

Institut Supérieur de l'Aéronautique et de l'Espace



N7PD Declarative Programming

The SAT problem: theory and solvers

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Outline

- Introduction and basic definitions
- 2 Complexity
- Resolution and the DPLL procedure
- SAT applications
- **5** SAT implementation

What is the SAT problem?

SAT is the abbreviation of the **Boolean Satisfiability Problem**: given a propositional formula, is there a propositional interpretation that satisfies it?

SAT is a important **theoretical** problem for CS: first problem to be proved to be NP-complete, phase transition...

What is the SAT problem?

SAT is the abbreviation of the **Boolean Satisfiability Problem**: given a propositional formula, is there a propositional interpretation that satisfies it?

SAT is a important **theoretical** problem for CS: first problem to be proved to be NP-complete, phase transition...

But SAT has also lots of **practical applications**:

- scheduling
- planning
- software verification
- tooling
- ...

The propositional language

Definition (syntax of \mathcal{L}_{PL})

Let Var be a set of propositional variables. The syntax of well-formed formulas of \mathcal{L}_{PL} is given by the following EBNF:

$$\varphi ::= \text{'}A\text{'} \mid \text{'}\top\text{'} \mid \text{'}\bot\text{'} \mid \neg \varphi \mid \varphi \wedge \varphi \mid \varphi \vee \varphi \mid \varphi \rightarrow \varphi \mid \varphi \leftrightarrow \varphi$$

where $A \in Var$.

The semantics of propositional logic is defined classically (cf. OMI first year lecture).

Interpretation, satisfiability, validity

Definition (interpretation)

An **interpretation** is a total function $Var \mapsto \{T, F\}$.

The **truth value** of a formula φ can be evaluated in an interretation $\mathcal I$ using only the truth values of its subformulae.

The truth value of φ in $\mathcal I$ is denoted by $[\![\varphi]\!]_{\mathcal I}$

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Definition (satisfiability)

A wff φ is **satisfiable** iff there is an interpretation $\mathcal I$ s.t. $[\![\varphi]\!]_{\mathcal I}=\mathcal T$.

Definition (validity)

A wff φ is **valid** iff for all interpretations \mathcal{I} , $[\![\varphi]\!]_{\mathcal{I}} = T$. This is denoted by $\models \varphi$.

SAT and UNSAT

Notice that if a wff φ is **not satisfiable** (noted **UNSAT**), it means that $[\![\varphi]\!]_{\mathcal{I}} = F$ for **all interpretations** \mathcal{I} .

Thus, the following equivalence holds:

 φ is valid $\Leftrightarrow \neg \varphi$ is UNSAT.

Conjunctive Normal Form

We have seen in previous lectures that Conjunctive Normal Form (CNF) is a particular form of wff easy to manipulate.

Remember:

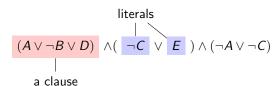
- a CNF is a conjunction of clauses
- a clause is a disjunction of literals
- a literal is either a prop. variable or the negation of a prop. variable

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Remember:

- a CNF is a conjunction of clauses
- a clause is a disjunction of literals
- a literal is either a prop. variable or the negation of a prop. variable



How to compute a CNF?

We have seen a simple algorithm to translate a wff φ into an equivalent CNF:

$$\begin{array}{l} \text{step 1 (remove impl.)} & \begin{cases} \varphi \leftrightarrow \psi \ \equiv (\varphi \rightarrow \psi) \land (\psi \rightarrow \varphi) \\ \varphi \rightarrow \psi \ \equiv \neg \varphi \lor \psi \end{cases} \\ \\ \text{step 2 (NNF)} & \begin{cases} \neg (\neg \varphi) \ \equiv \varphi \\ \neg (\varphi \land \psi) \ \equiv \neg \varphi \lor \neg \psi \\ \neg (\varphi \lor \psi) \ \equiv \neg \varphi \land \neg \psi \end{cases} \\ \\ \text{step 3 (CNF)} & \begin{cases} \varphi \lor (\psi \land \gamma) \ \equiv (\varphi \lor \psi) \land (\varphi \lor \gamma) \\ (\psi \land \gamma) \lor \varphi \ \equiv (\psi \lor \varphi) \land (\gamma \lor \varphi) \end{cases} \end{aligned}$$

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Problem

This algorithm may lead to an exponentially bigger formula!



Tseytin, G. S. (1970).

"On the complexity of derivation in propositional calculus".

In:

Studies in Constructive Mathematics and Mathematical Logic, part II.

Ed. by A. O. Slisenko.

Steklov Mathematical Institute,

Pp. 115-125.

