

Example 1 shows a larger formula that is *unsatisfiable*—that is, not satisfied by any assignment. The focus on CNF formulas is not a restriction. The so-called Tseitin transformation³⁹ efficiently transforms any propositional formula into CNF without affecting its satisfiability.

$$\begin{aligned}
 & \overbrace{(x_1 \vee \neg x_2)}^{c_1} \wedge \overbrace{(x_1 \vee \neg x_3)}^{c_2} \wedge \overbrace{(x_1 \vee \neg x_8)}^{c_3} \wedge \overbrace{(x_1 \vee \neg x_7)}^{c_4} \wedge \\
 & \overbrace{(\neg x_4 \vee x_3)}^{c_5} \wedge \overbrace{(\neg x_5 \vee \neg x_6)}^{c_6} \wedge \overbrace{(\neg x_2 \vee \neg x_3 \vee x_4)}^{c_7} \wedge \\
 & \overbrace{(\neg x_4 \vee x_6 \vee x_9)}^{c_8} \wedge \overbrace{(\neg x_3 \vee \neg x_7 \vee x_8)}^{c_9} \wedge \overbrace{(x_1 \vee x_8)}^{c_{10}} \wedge \overbrace{(x_1 \vee x_7)}^{c_{11}} \wedge \\
 & \overbrace{(x_4 \vee x_5 \vee \neg x_1)}^{c_{12}} \wedge \overbrace{(x_4 \vee \neg x_6 \vee \neg x_1)}^{c_{13}} \wedge \overbrace{(\neg x_6 \vee \neg x_4 \vee \neg x_1)}^{c_{14}} \wedge \\
 & \overbrace{(x_6 \vee \neg x_7 \vee \neg x_1)}^{c_{15}} \wedge \overbrace{(\neg x_7 \vee x_6 \vee \neg x_1)}^{c_{16}} \wedge \overbrace{(x_7 \vee x_6 \vee \neg x_1)}^{c_{17}} \wedge
 \end{aligned}$$

Figure. Example 1. Under each of the 2^9 truth assignments to the variables x_1, \dots, x_9 , at least one of G 's clauses evaluates to 0, making the formula G unsatisfiable.*

At first glance, the SAT problem looks inconspicuous since it is simple to state, does not look difficult to solve, and seems uninteresting for practical purposes. Still, Stephen Cook⁷ and Leonid Levin²⁹ showed independently in the 1970s that SAT is NP-complete, making it the first NP-complete problem. So, suppose one could solve SAT in polynomial time on arbitrary input. In that case, one could also solve any NP-complete problem in polynomial time, and it would follow that P equals NP. Thus, in terms of worst-case complexity theory, SAT embodies computational hardness. Also, in modern complexity theory, SAT continues to serve as a hard benchmark problem in the form of the (Strong) Exponential Time Hypothesis.⁴

In stark contrast to its theoretical worst-case hardness, the SAT problem has emerged as an essential instrument for efficiently solving a wide variety of computational problems, ranging from hardware and software verification to planning, combinatorial design, and software dependency.^{1,4} In this way, SAT significantly impacts today's technological innovation. SAT is widely applied in knowledge representation, reasoning,¹⁹ and artificial intelligence (AI).⁹ Although SAT is mainly associated with symbolic AI, it contributes to non-symbolic AI by providing model-counting algorithms, which are essential tools for probabilistic reasoning,⁹ and allocates a main backbone for neurosymbolic AI.²⁴ Notably, using SAT, long-standing open problems in mathematical combinatorics were successfully solved—for example, the Pythagorean Triples Problem.^{4,21} Solving such challenging problems with SAT requires the ability to efficiently translate the original problem into an instance of the SAT problem and the availability of computer programs, called *SAT solvers*, which efficiently evaluate SAT instances. Initial progress in practical SAT solving began in the early 1990s, leading to a breakthrough around the millennium. The last two decades have brought further enormous technological advancement and innovation to SAT solving. Today, SAT solvers are so powerful and robust that they have become primary tools for solving hard computational problems. Solvers have been embedded into complex procedures to solve more complex problems, such as optimization problems (MaxSAT, Pseudo-Boolean Optimization) or quantified satisfiability (QSAT).

"The story of satisfiability is the tale of a triumph of software engineering, blended with rich doses of beautiful mathematics," writes Donald E. Knuth in the preface to the second part of the fourth volume of *The Art of Computer Programming*,²⁸ which contains a section on satisfiability that stretches well over 300 pages.

As we observed incredible advances in computer hardware, yielding ever-faster processors, large and efficient memory, and massively parallel computing units, one could ask whether progress in SAT solving is the sole result of hardware advancement. A recent *Time Leap Challenge* addressed this question by running a race between 20-year-old SAT solvers on new computer hardware and modern SAT solvers on 20-year-old computer hardware.¹⁶ The experiments confirm Knuth's statement on engineering and mathematics. Although hardware improvements make old solvers faster, algorithmic progress dominates and drives today's SAT solving.

