

A gentle introduction to SAT

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The Boolean Satisfiability Problem

Propositional formula

Definition

Let \mathcal{V} be a finite set of Boolean valued variables. A *propositional formula* on \mathcal{V} is defined inductively as follows:

- each of the constants **false**, **true** is a propositional formula on \mathcal{V} ;
- if ϕ and ϕ' are propositional formulas on \mathcal{V} then $\neg\phi$, $\phi \wedge \phi'$, $\phi \vee \phi'$, $\phi \Leftrightarrow \phi'$, $\phi \rightarrow \phi'$ are propositional formulas on \mathcal{V} as well.
- An *assignment* on \mathcal{V} is any map from \mathcal{V} to $\{\text{false}, \text{true}\}$



Definition

Let \mathcal{V} be a finite set of Boolean variables and let ϕ be a propositional formula on \mathcal{V} .

- An assignment \mathbf{v} on \mathcal{V} is a *satisfying assignment* for ϕ if we have $\mathbf{v}(\phi) = \text{true}$;
- The propositional formula ϕ is said **satisfiable** if there exists a satisfying assignment for ϕ .
- Deciding whether or not a propositional formula is **satisfiable** is called the *Boolean satisfiability problem*, denoted by **SAT**.

Conjunctive normal form

Literals

A literal (a, b, \dots) is either a boolean variable x or this negation $\neg x$

Clauses

A clause C is a **disjunction** of literals *i.e.*:

$$C = a \vee b \vee \dots \vee z$$

Formula

A formula Φ is a **conjunction** of clauses *i.e.*:

$$\Phi = C_1 \wedge C_2 \wedge \dots \wedge C_m$$

Example

$$\Phi = (a \vee \neg b) \wedge a \wedge (\neg a \vee \neg b)$$



Resolution of a SAT formula

Let $\Phi_1 = (a \vee \neg b) \wedge a \wedge (\neg a \vee \neg b)$

Resolution

a $\neg b$

a

$\neg a$ $\neg b$

Goal: Find an assignment of a and b such that each line is true ✓

a = ?

b = ?



Resolution of a SAT formula

Let $\Phi_1 = (a \vee \neg b) \wedge a \wedge (\neg a \vee \neg b)$

Resolution

a	$\neg b$ ✓
a	✓
$\neg a$	$\neg b$

Goal: Find an assignment of a and b such that each line is true ✓

a = True

b = ?



Resolution of a SAT formula

Let $\Phi_1 = (a \vee \neg b) \wedge a \wedge (\neg a \vee \neg b)$

Resolution

a	$\neg b$	✓
a		✓
$\neg a$	$\neg b$	✓

Goal: Find an assignment of a and b such that each line is true ✓

a = True

b = False

Φ_1 is SAT 😊



Another resolution of a SAT formula

Let $\Phi_2 = (a \vee \neg b) \wedge b \wedge (\neg a \vee \neg b)$

Resolution

a	$\neg b$
b	
$\neg a$	$\neg b$

Goal: Find an assignment of a and b such that each line is true ✓

a = ?

b = ?



Another resolution of a SAT formula

Let $\Phi_2 = (a \vee \neg b) \wedge b \wedge (\neg a \vee \neg b)$

Resolution

a	$\neg b$
b	✓
$\neg a$	$\neg b$

Goal: Find an assignment of a and b such that each line is True ✓

a = ?

b = True



Another resolution of a SAT formula

Let $\Phi_2 = (a \vee \neg b) \wedge b \wedge (\neg a \vee \neg b)$

Resolution

a	$\neg b$ x
b	✓
$\neg a$	$\neg b$ x

Goal: Find an assignment of a and b such that each line is True ✓

a = ☹️

b = True

Φ_2 is UNSAT ☹️



Complexity and restricted versions

Complexity

- First known **NP-complete** problem, as proved by *Stephen Cook* in 1971 and *Leonid Levin* in 1973;
- Every decision problem in NP can be reduced to the SAT problem;
- Cook's reduction preserves the number of accepting answers.

Some restricted versions

- **3-SAT**: each clause is limited to at most 3 literals → **NP-complete**
- **2-SAT**: each clause is limited to at most 2 literals → **Polynomial**
- **MAX-SAT**: the problem of determining the maximum number of clauses that can be made true by an assignment. → **APX-Complete**



Complexity and restricted versions

Some restricted versions

- **3-SAT**: each clause is limited to at most 3 literals → **NP-complete**
- **2-SAT**: each clause is limited to at most 2 literals → **Polynomial**
- **MAX-SAT**: the problem of determining the maximum number of clauses that can be made true by an assignment. → **APX-Complete**

MAX-SAT

$$\phi = (x_0 \vee x_1) \wedge (x_0 \vee \neg x_1) \wedge (\neg x_0 \vee x_1) \wedge (\neg x_0 \vee \neg x_1)$$

ϕ is not **satisfiable** 😞. However, there exists an assignment of ϕ s.t 3 of 4 clauses are true.