Idea: start from the NNF and replace subformulas by new prop. variables.

$$\text{step 3 (CNF)} \qquad \begin{cases} \varphi \lor \psi \ \equiv (\varphi \lor \psi \lor \neg X) \land (\neg \varphi \lor X) \land (\neg \psi \lor X) \\ \varphi \land \psi \ \equiv (\neg \varphi \lor \neg \psi \lor X) \land (\varphi \lor \neg X) \land (\psi \lor \neg X) \end{cases}$$

Idea: start from the NNF and replace subformulas by new prop. variables.

$$\text{step 3 (CNF)} \qquad \begin{cases} \varphi \vee \psi \ \equiv (\varphi \vee \psi \vee \neg X) \wedge (\neg \varphi \vee X) \wedge (\neg \psi \vee X) \\ \varphi \wedge \psi \ \equiv (\neg \varphi \vee \neg \psi \vee X) \wedge (\varphi \vee \neg X) \wedge (\psi \vee \neg X) \end{cases}$$

Property (equisatisfiability of Tseitin's trans.)

The CNF obtained by Tseitin's transformation is equisatisfiable to the original wff.

Property

The size of the CNF obtained by Tseitin's transformation is linear w.r.t. the size of the original formula.

Idea: start from the NNF and replace subformulas by new prop. variables.

Example:

Formula
$$\neg((A \land B) \lor C) \lor ((\neg A \lor C) \land (\neg C \lor A))$$

CNF

Idea: start from the NNF and replace subformulas by new prop. variables.

Example:

Formula
$$\neg((\mathbf{A} \land \mathbf{B}) \lor C) \lor ((\neg A \lor C) \land (\neg C \lor A))$$

CNF

Idea: start from the NNF and replace subformulas by new prop. variables.

Formula
$$\neg(\mathbf{X_1} \lor C) \lor ((\neg A \lor C) \land (\neg C \lor A))$$

CNF
$$(\neg A \lor \neg B \lor X_1) \land (A \lor \neg X_1) \land (B \lor \neg X_1)$$

Idea: start from the NNF and replace subformulas by new prop. variables.

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$$\neg(\mathbf{X_1} \lor \mathbf{C}) \lor ((\neg A \lor C) \land (\neg C \lor A))$$

CNF
$$(\neg A \lor \neg B \lor X_1) \land (A \lor \neg X_1) \land (B \lor \neg X_1)$$

Idea: start from the NNF and replace subformulas by new prop. variables.

Formula
$$\neg(\mathbf{X_2}) \lor ((\neg A \lor C) \land (\neg C \lor A))$$

CNF $(\neg A \lor \neg B \lor X_1) \land (A \lor \neg X_1) \land (B \lor \neg X_1) \land (X_1 \lor C \lor \neg X_2) \land (\neg X_1 \lor X_2) \land (\neg C \lor X_2)$

Idea: start from the NNF and replace subformulas by new prop. variables.

Formula
$$\neg(X_2) \lor ((\neg \mathbf{A} \lor \mathbf{C}) \land (\neg C \lor A))$$

$$\begin{array}{ccc} \mathsf{CNF} & & (\neg A \lor \neg B \lor X_1) \land (A \lor \neg X_1) \land (B \lor \neg X_1) \land \\ & & (X_1 \lor C \lor \neg X_2) \land (\neg X_1 \lor X_2) \land (\neg C \lor X_2) \end{array}$$

Idea: start from the NNF and replace subformulas by new prop. variables.

Formula
$$\neg(X_2) \lor (\mathbf{X_3} \land (\neg C \lor A))$$

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Formula
$$\neg(X_2) \lor (X_3 \land (\neg \mathbf{C} \lor \mathbf{A}))$$

CNF $(\neg A \lor \neg B \lor X_1) \land (A \lor \neg X_1) \land (B \lor \neg X_1) \land (X_1 \lor C \lor \neg X_2) \land (\neg X_1 \lor X_2) \land (\neg C \lor X_2) \land (\neg A \lor C \lor \neg X_3) \land (A \lor X_3) \land (\neg C \lor X_3)$

Idea: start from the NNF and replace subformulas by new prop. variables.

Formula
$$\neg(X_2) \lor (X_3 \land \mathbf{X_4})$$

CNF $(\neg A \lor \neg B \lor X_1) \land (A \lor \neg X_1) \land (B \lor \neg X_1) \land (X_1 \lor C \lor \neg X_2) \land (\neg X_1 \lor X_2) \land (\neg C \lor X_2) \land (\neg A \lor C \lor \neg X_3) \land (A \lor X_3) \land (\neg C \lor X_3) \land (\neg C \lor A \lor \neg X_4) \land (C \lor X_4) \land (\neg A \lor X_4)$

Idea: start from the NNF and replace subformulas by new prop. variables.

