Tutorial on Conflict-Driven Pseudo-Boolean Solving

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Pseudo-Boolean?

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

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

Such a function f can always be represented as polynomial

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

PB format richer than conjunctive normal form (CNF)

Compare

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

and

$$(x_{1} \lor x_{2} \lor x_{3} \lor x_{4}) \land (x_{1} \lor x_{2} \lor x_{3} \lor x_{5}) \land (x_{1} \lor x_{2} \lor x_{3} \lor x_{6})$$

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- 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

- Preliminaries
 - Pseudo-Boolean Constraints
 - Pseudo-Boolean Solving and Optimization
- Conflict-Driven Pseudo-Boolean Solving
 - The Conflict-Driven Paradigm
 - Pseudo-Boolean Reasoning Using Saturation
 - Pseudo-Boolean Reasoning Using Division
- 3 Going Beyond the State of the Art?
 - Challenges for Efficient PB Solving
 - Some Further References

Pseudo-Boolean Constraints and Normalized Form

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

$$\sum_{i} a_{i} \ell_{i} \bowtie A$$

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

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

$$\sum_{i} a_i \ell_i \ge A$$

- constraint always greater-than-or-equal
- $a_i, A \in \mathbb{N}$
- $A = deg(\sum_i a_i \ell_i \ge A)$ referred to as degree (of falsity)

Some Types of Pseudo-Boolean Constraints

Clauses are pseudo-Boolean constraints

$$x \vee \overline{y} \vee z \quad \Leftrightarrow \quad x + \overline{y} + z \ge 1$$

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General constraints

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

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

Make inequality non-strict

$$-x_1 + 2x_2 - 3x_3 + 4x_4 - 5x_5 \le -1$$

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② Multiply by -1 to get greater-than-or-equal

$$x_1 - 2x_2 + 3x_3 - 4x_4 + 5x_5 \ge 1$$

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$$x_1 - 2x_2 + 3x_3 - 4x_4 + 5x_5 \ge 1$$

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

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

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

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$$-x_1 + 2x_2 - 3x_3 + 4x_4 - 5x_5 \le -1$$

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Replace "=" by two inequalities ">" and "<"</p>

Pseudo-Boolean (PB) formula

Conjunction of pseudo-Boolean constraints

$$F \doteq C_1 \wedge C_2 \wedge \cdots \wedge C_m$$

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Decide whether F is satisfiable/feasible

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Find satisfying assignment to F minimizing objective function $\sum_i w_i \ell_i$ (Maximization: minimize $-\sum_i w_i \ell_i$)

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This lecture:

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

Input:

- undirected graph G = (V, E)
- weight function $w:V\to\mathbb{N}^+$

 $(u,v) \notin E$

Some Problems Expressed as PBO (1/2)

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Weighted maximum clique

$$\min - \sum_{v \in V} w(v) \cdot x_v$$

$$\overline{x}_u + \overline{x}_v \ge 1$$

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Weighted minimum vertex cover

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$$x_u + x_v \ge 1 \qquad (u, v) \in E$$

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Weighted minimum hitting set

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

- $H \cap S_i \neq \emptyset$ for all $i \in [m]$ (H is a hitting set)
- \bullet $\sum_{h \in H} w(h)$ is minimal

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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:

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- MaxSAT solving
- 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]

- Assign values to variables (in some smart way)
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CDCL Main Loop Pseudocode

CDCL(F)

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1 \mathcal{D} \leftarrow F ; // initialize clause database to contain formula
 2 \rho \leftarrow \emptyset; // initialize assignment trail to empty
   forever do
         if \rho falsifies some clause C \in \mathcal{D} then
              A \leftarrow \mathsf{analyzeConflict}(\mathcal{D}, \rho, C);
              if A = \bot then output UNSATISFIABLE and exit;
              else
                    add A to \mathcal{D} and backjump by shrinking \rho;
         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{D}{=} b to \rho;
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         else if time to restart then \rho \leftarrow \emptyset:
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         else if time for clause database reduction then
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              erase (roughly) half of learned clauses in \mathcal{D} \setminus F from \mathcal{D}
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         else if all variables assigned then output SATISFIABLE and exit;
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         else
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              use decision scheme to choose assignment x \stackrel{d}{=} b to add to \rho;
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Conflict Analysis Pseudocode

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Native reasoning with pseudo-Boolean constraints

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"Native" Pseudo-Boolean Conflict-Driven Search

