

SAT Solving with Conflict Driven Clause Learning

William Schultz

CS 7240 Final Project

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Overview and Project Goals

- Satisfiability is the canonical NP-complete problem.
- Much work has been devoted to building efficient SAT solvers over last decades.
- **Project Goal:** Implement a basic SAT solver based on *conflict driven clause learning* (CDCL), the dominant core technique used in modern solvers.
 - ▶ Gain a deeper understanding of the DPLL and CDCL based algorithms for SAT solving
 - ▶ Use as a platform for potentially exploring new SAT solving techniques
 - ▶ E.g. learning heuristics using a data-driven approach, extending methods of *CrystalBall* [SKM19]

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Given a boolean formula in conjunctive normal form (CNF), determine whether there exists an assignment to the variables of the formula that makes the overall formula true.

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CNF notation:

$$\{\{x_1, x_2\}, \{\neg x_3, \neg x_1\}\}$$

DPLL: SAT as Search

- A basic approach to solving SAT is to view it as a search problem over possible assignments.
- This is the basis of the Davis–Putnam–Logemann–Loveland (DPLL) algorithm [DLL62]
- Basic idea of DPLL is to do a depth first, brute force search with backtracking along with some basic formula simplification as you go.
 - ▶ Also employs the *unit propagation rule*

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$$\{\{\textcolor{blue}{b}\}, \{\neg \textcolor{red}{b}, \neg c\}, \{c, \neg d\}\}$$

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

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$$\{\{\neg d\}\}$$

$$\{\{\neg \textcolor{blue}{d}\}\}$$

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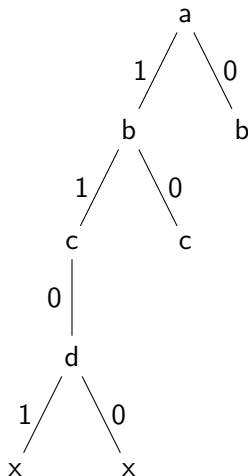
$$\{\{\neg d\}\}$$

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$$\{\} \quad (\text{SAT})$$

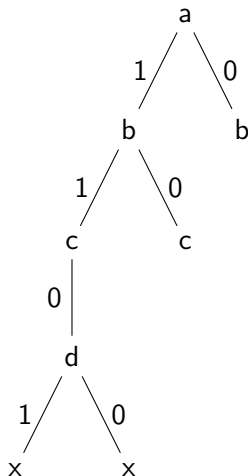
DPLL: Example

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



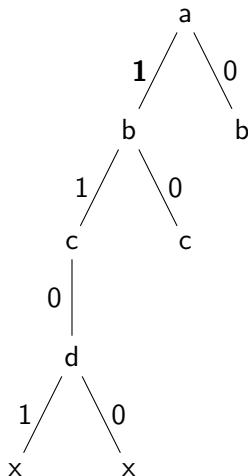
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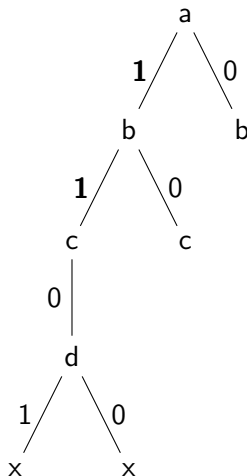
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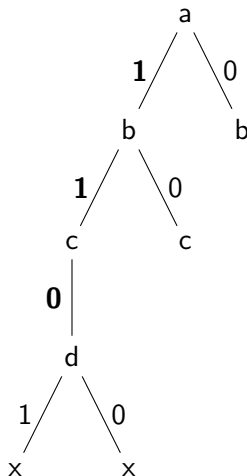
unit propagate b



