

**SMT:**  
**satisfiability**  
**modulo**  
**theories**

# Recap and overview

- In the previous lecture, we introduced **symbolic execution**.
- To be effective, symbolic execution requires an **efficient mechanism to prove path conditions**.
- **This lecture:** we explore how to handle **Boolean structures** when deciding **satisfiability modulo theories (SMT)**.
- In practice, we introduce the **foundations of SMT solvers**, which use **clever techniques to reason efficiently about Boolean and theory constraints**.

# Recap: What is the SAT problem?

**SAT** stands for **Boolean Satisfiability**.

It is the problem of determining whether there exists a **truth assignment** to a set of Boolean variables that makes a given logical formula **true**.

**Example:** the formula

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

*Is there an assignment of truth values to  $p$ ,  $q$ , and  $r$  that makes this formula true?*



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**Example:** the formula

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*Is there an assignment of truth values to  $p$ ,  $q$ , and  $r$  that makes this formula true?*

**Yes:** Under the assignment

$$p = \text{false}, q = \text{true}, r = \text{true}$$

The formula evaluates to **true**, so it is **satisfiable**.



# SAT: Boolean Satisfiability Problem

What is the SAT Problem?

**Input:** A Boolean formula

**Question:** *Is there an assignment of true/false values to variables that makes the formula true?*

The problem proven **NP-complete** (Cook, 1971)

# SAT is hard to solve!!

- The search space is **exponential**:  $2^n$  possible assignments for  $n$  variables
- SAT is **NP-complete**
  - No known polynomial-time algorithm for all inputs
- Many real-world problems reduce to SAT:
  - Circuit verification
  - Program analysis
  - Scheduling, planning
- Even **small changes** to input can change the solution space drastically

# SAT Solver

## OUTCOME

- **SAT** (satisfiable)
  - at least one assignment makes the formula true
- **UNSAT** (unsatisfiable)
  - no assignment satisfies the formula
- **UNKNOWN**
  - can't determine (e.g., due timeout)

# SMT SOLVERS

**Key idea:** SMT manages the **Boolean structure** of formulas, with one or more **theory solvers**, which handle the **theory-specific constraints** (e.g., arithmetic, arrays, bit-vectors).



**SMT = SAT + Theories:**

**SAT solver** manages Boolean structure,

**Theory solver** checks consistency within the chosen theory.

# Operationally

- To use SAT solver, we construct a propositional formula, called **boolean abstraction**, that overapproximates satisfiability
- If boolean abstraction is **UNSAT**,
  - we are done
- If boolean abstraction is **SAT**
  - Use theory solver to check if assignment returned by **SAT solver** is **satisfiable modulo theory**
- If not, add additional **boolean constraints** (called **theory conflict clauses**) to guide the search for an assignment that is satisfiable modulo theory

Handwritten mathematical notes and diagrams on a blackboard:

- Top right:  $\sum x \geq 947$ ,  $h=2$ ,  $\sqrt{2450}$ ,  $\rightarrow 352$ ,  $D(x) = 2 + 3 + 4.31447$ ,  $\frac{22}{2}$ .
- Middle left:  $\sqrt{a^2 + b^2} = x^2$ ,  $nx$ ,  $s$ .
- Middle right:  $c(x, y)$ ,  $\{$ ,  $\}$ .
- Bottom left:  $\beta_3$ ,  $24 \frac{tx}{y} + \frac{a^2 + b^2}{c} + \frac{1}{x}$ ,  $933+1$ .
- Bottom center:  $new = 584. + n^{30}$ .
- Bottom right:  $\sum_{x=1}^{n=14!} N^{30} - 1$ ,  $\frac{1}{2}$ .
- Bottom left:  $1112$ ,  $002$ ,  $002$ .
- Bottom right: A graph with a peak labeled  $B$ .

# Techniques to address SAT

## How Modern SAT Solvers Behave

- **DPLL algorithm** and its modern variants
- **Heuristics** for variable selection
- **Preprocessing and simplification**
- Solvers like **MiniSAT**, **Z3**, and **CryptoMiniSat** make SAT feasible in many cases

# DPLL



The **DPLL algorithm** (Davis–Putnam–Logemann–Loveland) is the foundation of most modern **SAT solvers**.



