# Conflict analysis in SAT solvers

Bjørnar Luteberget

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## Background

Why look at SAT solvers for real-world optimization problems?

- SAT solvers have state-of-the-art perf. on some optimization problems.
  - Example: "small-domain" but hard resource-constrained project scheduling.
  - Example: dynamic time-indexed models (DDD)
- SAT solvers have state-of-the-art perf. on some feasibility (sub)problems
  - Example: railway bound-to-deadlock detection
  - Example: geographical decomposition in railway scheduling problems

#### Today's topic:

- SAT solvers are built on tree search with "deduction/propagation/presolving"
  - Like MILP solvers and other optimization solvers
  - What is special about SAT solvers that MILP solvers don't have?



# Today's topic

#### Today's topic:

- SAT solvers are built on tree search with "deduction/propagation/presolving"
  - Like MILP solvers and other optimization solvers
  - What is special about SAT solvers that MILP solvers don't have?
- Answer: conflict-driven clause learning
  - Marques-Silva, J. P., & Sakallah, K. A. (1999). GRASP: A search algorithm for propositional satisfiability. IEEE Transactions on Computers, 48(5), 506-521.
- No original research today text-book lecture based on
  - Biere, A., Heule, M., & van Maaren, H. (Eds.). (2009). Handbook of satisfiability (Vol. 185). IOS press.

Systematic (complete) solvers for discrete "variables and constraints" problems:

Splitting the search space: tree of assignments

• Simplifying the problem under a partial assignment

• Backtracking when infeasible

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  - SAT: unit propagation
  - MILP: node pre-solving (+cutting planes)
- Backtracking when infeasible

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- Simplifying the problem under a partial assignment
  - SAT: unit propagation
  - MILP: node pre-solving (+cutting planes)
- Backtracking when infeasible
  - SAT: conflict analysis, clause learning, backtracking
  - MILP: best-bound node queue

## Two prerequisites

- SAT problem description: Conjunctive normal form
- SAT problem simplification: Unit propagation

## Conjunctive normal form

Most SAT solvers take only formulas given in conjunctive normal form

$$(x \vee \overline{y} \vee \ldots) \wedge (z \vee \overline{w} \vee \ldots) \wedge \ldots$$

- Variables and negated variables are called literals.
- Disjunctions of literals are called *clauses*.

$$x \lor y \lor \overline{z}$$
  $(x + y + (1 - z) \ge 1)$ 

- CNF is a conjunction of clauses.
- By adding some variables, we can transform any propositional logic formula to CNF (with worst-case linear increase in size).



# Unit propagation

A simple and efficient preprocessing/deduction technique:

- Any clauses that...
  - are not already satisfied by the current assignment, and ...
  - have only one remaining unassigned variable ...

... forces the assignment of the remaining variable.

• Example:  $a \vee \overline{b} \vee c$ , under the partial assignment,  $a = \bot, c = \bot$ , propagates

$$b = \bot$$
.

• (Special case of domain propagation for linear constraints.)



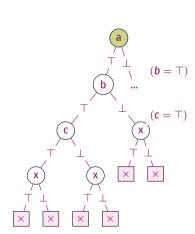
## Worked example

#### Consider the CNF problem:

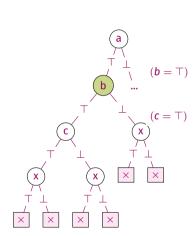
$$(a \lor b) \land \\ (b \lor c) \land \\ (\overline{a} \lor \overline{x} \lor y) \land \\ (\overline{a} \lor x \lor z) \land \\ (\overline{a} \lor \overline{y} \lor z) \land \\ (\overline{a} \lor x \lor \overline{z}) \land \\ (\overline{a} \lor \overline{y} \lor \overline{z})$$

... and fix the variable ordering to a, b, c, x, y, z.

