

SS 2024 lecture 3



Constraint Solving

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Outline

- 1. Summary of Previous Lecture
- 2. Example SAT Reduction: Shakashaka
- 3. Maximal Satisfiability
- 4. Incremental SAT Solving
- 5. Further Reading

SAT Solving

- conflict graph is used to compute backjump clauses
- two new inference rules: learn (a backjump clause) and restart

Theorem (Cook-Levin)

SAT is NP-complete

SAT Variation

k-SAT: every clause has (at most) *k* literals

Theorem

- 3SAT is NP-complete
- 2SAT is solvable in polynomial time

Planar 3SAT

instance is 3SAT formula φ whose incidence graph is planar

- φ with clauses $C = \{C_1, \ldots, C_m\}$ over variables $\mathcal{V} = \{x_1, \ldots, x_n\}$
- bipartite graph $(C \cup V, E)$ with E containing edge $C_i x_j$ if and only if C_i contains x_j or $\neg x_j$

Theorem (Lichtenstein 1982)

planar 3SAT is NP-complete

Remark

planar 3SAT is often used in reductions to show NP-hardness of particular problems



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Shakashaka



- fill grid with triangles \mathbf{k} \mathbf{v} \mathbf{v} \mathbf{v} to obtain white rectangles
- numbered cells must have right number of neighbouring triangles

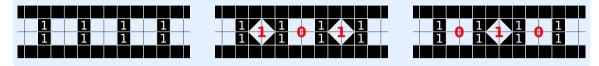
Theorem

Shakashaka is NP-hard

Proof

reduction from planar 3SAT

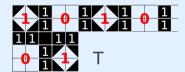




Variable Gadgets

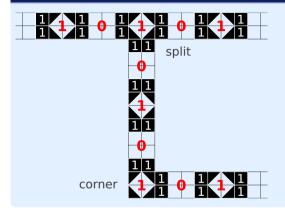




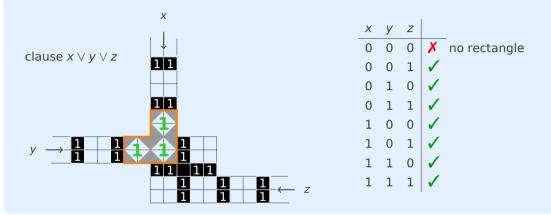


two possible solutions $\,pprox\,$ two possible valuations

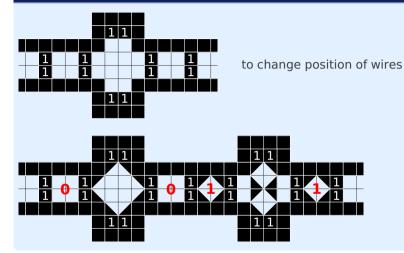
Split and Corner Gadgets



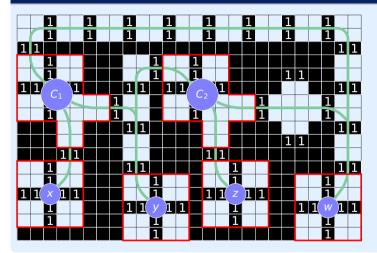
Clause Gadget



Parity Gadget



Example



- 4 variables x y z w
- 2 clauses $C_1 C_2$

$$C_1 = \{x, \neg y, w\}$$

$$C_2 = \{y, \neg z, \neg w\}$$

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MaxSAT

input: propositional CNF φ

output: valuation v that maximizes number of satisfied clauses in φ

Example

- CNF $(q \lor \neg r) \land (\neg q \lor r) \land p \land (\neg p \lor r) \land \neg p \land (\neg p \lor \neg r \lor q)$ is unsatisfiable
- v(p) = v(q) = v(r) = T satisfies 5 out of 6 clauses

Variation

- hard clauses that must be satisfied
- soft clauses that are desirable to be satisfied
- weights for soft clauses
- goal: maximize sum of weights of soft clauses while satisfying all hard clauses

Branch and Bound — Notation

- φ_x denotes formula φ with all occurrences of x replaced by T
- $\varphi_{\overline{x}}$ denotes formula φ with all occurrences of x replaced by F
- function $simp(\varphi)$
 - replaces \neg T by F and \neg F by T
 - removes all clauses which contain T
 - removes F from remaining clauses
- $\texttt{#empty}(\varphi)$ denotes number of empty clauses in φ
- CNF φ is presented as list of clauses

Branch & Bound — Algorithm

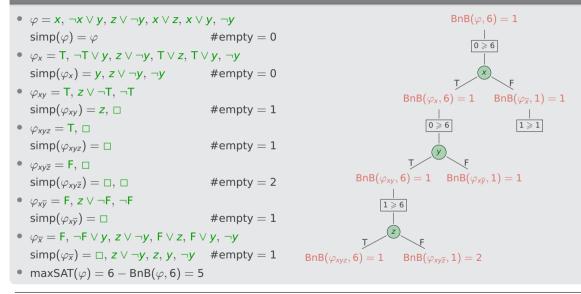
function BnB(φ , b) -- initial call: b is number $|\varphi|$ of clauses in φ $\varphi \leftarrow simp(\varphi)$ if φ contains only empty clauses then return #empty(φ) if #empty(φ) \ge b then return b $x \leftarrow$ select variable in φ

return min(b, BnB($\varphi_{\mathbf{x}}, b$), BnB($\varphi_{\overline{\mathbf{x}}}, BnB(\varphi_{\overline{\mathbf{x}}}, b)$)))

