

# Tutorial on Conflict-Driven Pseudo-Boolean Solving

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# Pseudo-Boolean?

Pseudo-Boolean (PB) function:  $f : \{0, 1\}^n \rightarrow \mathbb{R}$

Studied since 1960s in operations research and 0–1 integer linear programming [BH02]

Such function  $f$  can always be represented as multivariate **polynomial** of total degree  $\leq n$

**Restriction for these lectures:**  $f$  represented as **linear form**

Many problems expressible as optimizing value of linear pseudo-Boolean function under linear pseudo-Boolean constraints

# Pseudo-Boolean vs. SAT

- PB format richer than conjunctive normal form (CNF)

Compare

$$x_1 + x_2 + x_3 + x_4 + x_5 + x_6 \geq 3$$

and

$$\begin{aligned} & (x_1 \vee x_2 \vee x_3 \vee x_4) \wedge (x_1 \vee x_2 \vee x_3 \vee x_5) \wedge (x_1 \vee x_2 \vee x_3 \vee x_6) \\ & \wedge (x_1 \vee x_2 \vee x_4 \vee x_5) \wedge (x_1 \vee x_2 \vee x_4 \vee x_6) \wedge (x_1 \vee x_2 \vee x_5 \vee x_6) \\ & \wedge (x_1 \vee x_3 \vee x_4 \vee x_5) \wedge (x_1 \vee x_3 \vee x_4 \vee x_6) \wedge (x_1 \vee x_3 \vee x_5 \vee x_6) \\ & \wedge (x_1 \vee x_4 \vee x_5 \vee x_6) \wedge (x_2 \vee x_3 \vee x_4 \vee x_5) \wedge (x_2 \vee x_3 \vee x_4 \vee x_6) \\ & \wedge (x_2 \vee x_3 \vee x_5 \vee x_6) \wedge (x_2 \vee x_4 \vee x_5 \vee x_6) \wedge (x_3 \vee x_4 \vee x_5 \vee x_6) \end{aligned}$$

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- And pseudo-Boolean reasoning exponentially stronger than conflict-driven clause learning (CDCL)
- Yet close enough to SAT to benefit from SAT solving advances
- Also possible synergies with 0–1 integer linear programming (ILP)

# Outline of Tutorial on Pseudo-Boolean Solving

## 1 Preliminaries

- Pseudo-Boolean Constraints
- Pseudo-Boolean Solving and Optimization

## 2 Conflict-Driven Pseudo-Boolean Solving

- The Conflict-Driven Paradigm
- Pseudo-Boolean Conflict Analysis Using Saturation
- Pseudo-Boolean Conflict Analysis Using Division

## 3 More About Pseudo-Boolean Reasoning

- Other Pseudo-Boolean Reasoning Rules
- Challenges for Efficient PB Solving
- Some Further References

# Linear Pseudo-Boolean Constraints and Normalized Form

For us, **pseudo-Boolean constraints** are always **0–1 integer linear constraints**

$$\sum_i a_i l_i \bowtie A$$

- $\bowtie \in \{\geq, \leq, =, >, <\}$
- $a_i, A \in \mathbb{Z}$
- **literals**  $l_i$ :  $x_i$  or  $\bar{x}_i$  (where  $x_i + \bar{x}_i = 1$ )
- variables  $x_i$  take values  $0 = \textit{false}$  or  $1 = \textit{true}$



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Convenient to use **normalized form** [Bar95] (without loss of generality)

$$\sum_i a_i l_i \geq A$$

- constraint always greater-than-or-equal
- $a_i, A \in \mathbb{N}$  non-negative
- $A = \text{deg}(\sum_i a_i l_i \geq A)$  referred to as **degree (of falsity)**

# Some Types of Pseudo-Boolean Constraints

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- 3 **General constraints**

$$x_1 + 2\bar{x}_2 + 3x_3 + 4\bar{x}_4 + 5x_5 \geq 7$$

## Conversion to Normalized Form: Example

Normalized form used for convenience and without loss of generality

$$-x_1 + 2x_2 - 3x_3 + 4x_4 - 5x_5 < 0$$

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- 3 Replace  $-\ell$  by  $-(1 - \bar{\ell})$  [where we define  $\bar{x} \doteq x$ ]

$$x_1 - 2(1 - \bar{x}_2) + 3x_3 - 4(1 - \bar{x}_4) + 5x_5 \geq 1$$

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- 4 Replace “=” by two inequalities “ $\geq$ ” and “ $\leq$ ”