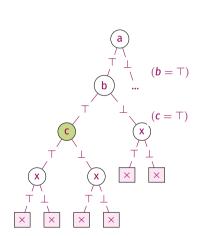
 $(a \lor b) \land$  $(b \lor c) \land$  $(\overline{a} \lor \overline{x} \lor y) \land$  $(\overline{a} \lor \overline{y} \lor z) \land$  $(\overline{a} \lor \overline{y} \lor \overline{z}) \land$  $(\overline{a} \lor \overline{y} \lor \overline{z})$ 



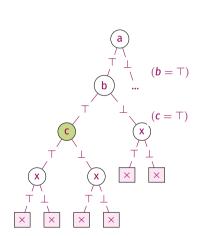




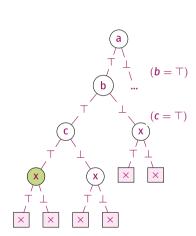




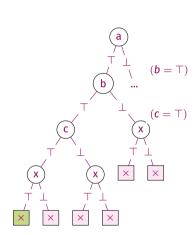




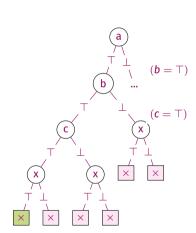
$$(a \lor b) \land (b \lor c) \land (\overline{a} \lor \overline{x} \lor y) \land (\overline{a} \lor \overline{x} \lor z) \land (\overline{a} \lor \overline{y} \lor z) \land (\overline{a} \lor \overline{x} \lor \overline{z}) \land (\overline{a} \lor \overline{y} \lor \overline{z})$$



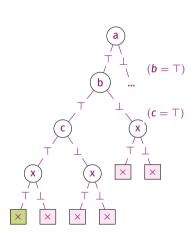




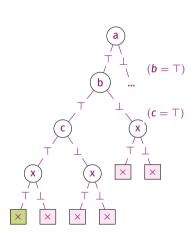




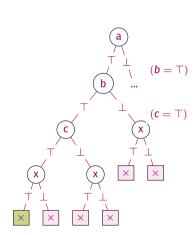




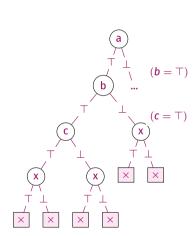








 $(a \lor b) \land \\ (b \lor c) \land \\ (\overline{a} \lor \overline{x} \lor y) \land \\ (\overline{a} \lor \overline{x} \lor z) \land \\ (\overline{a} \lor \overline{y} \lor z) \land \\ (\overline{a} \lor x \lor \overline{z}) \land \\ (\overline{a} \lor \overline{y} \lor \overline{z})$ 



## Conflict analysis

 Can we do something better than simple backtracking when reaching a conflict?

# Conflict analysis

## Definition (Implication graph)

Let  $\pi$  be a path in the search tree. The Implication graph  $G_{\pi}$  is the directed acyclic graph (V, E) where

- $l \in V$  for each variable assignment (both decisions and unit propagations)
- For any unit propagation along  $\pi$ , derived from clause  $C = (l_1 \vee \ldots \vee l_k \vee l)$ , E contains the edges  $(\overline{l_1}, l)$ , ...,  $(\overline{l_k}, l)$ .
- If  $\pi$  falsifies a clause,  $G_{\pi}$  contains the special *conflict vertex*  $\bot$  and edges  $(\overline{l_1},\bot),\ldots,(\overline{l_k},\bot)$  for exactly one falsified clause  $(l_1\lor\ldots\lor l_k)$ .



$$(a \lor b) \land \qquad \qquad \boxed{1 : a = \top}$$

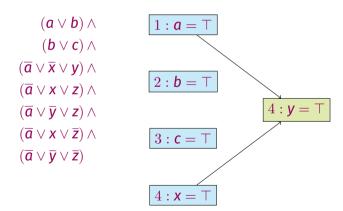
$$(b \lor c) \land \qquad \qquad \boxed{\overline{a} \lor \overline{x} \lor y) \land}$$

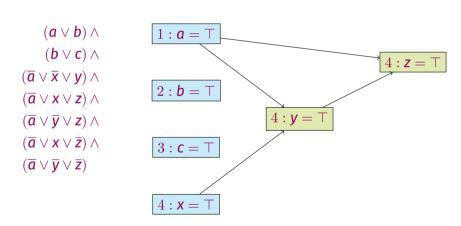
$$(\overline{a} \lor x \lor z) \land \qquad \qquad \boxed{2 : b = \top}$$

