

SAT Solvers: Clause Learning

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A search algorithm

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- Algorithm $A(F)$
- outputs *sat* or *unsat*
- Pseudocode:

if $\text{var}(F) = \emptyset$ then

 if $F = \emptyset$ then exit(sat).

 else exit(unsat). /* $F = \{\square\}$ where \square is empty clause */

else choose $x \in \text{var}(F)$,

/* x is the branching variable */

if $A(F[x = 0]) = \text{sat}$ then exit(sat).

else if $A(F[x = 1]) = \text{sat}$ then exit(sat).

else exit(unsat).

Pure Literals

- A literal x of a clause-set F is a **pure literal** of F if some clauses of F contain x but no clause of F contains \bar{x} .
- Example: $F = \{\{x, y\}, \{\bar{y}, \bar{z}\}, \{z, x\}, \{u, \bar{z}\}\}$.
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 x and u are the pure literals of F .
- Let F' be the clause-set obtained from F by removing all clauses that contain pure literals.

Then F and F' are equisatisfiable (why?).

We say that F' is obtained from F by **pure literal elimination**.

Applying Pure Literal Elimination

- Example: $F = \{\{x, y\}, \{\bar{y}, \bar{z}\}, \{z, x\}, \{u, \bar{z}\}\}$.
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- In the above example we obtain $F' = \{\{\bar{y}, \bar{z}\}\}$. Now \bar{y} and \bar{z} are pure literals of F' , and we can apply pure literal elimination again, obtaining the empty clause-set.

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- For a clause-set F we denote by $PL(F)$ the smallest clause-set that can be obtained from F by (possibly repeated) applications of pure literal elimination.
- In the above example we have $PL(F) = \emptyset$.

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- For a clause-set F we denote by $PL(F)$ the smallest clause-set that can be obtained from F by (possibly repeated) applications of pure literal elimination.
- In the above example we have $PL(F) = \emptyset$.
- F and $PL(F)$ are always equisatisfiable.

Unit Propagation

- When a clause-set F contains a unit clause $\{\ell\}$, we can obtain by **unit propagation** the clause-set $F[\ell = 1]$ from F .
- In that case F and $F[\ell = 1]$ are equisatisfiable (why?)
- We write $UP(F)$ for the clause-set obtained from F by applying unit propagation as often as possible.

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- We write $UP(F)$ for the clause-set obtained from F by applying unit propagation as often as possible.
- Example: Let $F = \{\{x, y\}, \{\bar{y}\}, \{z, \bar{x}, v\}\}$.
 - From F we obtain by unit propagation the clause set $F' = \{\{x\}, \{z, \bar{x}, v\}\}$.
 - With a second step of unit propagation we obtain from F' the clause-set $F'' = \{\{z, v\}\}$.Consequently $UP(F) = \{\{z, v\}\}$.
- F and $UP(F)$ are always equisatisfiable.

First UP and then PL, or vice versa?

Fact

For any clause-set F , we have $UP(PL(UP(F))) = PL(UP(F))$.

Proof: exercise (Question 3a.i in 2009 Advanced AI exam)

Fact

There is a clause-set F such that $PL(UP(PL(F))) \neq UP(PL(F))$.

Proof: exercise (Question 3a.ii in 2009 Advanced AI exam)

So, first UP and then PL, or the other way around?

The DPLL algorithm

- Algorithm DPLL(F)
- outputs *sat* or *unsat*
 $F := UP(F)$.
 $F := PL(F)$.
if $\text{var}(F) = \emptyset$ then
 if $F = \emptyset$ then exit(*sat*).
 else exit(*unsat*). /* $F = \{\square\}$ */
else choose $x \in \text{var}(F)$,
/* x is the branching variable */
if $A(F[x = 0]) = \text{sat}$ then exit(*sat*).
else if $A(F[x = 1]) = \text{sat}$ then exit(*sat*).
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Some Well-Known DPLL-based SAT Solvers

- Important SAT solvers:
 - Grasp (Marques-Silva & Sakallah 1996)
 - Relsat (Bayardo Jr. & Schrag 1997)
 - chaff (Moskewicz et al 2001), zChaff (Zhang 2001)
 - Minisat (Een & Sörensson 2003)
 - RSat (Pipatsrisawat & Darwiche 2007)
 - Glucose (Audemard & Simon 2009)
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- Many of them are available for free and continually improved.
- Key improvements to DPLL that boosted the performance:
 - combination of clever **branching heuristics** with
 - **clause learning**,
 - **non-chronological backtracking**,
 - **restart strategies**,
 - **implementation of propagation**.
- Check *www.satlive.org* for more info on SAT solvers!