# Conversion to Normalized Form: Formal Details

Given linear form  $\sum_i a_i l_i$  with  $\sum_i a_i = W$

## Syntactic sugar

$$\sum_i a_i l_i > A$$

$$\sum_i a_i l_i \leq A$$

$$\sum_i a_i l_i < A$$

$$\sum_i a_i l_i = A$$

## Meaning

$$\sum_i a_i l_i \geq A + 1$$

$$\sum_i a_i \bar{l}_i \geq W - A$$

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$$\sum_i a_i l_i \geq A \quad \text{and}$$

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In what follows:

- Use syntactic sugar when convenient
- Assume (implicit) normalization whenever it matters
- Write  $\doteq$  for syntactic equality

# Some Notation for Operations on Constraints (1/2)

Given

- constraints  $C_1 \doteq \sum_i a_i l_i \geq A$  and  $C_2 \doteq \sum_i b_i l_i \geq B$
- linear form  $L \doteq \sum_i c_i l_i$
- positive integer  $k \in \mathbb{N}^+$

we will use notation:

$$C_1 + C_2 \doteq \sum_i (a_i + b_i) \cdot l_i \geq A + B$$

$$C_1 + L \doteq \sum_i (a_i + c_i) \cdot l_i \geq A$$

$$k \cdot C_1 \doteq \sum_i k a_i \cdot l_i \geq kA$$

(assuming appropriate normalization whenever needed)

## Some Notation for Operations on Constraints (2/2)

Given constraint  $C \doteq \sum_i a_i l_i \geq A$  with  $\sum_i a_i = W$

**Negation**

$$\neg C \doteq \sum_i a_i \bar{l}_i \geq W - A + 1$$

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### Negation

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### Reification

$$z \Rightarrow C \doteq A \cdot \bar{z} + \sum_i a_i l_i \geq A$$

$$z \Leftarrow C \doteq (W - A + 1) \cdot z + \sum_i a_i \bar{l}_i \geq W - A + 1$$

$$z \Leftrightarrow C \doteq z \Rightarrow C \text{ and } z \Leftarrow C$$

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### Some calculations

$$C + \neg C \doteq 0 \geq 1$$

$$z \Leftarrow C \doteq \bar{z} \Rightarrow \neg C$$

$$\text{deg}(C) \cdot (z \geq 1) + (z \Rightarrow C) \doteq C$$

$$C + (z \Leftarrow C) \doteq \text{deg}(\neg C) \cdot z \geq 1$$

# Linearization

Possible to **linearize** nonlinear pseudo-Boolean constraints

$$\sum_{i=1}^k a_i m_i \geq A$$

with

$$m_i \doteq \prod_{j=1}^{d_i} l_{i,j}$$



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For instance, using fresh variables  $y_i$  we can write:

$$\begin{aligned} \sum_{i=1}^k a_i y_i &\geq A \\ d_i \cdot \bar{y}_i + \sum_{j=1}^{d_i} \ell_{i,j} &\geq d_i && i \in [k] \\ y_i + \sum_{j=1}^{d_i} \bar{\ell}_{i,j} &\geq 1 && i \in [k] \end{aligned}$$

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We won't go further into this in this presentation, though...

# Formulas, Decision Problems, and Optimization Problems

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This lecture:

- Focus on pseudo-Boolean solving
- But not hard to extend to (simple) optimization algorithm

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- undirected graph  $G = (V, E)$
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## Weighted minimum vertex cover

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Find  $H \subseteq \mathcal{U}$  such that

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$$\begin{aligned} \min \quad & \sum_{e \in \mathcal{U}} w(e) \cdot x_e \\ & \sum_{e \in S_i} x_e \geq 1 \end{aligned} \quad i \in [m]$$

Note: In all of these examples, the problem is to

- optimize a linear function
- subject to a CNF formula (all constraints are clausal)

Already expressive framework!

