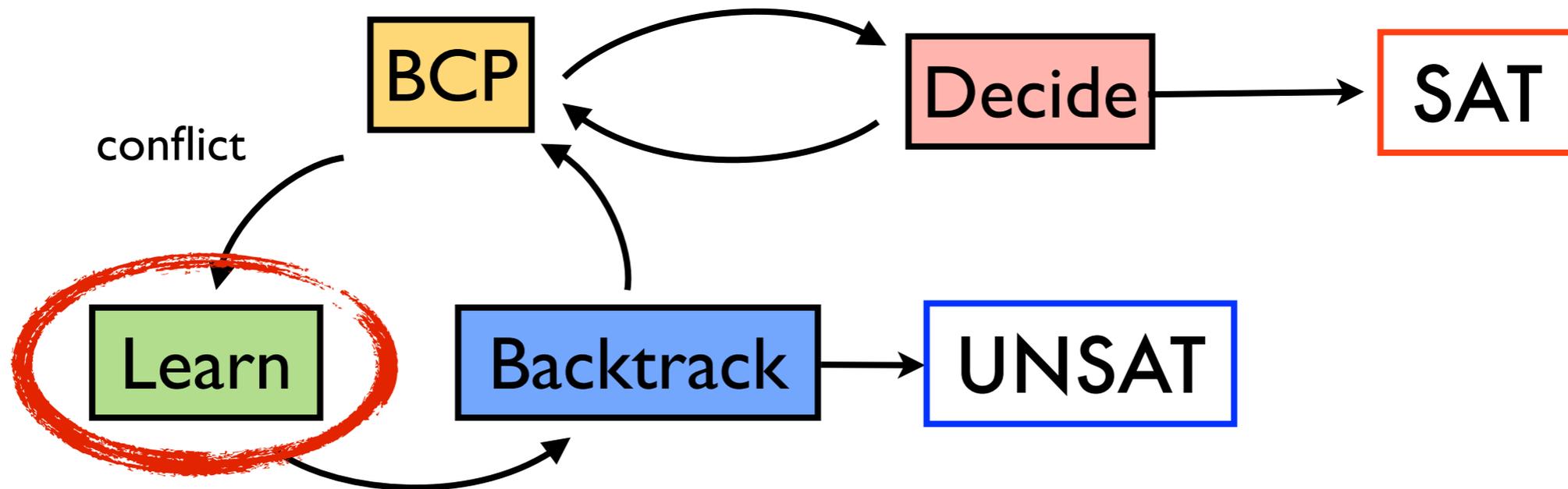
$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$



$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

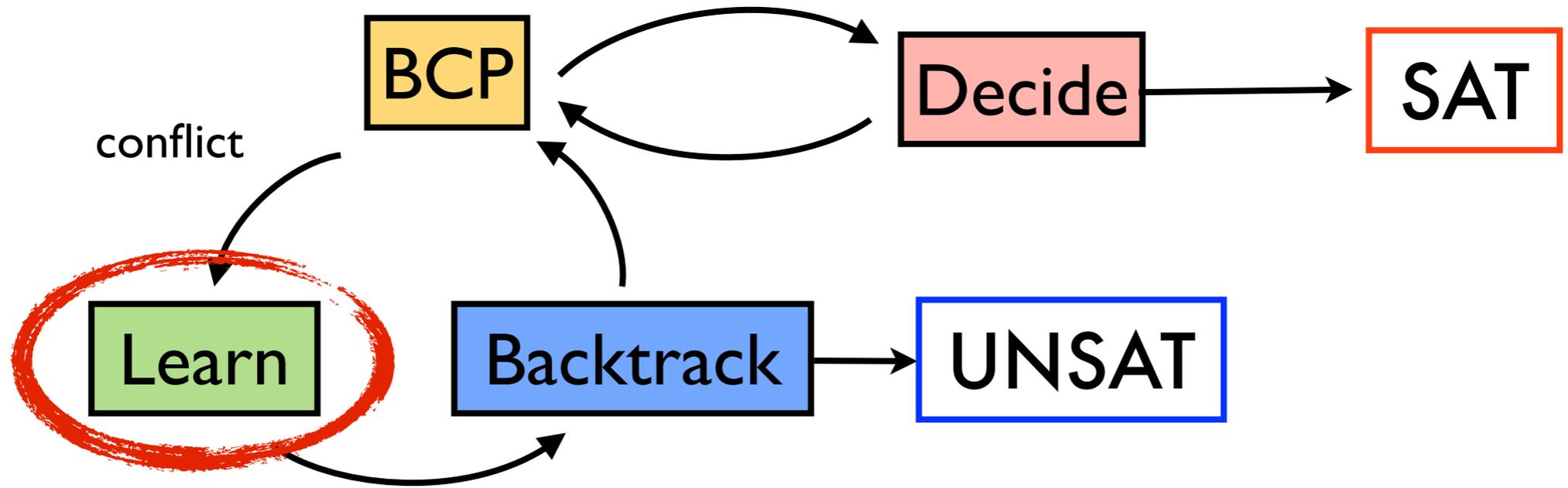


$$p \mapsto t$$

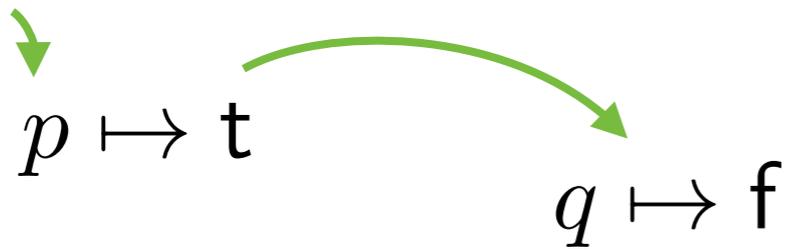


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

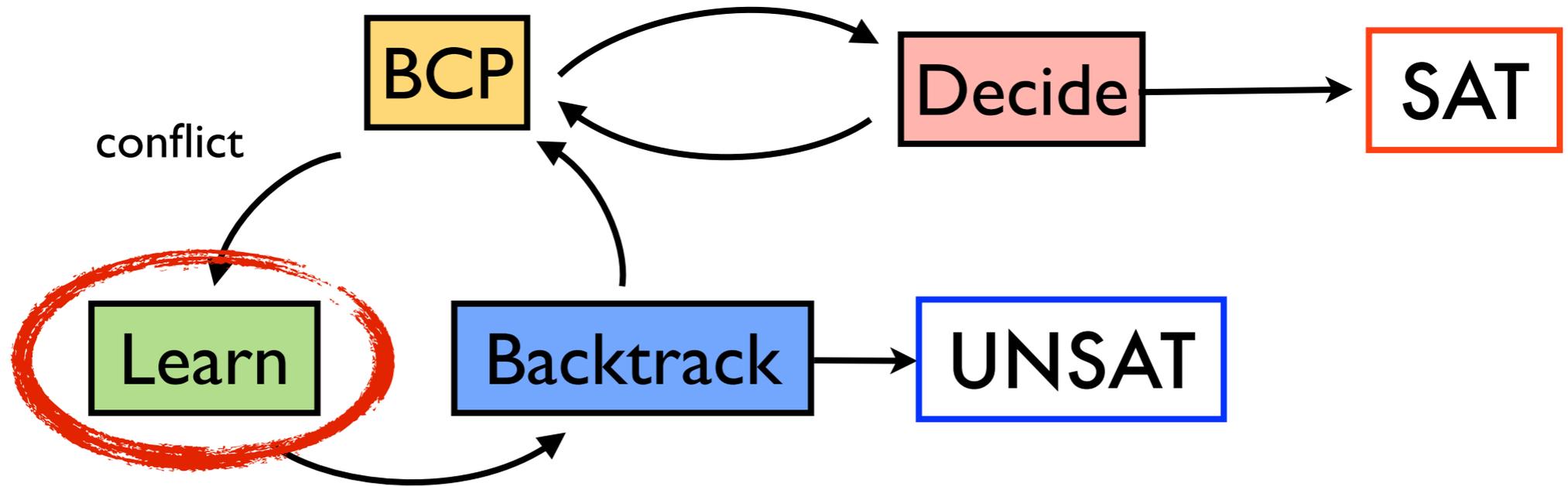
$p \mapsto \text{t}$
 $q \mapsto \text{f}$



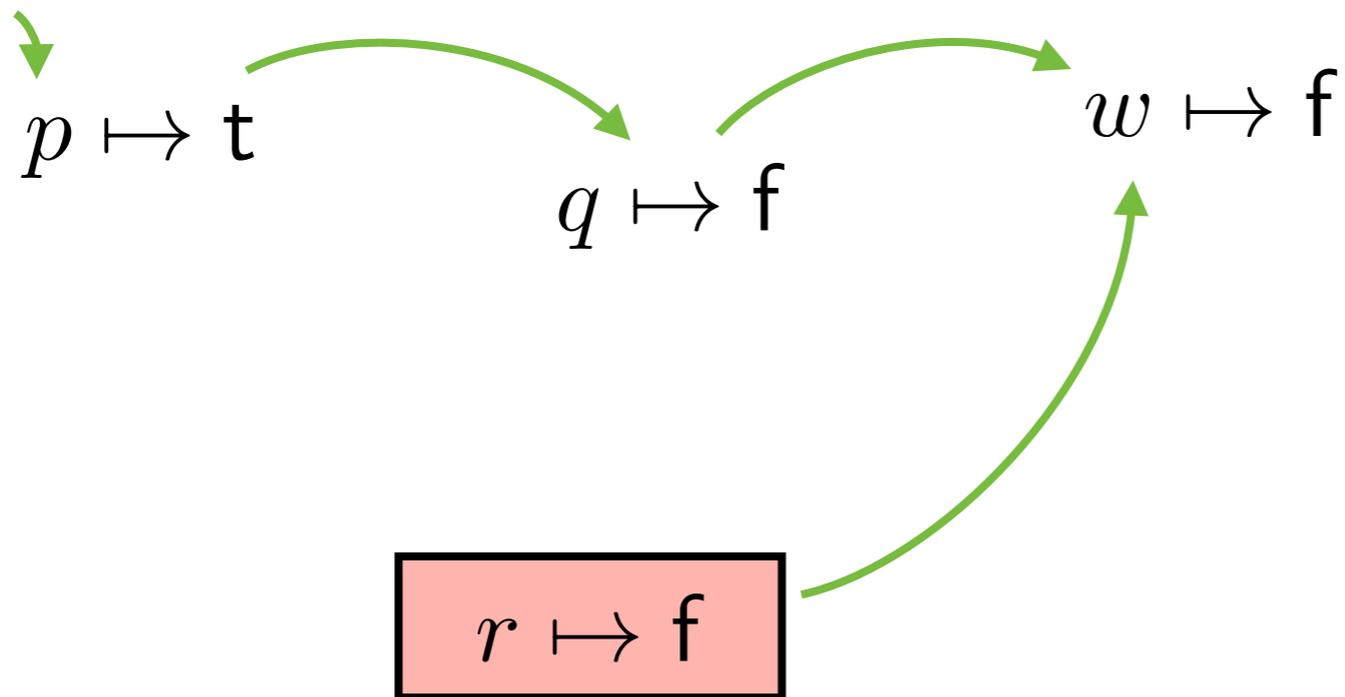
$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

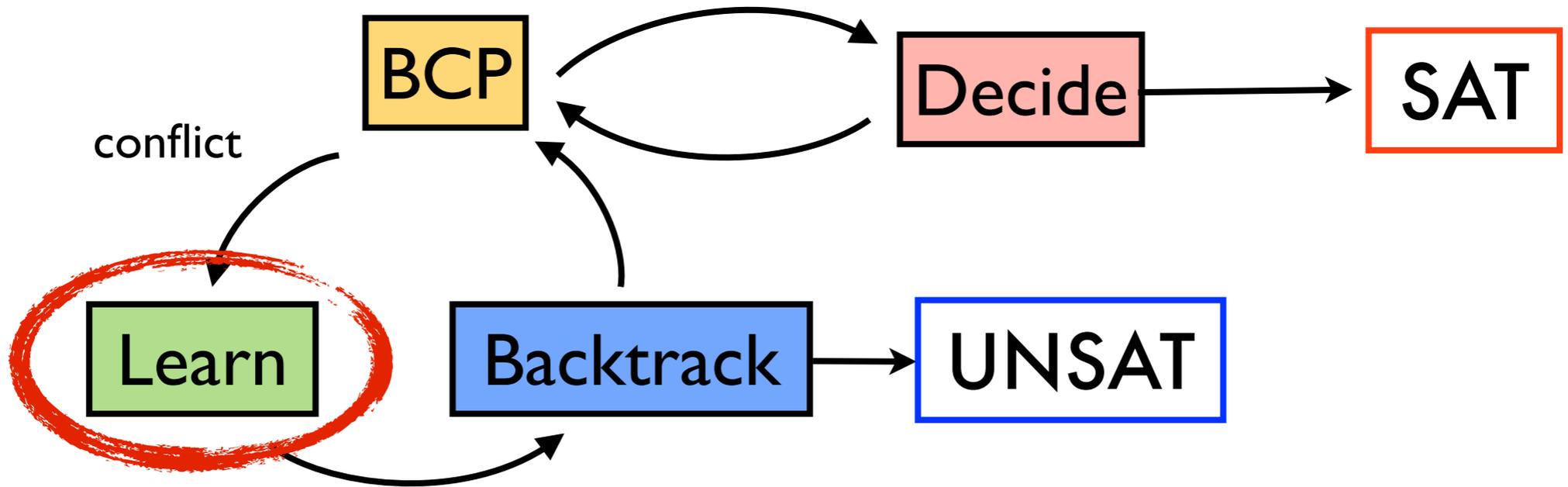


$$r \mapsto f$$

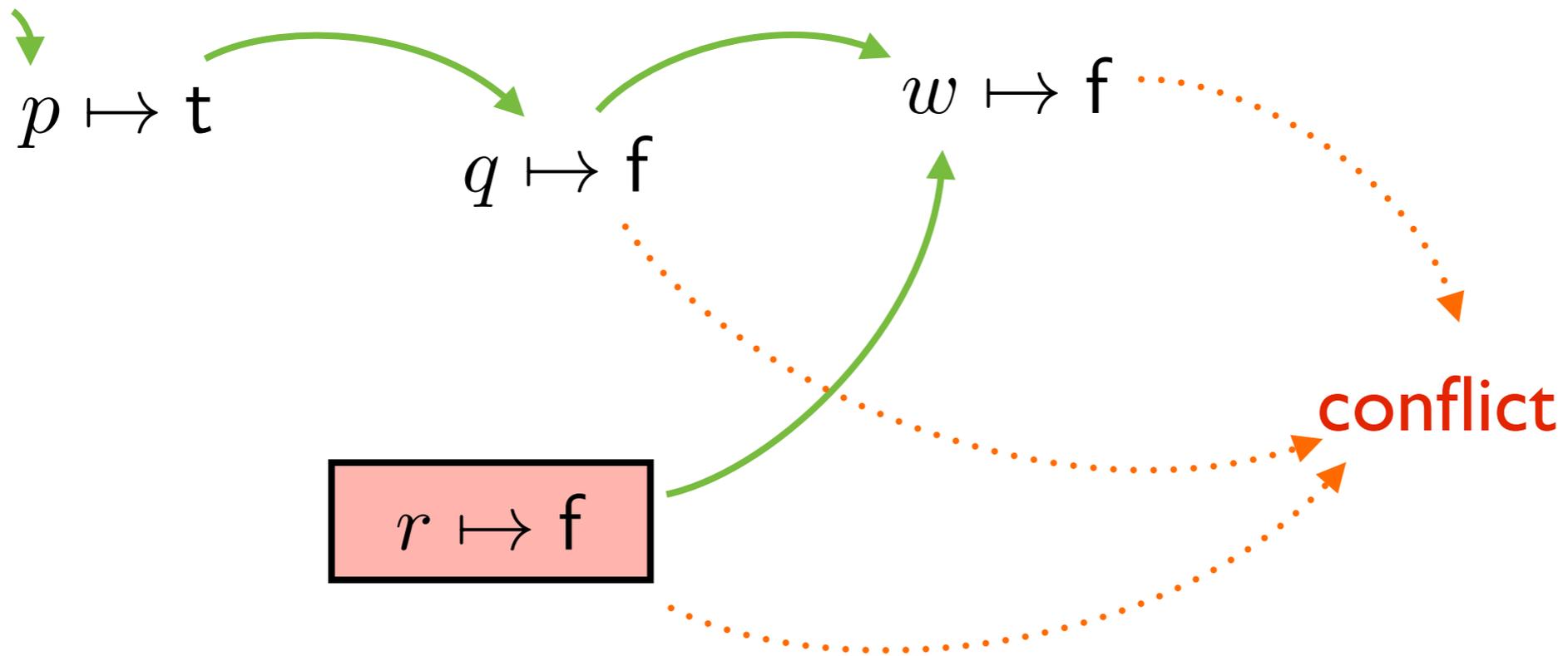


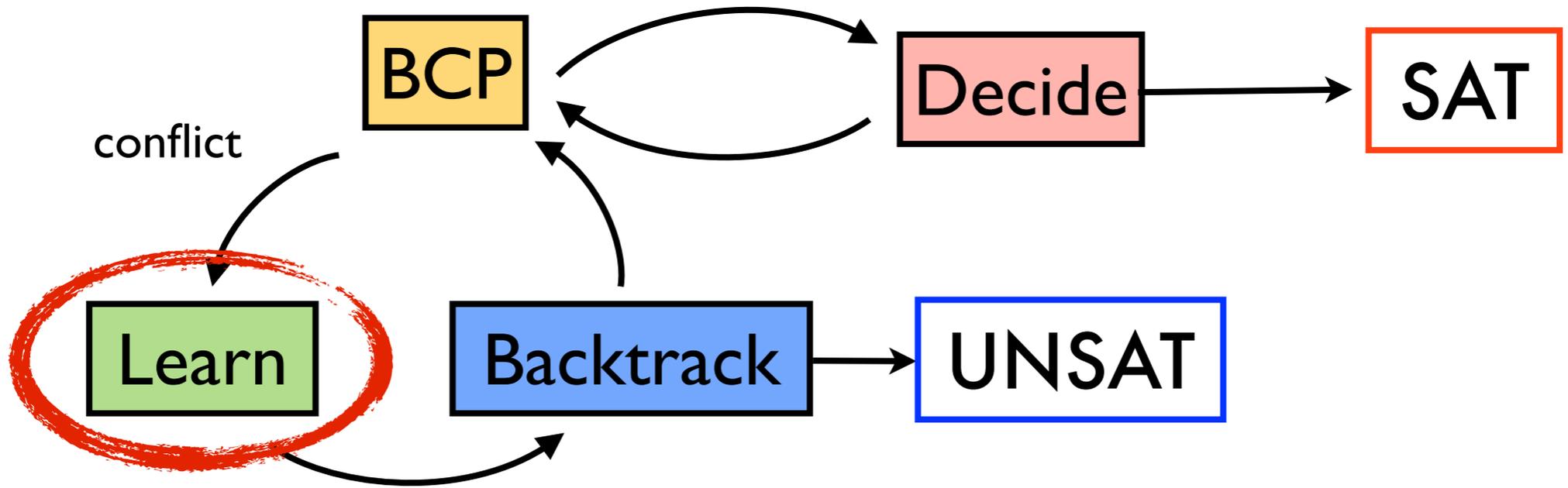
$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$



