#16: How SAT/SMT Solvers Work

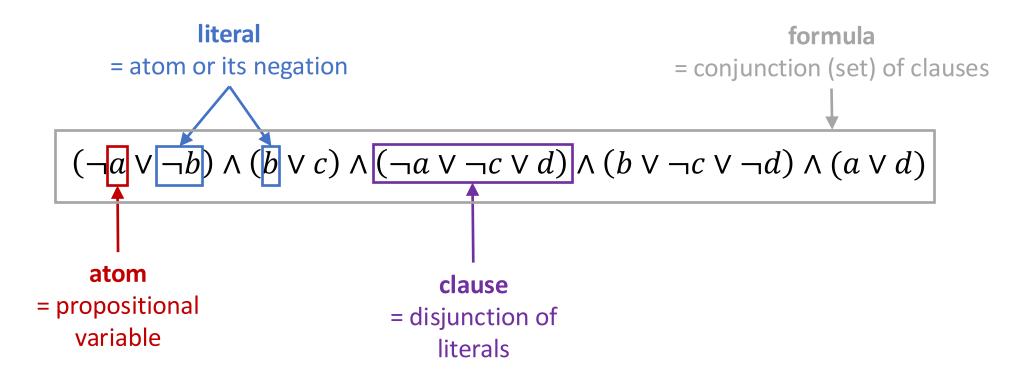
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EECS 700: Introduction to Program Synthesis



The SAT problem

• Input: propositional formula in CNF



The SAT problem

- **Problem:** find a *satisfying assignment* (also called a *model*)
 - or determine that the formula is *unsatisfiable*

$$(\neg a \lor \neg b) \land (b \lor c) \land (\neg a \lor \neg c \lor d) \land (b \lor \neg c \lor \neg d) \land (a \lor d)$$

a satisfying assignment:

$$\{a \mapsto 0, b \mapsto 1, c \mapsto 0, d \mapsto 1\}$$

can be written as a set of literals:

$$\{\neg a, b, \neg c, d\}$$

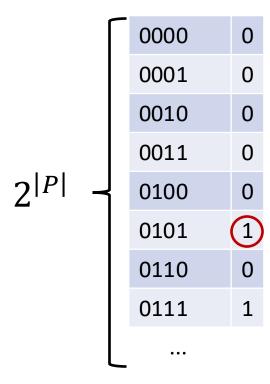
or as a formula:

$$\neg a \land b \land \neg c \land d$$

Naive solution

$$(\neg a \lor \neg b) \land (b \lor c) \land (\neg a \lor \neg c \lor d) \land (b \lor \neg c \lor \neg d) \land (a \lor d)$$

- Build a truth table!
 - We can't do fundamentally better: it's an NP-complete problem
 - But we can do way better in practice for common instances

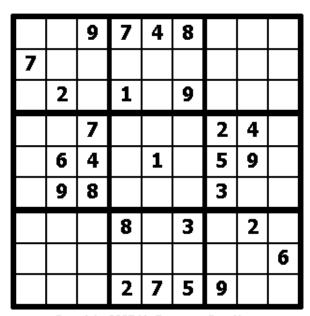


Intuition: Sudoku

• Easy vs hard: what's the difference?

7	9					3		
					6	9		
8				3			7	6
			9	6	5			2
		5	4	1	8	7		
4			7	2	3			
6	1			9				8
		2	3					
		9					5	4

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• Most real-world SAT instances allow a lot of inference

DPLL algorithm

[Davis, Putnam '60]

[Davis, Logemann, Loveland '62]

• **State:** current model *M* (a sequence of annotated literals)

$$M = a^{d} \neg b \ c$$
 decision literal

• Transitions:

- decide $M \longrightarrow M l^d$ if I undefined in M
- unit-propagate $M \longrightarrow M \ l$ if there is a clause where all literals are false except \emph{I} , which is undefined
- backtrack $Ml^dM' \longrightarrow M \neg l$ if there is a conflicting clause and M' has no decision literals
- fail $M \longrightarrow Unsat$ if there is a conflicting clause and no decision literals