# Approaches for Pseudo-Boolean Problems

What we will discuss in the coming lectures:

- 1 Pseudo-Boolean (PB) solving and optimization
- 2 MaxSAT solving
- 3 Integer linear programming (ILP) — or, more generally, mixed integer linear programming (MIP)

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Rough conceptual difference:

- **PB/SAT**: Focus on integral solutions, try to find optimal one
- **ILP/MIP**: Find optimal non-integer solution; search for integral solutions nearby

Basic trade-off: Inference power vs. inference speed

# A Quick Recap of Modern SAT Solving

## DPLL method [DP60, DLL62]

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- More efficient backtracking
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# CDCL Main Loop Pseudocode

## CDCL( $F$ )

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2  $\rho \leftarrow \emptyset$  ; // initialize assignment trail to empty
3 forever do
4   if  $\rho$  falsifies some clause  $C \in \mathcal{D}$  then
5      $A \leftarrow \text{analyzeConflict}(\mathcal{D}, \rho, C)$  ;
6     if  $A = \perp$  then output UNSATISFIABLE and exit ;
7     else add learned clause  $A$  to  $\mathcal{D}$  and backjump by shrinking  $\rho$  ;
8   else if exists clause  $C \in \mathcal{D}$  unit propagating  $x$  to  $b \in \{0, 1\}$  under  $\rho$  then
9     add propagated assignment  $x \stackrel{C}{=} b$  to  $\rho$  ;
10  else if time to restart then  $\rho \leftarrow \emptyset$  ;
11  else if time for clause database reduction then
12    erase (roughly) half of learned clauses in  $\mathcal{D} \setminus F$  from  $\mathcal{D}$ 
13  else if all variables assigned then output SATISFIABLE and exit ;
14  else
15    use decision scheme to choose  $x$  and  $b$  and add assignment  $x \stackrel{d}{=} b$  to  $\rho$  ;

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15    use decision scheme to choose  $x$  and  $b$  and add assignment  $x \stackrel{d}{=} b$  to  $\rho$  ;

```

# Conflict Analysis Pseudocode

$\text{analyzeConflict}(\mathcal{D}, \rho, C_{\text{confl}})$