This article aims to shed light on the continuing progress of practical SAT solving through a series of evolutionary innovations and improvements that have been ongoing since the revolutionary breakthrough around the millennium. Overall, we argue that SAT has earned the title of a *silent (r)evolution*. We tell the story of SAT divided into three eras: the pre-revolution, the revolution, and the evolution.

[Back to Top](#)

Eras of Practical SAT Solving

perform conflict analysis and clause learning, which prominently drives the search. Modern SAT solvers use the *trail* data structure proposed by MiniSat¹³ to capture the search tree and the implication graph.

The second pillar was the CDCL-based solver Chaff,³² specially designed to solve large benchmark instances by taking the characteristics of the host computer into account and achieving an unprecedented balance between the sophistication of algorithms and data structures on the one side and the practical efficiency on the other. Chaff introduced the Watched Literal data structure, a "lazy" scheme for performing unit propagation that allowed cost-free backtracking. The branching heuristics (VSIDS) and conflict analysis procedure were carefully designed with a new tradeoff between reasoning power and computation cost: The emphasis on recent conflicts leads to a locality-based search.

We illustrate CDCL for our running example in Example 4. Many conflict clauses are learned during the search, which is quite demanding on memory. Modern CDCL solvers frequently delete learned clauses and heuristically predict the ones to keep.⁴ Various heuristics, such as VSIDS,³² EVSIDS,¹³ or LRB,⁴ are available for optimizing the search and assigning the variables. Those heuristics impose low overhead, generate almost no cost for backtracking, and are updated when learning clauses. To escape unlucky search tree exploration during the search, solvers frequently unassign all variables and restart the search (but keep the learned clauses). Common heuristic schemes that decide when to restart are Luby or Rapid Restarts.⁴ Also, machine-learning techniques have been used to optimize heuristics.⁴ Still, more careful analysis is needed to better understand how the components of the solver and their interaction affect its overall efficiency.^{14,27}

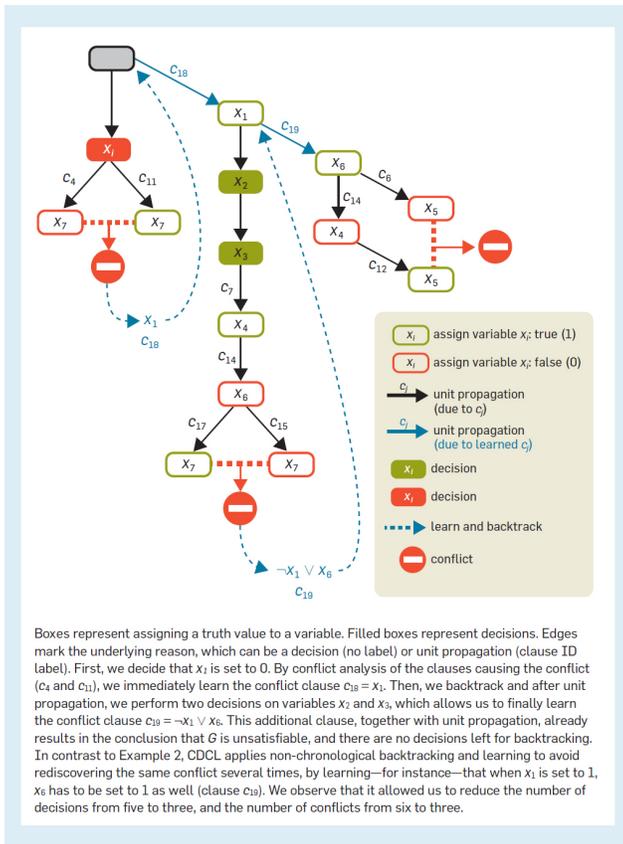


Figure. Example 4. Propagation Graph: Trace of a possible CDCL run on the formula G from Example 1.

Some critical applications drew much attention to practical SAT solving from academia and industry. For example, bounded model checking (BMC)⁴ provided numerous challenging benchmarks, which were soon tackled. BMC, which checks the correctness of sequential systems over a bounded number of steps, was proposed after the failure of standard model checking with binary decision diagrams (BDDs), a graph-based canonical representation of propositional formulas.⁶ The BMC benchmarks were extensive, with tens of thousands of variables and clauses. Combining conflict-driven heuristics with conflict analysis (CDCL) could solve BMC benchmarks up to two orders of magnitude faster than any other approach. These impressive results applied to other application benchmarks as well. The computer-aided verification (CAV) community acknowledged the central role of GRASP and Chaff for that outstanding progress by presenting their authors with the CAV 2009 award for "fundamental contributions to the development of high-performance Boolean satisfiability solvers."

Era III: The evolution. While improving solvers is an important goal, the community has progressed in new modeling techniques and methods for certifying results.

Efficient SAT encodings. It is challenging to express a computational problem as a CNF formula that the solver can solve efficiently. Encodings may blow up the resulting CNF formula quite notably, resulting in quadratic, cubic, or even worse overhead compared to the original problem instance. Usually, one faces a tradeoff between space and simplicity. Intuitively, one would try to keep the instance as small and concise as possible, balancing the number of variables and the number of clauses. If we have n variables and add m auxiliary variables, the potential search space grows from 2^n to 2^{n+m} . Still, in practice, adding such variables can reduce the number of clauses, thereby speeding up the search.⁴ A similar pattern was observed by early automatic test pattern-generation programs, such as path-oriented decision making (PODEM).⁴ This is particularly relevant when encoding properties that constrain the number of variables from a set of variables that must be set to 1, called *cardinality constraints*. We give a simple example in [Example 5](#).