Formula
$$\neg(X_2) \lor (\mathbf{X_3} \land \mathbf{X_4})$$

CNF $(\neg A \lor \neg B \lor X_1) \land (A \lor \neg X_1) \land (B \lor \neg X_1) \land (X_1 \lor C \lor \neg X_2) \land (\neg X_1 \lor X_2) \land (\neg C \lor X_2) \land (\neg A \lor C \lor \neg X_3) \land (A \lor X_3) \land (\neg C \lor X_3) \land (\neg C \lor A \lor \neg X_4) \land (C \lor X_4) \land (\neg A \lor X_4)$

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Formula
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$$\begin{array}{l} (\neg A \vee \neg B \vee X_1) \wedge (A \vee \neg X_1) \wedge (B \vee \neg X_1) \wedge \\ (X_1 \vee C \vee \neg X_2) \wedge (\neg X_1 \vee X_2) \wedge (\neg C \vee X_2) \wedge \\ (\neg A \vee C \vee \neg X_3) \wedge (A \vee X_3) \wedge (\neg C \vee X_3) \wedge \\ (\neg C \vee A \vee \neg X_4) \wedge (C \vee X_4) \wedge (\neg A \vee X_4) \wedge \\ (\neg X_3 \vee \neg X_4 \vee X_5) \wedge (X_3 \vee \neg X_5) \wedge (X_4 \vee \neg X_5) \wedge \\ (\neg X_2 \vee X_5 \vee \neg X_6) \wedge (X_2 \vee X_6) \wedge (\neg X_5 \vee X_6) \end{array}$$

Using CNF

As there is a linear transformation of wff to CNF, we will restrict our presentation on SAT to CNF.

For readability, we will denote a CNF by a set of clauses, each clause being denoted by a set of literals.

For instance:

$$(x_{1} \vee \neg x_{2}) \wedge (x_{3} \vee x_{4} \vee x_{5}) \wedge (x_{5} \vee \neg x_{2})$$

$$\equiv$$

$$\{\{x_{1}, \bar{x_{2}}\}, \{x_{3}, x_{4}, x_{5}\}, \{x_{5}, \bar{x_{2}}\}\}$$

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First, let us look at the simpliest algorithm to check if a wff is SAT or not: **truth tables**.

Truth table complexity is clearly $O(2^n)$ where n is the number of propositional variables involved in the wff.

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The answer is: we do not know!

But if there is an efficient (i.e. polynomial) algorithm for SAT, then it would solve the $P=\mathit{NP}$ question...

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In order to explain that, let us go back to the basics of computation: Turing machines.

A mathematical model for computation: the Turing machine



The Turing machine (Turing, 1936)



This is the theoretical foundation of computers and **imperative programming**:

- tape: memory with stored program
- automaton: microprocessor



École Normale Supérieure de Lyon (2015).

The RubENS project.

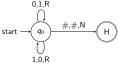
http://rubens.ens-lyon.fr/.

The Turing machine: how does it work?

The Turing machine can be viewed as an **automaton** with an **infinite tape** and a **read/write head**.

- the automaton is composed of **states**
- states can be linked by transitions
- transitions are triggered by the symbol read by the head
- during a transition, the head may write a new symbol and move on the new left/right position

current state current symbol next state symbol to write move hea					
	current state	current symbol	next state	symbol to write	move head
q_0 0 q_0 1 RIGHT	q_0	0	q_0	1	RIGHT
q_0 1 q_0 0 RIGHT	q_0	1	q_0	0	RIGHT
<i>q</i> ₀ # HALT # NONE	q_0	#	HALT	#	NONE



Again, see OMI first year lecture, part on languages.

Nondeterministic Turing machines

A **Nondeterministic Turing machine** (NTM) is a Turing machine for which transitions are no more represented by functions, but rather by **relations**.

This means that for each pair (state, symbol), there may be **more than one** tuple (state, symbol, action) or none.

Nondeterministic Turing machines

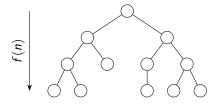
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A NTM will accept an input if there is **some** sequence of **nondeterministic** choices that results in YES.

Nondeterministic Turing machines

Intuitively, a NTM decides a language L in time f(n) where n is the size of the input if f(n) bounds the height of the "computational tree" induced by the machine:



For the moment, there is **no polynomial reduction** of NTM to (deterministic) Turing machine, only exponential ones!

NP problems

NP is a class of problems that can decided in **polynomial time** by a NTM.

Intuitively, a problem in NP is such that verifying if an alternative is a solution is polynomial.