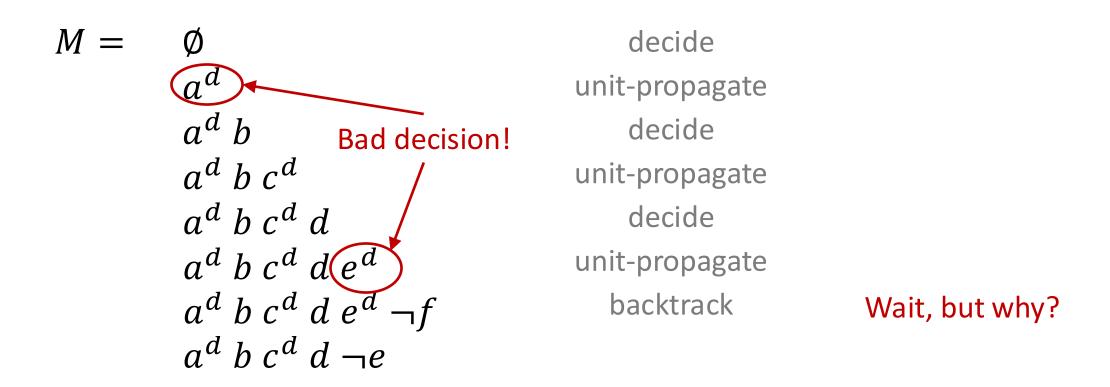
DPLL: example

$$(\neg a \lor \neg b) \land (b \lor c) \land (\neg a \lor \neg c \lor d) \land (b \lor \neg c \lor \neg d) \land (a \lor d)$$

```
M =
                                                 decide
           a^d
                                            unit-propagate
          a^d \neg b
                                            unit-propagate
          a^d \neg b c
                                            unit-propagate
           a^d \neg b c d
                                                backtrack
                                            unit-propagate
           \neg a
                                                 decide
           \neg a d
           \neg a \ d \neg c^a
                                            unit-propagate
           \neg a d \neg c^d b
                                                  SAT!
```

DPLL + clause learning

$$(\neg a \lor b) \land (\neg c \lor d) \land (\neg e \lor \neg f) \land (f \lor \neg b \lor \neg e) \land (\neg a \lor \neg e)$$



DPLL + clause learning

$$(\neg a \lor b) \land (\neg c \lor d) \land (\neg e \lor \neg f) \land (f \lor \neg b \lor \neg e) \land (\neg a \lor \neg e)$$

```
M = \emptyset decide a^d unit-propagate a^d b decide a^d b c^d unit-propagate a^d b c^d d decide a^d b c^d d e^d unit-propagate a^d b c^d d e^d unit-propagate a^d b c^d d e^d backjump a^d b \neg e
```

This lecture

- 1. Demo: how to use Z3 to
 - solve constraints
 - verify programs
 - synthesize programs
- 2. How do SAT solvers work?
- 3. How do SMT solvers work?

Beyond propositional logic

What if our formula looks like this?

$$(p \land \neg q \lor a = f(b-c)) \land (g(g(b) \neq c \lor a - c \leq 7))$$

- talks about integers, functions, sets, lists...
- One idea: bit-blast everything and use SAT
 - can only find solutions within bounds
 - very inefficient, so bounds are small
- Better idea: combine SAT with special solvers for theories
 - they "natively understand" integers, functions, etc.

