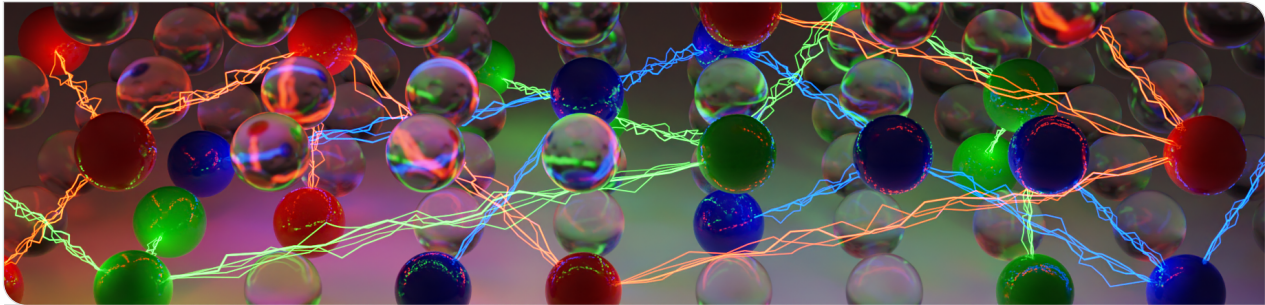


Practical SAT Solving

Lecture 3

Markus Iser, Dominik Schreiber, Tomáš Balyo | April 29, 2024



Overview

Recap. Lecture 2

- Tractable Subclasses
- Constraint Encodings and their Properties

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- Tractable Subclasses
- Constraint Encodings and their Properties

Today's Topics: Elementary SAT Algorithms

- Local Search
- Resolution
- DP Algorithm
- DPLL Algorithm

Stochastic Local Search (SLS)

Minimize the Number of Unsatisfied Clauses

Start with a **random** complete variable assignment α :

0	0	1	0	1	1	0	0	1	1	0	1	0	1	0
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

Repeatedly **flip** variables in α to decrease the number of unsatisfied clauses:

0	0	1	0	1	0	0	0	1	1	0	1	0	1	0
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

Stochastic Local Search (SLS)

Properties of SLS Algorithms

Local search algorithms are **incomplete**: They cannot show unsatisfiability!

Challenges:

- Which variable should be flipped next?

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- Which variable should be flipped next?
 - select variable from an **unsatisfied clause**
 - select variable that **maximizes** the number of satisfied clauses
- How to avoid getting stuck in **local minima**?

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Challenges:

- Which variable should be flipped next?
 - select variable from an **unsatisfied clause**
 - select variable that **maximizes** the number of satisfied clauses
- How to avoid getting stuck in **local minima**?
 - randomization

Classic SLS Algorithms

GSAT (Selman et al., 1992)