For instance, SAT is in NP: given an interpretation, you can check that the truth value of input formula is \mathcal{T} in polynomial time...

... but we do not know if SAT is in P.

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For instance, SAT is in NP: given an interpretation, you can check that the truth value of input formula is T in polynomial time... ... but we do not know if SAT is in P.

Of course, $P \subseteq NP$, but we do not know if $NP \subseteq P$ (this is a 1,000,000\$ prize ©).

NP-complete problems

A **NP-complete** problem is a problem that:

- is in NP
- is such that every problem in NP can be reduced to the problem in polynomial time

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A **NP-complete** problem is a problem that:

- is in NP
- is such that every problem in NP can be reduced to the problem in polynomial time

Therefore:

- showing that a NP-complete problem is in P implies that all problems in NP are in P
- showing that a problem is in NPC gives a good indication on the fact that the problem should be the least likely to be in P...

SAT is NP-complete

Theorem (Cook-Levin)

SAT is NP-complete.



Cook, Stephen (1971).

"The complexity of theorem proving procedures".

In: Proc. of the third annual ACM symposium on Theory of computing ,

Pp. 151-158.

http://4mhz.de/cook.html.

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Idea: given a NP problem \mathcal{P} , a NTM \mathcal{M} that solves it, and an entry \mathcal{I} for \mathcal{P} , build a formula that is satisfiable iff \mathcal{M} accepts \mathcal{I} for \mathcal{P} .

SAT variants

There are restricted versions of SAT:

Problem	Complexity
CNFSAT	NP-complete
2SAT	Р
3SAT	NP-complete
HORNSAT	Р

In the following, we will use CNFSAT instead of SAT.

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Back to Resolution

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⇒ we could use Resolution to do that!

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We want to show that a set of clauses is UNSAT.

we could use Resolution to do that!

Remember:

• Resolution has only two rules:

$$\frac{\{1, l_1, \dots, l_n\} \qquad \{\bar{1}, l'_1, \dots, l'_m\}}{\{l_1, \dots, l_n, l'_1, \dots, l'_m\}} (R) \qquad \frac{\{1, 1, l_1, \dots, l_n\}}{\{l, l_1, \dots, l_n\}} (F)$$

• we can also add a subsumption rule:

$$\frac{\{\mathbf{l_1},\ldots,\mathbf{l_n}\}\quad \{\mathbf{l_1},\ldots,\mathbf{l_n},l_1',\ldots,l_m'\}}{\{l_1,\ldots,l_n\}} (S)$$

• Resolution is sound and complete for refutation

How to efficiently use Resolution?

Resolution: saturation method

A first idea: apply Resolution again and again (there is a fixed point!).

Resolution: saturation method

Algorithm 3.1: Resolution by saturation algorithm

```
Input: a set of clauses S
   Output: SAT if S is satisfiable, UNSAT else
1 S' \leftarrow \emptyset:
2 while S' \neq S do
3
       S' \leftarrow S:
       generate all possible resolvent and stores them in R
4
       foreach resolvent r do
5
           if r = \square then
 6
               return UNSAT;
           end
8
           if there is no clause C such that C subsumes r then
9
               remove all clauses subsumed by r;
10
              S = S \cup \{r\};
11
           end
12
       end
13
14 end
15 return SAT;
```

Resolution: saturation method

But

- huge memory consumption: intermediate resolvent are computed even if they are subsumed by another clause or are tautologies
- how to efficiently find the clauses on which to apply Resolution
- in which order should you apply Resolution to optimize the process?

The Davis and Putnam procedure

Davis and Putnam developed in 1960 an algorithm using Resolution to check if a set of clauses is SAT or UNSAT.



Davis, Martin and Hilary Putnam (July 1960). "A Computing Procedure for Quantification Theory".

In: Journal of the ACM 7.3,

Pp. 201–215.

DOI: 10.1145/321033.321034.

http://doi.acm.org/10.1145/321033.321034.

The Davis and Putnam procedure

Davis and Putnam developed in 1960 an algorithm using Resolution to check if a set of clauses is SAT or UNSAT.

Three rules are used in the procedure:

taut a clause $\{\mathbf{x}, \bar{\mathbf{x}}, l_1, \dots, l_n\}$ can be eliminated

pure if a variable appears **exclusively** as a positive (or negative) literal I, then all the clauses containing I can be eliminated

res(x) that applies Resolution rule using variable x:

- for each pair of clauses $\{x, l_1, \ldots, l_n\}$ and $\{\bar{x}, l'_1, \ldots, l'_m\}$ generate $\{l_1, \ldots, l_n, l'_1, \ldots, l'_m\}$
- ullet remove all clauses containing either x or \bar{x}

The Davis and Putnam procedure

Davis and Putnam developed in 1960 an algorithm using Resolution to check if a set of clauses is SAT or UNSAT.

