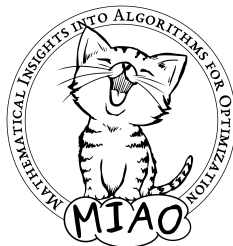


Certified Core-Guided MaxSAT Solving

Andy Oertel

Lund University and
University of Copenhagen

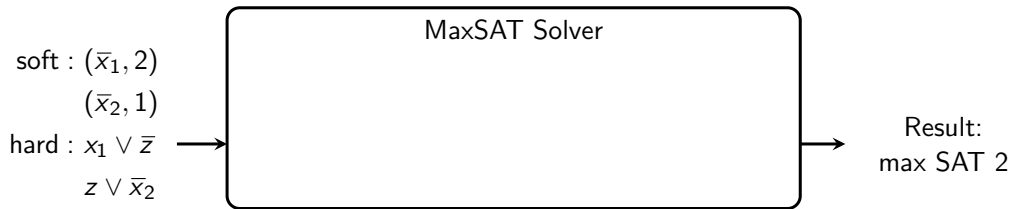


Extended Reunion: Satisfiability 2023

April 24, 2023

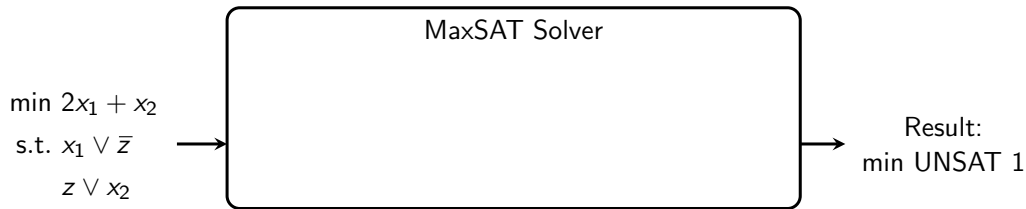
Joint work with Jeremias Berg, Bart Bogaerts, Jakob Nordström and Dieter Vandesande

Maximum Satisfiability (MaxSAT) Solving



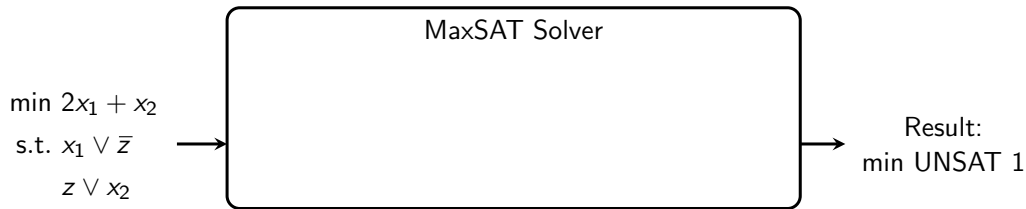
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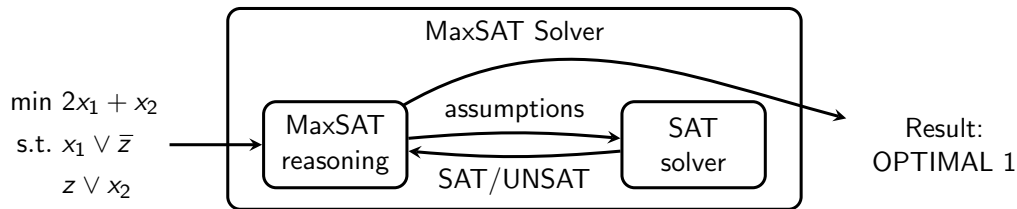
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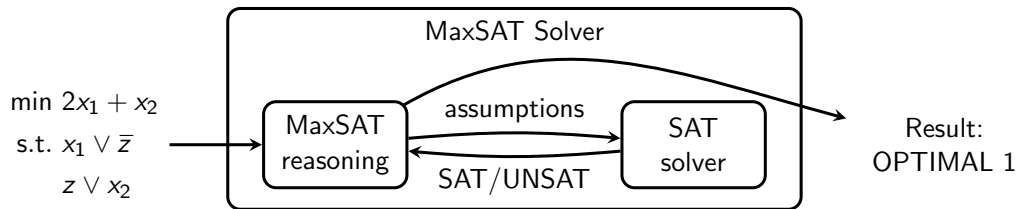
- ▶ Maximize sum of weight of satisfied soft clauses subject to satisfying hard clauses
- ▶ Alternatively: Minimize linear objective subject to satisfying a CNF formula
- ▶ Main approaches:
 - ▶ Solution-improving or linear SAT-UNSAT search [ES06, LP10, PRB18]
 - ▶ Implicit hitting set (IHS) search [DB13a, DB13b]
 - ▶ **Core-guided search** [FM06, NB14, ADR15, AG17]