Let H be a formula that contains many variables, say $v_1, v_2, \dots, v_{1000}$. Assume that for modeling purposes, we are interested in restricting the formula in such a way that at most one of these variables is allowed to be set to 1. We can achieve this by adding all the $\binom{1000}{2} = 499,500$ binary clauses $\neg v_i \vee \neg v_j, 1 \leq i < j \leq 1,000$; this generates a huge formula. However, we can avoid this quadratic space requirement and express the restriction much more succinctly with only a linear overhead. Namely, we can mimic well-known logic circuits that form binary adders with carryover bits in terms of clauses, involving the original variables v_i and additional auxiliary variables.

Figure. Example 5. Encoding techniques based on binary adders.³⁷

Assumptions. Using SAT solvers as "oracles" is far more complex in practice than just having an NP oracle in theoretical considerations. On the one hand, as successful as SAT solvers are, they are not NP oracles. SAT solvers need time for solving and may not even answer within a reasonable time. On the other hand, modern SAT solvers are more sophisticated than NP oracles. They admit *stateful* procedures, where clauses may be added or removed during solving. To control added clauses without invalidating learned clauses, modern solvers support *assumptions*, popularized by MiniSat,¹³ which are additional literals introduced for representing the state of clauses. It turned out that assumptions are highly versatile and useful. We demonstrate assumptions in [Example 6](#).

Think of a situation where a SAT solver has already solved a formula—for example, formula G from [Example 1](#). Now, assume that the application from which the formula arose changes, and suddenly clause c_7 is no longer present. Instead of solving the modified formula from scratch, SAT solvers can more efficiently handle such changes through *assumptions*. We can imagine the solver keeping a special assumption literal in each clause that indicates whether the clause should be disregarded. By default, these literals are assumed false, and therefore all clauses need to be satisfied. Typically, the SAT solver does not terminate after solving a formula but keeps its state and learned clauses. When we remove clause c_7 from G , the assumption literal corresponding to c_7 flips to true, which deactivates the clause. Since assumption literals are internally also considered for learned clauses, the learned clause c_{13} implicitly depends on c_7 . Retracting c_7 deactivates the learned clause, as it is already satisfied by the assumption literal. From [Example 4](#), we can see that the conflict in the middle disappears without clause c_7 . Instead, we can immediately construct a satisfying assignment. Thus, the already-spent effort on solving can be fruitfully used without re-solving the entire formula again, similar to how an experienced human proceeds when updating the search procedure with a pen on paper.

Figure. Example 6. Assumptions make our running formula satisfiable again.

Inprocessing/preprocessing. SAT solvers run various simplification rules to eliminate unnecessary variables or clauses. Several simplification rules exist; some can be carried out in linear time while others require quadratic time. Extremely beneficial is preprocessing, where the instance is simplified before the actual solver is started.⁴ Interestingly, one such preprocessing task is to run a restricted form of the Davis-Putnam

procedure on a subset of variables (bounded variable elimination). However, modern solvers such as Lingeling implement more sophisticated rules, which are run during the search before the next variables are assigned (inprocessing) and take learned clauses into account.⁴ More time-consuming inprocessing techniques such as equivalence learning, cardinality constraints, or parity detection can be applied with a limited budget and interleaved with search.

Parallel solving. In the 2000s, Moore's law started approaching its limits in CPU performance on single cores, and the clock-speed improvements for silicon-based chips started to slow down. Parallel computation was one way to compensate for this trend, and it found its way into consumer hardware. Around the same time, parallel computing also started to become more fashionable in SAT solving, aiming to improve overall processing performance and tackle huge instances.²¹ The two main techniques that evolved are *parallel-portfolio* and *divide-and-conquer* solving.

In parallel-portfolio solving, a problem instance is independently given to a collection of solvers competing for a solution in parallel. Usually, the collection comprises different solvers or one solver with different heuristics. While parallel SAT solvers optimize performance to solve large instances, they may produce different satisfying assignments or unsatisfiability proofs for a given input formula because they are inherently non-deterministic due to race conditions. Nevertheless, some recent parallel solvers achieve determinism with a reasonable runtime overhead. Determinism is critical for applications requiring reproducibility, such as scheduling or model checking. Over the last years, massive parallelization using graphics processing units (GPUs) or tensor processing units (TPUs) has become a popular approach in computer science and ML. Aspects of modern SAT solving have been successfully implemented and tested on GPUs, including solvers tailored for counting the number of satisfying assignments.¹⁷ Still, SAT solving has not yet benefited from massive parallelization.