DPLL is a **complete backtracking-based search algorithm** for solving the **SAT problem**. It determines whether a **Boolean formula in CNF (conjunctive normal form)** is **satisfiable**.



DPLL improves brute-force search by introducing **smart pruning and inference techniques**.

# Toward DPLL

Boolean Constraint Propagation



If a clause has **only one literal unassigned** (a *unit clause*), assign it in a way that satisfies the clause.

Clause:  $(x)$  the set  $x=true$

# Boolean Constraint Propagation: example

**CNF Formula** 
$$\underbrace{(p_1 \vee \neg p_3 \vee \neg p_5)}_{C_1} \wedge \underbrace{(\neg p_1 \vee p_2)}_{C_2} \wedge \underbrace{(\neg p_1 \vee \neg p_3 \vee p_4)}_{C_3} \wedge \underbrace{(\neg p_1 \vee \neg p_2 \vee p_3)}_{C_5} \wedge \underbrace{(\neg p_4 \vee \neg p_2)}_{C_6}$$

**SAT begins with the assignment  $p_1 = \text{true}$**

$$\begin{aligned} & (p_1 \vee \neg p_3 \vee \neg p_5) \wedge (\neg p_1 \vee p_2) \wedge (\neg p_1 \vee \neg p_3 \vee p_4) \wedge (\neg p_1 \vee \neg p_2 \vee p_3) \wedge (\neg p_4 \vee \neg p_2) \\ \leftrightarrow & (\top \vee \neg p_3 \vee \neg p_5) \wedge (\perp \vee p_2) \wedge (\perp \vee \neg p_3 \vee p_4) \wedge (\perp \vee \neg p_2 \vee p_3) \wedge (\neg p_4 \vee \neg p_2) \\ \leftrightarrow & \top \wedge p_2 \wedge (\neg p_3 \vee p_4) \wedge (\neg p_2 \vee p_3) \wedge (\neg p_4 \vee \neg p_2) \\ \leftrightarrow & p_2 \wedge (\neg p_3 \vee p_4) \wedge (\neg p_2 \vee p_3) \wedge (\neg p_4 \vee \neg p_2) \end{aligned}$$

# Boolean Constraint Propagation: example

$$\underbrace{(p_1 \vee \neg p_3 \vee \neg p_5)}_{C_1} \wedge \underbrace{(\neg p_1 \vee p_2)}_{C_2} \wedge \underbrace{(\neg p_1 \vee \neg p_3 \vee p_4)}_{C_3} \wedge \underbrace{(\neg p_1 \vee \neg p_2 \vee p_3)}_{C_5} \wedge \underbrace{(\neg p_4 \vee \neg p_2)}_{C_6}$$

The assignment  $p_1 = \text{true}$  allows one to reduce the original problem to the satisfaction of the formula

$$p_2 \wedge (\neg p_3 \vee p_4) \wedge (\neg p_2 \vee p_3) \wedge (\neg p_4 \vee \neg p_2)$$

# Boolean Constraint Propagation: example

$$\underbrace{(p_1 \vee \neg p_3 \vee \neg p_5)}_{C_1} \wedge \underbrace{(\neg p_1 \vee p_2)}_{C_2} \wedge \underbrace{(\neg p_1 \vee \neg p_3 \vee p_4)}_{C_3} \wedge \underbrace{(\neg p_1 \vee \neg p_2 \vee p_3)}_{C_5} \wedge \underbrace{(\neg p_4 \vee \neg p_2)}_{C_6}$$

$$p_2 \wedge (\neg p_3 \vee p_4) \wedge (\neg p_2 \vee p_3) \wedge (\neg p_4 \vee \neg p_2)$$

any satisfying interpretation must contain the assignment  $p_2 = \text{true}$

No choice to satisfy this formula.