Conflict-Driven Clause Learning (CDCL): Basics

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- Clauses of conflict are cached and learnt
- Learnt clauses allow us to prune the search space in different parts of the search encountered later.

Iterative (CDCL) DPLL Algorithm

■ initialise:

- F is the given clause-set
- τ is the empty assignment.

while(true) do

 if $UP(F[\tau]) = \emptyset$ then exit(sat).

 elseif $\square \in UP(F[\tau])$ and $\tau = \emptyset$ then exit(unsat)

 elseif $\square \in UP(F[\tau])$ then

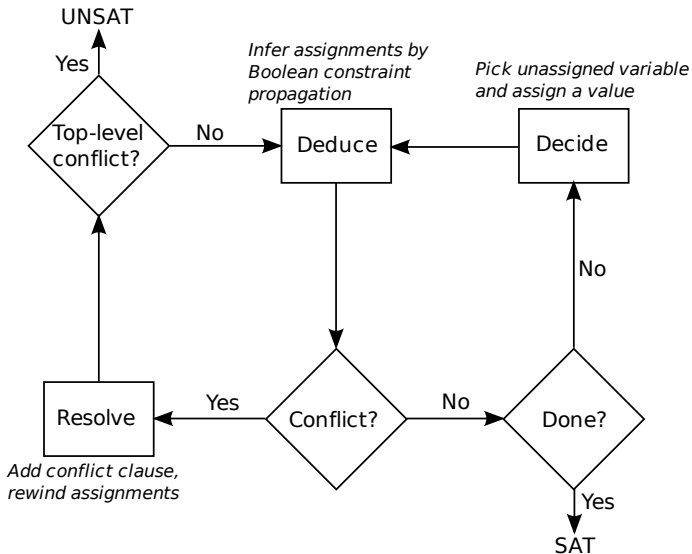
$C = \text{CONFLICT-CLAUSE}(F, \tau)$, set $F := F \cup \{C\}$

$\tau := \text{BACKTRACK}(\tau)$

 else CHOOSE VARIABLE $x \in \text{var}(UP(F[\tau]))$, CHOOSE
 VALUE $b \in \{0, 1\}$

 Set $\tau := \tau \cup \{(x, b)\}$.

CDCL DPLL diagram



Remarks

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- The algorithm also remembers the **order** in which decision literals are added to D
- In the step BACKTRACK, (one or more) most recent variable assignment is undone. This causes a **backtracking**.
- Instead of *UP* the solver can use more sophisticated propagation techniques known as **boolean constraint propagation (BCP)**.

Simple Example

- Init: $F = \{\{x, y\}, \{\bar{x}, y\}, \{x, \bar{y}\}, \{\bar{x}, \bar{y}\}\}$, $\tau = \emptyset$
- CHOOSE $x, 1$, set $\tau = \{(x, 1)\}$
- $\square \in UP(F[\tau])$
 $\{\bar{x}\} = \text{CONFLICT-CLAUSE}(F, \tau)$ (explain later why)
 $F = \{\{\bar{x}\}, \{x, y\}, \{\bar{x}, y\}, \{x, \bar{y}\}, \{\bar{x}, \bar{y}\}\}$,
 $\tau = \emptyset = \text{BACKTRACK}(\{(x, 1)\})$
- $\square \in UP(F[\tau])$
Since $\tau = \emptyset$ exit(unsat).

The Implication Graph

The **implication graph** G is a directed graph defined w.r.t a particular state (F, τ) of the iterative DPLL algorithm. The nodes of G are literals. G is constructed as follows:

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The nodes of G are literals. G is constructed as follows:

- (1) Add all literals true under τ . These are called **decision literals** and form the sources of G (no incoming edges).
- (2) If ℓ is not in G yet, but there is a clause $\{\ell_1, \dots, \ell_k, \ell\} \in F$ such that $\overline{\ell_1}, \dots, \overline{\ell_k}$ are already in G , then add node ℓ (called an **implied literal**) and add edges from $\overline{\ell_i}$ to ℓ for $1 \leq i \leq k$ (that aren't already there).

Repeat this step until stable.

- If the graph contains two complementary literals x and \overline{x} , then these literals are called **conflict literals**.
- Can stop here if a complementary pair of literals is found.

- (3) Finally, add a special node “ \bot ” and add edges from conflict literals (if there are any) to this node.