```

1  $C_{\text{learn}} \leftarrow C_{\text{confl}} ;$ 
2 while  $C_{\text{learn}}$  not UIP clause and  $C_{\text{learn}} \neq \perp$  do
3    $l \leftarrow$  literal assigned last on trail  $\rho ;$ 
4   if  $l$  propagated and  $\bar{l}$  occurs in  $C_{\text{learn}}$  then
5      $C_{\text{reason}} \leftarrow \text{reason}(l, \rho, \mathcal{D}) ;$ 
6      $C_{\text{learn}} \leftarrow \text{resolve}(C_{\text{learn}}, C_{\text{reason}}) ;$ 
7    $\rho \leftarrow \rho \setminus \{l\} ;$ 
8 return  $C_{\text{learn}} ;$ 

```

# SAT-Based Approaches to Pseudo-Boolean Solving

## Conversion to disjunctive clauses

- Lazy approach: learn clauses from PB constraints
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- Variable assignments
  - 1 Always **propagate** forced assignment if possible
  - 2 Otherwise make assignment using **decision** heuristic
- At conflict
  - 1 Do **conflict analysis** to derive new constraint
  - 2 Add new constraint to constraint database
  - 3 **Backjump** by rolling back decisions so that learned constraint propagates **asserting literal** (flipping it to opposite value)

# Propagation, Conflict, and Slack

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$\rho$	$\text{slack}(C; \rho)$	comment
$\{\}$	8	
$\{\bar{x}_5\}$	3	propagates $\bar{x}_4$ (coefficient > slack)
$\{\bar{x}_5, \bar{x}_4\}$	3	propagation doesn't change slack
$\{\bar{x}_5, \bar{x}_4, \bar{x}_3, x_2\}$	-2	conflict (slack < 0)

Note: constraint can be conflicting though not all variables assigned!

# Conflict Analysis Invariant

Consider example CDCL conflict analysis from SAT solving lecture

$$(p \vee \bar{u}) \wedge (q \vee r) \wedge (\bar{r} \vee w) \wedge (u \vee x \vee y) \wedge (x \vee \bar{y} \vee z) \wedge (\bar{x} \vee z) \wedge (\bar{y} \vee \bar{z}) \wedge (\bar{x} \vee \bar{z}) \wedge (\bar{p} \vee \bar{u})$$

$$p \stackrel{d}{=} 0$$

$$u \stackrel{p \vee \bar{u}}{=} 0$$

$$q \stackrel{d}{=} 0$$

$$r \stackrel{q \vee r}{=} 1$$

$$w \stackrel{\bar{r} \vee w}{=} 1$$

$$x \stackrel{d}{=} 0$$

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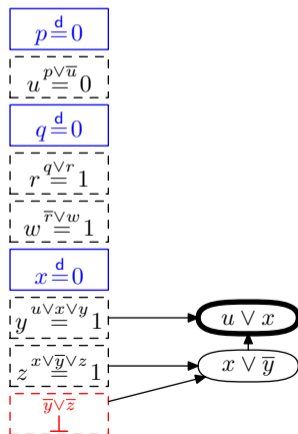
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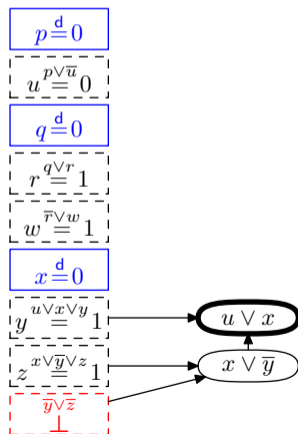
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Terminate analysis when  
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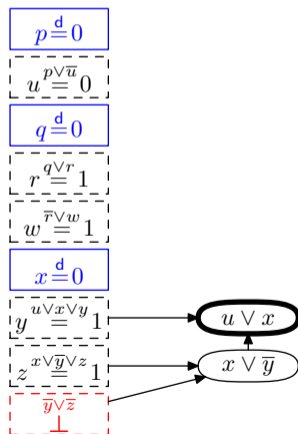
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$\Rightarrow$  every derived constraint  
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Terminate analysis when  
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“Nice” means **asserting**:  
after backjump, some  
variable guaranteed to flip

# Generalized Resolution

Can mimic resolution step

$$\frac{x \vee \bar{y} \vee z \quad \bar{y} \vee \bar{z}}{x \vee \bar{y}}$$

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by adding clauses as pseudo-Boolean constraints

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(Recall  $z + \bar{z} = 1$ )

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**Generalized resolution rule** (from [Hoo88, Hoo92])

Positive linear combination so that some variable cancels

$$\frac{a_1 x_1 + \sum_{i \geq 2} a_i \ell_i \geq A \quad b_1 \bar{x}_1 + \sum_{i \geq 2} b_i \ell_i \geq B}{\sum_{i \geq 2} \left( \frac{c}{a_1} a_i + \frac{c}{b_1} b_i \right) \ell_i \geq \frac{c}{a_1} A + \frac{c}{b_1} B - c} \quad [c = \text{lcm}(a_1, b_1)]$$

# Saturation

Actually, not quite the right constraint in mimicking of resolution

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## Saturation rule

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Sound over integers, not over reals (need such rules for SAT solving)

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[Generalized resolution as defined in [Hoo88, Hoo92] includes fix above, but convenient here to make the two separate steps explicit]

# Analyze Conflict with Generalized Resolution + Saturation!

$$C_1 \doteq 2x_1 + 2x_2 + 2x_3 + x_4 \geq 4$$

$$C_2 \doteq 2\bar{x}_1 + 2\bar{x}_2 + 2\bar{x}_3 \geq 3$$

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Trail  $\rho = \{x_1 \stackrel{d}{=} 0, x_2 \stackrel{C_1}{=} 1, x_3 \stackrel{C_1}{=} 1\} \Rightarrow$  **Conflict with  $C_2$**