Algorithm 3.2: Davis and Putnam algorithm

```
Input: a set of clauses S
```

13 end

Output: SAT if *S* is satisfiable, UNSAT else

```
1 S' \leftarrow \emptyset:
 2 while S' \neq S do
    S' \leftarrow S:
    apply taut rule;
    apply unit rule;
 5
 6
    apply pure rule;
       choose a variable x and apply res using x;
 8 end
9 if S = \emptyset then
      return UNSAT;
10
11 else
      return SAT;
```

DP procedure: example

```
 \begin{array}{lll} & \text{init.} & \{\{x_1\bar{x_2}\bar{x_3}\}\{x_1\bar{x_2}\bar{x_3}\}\{x_2x_3\}\{x_3x_4\}\{x_3\bar{x_4}\}\{\bar{x_3}\}\{\bar{x_5}x_4\}\} \} \\ & \text{pure on } x_5. & \sim & \{\{\mathbf{x_1}\bar{x_2}\bar{x_3}\}\{\bar{x_1}\bar{x_2}\bar{x_3}\}\{x_2x_3\}\{x_3x_4\}\{x_3\bar{x_4}\}\{\bar{x_3}\}\} \} \\ & \text{res on } x_1 & \sim & \{\{\bar{\mathbf{x_2}}\bar{x_3}\}\{x_2x_3\}\{x_3x_4\}\{x_3\bar{x_4}\}\{\bar{x_3}\}\} \} \\ & \text{res on } x_2 & \sim & \{\{\mathbf{x_3}\bar{\mathbf{x_3}}\}\{x_3x_4\}\{x_3\bar{x_4}\}\{\bar{x_3}\}\} \} \\ & \text{taut} & \sim & \{\{x_3\}\{x_3\}\{\bar{x_3}\}\} \} \\ & \text{res on } x_4 & \sim & \{\{\mathbf{x_3}\}\{\bar{\mathbf{x_3}}\}\} \} \\ & \text{res on } x_3 & \sim & \emptyset \\ & \text{UNSAT} \end{array}
```

DP procedure: example

In practise, DP is not efficient:

- takes a lot of time to find clauses on which res can be applied
- memory is saturated with the computed resolvents

Outline

- Introduction and basic definitions
- 2 Complexity
- 3 Resolution and the DPLL procedure
 - Resolution
 - The original DPPL procedure
 - DPPL: a modern view
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DPPL principles

The DPPL procedure is a refinement of the DP procedure.



Davis, Martin, Georges Logemann, and Donald Loveland (1962). "A machine program for theorem proving"

"A machine program for theorem proving". In: Communications of the ACM 5.7.

Pp. 394-397.

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The principles of the procedure are the following:

- ullet an interpretation/a model M satisfying the formula arphi is built incrementally
- M is extended
 - ullet either by **deduction** of the value of a literal I from M and φ
 - ullet either by **deciding** the value of a literal I that does not appear in M
- if a decision leads to a failure node (a clause is valuated to F), the algorithm **backtracks** and inverse the decision

Operation	Model	Formula
		$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$

Operation	Model	Formula
		$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$
Deduce x_1	x_1	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$

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Deduce x_1	x_1	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$
Deduce x_2	x_1, x_2	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$

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Deduce x_2	x_1, x_2	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$
Decide x_3	x_1, x_2, x_3	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$

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Deduce x_1	x_1	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$
Deduce x_2	x_1, x_2	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$
Decide x_3	x_1, x_2, x_3	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$
Deduce x_4	x_1, x_2, x_3, x_4	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{\bar{x_1}\}$

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Undo x_3	x_1, x_2	$\{x_1, x_2\}, \{x_2, \bar{x_3}, x_4\}, \{\bar{x_1}, \bar{x_2}\}, \{\bar{x_1}, \bar{x_3}, \bar{x_4}\}, \{x_1\}$

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SAT: an abstract framework

In Nieuwenhuis, Oliveras, and Tinelli 2004, Nieuwenhuis et al. give an abstract framework for SAT algorithms.



Nieuwenhuis, R., A. Oliveras, and C. Tinelli (2004). "Abstract DPLL and Abstract DPLL Modulo Theories". In: **LPAR**, Pp. 36–50.

This framework is based on an abstract transition system.