The literal  $p_2$  is called the unit literal

# Boolean Constraint Propagation: example

$$\underbrace{(p_1 \vee \neg p_3 \vee \neg p_5)}_{C_1} \wedge \underbrace{(\neg p_1 \vee p_2)}_{C_2} \wedge \underbrace{(\neg p_1 \vee \neg p_3 \vee p_4)}_{C_3} \wedge \underbrace{(\neg p_1 \vee \neg p_2 \vee p_3)}_{C_5} \wedge \underbrace{(\neg p_4 \vee \neg p_2)}_{C_6}$$

$$p_2 \wedge (\neg p_3 \vee p_4) \wedge (\neg p_2 \vee p_3) \wedge (\neg p_4 \vee \neg p_2)$$

Set  $p_2 = \text{true}$

$$\begin{aligned} & \top \wedge (\neg p_3 \vee p_4) \wedge (\neg \top \vee p_3) \wedge (\neg p_4 \vee \neg \top) \\ \leftrightarrow & (\neg p_3 \vee p_4) \wedge (\perp \vee p_3) \wedge (\neg p_4 \vee \perp) \\ \leftrightarrow & (\neg p_3 \vee p_4) \wedge p_3 \wedge \neg p_4 \end{aligned}$$

# Boolean Constraint Propagation: example

$$\underbrace{(p_1 \vee \neg p_3 \vee \neg p_5)}_{C_1} \wedge \underbrace{(\neg p_1 \vee p_2)}_{C_2} \wedge \underbrace{(\neg p_1 \vee \neg p_3 \vee p_4)}_{C_3} \wedge \underbrace{(\neg p_1 \vee \neg p_2 \vee p_3)}_{C_5} \wedge \underbrace{(\neg p_4 \vee \neg p_2)}_{C_6}$$

$$p_2 \wedge (\neg p_3 \vee p_4) \wedge (\neg p_2 \vee p_3) \wedge (\neg p_4 \vee \neg p_2)$$

$$(\neg p_3 \vee p_4) \wedge p_3 \wedge \neg p_4 \quad \text{Set } p_3 = \text{true}$$

$$(\neg \top \vee p_4) \wedge \top \wedge \neg p_4$$

$$\leftrightarrow (\perp \vee p_4) \wedge \neg p_4$$

$$\leftrightarrow p_4 \wedge \neg p_4$$

# Overall

$$\underbrace{(p_1 \vee \neg p_3 \vee \neg p_5)}_{C_1} \wedge \underbrace{(\neg p_1 \vee p_2)}_{C_2} \wedge \underbrace{(\neg p_1 \vee \neg p_3 \vee p_4)}_{C_3} \wedge \underbrace{(\neg p_1 \vee \neg p_2 \vee p_3)}_{C_5} \wedge \underbrace{(\neg p_4 \vee \neg p_2)}_{C_6}$$

$$p_2 \wedge (\neg p_3 \vee p_4) \wedge (\neg p_2 \vee p_3) \wedge (\neg p_4 \vee \neg p_2)$$