Therefore, if this formula is given as an instance of the MAX-SAT problem, the solution to the problem is 3 😊.



Applications

Example of a application (in real life)

The Sudoku problem

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

Figure 1: A typical Sudoku puzzle

Rules

The objective is to fill a 9×9 grid with digits so that each column, each row, and each of the nine 3×3 subgrids that compose the grid contain all of the digits from 1 to 9.

How to do this?

Reduce Sudoku to SAT

Goal: Reduce an instance of Sudoku to an instance (formula) ϕ_G of SAT

Rules

- Definedness: each **cell**, each **row**, each **column** and each **block** having *at least* one number from 1 to n ;
- Uniqueness: same but with *at most* one number from 1 to n .



How to do this?

Rules

- Definedness: each cell, each row, each column and each sub-grid having *at least* one number from 1 to n ;
- Uniqueness: same but with *at most* one number from 1 to n .

Variable s_{xyz} is assigned true *iff* the entry in row x and column y is assigned to number z .

	Definedness	Uniqueness
--	-------------	------------



How to do this?

Rules

- Definedness: each cell, each row, each column and each sub-grid having *at least* one number from 1 to n;
- Uniqueness: same but with *at most* one number from 1 to n.

Variable s_{xyz} is assigned true *iff* the entry in row x and column y is assigned to number z .

	Definedness	Uniqueness
Cell	$\bigwedge_{x=1}^9 \bigwedge_{y=1}^9 \bigvee_{z=1}^9 s_{xyz}$	$\bigwedge_{x=1}^9 \bigwedge_{y=1}^9 \bigwedge_{z=1}^8 \bigwedge_{i=z+1}^9 (\neg s_{xyz} \vee \neg s_{xyi})$

How to do this?

Rules

- Definedness: each cell, each row, each column and each sub-grid having *at least* one number from 1 to n;
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Row	$\bigwedge_{y=1}^9 \bigwedge_{z=1}^9 \bigvee_{x=1}^9 s_{xyz}$	$\bigwedge_{y=1}^9 \bigwedge_{z=1}^9 \bigwedge_{x=1}^8 \bigwedge_{i=x+1}^9 (\neg s_{xyz} \vee \neg s_{iyz})$



How to do this?

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- Definedness: each cell, each row, each column and each sub-grid having *at least* one number from 1 to n;
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Variable s_{xyz} is assigned true *iff* the entry in row x and column y is assigned to number z .

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Row	$\bigwedge_{y=1}^9 \bigwedge_{z=1}^9 \bigvee_{x=1}^9 s_{xyz}$	$\bigwedge_{y=1}^9 \bigwedge_{z=1}^9 \bigwedge_{x=1}^8 \bigwedge_{i=x+1}^9 (\neg s_{xyz} \vee \neg s_{iyz})$
Column	$\bigwedge_{x=1}^9 \bigwedge_{z=1}^9 \bigvee_{y=1}^9 s_{xyz}$	$\bigwedge_{x=1}^9 \bigwedge_{z=1}^9 \bigwedge_{y=1}^8 \bigwedge_{i=y+1}^9 (\neg s_{xyz} \vee \neg s_{xiz})$



How to do this?

Rules

- Definedness: each cell, each row, each column and each sub-grid having *at least* one number from 1 to n;
- Uniqueness: same but with *at most* one number from 1 to n.

Variable s_{xyz} is assigned true *iff* the entry in row x and column y is assigned to number z .

	Definedness	Uniqueness
Cell	$\bigwedge_{x=1}^9 \bigwedge_{y=1}^9 \bigvee_{z=1}^9 s_{xyz}$	$\bigwedge_{x=1}^9 \bigwedge_{y=1}^9 \bigwedge_{z=1}^8 \bigwedge_{i=z+1}^9 (\neg s_{xyz} \vee \neg s_{xyi})$
Row	$\bigwedge_{y=1}^9 \bigwedge_{z=1}^9 \bigvee_{x=1}^9 s_{xyz}$	$\bigwedge_{y=1}^9 \bigwedge_{z=1}^9 \bigwedge_{x=1}^8 \bigwedge_{i=x+1}^9 (\neg s_{xyz} \vee \neg s_{iyz})$
Column	$\bigwedge_{x=1}^9 \bigwedge_{z=1}^9 \bigvee_{y=1}^9 s_{xyz}$	$\bigwedge_{x=1}^9 \bigwedge_{z=1}^9 \bigwedge_{y=1}^8 \bigwedge_{i=y+1}^9 (\neg s_{xyz} \vee \neg s_{xiz})$
Sub-grid	$\bigwedge_{i=0}^2 \bigwedge_{j=0}^2 \bigwedge_{x=1}^3 \bigwedge_{y=1}^3 \bigvee_{z=1}^9 s_{(3i+x)(3j+y)z}$	Not enough space to write it down but you have the idea ☺