Core-Guided MaxSAT Solving



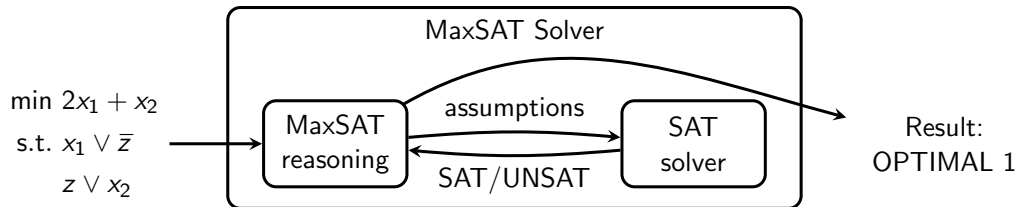
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Core-Guided MaxSAT Solving



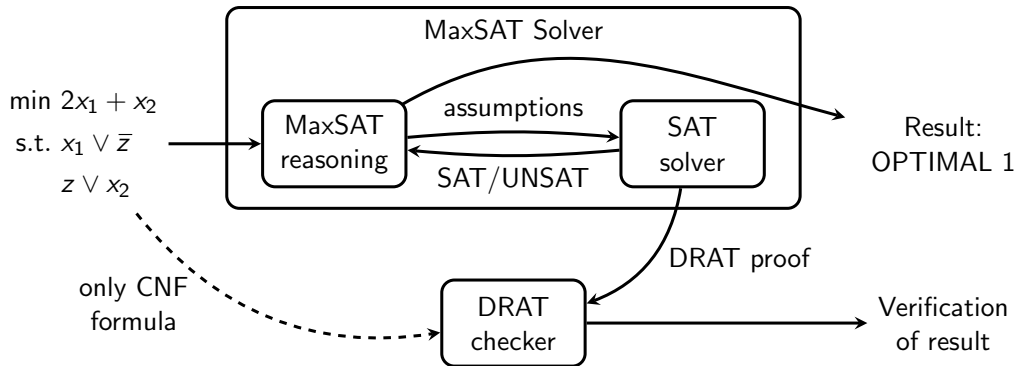
- ▶ Call SAT solver with optimistic assumptions (assignment to objective variables)
- ▶ If UNSAT, SAT solver returns core clause over assumptions explaining UNSAT
 - ▶ Reformulate objective, relax assumptions, increase lower bound
- ▶ If SAT, optimal solution found

Correctness of Core-Guided MaxSAT Solving



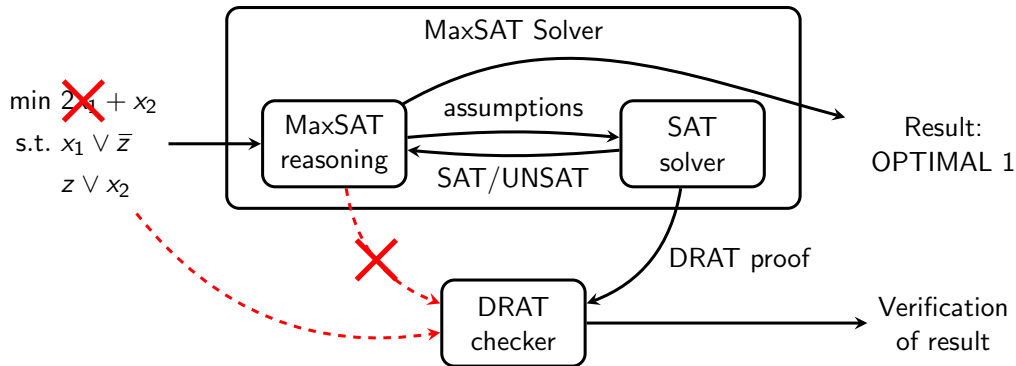
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- ▶ Know cases of buggy MaxSAT solvers in MaxSAT evaluation
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- ▶ **Core-guided MaxSAT reasoning not certified!**