$$(\neg p_3 \vee p_4) \wedge p_3 \wedge \neg p_4$$

With the assignment  $p_1 = \text{true}$

$$(\neg \top \vee p_4) \wedge \top \wedge \neg p_4$$

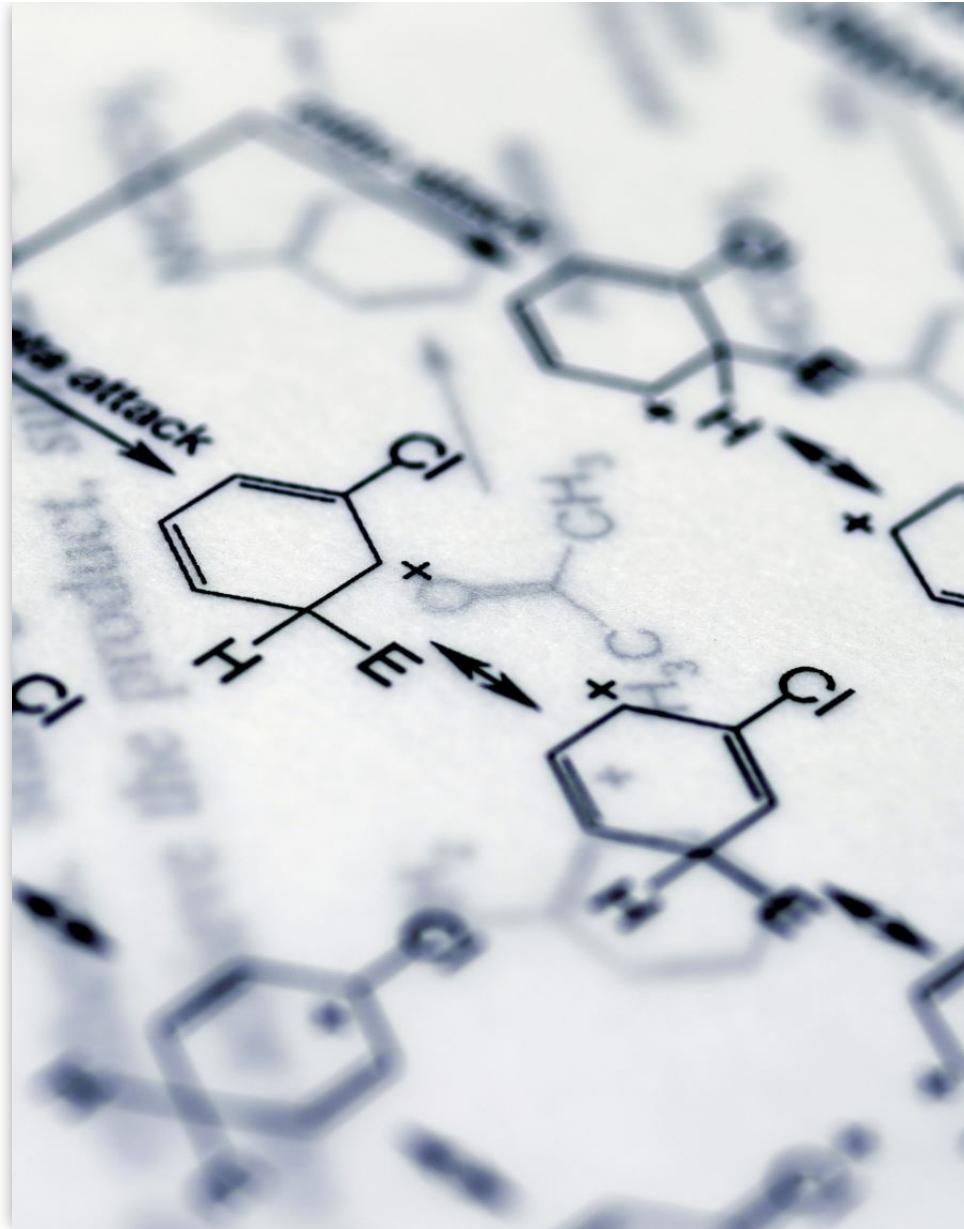
**the formula is not satisfiable**

$$\leftrightarrow (\perp \vee p_4) \wedge \neg p_4$$

$$\leftrightarrow p_4 \wedge \neg p_4$$

# Unit propagation

The process we described is called Boolean constraint propagation (BCP), or sometimes unit propagation for short.



# How DLLP Works

## Boolean Constraint Propagation (or Unit Propagation)

- If a clause has **only one literal unassigned** (a *unit clause*), assign it in a way that satisfies the clause.
  - Clause:  $(x)$  the set  $x=true$

## Pure Literal Elimination (optional)

- If a literal appears with **only one polarity** (always positive or always negative) in all clauses, assign it to satisfy all such clauses.
  - If  $x$  appears only as  $x$  (never as  $\neg x$ ), set  $x = \text{true}$ .

## Variable Assignment (Decision Step)

- Pick an unassigned variable and try assigning true or false.

