# Formal Methods: Module I: Automated Reasoning Ch. 01: Reasoning in Propositional Logic

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#### **Outline**

- Boolean Logics and SAT
- Basic SAT-Solving Techniques
  - Resolution
  - Tableaux
  - DPLL
  - Stochastic Local Search for SAT
- 3 Ordered Binary Decision Diagrams OBDDs
- Modern CDCL SAT Solvers
  - Limitations of Chronological Backtracking
  - Conflict-Driven Clause-Learning SAT solvers
  - Further Improvements
  - SAT Under Assumptions & Incremental SAT
- SAT Functionalities: proofs, unsat cores, interpolants, optimization

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## Propositional Logic (aka Boolean Logic)



#### **Basic Definitions**

- Propositional formula (aka Boolean formula)
  - $\bullet$   $\top$ ,  $\bot$  are formulas
  - a propositional atom  $A_1, A_2, A_3, ...$  is a formula;
  - if  $\varphi_1$  and  $\varphi_2$  are formulas, then

```
\neg \varphi_1, \varphi_1 \land \varphi_2, \varphi_1 \lor \varphi_2, \varphi_1 \rightarrow \varphi_2, \varphi_1 \leftarrow \varphi_2, \varphi_1 \leftrightarrow \varphi_2, \varphi_1 \oplus \varphi_2 are formulas.
```

- Ex:  $\varphi \stackrel{\text{def}}{=} (\neg (A_1 \to A_2)) \wedge (A_3 \leftrightarrow (\neg A_1 \oplus (A_2 \vee \neg A_4))))$
- $Atoms(\varphi)$ : the set  $\{A_1,...,A_N\}$  of atoms occurring in  $\varphi$ .
  - Ex:  $Atoms(\varphi) = \{A_1, A_2, A_3, A_4\}$
- Literal: a propositional atom  $A_i$  (positive literal) or its negation  $\neg A_i$  (negative literal)
  - Notation: if  $I := \neg A_i$ , then  $\neg I := A_i$
- Clause: a disjunction of literals  $\bigvee_{i} I_{i}$  (e.g.,  $(A_{1} \vee \neg A_{2} \vee A_{3} \vee ...))$
- Cube: a conjunction of literals  $\bigwedge_i I_i$  (e.g.,  $(A_1 \land \neg A_2 \land A_3 \land ...)$ )

## Semantics of Boolean operators

#### Truth Table

$\alpha$	β	$\neg \alpha$	$\alpha \wedge \beta$	$\alpha \vee \beta$	$\alpha \rightarrow \beta$	$\alpha \leftarrow \beta$	$\alpha \leftrightarrow \beta$	$\alpha \oplus \beta$
上	$\perp$	T	上	上	Т	Т	Т	
1	T	T	上	T	T	1		T
T			丄	T		Т		T
Т	Т	上	Т	Т	Т	Т	Т	

## Semantics of Boolean operators (cont.)

#### Note

 $\bullet$   $\land$ ,  $\lor$ ,  $\leftrightarrow$  and  $\oplus$  are commutative:

$$\begin{array}{ccc}
(\alpha \wedge \beta) & \iff & (\beta \wedge \alpha) \\
(\alpha \vee \beta) & \iff & (\beta \vee \alpha) \\
(\alpha \leftrightarrow \beta) & \iff & (\beta \leftrightarrow \alpha) \\
(\alpha \oplus \beta) & \iff & (\beta \oplus \alpha)
\end{array}$$

 $\bullet$   $\land$ ,  $\lor$ ,  $\leftrightarrow$  and  $\oplus$  are associative:

$$((\alpha \land \beta) \land \gamma) \iff (\alpha \land (\beta \land \gamma)) \iff (\alpha \land \beta \land \gamma)$$

$$((\alpha \lor \beta) \lor \gamma) \iff (\alpha \lor (\beta \lor \gamma)) \iff (\alpha \lor \beta \lor \gamma)$$

$$((\alpha \leftrightarrow \beta) \leftrightarrow \gamma) \iff (\alpha \leftrightarrow (\beta \leftrightarrow \gamma)) \iff (\alpha \leftrightarrow \beta \leftrightarrow \gamma)$$

$$((\alpha \oplus \beta) \oplus \gamma) \iff (\alpha \oplus (\beta \oplus \gamma)) \iff (\alpha \oplus \beta \oplus \gamma)$$

ullet  $\to$ ,  $\leftarrow$  are neither commutative nor associative:

$$(\alpha \to \beta) \iff (\beta \to \alpha)$$
$$((\alpha \to \beta) \to \gamma) \iff (\alpha \to (\beta \to \gamma))$$

## Remark: Semantics of Implication " $\rightarrow$ " (aka " $\Rightarrow$ ", " $\supset$ ")

#### The semantics of Implication " $\alpha \rightarrow \beta$ " may be counter-intuitive

 $\alpha \to \beta$ : "the antecedent (aka premise)  $\alpha$  implies the consequent (aka conclusion)  $\beta$ " (aka "if  $\alpha$  holds, then  $\beta$  holds" (but not vice versa))

- ullet does not require causation or relevance between lpha and eta
  - ex: "5 is odd implies Tokyo is the capital of Japan" is true in p.l. (under standard interpretation of "5", "odd", "Tokyo", "Japan")
  - relation between antecedent & consequent: they are both true
- is true whenever its antecedent is false
  - ex: "5 is even implies Sam is smart" is true (regardless the smartness of Sam)
  - ex: "5 is even implies Tokyo is in Italy" is true (!)
  - relation between antecedent & consequent: the former is false
- does not require temporal precedence of  $\alpha$  wrt.  $\beta$ 
  - ex: "the grass is wet implies it must have rained" is true (the consequent precedes temporally the antecedent)

## Syntactic Properties of Boolean Operators

Boolean logic can be expressed in terms of  $\{\neg, \land\}$  (or  $\{\neg, \lor\}$ ) only!

#### **Exercises**

• For every pair of formulas  $\alpha \Longleftrightarrow \beta$  below, show that  $\alpha$  and  $\beta$  can be rewritten into each other by applying the syntactic properties of the previous slide

$$\bullet \ (A_1 \wedge A_2) \vee A_3 \iff (A_1 \vee A_3) \wedge (A_2 \vee A_3)$$

$$\bullet \ (A_1 \lor A_2) \land A_3 \iff (A_1 \land A_3) \lor (A_2 \land A_3)$$

$$\bullet \ \ A_1 \rightarrow (A_2 \rightarrow (A_3 \rightarrow A_4)) \iff (A_1 \land A_2 \land A_3) \rightarrow A_4$$

$$\bullet \ A_1 \to (A_2 \land A_3) \iff (A_1 \to A_2) \land (A_1 \to A_3)$$

$$\bullet \ (A_1 \lor A_2) \to A_3 \iff (A_1 \to A_3) \land (A_2 \to A_3)$$

$$\bullet \ A_1 \oplus A_2 \iff (A_1 \vee A_2) \wedge (\neg A_1 \vee \neg A_2)$$

$$\bullet \ \neg A_1 \leftrightarrow \neg A_2 \iff A_1 \leftrightarrow A_2$$

$$\bullet \ A_1 \leftrightarrow A_2 \leftrightarrow A_3 \iff A_1 \oplus A_2 \oplus A_3$$

## Tree & DAG Representations of Formulas

- Formulas can be represented either as trees or as DAGS (Directed Acyclic Graphs)
- DAG representation can be up to exponentially smaller
  - in particular, when ↔'s are involved

$$(A_1 \leftrightarrow A_2) \leftrightarrow (A_3 \leftrightarrow A_4)$$

$$\downarrow \downarrow$$

$$(((A_1 \leftrightarrow A_2) \rightarrow (A_3 \leftrightarrow A_4)) \land$$

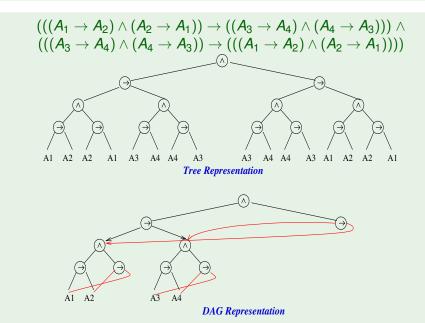
$$((A_3 \leftrightarrow A_4) \rightarrow (A_1 \leftrightarrow A_2)))$$

$$\downarrow \downarrow$$

$$(((A_1 \rightarrow A_2) \land (A_2 \rightarrow A_1)) \rightarrow ((A_3 \rightarrow A_4) \land (A_4 \rightarrow A_3))) \land$$

$$(((A_3 \rightarrow A_4) \land (A_4 \rightarrow A_3)) \rightarrow (((A_1 \rightarrow A_2) \land (A_2 \rightarrow A_1))))$$

## Tree & DAG Representations of Formulas: Example



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#### Semantics: Basic Definitions

- Total truth assignment  $\mu$  for  $\varphi$ :
  - $\mu : Atoms(\varphi) \longmapsto \{\top, \bot\}.$ 
    - represents a possible world or a possible state of the world
- Partial Truth assignment  $\mu$  for  $\varphi$ :
  - $\mu: \mathcal{A} \longmapsto \{\top, \bot\}, \mathcal{A} \subset Atoms(\varphi).$ 
    - represents  $2^k$  total assignments, k is # unassigned variables
- Notation: set and formula representations of an assignment
  - ullet  $\mu$  can be represented as a set of literals:

EX: 
$$\{\mu(A_1) := \top, \mu(A_2) := \bot\} \implies \{A_1, \neg A_2\}$$

•  $\mu$  can be represented as a formula (cube):

$$\mathsf{EX} \colon \{ \mu(A_1) := \top, \mu(A_2) := \bot \} \implies (A_1 \land \neg A_2)$$

## Semantics: Basic Definitions [cont.]

• A total truth assignment  $\mu$  satisfies  $\varphi$  ( $\mu$  is a model of  $\varphi$ ,  $\mu \models \varphi$ ):

$$\mu \models A_{i} \iff \mu(A_{i}) = \top$$

$$\mu \models \neg \varphi \iff \text{not } \mu \models \varphi$$

$$\mu \models \alpha \land \beta \iff \mu \models \alpha \text{ and } \mu \models \beta$$

$$\mu \models \alpha \lor \beta \iff \mu \models \alpha \text{ or } \mu \models \beta$$

$$\mu \models \alpha \to \beta \iff \text{if } \mu \models \alpha, \text{ then } \mu \models \beta$$

$$\mu \models \alpha \leftrightarrow \beta \iff \mu \models \alpha \text{ iff } \mu \models \beta$$

$$\mu \models \alpha \oplus \beta \iff \mu \models \alpha \text{ iff not } \mu \models \beta$$

- $M(\varphi) \stackrel{\text{def}}{=} \{ \mu \mid \mu \models \varphi \}$  (the set of models of  $\varphi$ )
- A partial truth assignment  $\mu$  satisfies  $\varphi$  iff all total assignments extending  $\mu$  satisfy  $\varphi$ 
  - Ex:  $\{A_1\} \models (A_1 \lor A_2)$ ) because both  $\{A_1, A_2\} \models (A_1 \lor A_2)$  and  $\{A_1, \neg A_2\} \models (A_1 \lor A_2)$
- $\varphi$  is satisfiable iff  $\mu \models \varphi$  for some  $\mu$  (i.e.  $M(\varphi) \neq \emptyset$ )
- $\alpha$  entails  $\beta$  ( $\alpha \models \beta$ ):  $\alpha \models \beta$  iff  $\mu \models \alpha \Longrightarrow \mu \models \beta$  for all  $\mu$ s (i.e.,  $M(\alpha) \subseteq M(\beta)$ )
- (i.e.,  $M(\alpha) \subseteq M(\beta)$ )

    $\varphi$  is valid ( $\models \varphi$ ):  $\models \varphi$  iff  $\mu \models \varphi$  forall  $\mu$ s (i.e.,  $\mu \in M(\varphi)$  forall  $\mu$ s)

## Properties & Results

#### **Property**

 $\varphi$  is valid iff  $\neg \varphi$  is not satisfiable

#### **Deduction Theorem**

$$\alpha \models \beta \text{ iff } \alpha \rightarrow \beta \text{ is valid } (\models \alpha \rightarrow \beta)$$

#### Corollary

 $\alpha \models \beta$  iff  $\alpha \land \neg \beta$  is not satisfiable

Validity and entailment checking can be straightforwardly reduced to (un)satisfiability checking!

## Equivalence and Equi-Satisfiability

- $\alpha$  and  $\beta$  are equivalent iff, for every  $\mu$ ,  $\mu \models \alpha$  iff  $\mu \models \beta$  (i.e., if  $M(\alpha) = M(\beta)$ )
- $\alpha$  and  $\beta$  are equi-satisfiable iff exists  $\mu_1$  s.t.  $\mu_1 \models \alpha$  iff exists  $\mu_2$  s.t.  $\mu_2 \models \beta$ (i.e., if  $M(\alpha) \neq \emptyset$  iff  $M(\beta) \neq \emptyset$ )
- $\alpha$ ,  $\beta$  equivalent  $\downarrow \quad \not \uparrow$  $\alpha$ ,  $\beta$  equi-satisfiable
- EX:  $A_1 \vee A_2$  and  $(A_1 \vee \neg A_3) \wedge (A_3 \vee A_2)$  are equi-satisfiable, not equivalent.

$$\{\neg A_1, A_2, A_3\} \models (A_1 \lor A_2), \text{ but } \{\neg A_1, A_2, A_3\} \not\models (A_1 \lor \neg A_3) \land (A_3 \lor A_2)$$

- Typically used when  $\beta$  is the result of applying some transformation T to  $\alpha$ :  $\beta \stackrel{\text{def}}{=} T(\alpha)$ :
  - T is validity-preserving [resp. satisfiability-preserving] iff  $T(\alpha)$  and  $\alpha$  are equivalent [resp. equi-satisfiable]

## Complexity

- For N variables, there are up to 2<sup>N</sup> truth assignments to be checked.
- The problem of deciding the satisfiability of a propositional formula is NP-complete
- The most important logical problems (validity, inference, entailment, equivalence, ...) can be straightforwardly reduced to (un)satisfiability, and are thus (co)NP-complete.



No existing worst-case-polynomial algorithm.