Abstract SAT: states

Definition (states)

A state in the transition system is either

- fail
- $M \| \varphi$ where
 - $\bullet \varphi$ is a CNF
 - M is a (partial) interpretation $I_1, \ldots, I_i^d, \ldots, I_k$ where the I_i are literals and d a **decision level**

Abstract SAT: states

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- $M \| \varphi$ where
 - $\bullet \ \varphi$ is a CNF
 - M is a (partial) interpretation $l_1, \ldots, l_i^d, \ldots, l_k$ where the l_i are literals and d a **decision level**

Definition (initial and final states)

- ullet initial state: $\emptyset \| \varphi$
- final states:
 - ullet fail if φ is UNSAT
 - \bullet $\mathit{M} \| \psi$ where ψ is equivalent to φ and M is a model of ψ

How does DPPL work?

DPLL builds incrementally a model for the initial formula.

During the space exploration:

- a variable may have for value T (true), F (false) or X (unassigned)
- a clause can be

```
sat iff one of its literals is T
unit iff all of its literals are F except one
conflict iff all of its literals are F
undef otherwise
```

a CNF is SAT iff all its clauses are sat

DPLL: model extension rules

Rule (UnitProp)

$$M\|\varphi, C \lor I \to M I\|\varphi, C \lor I \text{ if } \begin{cases} M \models \neg C \\ I \text{ is not defined in } M \end{cases}$$

DPLL: model extension rules

Rule (UnitProp)

$$M\|\varphi, C \lor I \to M I\|\varphi, C \lor I \text{ if } \begin{cases} M \models \neg C \\ I \text{ is not defined in } M \end{cases}$$

Rule (Decide)

$$M\|\varphi \to M I^d\|\varphi$$
 if $\begin{cases} I \text{ or } \overline{I} \text{ is in } \varphi \\ I \text{ is not defined in } M \end{cases}$

 I^d is identified as a literal of decision level d.

DPLL: model repairing rules

Rule (Fail)

$$M\|arphi',\, C o fail$$
 if $egin{cases} M\models \neg C\ M ext{ has no decision literal} \end{cases}$

DPLL: model repairing rules

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Rule (Backtrack)

$$M\ I^d\ N\|\varphi',C \to M\ \overline{I}\|\varphi',C$$
 if $\begin{cases} M\ I^d\ N \models \neg C \\ I^d\$ is the last decision literal

DPLL basic procedure

Definition (DPLL basic procedure)

The original DPLL algorithm from Davis, Logemann, and Loveland 1962 uses the following rules:

- UnitProp
- Decide
- Fail
- Backtrack

until a model or fail is produced.

Some definitions:

Irreductible state state from which no transition can be fired sequence of transitions allowed by the rules

from an initial state $\emptyset \| arphi$

Saturated execution execution finishing with an irreductible state

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Every execution of DPPL is **finite**.

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Every execution of DPPL is finite.

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For each saturated execution from $\emptyset \| \varphi$ finishing in $M \| \varphi$, $M \models \varphi$.

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Theorem (completeness)

If φ is UNSAT, every saturated execution from $\emptyset \| \varphi$ finishes in fail.

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DPLL: from backtracking to backjumping

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DPLL: from backtracking to backjumping

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Rule (Backjump)

$$M \ l^d \ N \| \varphi', C \to M \ k \| \varphi', C \ \text{if} \ \begin{cases} 1. \ M \ l^d \ N \models \neg C \\ 2. \ \text{there is a clause} \ D \lor k \ \text{s.t.} \\ \varphi', C \models D \lor k \ \text{and} \ M \models \neg D \\ k \ \text{is not defined in} \ M \\ k \ \text{or} \ \bar{k} \ \text{occurs in} \ \varphi' \lor C \end{cases}$$

CDCL: learning from errors

How to avoid repeating the same errors when encountering a fail branch?

CDCL: learning from errors

How to avoid repeating the same errors when encountering a fail branch?

Idea: find the clause "responsible" for the conflict, add it and backjump to the highest decision level.

Adding the clause avoids getting in the same subtree if encountering the same subinterpretation.

This technics is called Conflict-Driven Clause Learning (CDCL).

Modern DPLL: new rules

Rule (Learn)

$$M\|\varphi \to M\|\varphi, C \text{ if } \begin{cases} \text{all atoms of } C \text{ appear in } \varphi \\ \varphi \models C \end{cases}$$

Modern DPLL: new rules

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$$M\|\varphi, C \to M\|\varphi \text{ if } \varphi \models C$$

Modern DPLL: new rules

Rule (Learn)

$$M\|\varphi \to M\|\varphi, C$$
 if $\begin{cases} \text{all atoms of } C \text{ appear in } \varphi \\ \varphi \models C \end{cases}$

Rule (Forget)

$$M\|\varphi, C \to M\|\varphi \text{ if } \varphi \models C$$

Rule (Restart)

$$M\|\varphi \to \emptyset\|\varphi$$
 if you want...