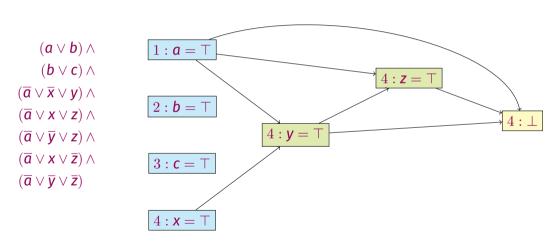
$$(\overline{a} \lor \overline{y} \lor z) \land \qquad \qquad \boxed{\overline{a} \lor x \lor \overline{z}) \land}$$

$$(\overline{a} \lor \overline{y} \lor \overline{z})$$

 $4: \mathbf{X} = \top$ 





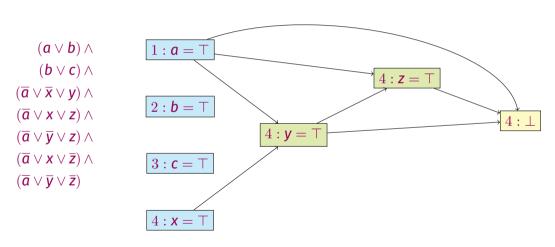


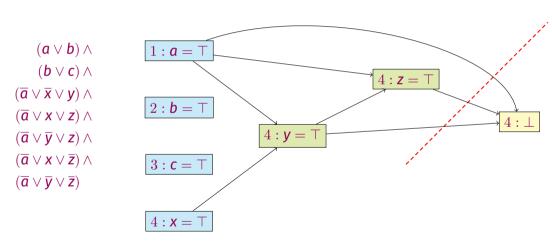
### Conflict cut

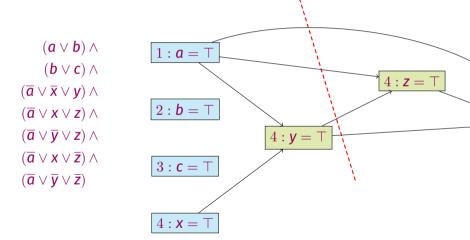
### Definition (Conflict cut)

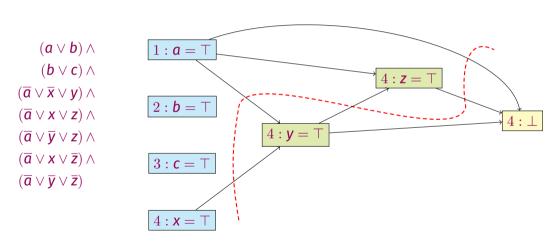
For an implication graph containing the conflict vertex  $\bot$ , a *conflict cut* is a partition W = (A, B) where:

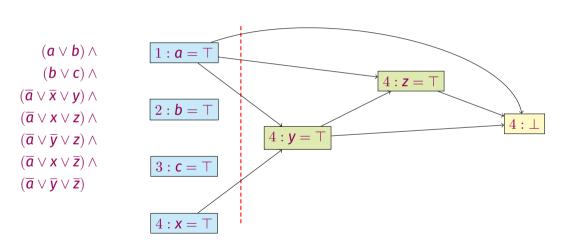
- all decisions belong to A
- the conflict vertex ⊥ belongs to B











#### Learnt clause

### Definition (Reason set)

The reason set of a conflict cut W is  $R = \{l \in A \mid \exists l' \in B : (l, l') \in E\}$ . (the nodes in A that have edges to B)

#### Definition (Learnt clause)

The learnt clause corresponding to W is  $\bigvee_{l \in R} \overline{l}$ .

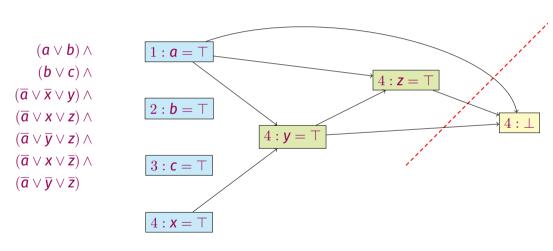
#### **Theorem**

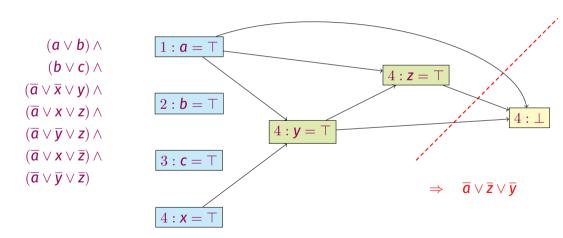
Learnt clauses are valid, i.e. they are implied by the formula.

