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Search

SAT - NP hard

• Intractable in worst-case

SAT Solvers

- Solve real world instances with millions of variables
- often run in near-linear time!
- Used in model checking, planning, bioinformatics, etc.

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Conflict-Driven Clause Learning (CDCL)

- Basis of state-of-the-art solvers
- Based on *Davis–Putnam–Logemann–Loveland (DPLL)* algorithm [DP60, DLL62] augmented with fine-tuned heuristics









$\mathcal{F} = (x_1 \lor x_2) \land (\bar{x}_1 \lor x_2) \land (x_1 \lor \bar{x}_2) \land (\bar{x}_1 \lor \bar{x}_2)$



Proof of unsatisfiability!

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Proof of unsatisfiability!

SAT solvers run on unsatisfiable CNFs output proofs.

- Proof complexity analysis applies to SAT solvers
- proof size = runtime of ideal implementation of search algorithm

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DPLL proofs=tree-like Resolution proofsQuery basedRule based

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 DPLL proofs
 =
 tree-like Resolution proofs

 Query based
 Rule based

CDCL augments DPLL with heuristics, clause learning, restarts, etc.

- Proofs still captured by Resolution
 - Weak proof system, cannot count

PseudoBoolean SAT Solvers

Reason about integer-linear inequalities rather than clauses

Most are based on Cutting Planes proof system

stronger proof system than Resolution

Worse performance than state-of-the-art solvers based on DPLL

Puzzle

Why is can't we develop good search algorithms based on stronger proof systems?

Many strong proof systems for which we can theoretically find proofs quickly.

• e.g. polynomial calculus

Best SAT algorithms based on DPLL

• DPLL can't even count, no gaussian elimination!

Puzzle

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Hypothesis:

Querying is more conducive to search algorithms

- Leads to simple divide-and-conquer style algorithms
- DPLL vs tree-like Resolution



Generalization of DPLL to reason about integerlinear inequalities, formalized as a proof system























 $\mathcal{F} = \{$ unsatisfiable set of linear inequalities $\}$ Variables $x, y \in [0, 1]$

Complexity measures

Size: Number of nodes

Depth: Tree-depth

SP Generalizes DPLL

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 $\mathcal{F} = \{x_1 + x_2 \ge 1, x_1 - x_2 \ge 0, x_2 - x_1 \ge 0, -x_1 - x_2 \ge -1\}$ Variables $x_1, x_2 \in [0, 1]$

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Polynomially equivalent to a *tree-like* variant of the R(CP) proof system introduced in [Krajíček98]

- R(CP) rule based
- Stabbing Planes query based

Query-based viewpoint valuable for upper bounds.

Theorem: Quasi-polynomial size SP proof of any system of linear equations over a finite field

Input: Unsatisfiable system of mod 2 linear equations

over $\{0, 1\}$ assignments

Input: Unsatisfiable system of mod 2 linear equations =>Exists subset which sum to $0 = 1 \mod 2$

Idea: Split set of constraints in half. For any $\{0, 1\}$ assignment, one of the halves has a falsified equation.

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$$\sum_{C_i \in S_1} \ge k \text{ for } k = 1, \dots, \max$$

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Suppose: $x_3 + x_7 \equiv 0 \mod 2$ $x_1 \ x_2 \ x_3 \ x_4 \ x_5 \ x_6 \ x_7$ C_1 1 1 0 1 1 0 0 1 C_2 0 1 0 0 1 1 0 () C_3 1 0 1 1 0 1 1 1 $\mod 2$ 1 1 0 1 1 C_A 1 1 () C_5 0 0 1 0 0 1 0 ()1 1 0 1 C_6 1 0 \mathbf{O}

Recurse

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- 3. Recurse on set whose sum is not satisfied

Suppose:

$$\begin{array}{c} x_1 + x_2 + x_3 + x_4 + x_5 + x_7 \equiv 0 \mod 2 \\ x_1 + x_2 + x_4 + x_5 \equiv 0 \mod 2 \end{array}$$

Recurse

Termination:

By recursive step we have derived $x_1 + x_2 + x_4 + x_5 \equiv 0 \mod 2$ Using the constraint $x_1 + x_2 + x_4 + x_5 \equiv 1 \mod 2$ we can derive $0 \ge 1$

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Analysis:

Each recursive step requires branches O(n) $O(\log n)$ recursive steps - Reduce the set of constraints by half each time

Other Results

SP can solve systems of linear equations over a finite field

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- size s CP proof \Rightarrow size O(s) SP proof
- Surprising because SP is tree-like, while CP is DAG-lik

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- Surprising, SP proofs are tree-like, while CP proofs are DAG-like

$\Omega(n/\log^2 n)$ depth lower bound

- reduction to real communication complexity
- same technique cannot give size lower bounds
 - real communication protocols can't be balanced,
 - SP proofs can't be balanced

Open Problem

Super-polynomial size lower bounds on SP?

Does SP proof size (#nodes) equal SP proof bit-size?

• [Muroga72] Any integer-linear inequality separating two subsets U,V subset $\{0,1\}^n$ can be represented by poly(n) bits

Separate Cutting Planes and Stabbing Planes

Candidate: Tseitin formulas

SP-based search algorithms?