Table 1: Rule table



What do we get ?

The same Sudoku problem solved

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

Figure 2: A typical Sudoku puzzle

Steps

1. Create the SAT formula using the different rules seen above;
2. Give this formula to a SAT solver;
3. Interpreting the result (i.e. $s_{134} = \text{true}$ means there is a 4 in the 1st line and 3rd column.)

Tseytin tranformation

Problem

How to transform any logical formula into CNF?

The tseytin transformation

Consider the following formula Φ :

$$\Phi = ((p \vee q) \wedge r) \rightarrow (\neg s)$$

Consider all subformulas (without variables):

$$\begin{array}{c} \neg s \\ p \vee q \\ (p \vee q) \wedge r \\ ((p \vee q) \wedge r) \rightarrow (\neg s) \end{array}$$



Tseytin tranformation

$$\Phi = ((p \vee q) \wedge r) \rightarrow (\neg s)$$

Introduce a new variable for each subformula:

$$x_1 \leftrightarrow \neg s$$

$$x_2 \leftrightarrow p \vee q$$

$$x_3 \leftrightarrow x_2 \wedge r$$

$$x_4 \leftrightarrow x_3 \rightarrow x_1$$

Conjunct all substitutions:

$$x_4 \wedge (x_4 \leftrightarrow x_3 \rightarrow x_1) \wedge (x_3 \leftrightarrow x_2 \wedge r) \wedge (x_2 \leftrightarrow p \vee q) \wedge (x_1 \leftrightarrow \neg s)$$

All substitutions can be transformed into CNF, e.g:

$$\begin{aligned} x_2 \leftrightarrow p \vee q &\equiv (x_2 \rightarrow (p \vee q)) \wedge ((p \vee q) \rightarrow x_2) \\ &\equiv (\neg x_2 \vee p \vee q) \wedge ((\neg p \wedge \neg q) \vee x_2) \\ &\equiv (\neg x_2 \vee p \vee q) \wedge (\neg p \vee x_2) \wedge (\neg q \vee x_2) \end{aligned}$$



Polynomial-time Reduction

Definition

Problem Y is **polynomial-time** reducible to problem X if arbitrary instances of problem Y can be solved using:

- Polynomial number of standard computational steps;
- Polynomial number of calls to the algorithm that solves problem X.

We note that $Y \leq_p X$

Consequences of $Y \leq_p X$

- if X can be solved in polynomial-time, then Y **can** also be solved in polynomial time;
- If Y cannot be solved in polynomial-time, then X **cannot** be solved in polynomial time.



3-SAT is reducible to Independent Set

Claim

$3\text{-SAT} \leq_p \text{INDEPENDENT-SET}$

Proof

Given an instance Φ of 3-SAT, we construct an instance (G, K) of INDEPENDENT-SET that has an independent set of size k iff Φ is satisfiable.



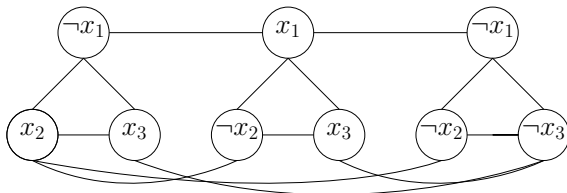
3-SAT is reducible to Independent Set

Claim

$3\text{-SAT} \leq_p \text{INDEPENDENT-SET}$

Construction

- G contains 3 vertices for each clause, one for each literal;
- Connect the 3 literals in a clause in a triangle;
- Connect literal to each of its negations.



$$\Phi = (\neg x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee \neg x_2 \vee \neg x_3)$$

3-SAT is reducible to Independent Set

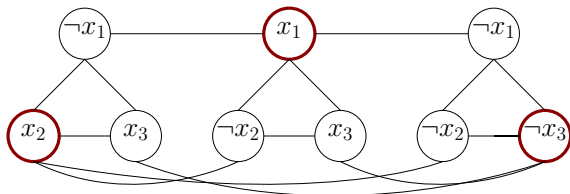
Claim

$3\text{-SAT} \leq_p \text{INDEPENDENT-SET}$

Proof of if-part

Let s be independent set of size k .