#### POLARITY of subformulas

#### Polarity: the number of nested negations modulo 2.

- Positive/negative occurrences
  - $\varphi$  occurs positively in  $\varphi$ ;
  - if  $\neg \varphi_1$  occurs positively [negatively] in  $\varphi$ , then  $\varphi_1$  occurs negatively [positively] in  $\varphi$
  - if φ<sub>1</sub> ∧ φ<sub>2</sub> or φ<sub>1</sub> ∨ φ<sub>2</sub> occur positively [negatively] in φ, then φ<sub>1</sub> and φ<sub>2</sub> occur positively [negatively] in φ;
  - if  $\varphi_1 \to \varphi_2$  occurs positively [negatively] in  $\varphi$ , then  $\varphi_1$  occurs negatively [positively] in  $\varphi$  and  $\varphi_2$  occurs positively [negatively] in  $\varphi$ ;
  - if φ<sub>1</sub> ↔ φ<sub>2</sub> or φ<sub>1</sub> ⊕ φ<sub>2</sub> occurs in φ,
     then φ<sub>1</sub> and φ<sub>2</sub> occur positively and negatively in φ;

## Negative Normal Form (NNF)

- φ is in Negative normal form iff it is given only by the recursive applications of ∧, ∨ to literals.
- every  $\varphi$  can be reduced into NNF:
  - (i) substituting all  $\rightarrow$ 's and  $\leftrightarrow$ 's:

$$\begin{array}{ccc} \alpha \to \beta & \Longrightarrow & \neg \alpha \lor \beta \\ \alpha \leftrightarrow \beta & \Longrightarrow & (\neg \alpha \lor \beta) \land (\alpha \lor \neg \beta) \end{array}$$

(ii) pushing down negations recursively:

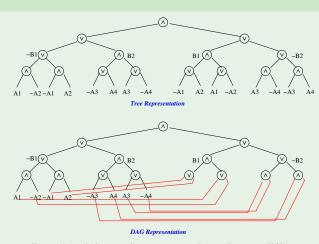
$$\neg(\alpha \land \beta) \implies \neg\alpha \lor \neg\beta 
\neg(\alpha \lor \beta) \implies \neg\alpha \land \neg\beta 
\neg\neg\alpha \implies \alpha$$

- The reduction is linear if a DAG representation is used.
- Preserves the equivalence of formulas.

## NNF: Example

## NNF: Example [cont.]

#### Note

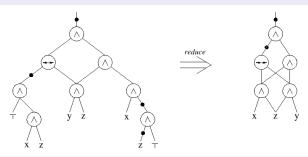


For each non-literal subformula  $\varphi$ ,  $\varphi$  and  $\neg \varphi$  have different representations  $\Longrightarrow$  they are not shared.

## Optimized polynomial representations

## And-Inverter Graphs, Reduced Boolean Circuits, Boolean Expression Diagrams

Maximize the sharing in DAG representations:
 {∧, ↔, ¬}-only, negations on arcs, sorting of subformulae, lifting of ¬'s over ↔'s,...



## Conjunctive Normal Form (CNF)

 φ is in Conjunctive normal form iff it is a conjunction of disjunctions of literals:

$$\bigwedge_{i=1}^{L} \bigvee_{j_i=1}^{K_i} I_{j_i}$$

- the disjunctions of literals  $\bigvee_{i=1}^{K_i} I_{j_i}$  are called clauses
- Easier to handle: list of lists of literals.
  - ⇒ no reasoning on the recursive structure of the formula

## Classic CNF Conversion $CNF(\varphi)$

- Every  $\varphi$  can be reduced into CNF by, e.g.,
  - (i) expanding implications and equivalences:

$$\begin{array}{ccc} \alpha \to \beta & \Longrightarrow & \neg \alpha \lor \beta \\ \alpha \leftrightarrow \beta & \Longrightarrow & (\neg \alpha \lor \beta) \land (\alpha \lor \neg \beta) \end{array}$$

(ii) pushing down negations recursively:

$$\neg(\alpha \land \beta) \implies \neg\alpha \lor \neg\beta 
\neg(\alpha \lor \beta) \implies \neg\alpha \land \neg\beta 
\neg\neg\alpha \implies \alpha$$

(iii) applying recursively the DeMorgan's Rule:

$$(\alpha \wedge \beta) \vee \gamma \implies (\alpha \vee \gamma) \wedge (\beta \vee \gamma)$$

- Resulting formula worst-case exponential:
  - ex:  $||CNF(\bigvee_{i=1}^{N}(I_{i1} \wedge I_{i2})|| =$

$$||(I_{11} \lor I_{21} \lor \dots \lor I_{N1}) \land (I_{12} \lor I_{21} \lor \dots \lor I_{N1}) \land \dots \land (I_{12} \lor I_{22} \lor \dots \lor I_{N2})|| = 2^{N}$$

- $Atoms(CNF(\varphi)) = Atoms(\varphi)$
- $CNF(\varphi)$  is equivalent to  $\varphi$ .
- Rarely used in practice.

## Labeling CNF conversion $CNF_{label}(\varphi)$

#### Labeling CNF conversion $CNF_{label}(\varphi)$ (aka Tseitin's CNF-ization)

• Every  $\varphi$  can be reduced into CNF by, e.g., applying recursively bottom-up the rules:

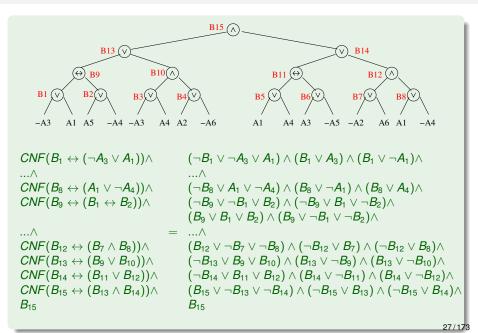
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\varphi \implies \varphi[(I_i \lor I_j)|B] \land CNF(B \leftrightarrow (I_i \lor I_j))
\varphi \implies \varphi[(I_i \land I_j)|B] \land CNF(B \leftrightarrow (I_i \land I_j))
\varphi \implies \varphi[(I_i \leftrightarrow I_j)|B] \land CNF(B \leftrightarrow (I_i \leftrightarrow I_j))
I_i, I_i being literals and B being a "new" variable.
```

- Worst-case linear!
- $Atoms(CNF_{label}(\varphi)) \supseteq Atoms(\varphi)$
- $CNF_{label}(\varphi)$  is equi-satisfiable (but not equivalent) to  $\varphi$ .
- Much more used than classic conversion in practice.

## Labeling CNF conversion $\mathit{CNF}_{\mathit{label}}(\varphi)$ (cont.)

$$\begin{array}{c|c} \textit{CNF}(B \leftrightarrow (l_i \lor l_j)) & \Longleftrightarrow & (\neg B \lor l_i \lor l_j) \land \\ & (B \lor \neg l_i) \land \\ & (B \lor \neg l_j) \\ \hline \textit{CNF}(B \leftrightarrow (l_i \land l_j)) & \Longleftrightarrow & (\neg B \lor l_i) \land \\ & (\neg B \lor l_j) \land \\ & (B \lor \neg l_i \neg l_j) \\ \hline \textit{CNF}(B \leftrightarrow (l_i \leftrightarrow l_j)) & \Longleftrightarrow & (\neg B \lor \neg l_i \lor l_j) \land \\ & (\neg B \lor l_i \lor \neg l_j) \land \\ & (B \lor \neg l_i \lor \neg l_j) \land \\ & (B \lor \neg l_i \lor \neg l_j) \\ \hline \end{array}$$

## Labeling CNF Conversion *CNF*<sub>label</sub> – Example



## Labeling CNF conversion *CNF*<sub>label</sub> (improved)

As in the previous case, applying instead the rules:

$$\begin{array}{lll} \varphi & \Longrightarrow & \varphi[(l_i \vee l_j)|B] & \wedge \ CNF(B \to (l_i \vee l_j)) & \text{if } (l_i \vee l_j) \ \text{pos.} \\ \varphi & \Longrightarrow & \varphi[(l_i \vee l_j)|B] & \wedge \ CNF((l_i \vee l_j) \to B) & \text{if } (l_i \vee l_j) \ \text{neg.} \\ \varphi & \Longrightarrow & \varphi[(l_i \wedge l_j)|B] & \wedge \ CNF(B \to (l_i \wedge l_j)) & \text{if } (l_i \wedge l_j) \ \text{pos.} \\ \varphi & \Longrightarrow & \varphi[(l_i \wedge l_j)|B] & \wedge \ CNF((l_i \wedge l_j) \to B) & \text{if } (l_i \wedge l_j) \ \text{neg.} \\ \varphi & \Longrightarrow & \varphi[(l_i \leftrightarrow l_j)|B] & \wedge \ CNF(B \to (l_i \leftrightarrow l_j)) & \text{if } (l_i \leftrightarrow l_j) \ \text{pos.} \\ \varphi & \Longrightarrow & \varphi[(l_i \leftrightarrow l_j)|B] & \wedge \ CNF((l_i \leftrightarrow l_j) \to B) & \text{if } (l_i \leftrightarrow l_j) \ \text{neg.} \end{array}$$

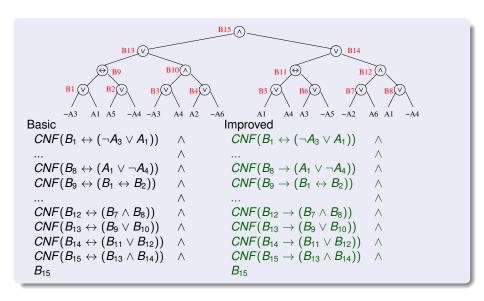
Smaller in size:

$$\begin{array}{ll} \textit{CNF}(B \rightarrow (\textit{I}_i \vee \textit{I}_j)) &= (\neg B \vee \textit{I}_i \vee \textit{I}_j) \\ \textit{CNF}(((\textit{I}_i \vee \textit{I}_i) \rightarrow B)) &= (\neg \textit{I}_i \vee B) \wedge (\neg \textit{I}_i \vee B) \end{array}$$

## Labeling CNF conversion $CNF_{label}(\varphi)$ (cont.)

$$\begin{array}{cccc} \textit{CNF}(B \rightarrow (l_i \lor l_j)) & \Longleftrightarrow & (\neg B \lor l_i \lor l_j) \\ \textit{CNF}(B \leftarrow (l_i \lor l_j)) & \Longleftrightarrow & (B \lor \neg l_i) \land \\ & & (B \lor \neg l_j) \\ \hline \textit{CNF}(B \rightarrow (l_i \land l_j)) & \Longleftrightarrow & (\neg B \lor l_i) \land \\ & & (\neg B \lor l_j) \\ \hline \textit{CNF}(B \leftarrow (l_i \land l_j)) & \Longleftrightarrow & (B \lor \neg l_i \neg l_j) \\ \hline \textit{CNF}(B \rightarrow (l_i \leftrightarrow l_j)) & \Longleftrightarrow & (\neg B \lor \neg l_i \lor l_j) \land \\ & & (\neg B \lor l_i \lor \neg l_j) \\ \hline \textit{CNF}(B \leftarrow (l_i \leftrightarrow l_j)) & \Longleftrightarrow & (B \lor l_i \lor l_j) \land \\ & & (B \lor \neg l_i \lor \neg l_j) \\ \hline \end{array}$$

## Labeling CNF conversion *CNF*<sub>label</sub> – example



## Labeling CNF conversion *CNF*<sub>label</sub> – optimizations

- Do not apply  $CNF_{label}$  when not necessary: (e.g.,  $CNF_{label}(\varphi_1 \land \varphi_2) \Longrightarrow CNF_{label}(\varphi_1) \land \varphi_2$ , if  $\varphi_2$  already in CNF)
- Apply DeMorgan's rules where it is more effective: (e.g.,  $CNF_{label}(\varphi_1 \land (A \rightarrow (B \land C))) \Longrightarrow CNF_{label}(\varphi_1) \land (\neg A \lor B) \land (\neg A \lor C)$
- exploit the associativity of  $\land$ 's and  $\lor$ 's: ...  $\underbrace{(A_1 \lor (A_2 \lor A_3))}_{B}$  ...  $\Longrightarrow$  ...  $CNF(B \leftrightarrow (A_1 \lor A_2 \lor A_3))$ ...
- before applying CNF<sub>label</sub>, rewrite the initial formula so that to maximize the sharing of subformulas (RBC, BED)
- ...

#### **Exercises**

- **①** Consider the following Boolean formula  $\varphi$ :
  - $\neg(((\neg A_1 \rightarrow A_2) \land (\neg A_3 \rightarrow A_4)) \lor ((A_5 \rightarrow A_6) \land (A_7 \rightarrow \neg A_8)))$ Compute the Negative Normal Form of  $\varphi$
- **2** Consider the following Boolean formula  $\varphi$ :

$$((\neg A_1 \land A_2) \lor (A_7 \land A_4) \lor (\neg A_3 \land \neg A_2) \lor (A_5 \land \neg A_4))$$

- Produce the CNF formula  $CNF(\varphi)$ .
- 2 Produce the CNF formula  $CNF_{label}(\varphi)$ .
- **3** Produce the CNF formula  $CNF_{label}(\varphi)$  (improved version)

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## Propositional Reasoning: Generalities

- Automated Reasoning in Propositional Logic fundamental task
  - AI, formal verification, circuit synthesis, operational research,....
- Important in AI:  $KB \models \alpha$ : entail fact  $\alpha$  from knowledge base KR (aka Model Checking:  $M(KB) \subseteq M(\alpha)$ )
  - typically  $KB >> \alpha$
- All propositional reasoning tasks reduced to satisfiability (SAT)
  - $KR \models \alpha \Longrightarrow SAT(KR \land \neg \alpha) = false$
  - input formula CNF-ized and fed to a SAT solver
- Current SAT solvers dramatically efficient:
  - handle industrial problems with  $10^6 10^7$  variables & clauses!
  - used as backend engines in a variety of systems

#### **Truth Tables**

• Exhaustive evaluation of all subformulas:

$\varphi_1$	$\varphi_2$	$\varphi_1 \wedge \varphi_2$	$\varphi_1 \lor \varphi_2$	$\varphi_1 \rightarrow \varphi_2$	$\varphi_1 \leftrightarrow \varphi_2$
1	$\perp$			Т	T
1	Т		Т	Т	
T	上		Т		
T	Т	Т	Т	Т	T

- Requires polynomial space (draw one line at a time).
- Requires analyzing  $2^{|Atoms(\varphi)|}$  lines.
- Never used in practice.

#### **Outline**

- Boolean Logics and SAT
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#### The Resolution Rule

 Resolution: deduction of a new clause from a pair of clauses with exactly one incompatible variable (resolvent):

$$\underbrace{\left(\underbrace{I_{1} \vee ... \vee I_{k}}_{l_{k}} \vee \underbrace{I}_{l_{k}}^{resolvent} \vee \underbrace{I'_{k+1} \vee ... \vee I'_{m}}_{common}\right)}_{common} \underbrace{\left(\underbrace{I_{1} \vee ... \vee I_{k}}_{l_{k}} \vee \underbrace{I'_{k+1} \vee ... \vee I'_{m}}_{l_{m}}\right)}_{common} \underbrace{\left(\underbrace{I_{1} \vee ... \vee I_{k}}_{l_{k}} \vee \underbrace{I'_{k+1} \vee ... \vee I'_{m}}_{l_{m}}\right)}_{common} \underbrace{\left(\underbrace{I_{1} \vee ... \vee I_{k}}_{l_{k}} \vee \underbrace{I'_{k+1} \vee ... \vee I'_{m}}_{l_{m}}\right)}_{common}$$

• Ex: 
$$\frac{(A \lor B \lor C \lor D \lor E) \qquad (A \lor B \lor \neg C \lor F)}{(A \lor B \lor D \lor E \lor F)}$$

• Note: many standard inference rules subcases of resolution: (recall that  $\alpha \to \beta \Longleftrightarrow \neg \alpha \lor \beta$ )

$$\frac{A \rightarrow B \quad B \rightarrow C}{A \rightarrow C} \; (\textit{trans.}) \quad \frac{A \quad A \rightarrow B}{B} \; (\textit{m. ponens}) \quad \frac{\neg B \quad A \rightarrow B}{\neg A} \; (\textit{m. tollens})$$

# Improvements: Subsumption & Unit Propagation

Alternative "set" notation ( $\Gamma$  clause set):

$$\frac{\Gamma, \phi_1, ..\phi_n}{\Gamma, \phi_1', ..\phi_{n'}'} \quad \left(e.g., \frac{\Gamma, C_1 \vee p, C_2 \vee \neg p}{\Gamma, C_1 \vee p, C_2 \vee \neg p, C_1 \vee C_2},\right)$$

• Clause Subsumption (C clause):

$$\frac{\Gamma \wedge C \wedge (C \vee \bigvee_{i} I_{i})}{\Gamma \wedge (C)}$$

• Unit Resolution:  $\frac{\Gamma \wedge (I) \wedge (\neg I \vee \bigvee_i I_i)}{\Gamma \wedge (I) \wedge (\bigvee_i I_i)}$ 

• Unit Subsumption:  $\frac{\Gamma \wedge (I) \wedge (I \vee \bigvee_{i} I_{i})}{\Gamma \wedge (I)}$ 

Unit Propagation = Unit Resolution + Unit Subsumption

"Deterministic" rule: applied before other "non-deterministic" rules!

# Basic Propositional Inference: Resolution [33, 10]

- Assume input formula in CNF
  - if not, apply Tseitin CNF-ization first
- $\implies \varphi$  is represented as a set of clauses
  - Search for a refutation of  $\varphi$  (is  $\varphi$  unsatisfiable?)
    - recall:  $\alpha \models \beta$  iff  $\alpha \land \neg \beta$  unsatisfiable
  - Basic idea: apply iteratively the resolution rule to pairs of clauses with a conflicting literal, producing novel clauses, until either
    - a false clause is generated, or
    - the resolution rule is no more applicable
  - Correct: if returns an empty clause, then  $\varphi$  unsat ( $\alpha \models \beta$ )
  - Complete: if  $\varphi$  unsat ( $\alpha \models \beta$ ), then it returns an empty clause
  - Time-inefficient
  - Very Memory-inefficient (exponential in memory)
  - Many different strategies

# Resolution: basic strategy [10]