Pseudo-Boolean (PB) Proof Logging

- ▶ **Multi-purpose** proof format
- ▶ Allows easy proof logging for
 - ▶ Reasoning with pseudo-Boolean constraints (by design)
 - ▶ SAT solving (including advanced techniques) [GN21, BGMN22]
 - ▶ Constraint programming [EGMN20, GMN22]
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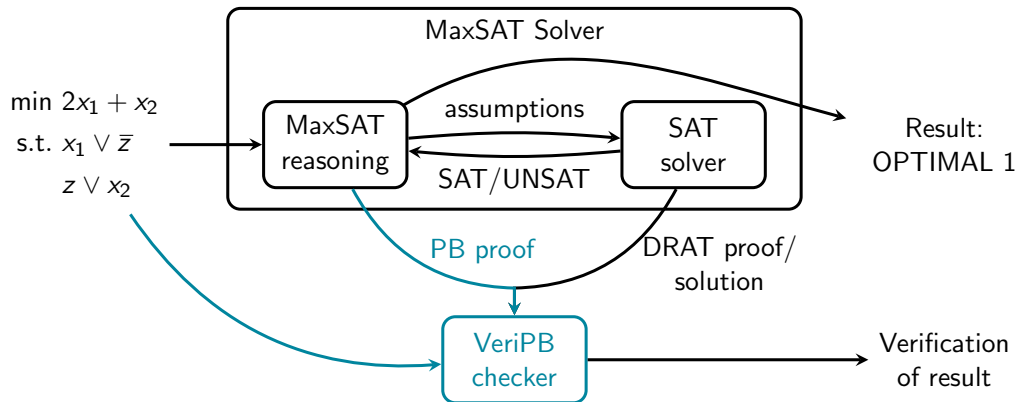
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This work:

- ▶ Proof logging for state-of-the-art core-guided MaxSAT solving [IMM19, IBJ21]

Workflow



- Single PB proof that interleaves MaxSAT reasoning and SAT solver proof

Basic Notation

- ▶ **Boolean variable x :** with domain 0 (false) and 1 (true)
- ▶ **Literal ℓ :** x or negation $\bar{x} = 1 - x$
- ▶ **Pseudo-Boolean (PB) constraint:** integer linear inequality over literals

$$3x_1 + 2x_2 + 5\bar{x}_3 \geq 5$$

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- ▶ **Pseudo-Boolean equality constraint:** syntactic sugar for 2 inequalities

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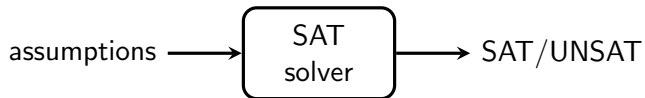
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- ▶ **Clause:** disjunction of literals / at-least-one constraint

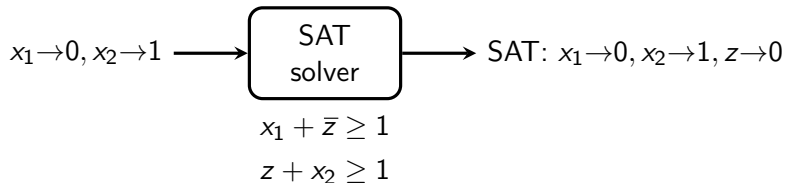
$$x_1 \vee \bar{x}_2 \vee \bar{x}_3 \iff x_1 + \bar{x}_2 + \bar{x}_3 \geq 1$$