- S must contain exactly one vertex in each triangle;
- Set these literals to true;
- Truth assignment is consistent and all clauses are satisfied.



$$\Phi = (\neg x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee \neg x_2 \vee \neg x_3)$$

3-SAT is reducible to Independent Set

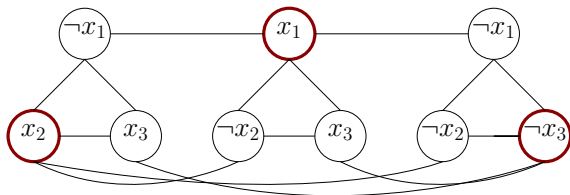
Claim

$3\text{-SAT} \leq_p \text{INDEPENDENT-SET}$

Proof of only-if part

Given satisfying assignment, select one true literals from each triangle.

This is an independent set of size k .



$$\Phi = (\neg x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee \neg x_2 \vee \neg x_3)$$

Many other applications

Example of applications

- Cryptography;
- Planification;
- Resolving software package dependencies

How do SAT solvers work?

The naive method

Using a truth table

The most obvious way to solve a SAT problem is to go through the truth table of the problem.

Example

$$\Phi = (a \vee b) \wedge (\neg a \vee \neg b)$$

a	b	$a \vee b$	$\neg a \vee \neg b$	Φ
true	true	true	false	false
true	false	true	true	true
false	true	true	true	true
false	false	false	true	false

\implies Complexity : $O(2^n)$

The DPLL algorithm (1962)

The **Davis–Putnam–Logemann–Loveland (DPLL)** algorithm is a complete, *backtracking-based* search algorithm for deciding the satisfiability of propositional logic formulae Φ

Major innovations

- Unit propagation
- Pure literal elimination
- Backtracking

Unit propagation

Unit propagation

If a clause is a **unit clause**, i.e. it contains only a single literal l , We can apply the following two rules:

- Every clause (other than the unit clause itself) containing l is removed;
- in every clause that contains $\neg l$, this literal is deleted.

Example

$$\Phi = (a \vee b) \wedge (\neg a \vee c) \wedge (\neg c \vee d) \wedge a$$

$$a \vee b$$

$$\neg a \vee c$$

$$\neg c \vee d$$

$$a$$

The following set of clauses can be simplified by **unit propagation** because it contains the unit clause a .

Unit propagation

Unit propagation

If a clause is a **unit clause**, i.e. it contains only a single literal l , We can apply the following two rules:

- Every clause (other than the unit clause itself) containing l is removed;
- in every clause that contains $\neg l$, this literal is deleted.

Example

$$\begin{array}{l} \cancel{a} \vee b \\ \neg \cancel{a} \vee c \\ \neg c \vee d \\ a \end{array}$$

The following set of clauses can be simplified by **unit propagation** because it contains the unit clause a .

Unit propagation

Unit propagation

If a clause is a **unit clause**, i.e. it contains only a single literal $/$, We can apply the following two rules:

- Every clause (other than the unit clause itself) containing $/$ is removed;
- in every clause that contains $\neg /$, this literal is deleted.

Example

$$\begin{array}{c} c \\ \neg c \vee d \\ a \end{array}$$

The following set of clauses can be simplified by **unit propagation** because it contains the unit clause c .

Unit propagation

Unit propagation

If a clause is a **unit clause**, i.e. it contains only a single literal l , We can apply the following two rules:

- Every clause (other than the unit clause itself) containing l is removed;
- in every clause that contains $\neg l$, this literal is deleted.

Example

c
 d
 a

The following set of clauses can be simplified by **unit propagation** because it contains the unit clause c .

Pure literal elimination

Pure literal elimination

If a literal l occurs with only one polarity in the formula, it is called **pure**. Pure literals can always be assigned in a way that makes all clauses containing them true.