```
function DP(\Gamma)
     if \bot \in \Gamma
                                                             /* unsat */
           then return False:
     if (Resolve() is no more applicable to \Gamma) /* sat
           then return True:
     if {a unit clause (I) occurs in Γ}
                                                             /* unit
           then \Gamma := Unit Propagate(I, \Gamma);
           return DP(\Gamma)
     A := select-variable(\Gamma):
                                                             /* resolve */
     \Gamma = \Gamma \cup \bigcup_{A \in C', \neg A \in C''} \{ Resolve(C', C'') \} \setminus \bigcup_{A \in C', \neg A \in C''} \{ C', C'' \} \};
     return DP(Γ)
```

Hint: drops one variable  $A \in Atoms(\Gamma)$  at a time

## Resolution: Examples

$$(A_{1} \lor A_{2}) \ (A_{1} \lor \neg A_{2}) \ (\neg A_{1} \lor A_{2}) \ (\neg A_{1} \lor \neg A_{2})$$

$$\downarrow \qquad \qquad \downarrow \qquad \qquad \downarrow$$

# Resolution: Examples (cont.)

## Resolution: Examples

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

$$\downarrow \downarrow \downarrow \downarrow \downarrow \downarrow$$

$$(C) (\neg C)$$

$$\downarrow \downarrow \downarrow \downarrow \downarrow \downarrow$$

$$\bot$$

$$\Rightarrow UNSAT$$

## Resolution – summary

- Requires CNF
- Not very much used in Boolean reasoning (unless integrated with DPLL procedure in recent implementations)

## **Outline**

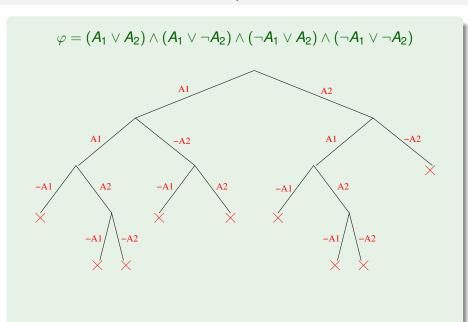
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# Semantic tableaux [39]

- Search for an assignment satisfying  $\varphi$
- applies recursively elimination rules to the connectives
- If a branch contains  $A_i$  and  $\neg A_i$ ,  $(\psi_i$  and  $\neg \psi_i)$  for some i, the branch is closed, otherwise it is open.
- if no rule can be applied to an open branch  $\mu$ , then  $\mu \models \varphi$ ;
- if all branches are closed, the formula is not satisfiable;

## Tableau elimination rules

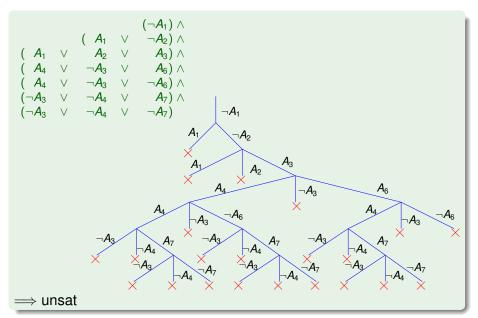
## Semantic Tableaux – Example



# Tableau algorithm

```
function Tableau(Γ)
       if A_i \in \Gamma and \neg A_i \in \Gamma
                                                                                   /* branch closed */
              then return False:
       if (\varphi_1 \wedge \varphi_2) \in \Gamma
                                                                                    /* ∧-elimination */
              then return Tableau(\Gamma \cup \{\varphi_1, \varphi_2\} \setminus \{(\varphi_1 \land \varphi_2)\});
                                                                                 /* ¬¬-elimination */
       if (\neg \neg \varphi_1) \in \Gamma
              then return Tableau(\Gamma \cup \{\varphi_1\} \setminus \{(\neg \neg \varphi_1)\});
                                                                                    /* ∨-elimination */
       if (\varphi_1 \vee \varphi_2) \in \Gamma
              then return Tableau(\Gamma \cup \{\varphi_1\} \setminus \{(\varphi_1 \vee \varphi_2)\}) or
                                        Tableau(\Gamma \cup \{\varphi_2\} \setminus \{(\varphi_1 \vee \varphi_2)\});
       return True:
                                                                              /* branch expanded */
```

# Semantic Tableaux: Example



# Semantic Tableaux - Summary

- Handles all propositional formulas (CNF not required).
- Branches on disjunctions
- Intuitive, modular, easy to extend
   ⇒ loved by logicians.
- Rather inefficient
   ⇒ avoided by computer scientists.
- Requires polynomial space

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# **DPLL** [10, 9]

- Davis-Putnam-Longeman-Loveland procedure (DPLL)
- Tries to build an assignment  $\mu$  satisfying  $\varphi$ ;
- At each step assigns a truth value to (all instances of) one atom.
- Performs deterministic choices first.

#### **DPLL** rules

$$\frac{\varphi_1 \wedge (I)}{\varphi_1[I|\top]} (Unit)$$

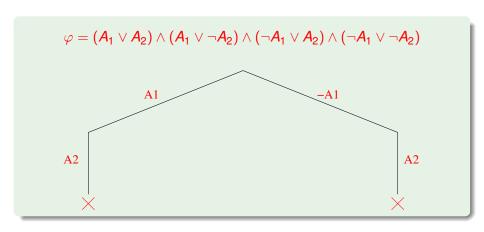
$$\frac{\varphi}{\varphi[I|\top]} (I Pure)$$

$$\frac{\varphi}{\varphi[I|\top]} \frac{\varphi}{\varphi[I|\bot]} (split)$$

(*I* is a pure literal in  $\varphi$  iff it occurs only positively).

- Split applied if and only if the others cannot be applied.
- Richer formalisms described in [40, 29, 30]

## DPLL – example



## **DPLL Algorithm**

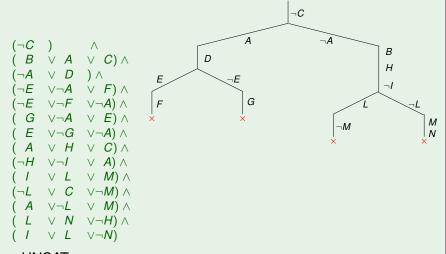
```
function DPLL(\varphi, \mu)
     if \varphi = \top
                                                            /* base
           then return True:
                                                            /* backtrack */
     if \varphi = \bot
           then return False:
     if {a unit clause (I) occurs in \varphi}
                                                            /* unit
           then return DPLL(assign(I, \varphi), \mu \wedge I);
     if {a literal I occurs pure in \varphi}
                                                            /* pure
           then return DPLL(assign(I, \varphi), \mu \wedge I);
     I := choose-literal(\varphi);
                                                            /* split
     return DPLL(assign(I, \varphi), \mu \wedge I) or
                DPLL(assign(\neg I, \varphi), \mu \land \neg I);
```

- The pure-literal rule is nowadays obsolete.
- choose-literal( $\varphi$ ) picks only variables still occurring in the formula

## DPLL – example

#### DPLL (without pure-literal rule)

Here "choose-literal" selects variable in alphabetic, selecting true first.



 $\Rightarrow$  UNSAT

## DPLL - summary

- Handles CNF formulas (non-CNF variant known [1, 15]).
- Branches on truth values
   all instances of an atom assigned simultaneously
- Postpones branching as much as possible.
- Mostly ignored by logicians.
- (The grandfather of) the most efficient SAT algorithms
   ⇒ loved by computer scientists.
- Requires polynomial space
- Choose\_literal() critical!
- Many very efficient implementations [42, 38, 2, 28].

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# Stochastic Local Search SAT techniques: GSAT, WSAT [37, 36]

- Hill-Climbing techniques: GSAT, WSAT
- looks for a complete assignment;
- starts from a random assignment;
- Greedy search: looks for a better "neighbor" assignment
- Avoid local minima: restart & random walk

## The GSAT algorithm [37]

```
function GSAT(\varphi)
     for i := 1 to Max-tries do
          \mu := \text{rand-assign}(\varphi);
          for j := 1 to Max-flips do
               if (score(\varphi, \mu) = 0)
                    then return True:
                    else Best-flips := hill-climb(\varphi, \mu);
                           A_i := \text{rand-pick}(\text{Best-flips});
                           \mu := flip(A_i, \mu):
          end
     end
     return "no satisfying assignment found".
```

# The WalkSAT algorithm(s) [36]