Greedy local search algorithm

Algorithm 1: GSAT

Input: ClauseSet S

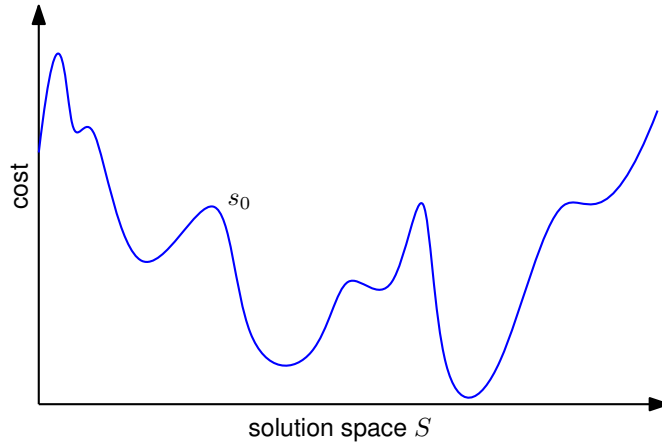
Output: Assignment α , or Nothing

```

1 for  $i = 1$  to  $MAX\_TRIES$  do
2    $\alpha =$  random-assignment to variables in  $S$ 
3   for  $j = 1$  to  $MAX\_FLIPS$  do
4     if  $\alpha$  satisfies all clauses in  $S$  then return  $\alpha$ 
5      $x =$  variable that produces least number of unsatisfied
      clauses when flipped
6     flip  $x$ 
7 return Nothing // no solution found

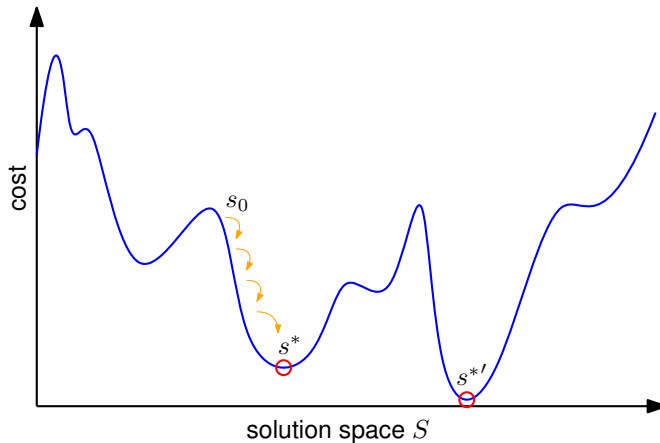
```

SLS: Local Minima



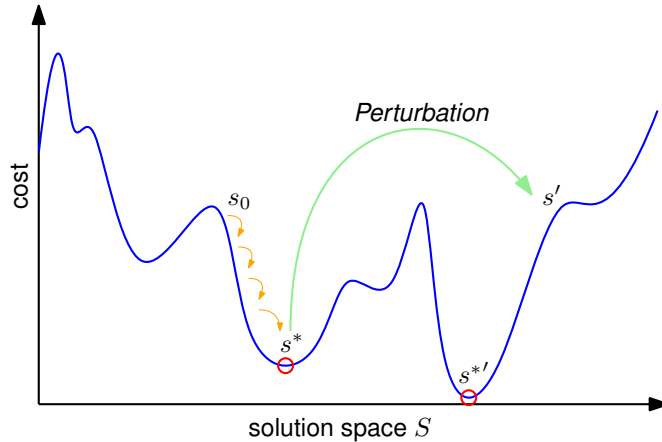
[Illustration Adapted from: Alan Mackworth, UBC, Canada]

SLS: Local Minima



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SLS: Local Minima



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Classic SLS Algorithms

WalkSAT (Selman et al., 1993)

Variant of GSAT

Try to avoid local minima by introducing **random noise**.

Algorithm 2: WalkSAT(S)

```

1 for  $i = 1$  to  $MAX\_TRIES$  do
2    $\alpha$  = random-assignment to variables in  $S$ 
3   for  $j = 1$  to  $MAX\_FLIPS$  do
4     if  $\alpha$  satisfies all clauses in  $S$  then return  $\alpha$ 
5      $C$  = random unsatisfied clause in  $S$ 
6     if by flipping an  $x \in C$  no new unsatisfied clauses
       emerges then flip  $x$ 
7     else with probability  $p$  flip an  $x \in C$  at random
8     otherwise, flip a variable that changes the least number
       of clauses from satisfied to unsatisfied
9 return Nothing // no solution found

```

SLS: Important Notions

Consider a flip taking α to α'

breakcount number of clauses **satisfied** in α , but **not satisfied** in α'

makecount number of clauses **not satisfied** in α , but **satisfied** in α'

diffscore # unsatisfied clauses in α – # unsatisfied clauses in α'

Typically, breakcount, makecount, and/or diffscore are used to select the variable to flip.