(Note: same constraint can propagate several times!)

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- Applying  $\text{saturate}(x_4 \geq 1)$  does nothing
- Non-negative slack w.r.t.  $\rho' = \{x_1 \stackrel{d}{=} 0, x_2 \stackrel{C_1}{=} 1\}$   
**Not conflicting!** Does not explain mistake in assignment



# What Went Wrong? And What to Do About It?

## Accident report

- Generalized resolution **sound over the reals**
- Given  $\rho' = \{x_1 = 0, x_2 = 1\}$ , over the reals have
  - $C_1 \doteq 2x_1 + 2x_2 + 2x_3 + x_4 \geq 4$  propagates  $x_3 \geq \frac{1}{2}$
  - $C_2 \doteq 2\bar{x}_1 + 2\bar{x}_2 + 2\bar{x}_3 \geq 3$  satisfied by  $x_3 \leq \frac{1}{2}$
- So after resolving away  $x_3$  **no conflict left!**

# What Went Wrong? And What to Do About It?

## Accident report

- Generalized resolution **sound over the reals**
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- So after resolving away  $x_3$  **no conflict left!**

## Remedial action

- Strengthen propagation to  $x_3 \geq 1$  also over the reals
- I.e., want reason  $C$  with  $slack(C; \rho') = 0$
- **Fix (non-obvious):** Apply weakening

$$\text{weaken}(\sum_i a_i l_i \geq A, l_j) \doteq \sum_{i \neq j} a_i l_i \geq A - a_j$$

to reason constraint and then saturate

- Approach in [CK05] (goes back to observations in [Wil76])

## Try to Reduce the Reason Constraint

$$C_1 \doteq 2x_1 + 2x_2 + 2x_3 + x_4 \geq 4$$

$$C_2 \doteq 2\bar{x}_1 + 2\bar{x}_2 + 2\bar{x}_3 \geq 3$$

Trail  $\rho = \{x_1 \stackrel{d}{=} 0, x_2 \stackrel{C_1}{=} 1, x_3 \stackrel{C_1}{=} 1\} \Rightarrow$  **Conflict with  $C_2$**

Let's try to

- 1 Weaken reason on non-falsified literal (but not last propagated)
- 2 Saturate weakened constraint
- 3 Resolve with conflicting constraint over propagated literal

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- ② Saturate weakened constraint
- ③ Resolve with conflicting constraint over propagated literal

$$\begin{array}{l}
 \text{weaken } x_2 \quad \frac{2x_1 + 2x_2 + 2x_3 + x_4 \geq 4}{2x_1 + 2x_3 + x_4 \geq 2} \\
 \text{saturate} \quad \frac{2x_1 + 2x_3 + x_4 \geq 2}{2x_1 + 2x_3 + x_4 \geq 2} \quad \frac{2\bar{x}_1 + 2\bar{x}_2 + 2\bar{x}_3 \geq 3}{2\bar{x}_2 + x_4 \geq 1} \\
 \text{resolve } x_3 \quad \frac{2x_1 + 2x_3 + x_4 \geq 2}{2\bar{x}_2 + x_4 \geq 1}
 \end{array}$$

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 \text{resolve } x_3 \quad \frac{2x_1 + 2x_3 + x_4 \geq 2}{2\bar{x}_2 + x_4 \geq 1}
 \end{array}$$

Bummer! Still non-negative slack — not conflicting

## Try Again to Reduce the Reason Constraint. . .

$$C_1 \doteq 2x_1 + 2x_2 + 2x_3 + x_4 \geq 4$$

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$$\begin{array}{l} \text{weaken } \{x_2, x_4\} \\ \text{saturnate} \\ \text{resolve } x_3 \end{array} \frac{\frac{2x_1 + 2x_2 + 2x_3 + x_4 \geq 4}{2x_1 + 2x_3 \geq 1}}{\frac{x_1 + x_3 \geq 1}{2\bar{x}_2 \geq 1}} \frac{2\bar{x}_1 + 2\bar{x}_2 + 2\bar{x}_3 \geq 3}{2\bar{x}_2 \geq 1}$$

**Negative slack — conflicting!** Derived constraint shows setting  $x_2$  true was a mistake



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**Negative slack — conflicting!** Derived constraint shows setting  $x_2$  true was a mistake

Backjump propagates to conflict without solver making any decisions

**Done!** Next conflict analysis will derive contradiction

(Or, in practice, solver terminates immediately at conflict without decisions)

# Reason Reduction Using Saturation [CK05]

$\text{reduceSat}(C_{\text{reason}}, C_{\text{learn}}, \ell, \rho)$

- 1 **while**  $\text{slack}(\text{resolve}(C_{\text{learn}}, C_{\text{reason}}, \ell); \rho) \geq 0$  **do**
- 2      $\ell' \leftarrow$  literal in  $C_{\text{reason}} \setminus \{\ell\}$  not falsified by  $\rho$  ;
- 3      $C_{\text{reason}} \leftarrow \text{saturate}(\text{weaken}(C_{\text{reason}}, \ell'))$  ;
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Why does this work?

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$$\text{slack}(c \cdot C + d \cdot D; \rho) \leq c \cdot \text{slack}(C; \rho) + d \cdot \text{slack}(D; \rho)$$

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- **Saturation decreases slack** — hit 0 when max #literals weakened

# Pseudo-Boolean Conflict Analysis Pseudocode

$\text{analyzePBconflict}(\mathcal{D}, \rho, C_{\text{confl}})$