```
function WalkSAT(\varphi)
    for i := 1 to Max-tries do
         \mu := \text{rand-assign}(\varphi);
         for j := 1 to Max-flips do
              if (score(\varphi, \mu) = 0)
                   then return True:
                   else C := randomly-pick-clause(unsat-clauses(\varphi, \mu));
                         A_i := \text{heuristically-select-variable}(C);
                         \mu := flip(A_i, \mu);
         end
    end
     return "no satisfying assignment found".
```

many variants available [18, 41, 3]

## SLS SAT solvers - summary

- Handle only CNF formulas.
- Incomplete
- Extremely efficient for some (satisfiable) problems.
- Require polynomial space
- Used in Artificial Intelligence (e.g., planning)
- Lots of variants (see e.g. [20])
- Non-CNF Variants: [34, 35, 4]

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# Ordered Binary Decision Diagrams (OBDDs) [8]]

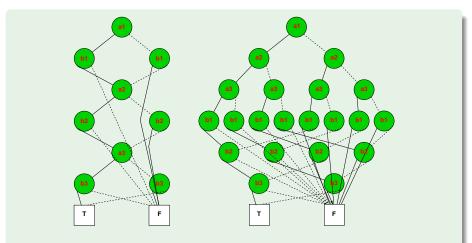
#### Canonical representation of Boolean formulas

- "If-then-else" binary direct acyclic graphs (DAGs) with one root and two leaves: 1, 0 (or ⊤,⊥; or T, F)
- Variable ordering  $A_1, A_2, ..., A_n$  imposed a priori.
- Paths leading to 1 represent models
   Paths leading to 0 represent counter-models

#### Note

Some authors call them Reduced Ordered Binary Decision Diagrams (ROBDDs)

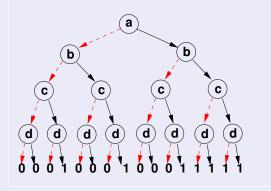
# **OBDD** - Examples



OBDDs of  $(a_1 \leftrightarrow b_1) \land (a_2 \leftrightarrow b_2) \land (a_3 \leftrightarrow b_3)$  with different variable orderings

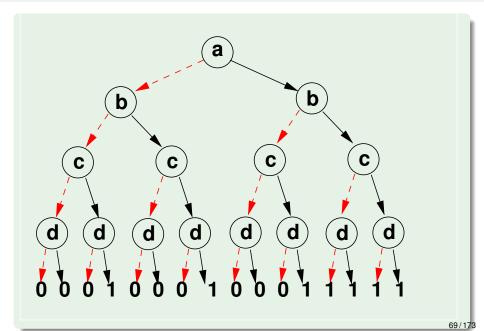
#### **Ordered Decision Trees**

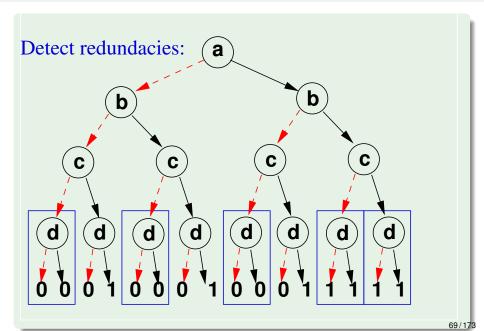
- Ordered Decision Tree: from root to leaves, variables are encountered always in the same order
- Example: Ordered Decision tree for  $\varphi = (a \land b) \lor (c \land d)$

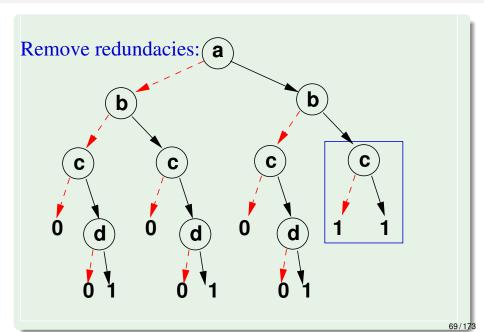


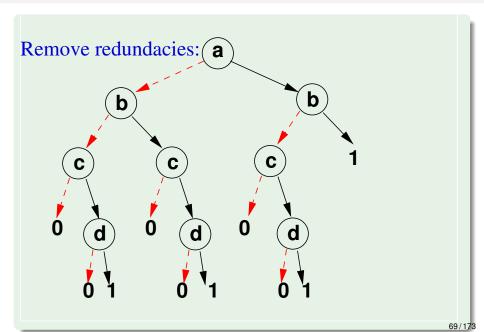
## From Ordered Decision Trees to OBDD's: reductions

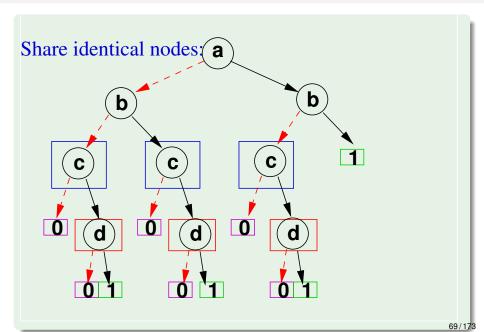
- Recursive applications of the following reductions:
  - share subnodes: point to the same occurrence of a subtree (via hash consing)
  - remove redundancies: nodes with same left and right children can be eliminated ("if A then B else B" ⇒ "B")

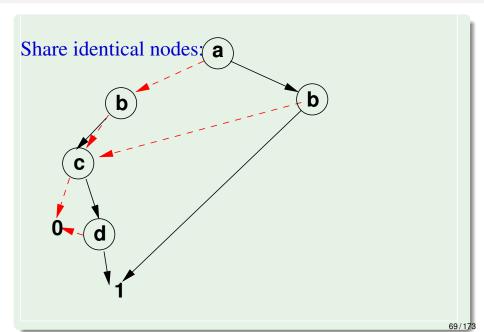


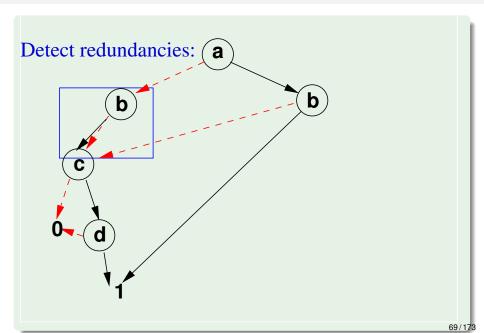


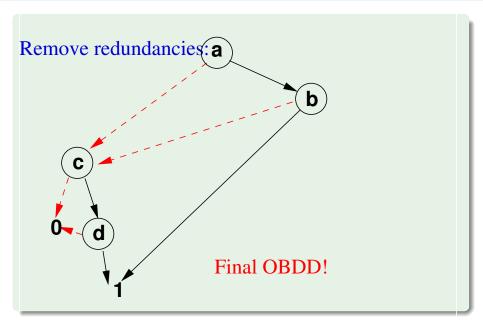












# If-Then-Else Operators: "ite(...)"

#### If-Then-Else Operators: "ite(...)"

- $ite(\phi, \varphi^{\top}, \varphi^{\perp})$ : "If  $\phi$  Then  $\varphi^{\top}$  Else  $\varphi^{\perp}$ "
- $ite(\phi, \varphi^{\top}, \varphi^{\perp}) \stackrel{\text{def}}{=} ((\neg \phi \lor \varphi^{\top}) \land (\phi \lor \varphi^{\perp}) \Longleftrightarrow ((\phi \land \varphi^{\top}) \lor (\neg \phi \land \varphi^{\perp}))$
- properties:

#### Recursive structure of an OBDD

#### Assume the variable ordering $A_1, A_2, ..., A_n$ :

```
OBDD(\top, \{A_1, A_2, ..., A_n\}) = 1

OBDD(\bot, \{A_1, A_2, ..., A_n\}) = 0

OBDD(\varphi, \{A_1, A_2, ..., A_n\}) = if A_1

then \ OBDD(\varphi[A_1|\top], \{A_2, ..., A_n\})

else \ OBDD(\varphi[A_1|\bot], \{A_2, ..., A_n\})
```

# Incrementally building an OBDD

```
• obdd build(\top, \{...\}) := \top,
• obdd build(\bot, {...}) := \bot,
• obdd build(A_i, \{...\}) := ite(A_i, \top, \bot),
• obdd build((\neg \varphi), \{A_1, ..., A_n\}) :=
    apply(\neg, obdd build(\varphi, {A_1, ..., A_n}))
• obdd build((\varphi_1 \text{ op } \varphi_2), \{A_1, ..., A_n\}) :=
     reduce(
      apply(
                  op,
                    obdd build(\varphi_1, \{A_1, ..., A_n\}),
                    obdd build(\varphi_2, {A_1, ..., A_n})
   op \in \{\land, \lor, \rightarrow, \leftarrow, \leftrightarrow, \oplus\}
```

# Incrementally building an OBDD (cont.)

```
• apply (op, O_i, O_i) := (O_i op O_i) if (O_i \in \{\top, \bot\}) or O_i \in \{\top, \bot\}
• apply (\neg, ite(A_i, \varphi_i^\top, \varphi_i^\perp)) :=
       ite(A_i, apply(\neg, \varphi_i^{\top}), apply(\neg, \varphi_i^{\perp}))
• apply (op, ite(A_i, \varphi_i^{\top}, \varphi_i^{\perp}), ite(A_i, \varphi_i^{\top}, \varphi_i^{\perp})) :=
      if (A_i = A_i) then ite(A_i, apply (op, \varphi_i^\top, \varphi_i^\top),
                                                         apply (op, \varphi_i^{\perp}, \varphi_i^{\perp})
      if (A_i < A_i) then ite(A_i, apply (op, \varphi_i^\top, ite(A_i, \varphi_i^\top, \varphi_i^\perp)),
                                                         apply (op, \varphi_i^{\perp}, ite(A_i, \varphi_i^{\top}, \varphi_i^{\perp})))
      if (A_i > A_i) then ite(A_i, apply (op, ite(A_i, \varphi_i^{\top}, \varphi_i^{\perp}), \varphi_i^{\top}),
                                                         apply (op, ite(A_i, \varphi_i^{\top}, \varphi_i^{\perp}), \varphi_i^{\perp}))
     op \in \{\land, \lor, \rightarrow, \leftarrow, \leftrightarrow, \oplus\}
```

# Incrementally building an OBDD (cont.)

• Ex: build the obdd for  $A_1 \vee A_2$  from those of  $A_1, A_2$  (order:

$$A_{1}, A_{2}): \underbrace{A_{1}}_{apply(\vee, ite(A_{1}, \top, \bot), ite(A_{2}, \top, \bot))}^{A_{2}}$$

$$= ite(A_{1}, apply(\vee, \top, ite(A_{1}, \top, \bot)), apply(\vee, \bot, ite(A_{2}, \top, \bot))$$

$$= ite(A_{1}, \top, ite(A_{2}, \top, \bot))$$

• Ex: build the obdd for  $(A_1 \lor A_2) \land (A_1 \lor \neg A_2)$  from those of  $(A_1 \lor A_2), (A_1 \lor \neg A_2)$  (order:  $A_1, A_2$ ):

$$apply(\wedge, ite(A_1, \top, ite(A_2, \top, \bot)), ite(A_1, \top, ite(A_2, \bot, \top)),$$

$$= ite(A_1, apply(\wedge, \top, \top), apply(\wedge, ite(A_2, \top, \bot), ite(A_2, \bot, \top))$$

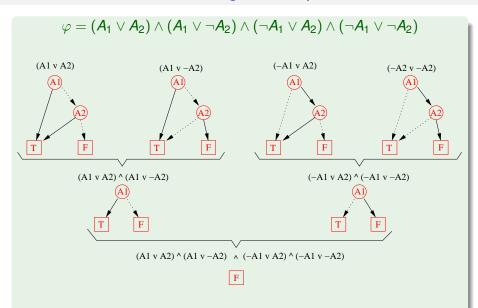
$$= ite(A_1, \top, ite(A_2, apply(\wedge, \top, \bot), apply(\wedge, \bot, \top)))$$

$$= ite(A_1, \top, ite(A_2, \bot, \bot))$$

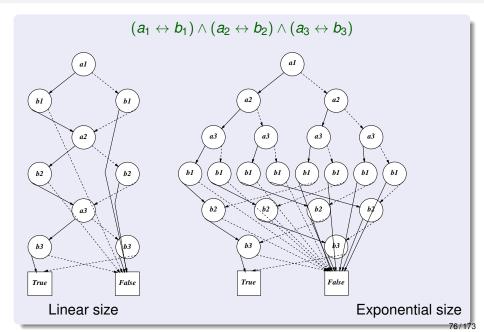
$$= ite(A_1, \top, ite(A_2, \bot, \bot))$$

$$= ite(A_1, \top, \bot, \bot)$$

#### OBBD incremental building – example



# Critical choice of variable Orderings in OBDD's



# OBDD's as canonical representation of Boolean formulas

 An OBDD is a canonical representation of a Boolean formula: once the variable ordering is established, equivalent formulas are represented by the same OBDD:

$$\varphi_1 \leftrightarrow \varphi_2 \iff OBDD(\varphi_1) = OBDD(\varphi_2)$$

- equivalence check requires constant time!
   ⇒validity check requires constant time! (φ ↔ ⊤)
   ⇒(un)satisfiability check requires constant time! (φ ↔ ⊥)
- the set of the paths from the root to 1 represent all the models of the formula
- the set of the paths from the root to 0 represent all the counter-models of the formula

# Exponentiality of OBDD's

- The size of OBDD's may grow exponentially wrt. the number of variables in worst-case
- Consequence of the canonicity of OBDD's (unless P = co-NP)
- Example: there exist no polynomial-size OBDD representing the electronic circuit of a bitwise multiplier

#### Note

The size of intermediate OBDD's may be bigger than that of the final one (e.g., inconsistent formula)

## **Useful Operations over OBDDs**

- the equivalence check between two OBDDs is simple
  - are they the same OBDD? (⇒ constant time)
- the size of a Boolean composition is up to the product of the size of the operands:  $|f \circ p g| = O(|f| \cdot |g|)$



### Boolean quantification

#### Shannon's expansion:

• If v is a Boolean variable and f is a Boolean formula, then

```
\exists v.f := f|_{v=0} \lor f|_{v=1}
\forall v.f := f|_{v=0} \land f|_{v=1}
```

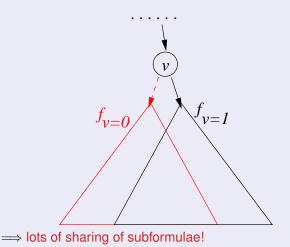
- v does no more occur in  $\exists v.f$  and  $\forall v.f$ !!
- Multi-variable quantification:  $\exists (w_1, \dots, w_n).f := \exists w_1 \dots \exists w_n.f$
- Intuition:
  - $\mu \models \exists v.f$  iff exists  $tvalue \in \{\top, \bot\}$  s.t.  $\mu \cup \{v := tvalue\} \models f$
  - $\mu \models \forall v.f$  iff forall  $tvalue \in \{\top, \bot\}, \ \mu \cup \{v := tvalue\} \models f$
- Example:  $\exists (b, c).((a \land b) \lor (c \land d)) = a \lor d$

#### Note

Naive expansion of quantifiers to propositional logic may cause a blow-up in size of the formulae

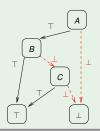
# OBDD's and Boolean quantification

- OBDD's handle quantification operations quite efficiently
  - if f is a sub-OBDD labeled by variable v, then  $f|_{v=1}$  and  $f|_{v=0}$  are the "then" and "else" branches of f



## Example

Let  $\varphi \stackrel{\text{def}}{=} (A \wedge (B \vee C))$  and  $\varphi' \stackrel{\text{def}}{=} \exists A. \forall B. \varphi$ . Using the variable ordering "A, B, C", draw the OBDD corresponding to the formulas  $\varphi$  and  $\varphi'$ .  $\varphi \stackrel{\text{def}}{=} (A \wedge (B \vee C))$ 



# Example (cont.)

```
\varphi' \stackrel{\text{def}}{=} \exists A. \forall B. (A \land (B \lor C))
\varphi' \stackrel{\text{def}}{=} \exists A. \forall B. \varphi
= \forall B. (A \land (B \lor C)))[A := \top] \qquad \qquad \lor \quad (\forall B. (A \land (B \lor C)))[A := \bot]
= \forall B. (B \lor C)) \qquad \lor \quad \forall B. \bot
= (B \lor C)[B := \top] \qquad \land \quad (B \lor C)[B := \bot]) \qquad \lor \quad \bot
= (T \qquad \land C)
= C
```

which corresponds to the following OBDD:



## OBDD – summary

- Factorize common parts of the search tree (DAG)
- Require setting a variable ordering a priori (critical!)
- Canonical representation of a Boolean formula.
- Once built, logical operations (satisfiability, validity, equivalence) immediate.
- Represents all models and counter-models of the formula.
- Require exponential space in worst-case
- Very efficient for some practical problems (circuits, symbolic model checking).

#### **Outline**

- Boolean Logics and SAT
- Basic SAT-Solving Techniques
  - Resolution
  - Tableaux
  - DPLL
  - Stochastic Local Search for SAT
- 3 Ordered Binary Decision Diagrams OBDDs
- Modern CDCL SAT Solvers
  - Limitations of Chronological Backtracking
  - Conflict-Driven Clause-Learning SAT solvers
  - Further Improvements
  - SAT Under Assumptions & Incremental SAT
- 5 SAT Functionalities: proofs, unsat cores, interpolants, optimization

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# DPLL: "Classic" chronological backtracking

#### DPLL implements "classic" chronological backtracking:

- variable assignments (literals) stored in a stack
- each variable assignments labeled as "unit", "open", "closed"
- when a conflict is encountered, the stack is popped up to the most recent open assignment /
- *I* is toggled, is labeled as "closed", and the search proceeds.

# DPLL Chronological Backtracking: Drawbacks

Chronological backtracking always backtracks to the most recent branching point, even though a higher backtrack could be possible

⇒ lots of useless search!