## Backtracking

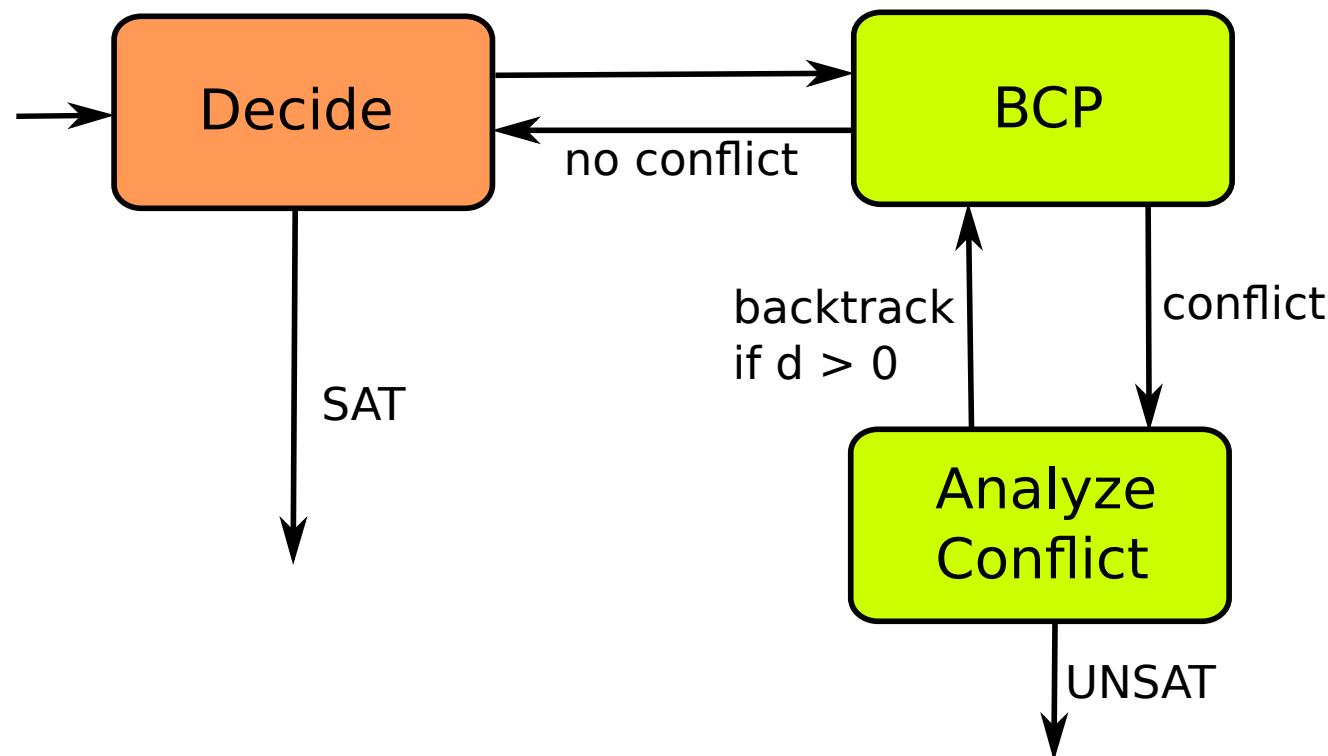
- If the current assignment leads to a **conflict** (unsatisfiable clause), **backtrack** and try the other assignment.
- If both fail, backtrack further.

# The code

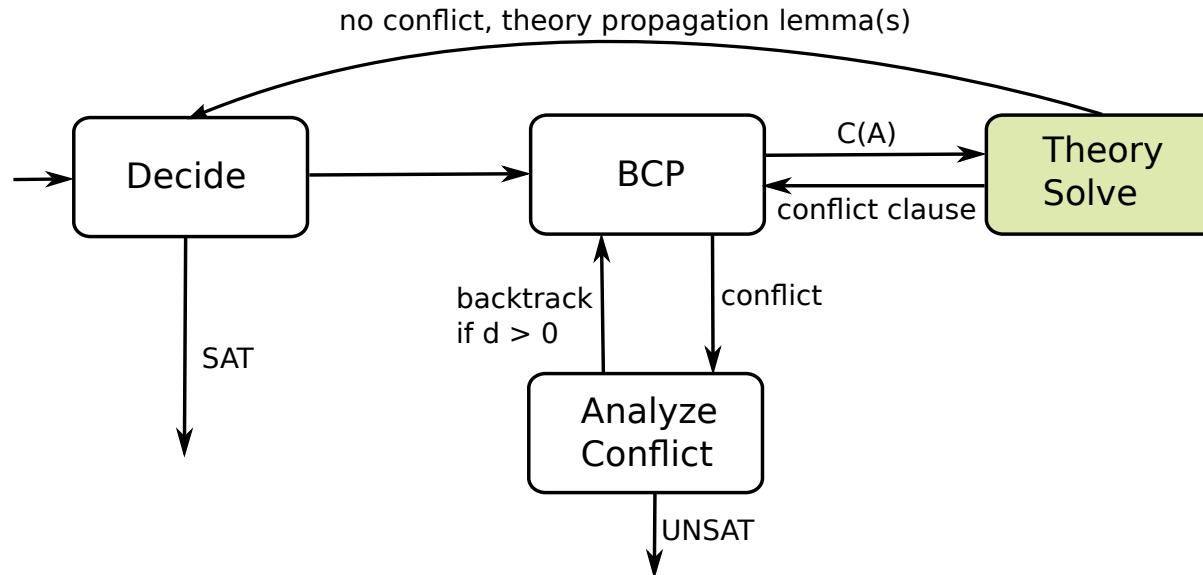
---

```
1 let rec dpll (f: formula) : bool =
2   let fp = bcp f in
3   match fp with
4   | Some True -> true
5   | Some False -> false
6   | None ->
7     begin
8       let p = choose_var f in
9       let ft = (subst_var f p true) in
10      let ff = (subst_var f p false) in
11      dpll ft || dpll ff
12    end
13  end
```