```

1  $C_{\text{learn}} \leftarrow C_{\text{confl}} ;$ 
2 while  $C_{\text{learn}}$  not asserting and  $C_{\text{learn}} \neq \perp$  do
3    $l \leftarrow$  literal assigned last on trail  $\rho ;$ 
4   if  $l$  propagated and  $\bar{l}$  occurs in  $C_{\text{learn}}$  then
5      $C_{\text{reason}} \leftarrow \text{reason}(l, \rho, \mathcal{D}) ;$ 
6      $C_{\text{reduced}} \leftarrow \text{reduceSat}(C_{\text{reason}}, C_{\text{learn}}, l, \rho) ;$ 
7      $C_{\text{learn}} \leftarrow \text{resolve}(C_{\text{learn}}, C_{\text{reduced}}, l) ;$ 
8      $C_{\text{learn}} \leftarrow \text{saturate}(C_{\text{learn}}) ;$ 
9    $\rho \leftarrow \rho \setminus \{l\} ;$ 
10 return  $C_{\text{learn}} ;$ 

```

Reduction of reason **new compared to CDCL** — otherwise same conflict analysis algorithm  
Essentially conflict analysis used in SAT4J [LP10]

# Some Problems Compared to CDCL

- Compared to clauses **harder to detect propagation** for constraints like

$$\sum_{i=1}^n x_i \geq n - 1$$



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  - ⇒ **coefficient sizes can explode** (expensive arithmetic)

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- Generalized resolution for general pseudo-Boolean constraints
  - ⇒ lots of lcm computations
  - ⇒ **coefficient sizes can explode** (expensive arithmetic)
- For CNF inputs, **degenerates to resolution!**
  - ⇒ CDCL but with super-expensive data structures

# The Cutting Planes Proof System

Cutting planes from the theory literature [CCT87] **doesn't use saturation** but instead **division** (a.k.a. **Chvátal-Gomory cut**) and can be defined as having rules

**Literal axioms**  $\frac{}{l_i \geq 0}$

**Linear combination**  $\frac{\sum_i a_i l_i \geq A \quad \sum_i b_i l_i \geq B}{\sum_i (c_A a_i + c_B b_i) l_i \geq c_A A + c_B B}$

**Division**  $\frac{\sum_i a_i l_i \geq A}{\sum_i \lceil a_i / c \rceil l_i \geq \lceil A / c \rceil}$

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$$\text{Division} \frac{\sum_i a_i l_i \geq A}{\sum_i \lceil a_i / c \rceil l_i \geq \lceil A / c \rceil}$$

- Cutting planes with division **implicationally complete**
- Cutting planes with **saturation** is **not** [VEG<sup>+</sup>18]
- Can division yield stronger conflict analysis?

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- Cutting planes with division **implicationally complete**
- Cutting planes with **saturation** is **not** [VEG<sup>+</sup>18]
- Can division yield stronger conflict analysis?

(Explored for integer linear programming in CUTSAT [JdM13])

## Using Division to Reduce the Reason

$$C_1 \doteq 2x_1 + 2x_2 + 2x_3 + x_4 \geq 4$$

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$$\begin{array}{l} \text{weaken } x_4 \frac{2x_1 + 2x_2 + 2x_3 + x_4 \geq 4}{2} \\ \text{divide by } 2 \frac{2x_1 + 2x_2 + 2x_3 \geq 3}{2} \\ \text{resolve } x_3 \frac{x_1 + x_2 + x_3 \geq 2}{2\bar{x}_1 + 2\bar{x}_2 + 2\bar{x}_3 \geq 3} \\ \phantom{\text{resolve } x_3} 0 \geq 1 \end{array}$$

**Terminate immediately!**

## Reason Reduction Using Division [EN18]

$$\text{reduceDiv}(C_{\text{reason}}, C_{\text{learn}}, \ell, \rho)$$

- 1  $c \leftarrow \text{coeff}(C_{\text{reason}}, \ell)$  ;
- 2 **while**  $\text{slack}(\text{resolve}(C_{\text{learn}}, \text{divide}(C_{\text{reason}}, c), \ell); \rho) \geq 0$  **do**
- 3      $\ell_j \leftarrow \text{literal in } C_{\text{reason}} \setminus \{\ell\} \text{ such that } \bar{\ell}_j \notin \rho \text{ and } c \uparrow \text{coeff}(C, \ell_j)$  ;
- 4      $C_{\text{reason}} \leftarrow \text{weaken}(C_{\text{reason}}, \ell_j)$  ;
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- 5 **return**  $\text{divide}(C_{\text{reason}}, c)$  ;

So now why does **this** work?

- Sufficient to get **reason with slack 0** since
  - ①  $\text{slack}(C_{\text{learn}}; \rho) < 0$
  - ② slack is subadditive

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  - ② slack is subadditive
- Slack same after weakening  $\Rightarrow$  always  $0 \leq \text{slack}(C_{\text{reason}}; \rho) < c$
- After max #weakenings have  $0 \leq \text{slack}(\text{divide}(C_{\text{reason}}, c); \rho) < 1$

# Round-to-1 Reduction used in ROUNDINGSAT

Reduction method in ROUNDINGSAT [EN18] does maximal weakening right away

`roundToOne( $C, \ell, \rho$ )`