DPLL: Example

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

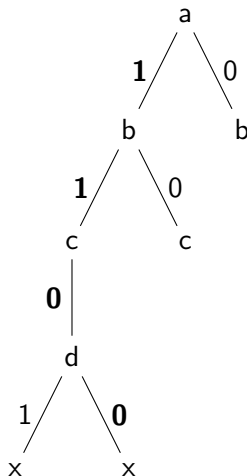
unit propagate $\neg c$



DPLL: Example

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- When you encounter a conflict in the search tree, *learn* a clause that prevents you from making the similar mistakes again
- This fundamental approach is known as *conflict-driven clause learning* (CDCL) and started being employed in SAT solvers around the late 90s and early 2000s.
- In addition, employ *non-chronological backtracking*

CDCL Example

- $c_1 \quad \{a, b\}$
- $c_2 \quad \{b, c\}$
- $c_3 \quad \{\neg a, \neg x, y\}$
- $c_4 \quad \{\neg a, x, z\}$
- $c_5 \quad \{\neg a, \neg y, z\}$
- $c_6 \quad \{\neg a, x, \neg z\}$
- $c_7 \quad \{\neg a, \neg y, \neg z\}$

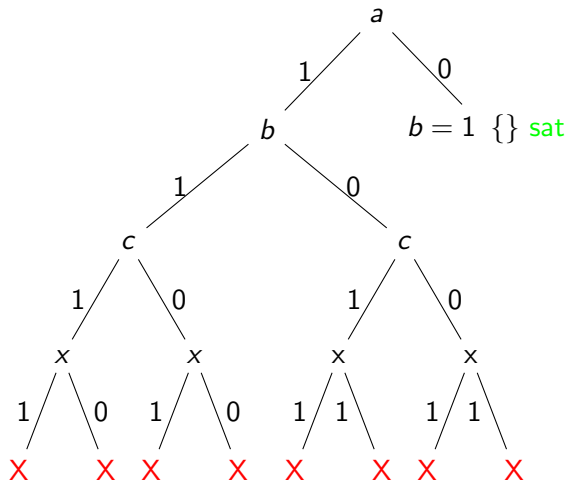


Figure: Basic DPLL termination tree. Explores large portion of left search tree.

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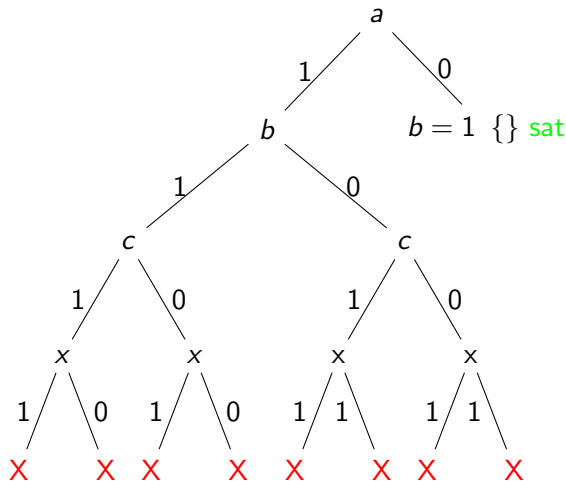


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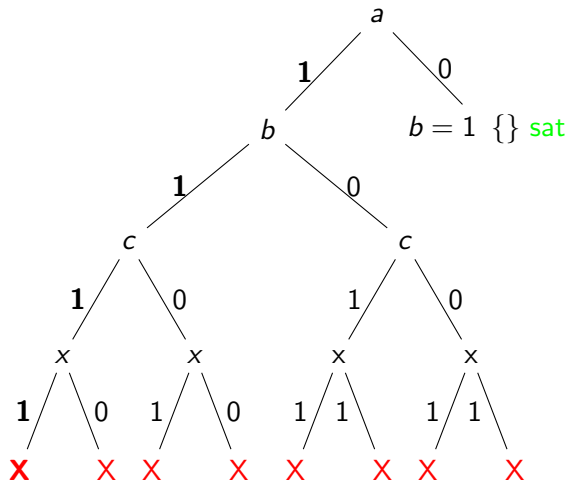