Calling SAT Solver with Assumptions



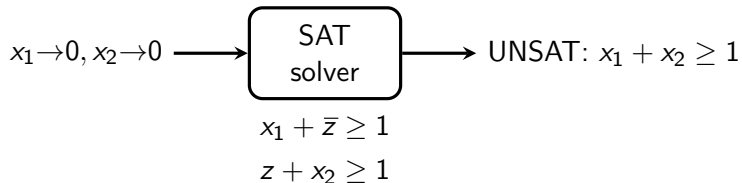
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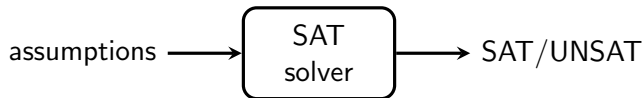
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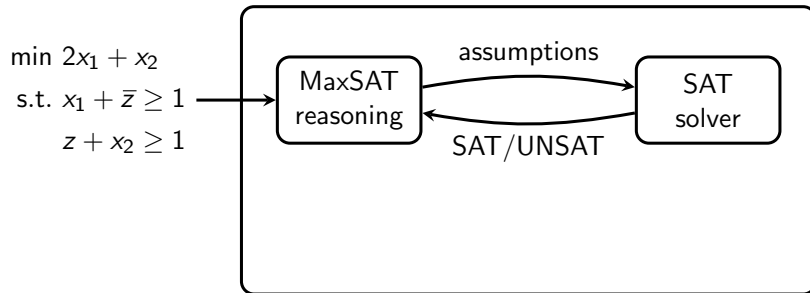
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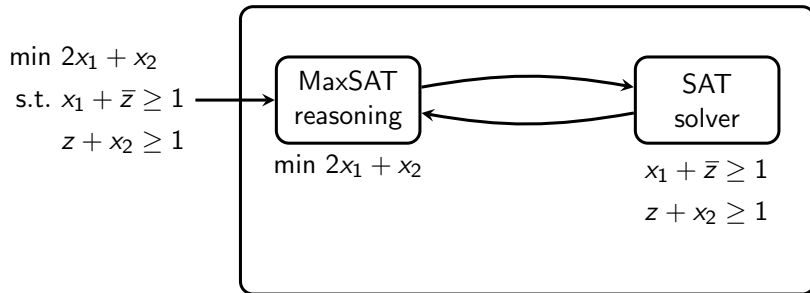


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- ▶ Supported by modern SAT solvers

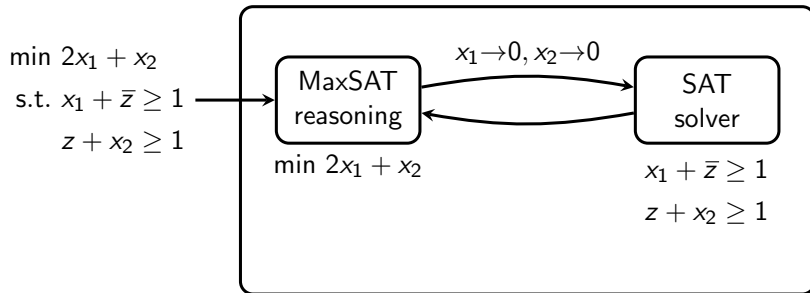
OLL-Style Core-Guided MaxSAT Solving [MDM14]



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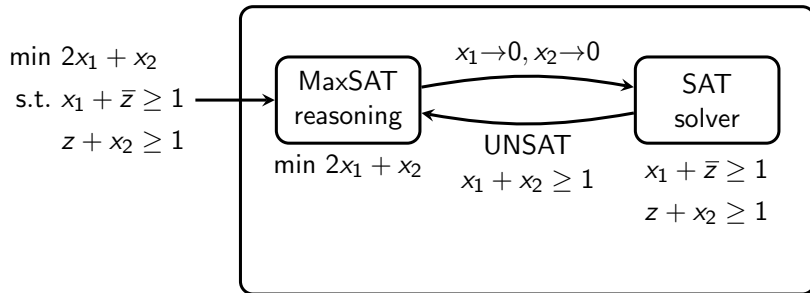


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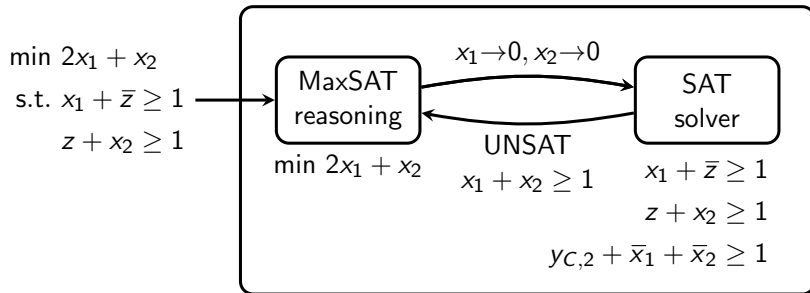
- Call with assumptions $x_1 \rightarrow 0, x_2 \rightarrow 0$