```

1  $c \leftarrow \text{coeff}(C, \ell)$  ;
2 foreach literal  $l_j$  in  $C$  do
3   if  $\bar{l}_j \notin \rho$  and  $c \nmid \text{coeff}(C, l_j)$  then
4      $C \leftarrow \text{weaken}(C, l_j)$  ;
5 return  $\text{divide}(C, c)$  ;
```

Guaranteed to work by same proof as before

And `roundToOne` also used more aggressively in conflict analysis  
(though modifications of this explored in more recent versions of ROUNDINGSAT...)

## ROUNDINGSAT Conflict Analysis [EN18]

analyzePBconflictRS( $\mathcal{D}, \rho, C_{\text{confl}}$ )

```

1  $C_{\text{learn}} \leftarrow C_{\text{confl}}$  ;
2 while  $C_{\text{learn}}$  contains no or multiple falsified literals on last level do
3   if no decisions in  $\rho$  then output UNSATISFIABLE and terminate ;
4    $\ell \leftarrow$  literal assigned last on trail  $\rho$  ;
5   if  $\ell$  propagated and  $\bar{\ell}$  occurs in  $C_{\text{learn}}$  then
6      $C_{\text{learn}} \leftarrow$  roundToOne( $C_{\text{learn}}, \bar{\ell}, \rho$ ) ;
7      $C_{\text{reduced}} \leftarrow$  roundToOne(reason( $\ell, \rho, \mathcal{D}$ ),  $\ell, \rho$ );
8      $C_{\text{learn}} \leftarrow$  resolve( $C_{\text{learn}}, C_{\text{reduced}}, \ell$ );
9    $\rho \leftarrow \rho \setminus \{\ell\}$ ;
10  $\ell \leftarrow$  literal in  $C_{\text{learn}}$  last falsified by  $\rho$  ;
11 return roundToOne( $C_{\text{learn}}, \ell, \rho$ ) ;

```

## Division vs. Saturation

- Higher conflict speed when PB reasoning doesn't help [EN18]
- Seems to perform better when PB reasoning crucial [EGNV18]
- Keeps coefficients small — can (often) do fixed-precision arithmetic
- But SAT4J still better for some circuit verification problems [LBD<sup>+</sup>20]
- And it is still equally hard to detect propagation
- Also, conflict analysis still degenerates to resolution for CNF inputs
- Sometimes very poor performance even on infeasible 0–1 LPs!



## Other PB Rules I: Cardinality Constraint Reduction

Given PB constraint

$$3x_1 + 2x_2 + x_3 + x_4 \geq 4$$

can compute least #literals that have to be true

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$$x_1 + x_2 + x_3 + x_4 \geq 2$$

GALENA [CK05] learns only cardinality constraints — easier to deal with

## Other PB Rules I: Cardinality Constraint Reduction

Given PB constraint

$$3x_1 + 2x_2 + x_3 + x_4 \geq 4$$

can compute least #literals that have to be true

$$x_1 + x_2 + x_3 + x_4 \geq 2$$

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---

### Cardinality constraint reduction rule

$$\frac{\sum_i a_i l_i \geq A}{\sum_{i: a_i > 0} l_i \geq T} \quad T = \min\{|I| : I \subseteq [n], \sum_{i \in I} a_i \geq A\}$$

Can be simulated with weakening + division

## Other PB Rules II: Strengthening

Strengthening by example:

- Set  $x = 0$  and propagate on constraints

$$x + y \geq 1 \quad x + z \geq 1 \quad y + z \geq 1$$

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**Strengthening rule** (imported by [DG02] from operations research)

- Suppose  $\ell = 0 \Rightarrow \sum_i a_i \ell_i \geq A$  oversatisfied by amount  $K$
- Then can deduce  $K\ell + \sum_i a_i \ell_i \geq A + K$



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In theory, can recover from bad encodings (e.g., CNF)

In practice, seems inefficient and hard to get to work. . .

## Other PB Rules III: “Fusion Resolution”

Suppose have constraints

$$2x + 3y + 2z + w \geq 3 \quad 2\bar{x} + 3y + 2z + w \geq 3$$

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But only get from resolution

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“Fusion resolution” [Goc17]