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unit propagate y

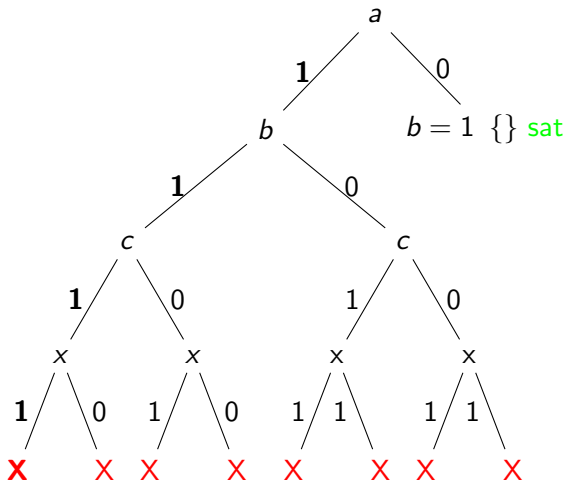


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CDCL Example

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unit propagate z

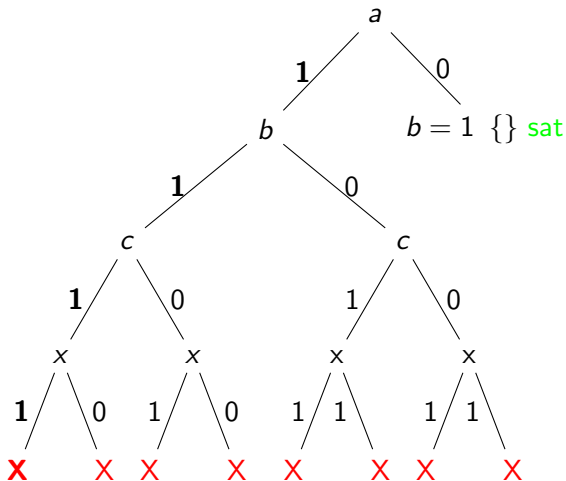


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- c_5 $\{\neg a, \neg y, z\}$
- c_6 $\{\neg a, x, \neg z\}$
- c_7 $\{\neg a, \neg y, \neg z\}$

Note that b and c are irrelevant to the c_7 conflict. $(a \wedge x)$ or $(a \wedge y)$ are sufficient.

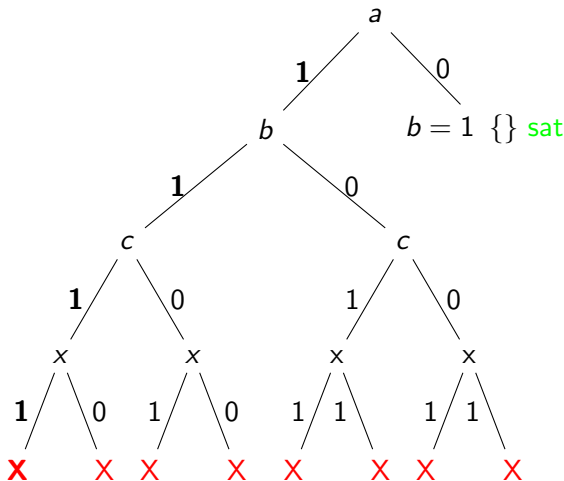


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So, we can learn
 $\neg(a \wedge x) = (\neg a \vee \neg x)$
as a new constraint
i.e. a *learned clause*.