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- Variable assignments
 - 4 Always propagate forced assignment if possible
 - Otherwise make assignment using decision heuristic
- At conflict
 - Do conflict analysis to derive new constraint
 - 2 Add new constraint to constraint database
 - Backjump by rolling back decisions so that learned constraint propagates asserting literal (flipping it to opposite value)

```
Let \rho current assignment of solver (a.k.a. trail)
Represent as \rho = \{ (ordered) \text{ set of literals assigned true} \}
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$$\begin{array}{c|c} \rho & slack(C;\rho) & \text{comment} \end{array}$$

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$\{\overline{x}_5\}$	3	propagates \overline{x}_4 (coefficient $>$ slack)

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$\{\overline{x}_5\}$		
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$\{\overline{x}_5,\overline{x}_4,\overline{x}_3,x_2\}$	-2	conflict (slack < 0)

Let ρ current assignment of solver (a.k.a. trail) Represent as $\rho = \{(\text{ordered}) \text{ set of literals assigned true}\}$

Slack measures how far ρ is from falsifying $\sum_i a_i \ell_i \geq A$

$$slack(\sum_i a_i \ell_i \ge A; \rho) = \sum_{\ell_i \text{ not falsified by } \rho} a_i - A$$

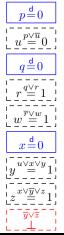
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Note: constraint can be conflicting though not all variables assigned

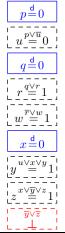
Consider example CDCL conflict analysis from SAT solving lecture

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



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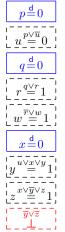
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Assignment "left on trail" always falsifies derived clause

Consider example CDCL conflict analysis from SAT solving lecture

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

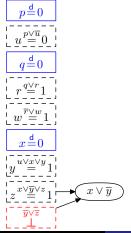


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```
\overline{y} \vee \overline{z} falsified by
  trail \rho = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}, y, z\}
Conflict-Driven Pseudo-Boolean Solving
```

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

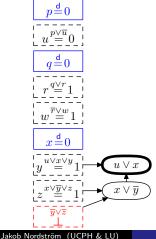


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```
x \vee \overline{y} falsified by
\mathsf{trail}\check{\rho}' = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}, y\}
\overline{u} \vee \overline{z} falsified by
trail \rho = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}, y, z\}
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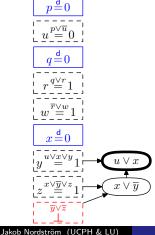
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```
u \vee x falsified by
trail \rho'' = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}\}
x \vee \overline{y} falsified by
\mathsf{trail}\check{\rho}' = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}, y\}
\overline{u} \vee \overline{z} falsified by
```

trail $ho = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}, y, z\}$

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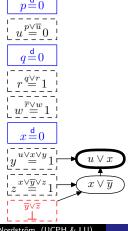
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⇒ derived clause "explains" conflict

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 $u \vee x$ falsified by trail $\rho'' = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}\}$ $x \vee \overline{y}$ falsified by $\mathsf{trail}\check{\rho}' = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}, y\}$ $\overline{u} \vee \overline{z}$ falsified by trail $ho = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}, y, z\}$

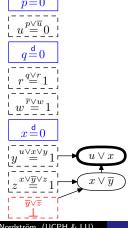
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⇒ derived clause "explains" conflict

Terminate analysis when explanation "looks nice"

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 $u \lor x$ falsified by trail $\rho'' = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}\}$ $x \lor \overline{y}$ falsified by trail $\rho' = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}, y\}$ $\overline{y} \lor \overline{z}$ falsified by trail $\rho = \{\overline{p}, \overline{u}, \overline{q}, r, w, \overline{x}, y, z\}$

Assignment "left on trail" always falsifies derived clause

⇒ derived clause "explains" conflict

Terminate analysis when explanation "looks nice"

Namely: after backjump, some variable guaranteed to flip

Generalized Resolution

Can mimic resolution step

$$\frac{x \vee \overline{y} \vee z \qquad \overline{y} \vee \overline{z}}{x \vee \overline{y}}$$

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by adding clauses as pseudo-Boolean constraints

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(Recall
$$z + \overline{z} = 1$$
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(Recall
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Generalized resolution rule (from [Hoo88, Hoo92])

Positive linear combination so that some variable cancels

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

Actually, not quite the right constraint in mimicking of resolution

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Saturation rule

$$\frac{\sum_{i} a_{i} \ell_{i} \ge A}{\sum_{i} \min\{a_{i}, A\} \cdot \ell_{i} \ge A}$$

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

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

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

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

 $C_2 \doteq 2\overline{x}_1 + 2\overline{x}_2 + 2\overline{x}_3 \ge 3$

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Trail $\rho = \{x_1 \stackrel{d}{=} 0, x_2 \stackrel{C_1}{=} 1, x_3 \stackrel{C_1}{=} 1\} \Rightarrow \text{Conflict with } C_2$ (Note: same constraint can propagate several times!)

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$$\frac{2x_1 + 2x_2 + 2x_3 + x_4 \ge 4}{x_4 \ge 1} \quad \frac{2\overline{x}_1 + 2\overline{x}_2 + 2\overline{x}_3 \ge 3}{2\overline{x}_1 + 2\overline{x}_2 + 2\overline{x}_3 \ge 3}$$

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• Applying saturate($x_4 \ge 1$) does nothing

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- Applying saturate($x_4 \ge 1$) 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

•
$$C_1 \doteq 2x_1 + 2x_2 + 2x_3 + x_4 \ge 4$$
 propagates $x_3 \ge \frac{1}{2}$

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Remedial action

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

weaken
$$(\sum_i a_i \ell_i \ge A, \ell_j) \doteq \sum_{i \ne j} a_i \ell_i \ge A - a_j$$

to reason constraint and then saturate

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

Try to Reduce the Reason Constraint

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

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Let's try to

- Weaken reason on non-falsified literal (but not last propagated)
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Bummer! Still non-negative slack — not conflicting

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$$\text{weaken } \{x_2, x_4\} \frac{2x_1 + 2x_2 + 2x_3 + x_4 \geq 4}{\text{saturate}} \\ \frac{2x_1 + 2x_3 \geq 1}{x_1 + x_3 \geq 1} \\ \text{resolve } x_3 \frac{2\overline{x}_1 + 2\overline{x}_2 + 2\overline{x}_3 \geq 3}{2\overline{x}_2 \geq 1}$$

Negative slack — conflicting! Shows setting x_2 true was a mistake

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Backjump propagates to conflict without solver making any decisions **Done!** Next conflict analysis will derive contradiction (Or, in practice, terminate immediately at conflict without decisions)