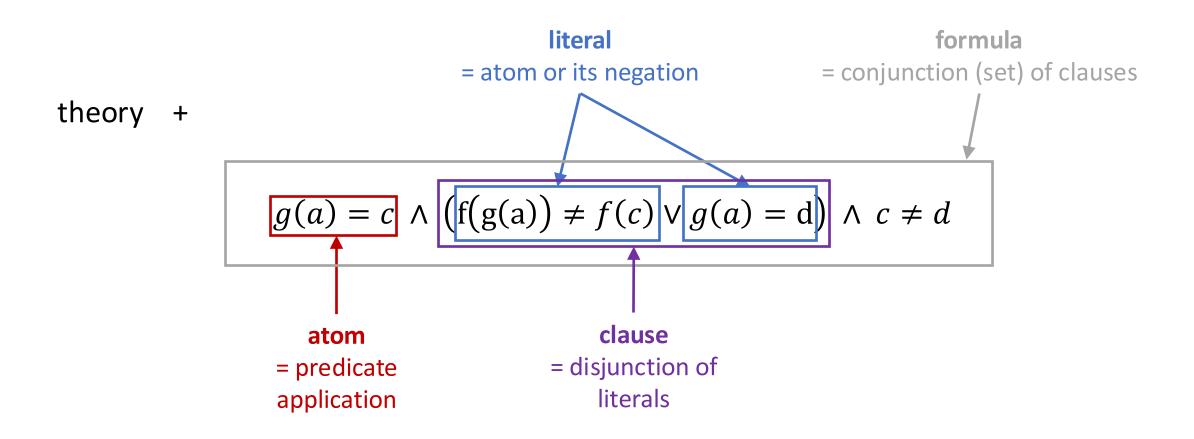
First-order theories

theory = <function symbols, predicate symbols, axioms>

ground first-order formulas over functions and predicates

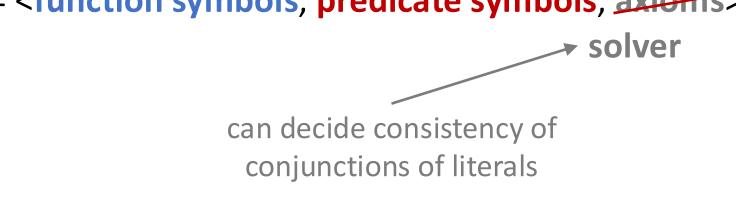
- Example: theory of Equality and Uninterpreted Functions
- EUF = $\{f, g, h, ...\}, \{=\}, \{$ $\forall x. x = x$ $\forall x. y. x = y \Rightarrow y = x$ $\forall x. y. x = y \land y = z \Rightarrow x = z$ $\forall x. y. x = y \land y = z \Rightarrow x = z$ $\forall x. y. x = y \Rightarrow f(x) = f(y)$ $\} >$

The SMT problem



Theories for our purpose

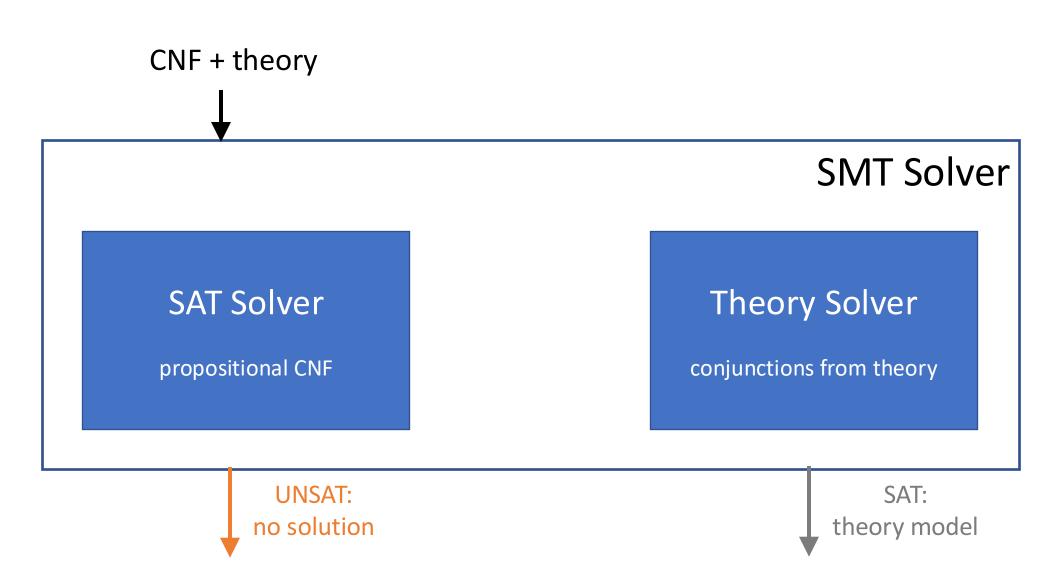
theory = <function symbols, predicate symbols, axioms>



$$f(a) = c$$
 $f(b) \neq d$
 $c = d$
 $a = b$

EUF solver
Inconsistent!