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Remarks
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- BnB $(\varphi, |\varphi|)$ returns minimum number of unsatisfied clauses (minUNSAT (φ))
- maxSAT answer is $|arphi| \mathsf{BnB}(arphi, |arphi|)$
- $\# empty(\varphi)$ denotes number of clauses falsified by current valuation

Example

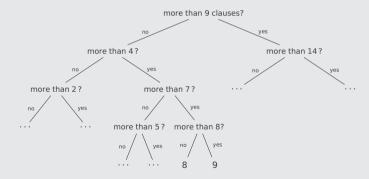


Binary Search — Idea

repeatedly call SAT solver in binary search fashion and return minUNSAT(φ)

Example

consider formula with 18 clauses; can we satisfy



Binary Search

function BinarySearch($\{C_1, \ldots, C_m\}$) $\varphi \leftarrow \{C_1 \lor b_1, \ldots, C_m \lor b_m\}$ $--b_1,\ldots,b_m$ are fresh variables return search(φ , 0, m) function search(φ, L, U) if $L \ge U$ then return U $M = \lfloor \frac{L+U}{2} \rfloor$ if SAT($\varphi \wedge \text{CNF}(b_1 + \dots + b_m \leq M)$) then return search(φ, L, M) cardinality constraint else return search(φ , M + 1, U)

Theorem

BinarySearch(φ) = minUNSAT(φ)

6 V	$2 \vee b_1$	¬6∨2∨ b ₂	$ eg 2 \lor 1 \lor b_3$	$ eg 1 \lor b_4$
$\varphi = \left\{ \neg 6 \right\}$	∕8∨ b 5	6 ∨ ¬8 ∨ b ₆	2∨4∨ b 7	$ eg 4 \lor 5 \lor b_8$
[7 ∨ .	5∨ b 9	$\neg 6 \lor 2 \lor b_2$ $6 \lor \neg 8 \lor b_6$ $\neg 7 \lor 5 \lor b_{10}$	$ eg 3 \lor b_{11}$	$\neg 5 \lor 3 \lor \textbf{\textit{b}_{12}}$
				,
• <i>L</i> = 0, <i>U</i> = 12, <i>M</i> = 6	SAT(arphi /	$\nabla CNF(b_1 + \cdots)$	$+ b_{12} \leqslant 6))$?	\checkmark
• <i>L</i> = 0, <i>U</i> = 6, <i>M</i> = 3	SAT(arphi /	$\nabla CNF(b_1 + \cdots)$	$+b_{12}\leqslant 3))?$	\checkmark
• <i>L</i> = 0, <i>U</i> = 3, <i>M</i> = 1	SAT(arphi /	$\nabla CNF(b_1 + \cdots)$	$+ b_{12} \leqslant 1))$?	×
• <i>L</i> = 2, <i>U</i> = 3, <i>M</i> = 2	SAT(arphi /	$\nabla CNF(b_1 + \cdots)$	$+b_{12}\leqslant 2))?$	\checkmark
• <i>L</i> = 2, <i>U</i> = 2	minUNS	$\operatorname{SAT}(arphi)=$ 2 :	⇒ maxSA	${\sf F}(arphi)={\sf 10}$

MaxSAT Competition

Further Information

MaxSAT Evaluation 2023

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Motivation

- applications such as MaxSAT often require incremental interface
 - determine satisfiability of clauses C1
 - slightly change C₁ to C₂ and again determine satisfiability

• ...

- aims
 - do not restart SAT solver in every iteration
 - reuse learned clauses, keep knowledge of solver (decision heuristics, ...)
- challenge
 - keep learned clauses, even if some clauses are removed from input

Solution: Assumptions

- first introduced in SAT solver MiniSAT
- key idea: assumption literals (also called clause selectors)
 - create new assumption literal x_c for each clause c that might be activated or deactivated
 - change every such clause *c* in the CNF by $\{\neg x_c\} \cup c$; CNF is $\bigcup_i C_i$
 - run DPLL algorithm for C_1 with initial decisions $ec{x_c}$ for each $c\in C_1$
 - as soon as DPLL algorithm backtracks below this initial decision level, report unsat of C_1
 - for switching from clauses C_1 to C_2 perform two steps
 - undo decisions $\overset{a}{x_c}$ for all $c \in C_1 \setminus C_2$ (deactivate) and
 - add decisions x_c^a for all $c \in C_2 \setminus C_1$ (activate)
 - then continue with DPLL algorithm as in previous step, continue with C_3, \ldots

Observation

- since the set of clauses stays identical, learned clauses stay valid
- learned clauses that contain clause selectors can only be applied if these clauses are currently activated; other learned clauses can be used for all runs

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Sections 2.2 and 2.4

Further Reading

 Erik D. Demaine, Yoshio Okamata, Ryuhei Uehara, and Yushi Uno Computational Complexity and an Integer Programming Model of Shakashaka Proc. 25th Canadian Conference on Computational Geometry, 2013

Motivation for extending SAT to first-order theories

predicates instead of propositional variables

Examples

equalities and disequalities over the reals

 $(x_1=x_2 \lor x_1=x_3) \land (x_1=x_2 \lor x_1=x_4) \land x_1 \neq x_2 \land x_1 \neq x_3 \land x_1 \neq x_4$

boolean combination of linear-arithmethic predicates

$$(x_1+2x_3<5) \lor \neg (x_3 \leqslant 1) \land (x_1 \geqslant x_3)$$

• formula over arrays

$$(i = j \land a[j] = 1) \land \neg(a[i] = 1)$$

Important Concepts

- assumption literal (clause selector)
- binary search
- branch and bound
- hard and soft clause

- incremental SAT solving
- maximal satisfiability
- minUNSAT
- Shakashaka gadget