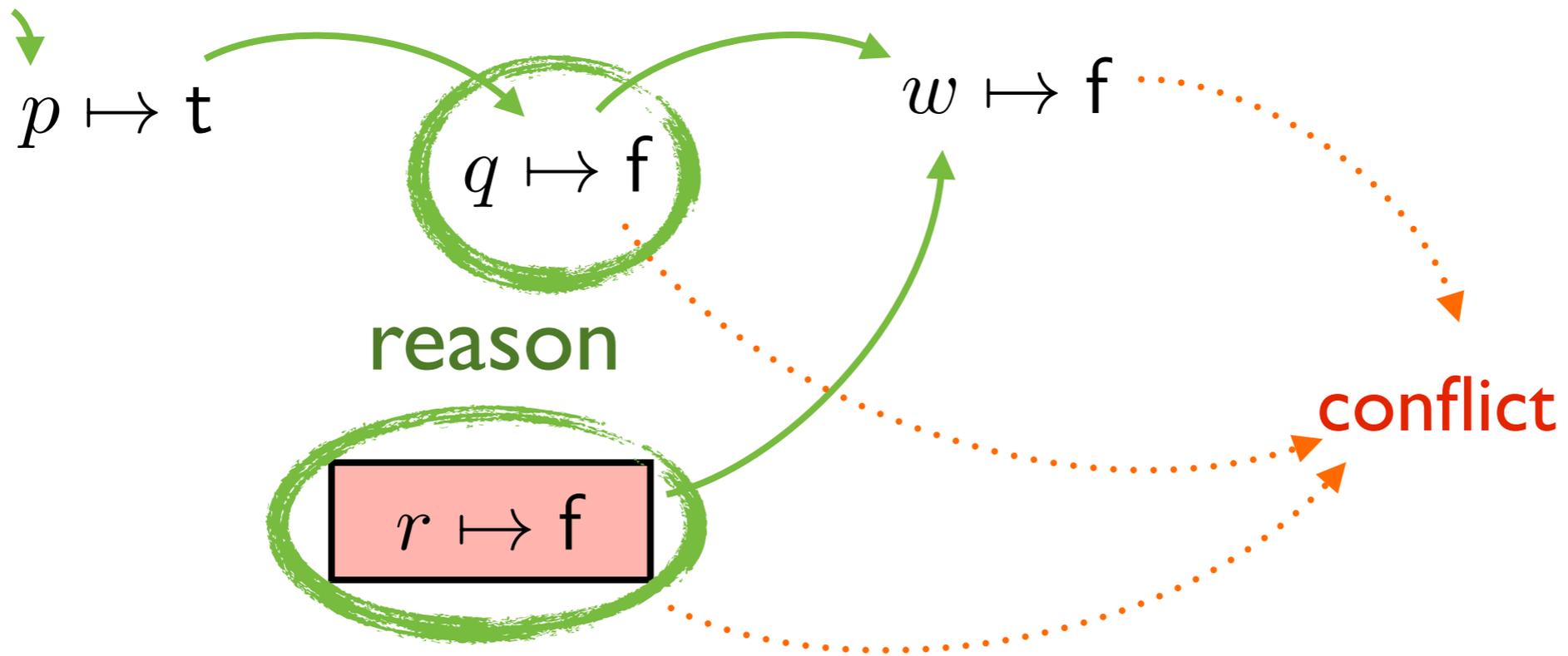


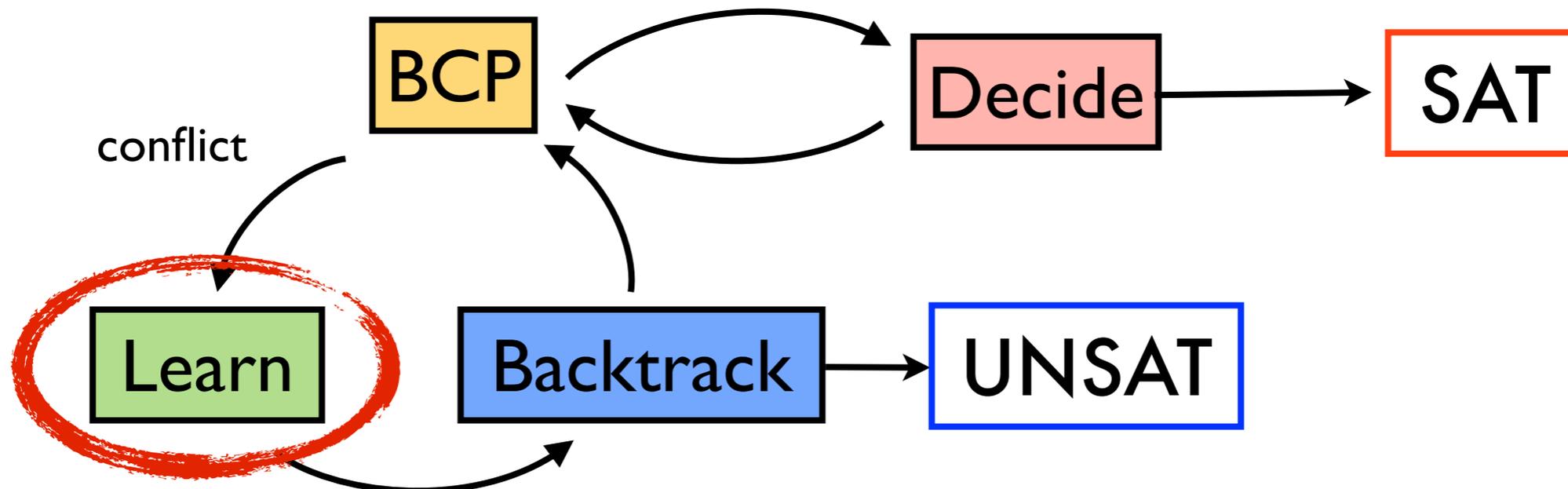
$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$



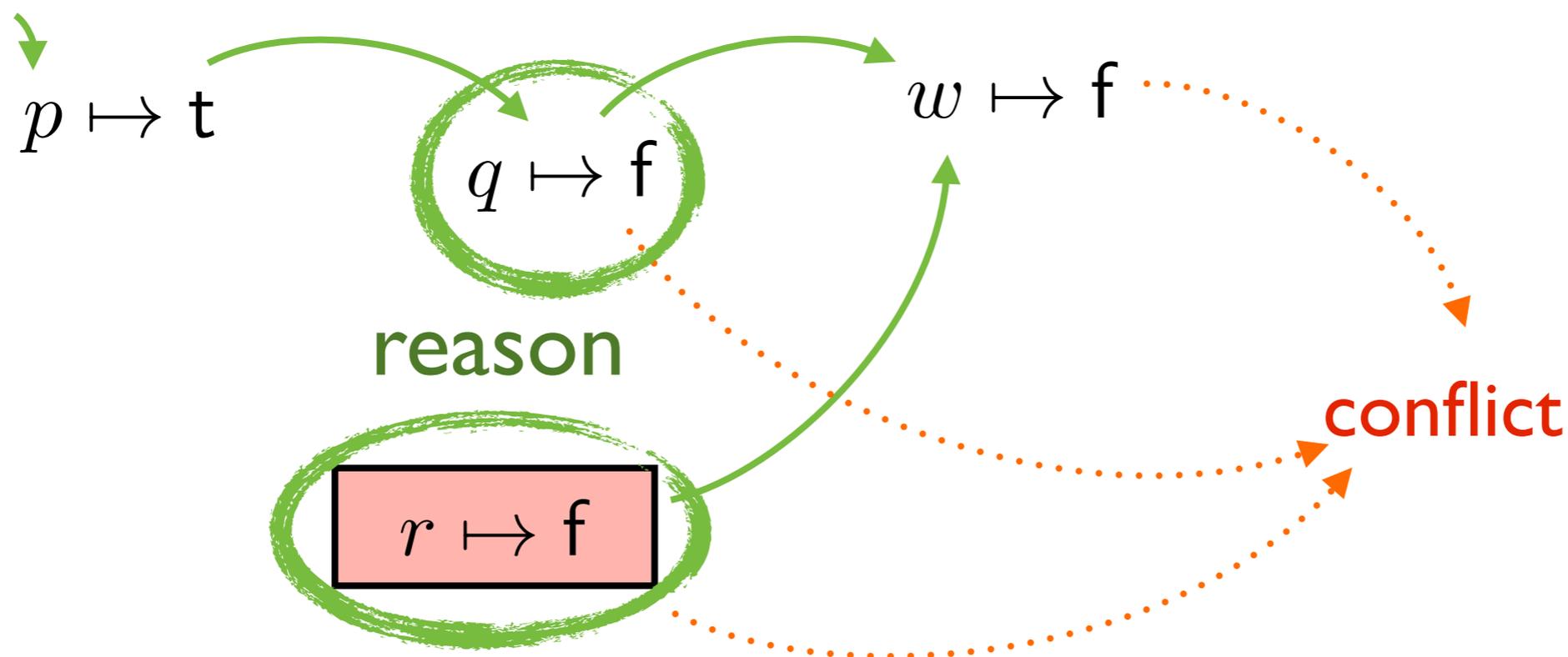


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

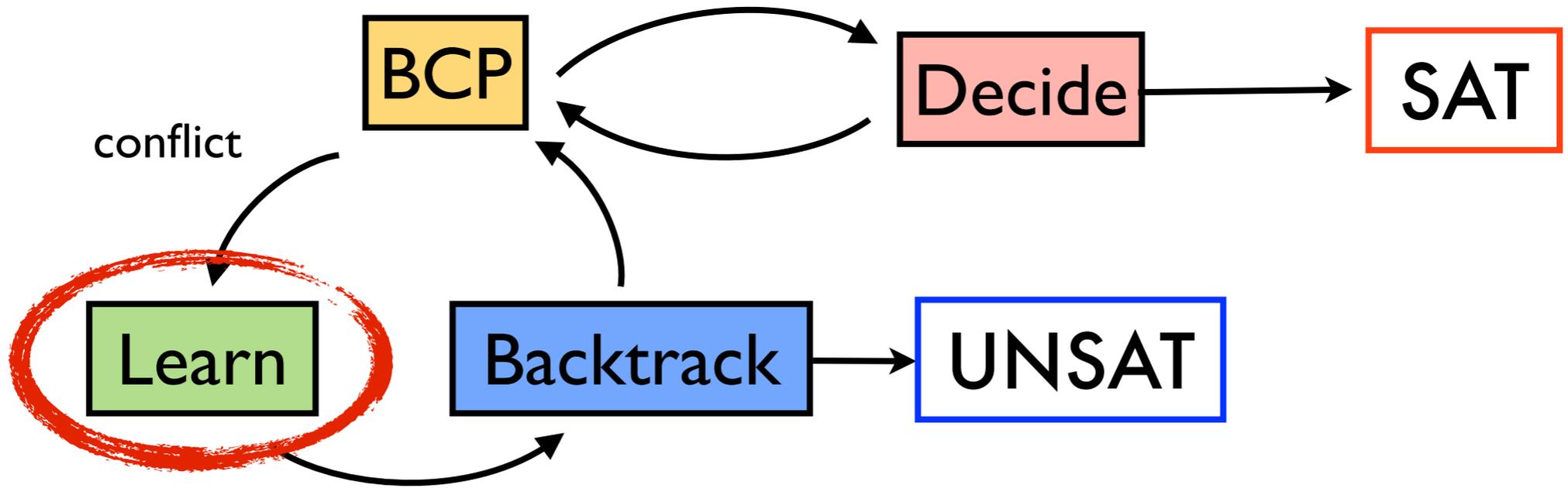




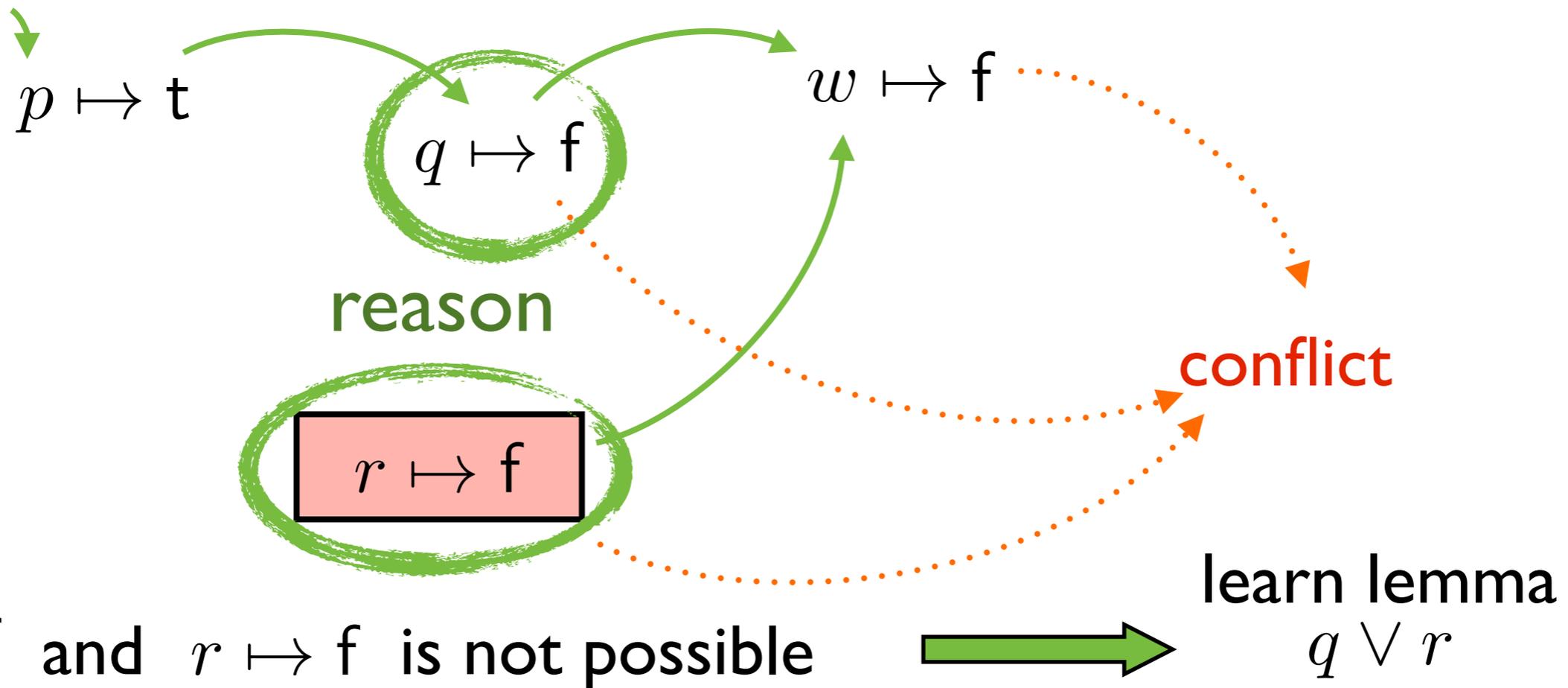
$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

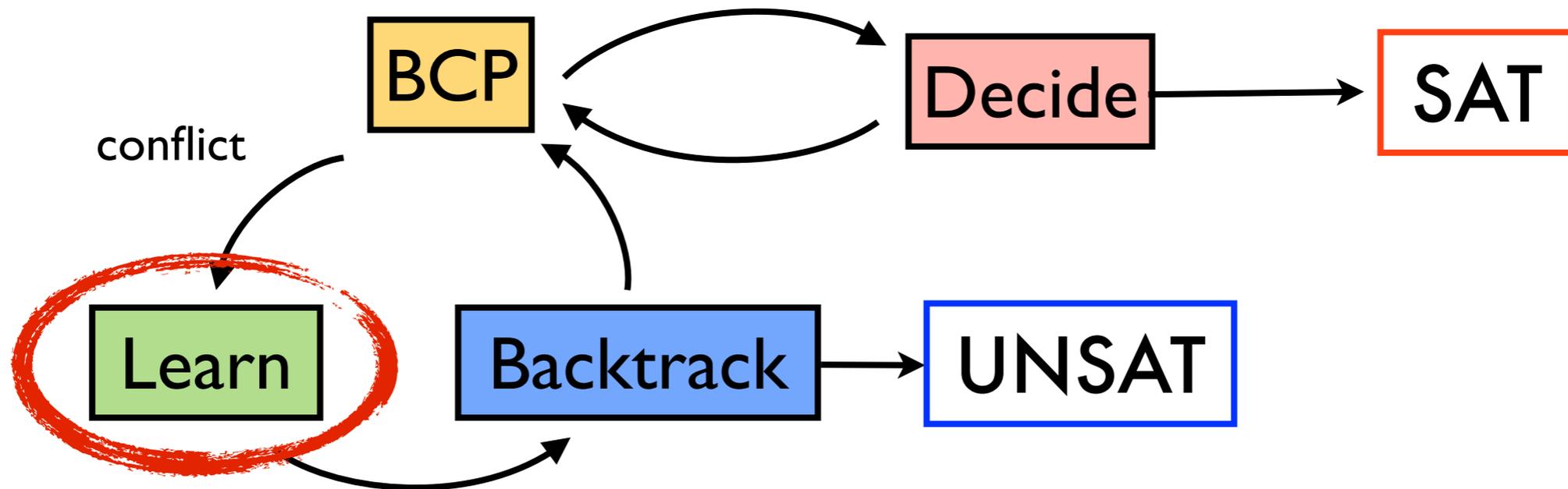


$q \mapsto f$ and $r \mapsto f$ is not possible

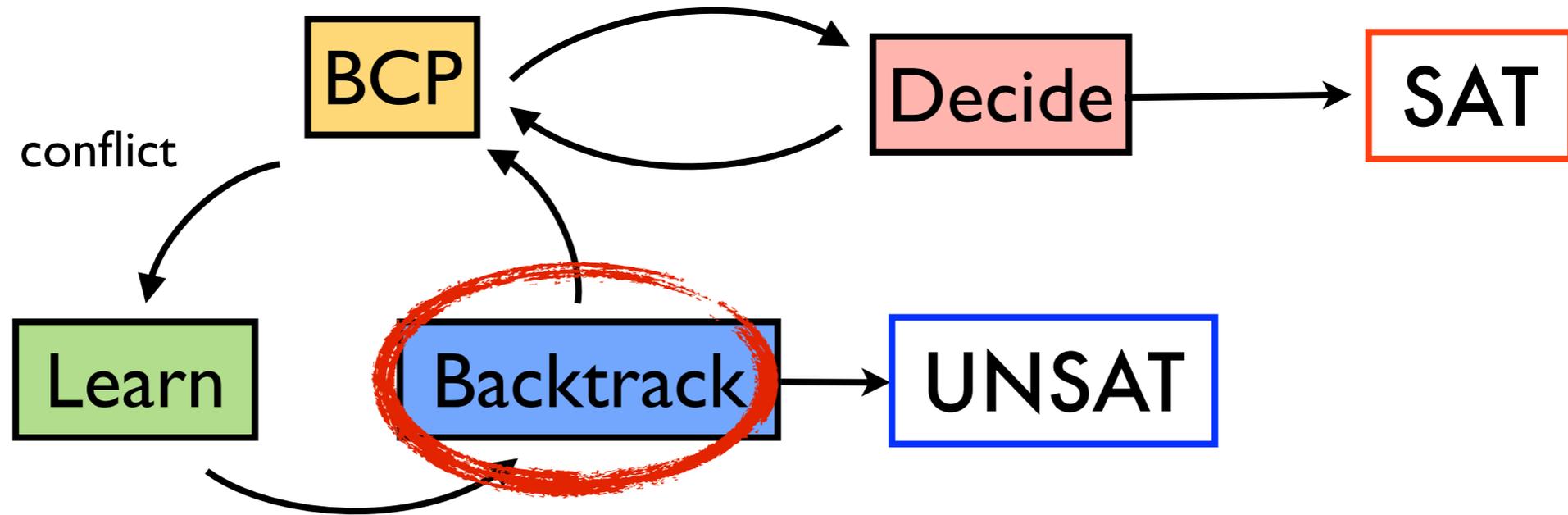


$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

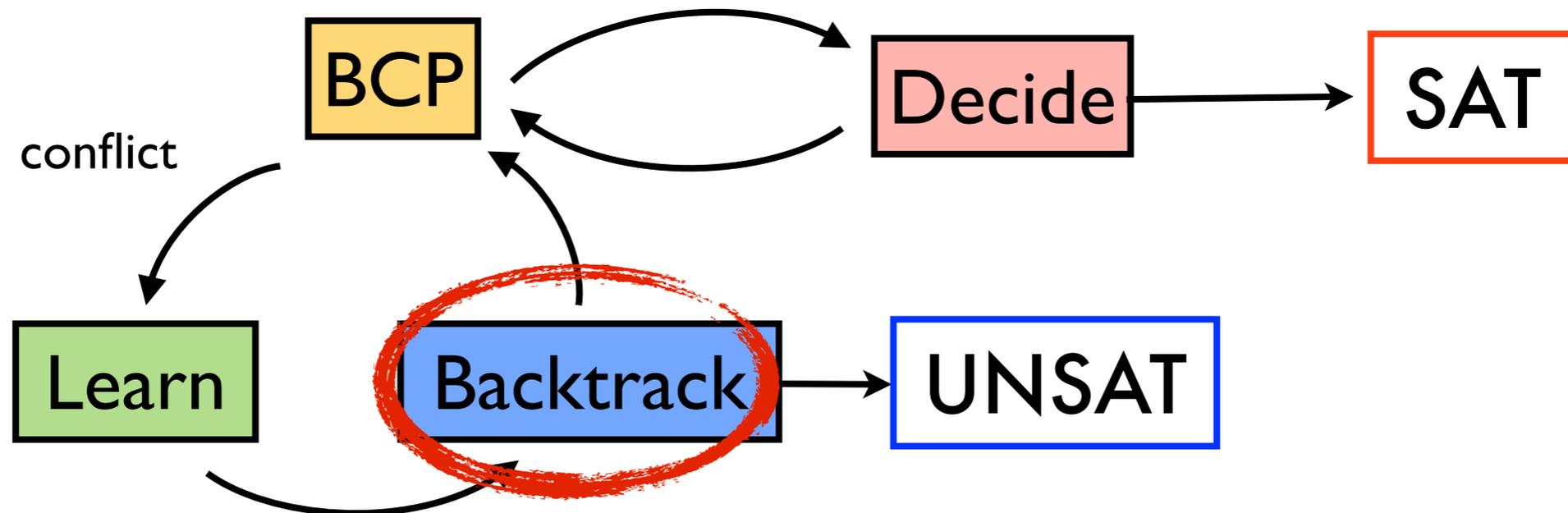




$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w) \quad q \vee r$$



$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w) \wedge (q \vee r)$$



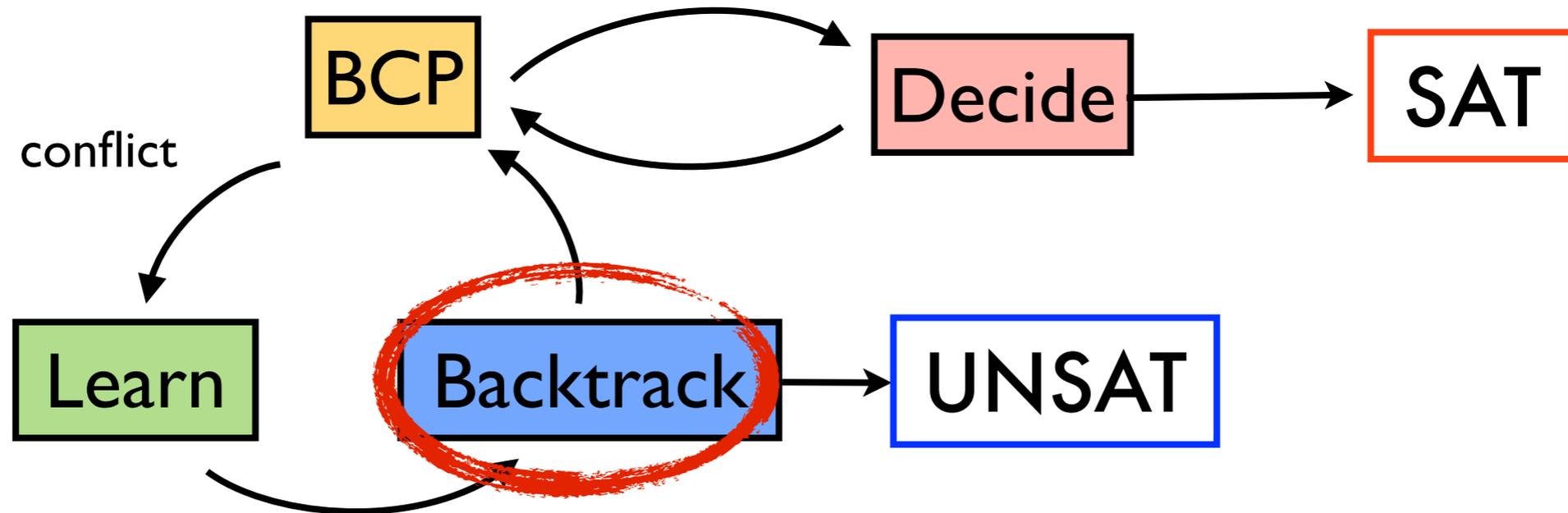
$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w) \wedge (q \vee r)$$