Divide-and-conquer divides a formula into multiple formulas. The workload is shared among multiple solvers that run in parallel and can even synchronize learned clauses. However, modern sequential SAT solvers do not need to exhaust the search space to find a solution or refute a formula; learned clauses allow for shortcuts, making it hard to decompose instances because of the increased synchronization efforts for learned clauses. A popular version is *cube-and-conquer*, which partitions an instance by a look-ahead technique into up to a million sub-instances and then solves the sub-instances with a CDCL-based solver.²¹

Correctness of solvers and emitting proofs. The results of early SAT solvers were hard to validate. While it is easy to check whether an assignment returned by a solver satisfies the given formula, in the past, no technique was available to verify correctness if the solver claimed that an instance is unsatisfiable. During the first competitions, one could only check whether emitted assignments were correct and that solvers did not provide inconsistent results. If solver A outputs "satisfiable" and solver B outputs "unsatisfiable" on the same formula, one would check whether the assignment given by A indeed satisfies the formula. If so, solver B is incorrect; otherwise, solver A is incorrect, but nothing can be concluded about solver B. Solver correctness has been addressed by intensive testing, including fuzzing and asking for traces that give rise to an unsatisfiability proof within a dedicated propositional proof system.⁴ Such traces can be automatically checked using third-party tools, which can be specified, implemented, and fully verified. The relationship between CDCL runs and propositional proof systems is now well understood. All the relevant proof systems rely on the *resolution rule*, which derives a new clause from two clauses containing exactly one opposite literal. For instance, in [Example 4](#), the clause $c_{18} = x_1$ can be derived by resolution from $c_4 = x_1 \vee \neg x_7$ and $c_{11} = x_1 \vee x_7$; clause $\neg x_1 \vee x_6$ can be derived by resolution from $c_{17} = x_7 \vee x_6 \vee \neg x_1$ and $c_{15} = x_6 \vee \neg x_7 \vee \neg x_1$. In theory, CDCL-solvers follow resolution proofs that reuse derived clauses (DAG-like resolution).^{3,34} They can be exponentially more succinct than tree-like resolution proofs, corresponding to DPLL-solvers.⁴ In the early 2000s, techniques to ensure the correctness of unsatisfiability results using variants of resolution proofs were presented.⁴ However, they were invasive to the solver and produced enormous proofs. In the 2010s, techniques emerged that provide proofs that are compact, easy to emit, can be checked efficiently, and offer high expressiveness. One popular proof format is Deletion and Resolution Asymmetric Tautology (DRAT).⁴ [Example 7a](#) provides a DRAT proof for our running example but uses only a fragment of DRAT's features.

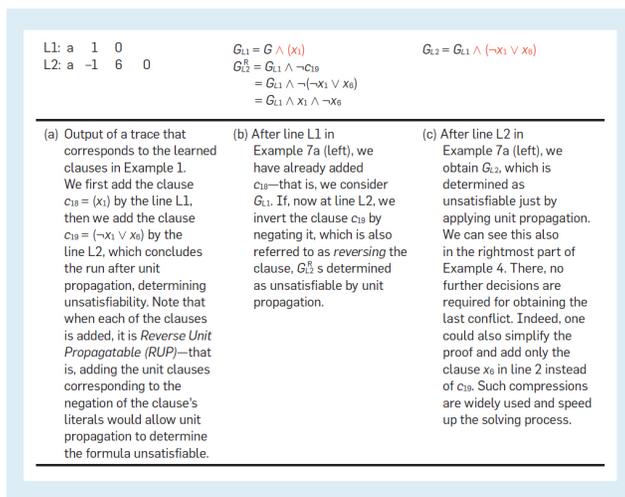


Figure. Example 7. Illustration of a DRAT proof for our running example.

Problem decomposition and verification. Problem decomposition and verification were a game-changer for solving long-standing open math problems using SAT technology—for example, invalidating a hypothesis on Pythagorean triples.²² As described previously, modern SAT solvers emit proofs that cover all types of present solving techniques, including preprocessing and inprocessing. A proof of a mathematical statement such as the propositional Pythagorean triples problem can be longer than 200TB, which is more data than the Hubble Space Telescope accumulated in about 20 years. Such proofs are clearly beyond human understanding and not human-verifiable simply because of their length but can still be automatically checked. As a result, it leads to using SAT solvers as brute-force technology for mathematical applications. This progress in SAT solving fulfills, finally, some of the early promises in automated reasoning and deduction from the 1960s.

Modern competitions and open source. Since 2002, the SAT community has organized annual competitive events that encourage novel solver design and gather new benchmark instances.²⁶ Competitions continue to impact progress in solver development and provide a way to independently assess the efficiency of submitted solvers. In 2002, few solvers used the CDCL architecture (4 out of 19). Solvers were not robust, and many of them crashed during the competition—for example, on instances with many variables, many clauses, or very long clauses. Fortunately, this changed the following year due to various widely available benchmarks and published expected results. Initially, many solvers were closed source. Strict submission requirements and the success of the free solver MiniSat¹³ shifted the community to open source. MiniSat code was simple to read, compact, and designed for extensibility. It implemented CDCL and outperformed all other solvers in 2005 due to minimizing learned clauses and the preprocessor SatELite.⁴ Over time, the open source principle enabled researchers to implement their ideas on top of the best available solvers and understand crucial implementation details usually not shared in papers. As of 2023, offsprings of MiniSat, such as Glucose, MapleSAT, and MapleCOMSPS, still participate in the SAT competition. While competitions continuously raise standards in efficient solving, there is no single best solver in practice. Various solvers perform differently depending on the considered class of benchmarks or the configuration of their internal heuristics. This diversity can be exploited by systems such as SATzilla,⁴ which predict the performance of existing solvers and select the most promising ones. A more sophisticated approach is automatic algorithm selection and tuning. Tools such as AUTOFOLIO or SMAC⁴ find good parameters for a given solver on a target set of benchmarks.