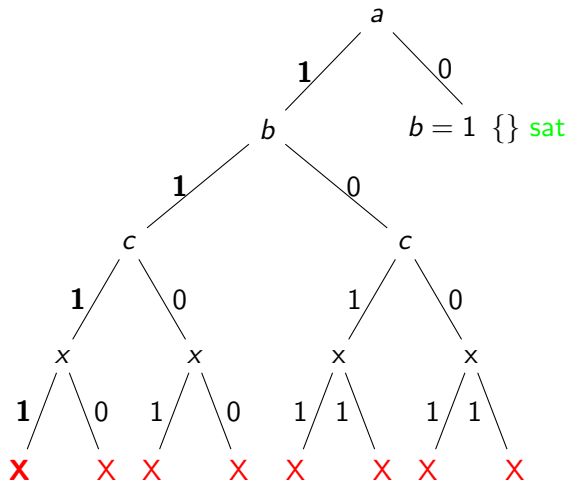


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CDCL Example

l_1	$\{\neg a, \neg x\}$
<hr/>	
c_1	$\{a, b\}$
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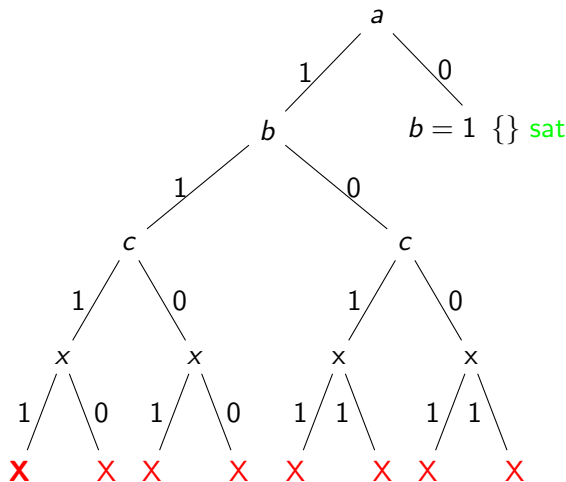


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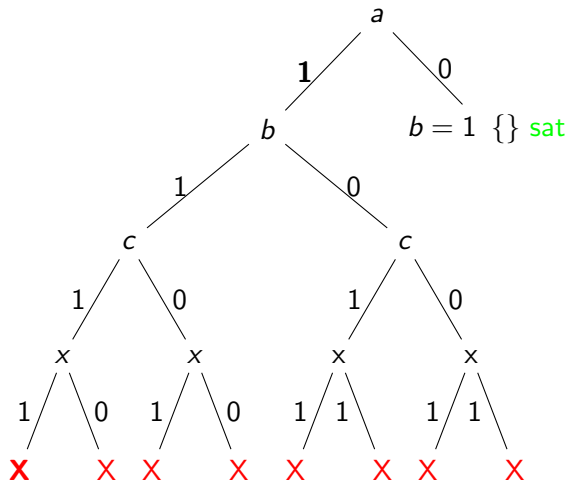


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With the learned clause, we come to the conflict quickly.

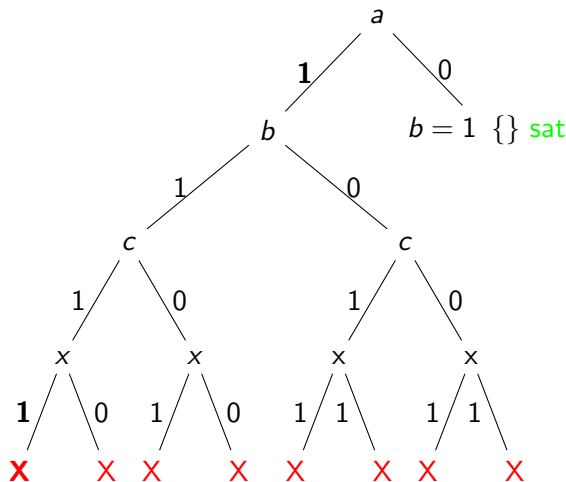


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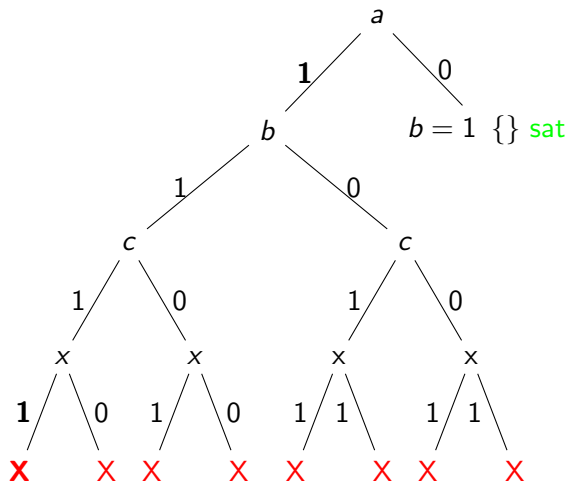


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This time, a is sufficient to cause the conflict, so we learn $\neg a$.