$$p \mapsto \text{t}$$

$$q \mapsto \text{f}$$

$$r \mapsto \text{f}$$

$$w \mapsto \text{f}$$



$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w) \wedge (q \vee r)$$

$$p \mapsto \mathbf{t}$$

$$q \mapsto \mathbf{f}$$

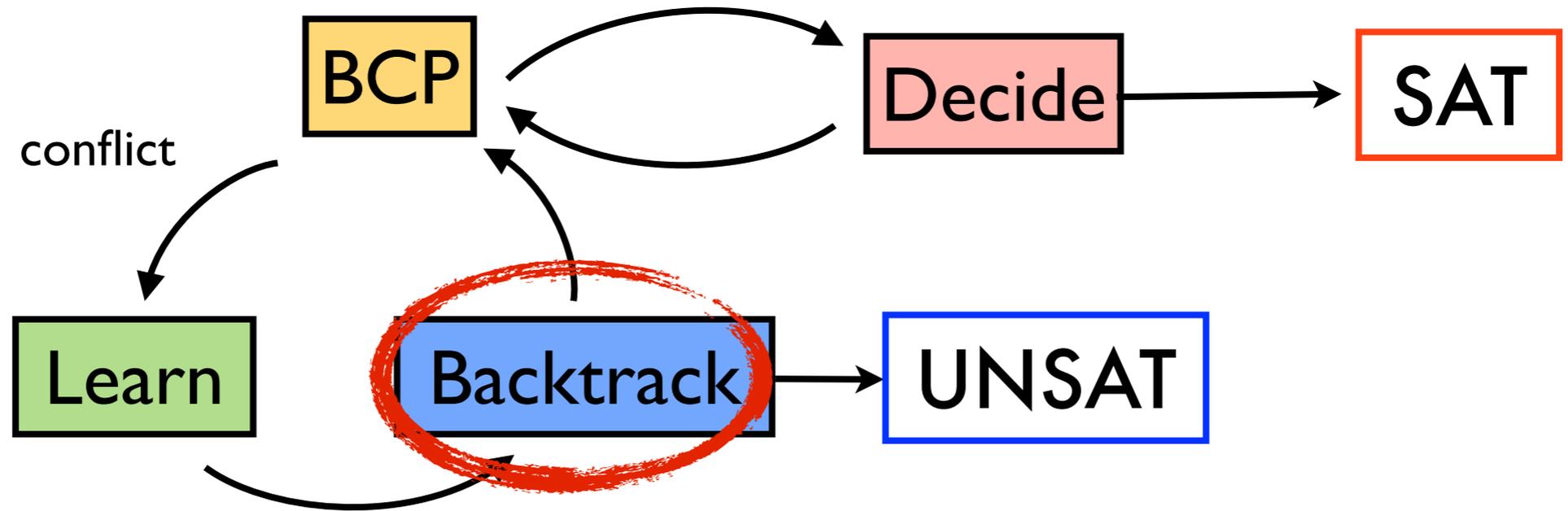
$$r \mapsto \mathbf{f}$$

$$w \mapsto \mathbf{f}$$

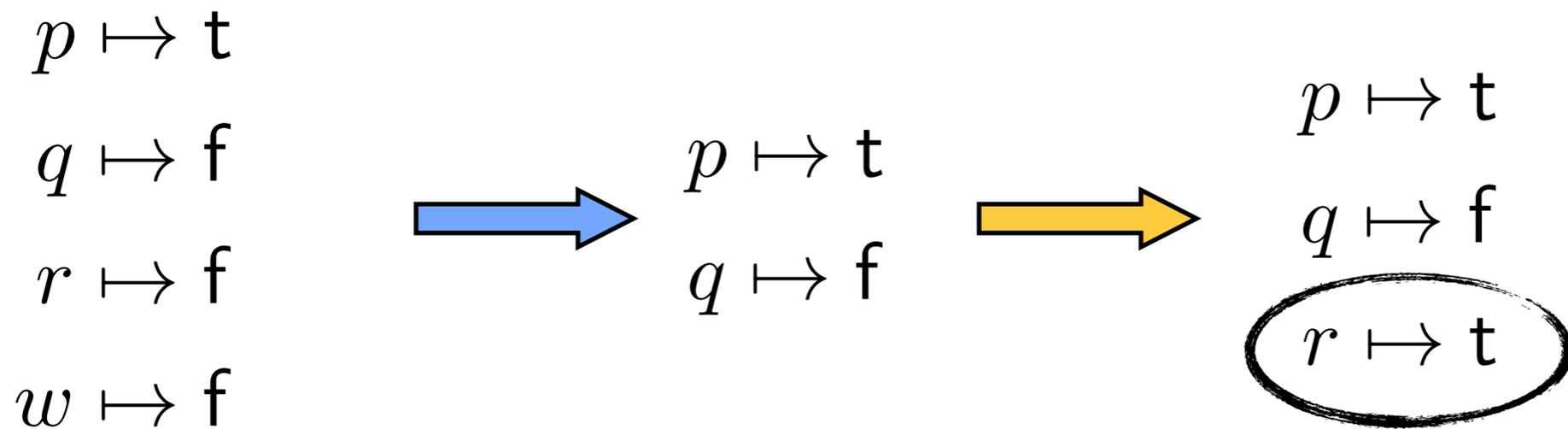


$$p \mapsto \mathbf{t}$$

$$q \mapsto \mathbf{f}$$



$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w) \wedge (q \vee r)$$



The CDCL Algorithm

One Line Summaries

BCP and decisions construct an assignment

Learning infers new clauses

Model theoretic search guides proof theoretic search

Important: CDCL is more than case splitting

Conflict Driven Clause Learning

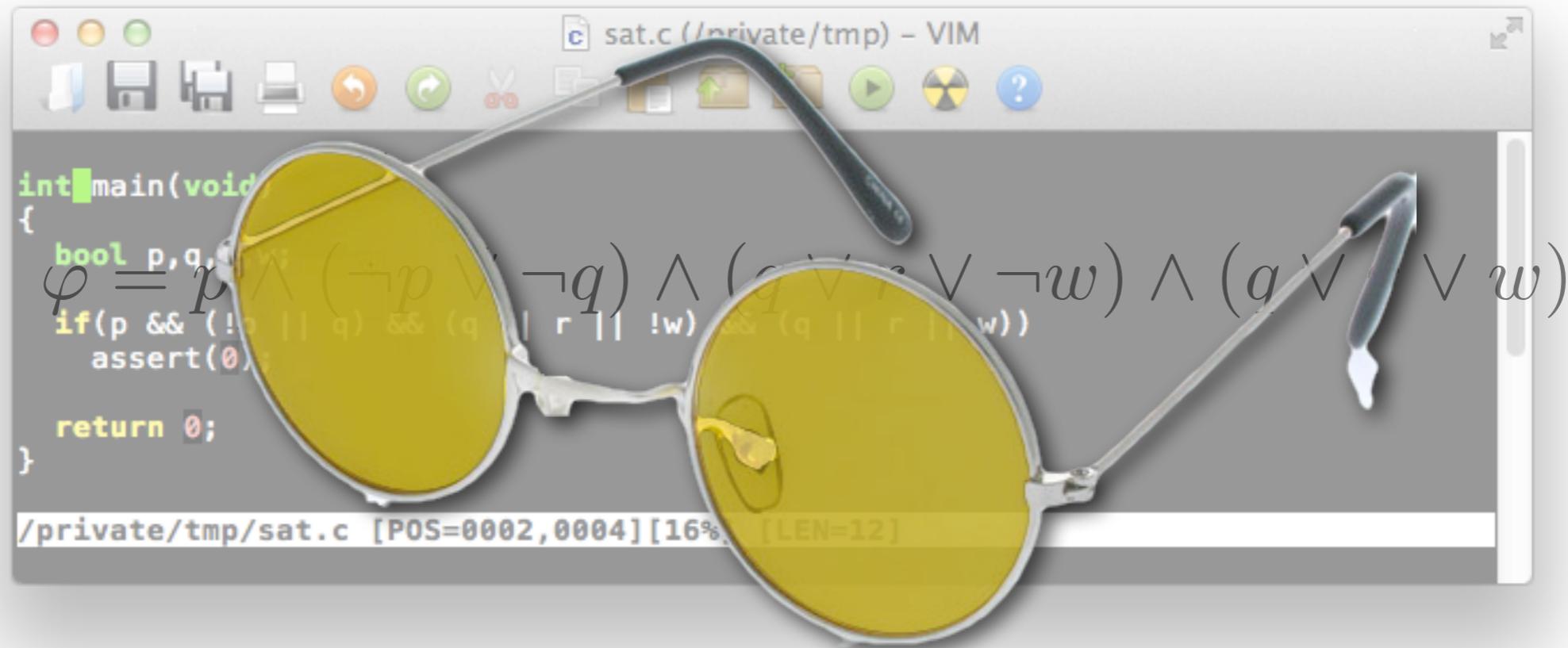
Interpreting Logic

CDCL is Abstract Interpretation

ACDCL(A)

$$\varphi = p \wedge (\neg p \vee \neg q) \wedge (q \vee r \vee \neg w) \wedge (q \vee r \vee w)$$

Imagine no assignments,
it's easy if you try



Imagine only Booleans,
I wonder if you can

sat.c (/private/tmp) - VIM

```
int main(void)
{
    bool p,q,r,w;

    if(p && (!p || q) && (q || r || !w) && (q || r || w))
        assert(0);

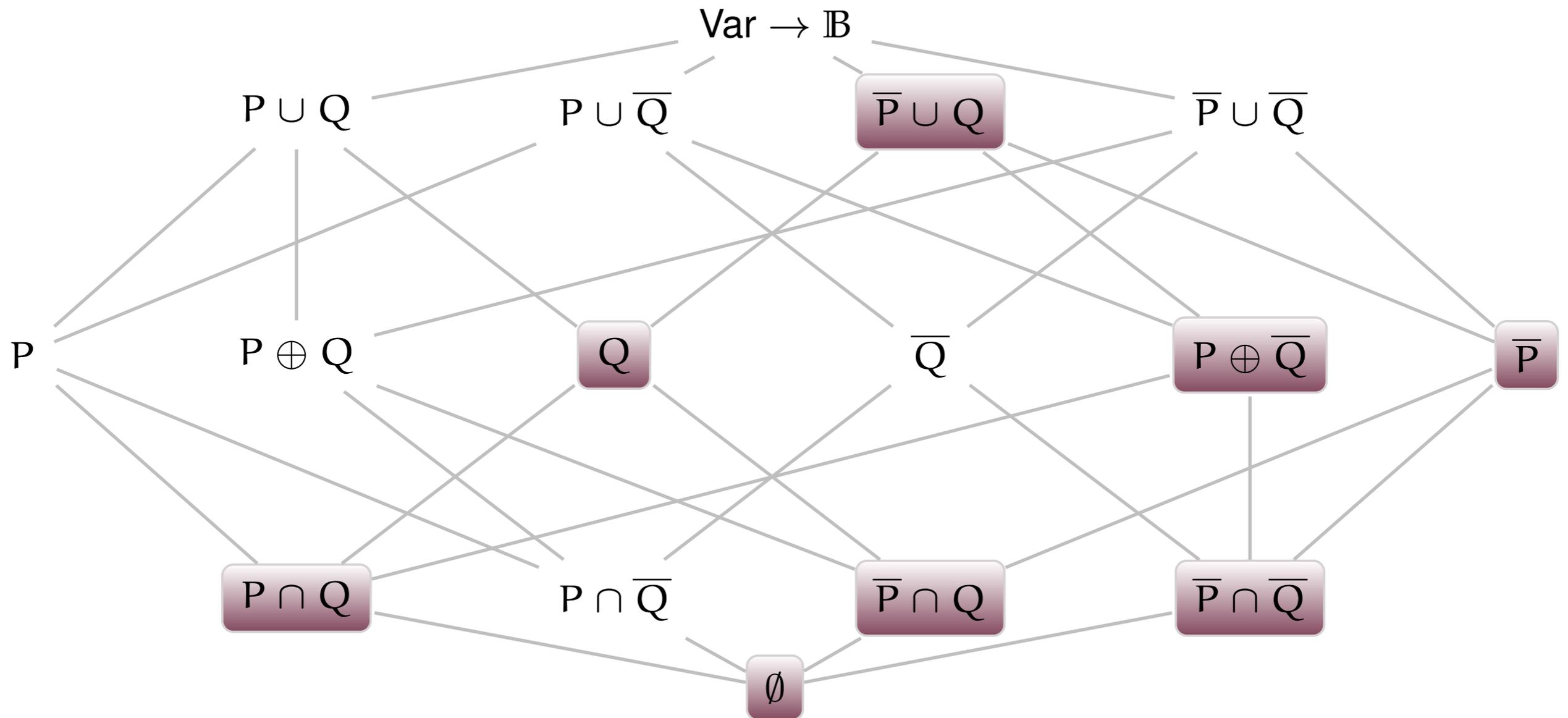
    return 0;
}
```

/private/tmp/sat.c [POS=0002,0004] [16%] [LEN=12]

Concrete Interpretation

$$P = \{\langle p \mapsto t, q \mapsto t \rangle, \langle p \mapsto t, q \mapsto f \rangle\}$$

$$Q = \{\langle p \mapsto t, q \mapsto t \rangle, \langle p \mapsto f, q \mapsto t \rangle\}$$



Shaded: Strongest post-condition for $\text{assume}(!p \parallel q)$

Satisfiability as Concrete Analysis

$$C = \langle \wp(V \rightarrow \mathbb{B}), \subseteq, \cap, \cup \rangle$$

$$\top = V \rightarrow \mathbb{B}$$

$$\perp = \emptyset$$

$$post_{\varphi}(X) = \{\varepsilon \in X \mid \varepsilon \text{ satisfies } \varphi\}$$

Concrete domain

All environments

No environment

Strongest post-condition

Concrete Satisfiability:

φ is satisfiable exactly if $post_{\varphi}(\top) \neq \emptyset$

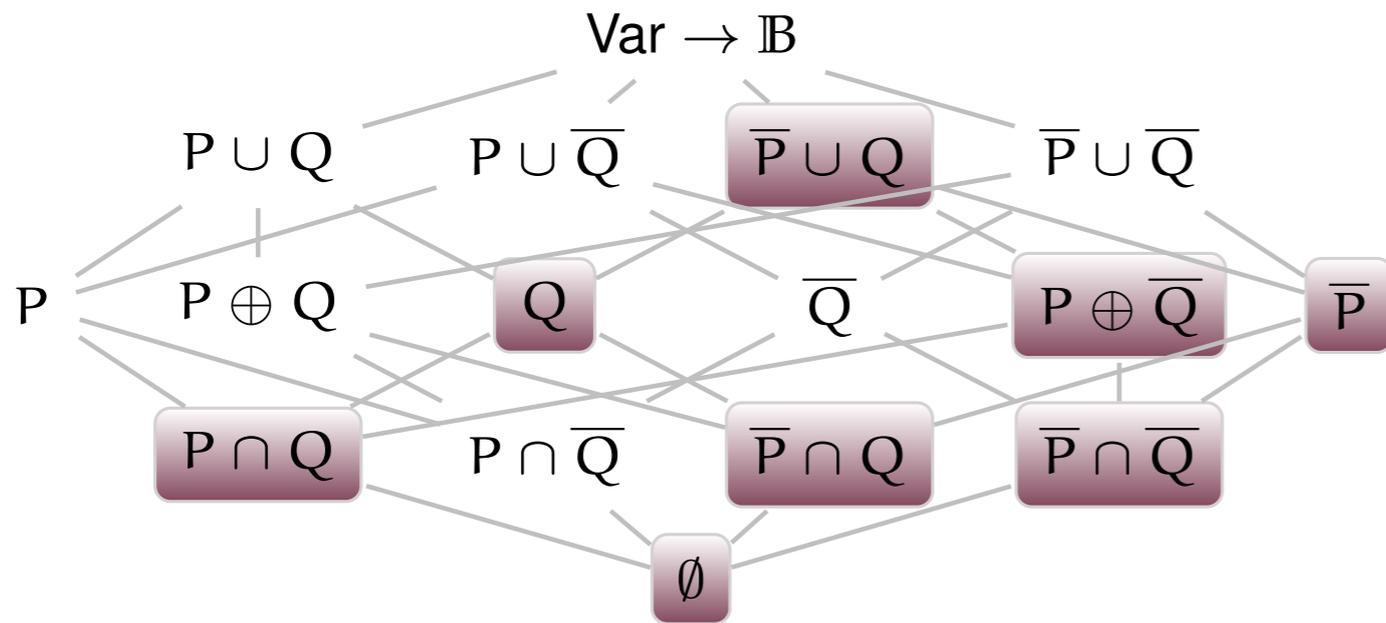
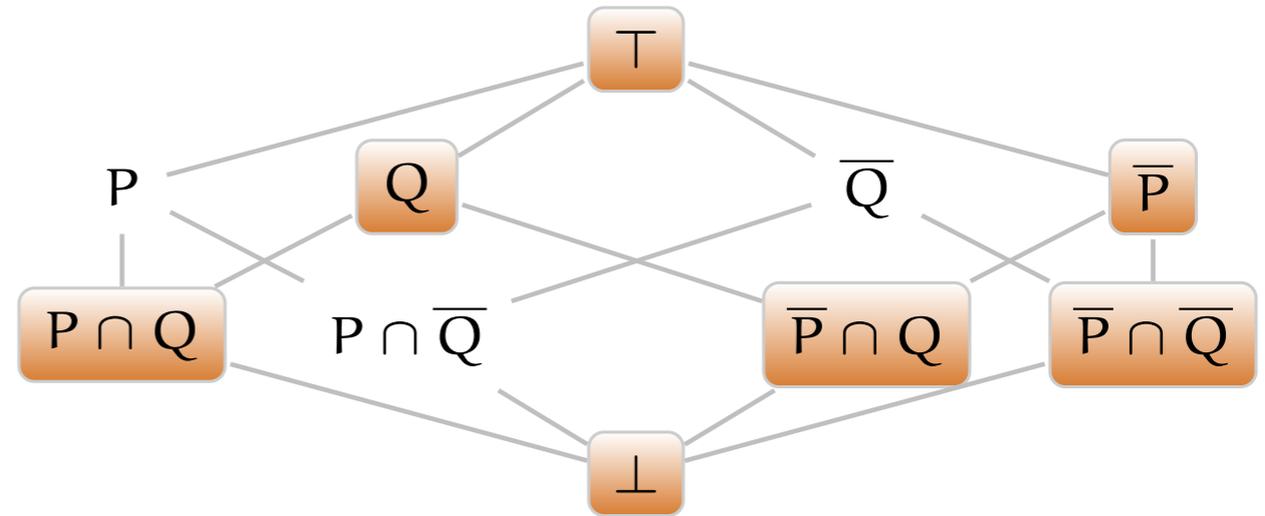
Cartesian Abstract Domain

$$\begin{array}{c} \wp(V \rightarrow \mathbb{B}) \\ \alpha \updownarrow \gamma \\ V \rightarrow \wp(\mathbb{B}) \end{array}$$

Concrete
Set of environments

Abstract
Environment of sets

Cartesian Abstract Domain



Shaded: Abstract strongest post-condition for `assume(!p || q)`

Cartesian Abstract Interpretation

$$C = \langle \wp(V \rightarrow \mathbb{B}), \subseteq, \cap, \cup \rangle$$

$$A = \langle V \rightarrow \wp(\mathbb{B}), \sqsubseteq, \sqcap, \sqcup \rangle$$

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

$$apost_{\varphi} = \alpha \circ post_{\varphi} \circ \gamma$$

Concrete domain

Abstract domain

Galois connection

Best abstract transformer

$$P = \{ \varepsilon \mid \varepsilon(p) = \mathbf{t} \}$$

$$\alpha(P) = \langle p \mapsto \{ \mathbf{t} \}, q \mapsto \mathbb{B} \rangle$$

$$post_{p \wedge q}(\overline{P}) = \emptyset$$

$$apost_{p \wedge q}(\alpha(\overline{P})) = \perp$$

$$post_{p \vee \neg q}(\overline{P}) = \{ \langle p \mapsto \mathbf{f}, q \mapsto \mathbf{f} \rangle \}$$

$$apost_{p \vee \neg q}(\alpha(\overline{P})) = \langle p \mapsto \{ \mathbf{f} \}, q \mapsto \{ \mathbf{f} \} \rangle$$

$$post_{p \text{ xor } q}(\top) = \{ \langle p \mapsto \mathbf{f}, q \mapsto \mathbf{t} \rangle$$

$$apost_{p \text{ xor } q}(\top) = \top$$

$$\langle p \mapsto \mathbf{t}, q \mapsto \mathbf{f} \rangle \}$$

Transformers are sound ...