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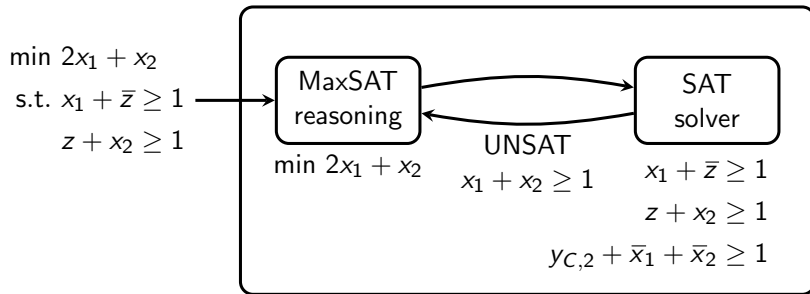
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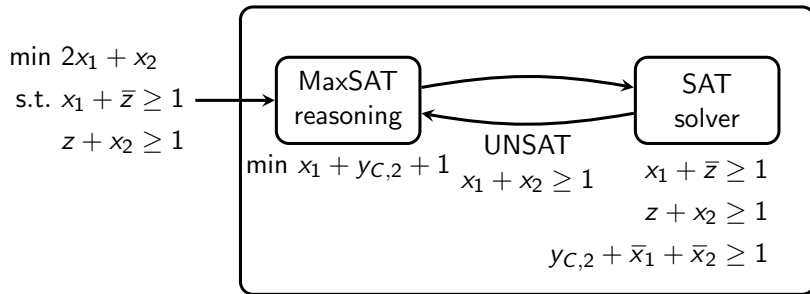
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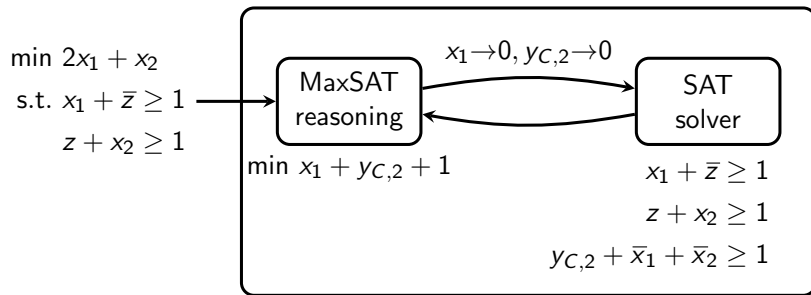
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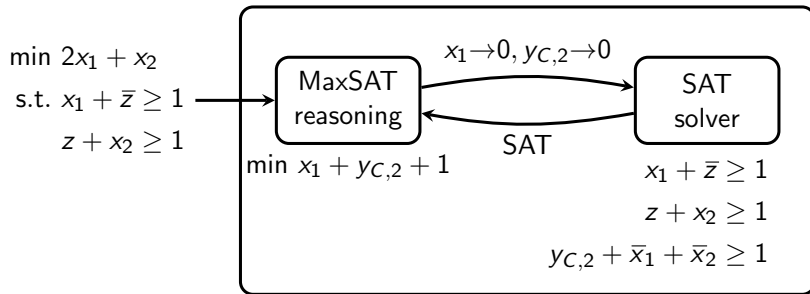
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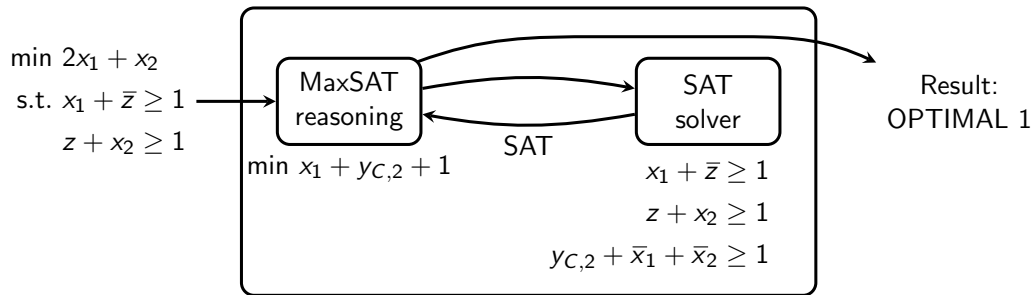
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- ▶ Optimal solution found with value 1

Our Work: Correctness of Algorithm

- ▶ State-of-the-art solvers are way more complex [IMM19, IBJ21]
- ▶ Algorithm correct in theory [AKMS12, MDM14]
- ▶ But did we implement it correctly?