```
 \begin{split} & \text{reduceSat}(C_{\text{reason}}, C_{\text{learn}}, \ell, \rho) \\ & \text{1} \quad \text{while} \ slack(\text{resolve}(C_{\text{learn}}, C_{\text{reason}}, \ell); \rho) \geq 0 \ \text{do} \\ & \text{2} \quad \left| \quad \ell' \leftarrow \text{literal in } C_{\text{reason}} \setminus \{\ell\} \ \text{not falsified by } \rho; \\ & \text{3} \quad \left| \quad C_{\text{reason}} \leftarrow \text{saturate}(\text{weaken}(C_{\text{reason}}, \ell')); \\ & \text{4} \quad \text{return } C_{\text{reason}}; \end{split}
```

```
reduceSat(C_{\mathrm{reason}}, C_{\mathrm{learn}}, \ell, \rho)

1 while slack(\text{resolve}(C_{\mathrm{learn}}, C_{\mathrm{reason}}, \ell); \rho) \geq 0 do

2 \ell' \leftarrow \text{literal in } C_{\mathrm{reason}} \setminus \{\ell\} \text{ not falsified by } \rho;

3 C_{\mathrm{reason}} \leftarrow \text{saturate}(\text{weaken}(C_{\mathrm{reason}}, \ell'));

4 return C_{\mathrm{reason}}:
```

Why does this work?

Slack is subadditive

$$slack(c \cdot C + d \cdot D; \rho) \le c \cdot slack(C; \rho) + d \cdot slack(D; \rho)$$

```
\mathsf{reduceSat}(C_{\mathsf{reason}}, C_{\mathsf{learn}}, \ell, \rho)
```

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 ho)$ unchanged
- Saturation decreases slack hit 0 when max #literals weakened

Pseudo-Boolean Conflict Analysis Pseudocode