Computing the best abstract transformer is SAT-hard

Use best abstract transformer only for literals

conjunction	meet
disjunction	join

If $apost_{\varphi} = \perp$ then φ is unsatisfiable.

(follows from the standard soundness theorem of abstract interpretation)

but they are not complete ...

... but not complete

Abbreviate $\langle p \mapsto \{t\}, q \mapsto \mathbb{B} \rangle$ as $\langle p \mapsto t \rangle$

$$\varphi = p \wedge (\neg p \vee q)$$

$$apost_{\varphi}(\top) = apost_p(\top) \sqcap (apost_{\neg p}(\top) \sqcup apost_q(\top))$$

$$= \langle p \mapsto t \rangle \sqcap (\langle p \mapsto f \rangle \sqcup \langle q \mapsto t \rangle)$$

$$= \langle p \mapsto t \rangle \sqcap \top$$

$$= \langle p \mapsto t \rangle$$

\neq

$$post_{\varphi}(\top) = \{ \langle p \mapsto t, q \mapsto f \rangle \}$$

Recovering Precision

Theorem (Cousot and Cousot 1979)

$$post(\gamma(a)) \subseteq \gamma(\mathbf{gfp}_x(apost(x \sqcap a))) \subseteq \gamma(apost(a))$$

$$\varphi = p \wedge (\neg p \vee q)$$

$$\begin{aligned} apost_{\varphi}(\top) &= apost_p(\top) \sqcap (apost_{\neg p}(\top) \sqcup apost_q(\top)) \\ &= \langle p \mapsto \mathbf{t} \rangle \end{aligned}$$

$$\begin{aligned} apost_{\varphi}(\langle p \mapsto \mathbf{t} \rangle) &= apost_p(\langle p \mapsto \mathbf{t} \rangle) \sqcap (apost_{\neg p}(\langle p \mapsto \mathbf{t} \rangle) \sqcup apost_q(\langle p \mapsto \mathbf{t} \rangle)) \\ &= \langle p \mapsto \mathbf{t} \rangle \sqcap (\perp \sqcup \langle p \mapsto \mathbf{t}, q \mapsto \mathbf{t} \rangle) \\ &= \langle p \mapsto \mathbf{t} \rangle \sqcap \langle p \mapsto \mathbf{t}, q \mapsto \mathbf{t} \rangle \\ &= \langle p \mapsto \mathbf{t}, q \mapsto \mathbf{t} \rangle \end{aligned}$$

Interpreting Logic

One Line Summaries

Satisfying assignments are fixed points of the semantics

Cartesian abstract interpretation is sound but imprecise

gfp improves precision in the abstract

Conflict Driven Clause Learning

Interpreting Logic

CDCL is Abstract Interpretation

ACDCL(A)

A SAT solver and an abstract interpreter walk into a bar

```
#define l_True  (lbool (( uint8_t )0))
#define l_False (lbool (( uint8_t )1))
#define l_Undef (lbool (( uint8_t )2))

class lbool { [...] };

class Solver {
    [...]
    // FALSE means solver is in a conflicting state
    bool      okay      () const;
    vec<lbool> assigns; // The current assignments.
    // Enqueue a literal . Assumes value of literal is undefined.
    void      uncheckedEnqueue (Lit p, CRef from = CRef_Undef);
    // Perform unit propagation . Return possibly conflicting clause .
    CRef      propagate ();
};
```

MiniSAT 2.2.0

Partial assignments

A SAT solver uses partial assignments

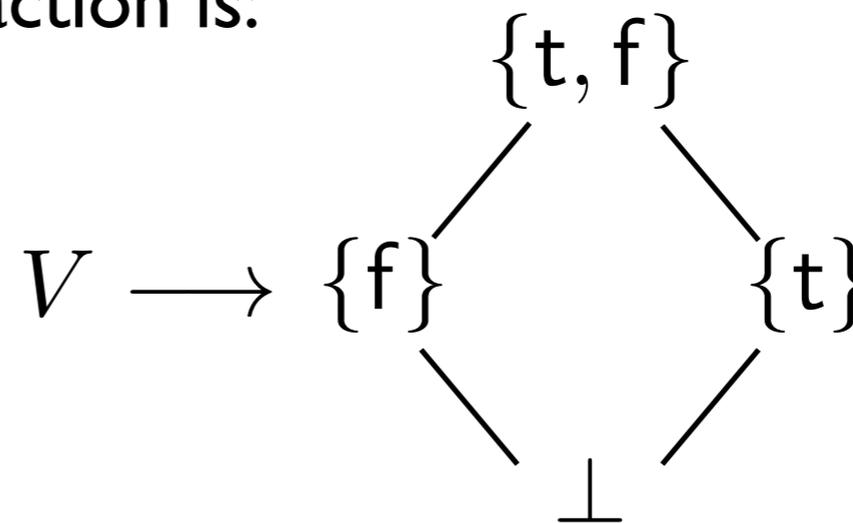
`l_Undef`

$V \longrightarrow$ `l_True`

`l_False`

\neg okay

An element of the Cartesian abstraction is:



Partial assignments are order isomorphic to the reduced Cartesian abstraction

Unit rule

assignment

Clause

$$\text{unit}(\pi, C) = \begin{cases} \text{conflict} & \text{if } \pi \text{ makes all literals in } C \text{ false} \\ \pi[p \mapsto \text{t}] & \text{if } \pi \text{ makes all literals in } C \text{ but } p \text{ false} \\ \pi & \text{otherwise} \end{cases}$$

Unit rule and abstract transformer

Order isomorphism

$$h(\text{unit}(\pi, C)) = \text{apost}_C(h(\pi))$$

The unit rule is the best abstract transformer

BCP

```
BCP( $\varphi, \pi$ ) {  
  repeat  
     $\pi' \leftarrow \pi$ ;  
    for Clause  $C \in \varphi$  do  $\pi \leftarrow \text{unit}(C, \pi')$   
  until  $\pi' = \pi$ ;  
}
```

Theorem: BCP as fixed point

$$h(\text{BCP}(\varphi, \pi)) = \text{gfp}_x(\text{apost}_\varphi(h(\pi) \sqcap x))$$

BCP is a greatest fixed point

A SAT solver and an abstract interpreter walk into a bar

```
#define l_True  (lbool (( uint8_t )0))
#define l_False (lbool (( uint8_t )1))
#define l_Undef (lbool (( uint8_t )2))

class lbool { [...] };

class Solver {
    [...]
    // FALSE means solver is in a conflicting state
    bool      okay      () const;
    vec<lbool> assigns; // The current assignments.
    // Enqueue a literal . Assumes value of literal is undefined.
    void      uncheckedEnqueue (Lit p, CRef from = CRef_Undef);
    // Perform unit propagation . Return possibly conflicting clause .
    CRef      propagate ();
};
```

MiniSAT 2.2.0

Another learning example

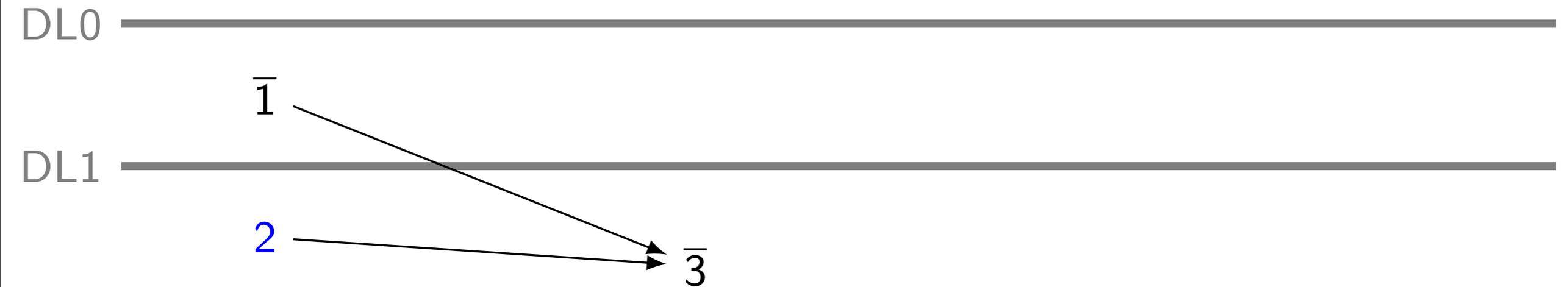
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$