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Recap using new nomenclature

GSAT select variable with highest diffscore

WalkSAT select variable with minimal breakcount

Stochastic Local Search (SLS)

Legacy of SLS

- Extremely **successful and popular** in early days of SAT
 - SLS outperformed early resolution-based solvers, e.g., based on DP or DPLL
 - for example, state of the art engine for **automated planning** in the 90s

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 - Faster, more reliable, and **complete!**

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 - for example, state of the art engine for **automated planning** in the 90s
- Today, sophisticated resolution-based systematic search solvers dominate in most practical applications
 - Faster, more reliable, and **complete!**
- Still useful as a component in more complex solvers
 - Part of (parallel) **algorithm portfolios**
 - Control **branching heuristics** in complete search algorithms
 - Detection of autarkies in **formula simplification** algorithms
 - In combination with complete solvers for optimization problems (e.g., **MaxSAT**)

Recap

Elementary Algorithms

- Local Search
 - Examples: GSAT, WalkSAT
 - Terminology: breakcount, makecount, diffscore

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Next Up

- Resolution

Resolution

The Resolution Rule

$$\frac{P_1 \cup \{x\}, \quad P_2 \cup \{\neg x\}}{P_1 \cup P_2}$$

Resolution is a logical **inference rule** to infer a **conclusion** (resolvent) from given **premises** (input clauses).

Example (Resolution)

$$\{x_1, x_3, \neg x_7\}, \{\neg x_1, x_2\} \vdash \{x_3, \neg x_7, x_2\}$$

$$\{x_4, x_5\}, \{\neg x_5\} \vdash \{x_4\} \quad \text{(Fact)}$$

$$\{x_1, x_2\}, \{\neg x_1, \neg x_2\} \vdash \{x_1, \neg x_1\} \quad \text{(Tautological Resolvent)}$$

$$\{x_1\}, \{\neg x_1\} \vdash \{\} \quad \text{(Empty Clause)}$$

Resolution

Theorem: Resolution is Sound

Given a CNF formula F with two resolvable clauses $C_1, C_2 \subseteq F$ with resolvent $R(C_1, C_2)$, the following holds:

$$F \equiv F \wedge R(C_1, C_2)$$

Proof

Let $C_1 := \{x\} \cup P_1$ and $C_2 := \{\neg x\} \cup P_2$ such that $R(C_1, C_2) = P_1 \cup P_2 =: D$.

Soundness: $F \vdash F \wedge D \implies F \models F \wedge D$

Any satisfying assignment ϕ of F is also a satisfying assignment of D : Since ϕ satisfies both C_1 and C_2 , it necessarily **satisfies at least one literal in D** . If ϕ satisfies x then it satisfies some literal in P_2 . Otherwise, if ϕ satisfies $\neg x$ then it satisfies some literal in P_1 .

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Equivalence: $F \vdash F \wedge D \implies F \wedge D \models F$

Since D does not introduce new variables, $F \wedge D$ can not have more satisfying assignments than F .

Resolution

Resolution is Sound and Refutation Complete

- If we manage to infer the **empty clause** from a CNF formula F , then F is unsatisfiable. (sound)
- If F is unsatisfiable, then there **exists a refutation by resolution**. (complete)
- **Not all possible** consequences of F can be derived by resolution. (“only” refutation complete)

Resolution Proof

A **resolution proof** for F is a sequence of clauses $\langle C_1, C_2, \dots, C_{k-1}, C_k = \emptyset \rangle$ where each C_i is either an original clause of F or a resolvent of two earlier clauses.

Example (Resolution Proof)

$$F = \{x_1, x_2\}, \{\neg x_1, x_2\}, \{x_1, \neg x_2\}, \{\neg x_1, \neg x_2\}$$

(Formula)
(Refutation)

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Example (Resolution Proof)

$$\begin{aligned}
 F &= \{x_1, x_2\}, \{\neg x_1, x_2\}, \{x_1, \neg x_2\}, \{\neg x_1, \neg x_2\} && \text{(Formula)} \\
 &\equiv \{x_1, x_2\}, \{\neg x_1, x_2\}, \{x_1, \neg x_2\}, \{\neg x_1, \neg x_2\}, \{x_2\}, \{\neg x_2\}, \{\} && \text{(Refutation)}
 \end{aligned}$$

Saturation Algorithm

Properties

- **sound and complete** – always terminates and answers correctly
- **exponential** time and space complexity

Algorithm 3: Saturation Algorithm

Input: CNF formula F

Output: {SAT, UNSAT}

```
1 while true do
2    $R := \text{resolveAll}(F)$ 
3   if  $R \cap F \neq R$  then  $F := F \cup R$ 
4   else break
5 if  $\perp \in F$  then return UNSAT
6 else return SAT
```

Unit Propagation

Unit Resolution

Resolution where at least one of the resolved clauses is a **unit clause**, i.e. has size one.