Example

$$\phi = (a \vee b) \wedge (\neg a \vee c) \wedge (\neg c \vee d \vee b) \wedge a$$

$$\begin{array}{c} a \vee b \\ \neg a \vee c \\ \neg c \vee d \vee b \\ a \end{array}$$

We have the following variable assignment:

$$\begin{array}{ll} b = \text{True} & d = \text{True} \\ a = \text{True} & c = \text{True} \end{array}$$

Let's take the following **formula** Φ , represented by a set of clauses :

$$a \vee b \vee c$$

$$a \vee \neg b \vee \neg c$$

$$a \vee b \vee \neg c$$

$$\neg a \vee \neg b \vee c$$

Action taken

First of all, we choose **arbitrarily** a variable

$$a \vee b \vee c$$

$$a \vee \neg b \vee \neg c$$

$$a \vee b \vee \neg c$$

$$\neg a \vee \neg b \vee c$$

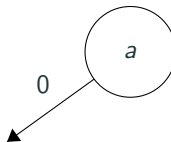


Backtracking

Action taken

We make a **choice**, the variable takes the value **0**. Some clauses become **true** ✓.

$$\begin{array}{l} a \vee b \vee c \\ a \vee \neg b \vee \neg c \\ a \vee b \vee \neg c \\ \neg a \vee \neg b \vee c \quad \checkmark \end{array}$$

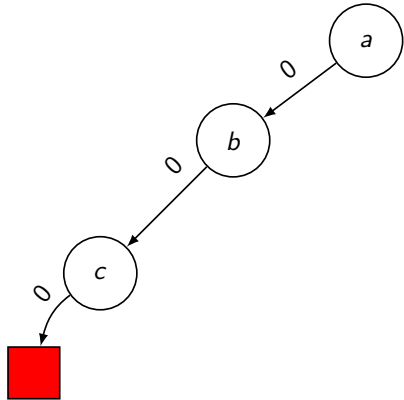


Backtracking

Action taken

After several decisions, we have a conflict **conflict x**

$a \vee b \vee c$ **x**
 $a \vee \neg b \vee \neg c$ ✓
 $a \vee b \vee \neg c$ ✓
 $\neg a \vee \neg b \vee c$ ✓

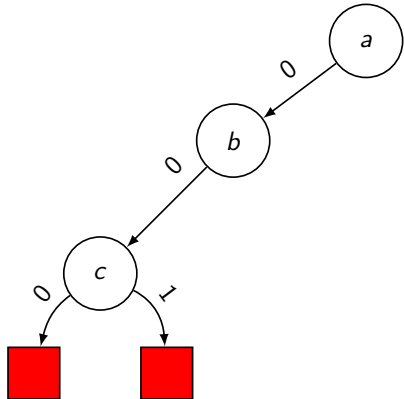


Backtracking

Action taken

We make an **backtrack** to the upper level and try to assign the variable by the **opposite** value.

$a \vee b \vee c$ ✓
 $a \vee \neg b \vee \neg c$ ✓
 $a \vee b \vee \neg c$ ✗
 $\neg a \vee \neg b \vee c$ ✓

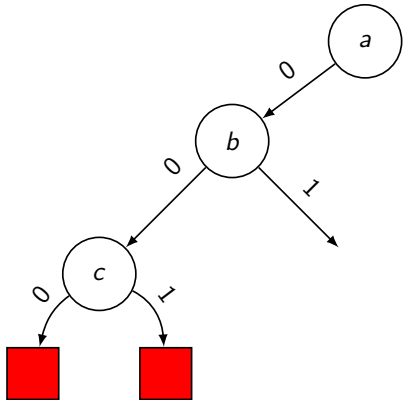


Backtracking

Action taken

Actions are repeated until all clauses are **true** or have gone through the tree.

$a \vee b \vee \neg c$ ✓
 $a \vee \neg b \vee \neg c$
 $a \vee b \vee \neg c$ ✓
 $\neg a \vee \neg b \vee c$ ✓

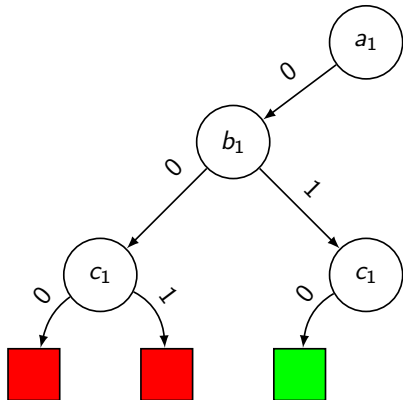


Backtracking

Action taken

Actions are repeated until all clauses are **true** or have gone through the tree.