DL0

$\bar{1}$

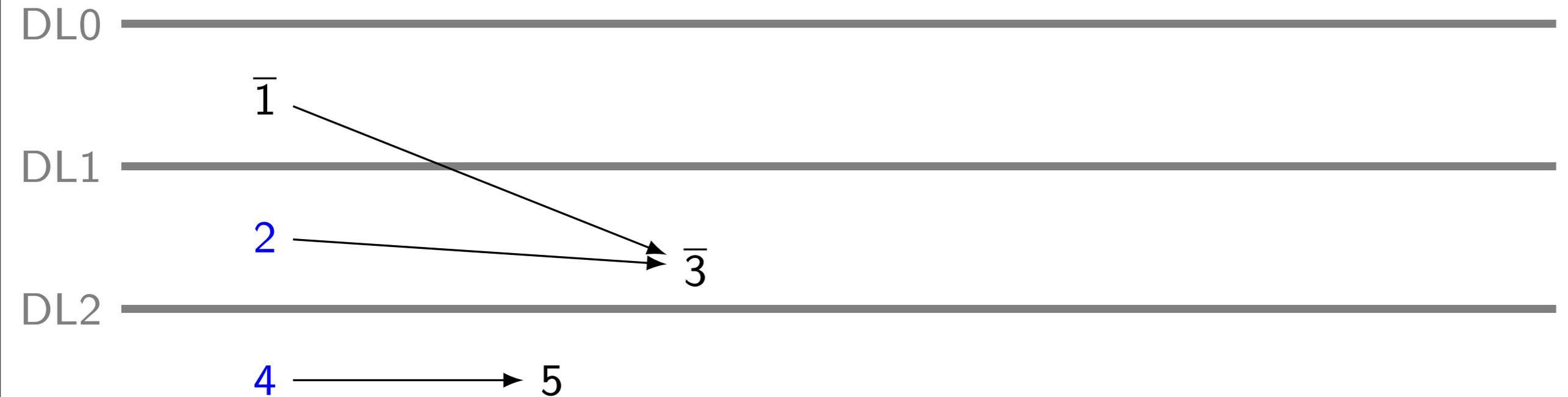
Another learning example

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



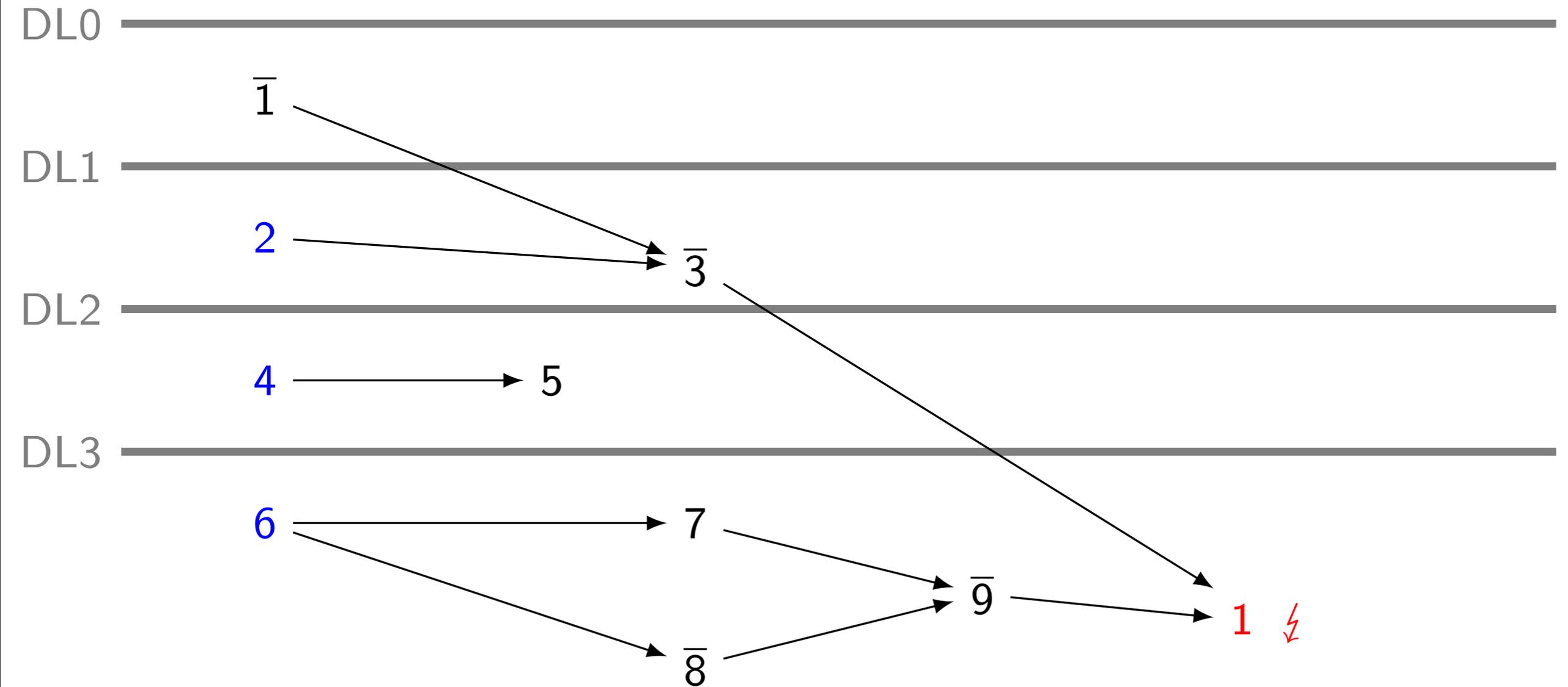
Another learning example

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



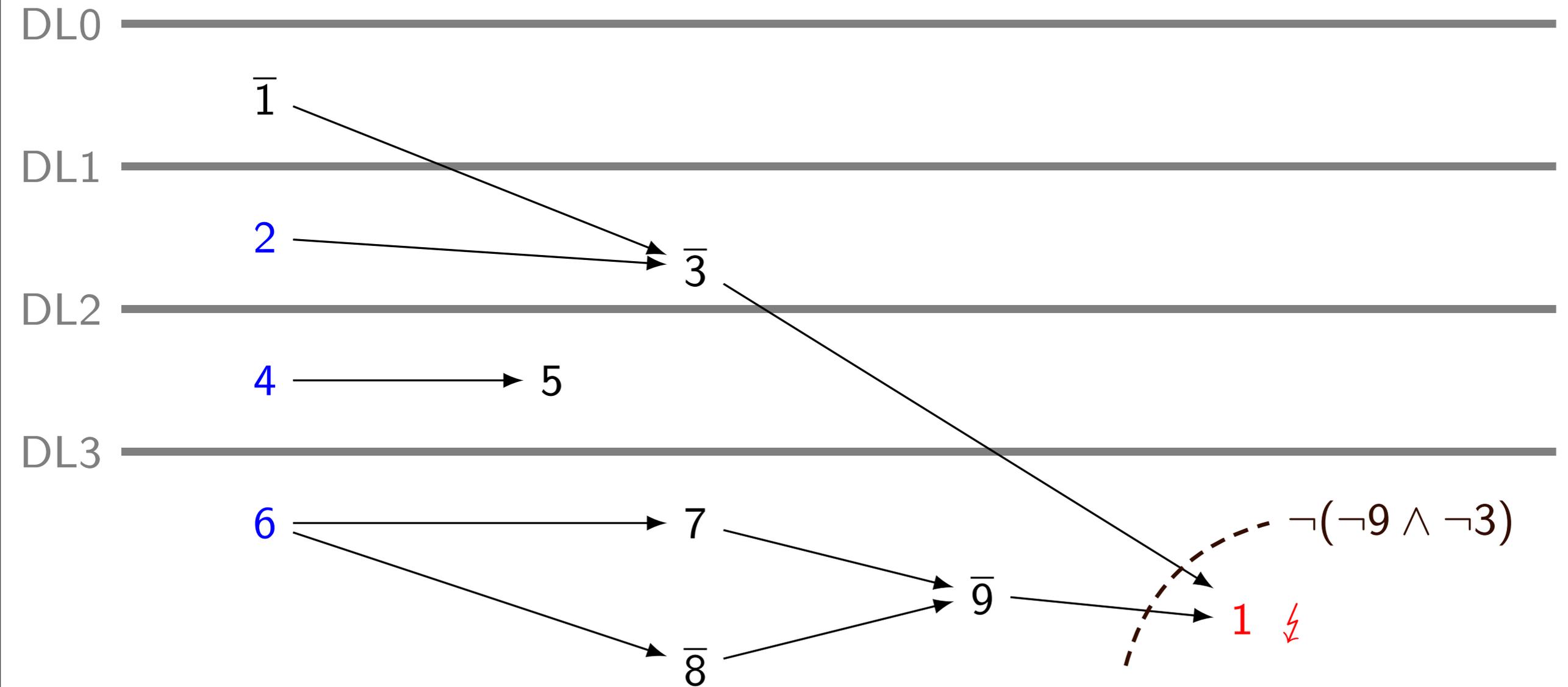
Another learning example

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



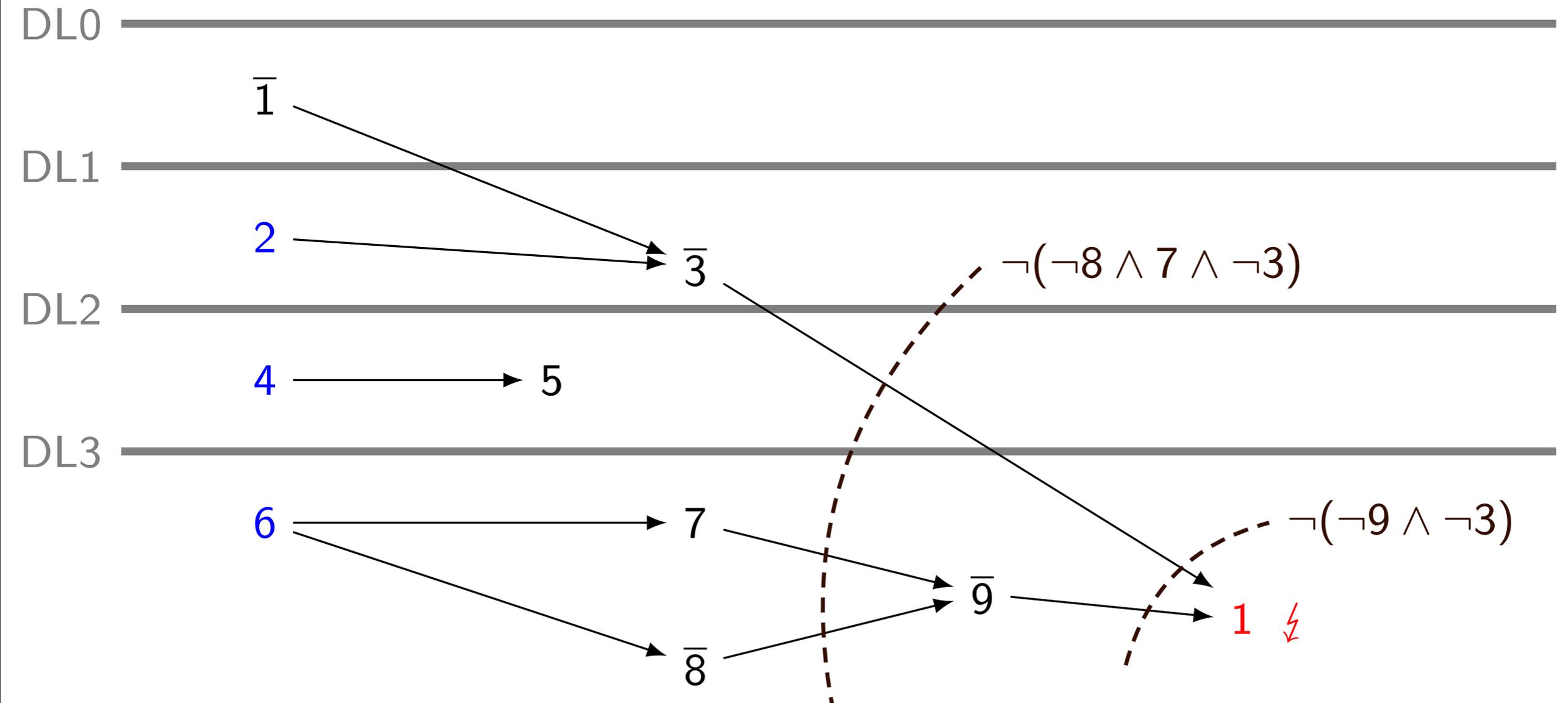
Another learning example

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



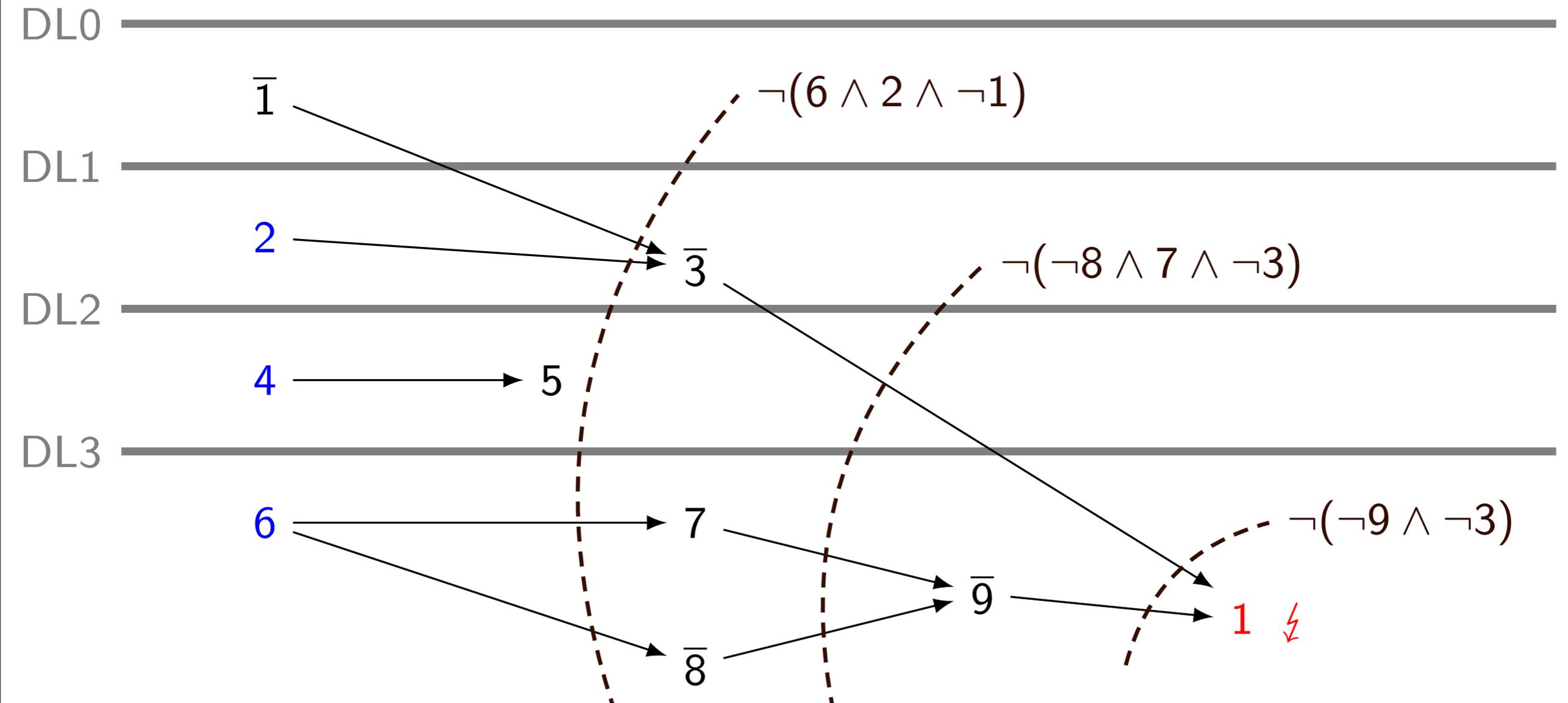
Another learning example

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



Another learning example

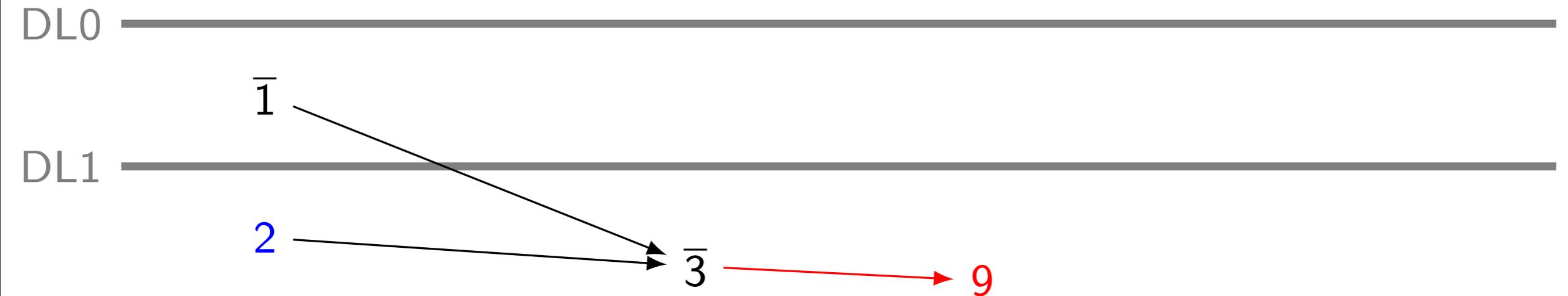
$$\neg 1 \wedge (1 \vee \neg 2 \vee \neg 3) \wedge (\neg 4 \vee 5) \wedge (\neg 6 \vee 7) \wedge (\neg 6 \vee \neg 8) \wedge (\neg 7 \vee 8 \vee \neg 9) \wedge (3 \vee 9 \vee 1)$$



Cuts = Heuristic underapproximation of the weakest precondition

Another learning example

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



Trace Partitioning

(Mauborgne and Rival, 2005)

```
int main(void)
{
  int x,y;
  x = y;
  if(x < 5)
    assert(y < 5);
  return 0;
}
```

Analysis too imprecise

Domain of Intervals:

$$V \rightarrow \mathbb{Z} \times \mathbb{Z}$$

Transform program

```
int main(void)
{
  int x,y;
  if(y < 5)
  {
    x = y;
    if(x < 5)
      assert(y < 5);
  }
  else
  {
    x = y;
    if(x < 5)
      assert(y < 5);
  }
  return 0;
}
```

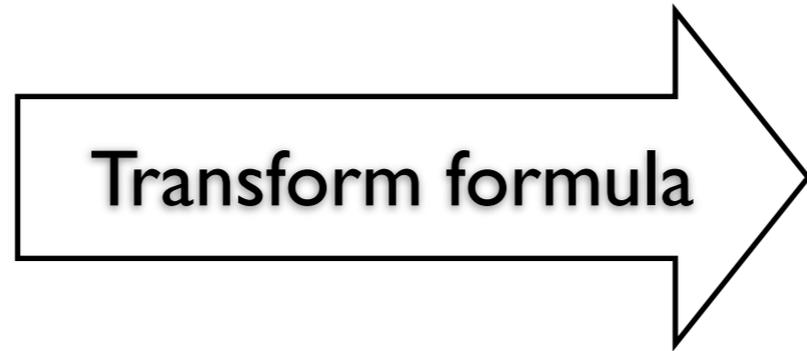
Same analysis is precise

Changing the equation allows one to prove more with the same analysis.

Instance of a power domain (Cousot and Cousot, 1979)

Learning in SAT

```
if( phi )  
  assert(0)
```



```
if( p = true && q = true )  
{  
  if( phi )  
    assert(0); Safe  
}  
else  
if( !p || !q )  
{  
  if( phi )  
    assert(0);  
}
```

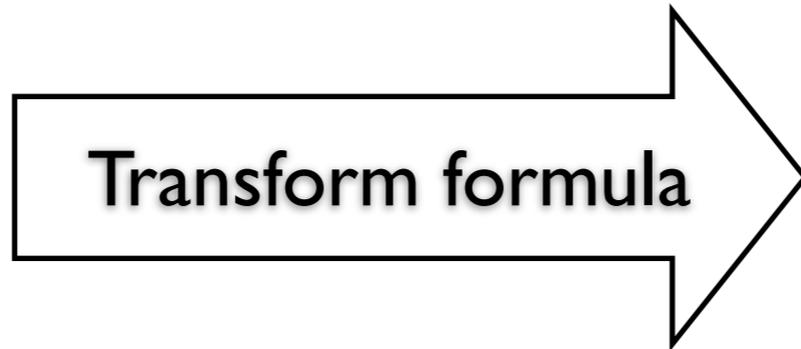
Conflict reason

Learned clause

Decisions and learning are dynamic “trace” partitioning

Learning in SAT

```
if( phi )  
  assert(0)
```



Conflict reason

```
if( p = true && q = true )  
{  
  if( phi )  
    assert(0); Safe  
}  
else  
if( !p || !q )  
{  
  if( phi )  
    assert(0);  
}
```

Learned clause

Decisions and learning are dynamic “trace” partitioning

CDCL is Abstract Interpretation

One Line Summaries

CDCL implements the Cartesian abstract domain as its main data structure

The unit rule is the application of the best abstract clause transformer

BCP is fixed point computation

Decisions & Learning are discovery of trace partitions

CDCL is Abstract Interpretation

Summary of Summaries

CDCL = Partial assignments = Cartesian abstract domain
+ Unit rule & BCP + Abstract transformer & GFP
+ Decisions & Learning + Trace partitioning

Not an ANALOGY but an ISOMORPHISM

Precise results using a strict abstraction!

Conflict Driven Clause Learning

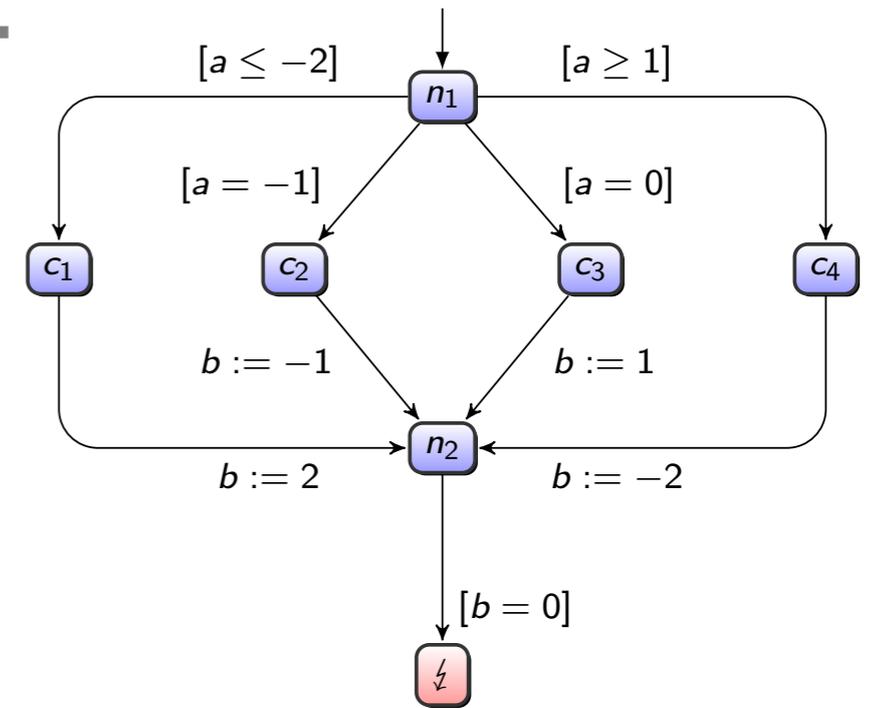
Interpreting Logic

CDCL is Abstract Interpretation

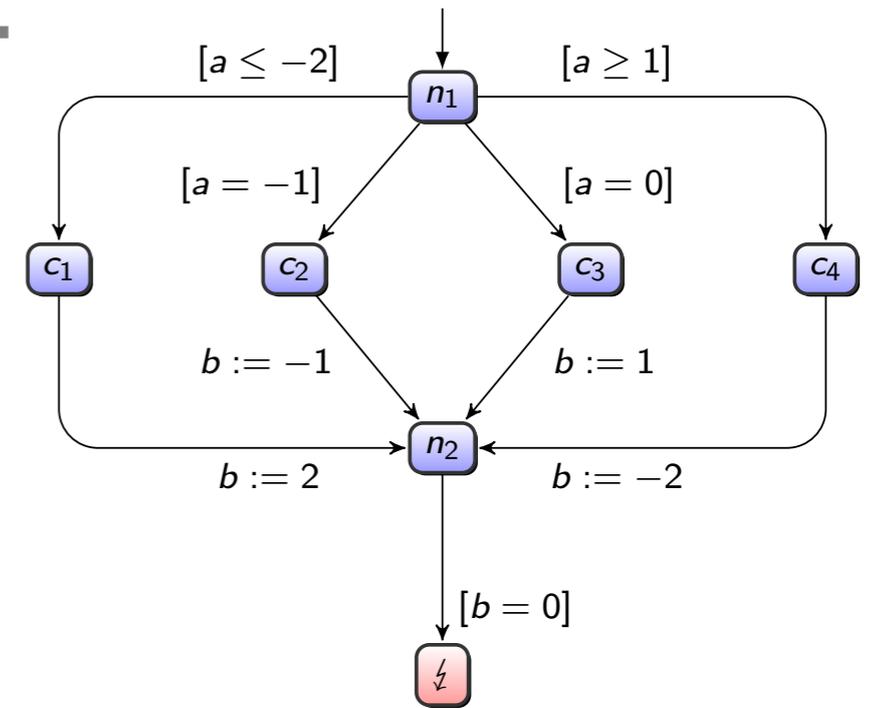
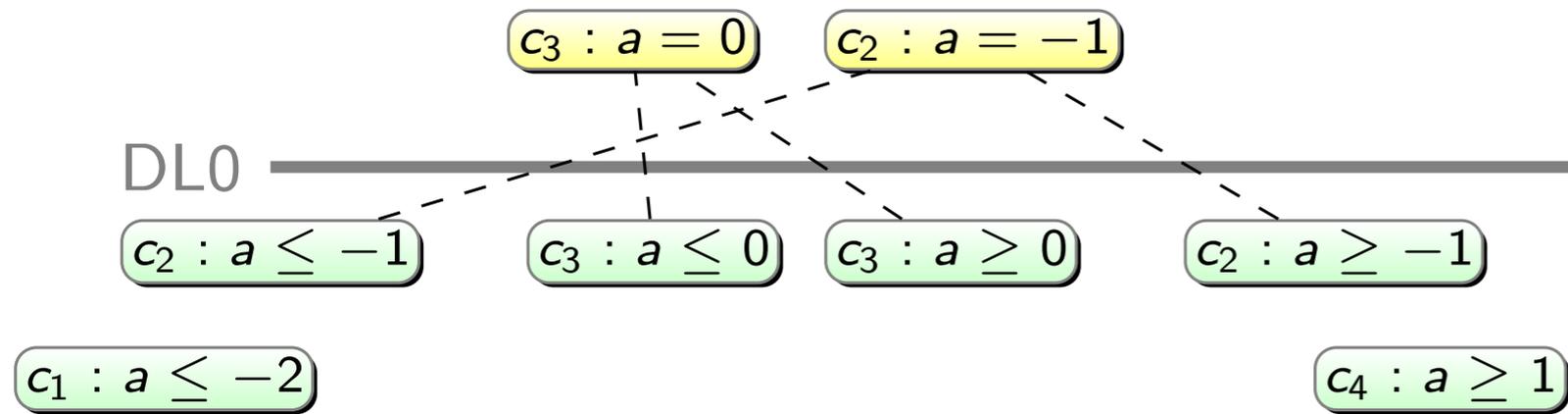
ACDCL(A)

What about programs?

DL0

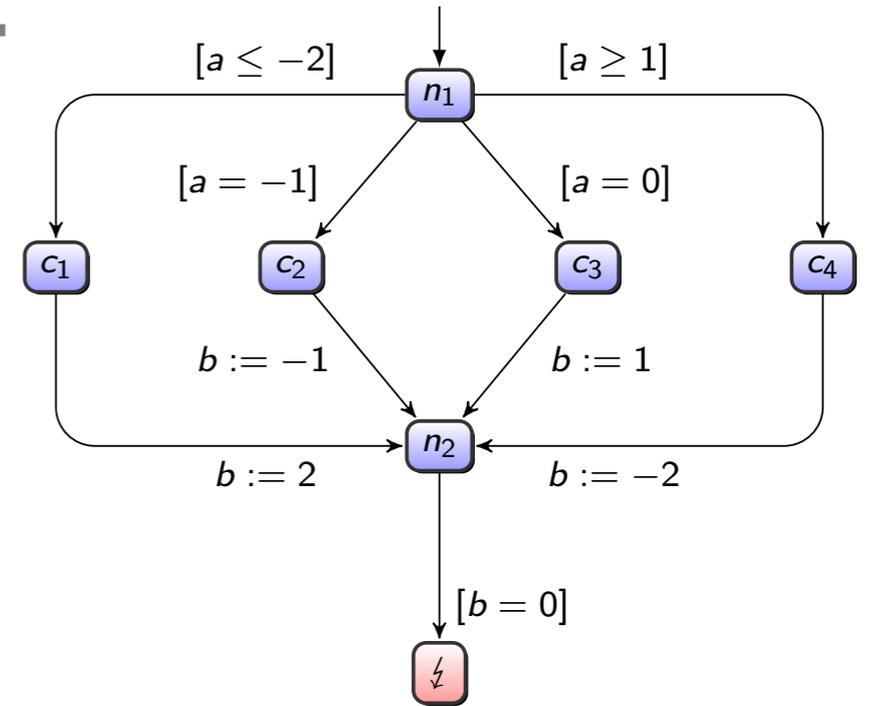
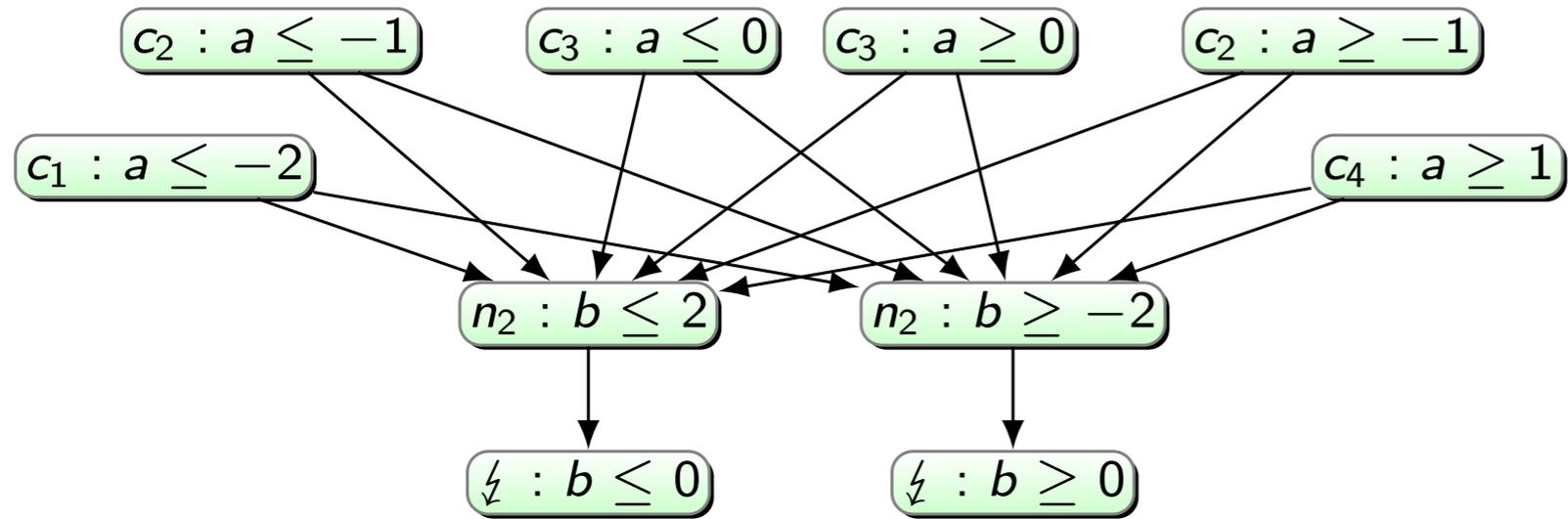


What about programs?