# Discussion



# What about theory?



- ▶ Combination of DPLL-based SAT solver and decision procedure for conjunctive  $\mathcal{T}$  formula called **DPLL( $\mathcal{T}$ ) framework**

# Theory propagation

Assume that the original formula contains literals

$$x = y, y = z, x < z$$

with corresponding boolean variables  $b_1, b_2$  and  $b_3$

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$$b_1 = \text{true}, b_2 = \text{true}$$

Next computationalk step may decide to assign

$$b_3 = \text{true} \text{ or } b_3 = \text{false}$$

# Theory propagation

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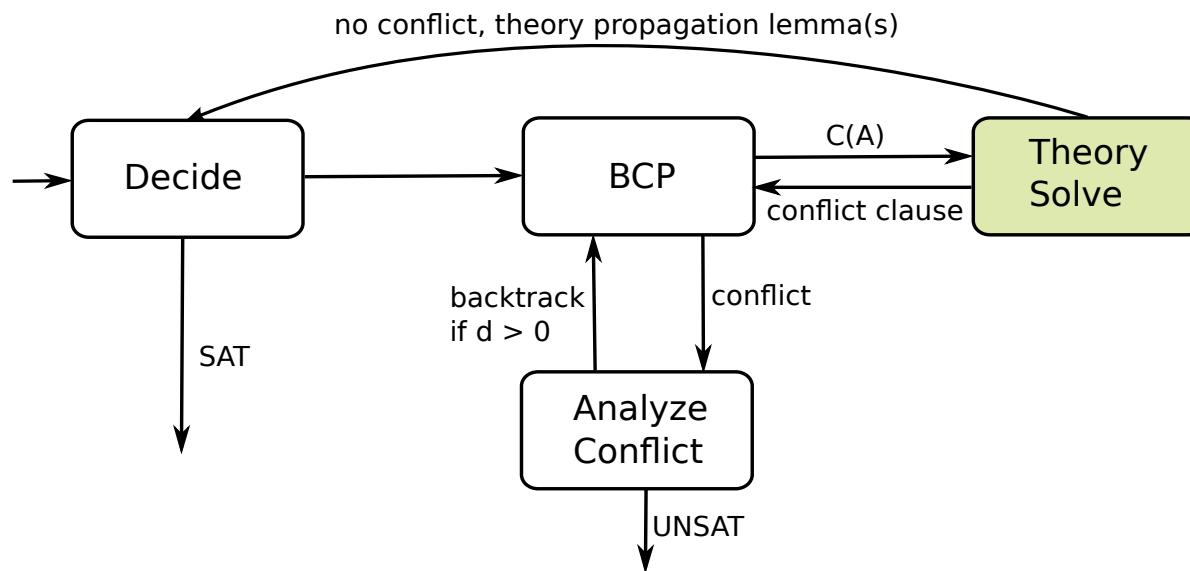
??  $b_3 = \text{true}$  ??