$a \vee b \vee \neg c$ ✓
 $a \vee \neg b \vee \neg c$ ✓
 $a \vee b \vee \neg c$ ✓
 $\neg a \vee \neg b \vee c$ ✓



Satisfiability

- To prove the **satisfiability**, it is enough to find an assignment of the variables **valid**.
- To prove the **non-satisfiability**, one must go through the tree **entirely**.

```
1: function DPLL(a set of clause  $\Phi$ )
2:   if  $\Phi$  is a consistent set of literals then
3:     return true;
4:   end if
5:   if  $\Phi$  contains an empty clause then
6:     return false;
7:   end if
8:   for every unit clause  $L$  in  $\Phi$  do
9:      $\Phi \leftarrow \text{unit-propagate}(L, \Phi)$ ;
10:  end for
11:  for every literal  $l$  that occurs pure in  $\Phi$  do
12:     $\Phi \leftarrow \text{pure-literal-assign}(l, \Phi)$ ;
13:  end for
14:   $l \leftarrow \text{choose-literal}(\Phi)$ ;
15:  return DPLL( $\Phi \wedge l$ ) or DPLL( $\Phi \wedge \bar{l}$ );
16: end function
```

Innovations

- **Learning phase** : Thanks to **the resolution rule**, we can create new clauses, which are called learned clauses;

Resolution rule [Robinson '65]

Let C_1 and C_2 two clauses such that:

$$C_1 = a \vee b \vee c \vee d$$

$$C_2 = \neg d \vee e \vee f$$

We apply the resolution rule on d :

$$\begin{array}{c} \textcolor{green}{C_1} \qquad \qquad \textcolor{blue}{C_2} \\ \hline (a \vee b \vee c \vee \textcolor{red}{d}) \wedge (\neg \textcolor{red}{d} \vee e \vee f) \\ \hline \vdash a \vee b \vee c \vee e \vee f \end{array}$$

Resolution rule [Robinson '65]

More formally,

Let C_1 and C_2 be two clauses, the resolution rule gives us:

$$(C_1 \vee x) \wedge (C_2 \vee \neg x) \vdash C_1 \vee C_2$$

We call $C_1 \vee C_2$ the **resolvent** of $C_1 \vee x$ and $C_2 \vee \neg x$.

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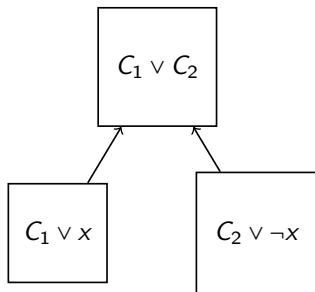


Figure 3: Graphical representation of the resolution

Algorithme CDCL (conflict-driven clause learning)

Innovations

- **Learning phase** : Thanks to **the resolution rule**, we can create new clauses, which are called learned clauses;
- **non-chronological backtracking** : It becomes possible to go back to a decision more **old** than the last decision;
- **restarts**: It is permitted for the **solver** to start the search again at any time.

Φ : set of **initials** clauses

Σ : set of **learnts** clauses.

Algorithm 1 modern SAT solvers

While $\square \notin \Phi \cup \Sigma$ **do**

$C \leftarrow \text{learntClause}()$

$\Sigma = \Sigma \cup C$

If $\text{Full}(\Sigma)$ **Then**

$\Delta = \text{DeleteClause}(\Sigma)$

$\Sigma = \Sigma \setminus \Delta$

End If

End While

Our work

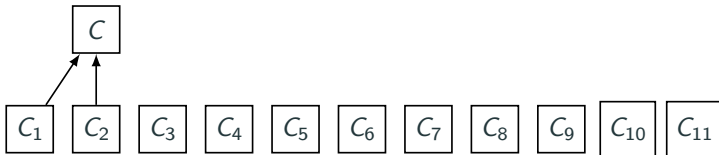
Sequence of resolution with a graph representation

Formula

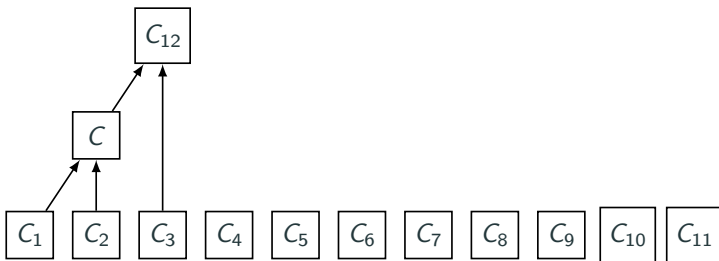
Let $\Phi = C_1 \wedge C_2 \wedge \dots \wedge C_{11}$, s.t. $\forall i \in [1..11], C_i$ any clause.