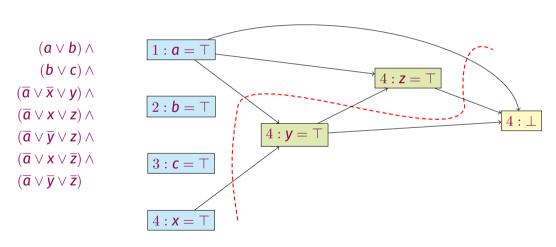
Setting all *R*-literals to true and performing unit propagation will produce a conflict. Therefore,  $\bigvee_{l \in R} \overline{l}$  is a logical consequence of the original formula.

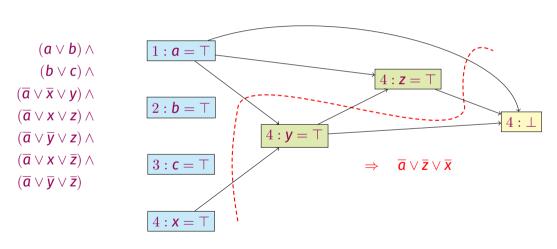
$$\bigwedge_{l \in R} l \quad \text{is contradictory, so} \quad \neg (\bigwedge_{l \in R} l) = \bigvee_{l \in R} \bar{l} \quad \text{is valid.}$$

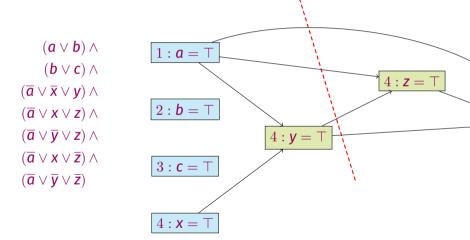


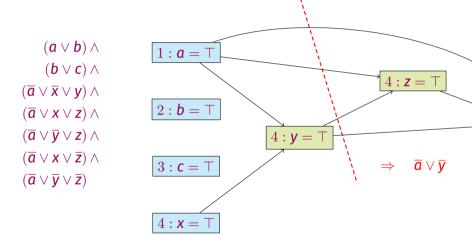


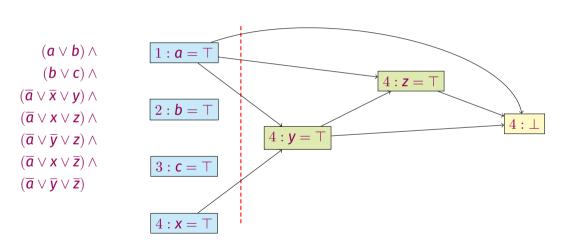


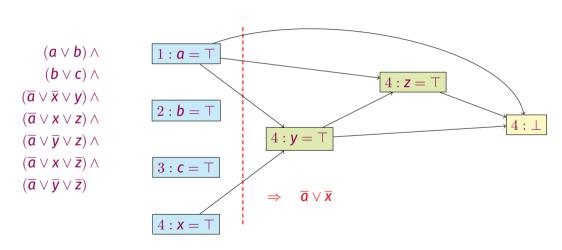








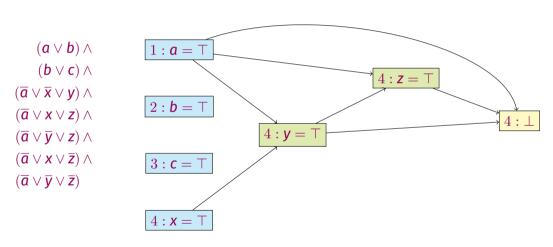


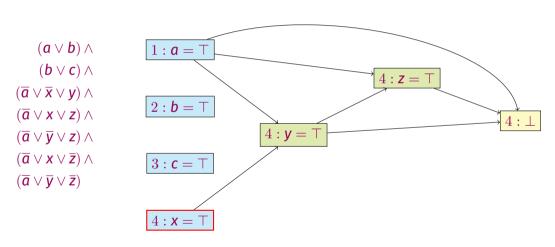


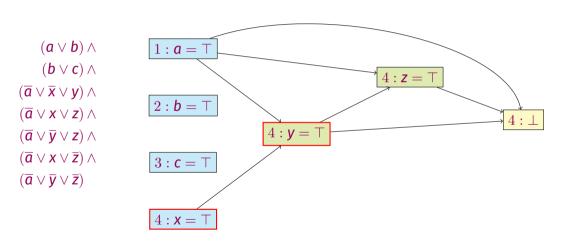
### **Unique Implication Point**

#### Definition (UIP)

A vertex l in the implication graph is a Unique Implication Point (UIP) if all the paths from the *last decision* to the conflict vertex  $\bot$  go through l.







