

## Restart

Runtimes of CDCL-style procedures depend extremely on the choice of branching variables.

If no solution is found within a certain time limit, it can be useful to *restart* from scratch with an adapted variable selection heuristics. Learned clauses, however, are kept.

In addition, it is useful to restart after a unit clause has been learned.

The restart rule is typically applied after a certain number of clauses have been learned or a unit is derived:

Restart:

$$M \parallel N \Rightarrow_{\text{CDCL}} \varepsilon \parallel N$$

If Restart is only applied finitely often, termination is guaranteed.

## 2.8 Implementing CDCL

The formalization of CDCL that we have seen so far leaves many aspects unspecified.

To get a fast solver, we must use good heuristics, for instance to choose the next undefined variable, and we must implement basic operations efficiently.

### Variable Order Heuristic

Choosing the right undefined variable to branch is important for efficiency, but the branching heuristics may be expensive itself.

State of the art: Use branching heuristics that need not be recomputed too frequently.

In general: Choose variables that occur frequently; after a restart prefer variables from recent conflicts.

The VSIDS (Variable State Independent Decaying Sum) heuristic:

- We associate a positive *score* to every propositional variable  $P_i$ . At the start,  $k_i$  is the number of occurrences of  $P_i$  in  $N$ .
- The variable order is then the descending ordering of the  $P_i$  according to the  $k_i$ .

The scores  $k_i$  are adjusted during a CDCL run.

- Every time a learned clause is computed after a conflict, the propositional variables in the learned clause obtain a bonus  $b$ , i.e.,  $k_i := k_i + b$ .
- Periodically, the scores are leveled:  $k_i := k_i/l$  for some  $l$ .

- After each restart, the variable order is recomputed, using the new scores.

The purpose of these mechanisms is to keep the search focused. The parameter  $b$  directs the search around the conflict,

Further refinements:

- Add the bonus to all literals in the clauses that occur in the resolution steps to generate a backjump clause.
- If the score of a variable reaches a certain limit, all scores are rescaled by a constant.
- Occasionally (with low probability) choose a variable at random, otherwise choose the undefined variable with the highest score.

### Implementing Unit Propagation Efficiently

For applying the unit rule, we need to know the number of literals in a clause that are not false.

Maintaining this number is expensive, however.

Better approach: “*Two watched literals*”:

In each clause, select two (currently undefined) “watched” literals.

For each variable  $P$ , keep a list of all clauses in which  $P$  is watched and a list of all clauses in which  $\neg P$  is watched.

If an undefined variable is set to 0 (or to 1), check all clauses in which  $P$  (or  $\neg P$ ) is watched and watch another literal (that is true or undefined) in this clause if possible.

Watched literal information need not be restored upon backtracking.

### Preprocessing

Some operations are only needed once at the beginning of the CDCL run.

- (i) Deletion of tautologies
- (ii) Deletion of duplicated literals

## Inprocessing

Some operations are useful, but expensive. They are performed only initially and after restarts (before computation of the variable order heuristics), possibly with time limits.

Note: Some of these operations are only satisfiability-preserving; they do not yield equivalent clause sets.

Examples:

(i) Subsumption

$$N \cup \{C\} \cup \{D\} \Rightarrow N \cup \{C\}$$

if  $C \subseteq D$  considering  $C, D$  as multisets of literals.

(ii) Purity deletion

Delete all clauses containing a literal  $L$  where  $\bar{L}$  does not occur in the clause set.

(iii) Merging replacement resolution

$$N \cup \{C \vee L\} \cup \{D \vee \bar{L}\} \Rightarrow N \cup \{C \vee L\} \cup \{D\}$$

if  $C \subseteq D$  considering  $C, D$  as multisets of literals.

(vi) Bounded variable elimination

Compute all possible resolution steps

$$\frac{C \vee L \quad D \vee \bar{L}}{C \vee D}$$

on a literal  $L$  with premises in  $N$ ; add all non-tautological conclusions to  $N$ ; then throw away all clauses containing  $L$  or  $\bar{L}$ ; repeat this as long as  $|N|$  does not grow.

(v) RAT (“Resolution asymmetric tautologies”)

$C$  is called an *asymmetric tautology* w.r.t.  $N$ , if its negation can be refuted by unit propagation using clauses in  $N$ .

$C$  has the *RAT property* w.r.t.  $N$ , if it is an asymmetric tautology w.r.t.  $N$ , or if there is a literal  $L$  in  $C$  such that  $C = C' \vee L$  and all clauses  $D' \vee C'$  for  $D' \vee \bar{L} \in N$  are asymmetric tautologies w.r.t.  $N$ .

RAT elimination:

$$N \cup \{C\} \Rightarrow N$$

if  $C$  has the RAT property w.r.t.  $N$ .

## Literature

Lintao Zhang and Sharad Malik: The Quest for Efficient Boolean Satisfiability Solvers; Proc. CADE-18, LNAI 2392, pp. 295–312, Springer, 2002.

Robert Nieuwenhuis, Albert Oliveras, Cesare Tinelli: Solving SAT and SAT Modulo Theories; From an abstract Davis-Putnam-Logemann-Loveland procedure to DPLL(T), pp. 937–977, Journal of the ACM, 53(6), 2006.

Armin Biere, Marijn Heule, Hans van Maaren, Toby Walsh (eds.): Handbook of Satisfiability; IOS Press, 2009

Daniel Le Berre's slides at VTSA'09: <http://www.mpi-inf.mpg.de/vtsa09/>.

## 2.9 OBDDs

Goal:

Efficient manipulation of (equivalence classes of) propositional formulas.

Method: Minimized graph representation of decision trees, based on a fixed ordering on propositional variables.

⇒ Canonical representation of formulas.

⇒ Satisfiability checking as a side effect.

BDD (Binary decision diagram):

Labelled DAG (directed acyclic graph).

Leaf nodes:

labelled with a truth value (0 or 1).

Non-leaf nodes (interior nodes):

labelled with a propositional variable,  
exactly two outgoing edges, labelled with 0 (--->) and 1 (—>)