Example (Unit Resolution)

$$R((x_1 \vee x_7 \vee \neg x_2 \vee x_4), (x_2)) = (x_1 \vee x_7 \vee x_4)$$

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Resolution where at least one of the resolved clauses is a **unit clause**, i.e. has size one.

Example (Unit Resolution)

$$R((x_1 \vee x_7 \vee \neg x_2 \vee x_4), (x_2)) = (x_1 \vee x_7 \vee x_4)$$

Unit Propagation

Apply unit resolution until fixpoint is reached.

Example (Unit Propagation)

Usually, we are only interested in the inferred facts (unit clauses) and conflicts (empty clauses).

$$\{x_1, x_2, x_3\}, \{x_1, \neg x_2\}, \{\neg x_1\} \vdash_1 \{\neg x_2\}, \{x_3\}$$

Recap

Elementary Algorithms

- Local Search
 - Examples: GSAT, WalkSAT
 - Terminology: breakcount, makecount, diffscore
- Resolution
 - Soundness and Completeness
 - Saturation Algorithm (Exponential Complexity)
 - Unit Propagation

Recap

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Next Up

Davis Putnam (DP) Algorithm (Improving upon saturation-based resolution)

Davis-Putnam Algorithm (Davis & Putnam, 1960)

Presented in 1960 as a SAT procedure for first-order logic.

Deduction Rules of DP Algorithm

- **Unit Resolution:** If there is a unit clause $C = \{\bar{x}\} \in F$, simplify all other clauses containing x
- **Pure Literal Elimination:** If a literal x never occurs negated in F , add clause $\{x\}$ to F
- **Case Splitting:** Put F in the form $(A \vee x) \wedge (B \vee \neg x) \wedge R$, where A , B , and R are clause sets free of x . Replace F by the clausification of $(A \vee B) \wedge R$

Apply above deduction rules (prioritizing rules 1 and 2) until one of the following situations occurs:

- $F = \emptyset \rightarrow \text{SAT}$
- $\emptyset \in F \rightarrow \text{UNSAT}$

Davis-Putnam Algorithm

Example (DP Algorithm)

$$F = \{\{x, y, \neg z, u\}, \{\neg x, y, u\}, \{x, \neg y, \neg z\}, \{z, v\}, \{z, \neg v\}, \{\neg z, \neg u\}, \{\neg x, \neg y, u\}\} \quad (\text{Split by } x)$$

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$$F_2 = \{\{\neg z, u\}, \{z, v\}, \{z, \neg v\}, \{\neg z, \neg u\}\} \quad (\text{Split by } z)$$

Davis-Putnam Algorithm

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$$A_2 = \{\{v\}, \{\neg v\}\} \quad B_2 = \{\{u\}, \{\neg u\}\} \quad R_2 = \{\} \quad ((A_2 \vee B_2) \wedge R_2)$$

Davis-Putnam Algorithm

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Davis-Putnam Algorithm

Example (DP Algorithm)

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$$F_4 = \{\{v\}, \{\neg v\}\} \vdash_1 \{\emptyset\} \quad (\text{Unit Resolution})$$

DP Variant: Bucket Elimination

Bucket Elimination

- Fix order \prec on variables.
- **Bucket:** set of clauses with same \prec -maximal variable
- **Bucket Elimination:** process buckets in decreasing \prec -order
 - resolve all clauses in bucket
 - put resolvents in fitting bucket

DP Variant: Bucket Elimination

Example (Bucket Elimination)

$$F = \{(x, y, \bar{z}, u), (\bar{x}, y, u), (x, \bar{y}, \bar{z}), (z, v), (z, \bar{v}), (\bar{z}, \bar{u}), (\bar{x}, \bar{y}, u)\} \quad (x \succ y \succ z \succ u \succ v)$$