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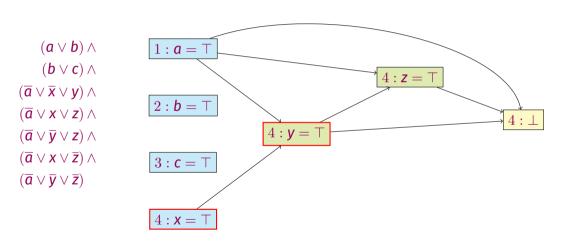
#### Definition (UIP cut)

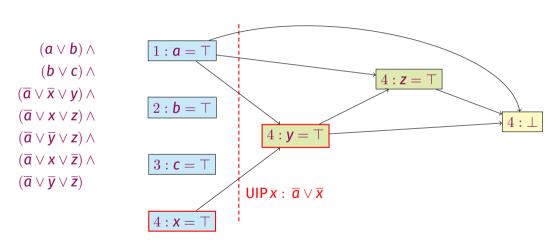
If *l* is a UIP, the corresponding **UIP cut** is W = (A, B) where *B* contains the successors of *l* from which there is a path to  $\bot$ .

#### Note that:

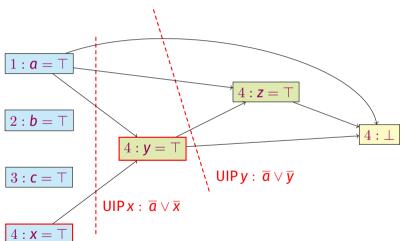
A UIP always exists: the last decision variable is itself a UIP.







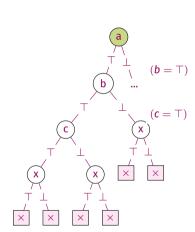




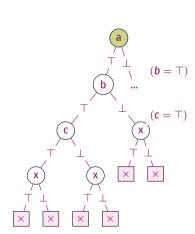
## Backjumping

- Add the clause from the UIP cut to the original formula.
- Backtrack to the second-highest decision level of literals used in the clause.
- Since UIP has only one literal at the highest decision level, unit propagation will happen.

 $(a \lor b) \land$  $(b \lor c) \land$  $(\overline{a} \lor \overline{x} \lor y) \land$  $(\overline{a} \lor x \lor z) \land$  $(\overline{a} \lor \overline{y} \lor z) \land$  $(\overline{a} \lor x \lor \overline{z}) \land$  $(\overline{a} \lor \overline{y} \lor \overline{z})$ 







```
(a \lor b) \land \\ (b \lor c) \land \\ (\overline{a} \lor \overline{x} \lor y) \land \\ (\overline{a} \lor x \lor z) \land \\ (\overline{a} \lor \overline{y} \lor z) \land \\ (\overline{a} \lor \overline{y} \lor \overline{z}) \land \\ (\overline{a} \lor \overline{y} \lor \overline{z}) \land \\ (\overline{a} \lor \overline{y})
```



```
(b \lor c) \land
(\overline{a} \vee \overline{x} \vee y) \wedge
(\overline{a} \lor x \lor z) \land
(\overline{a} \vee \overline{y} \vee z) \wedge
(\overline{a} \lor x \lor \overline{z}) \land
(\overline{a} \vee \overline{y} \vee \overline{z}) \wedge
            (\overline{a} \vee \overline{y})
```



```
(a \lor b) \land (b \lor c) \land (\overline{a} \lor \overline{x} \lor y) \land (\overline{a} \lor x \lor z) \land (\overline{a} \lor \overline{y} \lor \overline{z}) \land (\overline{a} \lor \overline{z}) \lor (\overline{a} \lor \overline{z}) \land (\overline{a} \lor \overline{z}) \lor (\overline{a} \lor \overline{z})
```



```
(\overrightarrow{a} \vee \overrightarrow{k}) \wedge (\overrightarrow{b} \vee \overrightarrow{c}) \wedge (\overline{a} \vee \overrightarrow{x} \vee \overrightarrow{y}) \wedge (\overline{a} \vee \overrightarrow{x} \vee \overrightarrow{z}) \wedge (\overline{a} \vee \overrightarrow{y} \vee \overrightarrow{z}) \wedge (\overline{a} \vee \overrightarrow{z})
```