**not the right choice**: conflict in the equational theory

# Theory propagation

- Theory solver tracks which literals are implied by the current assignment.
- Our example: literal  $\neg(x < y)$  is implied by the partial assignment  $b_1 = \text{true}, b_2 = \text{true}$
- The implication  $b_1 \wedge b_2 \rightarrow b_3$  can be safely added to the knowledge of clauses (the clause database)

# DPLL(T) framework



- ▶ Adding theory propagation lemmas prevents bad assignments to boolean abstraction

# Z3 SAT SOLVER



- **Z3** is an **SMT** solver developed by Microsoft Research
  - <https://github.com/Z3Prover/z3>
- **Z3 Input:** A set of **declarative constraints**, often expressed in logic over various domains:
  - Integers, reals, booleans, bitvectors, arrays, strings, etc.
- Converts the problem into a combination of **Boolean SAT solving + theory solvers** (for strings, integers, arrays, etc.)
- Uses **efficient heuristics and decision procedures** to prune infeasible choices

# Z3 in Action

**(x > 0 && x < 10) (x \* 2 == 15) {x:int}**

Z3>

```
(declare-const x Int)
  (assert (> x 0))           unsat
  (assert (< x 10))
  (assert (= (* x 2) 15))
(check-sat)
```

Z3 >

```
from z3 import *
# declare multiple variables
x, y = Bools('x y')
# create a solver instance
s = Solver()
# add conjuncts
s.add( Implies(x, y) )
s.add( Implies(y, x) )
# check satisfiability
print( s.check() )
print( s.model() )
s.add( x )
s.add( Not(y) )
# check satisfiability
print( s.check() )
```

The first two conjuncts are satisfiable,  
we get a model

```
sat
[y = False, x = False]
unsat
```

All four conjuncts together are unsatisfiable

# Z3 Theories

## Linear integer/real arithmetic

$$19 * x + 2 * y = 42$$

- (Unbounded) arithmetic is often used to approximate int and float
- Multiplication by constants is supported

## Non-linear integer/real arithmetic

$$x * y + 2 * x * y + 1 = (x + y) * (x + y)$$

- Useful for programs that perform multiplication and division, e.g., crypto libraries

## Equality logic with uninterpreted functions

$$(x = y \wedge u = v) \Rightarrow f(x, u) = f(y, v)$$

- Universal mechanism to encode operations not natively supported by a theory

## Fixed-size bitvector arithmetic

$$x \& y \leq x \mid y$$

- To encode bit-level operations
- To perform bit-precise reasoning, e.g., floats

## Array theory

$$\text{read}(\text{write}(a, i, v), i) = v$$

- To encode data types such as arrays

```
from z3 import *

# -----
# 1. Declare a new abstract sort (type) for pairs
# -----
Pair = DeclareSort('Pair')

# -----
# 2. Define constants and functions over the Pair sort
# -----
null = Const('null', Pair)          # A constant representinghe empty pair
cons = Function('cons', IntSort(), IntSort(), Pair) # Constructor: builds a Pair from two Ints
first = Function('first', Pair, IntSort())  # Selector: extracts the first Int from a Pair

# -----
# 3. Define axioms describing the behavior of our abstract model
# -----
# Axiom 1: the constant 'null' is equivalent to cons(0, 0)
ax1 = (null == cons(0, 0))

# Axiom 2: for all integers x, y — the first element of cons(x, y) is x
x, y = Ints('x y')
ax2 = ForAll([x, y], first(cons(x, y)) == x)
```

```
# -----
# 4. Create a solver and add the axioms
# -----
s = Solver()
s.add(ax1)
s.add(ax2)

# -----
# 5. Define the formula we want to prove: first(null) == 0
# -----
F = (first(null) == 0)

# -----
# 6. Check validity of F
#   To prove F is valid, we check whether  $\neg F$  is unsatisfiable
# -----
s.add(Not(F))
print("Checking validity of F = first(null) == 0 ...")
print("Result:", s.check())
```

When you run this, Z3 prints:

```
Checking validity of F = first(null) == 0 ...
Result: unsat
```

unsat means that the **negation** of the formula `first(null) != 0` is unsatisfiable — so the original formula `first(null) == 0` is **logically valid**, given the axioms.