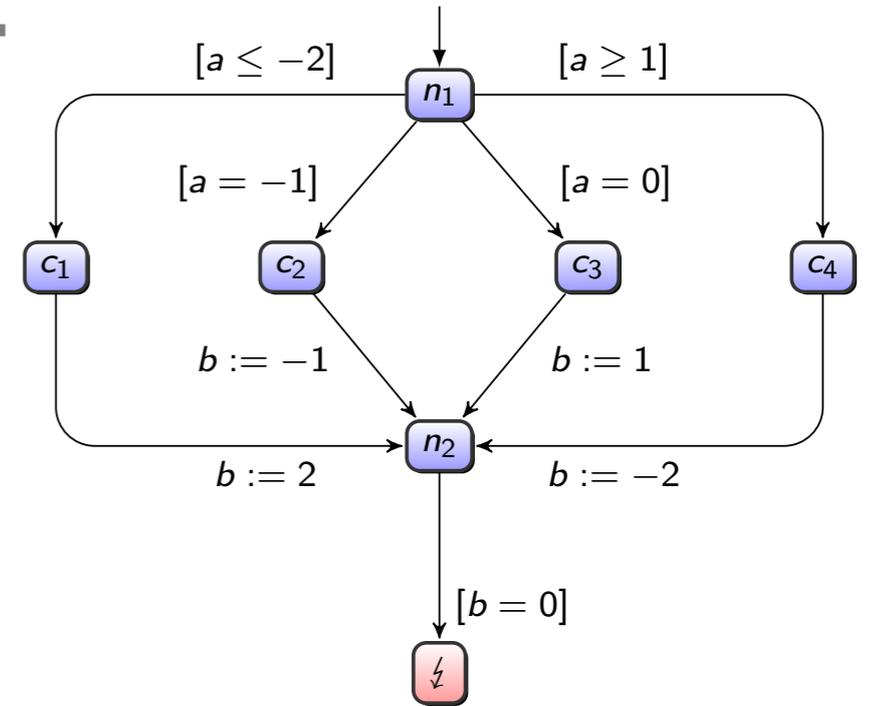
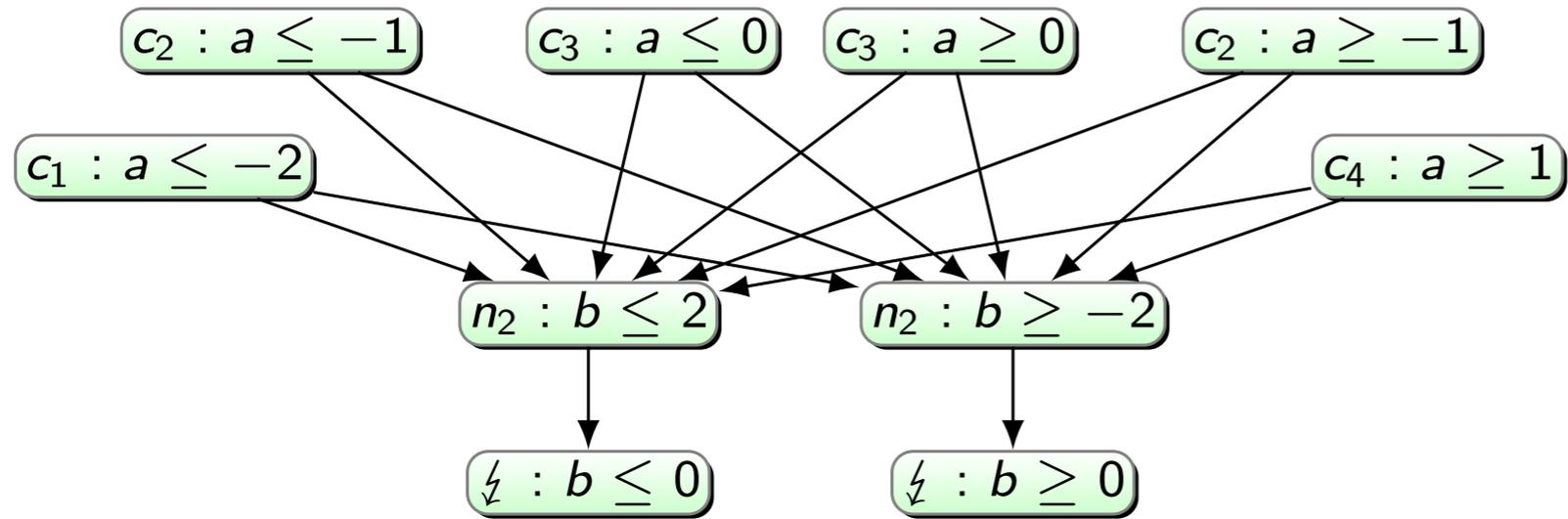
What about programs?

DL0



What about programs?

DL0

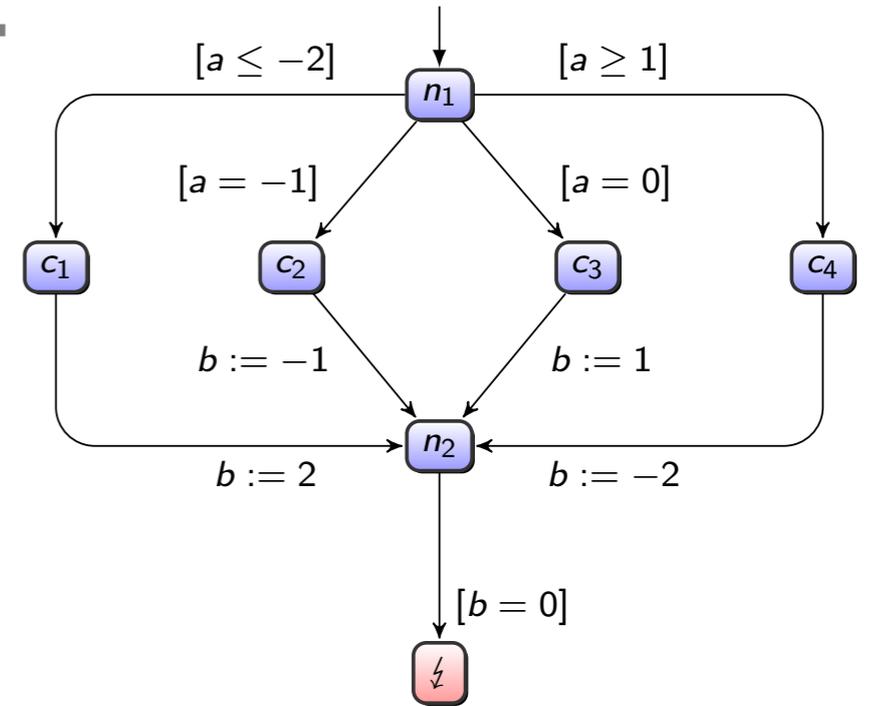
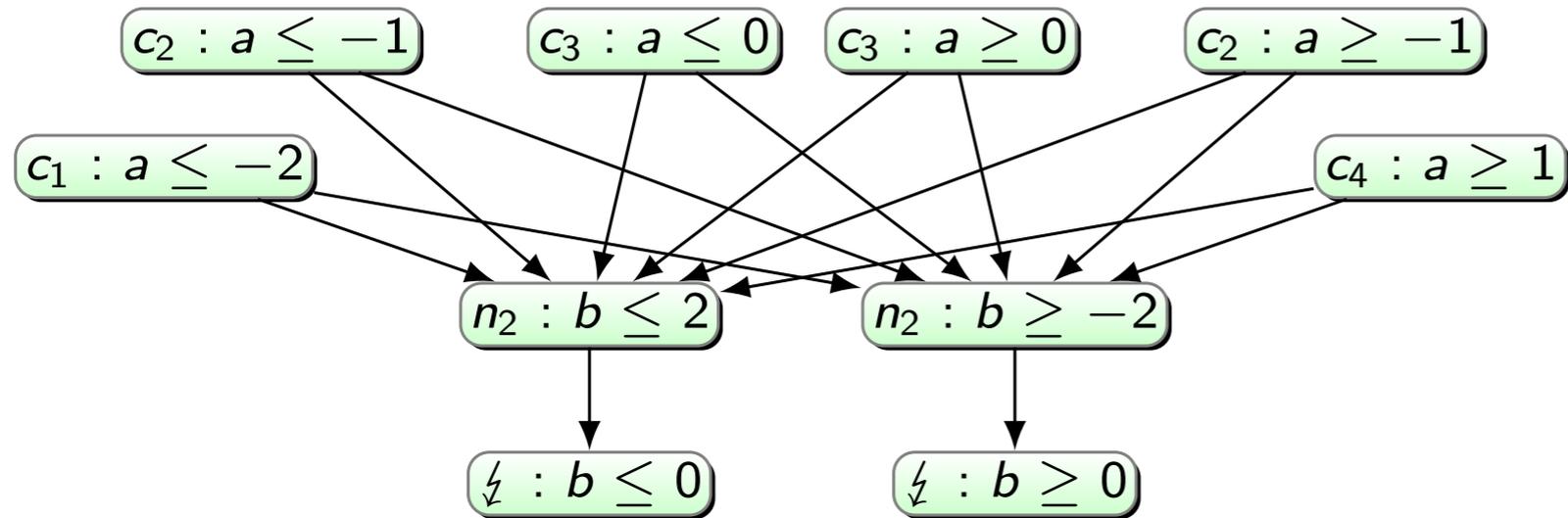


DL1

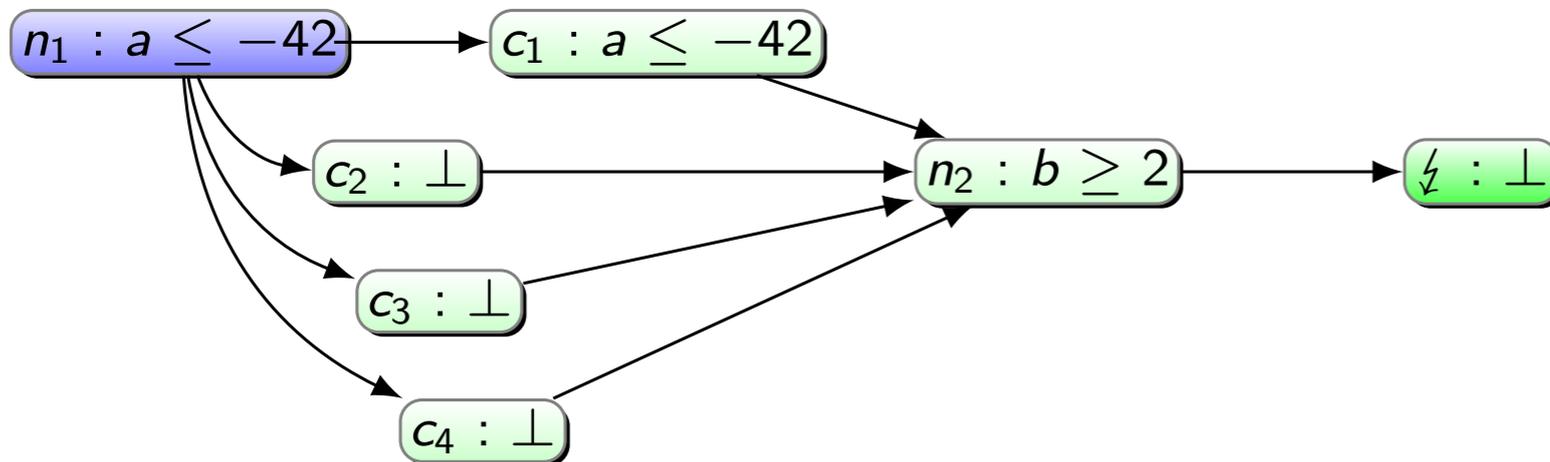
$n_1 : a \leq -42$

What about programs?

DL0



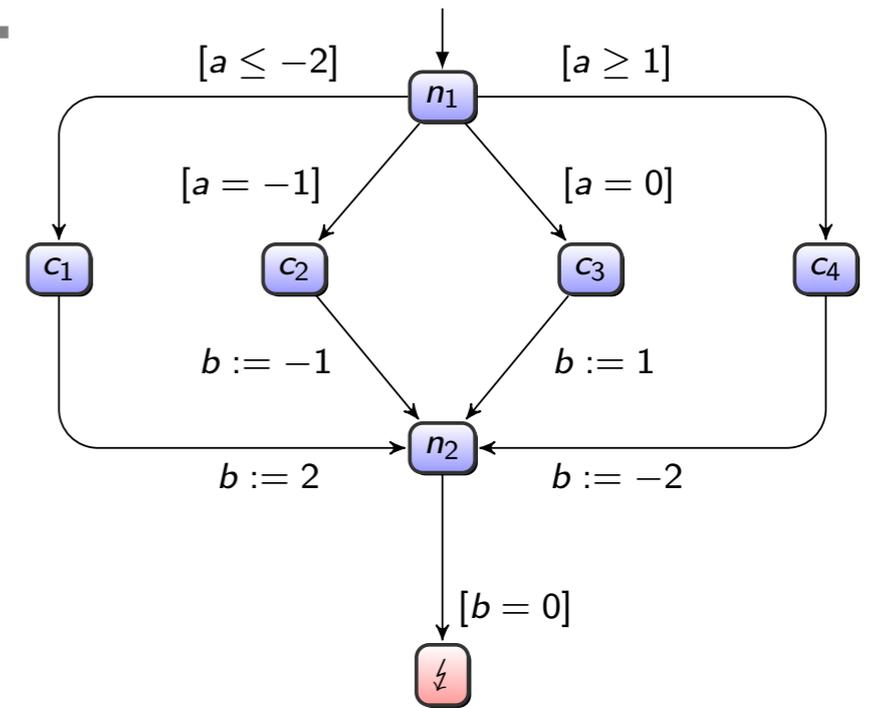
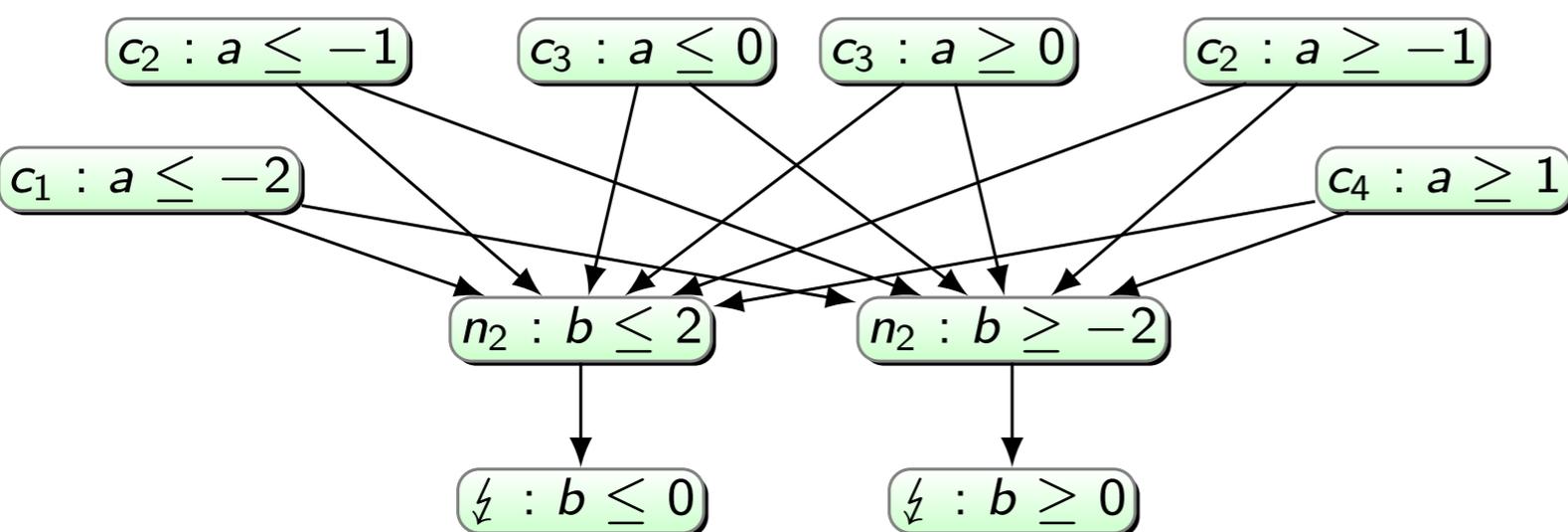
DL1



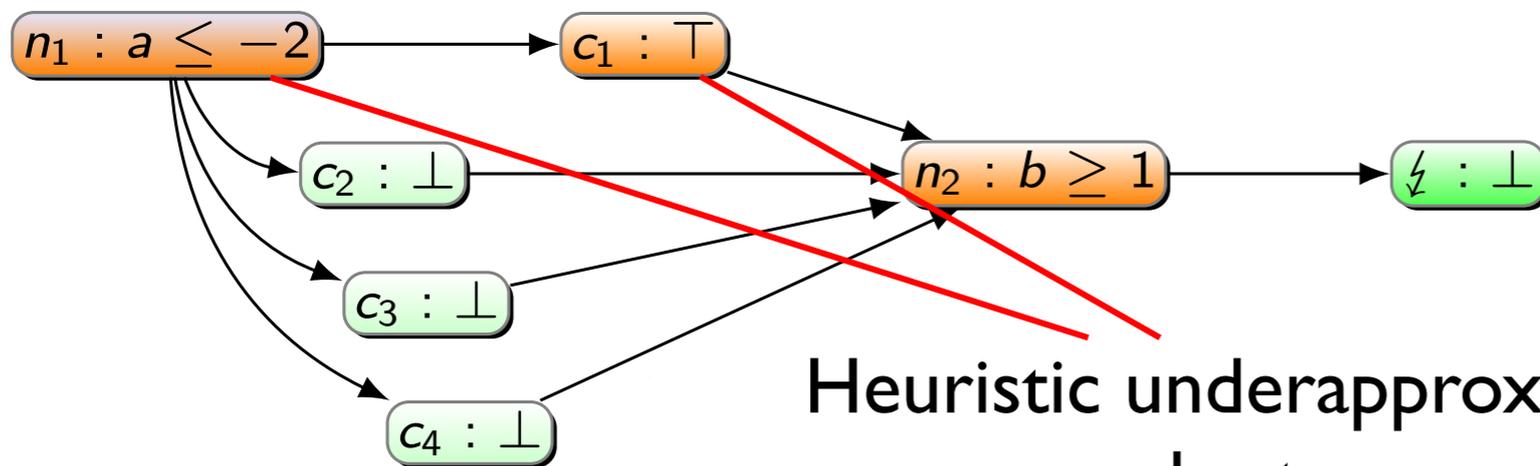
SAFE

What about programs?