Theoretical understanding of efficient solving. In 2014, Moshe Vardi pointed out the lack of theoretical understanding of the success in practical SAT solving.⁴⁰ Meanwhile, the understanding improved from various viewpoints.¹⁸ Solvers are well-engineered, constantly improved, and efficiently solve many classes of real-world instances. Still, they perform poorly on certain random and cryptographic instances. A standard view is that industrial instances contain a "hidden structure" that the SAT solver manages to use implicitly. Any theoretical analysis that ignores structural properties of the SAT instance hence cannot match up with the empirically observed solver performance. This shortcoming led to several research lines aiming to capture the hidden structure in a SAT instance mathematically. One line focuses on capturing structure that correlates well with empirically observed solver performance.² This provides a statistical correlation but no guarantee that every SAT instance that exhibits this structure is solved quickly. Another line of research takes a causal approach; it uses the theoretical framework of parameterized complexity to obtain asymptotic performance guarantees for algorithms that explicitly detect and exploit the hidden structure.⁴ The underlying fixed-parameter algorithms are specific to the parameter under consideration and generally do not aim at providing a theoretical explanation of CDCL-solver performance.

[Back to Top](#)

The Art of Using SAT Solvers

A SAT solver can be seen as a powerful engine; however, reaching a solution or guaranteeing that there is none requires more than an engine alone. Therefore, the SAT community developed innovative and powerful methods for using and adapting SAT engines.

Single-call solving. *Static encodings* transform an input instance of the problem of interest into a CNF formula. Encoding can be accomplished in a high-level programming language such as Python, which produces a DIMACS CNF file. Slightly higher-level access can be obtained by PySAT,²⁵ a popular Python library for encoding problems and using state-of-the-art SAT solvers. SAT engines are highly optimized on the low-level DIMACS CNF format for squeezing out every ounce of performance. Over time, engineers have shifted to more human-readable and reusable languages; some go beyond the propositional case. Examples include the ASP input language¹⁹ or the MiniZinc constraint modeling language.³⁸ The "Selected Formalisms..." sidebar on the previous page lists other formalisms that focus on modeling and problem solving with more expressive languages. Still, detailed domain knowledge and the skill of efficiently driving the engine are often helpful.

Multi-call solving. Modern SAT solvers can go beyond single-call solving. Many such solvers can modify an already-solved formula, reusing information from a previous solving process (*incremental solving*) and outputting a subset of the input clauses that remain unsatisfiable (*unsatisfiable core*). Some of these techniques resulted in efficient solving methods for problem formalisms beyond SAT, where the SAT engine drives the solving process. The "Propositional Problems" sidebar on this page lists such selected formalisms at the propositional level.

SAT solvers as subroutines. Many hard computational problems of practical significance, particularly in AI, are beyond NP. An unexpectedly successful application of SAT solvers comes in terms of QBF solvers for the QSAT problem ("Propositional Problems" sidebar). Several successful QBF solvers, such as CAQE and RAReQS,⁴ employ SAT solvers. RAReQS uses two interacting SAT solvers internally to determine the validity of the QSAT instance. Each solver acts as the existential or the universal player in a two-player game. The SAT solvers drive the procedure: The models found refine the abstraction of the players. This generic approach is called *Counter Example Guided Abstraction Refinement* (CEGAR). Other successful QBF solvers, such as DepQBF⁴ and Qute,³³ extend the CDCL procedure to the quantified case, with special methods for identifying and dealing with the dependencies between variables imposed by the quantifiers. In hardware or software verification, the model-checking tool IC3⁵ goes further than finding bugs by proving safety properties. IC3 uses incremental SAT to check the reachability of states from both the initial states and the states of interest. A different flavor of multi-call solving can be used for optimization problems, which are too large to be encoded into a single SAT or MaxSAT instance and where optimal solutions are out of reach. The *SAT-based Local Improvement Method* (SLIM) starts with an initial solution provided with some standard heuristics. Then, SLIM repeatedly replaces local parts with improved solutions obtained by a SAT or MaxSAT solver. The method has been successfully applied for graph decomposition, decision-tree induction, and Bayesian Network structure learning.³⁵

Core-guided optimization. SAT solvers can also solve optimization problems for minimizing or maximizing an objective function. For instance, such a function could count the variables from a subset of variables set to 1. Incremental solving provides the means to optimize with a SAT solver: The solver is used by progressively adding more and more clauses that further constrain the instance until it becomes unsatisfiable. Recall that a SAT solver can provide for an unsatisfiable instance with an unsatisfiable core.⁴ To satisfy the maximum number of clauses, at least one clause from the unsatisfiable core needs to be disregarded. This can be expressed using assumptions, a technique referred to as *core-guided optimization*. Notably, core-guided optimization is very successful when solving problems such as MaxSAT, the problem of maximizing the number of satisfied clauses (Propositional Problems sidebar). [Example 8](#) describes the use of soft clauses on our running example, which is the basis for MaxSAT. A popular approach for MaxSAT solving uses as a subroutine the computation of a minimal hitting set on unsatisfiable cores, usually achieved using a Mixed-Integer Programming (MIP) solver.