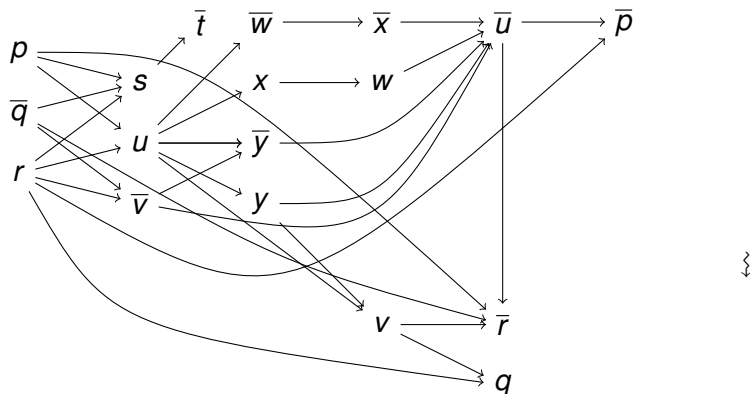
Example

Assume that

- current clause-set F is
$$\{\{\bar{p}, q, s\}, \{q, \bar{r}, s\}, \{\bar{p}, \bar{r}, u\}, \{q, \bar{r}, \bar{v}\},$$
$$\{\bar{s}, \bar{t}\}, \{\bar{u}, \bar{w}\}, \{\bar{u}, x\}, \{\bar{u}, y\}, \{\bar{u}, v, \bar{y}\}, \{w, \bar{x}\}\};$$
- current assignment $\tau = \{(p, 1), (q, 0), (r, 1)\}$.

Example of an implication graph

Note: The edges from conflict literals to \perp are not shown.



$$F = \{\{\bar{p}, q, s\}, \{q, \bar{r}, s\}, \{\bar{p}, \bar{r}, u\}, \{q, \bar{r}, \bar{v}\}, \{\bar{s}, \bar{t}\}, \{\bar{u}, \bar{w}\}, \{\bar{u}, x\}, \{\bar{u}, y\}, \{\bar{u}, v, \bar{y}\}, \{w, \bar{x}\}\};$$

Construction in detail

In the following “a” means “add the vertex a”;

“ $a \rightarrow b$ ” means “add an edge running from vertex a to vertex b”.

p, \bar{q}, r (decision literals)

$s, p \rightarrow s, \bar{q} \rightarrow s$

$r \rightarrow s$

$u, p \rightarrow u, r \rightarrow u$

$\bar{v}, \bar{q} \rightarrow \bar{v}, r \rightarrow \bar{v}$

$\bar{t}, s \rightarrow \bar{t}$

$\bar{w}, u \rightarrow \bar{w}$

$x, u \rightarrow x$

$y, u \rightarrow y$

$\bar{y}, u \rightarrow \bar{y}, \bar{v} \rightarrow \bar{y}.$

Now we have the conflict literals y, \bar{y} ; at this stage a SAT solver could already start to form a conflict graph; but we continue...

$$\begin{aligned}
&\bar{u}, \bar{y} \rightarrow \bar{u} \\
&\bar{v}, u \rightarrow \bar{v}, y \rightarrow \bar{v} \\
&\bar{v} \rightarrow \bar{u}, y \rightarrow \bar{u} \\
&\bar{x}, \bar{w} \rightarrow \bar{x} \\
&\bar{w}, x \rightarrow \bar{w} \\
&\bar{r}, p \rightarrow \bar{r}, \bar{u} \rightarrow \bar{r} \\
&\bar{p}, r \rightarrow \bar{p} \bar{u} \rightarrow \bar{p} \\
&\bar{q} \rightarrow \bar{r}, v \rightarrow \bar{r} \\
&q, r \rightarrow q, v \rightarrow q \\
&\bar{w} \rightarrow \bar{u} \\
&\bar{x} \rightarrow \bar{u}
\end{aligned}$$

Except for s all other added literals are conflict literals, therefore we connect all other literals to \bar{s} . (However, these edges are omitted in the drawing for sake of readability).

Conflict Graphs

- Assume that the implication graph G contains conflict literals. Then we can extract from G a **conflict graph** H with the following properties:
 - H contains exactly one pair of conflict variables.

Conflict Graphs

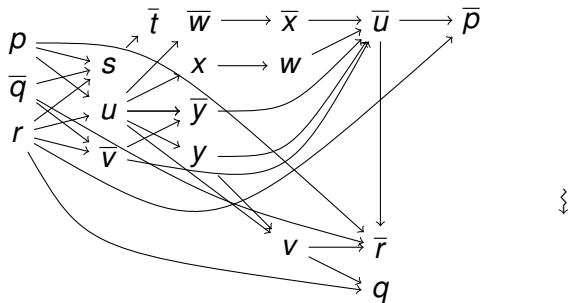
- Assume that the implication graph G contains conflict literals. Then we can extract from G a **conflict graph** H with the following properties:
 - H contains exactly one pair of conflict variables.
 - For every implied literal ℓ of H there is exactly one clause $\{\ell_1, \dots, \ell_k, \ell\} \in F$ such that the literals $\overline{\ell_1}, \dots, \overline{\ell_k}$ belong to H and there are edges from ℓ_i to ℓ .