DL0



DL1

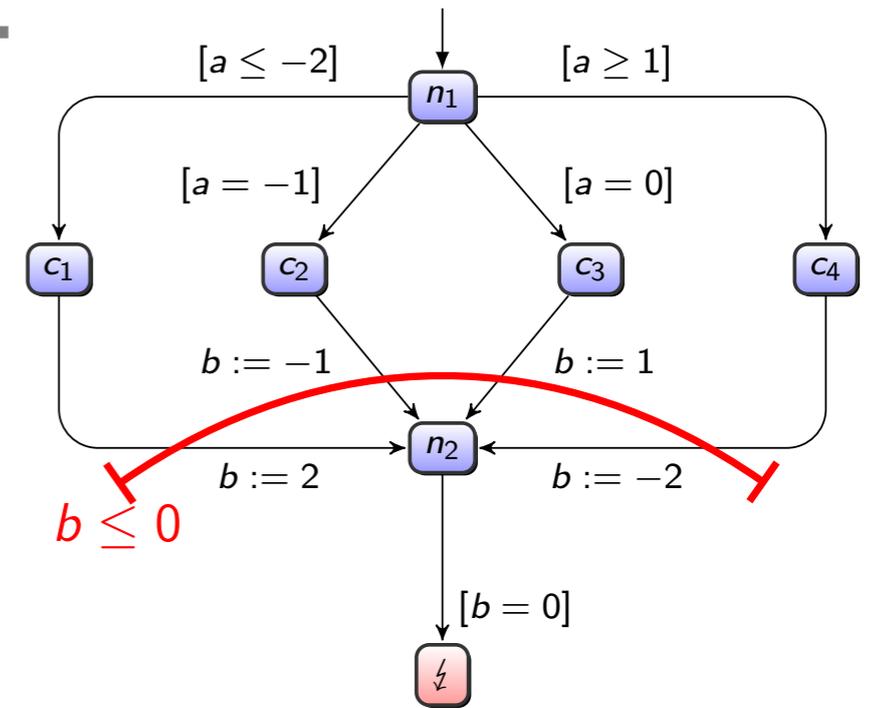
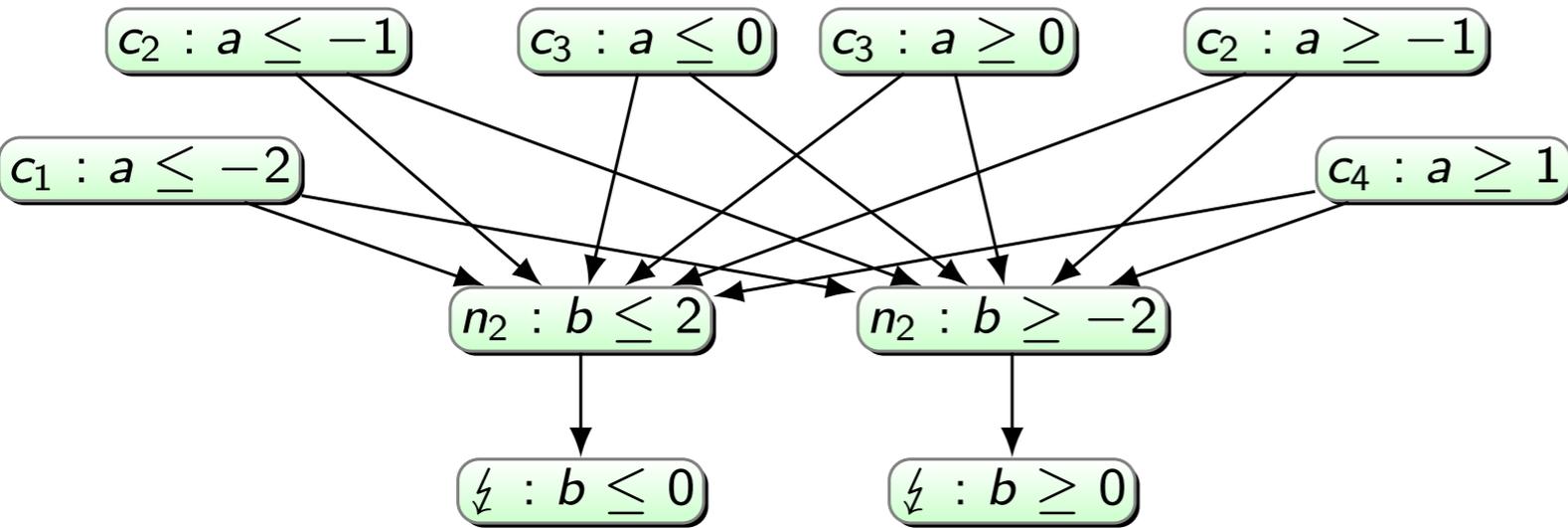


SAFE \rightarrow Generalise!

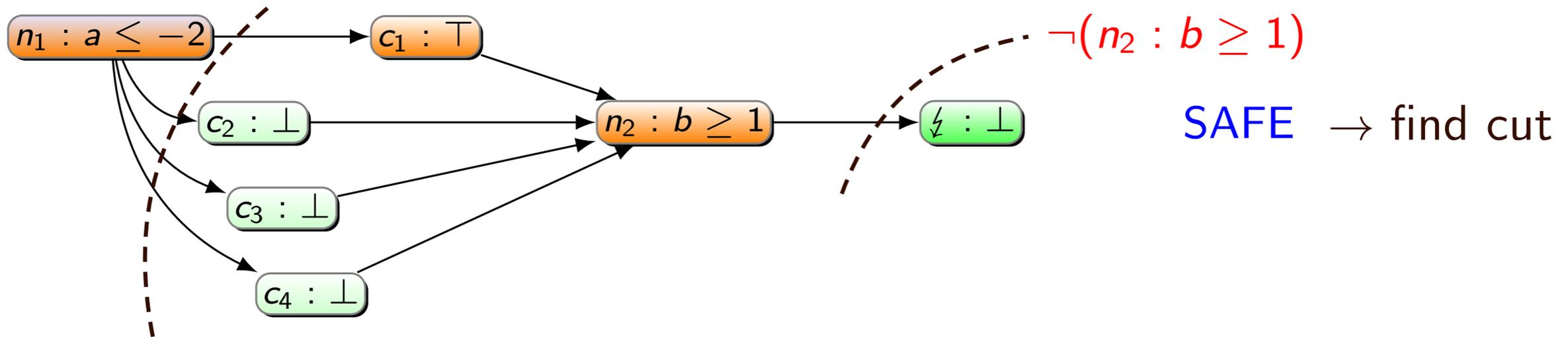
Heuristic underapproximation of the weakest pre-condition

What about programs?

DL0

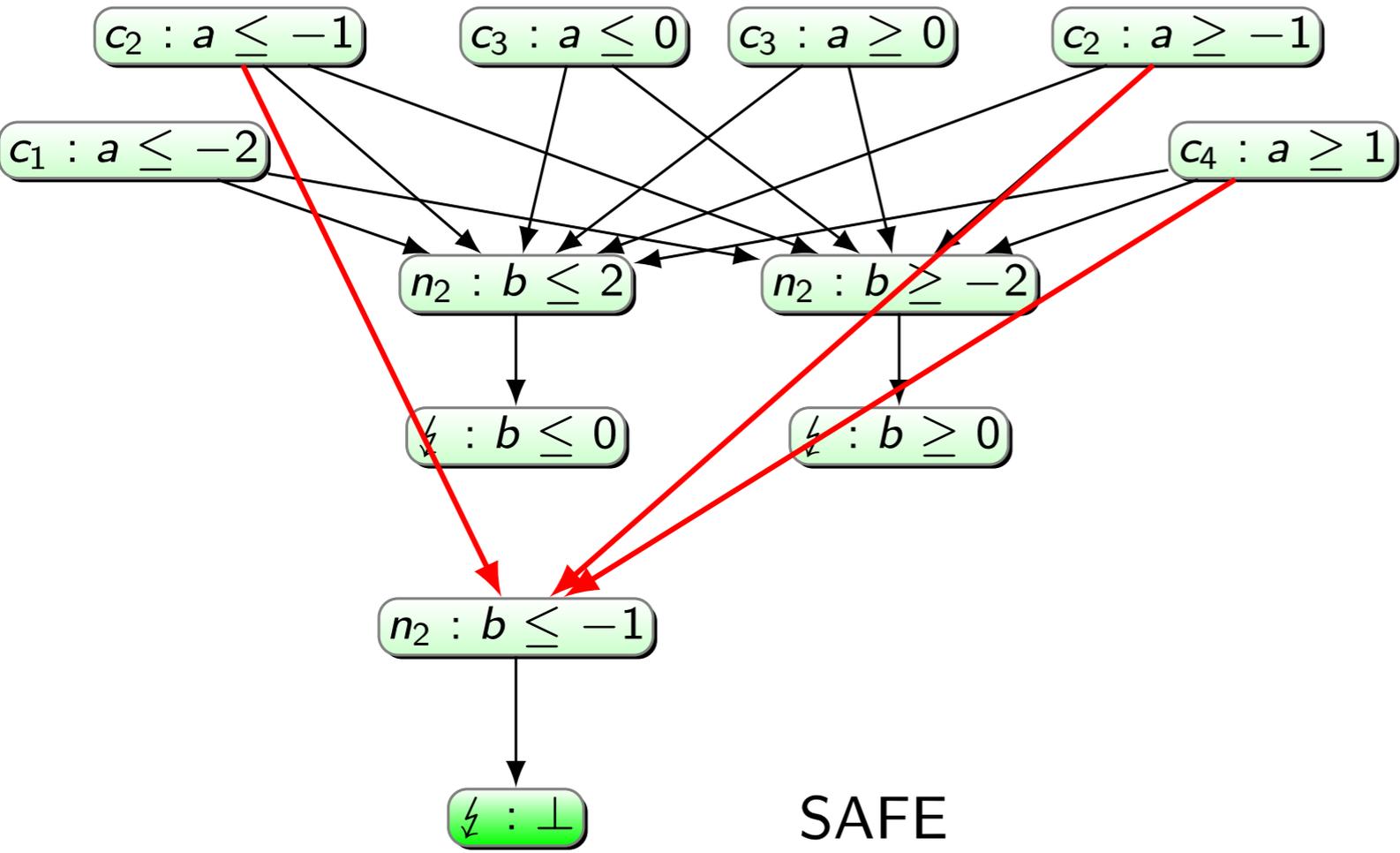


DL1

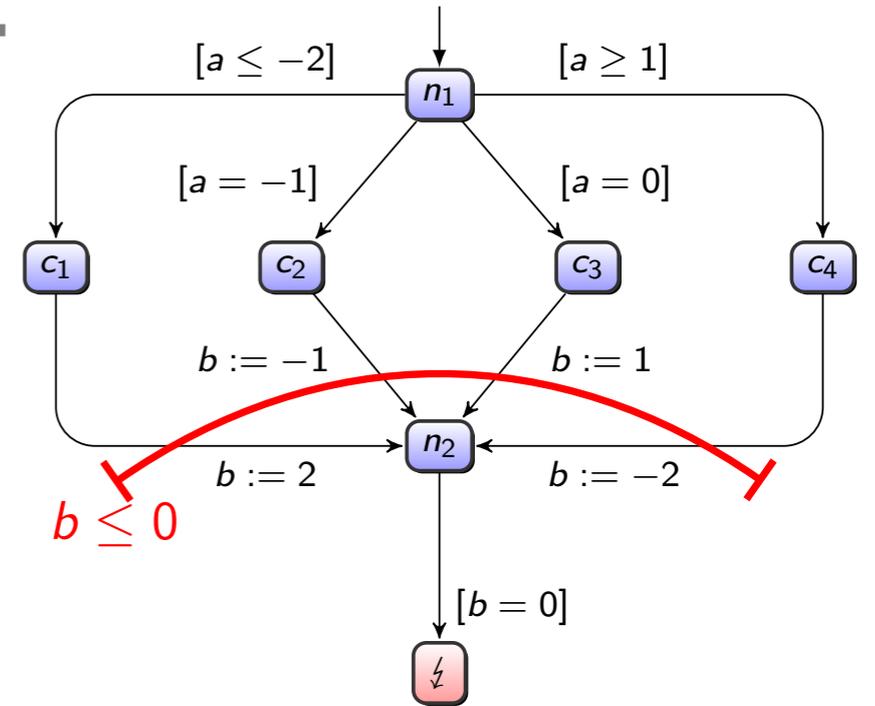


What about programs?

DL0



SAFE



ACDCL(A)

One Line Summaries

ACDCL(A) program analysers!

Techniques from SAT translate to programs

ACDCL(A) discovers small, property driven refinement

Something more practical

ACDCL(Interval) procedure over floating point and machine integer intervals

Automatically finds property-dependent partitioning

Example: Taylor expansion of sine-function

```
int main()
{
    float IN;
    __CPROVER_assume(IN > -HALFPI && IN < HALFPI);

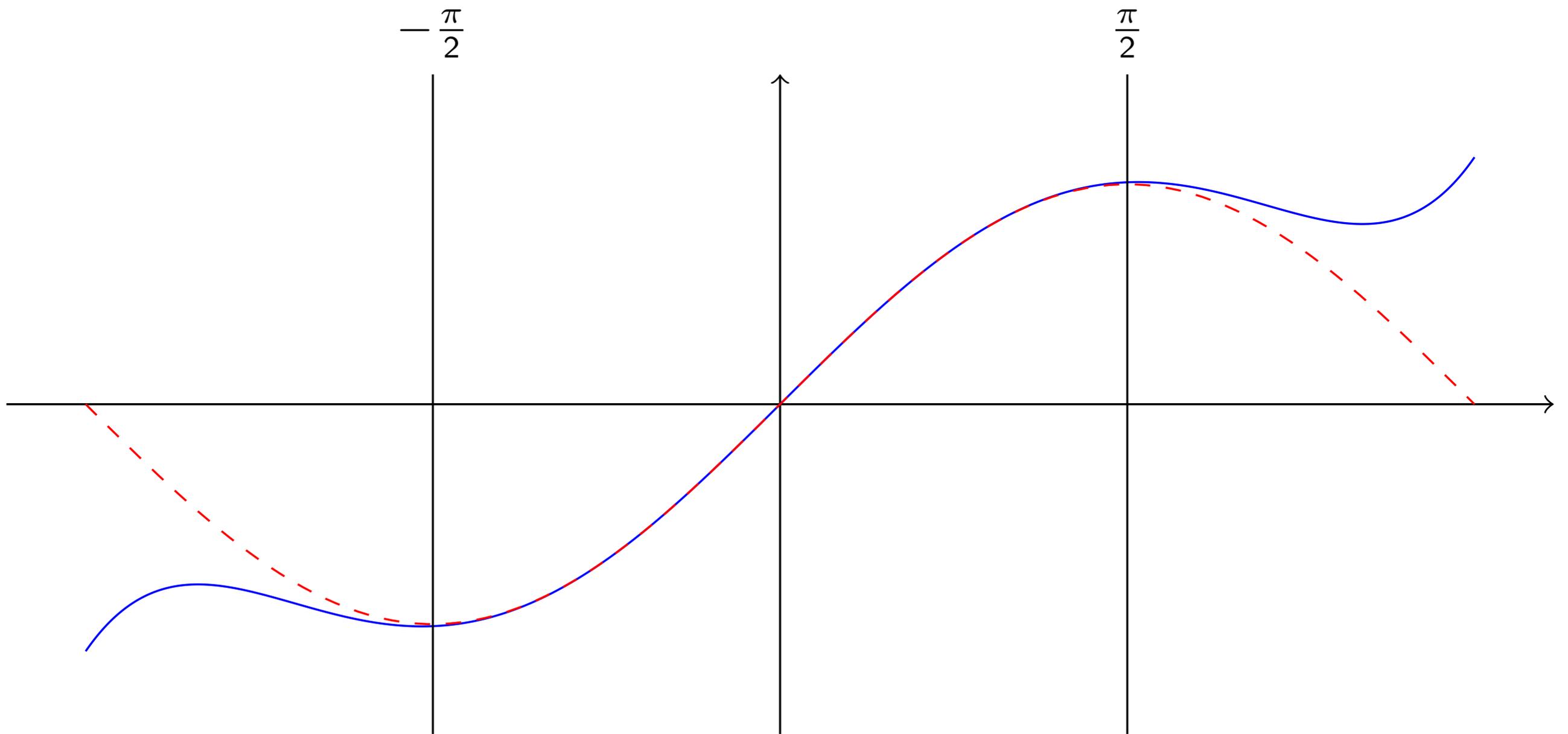
    float x = IN;

    float result = x - (x*x*x)/6.0f + (x*x*x*x*x)/120.0f + (x*x*x*x*x*x*x)/5040.0f;

    assert(result <= VAL && result >= -VAL);

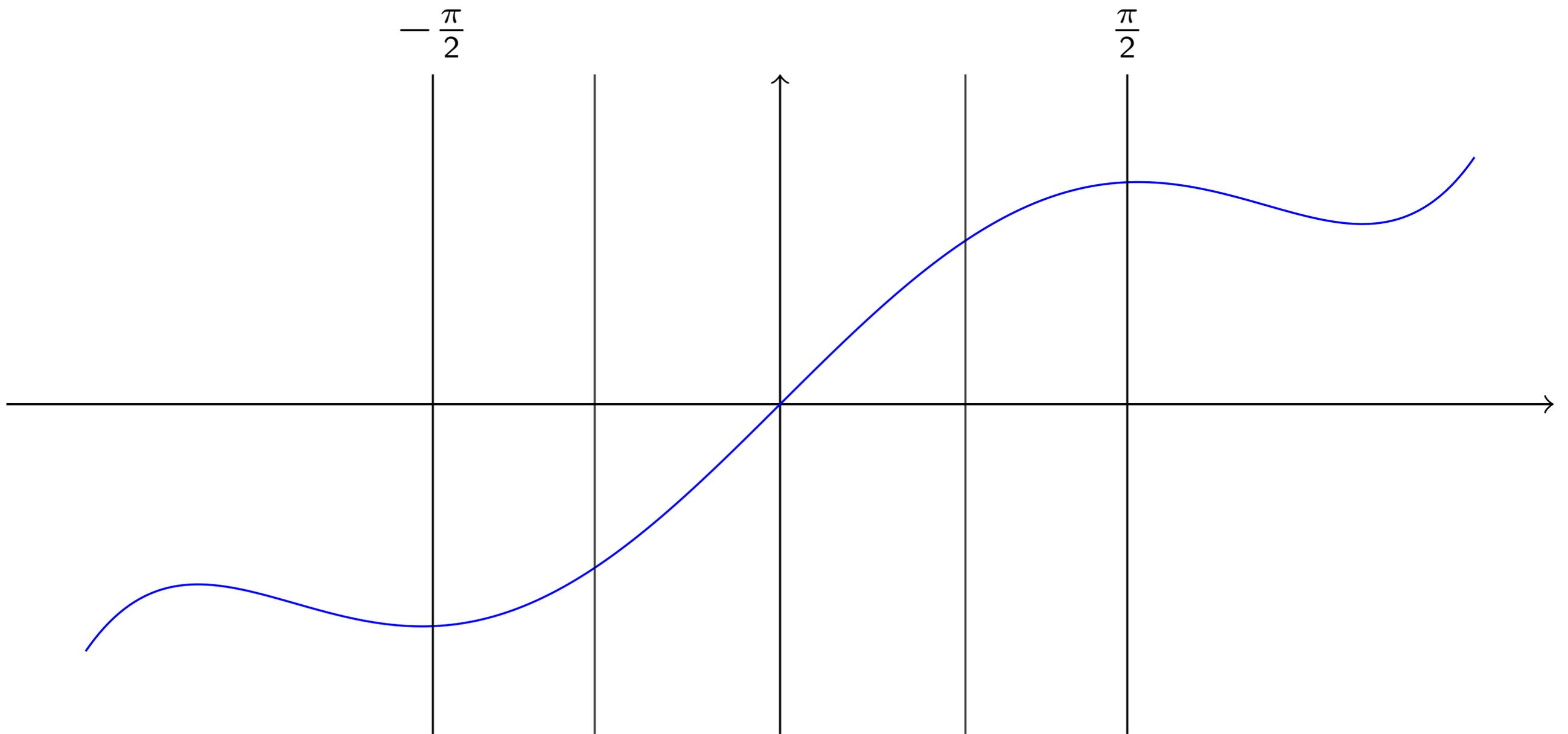
    return 0;
}
```