$$(a \lor b) \land (b \lor c) \land (\bar{a} \lor \bar{x} \lor \bar{y}) \land (\bar{a} \lor x \lor z) \land (\bar{a} \lor \bar{x} \lor \bar{z}) \land (\bar{a} \lor \bar{x} \lor \bar{z}) \land (\bar{a} \lor \bar{y} \lor \bar{z}) \land (\bar{a} \lor \bar{$$



```
(a \lor b) \land
            (b \lor c) \land
(\overline{a} \vee \overline{x} \vee y) \wedge
                                                                   1: \boldsymbol{a} = \top
(\overline{a} \lor x \lor z) \land
(\overline{a} \vee \overline{y} \vee z) \wedge
(\overline{a} \lor x \lor \overline{z}) \land
(\overline{a} \vee \overline{y} \vee \overline{z}) \wedge
           (\overline{a} \vee \overline{y})
```

```
(a \lor b) \land 

(b \lor c) \land 

(\overline{a} \lor \overline{x} \lor y) \land 

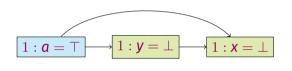
(\overline{a} \lor x \lor z) \land 

(\overline{a} \lor \overline{y} \lor z) \land 

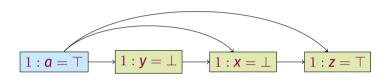
(\overline{a} \lor \overline{y} \lor \overline{z}) \land 

(\overline{a} \lor \overline{y})
(\overline{a} \lor \overline{y})
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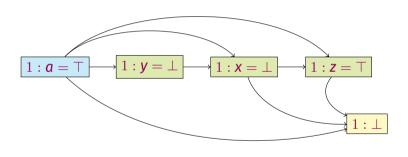
$$\begin{array}{c} (a \lor b) \land \\ (b \lor c) \land \\ (\overline{a} \lor \overline{x} \lor y) \land \\ (\overline{a} \lor \overline{y} \lor z) \land \\ (\overline{a} \lor \overline{y} \lor z) \land \\ (\overline{a} \lor \overline{y} \lor \overline{z}) \land \\ (\overline{a} \lor \overline{y} \lor \overline{y}) \end{array}$$



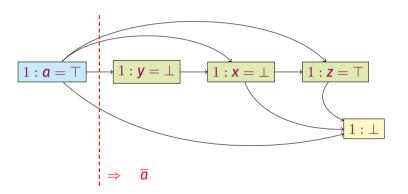




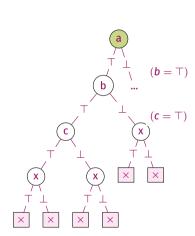




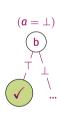




 $(a \lor b) \land$  $(b \lor c) \land$  $(\overline{a} \lor \overline{x} \lor y) \land$  $(\overline{a} \lor \overline{y} \lor z) \land$  $(\overline{a} \lor \overline{y} \lor z) \land$  $(\overline{a} \lor \overline{y} \lor \overline{z}) \land$  $(\overline{a} \lor \overline{y} \lor \overline{z})$ 



```
(a \lor b) \land
            (b \lor c) \land
(\overline{a} \vee \overline{x} \vee y) \wedge
(\overline{a} \lor x \lor z) \land
(\overline{a} \vee \overline{y} \vee z) \wedge
(\overline{a} \lor x \lor \overline{z}) \land
(\overline{a} \vee \overline{y} \vee \overline{z}) \wedge
           (\overline{a} \vee \overline{y}) \wedge
                         (\overline{a})
```



## Nice properties

- Adding a UIP clause will cause new unit propagation to happen in the search tree (the search tree becomes smaller).
- The same assignment and implication graph can never be reached again.
- ... even if you re-start the search tree, change the branching.

### Conflict analysis for MILPs?

- Has been tried in SCIP.
  - Achterberg, T. (2007). Conflict analysis in mixed integer programming. Discrete Optimization, 4(1), 4-20.
  - Sandholm, T., & Shields, R. (2006). Nogood learning for mixed integer programming. In Workshop on Hybrid Methods and Branching Rules in Combinatorial Optimization, Montréal.
  - Witzig, J., Berthold, T., & Heinz, S. (2017). Experiments with conflict analysis in mixed integer programming. In Integration of AI and OR Techniques in Constraint Programming (CPAIOR 2017).
- Logical conflict analysis can be generalized to incompatible combinations of bound changes for MILPs, but linearization of combinations of bound changes involving general integer and continuous variables might be weak.
- Not sure if it's much used in commercial solvers.