Strategies for modern DPLL

- applying a rule of basic DPPL between each Learn and applying Restart less and less often maintains termination.
- in practise, Learn is applied just after each Backjump
- the most common strategy uses these priorities:
 - lacksquare if n > 0 conflicts have been found, then increment n and apply Restart
 - if a clause is falsified by the current interpretation, apply Fail or Backjump + Learn
 - apply UnitProp until saturation

Modern DPLL: correctness

Theorem (termination)

Every execution in which

- Learn/Forget are applied a fixed number of times
- Restart is applied with a growing periodicity

is finite.

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If φ is UNSAT, every saturated execution from $\emptyset \| \varphi$ finishes in fail.

Actual solvers

Current solvers combine

- a preprocessing phase using Resolution to simplify the initial formula before using DPLL
- a parallel implementation of modern DPLL
- inprocessing phases using Resolution to simplify Resolution the formula during DPLL

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- a preprocessing phase using Resolution to simplify the initial formula before using DPLL
- a parallel implementation of modern DPLL
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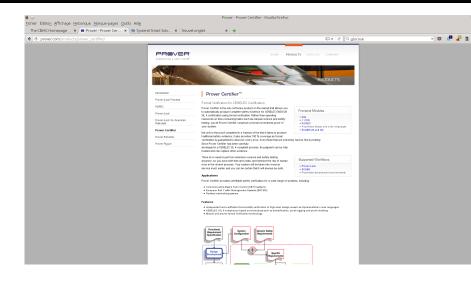
Some interesting solvers:

- Chaff (2000), minisat (2004), PicoSAT (2006)
- SAT4J (written in Java, integrated in Eclipse for libraries dependency)
- Glucose 4.0 (written in C++, winner of several contests)
- Lingeling (written in C, winner of several contests)

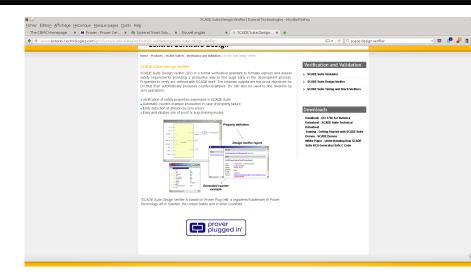
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Prover Technology



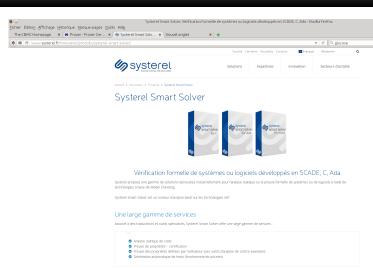
Scade Design Verifier



Simulink Design Verifier



Systerel

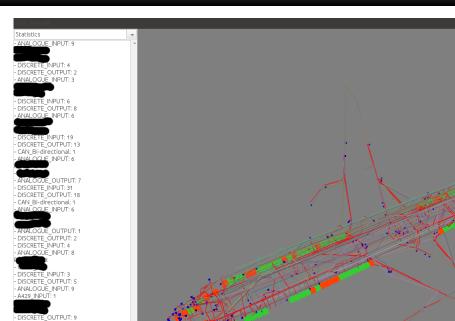


CProver

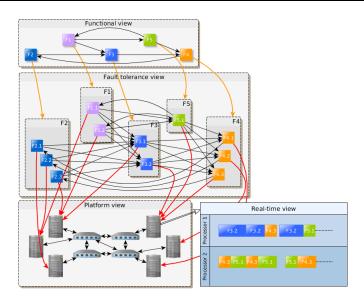


CBMC.

ONERA



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DPPL algorithm

```
if (propagate(F, V) == CONFLICT) { return UNSAT; }
dl = 0:
while( !satisfied(F, V) ) {
  (x, p) = decide(F, V); // select variable and phase
  dl += 1:
                      // bump decision level
 V += (x -> p); // extend assignment
  if (propagate(F, V) == CONFLICT) {
   (bl, ccl) = analyseConflict(F, V);
   if (bl < 0) { // backjump past root
     return UNSAT:
   } else { // backjump somewhere
      backjump(F, V, bl, ccl);
     dl = bl;
return SAT;
```

Two watched literals

How to detect **efficiently** that a clause is **unit**?

- associate to each variable x_i the set C_{x_i} of clauses in which x_i appears
- for each $c \in C_{x_i}$, watch two literals I and I'
- if x_i is assigned to T or F, for each $c \in C_{x_i}$
 - if I (resp. I') is X, the clause is **not unit**
 - if / (resp. /') is T or F, look for another literal /" with value X in the clause
 - if such a literal exists, watch I'' instead of I (resp. I')
 - else, c is unit, propagate l' (resp. l).