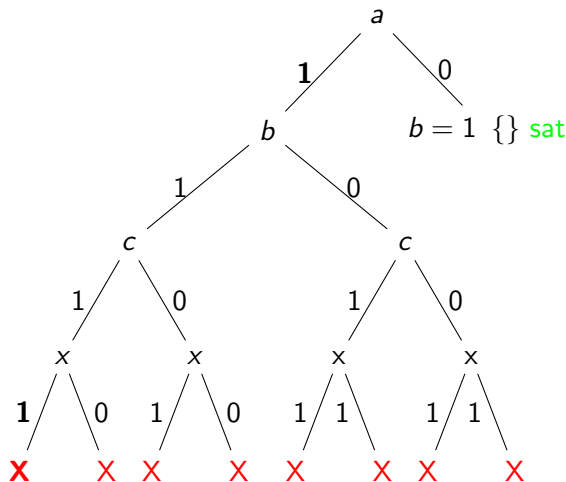


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CDCL Example

l_2	$\{\neg a\}$
l_1	$\{\neg a, \neg x\}$
<hr/>	
c_1	$\{a, b\}$
c_2	$\{b, c\}$
c_3	$\{\neg a, \neg x, y\}$
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With $l_2 = \neg a$, we now get out of the unfruitful search space region.

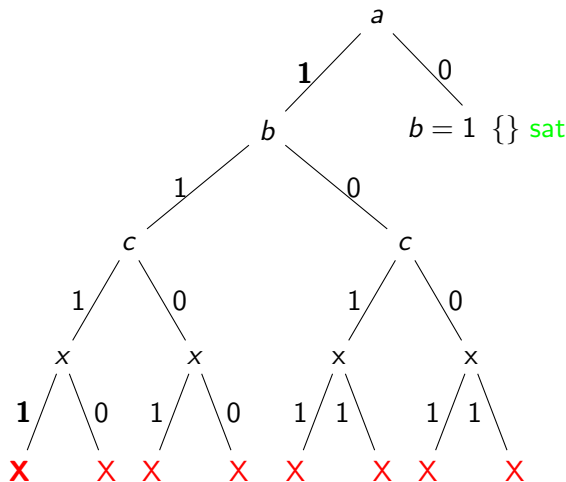


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CDCL Example

- From basic DPLL traversal we can see that there is no satisfying assignment where $a = 1$
- But, we could have learned earlier on that this was an unfruitful section of the search space
- Idea is to analyze the conflict that occurred from partial assignment $\{a = 1, b = 1, c = 1, x = 1\}$

CDCL: Implication Graph

- Can represent the propagation of variable assignments in an *implication graph*
- Nodes of this graph represent variable assignments made in the current search path
- Edges correspond to dependencies between these assignments.

SAT Solver Implementation

- implementing my own CDCL SAT solver as a framework for exploring future potential SAT enhancements
- Around 1500 lines of C++, tested on a variety of easy to medium SAT benchmark problems
- <https://github.com/will162794/mysat>

Evaluation

- Some performance results of my SAT solver against a performant, modern solver.

Future Extensions and Learning Heuristics

- Modern CDCL based SAT solvers employ many heuristics
 - ▶ Variable ordering
 - ▶ Clause deletion policies
- Often these are “expertly tuned” heuristics
- *CrystalBall* [SKM19]: Possible to learn better heuristics from data on SAT solver executions?

- CrystalBall

Questions?



Martin Davis, George Logemann, and Donald Loveland.

A machine program for theorem-proving.

Commun. ACM, 5(7):394–397, jul 1962.



Mate Soos, Raghav Kulkarni, and Kuldeep S. Meel.

CrystalBall: Gazing in the Black Box of SAT Solving.

In Mikoláš Janota and Inês Lynce, editors, *Theory and Applications of Satisfiability Testing – SAT 2019*, pages 371–387, Cham, 2019.

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