```
analyze PB conflict (\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 \bot do
              \ell \leftarrow literal assigned last on trail \rho;
              if \ell propagated and \ell occurs in C_{\text{learn}} then
                    C_{\text{reason}} \leftarrow \text{reason}(\ell, \rho, \mathcal{D});
                    C_{\text{reason}} \leftarrow \text{reduceSat}(C_{\text{reason}}, C_{\text{learn}}, \ell, \rho);
                    C_{\text{learn}} \leftarrow \mathsf{resolve}(C_{\text{learn}}, C_{\text{reason}}, \ell);
                C_{\text{learn}} \leftarrow \text{saturate}(C_{\text{learn}});
          \rho \leftarrow \rho \setminus \{\ell\};
10 return C_{\text{learn}};
```

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

Some Problems Compared to CDCL

 Compared to clauses harder to detect propagation for constraints like

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

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 Compared to clauses harder to detect propagation for constraints like

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

- Generalized resolution for general pseudo-Boolean constraints
 - \Rightarrow 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 as defined in theory literature [CCT87] doesn't use saturation but instead division (a.k.a. Chvátal-Gomory cut)

Literal axioms
$$\overline{-\ell_i \geq 0}$$
 Linear combination $\overline{\sum_i a_i \ell_i \geq A} \quad \sum_i b_i \ell_i \geq B$ $\overline{\sum_i (c_A a_i + c_B b_i) \ell_i \geq c_A A + c_B B}$ Division $\overline{\sum_i a_i \ell_i \geq A}$ $\overline{\sum_i [a_i/c] \ell_i \geq [A/c]}$

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

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 Linear combination $\cfrac{\sum_i a_i \ell_i \geq A}{\sum_i (c_A a_i + c_B b_i) \ell_i \geq c_A A + c_B B}$

Division
$$\frac{\sum_{i} a_{i} \ell_{i} \geq A}{\sum_{i} \lceil a_{i} / c \rceil \ell_{i} \geq \lceil A / c \rceil}$$

- Cutting planes with division implicationally complete
- Cutting planes with saturation is **not** [VEG⁺18]
- Can division yield stronger conflict analysis?
 (Used for integer linear programming in CutSat [JdM13])

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

 $C_2 \doteq 2\overline{x}_1 + 2\overline{x}_2 + 2\overline{x}_3 \ge 3$

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

Terminate immediately!

```
\begin{split} & \operatorname{reduceDiv}(C_{\operatorname{reason}}, C_{\operatorname{learn}}, \ell, \rho) \\ & \quad 1 \ c \leftarrow coeff(C_{\operatorname{reason}}, \ell); \\ & \quad 2 \ \text{while} \ slack(\operatorname{resolve}(C_{\operatorname{learn}}, \operatorname{divide}(C_{\operatorname{reason}}, c), \ell); \rho) \geq 0 \ \text{do} \\ & \quad 3 \quad \left| \begin{array}{c} \ell_j \leftarrow \operatorname{literal} \ \operatorname{in} \ C_{\operatorname{reason}} \setminus \{\ell\} \ \operatorname{such} \ \operatorname{that} \ \bar{\ell}_j \notin \rho \ \operatorname{and} \ c \nmid coeff(C, \ell_j); \\ & \quad 4 \quad \left| \begin{array}{c} C_{\operatorname{reason}} \leftarrow \operatorname{weaken}(C_{\operatorname{reason}}, \ell_j); \\ & \quad 5 \ \operatorname{return} \ \operatorname{divide}(C_{\operatorname{reason}}, c); \\ \end{split}
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- Sufficient to get reason with slack 0 since
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- Slack same after weakening \Rightarrow always $0 \le slack(C_{\text{reason}}; \rho) < c$
- After max #weakenings have $0 \le slack(divide(C_{reason}, c); \rho) < 1$

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+20]
- And still equally hard to detect propagation
- Also, still degenerates to resolution for CNF inputs
- Sometimes very poor performance even on infeasible 0-1 LPs!

- ONF: PB solvers degenerate to CDCL for CNF inputs how to harness power of cutting planes in this setting?
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 - Use presolver PAPILO [PaP] from mixed integer linear programming (MIP) solver SCIP [SCI]?
- Robustness: Make PB solvers less sensitive to presence of extra constraints (anecdotally, CDCL solvers seem more stable)

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- Choice of Boolean rule:
 - Division, saturation, or select adaptively?
 - Or some other cut rule from ILP?
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- Oconstraint minimization à la [SB09, HS09]?
- How to assess quality of learned constraints?
- **⑤** Theoretical potential & limitations poorly understood [VEG⁺18]
 - Separations in power between different methods of PB reasoning?
 - In particular, is division-based reasoning stronger than saturation-based reasoning? [GNY19]

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

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- Oblifferent "modes" for SAT-focused and UNSAT-focused search?

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

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- Efficient detection of assertiveness during conflict analysis

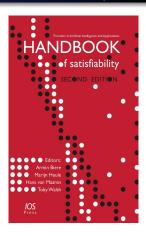
Some PB Solving Challenges IV: Efficiency and Correctness

- Efficient unit propagation for PB constraints is a major challenge
 latest news in [Dev20], but still much left to do
- Efficient detection of assertiveness during conflict analysis
- Efficient and concise proof logging for pseudo-Boolean solving (shameless self-plug: ongoing work on pseudo-Boolean proof checker VERIPB [Ver, GMN20b] in [EGMN20, GMN20a, GMM+20, GN21, BGMN22, GMNO22])

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
- Chapter 28: Pseudo-Boolean and Cardinality Constraints



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Video tutorials on pseudo-Boolean solving

From the Satisfiability: Theory, Practice, and Beyond program at UC Berkeley in spring 2021 https://tinyurl.com/PBSATtutorial [Try to cover as much of this as possible today]



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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