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Verification of core-guided MaxSAT solving!

Cutting Planes Proof System [CCT87]

Rules:

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$$\text{Addition } \frac{x_1 + 2\bar{x}_2 + 2\bar{x}_3 \geq 3 \quad \bar{x}_2 + 3x_3 \geq 3}{x_1 + 3\bar{x}_2 + x_3 \geq 4}$$

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Extended Cutting Planes: Reification

- **Reification** (special case of redundance rule in [GN21, BGMN22])

$$a \Leftrightarrow x_1 + \bar{x}_2 + 2x_3 \geq 2 \longrightarrow \begin{array}{ll} 2\bar{a} + x_1 + \bar{x}_2 + 2x_3 \geq 2 & (a \Rightarrow x_1 + \bar{x}_2 + 2x_3 \geq 2) \\ 3a + \bar{x}_1 + x_2 + 2\bar{x}_3 \geq 3 & (a \Leftarrow x_1 + \bar{x}_2 + 2x_3 \geq 2) \end{array}$$

- Variable a was not used in proof so far

Roadmap to Certifying Core-Guided MaxSAT

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If SAT solver returns UNSAT:

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$$\text{core: } x_1 + x_2 \geq 1$$

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If SAT solver returns SAT:

- ▶ Solution is recorded in the proof

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$$\begin{aligned}
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 \end{aligned}$$

- ▶ Encode constraints from PB to CNF using totalizers
- ▶ Output of totalizers are counter variables
- ▶ Prove that clausal encoding follows from PB definition as in [GMNO22, VDB22]

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$$\bar{y}_{C,1} + x_1 + x_2 \geq 1$$

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Objective Reformulation (Simplified Version)

- ▶ Maintain invariance $f_{orig} = f_{reform}$ as constraint
- ▶ For each core derive reformulation due to this core [GMNO22]

$$\min 2x_1 + x_2 \quad C : x_1 + x_2 \geq 1 \quad \Longrightarrow \quad \min x_1 + y_{C,2} + 1$$

$$\bar{x}_1 + \bar{x}_2 \geq 0$$

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- ▶ Add reformulation due to each core together to get $f_{orig} = f_{reform}$

Roadmap to Certifying Core-Guided MaxSAT

1. Record solution in proof to establish upper bound UB ✓
2. Establish lower bound LB ✓
 - ▶ Prove objective function reformulation (which contains LB) ✓
 - ▶ Show that core clauses are valid ✓
 - ▶ Introduce clauses defining counter variables ✓
3. Obtain proof of optimality if $LB = UB$

Proving Optimality

- **Idea:** Finding a better solution than the optimal solution is contradicting

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min $2x_1 + x_2$ and solution: $x_1 \rightarrow 0, x_2 \rightarrow 1$

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- ▶ The result is contradicting

Certifying Advanced Techniques

- ▶ State-of-the-art core-guided MaxSAT solvers use additional techniques
 - ▶ Intrinsic at-most-one constraints [IMM19]
 - ▶ Hardening [ABGL12]
 - ▶ Lazy counter variables [MJML14]
- ▶ Proof logging also required for these techniques

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Very convenient with pseudo-Boolean reasoning!

Experiments

- ▶ Implemented certifying version of state-of-the-art solver CGSS¹ [IBJ21]
- ▶ Proof checked with proof checker VERIPB²
- ▶ Benchmarks from MaxSAT Evaluation 2022³
 - ▶ 607 unweighted instances and 594 weighted instances

¹<https://gitlab.com/MIAOresearch/software/certified-cgss>

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First result:

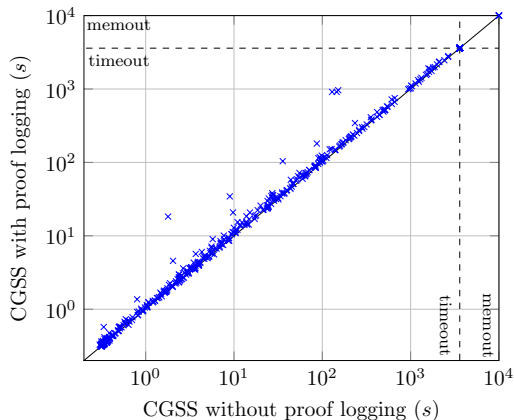
- ▶ Discovered bug in RC2 on which CGSS is based
 - ▶ Optimal solution correct for all instances in our set, but reasoning sometimes wrong
 - ▶ Can lead to solver claiming optimality for non-optimal solution

¹<https://gitlab.com/MIAOresearch/software/certified-cgss>

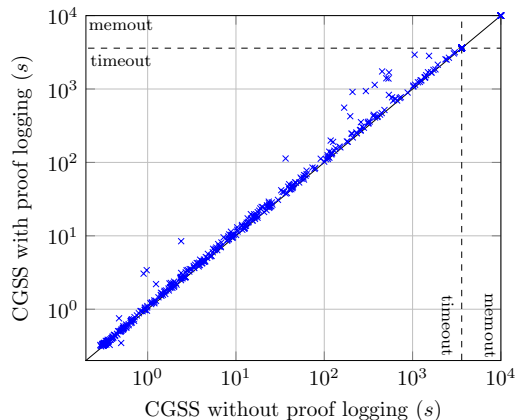
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Overhead for Proof Logging in Seconds



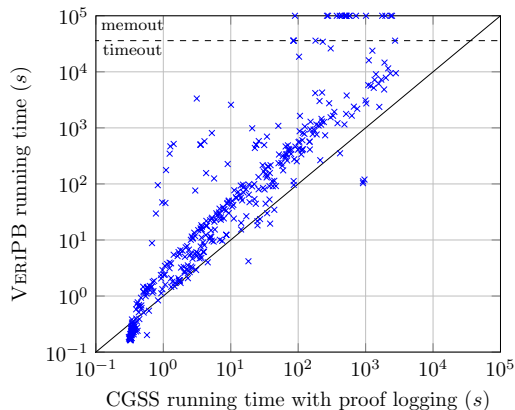
(a) Unweighted instances.



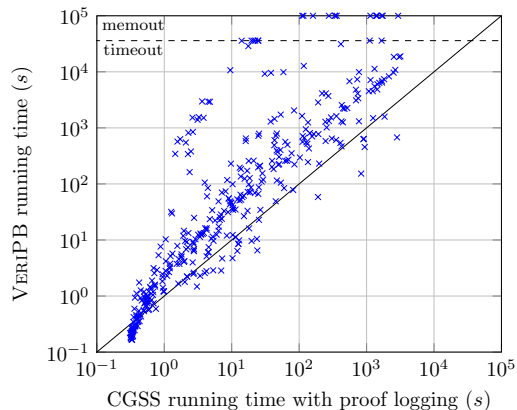
(b) Weighted instances.

- Low proof logging overhead (6.5% overhead in median)

Solving versus Checking in Seconds



(a) Unweighted instances.



(b) Weighted instances.

- Checking time could be improved (VERIPB not optimized for SAT solver proofs)

Future Work

Further proof logging:

- ▶ State-of-the-art linear SAT-UNSAT search solver (like Pacose)
- ▶ Implicit hitting set MaxSAT solver
 - ▶ Fundamental challenge: proof logging for MIP solver
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Improving performance:

- ▶ Optimize VERIPB for SAT solver proofs
- ▶ Backwards checking/trimming for verification (as in DRAT-trim [HHW13a])

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Sounds interesting? Join us! We are hiring!

Conclusion

- ▶ MaxSAT: successful optimization paradigm, but without proof logging
- ▶ DRAT not sufficient, but PB reasoning supports MaxSAT proof logging
- ▶ **This work:** Proof logging for state-of-the-art core-guided MaxSAT solving
- ▶ Hopefully step towards general adoption of proof logging for MaxSAT

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Pseudo-Boolean reasoning provides unified proof logging method for:

- ▶ SAT solving (including advanced techniques) [GN21, BGMN22]
- ▶ Constraint programming [EGMN20, GMN22]
- ▶ Subgraph problems [GMN20, GMM⁺20]
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Thank you for your attention!

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