$$\frac{al + \sum_i b_i l_i \geq B \quad a\bar{l} + \sum_i b_i l_i \geq B'}{\sum_i b_i l_i \geq \min\{B, B'\}}$$

No obvious way for cutting planes to immediately derive this

Shows up in some tricky benchmarks in [EGNV18]

## Some PB Solving Challenges I: Input Format

- 1 **CNF**: PB solvers degenerate to CDCL for CNF inputs — how to harness power of cutting planes in this setting?
  - **Cardinality constraint detection** proposed as preprocessing [BLLM14] or inprocessing [EN20]
  - Has not (yet) been made competitive in practice



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- 4 **Robustness**: Make PB solvers less sensitive to presence of extra constraints (anecdotally, CDCL solvers seem more stable)

## Some PB Solving Challenges II: Conflict Analysis

### ① Choice of Boolean rule:

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### ④ How to assess **quality of learned constraints**?

### ⑤ **Theoretical potential & limitations** poorly understood [VEG<sup>+</sup>18]

- Separations in power between different methods of PB reasoning?
- In particular, is reasoning with division stronger than with saturation [GNY19]?



## Some PB Solving Challenges III: Solver Heuristics

Many heuristics copied from CDCL — maybe tailor more carefully to PB setting?

- 1 **Variable selection:** VSIDS [MMZ<sup>+</sup>01] or VMTF [Rya04] or something else?

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- 4 **Different “modes”** for SAT-focused and UNSAT-focused search?
- 5 **Local search** for more efficient finding of solutions?

See [Wal20] for a first in-depth investigation of some of these questions

## Some PB Solving Challenges IV: Efficiency and Correctness

- 1 Efficient **unit propagation** for PB constraints is a major challenge — latest news in [Dev20, NORZ24], but still much left to do

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## Some PB Solving Challenges IV: Efficiency and Correctness

- 1 Efficient **unit propagation** for PB constraints is a major challenge — latest news in [Dev20, NORZ24], but still much left to do
- 2 Efficient **detection of assertiveness** during conflict analysis
- 3 Efficient and concise **proof logging** for pseudo-Boolean solving (shameless self-plug: ongoing work on pseudo-Boolean proof checker **VERIPB** [Ver, BMN22] in [EGMN20, GMN20, GMM<sup>+</sup>20, GN21, GMN22, GMNO22, BBN<sup>+</sup>23, BGMN23, BBN<sup>+</sup>24, DMM<sup>+</sup>24, GMM<sup>+</sup>24, HOGN24, IOT<sup>+</sup>24, MMN24])



## Some References for Further Reading (and Watching)

### Handbook of Satisfiability [BHvMW21]

- Chapter 7: Proof Complexity and SAT Solving
- Chapter 23: MaxSAT, Hard and Soft Constraints
- Chapter 24: Maximum Satisfiability
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- Chapter 28: Pseudo-Boolean and Cardinality Constraints

### Video tutorials on pseudo-Boolean solving

Presentations from today will be available at the MIAO YouTube channel [youtube.com/@MIAOresearch](https://youtube.com/@MIAOresearch)



## Summing up

- Pseudo-Boolean framework expressive and powerful
- Can be approached using successful conflict-driven paradigm from SAT solving
- In theory, potential for exponential increase in performance
- In practice, some highly nontrivial challenges regarding
  - Algorithm design
  - Efficient implementation
  - Theoretical understanding
- But maybe also quite a bit of low-hanging fruit?  
(And clause-based SAT solving took 50+ years to get right)
- In any case, lots of fun questions to work on! 😊

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*Thank you for your attention!*

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