```
\begin{array}{l} c_1: \neg A_1 \lor A_2 \\ c_2: \neg A_1 \lor A_3 \lor A_9 \\ c_3: \neg A_2 \lor \neg A_3 \lor A_4 \\ c_4: \neg A_4 \lor A_5 \lor A_{10} \\ c_5: \neg A_4 \lor A_6 \lor A_{11} \\ c_6: \neg A_5 \lor \neg A_6 \\ c_7: A_1 \lor A_7 \lor \neg A_{12} \\ c_8: A_1 \lor A_8 \\ c_9: \neg A_7 \lor \neg A_8 \lor \neg A_{13} \end{array}
```

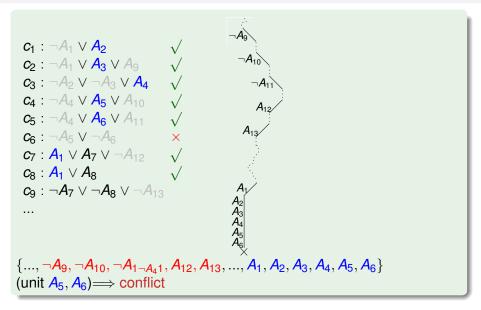
. . .

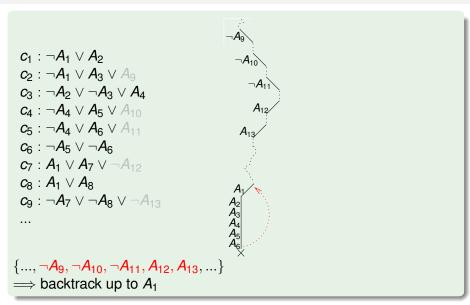
```
c_1: \neg A_1 \vee A_2
 c_2: \neg A_1 \lor A_3 \lor A_9
 c_3: \neg A_2 \vee \neg A_3 \vee A_4
 c_4: \neg A_4 \lor A_5 \lor A_{10}
 c_5: \neg A_4 \lor A_6 \lor A_{11}
 c_6: \neg A_5 \vee \neg A_6
 c_7: A_1 \vee A_7 \vee \neg A_{12}
 c_8: A_1 \vee A_8
 c_9 : \neg A_7 \lor \neg A_8 \lor \neg A_{13}
 ...
\{..., \neg A_9, \neg A_{10}, \neg A_{11}, A_{12}, A_{13}, ...\}
(initial assignment)
```

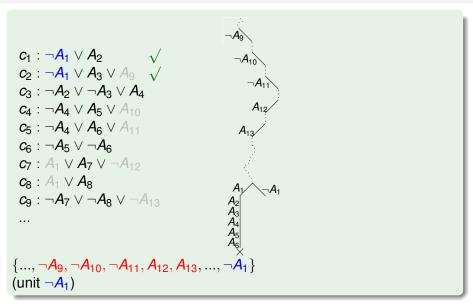
```
c_1: \neg A_1 \lor A_2
 c_2: \neg A_1 \lor A_3 \lor A_9
 c_3: \neg A_2 \vee \neg A_3 \vee A_4
 c_4: \neg A_4 \lor A_5 \lor A_{10}
 c_5: \neg A_4 \lor A_6 \lor A_{11}
 c_6: \neg A_5 \vee \neg A_6
 c_7: A_1 \vee A_7 \vee \neg A_{12} \sqrt{}
 C_8: A_1 \vee A_8 \qquad \sqrt{\phantom{a}}
 c_9 : \neg A_7 \lor \neg A_8 \lor \neg A_{13}
 ...
\{..., \neg A_9, \neg A_{10}, \neg A_{11}, A_{12}, A_{13}, ..., A_1\}
... (branch on A_1)
```

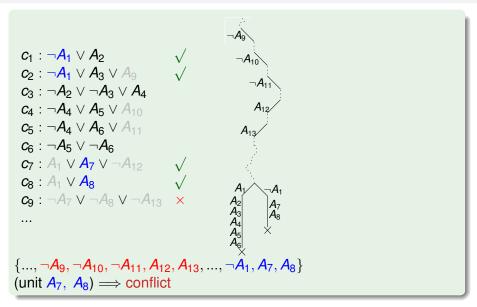
```
c_1: \neg A_1 \lor A_2 \qquad \checkmark
 c_2: \neg A_1 \lor A_3 \lor A_9  \checkmark
 c_3: \neg A_2 \lor \neg A_3 \lor A_4
 c_4: \neg A_4 \lor A_5 \lor A_{10}
 c_5: \neg A_4 \lor A_6 \lor A_{11}
 c_6: \neg A_5 \vee \neg A_6
 c_7: A_1 \vee A_7 \vee \neg A_{12} \sqrt{}
 C_8: A_1 \vee A_8 \qquad \sqrt{\phantom{a}}
 c_9 : \neg A_7 \lor \neg A_8 \lor \neg A_{13}
\{..., \neg A_9, \neg A_{10}, \neg A_{11}, A_{12}, A_{13}, ..., A_1, A_2, A_3\}
(unit A_2, A_3)
```

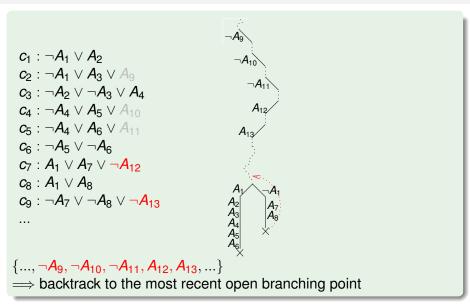
```
c_1: \neg A_1 \lor A_2 \qquad \checkmark
 c_2: \neg A_1 \lor A_3 \lor A_9 \checkmark
 c_3: \neg A_2 \lor \neg A_3 \lor A_4 \checkmark
 c_4: \neg A_4 \lor A_5 \lor A_{10}
 c_5: \neg A_4 \lor A_6 \lor A_{11}
 c_6: \neg A_5 \vee \neg A_6
 c_7: A_1 \vee A_7 \vee \neg A_{12} \sqrt{}
 C_8: A_1 \vee A_8 \qquad \sqrt{\phantom{a}}
 c_9 : \neg A_7 \lor \neg A_8 \lor \neg A_{13}
\{..., \neg A_9, \neg A_{10}, \neg A_{11}, A_{12}, A_{13}, ..., A_1, A_2, A_3, A_4\}
(unit A_4)
```

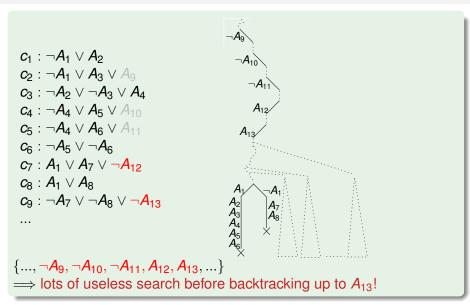












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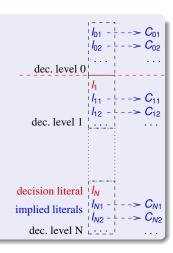
# Modern Conflict-Driven Clause-Learning SAT Solvers

- Non-recursive, stack-based implementations
- Based on Conflict-Driven Clause-Learning (CDCL) schema
  - inspired to conflict-driven backjumping and learning in CSPs
  - learns implied clauses as nogoods
- Random restarts
  - abandon the current search tree and restart on top level
  - previously-learned clauses maintained
- Smart literal selection heuristics (ex: VSIDS)
  - "static": scores updated only at the end of a branch
  - "local": privileges variable in recently learned clauses
- Smart preprocessing/inprocessing technique to simplify formulas
- Smart indexing techniques (e.g. 2-watched literals)
  - efficiently do/undo assignments and reveal unit clauses
- Allow Incremental Calls (stack-based interface)
  - allow for reusing previous search on "similar" problems

Can handle industrial problems with  $10^6 - 10^7$  variables and clauses!

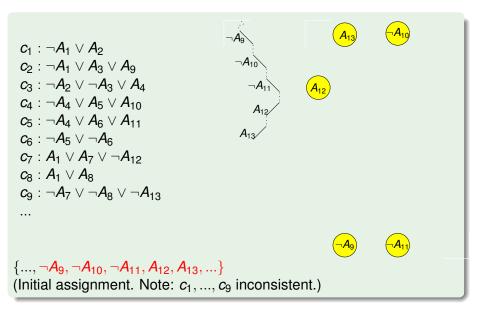
# Stack-based representation of a truth assignment $\mu$

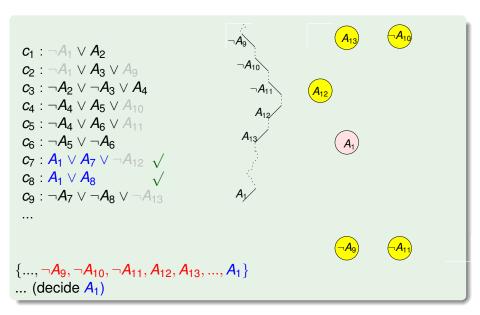
- assign one truth-value at a time (add one literal to a stack representing μ)
- stack partitioned into decision levels:
  - one decision literal
  - its implied literals
  - each implied literal tagged with the clause causing its unit-propagation (antecedent clause)
- equivalent to an implication graph

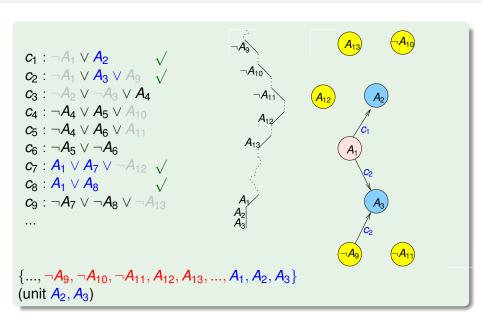


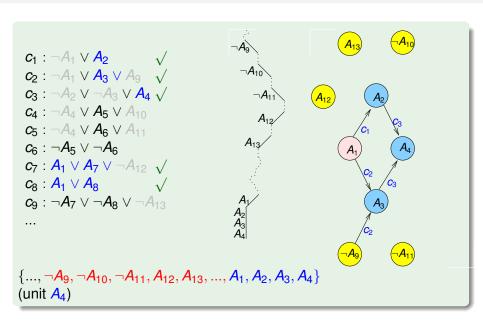
### Implication graph

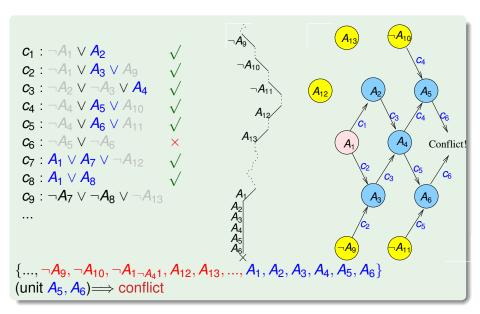
- An implication graph is a DAG s.t.:
  - each node represents a variable assignment (literal)
  - each edge  $l_i \stackrel{c}{\longmapsto} l$  is labeled with a clause
  - the node of a decision literal has no incoming edges
  - all edges incoming into a node I are labeled with the same clause c, s.t.  $I_1 \stackrel{c}{\longmapsto} I,...,I_n \stackrel{c}{\longmapsto} I$  iff  $c = \neg I_1 \lor ... \lor \neg I_n \lor I$  (c is said to be the antecedent clause of I)
  - when both I and  $\neg I$  occur in the graph, we have a conflict.
- Intuition:
  - ullet representation of the dependencies between literals in  $\mu$
  - the graph contains  $l_1 \stackrel{c}{\longmapsto} l,...,l_n \stackrel{c}{\longmapsto} l$  iff l has been obtained from  $l_1,...,l_n$  by unit propagation on c
  - a partition of the graph with all decision literals on one side and the conflict on the other represents a conflict set







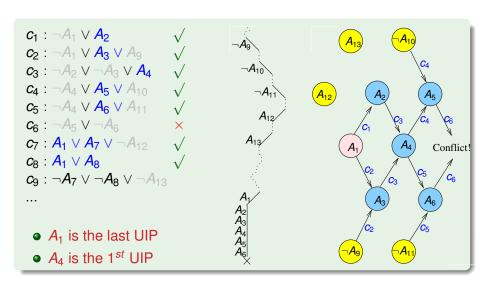




## Unique implication point - UIP [44]

- A node / in an implication graph is an unique implication point (UIP) for the last decision level iff every path from the last decision node to both the conflict nodes passes through /.
  - the most recent decision node is an UIP (last UIP)
  - all other UIP's have been assigned after the most recent decision

### Unique implication point - UIP - example



# Schema of a CDCL DPLL solver [38, 45]