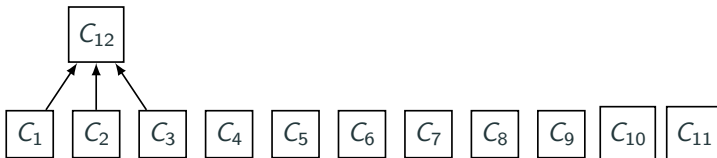
Sequence of resolution with a graph representation



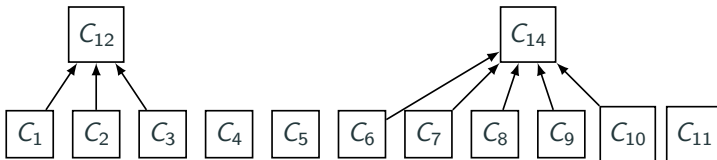
Sequence of resolution with a graph representation



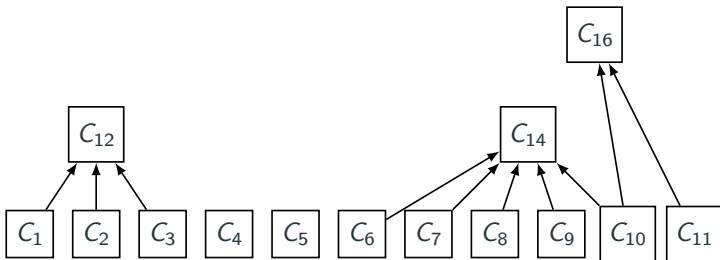
Sequence of resolution with a graph representation



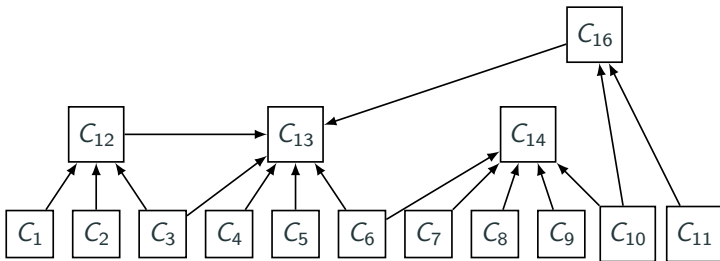
Sequence of resolution with a graph representation



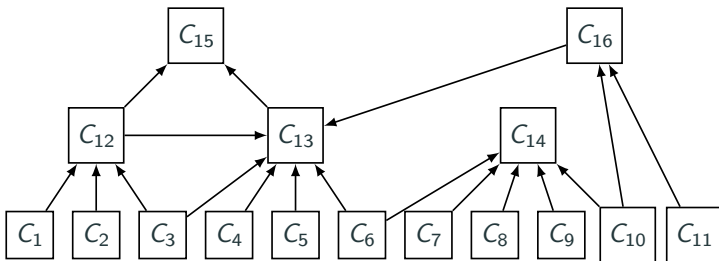
Sequence of resolution with a graph representation



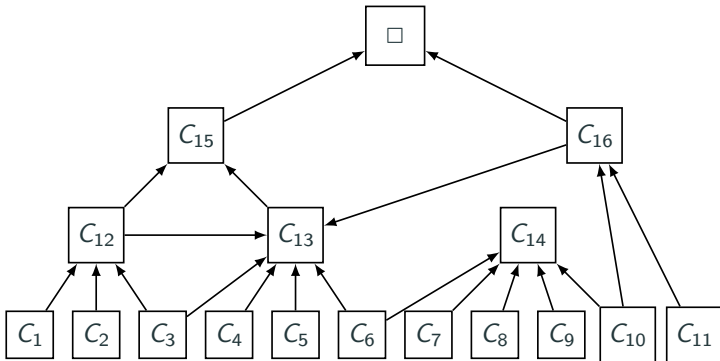
Sequence of resolution with a graph representation



Sequence of resolution with a graph representation



Sequence of resolution with a graph representation

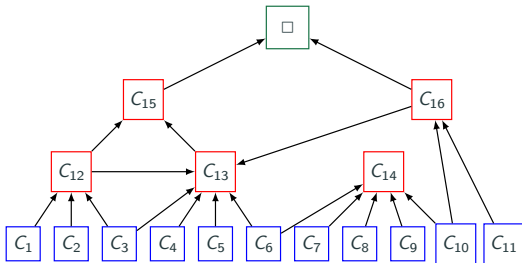


Resolution graph

Definition

The **resolution graph** is a directed acyclic graph (or **DAG**) such that:

- Leaves are **initials** clauses;
- Internal nodes are **learnts** clauses;
- The root is the **empty** clause.



We call it the **proof** produced by the SAT solver.