Recall Example 6, where we introduced an assumption on clause c_{17} . Instead, we could also declare clause c_{17} a *soft clause* that should be satisfied if possible, not mandatorily. From our example, we can see that this clause cannot be satisfied, as the entire formula with c_{17} is unsatisfiable.

Figure. Example 8. Soft clauses allow us to deal with inconsistent requirements.

[Back to Top](#)

Outlook

Over the last two decades, SAT solving techniques have changed how we tackle hard computational problems. The SAT revolution is significantly less known than the celebrated success of machine learning with its ubiquitous and widely reported impact on technology and society. SAT solvers have influenced modern technology more silently. They are used in computational biology,²⁰ for planning,⁴ to verify modern hardware,⁴ operating systems, software,⁴ and even mathematical statements.⁴ This makes SAT crucial to the progress of modern information technology. Still, critical Computer Science challenges related to SAT solving are still ahead: How can we further improve parallel search to take full advantage of modern massively parallel hardware? Why does SAT solving often work so well in practice, and what characterizes the cases where it struggles? How can we improve the process of coming up with good encodings? Finally, will SAT be widely applied also to computational physics, chemistry, or non-symbolic AI? To some extent, the revolutions of SAT and machine learning are complementary. There is much potential in combining the two.

[Back to Top](#)

Acknowledgments

This work was carried out while the authors visited the Simons Institute for the Theory of Computing. It has been supported by a Google Fellowship at the Simons Institute; the Austrian Science Fund (FWF); Grants J4656, Y698, and P32830; and the Vienna Science and Technology Fund, Grant WWTF ICT19-065.

[Back to Top](#)

References

1. Abate, P. et al. Dependency solving: A separate concern in component evolution management. *J. Systems and Software* 85, 10 (2012), 2228–2240.
2. Ansótegui, C. et al. Community structure in industrial SAT instances. *J. Artificial Intelligence Research* 66 (2019), 443–472.
3. Atserias, A., Fichte, J.K., and Thurley, M. Clause-learning algorithms with many restarts and bounded-width resolution. *J. Artificial Intelligence Research* 40, 1 (2011), 353–373.
4. A. Biere, M. Heule, H. van Maaren, and T. Walsh, (Eds.). *Handbook of Satisfiability (2nd Edition)*. IOS Press, Amsterdam, Netherlands (2021).
5. Bradley, A.R. SAT-based model checking without unrolling. In *Verification, Model Checking, and Abstract Interpretation-12th Intern. Conf. Proceedings (Lecture Notes in Computer Science 6538)*, R. Jhala and D.A. Schmidt (Eds.). Springer (January 2011), 70–87.
6. Bryant, R.E. Graph-based algorithms for Boolean function manipulation. *IEEE Transactions in Computing* C-35, 8 (August 1986), 677–691.
7. Cook, S.A. The complexity of theorem-proving procedures. In *Proceedings of the 3rd Annual Symp. on Theory of Computing*, ACM (1971), M.A. Harrison, R.B. Banerji, and J.D. Ullman (Eds.) 151–158.
8. Cook, S.A. and Mitchell, D.G. Finding hard instances of satisfiability problem: A survey. *DIMACS Series in Discrete Mathematics and Theoretical Computer Science* 5 (1997).
9. Darwiche, A. Three modern roles for logic in AI. In *Proceedings of the 39th ACM SIGMOD-SIGACT-SIGAI Symp. on Principles of Database Systems* (2020), 229–243.