```
Function CDCL-SAT (formula: \varphi, assignment & \mu) {
         status := preprocess (\varphi, \mu);
         while (1) {
             while (1) {
                 status := deduce (\varphi, \mu);
                 if (status == Sat)
                     return Sat;
                 if (status == Conflict) {
                     \langle \text{blevel}, \eta \rangle := \text{analyze conflict}(\varphi, \mu);
                     //\eta is a conflict set
                     if (blevel == 0)
                         return Unsat;
                     else backtrack (blevel, \varphi, \mu);
                 else break;
             decide_next_branch (\varphi, \mu);
```

### Schema of a CDCL DPLL solver [38, 45] (cont.)

- preprocess  $(\varphi, \mu)$  simplifies  $\varphi$  into an easier equisatisfiable formula, updating  $\mu$ .
- decide\_next\_branch  $(\varphi,\mu)$  chooses a new decision literal from  $\varphi$  according to some heuristic, and adds it to  $\mu$
- $deduce(\varphi, \mu)$  performs all deterministic assignments (unit-propagations plus others), and updates  $\varphi, \mu$  accordingly.
- analyze\_conflict  $(\varphi, \mu)$  Computes the subset  $\eta$  of  $\mu$  causing the conflict (conflict set), and returns the "wrong-decision" level suggested by  $\eta$  ("0" means that  $\eta$  is entirely assigned at level 0, i.e., a conflict exists even without branching);
- backtrack (blevel,  $\varphi$ ,  $\mu$ ) undoes the branches up to blevel, and updates  $\varphi$ ,  $\mu$  accordingly

## Backjumping and learning: general ideas [2, 38]

- When a branch  $\mu$  fails:
  - (i) conflict analysis: reveal the sub-assignment  $\eta \subseteq \mu$  causing the failure (conflict set  $\eta$ )
  - (ii) learning: add the conflict clause  $C \stackrel{\text{def}}{=} \neg \eta$  to the clause set
  - (iii) backjumping: use  $\eta$  to decide the point where to backtrack
- Jump back up much more than one decision level in the stack
   may avoid lots of redundant search!!.
- We illustrate two main backjumping & learning strategies:
  - the original strategy presented in [38]
  - the state-of-the-art 1st UIP strategy of [44]

- 1. C :=falsified clause (conflicting clause)
- 2. repeat
  - (i) resolve the current clause C with the antecedent clause of the last unit-propagated literal I in Cuntil C verifies some given termination criteria

- 1. C := falsified clause (conflicting clause)
- repeat
  - (i) resolve the current clause C with the antecedent clause of the last unit-propagated literal I in C until C verifies some given termination criteria

#### criterion: decision

...until C contains only decision literals

$$\frac{\neg A_{4} \lor A_{5} \lor A_{10}}{\neg A_{4} \lor A_{5} \lor A_{10}} \frac{\neg A_{4} \lor A_{5} \lor A_{11}}{\neg A_{5} \lor \neg A_{6}} (A_{6})$$

$$\frac{\neg A_{1} \lor A_{3} \lor A_{9}}{\neg A_{2} \lor \neg A_{3} \lor A_{10} \lor A_{11}} (A_{5})$$

$$\frac{\neg A_{1} \lor A_{2}}{\neg A_{1} \lor A_{2}} \frac{\neg A_{2} \lor \neg A_{1} \lor A_{9} \lor A_{10} \lor A_{11}}{\neg A_{2} \lor \neg A_{1} \lor A_{9} \lor A_{10} \lor A_{11}} (A_{2})$$

$$\frac{\neg A_{1} \lor A_{2}}{\neg A_{1} \lor A_{9} \lor A_{10} \lor A_{11}} (A_{2})$$

$$\frac{\neg A_{1} \lor A_{2} \lor \neg A_{1} \lor A_{2} \lor \neg A_{1} \lor A_{2} \lor \neg A_{1} \lor A_{2}}{\neg A_{1} \lor A_{2} \lor \neg A_{1} \lor A_{2}} (A_{2})$$

- 1. C := falsified clause (conflicting clause)
- repeat
  - (i) resolve the current clause C with the antecedent clause of the last unit-propagated literal I in C until C verifies some given termination criteria

#### criterion: last UIP

... until C contains only one literal assigned at current decision level: the decision literal (last UIP)

```
 \frac{\neg A_{1} \lor A_{2} \lor \neg A_{3} \lor A_{4}}{\neg A_{1} \lor A_{2} \lor \neg A_{3} \lor A_{4}} \frac{\neg A_{4} \lor A_{5} \lor A_{10}}{\neg A_{4} \lor A_{5} \lor A_{10}} \frac{\neg A_{4} \lor A_{5} \lor A_{11}}{\neg A_{4} \lor \neg A_{5} \lor A_{11}}}{\neg A_{2} \lor \neg A_{3} \lor A_{10} \lor A_{11}} (A_{2}) 
 \frac{\neg A_{1} \lor A_{2}}{\neg A_{2} \lor \neg A_{1} \lor A_{9} \lor A_{10} \lor A_{11}} (A_{2}) 
 \frac{\neg A_{1} \lor A_{2} \lor \neg A_{1} \lor A_{9} \lor A_{10} \lor A_{11}}{\neg A_{1} \lor A_{10} \lor A_{11}} (A_{2})
```

- 1. C := falsified clause (conflicting clause)
- 2. repeat
  - (i) resolve the current clause C with the antecedent clause of the last unit-propagated literal I in C
     until C verifies some given termination criteria

#### criterion: 1st UIP

... until *C* contains only one literal assigned at current decision level (1st UIP)

$$\frac{\neg A_4 \lor A_5 \lor A_{10}}{\neg A_4 \lor A_{10}} \frac{\neg A_4 \lor A_6 \lor A_{11}}{\neg A_5 \lor \neg A_6} \frac{\neg A_5 \lor \neg A_6}{\neg A_4 \lor \neg A_5 \lor A_{11}}}{\neg A_4 \lor A_{10} \lor A_{11}} (A_5)$$

- 1. *C* := falsified clause (conflicting clause)
- 2. repeat
  - (i) resolve the current clause C with the antecedent clause of the last unit-propagated literal I in C until C verifies some given termination criteria

#### Note:

 $\varphi \models C$ , so that C can be safely added to C.

#### Note:

Equivalent to finding a partition in the implication graph of  $\mu$  with all decision literals on one side and the conflict on the other.

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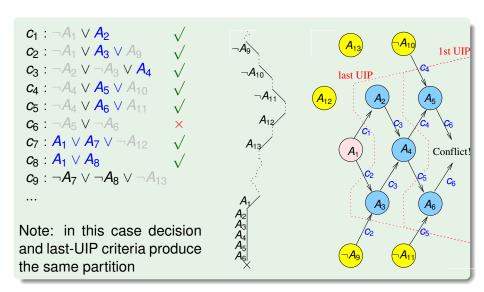
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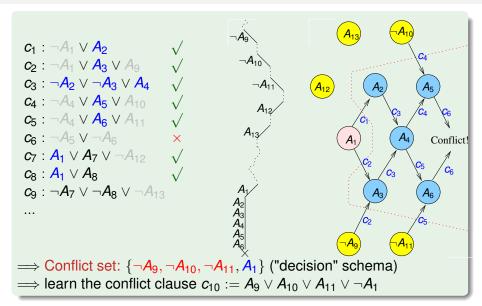
Equivalent to finding a partition in the implication graph of  $\mu$  with all decision literals on one side and the conflict on the other.

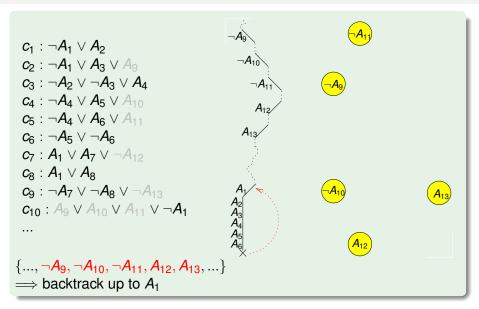
# Conflict analysis and implication graph - example

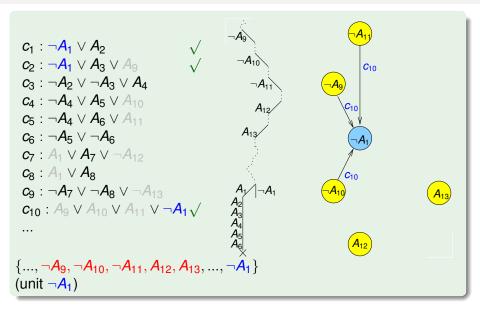


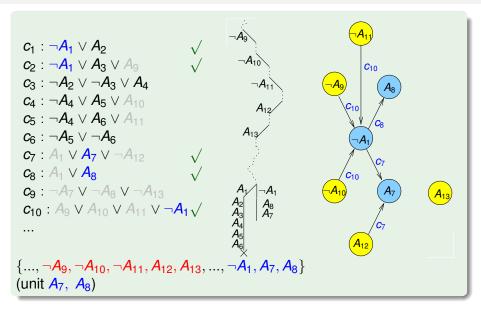
# The original backjumping and learning strategy of [38]

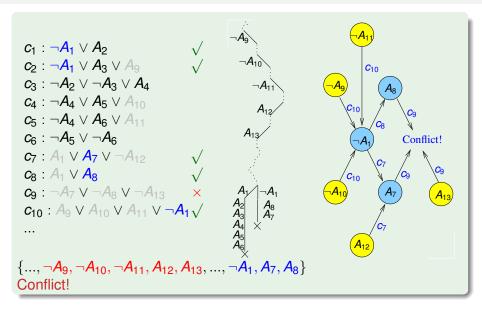
- Idea: when a branch  $\mu$  fails,
  - (i) conflict analysis: find the conflict set  $\eta \subseteq \mu$  by generating the conflict clause  $C \stackrel{\text{def}}{=} \neg \eta$  via resolution from the falsified clause (conflicting clause) using the "Decision" criterion;
  - (ii) learning: add the conflict clause C to the clause set
  - (iii) backjumping: backtrack to the most recent branching point s.t. the stack does not fully contain  $\eta$ , and then unit-propagate the unassigned literal on C

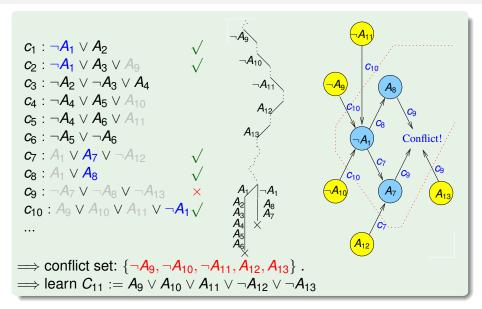


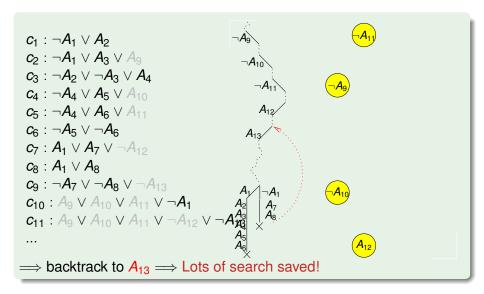


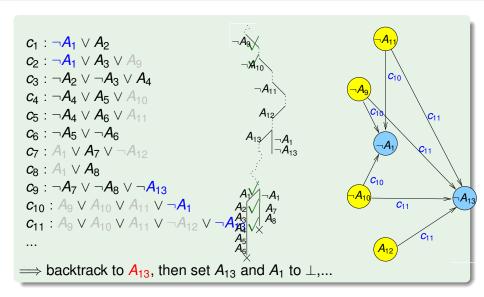








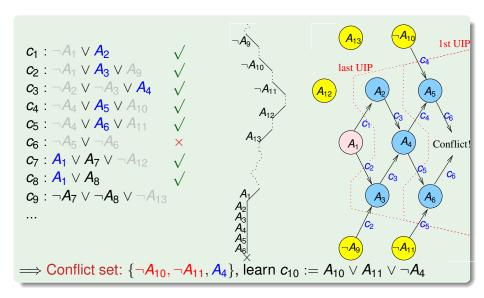




## State-of-the-art backjumping and learning [44]

- Idea: when a branch  $\mu$  fails,
  - (i) conflict analysis: find the conflict set  $\eta \subseteq \mu$  by generating the conflict clause  $C \stackrel{\text{def}}{=} \neg \eta$  via resolution from the falsified clause, according to the 1<sup>st</sup>UIP strategy
  - (ii) learning: add the conflict clause C to the clause set
  - (iii) backjumping: backtrack to the highest branching point s.t. the stack contains all-but-one literals in  $\eta$ , and then unit-propagate the unassigned literal on C

### 1st UIP strategy – example (7)

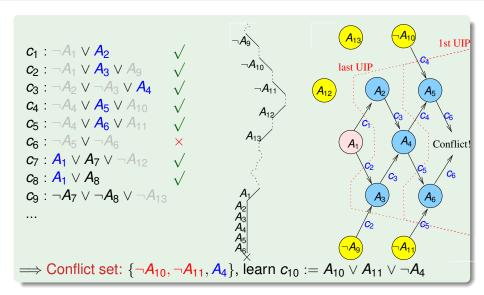


### 1st UIP strategy and backjumping [44]

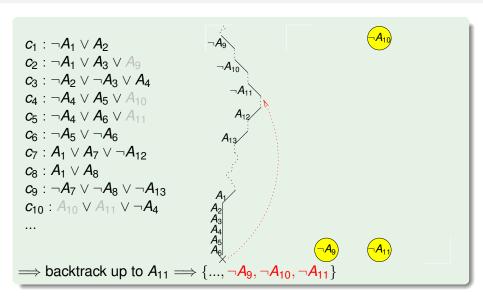
- The added conflict clause states the reason for the conflict
- The procedure backtracks to the most recent decision level of the variables in the conflict clause which are not the UIP.
- then the conflict clause forces the negation of the UIP by unit propagation.

E.g.: 
$$c_{10} := A_{10} \lor A_{11} \lor \neg A_4$$
  
 $\Longrightarrow$  backtrack to  $A_{11}$ , then assign  $\neg A_4$ 

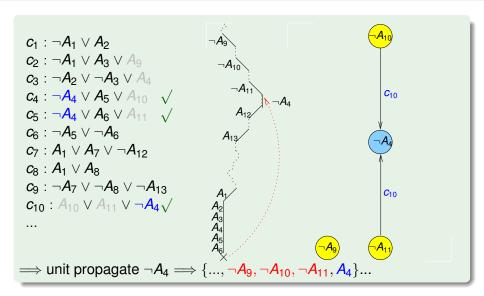
### 1st UIP strategy – example (7)



## 1st UIP strategy – example (8)



## 1st UIP strategy – example (9)



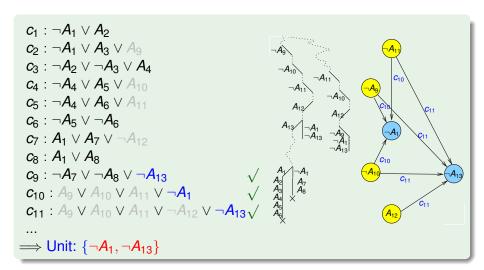
### 1st UIP strategy and backjumping – intuition

- An UIP is a single reason implying the conflict at the current level
- substituting the 1st UIP for the last UIP
  - does not enlarge the conflict
  - requires less resolution steps to compute C
  - may require involving less decision literals from other levels
- by backtracking to the most recent decision level of the variables in the conflict clause which are not the UIP:
  - jump higher
  - allows for assigning (the negation of) the UIP as high as possible in the search tree.

## Learning [2, 38]

Idea: When a conflict set  $\eta$  is revealed, then  $C \stackrel{\text{def}}{=} \neg \eta$  added to  $\varphi$   $\Longrightarrow$  the solver will no more generate an assignment containing  $\eta$ : when  $|\eta| - 1$  literals in  $\eta$  are assigned, the other is set  $\bot$  by unit-propagation on C  $\Longrightarrow$  Drastic pruning of the search!

## Learning – example



# Drawbacks of Learning & Clause discharging

#### Problem with Learning

Learning can generate exponentially-many clauses

- may cause a blowup in space
- may drastically slow down BCP

#### A solution: clause discharging

Techniques to drop learned clauses when necessary

- according to their size
- according to their activity.

A clause is currently active if it occurs in the current implication graph (i.e., it is the antecedent clause of a literal in the current assignment).

## Drawbacks of Learning & Clause discharging

- Is clause-discharging safe?
- Yes, if done properly.

#### Property (see, e.g., [30])

In order to guarantee correctness, completeness & termination of a CDCL solver, it suffices to keep each clause until it is active.

⇒ CDCL solvers require polynomial space

#### "Lazy" Strategy

- when a clause is involved in conflict analisis, increase its activity
- when needed, drop the least-active clauses

## State-of-the-art backjumping and learning: intuitions

- Backjumping: allows for climbing up to many decision levels in the stack
  - intuition: "go back to the oldest decision where you'd have done something different if only you had known *C*"
  - → may avoid lots of redundant search
- Learning: in future branches, when all-but-one literals in  $\eta$  are assigned, the remaining literal is assigned to false by unit-propagation:
  - intuition: "when you're about to repeat the mistake, do the opposite of the last step"
  - ⇒ avoid finding the same conflict again

### Remark: the "quality" of conflict sets

- Different ideas of "good" conflict set
  - Backjumping: if causes the highest backjump ("local" role)
  - Learning: if causes the maximum pruning ("global" role)
- Many different strategies implemented (see, e.g., [2, 38, 44])

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## Preprocessing/Inprocessing

- Part of preprocess () and deduce () steps respectively
- Simplify current formula into an equivalently-satisfiable one
- Must be fast (in particular inprocessing)
- Some techniques:
  - detect and remove subsumed clauses
  - detect & collapse equivalent literals
  - apply basic resolution steps
  - **.**...

# Preprocessing/Inprocessing (cont.)

#### Detect and remove subsumed clauses:

# Preprocessing/Inprocessing (cont.)

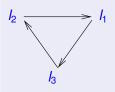
#### Detect & collapse equivalent literals [7]

#### Repeat:

- (i) build the implication graph induced by binary clauses
- (ii) detect strongly connected cycles ⇒ equivalence classes of literals
- (iii) perform substitutions
- (iv) perform unit and pure literal.

Until (no more simplification is possible).

• Ex:



$$\varphi_{1} \wedge (\neg l_{2} \vee l_{1}) \wedge \varphi_{2} \wedge (\neg l_{3} \vee l_{2}) \wedge \varphi_{3} \wedge (\neg l_{1} \vee l_{3}) \wedge \varphi_{4}$$

$$\downarrow l_{1} \leftrightarrow l_{2} \leftrightarrow l_{3}$$

$$(\varphi_{1} \wedge \varphi_{2} \wedge \varphi_{3} \wedge \varphi_{4})[l_{2} \leftarrow l_{1}; l_{3} \leftarrow l_{1};]$$

Very effective in many application domains.

# Preprocessing/Inprocessing (cont.)

### Apply some basic steps of resolution (and simplify)

$$\varphi_{1} \wedge (I_{2} \vee I_{1}) \wedge \varphi_{2} \wedge (I_{2} \vee \neg I_{1}) \wedge \varphi_{3}$$

$$\downarrow resolve$$

$$\varphi_{1} \wedge (I_{2}) \wedge \varphi_{2} \wedge \varphi_{3}$$

$$\downarrow unit-propagate$$

$$(\varphi_{1} \wedge \varphi_{2} \wedge \varphi_{3})[I_{2} \leftarrow \top]$$

## Literal-Decision Heuristics (aka Branching Heuristics)

- Implemented in decide\_next\_branch()
- Branch is the source of non-determinism for DPLL
   critical for efficiency
- Many literal-decision heuristics in literature (for DPLL & CDCL)

#### Some Heuristics

- MOMS heuristics (DPLL): pick the literal occurring most often in the minimal size clauses
  - ⇒ fast and simple, many variants
- Jeroslow-Wang (DPLL): choose the literal with maximum

$$score(I) := \sum_{I \in c \ \& \ c \in \varphi} 2^{-|c|}$$

- $\Longrightarrow$  estimates *I*'s contribution to the satisfiability of  $\varphi$
- Satz [21] (DPLL): selects a candidate set of literals, perform unit propagation, chooses the one leading to smaller clause set
   maximizes the effects of unit propagation
- VSIDS [28] (CDCL+): variable state independent decaying sum
  - "static": scores updated only at the end of a branch
  - "local": privileges variable in recently learned clauses

## Restarts [16]

Idea: (according to some strategy) restart the search

- abandon the current search tree and reconstruct a new one
- The clauses learned prior to the restart are still there after the restart and can help pruning the search space
- avoid getting stuck in certain areas of the search space
- → may significantly reduce the overall search space

### **Outline**

- Boolean Logics and SAT
- Basic SAT-Solving Techniques
  - Resolution
  - Tableaux
  - DPLL
  - Stochastic Local Search for SAT
- 3 Ordered Binary Decision Diagrams OBDDs
- Modern CDCL SAT Solvers
  - Limitations of Chronological Backtracking
  - Conflict-Driven Clause-Learning SAT solvers
  - Further Improvements
  - SAT Under Assumptions & Incremental SAT
- 5 SAT Functionalities: proofs, unsat cores, interpolants, optimization

## SAT under assumptions: $SAT(\varphi, \{l_1, ..., l_n\})$ [12]

- Many SAT solvers allow for solving a CNF formula  $\varphi$  under a set of assumption literals  $\mathcal{A} \stackrel{\text{def}}{=} \{I_1, ..., I_n\}$ :  $SAT(\varphi, \{I_1, ..., I_n\})$ 
  - $SAT(\varphi, \{l_1, ..., l_n\})$ : same result as  $SAT(\varphi \wedge \bigwedge_{i=1}^n l_i)$
  - often useful to call the same formula with different assumption lists:  $SAT(\varphi, A_1)$ ,  $SAT(\varphi, A_2)$ , ...
- Idea:
  - $I_1, ..., I_n$  "decided" at decision level 0 before starting the search
  - if backjump to level 0 on  $C\stackrel{\text{def}}{=} \neg \eta$  s.t.  $\eta \subseteq \mathcal{A}$ , then return UNSAT

#### **Property**

If the "decision" strategy for conflict analysis is used, then  $\eta$  is the subset of assumptions causing the inconsistency

### Selection of sub-formulas

#### Idea: select clauses [12, 23]

Let  $\varphi$  be  $\bigwedge_{i=1}^n C_i$ .

- let  $S_1...S_n$  be fresh Boolean atoms (selection variables).
- let  $A \stackrel{\text{def}}{=} \{S_{i_1}, ..., S_{i_K}\} \subseteq \{S_1, ..., S_n\}$
- $\implies$  SAT(  $\bigwedge_{i=1}^{n} (\neg S_i \lor C_i), A$ ): same as SAT(  $\bigwedge_{i=i}^{i_k} (C_i)$ )
  - ullet if  $S_i$  is not assumed, then  $\neg S_i \lor C_i$  does not contribute to search
- $\implies$  "Select" (activate) only a subset of the clauses in  $\varphi$  at each call.

#### Generalised Idea: select blocks of clauses

Let  $\varphi$  be  $\bigwedge_{i=1}^n (\bigwedge_{j=1}^{n_i} C_{ij})$ .

- let  $S_1...S_n$  be fresh Boolean atoms (selection variables).
- let  $\mathcal{A} \stackrel{\text{def}}{=} \{S_{i_1}, ..., S_{i_{k'}}\} \subseteq \{S_1, ..., S_n\}$
- SAT(  $\bigwedge_{i=1}^{n} (\bigwedge_{j=1}^{n_i} (\neg S_i \vee C_{ij})), A$ ): same as SAT(  $\bigwedge_{i=i_1}^{i_k} (\bigwedge_{j=1}^{n_i} C_{ij})$ )
- → Allows for "selecting" block of clauses at each call.

• Initial formula  $\varphi$ :

- $SAT(\varphi', \{S_2, S_3\})$ : activates group 2,3
- $SAT(\varphi', \{S_1, S_3\})$ : activates group 1,3

• Initial formula  $\varphi$ :

- $SAT(\varphi', \{S_2, S_3\})$ : activates group 2,3
- $SAT(\varphi', \{S_1, S_3\})$ : activates group 1,3

• Initial formula  $\varphi$ :