# Using an SMT solver to verify a program

```
{ a = 1 ∧ 0 ≤ b*b - 4*c }
// Check that this entailment is valid (its negation is unsatisfiable)
{ b*b - 4*a*c < 0 ∧ false ∨
  ¬(b*b - 4*a*c < 0) ∧ a*((-b + √b*b - 4*a*c) / 2)² + b*((-b + √b*b - 4*a*c) / 2) + c = 0 }
```

```
from z3 import *

a, b, c = Reals('a b c')
d = b*b - 4*a*c

P0 = Implies(
    And(a == 1, 0 <= b*b - 4*c),
    Or( And(d < 0, False),
        And(Not(d < 0),
            a*((-b + Sqrt(d))/2)*((-b + Sqrt(d))/2) + b*((-b + Sqrt(d))/2) + c == 0
        )))
# check validity
s = Solver()
s.add(Not(P0)); print( s.check() )
```

- Z3 selects theories based on the features appearing in formulas
  - Most verification problems require a combination of many theories

Quantifier-free linear integer arithmetic with uninterpreted functions

$$17 * x + 23 * f(y) > x + y + 42$$
- Some theories are decidable, e.g., quantifier-free linear arithmetic
  - SMT solver will terminate and report either “sat” or “unsat”
- Some theories are undecidable, e.g., nonlinear integer arithmetic
  - Especially in combination with quantifiers
  - SMT solver uses heuristics and may not terminate or return “unknown”
  - Results can be flaky, e.g., depend on order of declarations or random seeds

# Our first example

```
function f(a, b, c) {  
    var x = y = z = 0;  
    if (a) {  
        x = -2;  
    }  
    if (b > 5) {  
        if (!a && c) {  
            y = 1;  
        }  
        z = 2;  
    }  
    assert(x + y + z != 3);  
}
```

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        }  
        z = 2;  
    }  
    assert(x + y + z != 3);  
}
```

```
from z3 import *  
  
# Symbolic inputs  
a0, b0, c0 = Ints('a0 b0 c0')  
  
# Helpful predicates for "truthiness"  
A = (a0 != 0)  
B = (b0 > 5)  
C = (c0 != 0)  
  
def model_or_none(constraints):  
    s = Solver()  
    s.add(constraints)  
    return s.model() if s.check() == sat else None  
  
# Enumerate the relevant paths with their path conditions  
(PC) and compute x,y,z symbolically  
paths = []
```

```

# if (a)
#   then: x=-2
#   else: x=0
for condA, x_val in [(A, -2), (Not(A), 0)]:
    # if (b > 5)
    #   then:
    #     if (!a && c) y=1 else y=0
    #     z=2
    #   else: y=0; z=0
    # THEN branch of b>5
    pc_thenB = And(condA, B)
    y_thenB = If(And(Not(A), C), 1, 0)    # inner if only affects y
    z_thenB = 2
    s_thenB = x_val + y_thenB + z_thenB
    paths.append(("A?, B then", pc_thenB, x_val, y_thenB, z_thenB, s_thenB))

    # ELSE branch of b>5
    pc_elseB = And(condA, Not(B))
    y_elseB = 0
    z_elseB = 0
    s_elseB = x_val + y_elseB + z_elseB
    paths.append(("A?, B else", pc_elseB, x_val, y_elseB, z_elseB, s_elseB))
}

function f(a, b, c) {
    var x = y = z = 0;
    if (a) {
        x = -2;
    }
    if (b > 5) {
        if (!a && c) {
            y = 1;
        }
        z = 2;
    }
    assert(x + y + z != 3);
}

```

```

# Check each path: (1) feasibility; (2) assertion violation x+y+z != 3
for name, pc, x_sym, y_sym, z_sym, sum_sym in paths:
    # 1) Path feasibility
    m = model_or_none(pc)
    if m is None:
        continue # infeasible path

    # 2) Try to violate the assertion: sum == 3 (since assert(sum != 3))
    m_bad = model_or_none(And(pc, sum_sym == 3))
    if m_bad:
        print(f"[ASSERTION FAIL] Path: {name}")
        print(" Example input:", {d.name(): m_bad[d] for d in [a0,b0,c0] })
        print(" Computed (x,y,z,sum) =", 
              (x_sym if isinstance(x_sym, int) else m_bad.eval(x_sym),
               y_sym if isinstance(y_sym, int) else m_bad.eval(y_sym),
               z_sym if isinstance(z_sym, int) else m_bad.eval(z_sym),
               m_bad.eval(sum_sym)))
    else:
        # Also produce a concrete input that simply exercises the path (even if no bug)
        m_path = model_or_none(pc)
        print(f"[OK PATH] Path: {name}")
        print(" Example input:", {d.name(): m_path[d] for d in [a0,b0,c0] })
        print(" sum =", m_path.eval(sum_sym))
}

```