Conflict Graphs

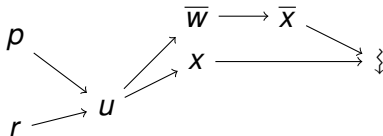
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 - From every node in H one can reach \downarrow via a directed path.

In a certain sense H represents succinctly one cause of conflict (from the decision variables via unit propagation).

Example of a conflict graph



The implication graph from above gives rise to the following conflict graph.



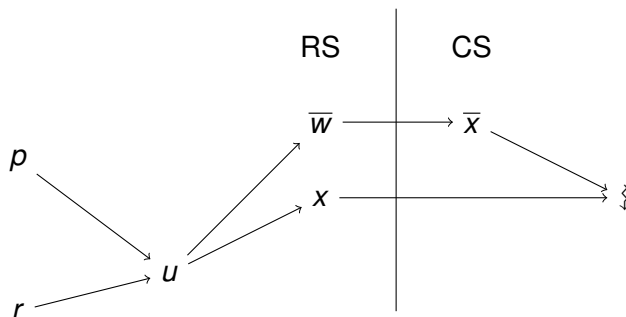
Remark

- Note that the implication graph is not necessarily acyclic, there can be directed cycles.
- However, a conflict graph is always acyclic.

Conflict Clauses

- Select a set of edges that divides the conflict graph into two parts, the reason side (RS) and the conflict side (CS) such that
 - RS contains all decision literals
 - CS contains \geq and at least one conflict literal.
- Form a clause C consisting of the complements of all literals in RS that have a neighbour in CS.
- This clause C is a **conflict clause**.
- The conflict clause is returned by the subroutine CONFLICT-CLAUSE and added to the given set of clauses.
- In general there are many different choices for the conflict clause, it is an important part of the solver's strategy which conflict clause is selected.

Example of a Conflict Clause



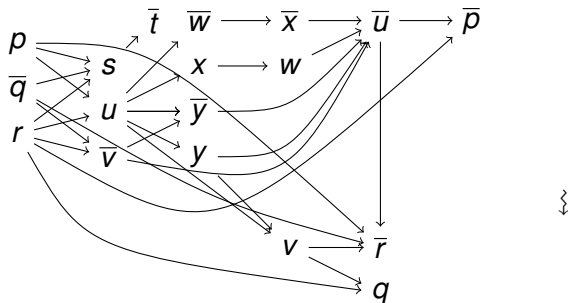
Conflict clause: $C = \{w, \bar{x}\}$.

Other possibilities: $C = \{\bar{p}, \bar{r}\}$, $C = \{\bar{u}\}$.

Backtracking

- After a clause is learnt we can backtrack via the subroutine BACKTRACK
- for example
$$\tau = \{(p, 1), (q, 0)\} = \text{BACKTRACK}(\{(p, 1), (q, 0), (r, 1)\})$$
- or even $\tau = \emptyset = \text{BACKTRACK}(\{(p, 1), (q, 0), (r, 1)\})$.

Decision Levels

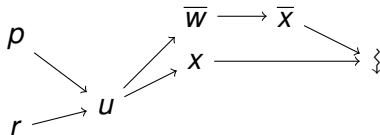


- A **decision level** consists of a decision literal ℓ and all implied literals that were added after ℓ has been added.
- Assume that in the example the latest decision literal is r .

The decision level of r contains the implied literals $r, u, \bar{v}, \bar{w}, x, y, \bar{y}, \bar{x}$. The implied literals s and \bar{t} belong to the previous decision level.

Unique Implication Points

- A **unique implication point (UIP)** is a literal ℓ of the current decision level such that every path from the current decision literal to any of the two conflict literals must run through ℓ .
- For example, the current decision literal is a UIP.
- Intuitively, a UIP is a *single reason* for a conflict.
- It is a common strategy to choose a cut that puts a UIP into the RS and its successors into CS.
- In the previous example, r and u are both UIPs. The corresponding conflict clauses are $\{\bar{p}, \bar{r}\}$ and $\{\bar{u}\}$.

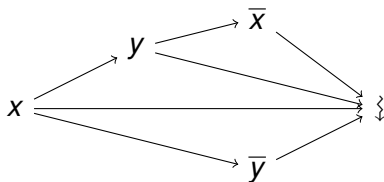


- For example the solver zChaff backtracks to decision level 0 if it learns a unit clause.