DPLL(T) architecture



Basic DPLL(T)

$$g(a) = c \land (f(g(a)) \neq f(c) \lor g(a) = d) \land c \neq d$$

$$p \land (\neg q \lor r) \land \neg s$$

$$p \neg q \neg s$$

$$\text{Inconsistent!} \qquad g(a) = c \qquad f(g(a)) \neq f(c) \qquad c \neq d$$

$$p \land (\neg q \lor r) \land \neg s \land (\neg p \lor q) \qquad p \neq r \neg s$$

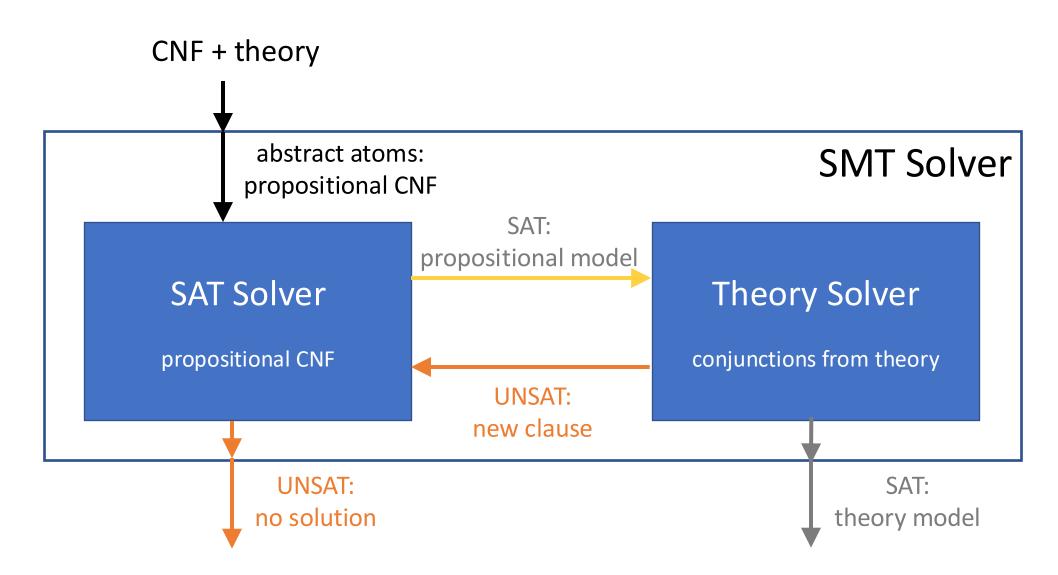
$$\text{Inconsistent!} \qquad g(a) = c \qquad f(g(a)) = f(c) \qquad g(a) = d \qquad c \neq d$$

$$p \land (\neg q \lor r) \land \neg s \land (\neg p \lor q) \land (\neg p \land \neg r \land s) \qquad \text{SAT solver}$$

$$p \land (\neg q \lor r) \land \neg s \land (\neg p \lor q) \land (\neg p \land \neg r \land s) \qquad \text{SAT solver}$$

$$p \land (\neg q \lor r) \land \neg s \land (\neg p \lor q) \land (\neg p \land \neg r \land s) \qquad \text{Unsat}$$

DPLL(T) architecture



Popular theories

- Equality and Uninterpreted Functions
- EUF = <{f, g, h, ...}, {=}, axioms of equality & congruence>
- Linear Integer Arithmetic
- LIA = <{0, 1, ..., +, -}, {=, ≤}, axioms of arithmetic>
- Arrays

Arrays =
$$\langle \{sel, store\}, \{=\}, \forall a \ i \ v. sel(store(a, i, v), i) = v$$

 $\forall a \ i \ j \ v. \ i \neq j \Rightarrow sel(store(a, i, v), j) = sel(a, j) >$

Theories can be combined!

Nelson-Oppen combination

Why do we care?

- If we can encode a synthesis problem as SAT/SMT, we can use solvers to do the search for us
- Get some inspiration from how solvers search
 - Unit propagation similar to top-down propagation (pruning through inference of consequences of a guess)
 - Backjumping / clause learning?
 - Feng, Martins, Bastani, Dillig: Program synthesis using conflict-driven learning. PLDI'18
 - Coarse-grained reasoning and gradual refinement like in DPLL(T)?
 - Wang, Dillig, Singh: Program synthesis using abstraction refinement. POPL'18