10. Darwiche, A. and Marquis, P. A knowledge compilation map. *J. Artificial Intelligence Research* 17, 1 (2002), 229–264.
11. Davis, M., Logemann, G., and Loveland, D. A machine program for theorem-proving. *Communications of the ACM* 5, 7 (July 1962), 394–397.
12. Davis, M. and Putnam, H. A computing procedure for quantification theory. *J. of the ACM* 7, 3 (1960), 201–215.
13. Eén, N. and Sörensson, N. An extensible SAT-solver. In *Proceedings of the 6th Intern. Conf. on Theory and Applications of Satisfiability Testing*, E. Giunchiglia and A. Tacchella (Eds.), Springer Verlag (2003), 502–518.
14. Elffers, J. et al. Seeking practical CDCL insights from theoretical SAT benchmarks. In *Proceedings of the 27th Intern. Joint Conf. on Artificial Intelligence*, J. Lang (Ed.), (2018), 1300–1308.
15. Fichte, J.K., Hecher, M., and Hamiti, F. The model counting competition 2020. *ACM J. Experimental Algorithmics* 26, 13 (December 2021).
16. Fichte, J.K., Hecher, M., and Szeider, S. A time leap challenge for SAT-solving. In *Proceedings of the 26th Intern. Conf. on Principles and Practice of Constraint Programming*, H. Simonis (Ed.). Springer Verlag, Louvain-la-Neuve, Belgium (2020), 267–285.
17. Fichte, J.K., Hecher, M., and Zisser, M. An improved GPU-based SAT model counter. In *Proceedings of the 25th Intern. Conf. on Principles and Practice of Constraint Programming*, T. Schiex and S. de Givry (Eds.), (2019), 491–509.
18. Ganesh, V. and Vardi, M.Y. *Beyond the Worst-Case Analysis of Algorithms*. Cambridge University Press, (2021), 547–566.
19. Gebser, M. et al. *Answer Set Solving in Practice*. Morgan & Claypool (2012).
20. Guerra, J. and Lynce, I. Reasoning over biological networks using maximum satisfiability. In *Proceedings of the 18th Intern. Conf. Principles and Practice of Constraint Programming (Lecture Notes in Computer Science 7514)*, M. Milano (Ed.). Springer Verlag, Québec City, QC, Canada (2012), 941–956.
21. Hamadi, Y. and Sais, L. (Eds.). *Handbook of Parallel Constraint Reasoning*. Springer (2018).
22. Heule, M.J.H. and Kullmann, O. The science of brute force. *Communications of the ACM* 60, 8 (July 2017), 70–79.
23. Hoos, H.H. and Stützle, T. Towards a characterisation of the behaviour of stochastic local search algorithms for SAT. *Artificial Intelligence* 112, 1 (1999), 213–232.
24. Ignatiev, A. et al. Reasoning-based learning of interpretable ML models. In *Proceedings of the 30th Intern. Joint Conf. on Artificial Intelligence*, Zhi-Hua Zhou (Ed.), (August 2021), 4458–4465.
25. Ignatiev, A., Morgado, A., and Marques-Silva, J. PySAT: A Python toolkit for prototyping with SAT oracles. In *Proceedings of the 21st Intern. Conf. on Theory and Applications of Satisfiability Testing (Lecture Notes in Computer Science 10929)*, O. Beyersdorff and C.M. Wintersteiger (Eds.). Springer Verlag (2018), 428–437.
26. Jarvisalo, M. et al. The International SAT Solver Competitions. *AI Magazine*. The AAAI Press (2012).
27. Katebi, H., Sakallah, K.A., and Marques-Silva, J.P. Empirical study of the anatomy of modern SAT solvers. In *Proceedings of the 14th Intern. Conf. on Theory and Applications of Satisfiability Testing (Lecture Notes in Computer Science 6695)*, K.A. Sakallah and L. Simon (Eds.). Springer Verlag (2011), 343–356.
28. Knuth, D.E. *The Art of Computer Programming Vol. 4B*, Combinatorial Algorithms, Part 2. Addison-Wesley (2023).
29. Levin, L. Universal sequential search problems. *Problems of Information Transmission* 9, 3 (1973), 265–266.
30. Malik, S. and Zhang, L. Boolean satisfiability from theoretical hardness to practical success. *Communications of the ACM* 52, 8 (August 2009), 76–82.
31. Marques-Silva, J. and Sakallah, K.A. GRASP: A search algorithm for propositional satisfiability. *IEEE Trans. Comput.* 48, 5 (May 1999), 506–521.
32. Moskewicz, M.W. et al. Chaff: Engineering an efficient SAT solver. In *Proceedings of the 38th Annual Design Automation Conf.*, J. Rabaey (Ed.). Association for Computing Machinery (2001), 530–535.
33. Peitl, T., Slivovsky, F., and Szeider, S. Dependency learning for QBF. *J. Artificial Intelligence Research* 65 (2019), 180–208.

34. Pipatsrisawat, K. and Darwiche, A. On the power of clause-learning SAT solvers as resolution engines. *Artificial Intelligence* 175, 2 (2011), 512–525.
35. Ramaswamy, V.P. and Szeider, S. Turbocharging treewidth-bounded Bayesian network structure learning. In *Proceedings of the 35th AAAI Conf. on Artificial Intelligence*, The AAAI Press (2021), 3895–3903.
36. Rossi, F., van Beek, P., and Walsh, T. *Handbook of Constraint Programming*. Elsevier Science Publishers, North-Holland, USA (2006).
37. Sinz, C. Towards an optimal CNF encoding of Boolean cardinality constraints. In *Proceedings of the 11th Intern. Conf. on Principles and Practice of Constraint Programming (Lecture Notes in Computer Science 3709)*, P. van Beek (Ed.). Springer Verlag, Sitges, Spain (2005), 827–831.
38. Stuckey, P.J. et al. The MiniZinc Challenge 2008–2013. *AI Magazine* 35, 2 (June 2014), 55–60.
39. Tseytin, G.S. On the complexity of derivation in propositional calculus. *Automation of Reasoning: Classical Papers in Computational Logic 2* (1983), 466–483.
40. Vardi, M.Y. Boolean satisfiability: Theory and engineering. *Communications of the ACM* 57, 3 (March 2014), 5.