Implementation



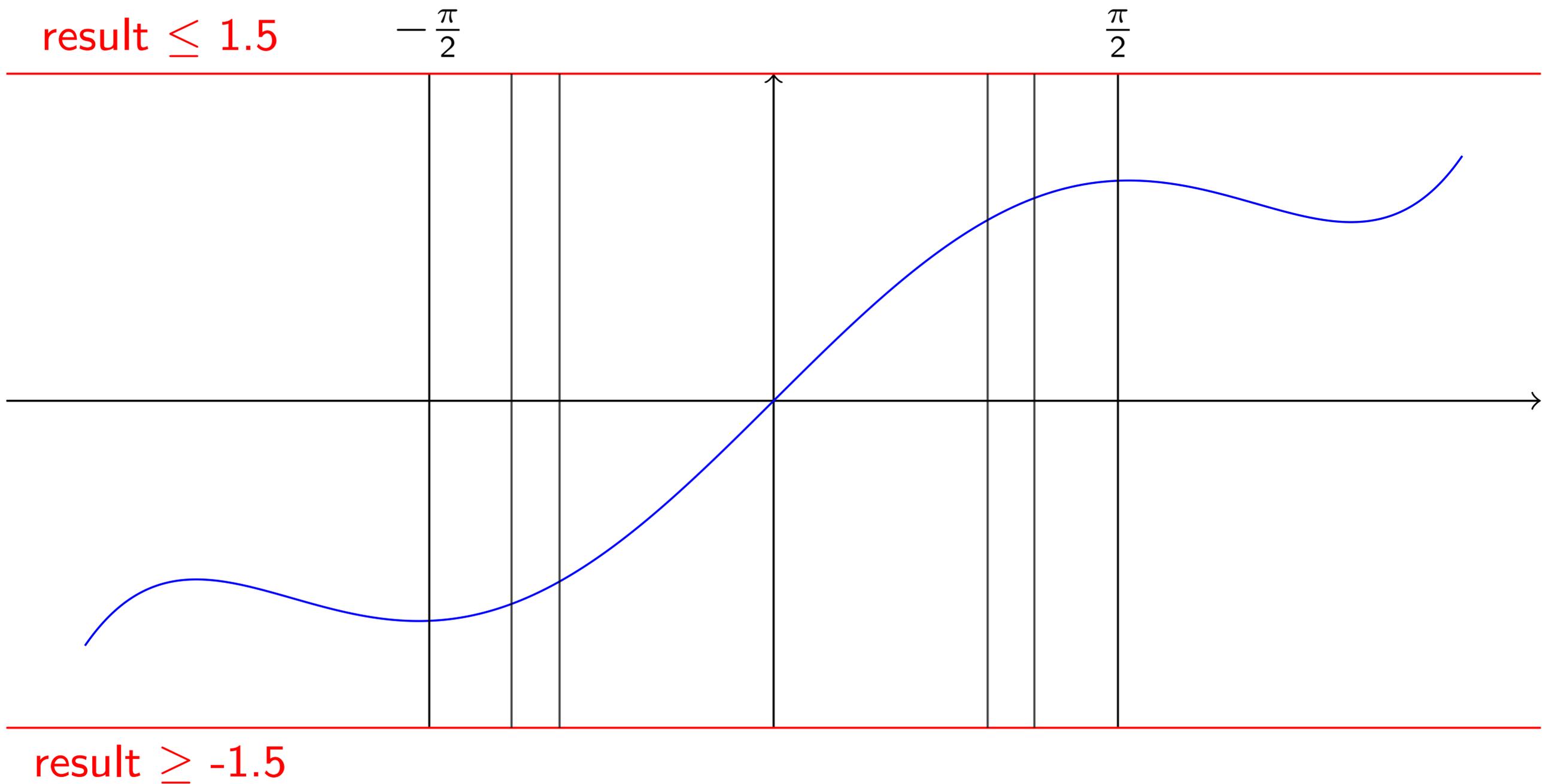
Number of partitions vs. tightness of bound

result ≤ 2.0

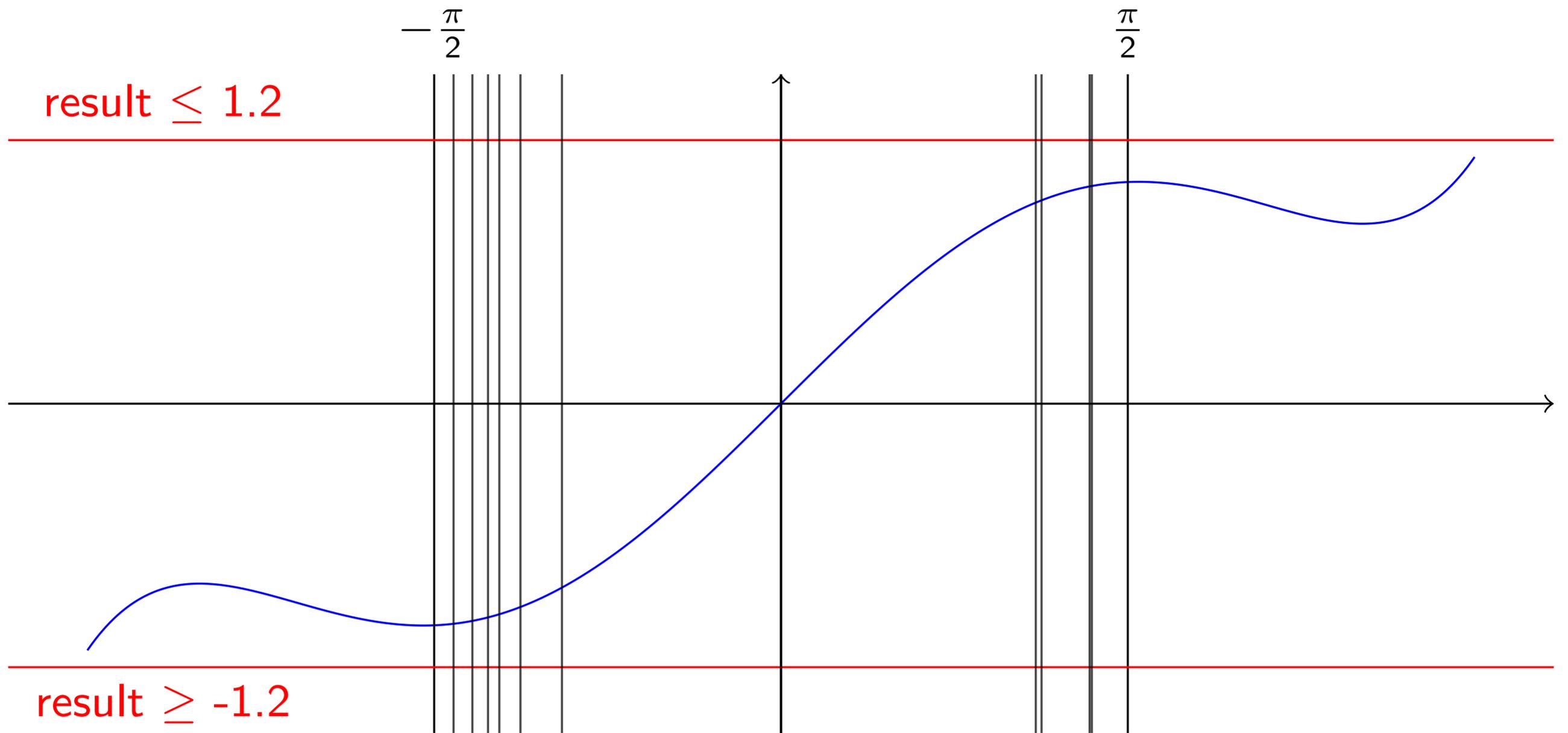


result ≥ -2.0

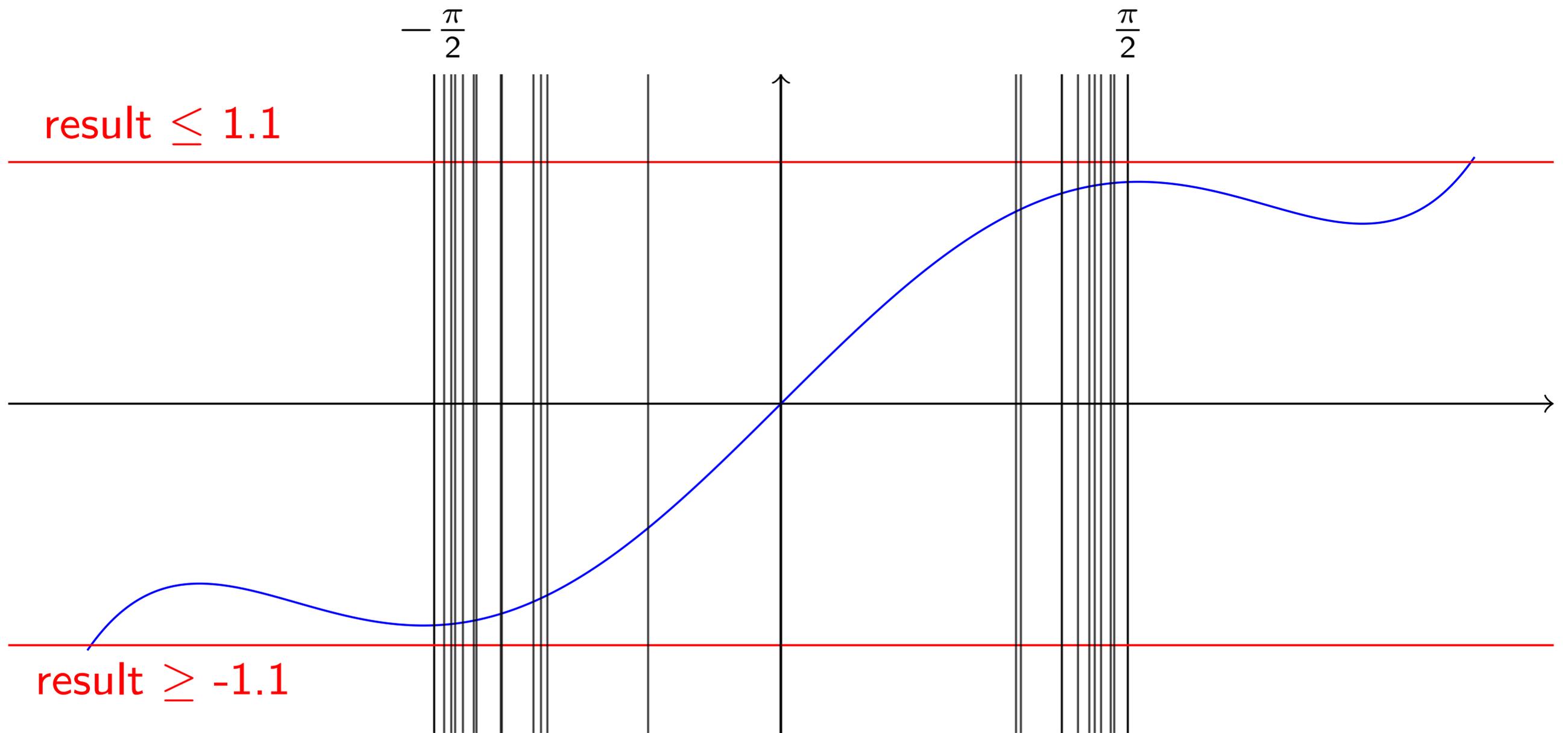
Number of partitions vs. tightness of bound



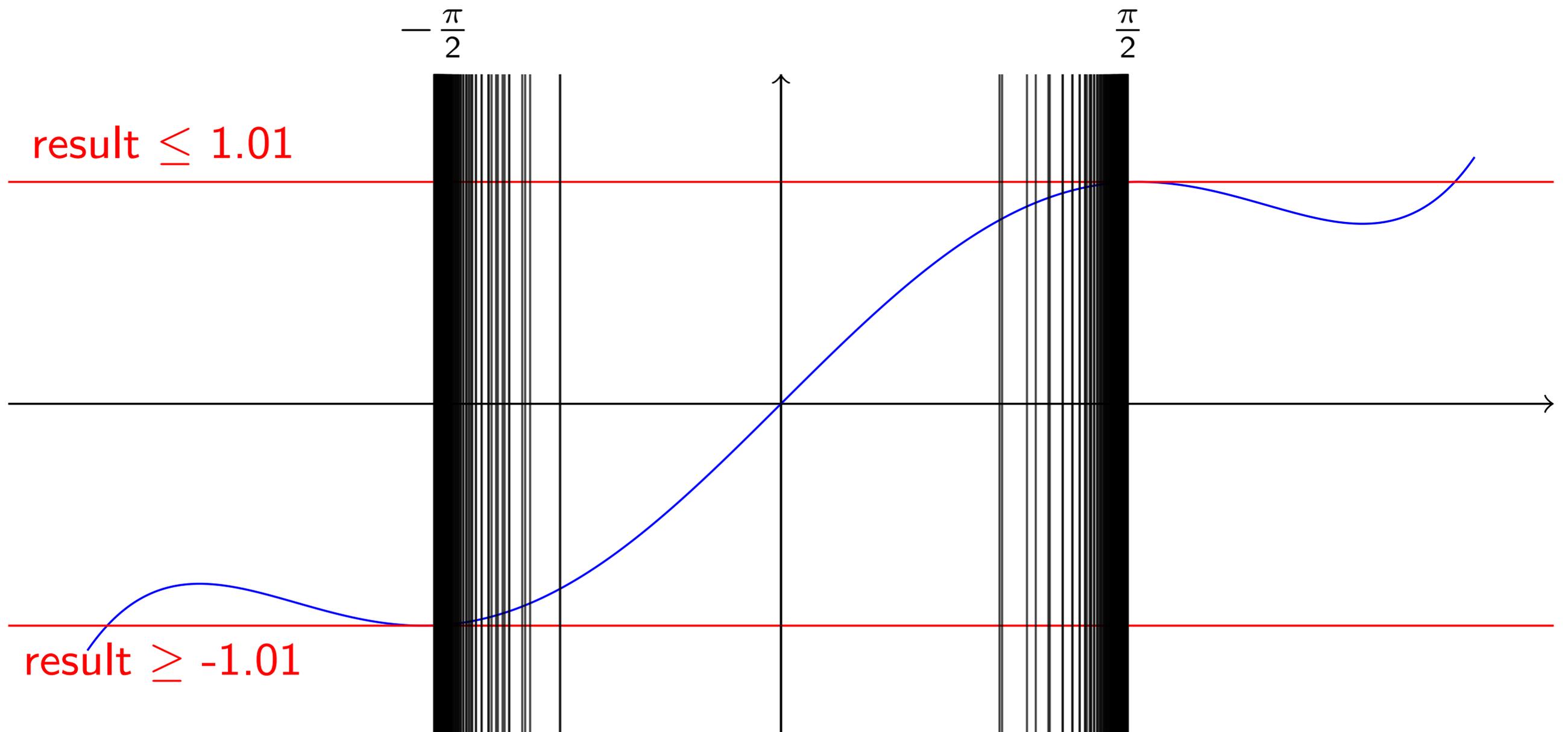
Number of partitions vs. tightness of bound



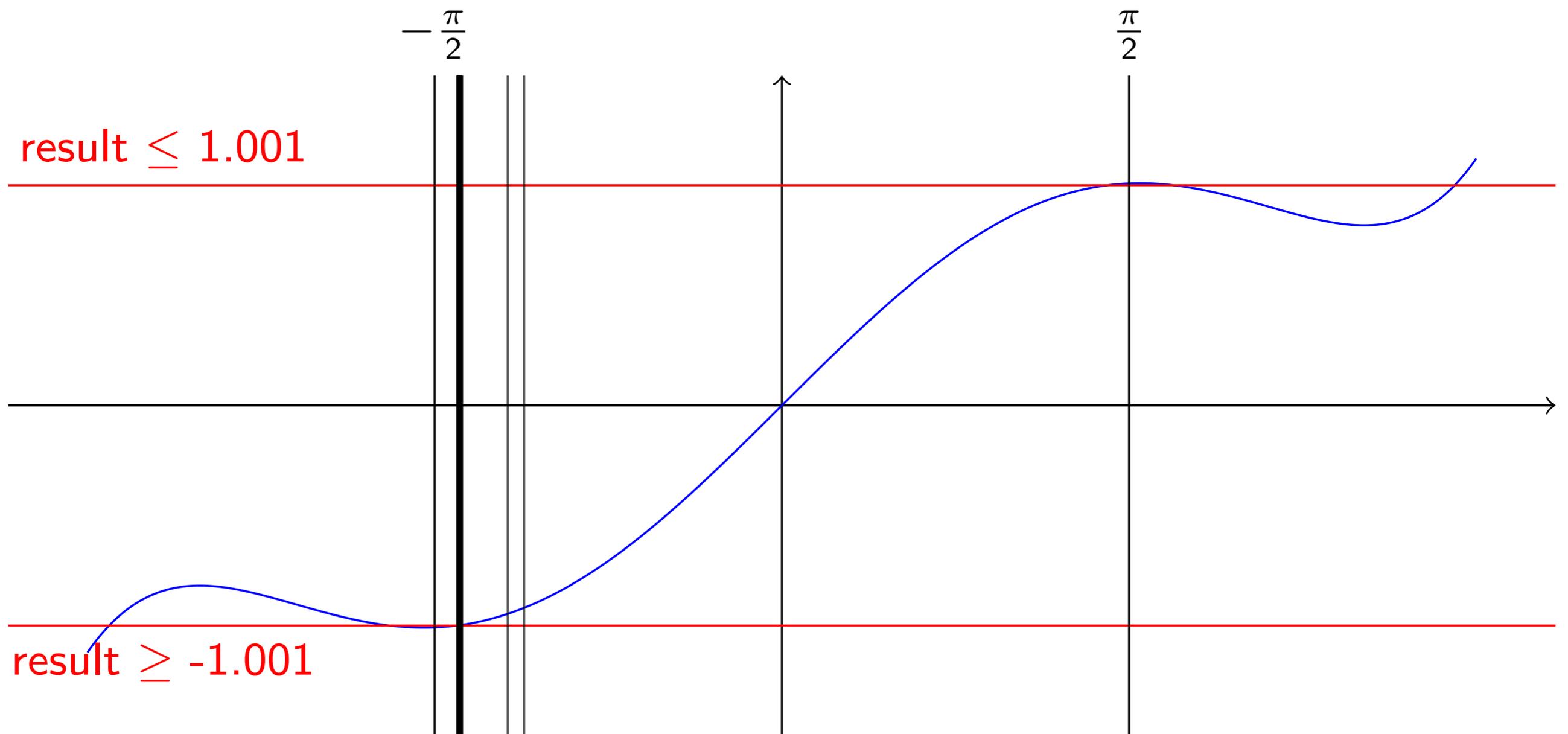
Number of partitions vs. tightness of bound



Number of partitions vs. tightness of bound



Number of partitions vs. tightness of bound



Precise results using a strict abstraction!
Orders of magnitude faster than propositional SAT

Conclusion

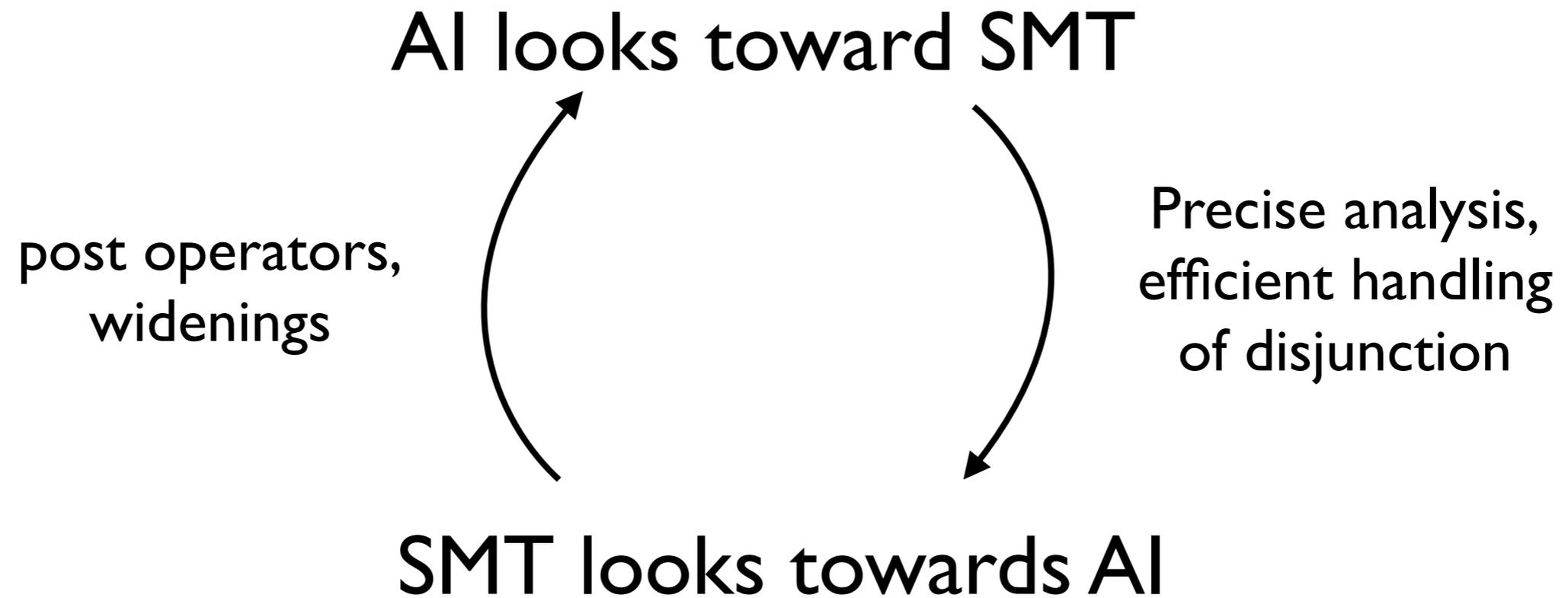
SAT solvers are abstract interpreters

partial assignments	Cartesian domain
unit rule	abstr. transformer
BCP	gfp
decisions	meet irreducibles
learning	trace partitioning

Abstract interpreters can be SAT solvers

ACDCL(A) for program analysis / SMT
precise results in an imprecise abstraction

... walk into a bar

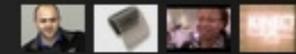


Include transcript search

Featured videos



Non-Visual Mainstream Smartphone and Camera Interactions for Blind and Low-Vision Users



Filter

Sort: most recent

1 2 3 4 5 6 7 Next ▶

1-10 of 2866 videos

Date recorded

From:



To:



Collections

 Captions available

Abstractions in Satisfiability Solvers

01:06:38 · 9 September 2011 · Vijay D'Silva



The Mathematical Challenge of Large Networks

01:12:12 · 7 September 2011 · László Lovász



Validation of a Quantum Simulator

00:56:37 · 6 September 2011 · Matthias Troyer



iSAX 2.0: Indexing and Mining One Billion Time Series/Database Cracking and the Path Towards Auto-tuning Database Kernels

01:25:12 · 6 September 2011 · Themis Palpanas and Stratos Idreos



SpecNet: Spectrum Sensing Sans Frontières

Abstractions in Satisfiability Solvers
Vijay D'Silva

Invited questions

Isn't this just CEGAR?

What if case splits are not enough?

Show me experiments!