Advantages: locality, nothing to modify when backjumping!

Clause learning

CDCL is performent mainly because it efficiently analyzes conflicts and learns clauses.

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CDCL is performent mainly because it efficiently analyzes conflicts and learns clauses.

Some notations:

value fixing

At devision level d, fixing x_i to T is noted $x_i@d$, fixing x_i to F is noted $\bar{x}_i@d$

antecedents

When the value of x_i is fixed by **propagation** through a unit clause c, c is called the **antecedent** of x_i

• implication graph

An implication graph is a graph in which

- nodes represent variables fixings at decision levels
- edges represent propagation and are labelled with antecedents
- decisions are nodes without antecedent

Example

$$F = \{c_1, c_2, c_3, c_4, c_5, c_6\}$$

$$c_1 = \{x_1, x_{31}, \bar{x}_2\}$$

$$c_2 = \{x_1, \bar{x}_3\}$$

$$c_3 = \{x_2, x_3, x_4\}$$

$$c_4 = \{\bar{x}_4, \bar{x}_5\}$$

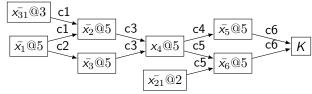
$$c_5 = \{x_{21}, \bar{x}_4, \bar{x}_6\}$$

$$c_6 = \{x_5, x_6\}$$

let use suppose that the decisions are the following:

- $x_{21}^-@2$
- $x_{31}@3$
- $\bar{x_1}$ @5 (current level)

propagate deduces at the same time x_5 and $\bar{x_5}$, or x_6 and $\bar{x_6}$, i.e. a **conflict** (K).



Conflict analysis

Starting from the conflict clause, a clause avoiding the conflict by Resolution is built by following the antecedents in the implication graph:

$$\mathcal{K} \xrightarrow{\{x_5, x_6\}} \{x_5, x_6\} \xrightarrow{\{\bar{x_4}, \bar{x_5}\}} \{x_6, \bar{x_4}\} \xrightarrow{\{x_{21}, \bar{x_4}, \bar{x_6}\}} \{x_{21}, \bar{x_4}\} \xrightarrow{\{x_{2}, x_{3}, x_4\}}$$

$$\{x_{2}, x_{3}, x_{21}\} \xrightarrow{\{x_{1}, \bar{x_3}\}} \{x_{2}, x_{21}, x_{1}\} \xrightarrow{\{x_{1}, x_{31}, \bar{x_2}\}} \{x_{1}, x_{21}, x_{31}\}$$

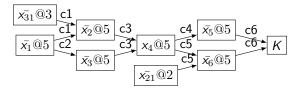
The conflict clause $\{x_{21}, x_{31}, x_1\}$ is added in the base of clauses and we backtrack to a decision level s.t. the clause is **unit** (to use a different phase for at least one variable in the clause).

Unique Implication Point

Reducing conflict clauses with Unique Implication Point (UIP):

- a UIP is a **dominant** of the conflict node in the propagation graph
- there is at least one UIP at each decision level (the decision itself)
- stop when the clause contains the first UIP of the current decision level and only decision variables from the lower levels

In the picture below, $x_4@5$ is the first UIP of level 5. The conflict clause is $\{x_{21}, \bar{x_4}\}$ instead of $\{x_{21}, x_{31}, x_1\}$.



Dynamic decision heuristics

Score each variable in conflict clause via Variable State Independent Decaying Sum (VSIDS), first seen in Chaff (2000)

- ullet each variable is associated to an activity counter, initialized to 0
- the counter is incremented each time the variable appears in a conflict clause
- each n conflicts, divide the activity of each variable by a constant to concentrate on most recent conflicts

A revolutionary idea for 2000, improved in Berkmin, MiniSat, picosat, etc.

Phase heuristics

When backjumping, a part of the current solution is lost and this part could be coherent on a subset of the formula.

The "reasoning" must be redone several times.

Idea: when backjumping, save the current assignment of variables for **satisfied clauses** and use it as heuristics.

Allows to reuse lots of decisions.

And more!

- restarting
- data structures
- clauses erasing
- etc.

Conclusion

SAT solvers are used in real-life applications, particularly for formal methods:

- they can solve problems with billions of variables and clauses
- plenty of theories can be encoded in SAT:
 - arithmetics modulo 2ⁿ
 - arithmetics with arbitrary precision
 - arrays
 - etc.
- lots of available solvers: zChaff, MiniSat, Glucose, SAT4J, Lingeling,
- an annual competition to test solvers, SAT-COMP