[Back to Top](#)

Authors

Johannes K. Fichte is an associate professor at IDA, Institutionen för datavetenskap, Linköping University, Sweden.

Daniel Le Berre is a professor at Artois University and CNRS, Centre de Recherche en Informatique de Lens, France.

Markus Hecher (hecher@mit.edu) is a PostDoc at the Computer Science & Artificial Intelligence Laboratory, Massachusetts Institute of Technology, Cambridge, USA.

Stefan Szeider is a professor and head of the Algorithms and Complexity Group at TU Wien, Vienna, Austria.

[Back to Top](#)

Footnotes

- a. DPLL combines DP and DLL to emphasize both contributions.

[Back to Top](#)

Sidebar

Selected Formalisms

Selected formalisms beyond propositional logic inspired by CDCL.

SAT Modulo Theories (SMT)

SMT⁴ extends SAT by theories of first-order logic, so that instances can express questions beyond CNF and propositional variables. Among the more prominent theories supported by SMT solvers are the theory of arithmetic over integers or real numbers, the theory of equality and uninterpreted functions, as well as theories over different data structures such as arrays and bit-vectors. These theories are readily available in many state-of-the-art SMT solvers, such as z3, cvc4, and MathSAT5. Initial attempts to solve SMT resulted in translating instances to propositional formulas, where a SAT solver was responsible for solving. Over time, more sophisticated techniques and architectures emerged. Still, the core of modern SMT architectures is powered by SAT engines and often referred to by CDCL(T), where T denotes the theory under consideration. The performance of current SMT solvers resulted in challenging SMT competitions, which further led to standardized collections and libraries of instances. Some of these instances indeed stem from crucial applications, mostly in the area of software verification.

Answer Set Programming (ASP)

Propositional ASP builds on top of SAT and adds concepts from knowledge representation and reasoning (stable models). It can solve problems from the second level of the polynomial hierarchy. Non-propositional ASP provides a declarative programming-oriented approach with first-order variables and extended statements toward compact and human-readable representations of encodings.¹⁹ There, problems are NEXPTIME-hard. Still, modern ASP solvers use CDCL-based techniques. ASP became a de facto successor of Prolog. Modern ASP solvers even offer features from SMT, including ways to compactly define own theories.

Constraint Programming (CP)

CP focuses on modeling and solving combinatorial problems while offering engineers a wide variety of constraints, which are not limited to the propositional domain.³⁶ Furthermore, available constraints are very expressive and high-level. Surprisingly, CDCL-based solvers have a strong influence as the core engine in some solvers, as witnessed in the MiniZinc 2022 Challenge—for instance, PicatSAT and OR-Tools.³⁸

[Back to Top](#)

Sidebar

Propositional Problems

A short list of selected propositional problems beyond SAT that employ CDCL.

Quantified Boolean Formulas (QBFs)

QBFs extend CNF formulas by quantifying variables universally (\forall) or existentially (\exists). SAT can be seen as the special case where all variables are existentially quantified. With QBFs, one can encode some problems exponentially more succinctly than with SAT, but checking whether a QBF is true (QSAT) is PSPACE complete.⁴

Pseudo-Boolean (PB) Solving

PB solving supports linear constraints, which are more expressive than clauses. A linear constraint is a linear combination of propositional variables—for example, $2x_1 + \dots - 3x_k \leq 5$. With the use of auxiliary variables and clauses, such constraints can also be encoded in CNF, but linear constraints eliminate the need for constructions, such as in [Example 5](#). Furthermore, one can use stronger proof systems on such instances—for example, Gaussian elimination or cutting planes.⁴

Maximum Satisfiability (MaxSAT)

One can extend CNFs by marking clauses as hard or soft.⁴ A hard clause must be satisfied and a soft clause should be satisfied if possible. Then, the problem MaxSAT asks to find an assignment that satisfies all the hard clauses and a maximum number of soft clauses. Today, there are many applications where MaxSAT thrives, and the list of use cases ranges from configuration problems in industry and software management, across combinatorial optimization, to data analysis and probabilistic reliability estimation of systems.

Sampling, Counting, Compilations

Advances in SAT solving have been extended to generating multiple diverse solutions (sampling), counting the number of solutions,^{4,15} and compiling a CNF formula into another normal form, such as d-DNNF, where various problems can be solved efficiently (knowledge compilation).¹⁰ Practical applications of counting and sampling can be found in probabilistic reasoning and bioinformatics. Sampling is of particular interest in testing or performance-model optimization. Knowledge compilation and compilers are ideal technologies for various problems in decision making and AI.



This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivs International 4.0 License

The Digital Library is published by the Association for Computing Machinery. Copyright © 2023 ACM, Inc.

Comments

Sergey Bulanov

May 26, 2023 08:34

A non-computational approach to the SAT solver. This work was made approximately at 2002.
https://youtu.be/TBB_yWQxXh4

Displaying 1 comment

Comment on this article

Signed comments submitted to this site are moderated and will appear if they are relevant to the topic and not abusive. Your comment will appear with your username if published. [View our policy on comments](#)

Notify me via email when subsequent user comments are published with this article.

SUBMIT FOR REVIEW