Representation of a real proof

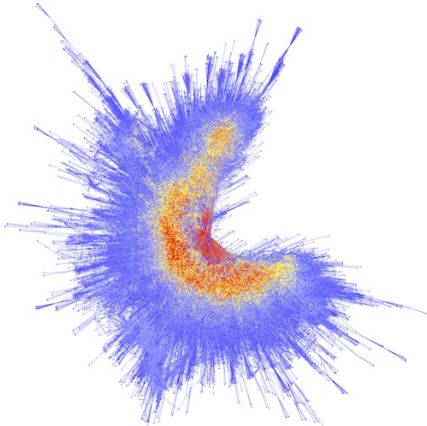


Figure 4: Force-Directed layout of the Dependency Graph for the benchmark een-pico-prop-05. The color shows the **degree** of each node.

Information

Formula

clauses:

55585

variables:

50076

Conflicts

conflicts:

59792

CPU time: 6s

Graph

vertices:

51274

edges:

960620

Examples of SAT solvers

Pysat: A toolkit for SAT-based prototyping in Python

PySAT

PySAT is a Python (2.7, 3.4+) toolkit, which aims at providing a simple and unified interface to a number of state-of-art SAT solvers.

Pros:

- In Python;
- Great documentation;
- Easy to install (*pip install python – SAT*)

(Major) Cons:

- Less powerful than other solvers

Pysat: A toolkit for SAT-based prototyping in Python

```
>>> from pysat.solvers import Glucose3
>>>
>>> g = Glucose3()
>>> g.add_clause([-1, 2])
>>> g.add_clause([-2, 3])
>>> print g.solve()
>>> print g.get_model()
...
True
[-1, -2, -3]
```

Figure 5: Trivial example using PySAT

Glucose

Glucose is a winning award SAT solvers developed in LaBRI and CRIL by Laurent Simon and Gilles Audemard.

Pros:

- Developed in LaBRI 😊
- Powerful;
- Relatively easy to implement.

Glucose

```

% ./glucose ~/Desktop/These/Benchs-POS14/2008-satrace/satelite/een-pico-prop05-75.satelite.cnf.gz
c
c This is glucose 4.0 -- based on MiniSAT (Many thanks to MiniSAT team)
c
c =====[ Problem Statistics ]=====
c
c   Number of variables:      18188
c   Number of clauses:       87504
c   Parse time:              0.05 s
c
c   Preprocessing is fully done
c   Eliminated clauses:      0.01 Mb
c   Simplification time:     0.05 s
c
c =====[ MAGIC CONSTANTS ]=====
c
c Constants are supposed to work well together :-)
c however, if you find better choices, please let us known...
c
c Adapt dynamically the solver after 100000 conflicts (restarts, reduction strategies...)
c
c
c   - Restarts:                - Reduce Clause DB:                - Minimize Asserting:
c   * LBD Queue : 50           * First : 2000                     * size < 30
c   * Trail Queue : 5000       * Inc : 300                      * lbd < 6
c   * K : 0.80                 * Special : 1000
c   * R : 1.40                 * Protected : (lbd)< 30
c
c =====[ Search Statistics (every 10000 conflicts) ]=====
c
c   | RESTARTS | ORIGINAL | LEARNT | Progress |
c   | NB   Blocked Avg Cfc | Vars   Clauses Literals | Red   Learnts LBD2   Removed |
c   |-----|-----|-----|-----|
c   | 38      0      263 | 18131  87321  328060 | 2     5160   2076   4716 | 0.236 %
c   | 89      85      224 | 18119  87230  327836 | 3     8927   3811  10918 | 0.302 %
c   | 129     161      202 | 18113  87198  327772 | 3    18921   5193  10918 | 0.335 %
c   | 200     227      200 | 18111  87186  327748 | 4    19552   5975  20285 | 0.346 %
c   | 243     312      205 | 18108  87165  327694 | 4    29479   6770  20285 | 0.363 %
c   | 324     376      185 | 18108  87165  327694 | 5    26139   7200  33625 | 0.363 %
c   | 418     406      167 | 18105  87140  327621 | 5    35430   7494  33625 | 0.379 %
c
c restarts : 451 (167 conflicts in avg)
c blocked restarts : 419 (multiple: 149)
c last block at restart : 451
c nb ReduceDB : 5
c nb removed Clauses : 33625
c nb learnts DL2 : 7613
c nb learnts size 2 : 2311
c nb learnts size 1 : 72
c conflicts : 75590 (28861 /sec)
c decisions : 338134 (0.00 % random) (129101 /sec)
c propagations : 22747444 (8685068 /sec)
c nb reduced Clauses : 4211
c CPU time : 2.61914 s
c
c UNSATISFIABLE

```

Conclusion

Thank you !
Questions ? 😊