```
(A_1 \lor \neg A_2 \lor \neg A_3) \land // group 1

(\neg A_3 \lor A_2 \lor \neg A_5) \land // group 1

(\neg A_2 \lor A_5 \lor A_7) \land // group 2

(A_3 \lor A_5 \lor \neg A_8) \land // group 2

(\neg A_1 \lor \neg A_3 \lor A_8) \land // group 3
```

- $SAT(\varphi', \{S_2, S_3\})$ : activates group 2,3
- $SAT(\varphi', \{S_1, S_3\})$ : activates group 1,3

```
• Initial formula \varphi:
(A_1 \lor \neg A_2 \lor \neg A_3) \land // group 1
(\neg A_3 \lor A_2 \lor \neg A_5) \land // group 1
(\neg A_2 \lor A_5 \lor A_7) \land // group 2
(A_3 \lor A_5 \lor \neg A_8) \land // group 3
(\neg A_1 \lor \neg A_3 \lor A_8) \land // group 3
```

- $SAT(\varphi', \{S_2, S_3\})$ : activates group 2,3
- $SAT(\varphi', \{S_1, S_3\})$ : activates group 1,3

## Incremental SAT solving [12, 11]

- Many CDCL solvers provide a stack-based incremental interface
  - it is possible to push/pop  $\phi_i$  into a stack of subformulas  $\{\phi_1,...,\phi_k\}$ • check incrementally the satisfiability of  $\varphi \stackrel{\text{def}}{=} \bigwedge_{i=1}^k \phi_i$ .
- Maintains the status of the search from one call to the other
  - in particular it records the learned clauses (plus other information)

    reuses search from one call to another
- Very useful in many applications (in particular in FV)
- Idea: incremental calls  $SAT(\varphi', A_1)$ ,  $SAT(\varphi', A_2)$ ,...
  - $\varphi' \stackrel{\text{def}}{=} \bigwedge_{i} (\neg S_{i} \lor \phi_{i}), A_{j} \subseteq \{S_{1}, ..., S_{k}\}, (\neg S_{i} \lor \bigwedge_{j} C_{ij}) \stackrel{\text{def}}{=} \bigwedge_{j} (\neg S_{i} \lor C_{ij})$  push/pop selection variables  $S_{i}$
  - in practice, also subformulas  $\phi_i$  can be pushed/popped
- Key efficiency issue: learned clauses safely reused from call to call (even if assumptions have been popped)
  - a learned clause  $C \stackrel{\text{def}}{=} \bigvee_{j} \neg S_{j} \lor C'$  is s.t.  $\bigwedge_{j} (\neg S_{j} \lor \phi_{j}) \models C$   $\Longrightarrow C$  contains the vars selecting the subformulas it is derived from
    - $\implies$  in  $SAT(\varphi', A)$ , if some  $S_i \notin A$ , then C is not active

• Initial formula  $\varphi$ :

• Augmented formula  $\varphi'$ :

[push( $S_1$ )]:  $SAT(\varphi', \{..., S_1\})$ :  $\phi_1$  active  $\Longrightarrow$  learn  $C_1$  from  $\phi_1$ 

- $C_1$  derived from  $\phi_1 \Longrightarrow C_1$  active only when  $\phi_1$  is active
- $C_2$  derived from  $\phi_1, \phi_2 \Longrightarrow C_2$  active only when both  $\phi_1, \phi_2$  are active

• Initial formula  $\varphi$ :

$$\begin{array}{ccccc} \dots & & & \wedge \\ \left( \begin{array}{cccc} A_1 & \vee \neg A_2 & \vee \neg A_3 & \right) \wedge & // \phi_1 \\ \left( \neg A_3 & \vee & A_2 & \vee \neg A_5 & \right) \wedge & // \phi_1 \end{array}$$

• Augmented formula  $\varphi'$ :

... 
$$(\neg S_1 \lor A_1 \lor \neg A_2 \lor \neg A_3) \land // \phi_1$$
  
 $(\neg S_1 \lor \neg A_3 \lor A_2 \lor \neg A_5) \land // \phi_1$ 

$$(\neg S_1 \lor A_1 \lor \neg A_3 \lor \neg A_5) \land // learned C_1$$

[push( $S_1$ )]:  $SAT(\varphi', \{..., S_1\})$ :  $\phi_1$  active  $\Longrightarrow$  learn  $C_1$  from  $\phi_1$ 

- $C_1$  derived from  $\phi_1 \Longrightarrow C_1$  active only when  $\phi_1$  is active
- $C_2$  derived from  $\phi_1, \phi_2 \Longrightarrow C_2$  active only when both  $\phi_1, \phi_2$  are active

• Initial formula  $\varphi$ :

• Augmented formula  $\varphi'$ :

```
(\neg S_1 \lor A_1 \lor \neg A_2 \lor \neg A_3) \land // \phi_1
(\neg S_1 \lor \neg A_3 \lor A_2 \lor \neg A_5) \land // \phi_1
(\neg S_2 \lor \neg A_2 \lor A_5 \lor A_7) \land // \phi_2 \text{ inactive}
(\neg S_2 \lor \neg A_1 \lor \neg A_3 \lor \neg A_5) \land // \phi_2 \text{ inactive}
(\neg S_1 \lor A_1 \lor \neg A_3 \lor \neg A_5) \land // \text{ learned } C_1
```

[push( $S_2$ )]:  $SAT(\varphi', \{..., S_1, S_2\})$ :  $\phi_1, \phi_2$  active  $\Longrightarrow$  learn  $C_2$  from  $\phi_1, \phi_2$ 

- $C_1$  derived from  $\phi_1 \Longrightarrow C_1$  active only when  $\phi_1$  is active
- $C_2$  derived from  $\phi_1, \phi_2 \Longrightarrow C_2$  active only when both  $\phi_1, \phi_2$  are active

• Initial formula  $\varphi$ :

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[push( $S_2$ )]:  $SAT(\varphi', \{..., S_1, S_2\})$ :  $\phi_1, \phi_2$  active  $\Longrightarrow$  learn  $C_2$  from  $\phi_1, \phi_2$ 

- $C_1$  derived from  $\phi_1 \Longrightarrow C_1$  active only when  $\phi_1$  is active
- $C_2$  derived from  $\phi_1, \phi_2 \Longrightarrow C_2$  active only when both  $\phi_1, \phi_2$  are active

• Initial formula  $\varphi$ :

... 
$$\wedge$$
  $\wedge$   $(A_1 \lor \neg A_2 \lor \neg A_3) \land // \phi_1 (\neg A_3 \lor A_2 \lor \neg A_5) \land // \phi_1$   $(\neg A_1 \lor \neg A_3 \lor A_8) \land // \phi_3$ 