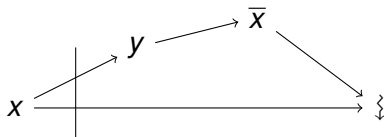
Simple Example (Continued)

Now we can see how clause $\{\bar{x}\}$ can be learnt in our example.

- $F = \{\{x, y\}, \{\bar{x}, y\}, \{x, \bar{y}\}, \{\bar{x}, \bar{y}\}\},$
- $\tau = \{(x, 1)\}$
- Implication graph:



- Conflict graph:



- $\{\bar{x}\} = \text{CONFLICT-CLAUSE}(F, \tau)$

Example 2

Assume that

- current clause-set F is

$\{\{\overline{x_1}, x_2\}, \{\overline{x_2}, x_3, x_4\}, \{\overline{x_2}, \overline{x_5}\}, \{\overline{x_4}, x_5, x_6\},$
 $\{\overline{x_7}, x_8\}, \{\overline{x_8}, \overline{x_9}\}, \{x_9, \overline{x_{10}}\}, \{x_3, \overline{x_8}, x_{10}\}\};$

- current assignment $\tau = \{(x_1, 1), (x_3, 0), (x_7, 1)\}.$

Clause Deletion

- The number of learnt clauses can sometimes be huge
- Efficient solvers have a “forgetting strategy”:
 - delete learnt causes that are too large, and/or
 - those that were not used in derivations recently

Backtracking

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- for example
$$\tau = \{(p, 1), (q, 0)\} = \text{BACKTRACK}(\{(p, 1), (q, 0), (r, 1)\})$$
- or even $\tau = \emptyset = \text{BACKTRACK}(\{(p, 1), (q, 0), (r, 1)\})$.

Non-Chronological Backtracking

- Normal backtracking undoes the most recent assignment
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Non-Chronological Backtracking

- Normal backtracking undoes the most recent assignment
- NCB (aka **backjumping**) can backtrack further back
- Assuming that we learnt a clause using a UIP
 - if the learnt clause is unit, NCB backtracks to $\tau = \emptyset$
 - otherwise, NCB backtracks to the second latest decision level of literals in learnt clause
 - The learnt clause will allow additional unit propagation
 - In the earlier example, if we learn $\{\bar{p}, \bar{r}\}$, then backtrack from $\tau = (\{(p, 1), (q, 0), (r, 1)\})$ to $\tau = \{(p, 1)\}$ and update the implication graph (e.g. add \bar{r} to the decision level of p).
- NCB maintains the completeness, while improving efficiency in practice.

Exercise

Let F be the clause-set consisting of the following clauses:

- $C_1 = \{x_1, x_2\}$
- $C_2 = \{x_1, x_3, x_7\}$
- $C_3 = \{\overline{x_2}, \overline{x_3}, x_4\}$
- $C_4 = \{\overline{x_4}, x_5, x_8\}$
- $C_5 = \{\overline{x_4}, x_6, x_9\}$
- $C_6 = \{\overline{x_5}, \overline{x_6}\}$

Let $\tau = \{(x_7, 0), (x_8, 0), (x_9, 0), (x_1, 0)\}$, in this order.

- Draw the implication graph and a conflict graph
- Identify UIPs and clauses that can be learnt the conflict
- Identify the effect of non-chronological backtracking
- What changes if we swap $(x_7, 0)$ and $(x_9, 0)$ in τ ?

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- Strategies for choosing the next variable to assign
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- Clause Learning, Non-Chronological Backtracking, and Restarts compensate for the difficulty
- Common tendency: favour variables that appear in many short clauses
 - this facilitates unit propagation

Examples of Decision Heuristics

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- **MOMS**: choose literal with Maximum number of occurrences in Minimum Size clauses
- **Jeroslow-Wang**: Let $C(x)$ be the set of open clauses containing either polarity of a given variable x . Define the weight of x as

$$w(x) = \sum_{c \in C(x)} 2^{-|c|}$$

Choose a variable with the maximum weight as the branching variable.

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- Variable State Independent Decaying Sum
- For each literal, keep counter of how many learnt clauses it appears in
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 - Learnt clauses are resolvents of earlier clauses
 - Assignment satisfying resolvent extends to original clauses
- Possibly leads to shorter learnt clauses
 - Learnt clauses share more literals, shortening resolvents

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- Classic (naive) implementation:
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 - When a literal is assigned or unassigned, visit all clauses with literal and update counters
- Drawback: assigning and unassigning expensive