```
... \land (\neg S_1 \lor A_1 \lor \neg A_2 \lor \neg A_3) \land // \phi_1 (\neg S_1 \lor \neg A_3 \lor A_2 \lor \neg A_5) \land // \phi_1 (\neg S_2 \lor \neg A_2 \lor A_5 \lor A_7) \land // \phi_2, inactive (\neg S_2 \lor \neg A_1 \lor \neg A_3 \lor \neg A_5) \land // \phi_2, inactive (\neg S_3 \lor \neg A_1 \lor \neg A_3 \lor \neg A_5) \land // \phi_3 (\neg S_1 \lor A_1 \lor \neg A_3 \lor \neg A_5) \land // learned C_1 (\neg S_1 \lor \neg S_2 \lor \neg A_3 \lor \neg A_5) \land // learned C_2, inactive [pop(S_2);push(S_3)]: SAT(\varphi', \{..., S_1, S_3\}): \phi_1, \phi_3 \text{ active } \Longrightarrow ...
```

- $C_1$  derived from  $\phi_1 \Longrightarrow C_1$  active only when  $\phi_1$  is active
- $C_2$  derived from  $\phi_1, \phi_2 \Longrightarrow C_2$  active only when both  $\phi_1, \phi_2$  are active

• Initial formula  $\varphi$ :

$$(\neg A_1 \lor \neg A_3 \lor A_8) \land // \phi_3$$

• Augmented formula  $\varphi'$ :

... 
$$\langle S_1 \lor A_1 \lor \neg A_2 \lor \neg A_3 \rangle \land // \phi_1$$
  
 $\langle S_1 \lor \neg A_3 \lor A_2 \lor \neg A_5 \rangle \land // \phi_1$   
 $\langle S_2 \lor \neg A_2 \lor A_5 \lor A_7 \rangle \land // \phi_2$ , inactive  
 $\langle S_2 \lor \neg A_1 \lor \neg A_3 \lor \neg A_5 \rangle \land // \phi_2$ , inactive  
 $\langle S_3 \lor \neg A_1 \lor \neg A_3 \lor A_8 \rangle \land // \phi_3$   
 $\langle S_1 \lor A_1 \lor \neg A_3 \lor \neg A_5 \rangle \land // learned C_1$   
 $\langle S_1 \lor \neg S_2 \lor \neg A_3 \lor \neg A_5 \rangle \land // learned C_2$ , inactive

[pop( $S_2$ );push( $S_3$ )]:  $SAT(\varphi', \{..., S_1, S_3\})$ :  $\phi_1, \phi_3$  active  $\Longrightarrow$ ...

- $C_1$  derived from  $\phi_1 \Longrightarrow C_1$  active only when  $\phi_1$  is active
- $C_2$  derived from  $\phi_1, \phi_2 \Longrightarrow C_2$  active only when both  $\phi_1, \phi_2$  are active

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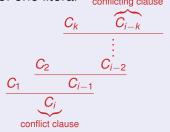
#### Advanced functionalities

Advanced SAT functionalities (very important in formal verification):

- Building proofs of unsatisfiability
- Extracting unsatisfiable Cores
- Computing Craig Interpolants
- Optimization in SAT: MaxSAT (hints)
- Enumeration on SAT: All-SAT and Model Counting (hints)

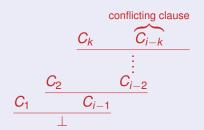
- When  $\varphi$  is unsat, it is very important to build a (resolution) proof of unsatisfiability:
  - to verify the result of the solver
  - to understand a "reason" for unsatisfiability
  - to build unsatisfiable cores and interpolants
- Can be built by keeping track of the resolution steps performed when constructing the conflict clauses.

• recall: each conflict clause  $C_i$  learned is computed from the conflicting clause  $C_{i-k}$  by backward resolving with the antecedent clause of one literal conflicting clause



- $C_1, ..., C_k$ , and  $C_{i-k}$  can be original or learned clauses
- each resolution (sub)proof can be easily tracked:

• ... in particular, if  $\varphi$  is unsatisfiable, the last step produces "false" as conflict clause



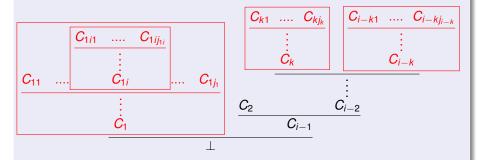
(we assume that level-0 literals are also resolved away)

- $C_1 = I$ ,  $C_{i-1} = \neg I$  for some literal I
- $C_1, ..., C_k$ , and  $C_{i-k}$  can be original or learned clauses...

Starting from the previous proof of unsatisfiability, repeat recursively:

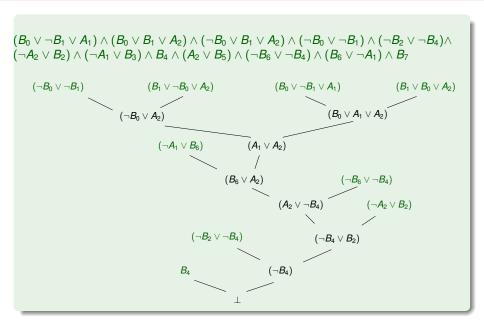
• for every learned leaf clause  $C_i$ , substitute  $C_i$  with the resolution proof generating it

until all leaf clauses are original clauses



 $\implies$  We obtain a resolution proof of unsatisfiability for (a subset of) the clauses in  $\varphi$ 

## Building Proofs of Unsatisfiability: example



#### Extraction of unsatisfiable cores

- Problem: given an unsatisfiable set of clauses, extract from it a (possibly small/minimal/minimum) unsatisfiable subset
  - ⇒ unsatisfiable cores (aka (Minimal) Unsatisfiable Subsets, (M)US)
- Lots of literature on the topic [46, 24, 26, 31, 43, 19, 13, 6]
- We recognize two main approaches:
  - Proof-based approach [46]: byproduct of finding a resolution proof
  - Assumption-based approach [24]: use extra variables labeling clauses
- Many optimizations for further reducing the size of the core:
  - repeat the process up to fixpoit
  - remove clauses one-by one, until satisfiability is obtained
  - combinations of the two processed above
  - ...

### The proof-based approach [46]

Unsat core: the set of leaf clauses of a resolution proof

$$(B_0 \vee \neg B_1 \vee A_1) \wedge (B_0 \vee B_1 \vee A_2) \wedge (\neg B_0 \vee B_1 \vee A_2) \wedge (\neg B_0 \vee \neg B_1) \wedge (\neg B_2 \vee \neg B_4) \wedge (\neg A_2 \vee B_2) \wedge (\neg A_1 \vee B_3) \wedge B_4 \wedge (A_2 \vee B_5) \wedge (\neg B_6 \vee \neg B_4) \wedge (B_6 \vee \neg A_1) \wedge B_7$$

$$(\neg B_0 \vee \neg B_1) \qquad (B_1 \vee \neg B_0 \vee A_2) \qquad (B_0 \vee \neg B_1 \vee A_1) \qquad (B_1 \vee B_0 \vee A_2)$$

$$(\neg B_0 \vee A_2) \qquad (B_0 \vee A_1 \vee A_2) \qquad (B_0 \vee \neg B_1) \wedge (A_1 \vee A_2)$$

$$(\neg B_0 \vee A_1 \vee A_2) \qquad (\neg B_0 \vee \neg B_1) \wedge (\neg B_0 \vee$$

# The assumption-based approach [24]

## Based on the following process:

- (i) each clause  $C_i$  is substituted by  $\neg S_i \lor C_i$ , s.t.  $S_i$  fresh "selector" variable
- (ii) before starting the search each  $S_i$  is forced to true.
- (iii) final conflict clause at dec. level 0:  $\bigvee_{i} \neg S_{i}$ 
  - $\implies \{C_i\}_i$  is the unsat core!

# The assumption-based approach to core extraction

#### Example

$$\begin{array}{l} (B_0 \vee \neg B_1 \vee A_1) \wedge (B_0 \vee B_1 \vee A_2) \wedge (\neg B_0 \vee B_1 \vee A_2) \wedge \\ (\neg B_0 \vee \neg B_1) \wedge (\neg B_2 \vee \neg B_4) \wedge (\neg A_2 \vee B_2) \wedge (\neg A_1 \vee B_3) \wedge \\ B_4 \wedge (A_2 \vee B_5) \wedge (\neg B_6 \vee \neg B_4) \wedge (B_6 \vee \neg A_1) \wedge B_7 \end{array}$$

(i) add selector variables:

$$\begin{array}{l} (\neg S_{1} \lor B_{0} \lor \neg B_{1} \lor A_{1}) \land (\neg S_{2} \lor B_{0} \lor B_{1} \lor A_{2}) \land (\neg S_{3} \lor \neg B_{0} \lor B_{1} \lor A_{2}) \land \\ (\neg S_{4} \lor \neg B_{0} \lor \neg B_{1}) \land (\neg S_{5} \lor \neg B_{2} \lor \neg B_{4}) \land (\neg S_{6} \lor \neg A_{2} \lor B_{2}) \land \\ (\neg S_{7} \lor \neg A_{1} \lor B_{3}) \land (\neg S_{8} \lor B_{4}) \land (\neg S_{9} \lor A_{2} \lor B_{5}) \land (\neg S_{10} \lor \neg B_{6} \lor \neg B_{4}) \land \\ (\neg S_{11} \lor B_{6} \lor \neg A_{1}) \land (\neg S_{12} \lor B_{7}) \end{array}$$

(ii) The conflict analysis returns:

$$\neg S_1 \vee \neg S_2 \vee \neg S_3 \vee \neg S_4 \vee \neg S_5 \vee \neg S_6 \vee \neg S_8 \vee \neg S_{10} \vee \neg S_{11},$$

(iii) corresponding to the unsat core:

$$\begin{array}{l} (B_0 \vee \neg B_1 \vee A_1) \wedge (B_0 \vee B_1 \vee A_2) \wedge (\neg B_0 \vee B_1 \vee A_2) \wedge \\ (\neg B_0 \vee \neg B_1) \wedge (\neg B_2 \vee \neg B_4) \wedge (\neg A_2 \vee B_2) \wedge \\ B_4 \wedge (\neg B_6 \vee \neg B_4) \wedge (B_6 \vee \neg A_1) \end{array}$$

# Computing Craig Interpolants in SAT

Notation: Let " $X \subseteq Y$ ", X, Y being Boolean formulas, denote the fact that all Boolean atoms in X occur also in Y.

## Definition: Craig Interpolant

Given an ordered pair (A, B) of formulas such that  $A \wedge B \models \bot$ , a *Craig interpolant* is a formula I s.t.:

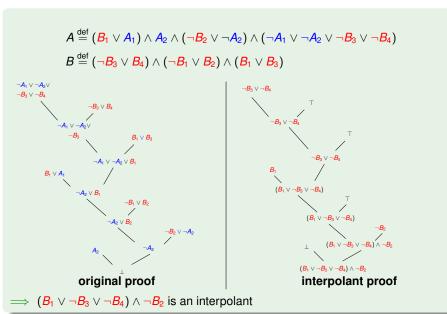
- a)  $A \models I$ ,
- b)  $I \wedge B \models \bot$ ,
- c)  $I \leq A$  and  $I \leq B$ .
  - Very important in many Formal Verification applications
- A few works presented [32, 25, 27]

# Computing Craig Interpolants in SAT: a General Algorithm [32]

## Algorithm: Interpolant generation (for SAT)

- (i) Generate a resolution proof of unsatisfiability  $\mathcal{P}$  for  $A \wedge B$ .
- (ii) ...
- (iii) For every leaf clause C in  $\mathcal{P}$ , set  $I_C \stackrel{\text{def}}{=} C \downarrow B$  if  $C \in A$ , and  $I_C \stackrel{\text{def}}{=} \top$  if  $C \in B$ .
- (iv) For every inner node C of  $\mathcal P$  obtained by resolution from  $C_1 \stackrel{\mathsf{def}}{=} p \lor \phi_1$  and  $C_2 \stackrel{\mathsf{def}}{=} \neg p \lor \phi_2$ , set  $I_C \stackrel{\mathsf{def}}{=} I_{C_1} \lor I_{C_2}$  if p does not occur in B, and  $I_C \stackrel{\mathsf{def}}{=} I_{C_1} \land I_{C_2}$  otherwise.
- (v) Output  $I_{\perp}$  as an interpolant for (A, B).
- " $\eta \setminus B$ " [resp. " $\eta \downarrow B$ "] is the set of literals in  $\eta$  whose atoms do not [resp. do] occur in B.
  - optimized versions for the purely-propositional case [25, 27]

# Computing Craig Interpolants in SAT: example



## MaxSAT (hints)

- MaxSAT: given a pair of CNF formulas  $\langle \varphi_h, \varphi_s \rangle$  s.t.  $\varphi_h \wedge \varphi_s \models \bot$ ,  $\varphi_s \stackrel{\text{def}}{=} \{C_1, ..., C_k\}$ , find a truth assignment  $\mu$  satisfying  $\varphi_h$  and maximizing the amount of the satisfied clauses in  $\varphi_s$ .
- Weighted MaxSAT: given also the positive integer penalties  $\{w_1,...,w_k\}$ ,  $\mu$  must satisfy  $\varphi_h$  and maximize the sum of penalties of the satisfied clauses in  $\varphi_s$
- Generalization of SAT to optimization
   much harder than SAT
- Many different approaches (see e.g. [22])
- EX:

$$\varphi_h \stackrel{\text{def}}{=} (A_1 \lor A_2) \qquad \varphi_s \stackrel{\text{def}}{=} \left( \begin{array}{ccc} (A_1 \lor \neg A_2) & \land & [4] \\ (\neg A_1 \lor A_2) & \land & [3] \\ (\neg A_1 \lor \neg A_2) & \land & [2] \end{array} \right)$$

$$\Longrightarrow \mu = \{A_1, A_2\}$$
 (penalty = 2)

# All-SAT & Model Counting (hints)

- All-SAT: enumerate all truth assignments satisfying φ
   a partial model μ not assigning k atoms represents 2<sup>k</sup> models
- All-SAT over an "important" subset of atoms  $\mathbf{P} \stackrel{\text{def}}{=} \{P_i\}_i$ : enumerate all assignments over  $\mathbf{P}$  which can be extended to satisfiable truth assignments propositionally satisfying  $\varphi$
- Model Counting (aka #SAT) [17]: like All-SAT, but count models rathern than enumerate them.
  - a partial assignment  $\mu$  not assigning k atoms is counted for  $2^k$

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- Combination Methods in Automated Reasoning http://combination.cs.uiowa.edu/
- The SAT Association http://satassociation.org/
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- SATLIB The Satisfiability Library
   http://www.intellektik.informatik.tu-darmstadt.de/SATLIB/