Variable	Bucket
x	$(x, y, \bar{z}, u), (\bar{x}, y, u), (x, \bar{y}, \bar{z}), (\bar{x}, \bar{y}, u)$
y	
z	$(z, v), (z, \bar{v}), (\bar{z}, \bar{u})$
u	
v	

DP Variant: Bucket Elimination

Example (Bucket Elimination)

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Variable	Bucket
x	processed
y	$(y, \bar{z}, u), (\bar{y}, \bar{z}, u)$
z	$(z, v), (z, \bar{v}), (\bar{z}, \bar{u})$
u	
v	

DP Variant: Bucket Elimination

Example (Bucket Elimination)

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Variable	Bucket
x	processed
y	processed
z	processed
u	$(\bar{u}, v), (u, v), (\bar{u}, \bar{v}), (u, \bar{v})$
v	

DP Variant: Bucket Elimination

Example (Bucket Elimination)

$$F = \{(x, y, \bar{z}, u), (\bar{x}, y, u), (x, \bar{y}, \bar{z}), (z, v), (z, \bar{v}), (\bar{z}, \bar{u}), (\bar{x}, \bar{y}, u)\} \quad (x \succ y \succ z \succ u \succ v)$$

Variable	Bucket
x	processed
y	processed
z	processed
u	processed
v	$(v), (\bar{v})$

DP: Discussion

*The superiority of the present procedure over those previously available is indicated in part by the fact that a formula on which **Gilmore's routine for the IBM 704** causes the machine to compute for **21 minutes without obtaining a result** was worked successfully by hand computation using [DP] in 30 minutes.*

—from Davis' and Putnam's Paper

- Does DP improve on saturation's average time complexity?

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- Does DP improve on saturation's average time complexity?
⇒ **yes** — if we split over the right variables
- Does DP avoid saturation's exponential space complexity?
⇒ **no** — **quadratic blowup in size** for eliminating one variable

DPLL Algorithm (Davis et al., 1962)

Davis Putnam Logemann Loveland (DPLL) Algorithm

- DPLL is a backtracking search over partial variable assignments.
- Case splitting over a variable x branches the search over two cases x and $\neg x$: resulting in the simplified formulas $F|_{x=\text{true}}$ and $F|_{x=\text{false}}$
- Simplification rules:
 - **Unit Propagation:** If $\{l\} \in F$, l must be set to true.
 - **Pure Literal Elimination:** If x occurs only positively (or only negatively), it may be fixed to the respective value.

DPLL Algorithm

start with
simplifications

recurse on
subformulas obtained
by case-splitting

stop if **satisfying
assignment** found or
**all branches are
unsatisfiable**

Algorithm 4: DPLL(ClauseSet S)

```

1 while  $S$  contains a unit clause  $\{L\}$  do
2   | delete from  $S$  clauses containing  $L$  // unit-subsumption
3   | delete  $\neg L$  from all clauses in  $S$  // unit-resolution
4 if  $\emptyset \in S$  then return false // empty clause
5 while  $S$  contains a pure literal  $L$  do
6   | delete from  $S$  all clauses containing  $L$  // pure literal elimination
7 if  $S = \emptyset$  then return true // no clauses
8 choose a literal  $L$  occurring in  $S$  // case-splitting
9 if  $DPLL(S \cup \{\{L\}\})$  then return true // first branch
10 else if  $DPLL(S \cup \{\{\neg L\}\})$  then return true // second branch
11 else return false

```

DPLL Algorithm with Trail

(S, α) is the clause set S as “seen” under partial assignment α

No explicit pure literal elimination (it is too slow for the benefit it provides)

trailDPLL() leads to efficient iterative DPLL implementation

Algorithm 5: trailDPLL(ClauseSet S , PartialAssignment α)

```

1 while  $(S, \alpha)$  contains a unit clause  $\{L\}$  do
2   |   add  $\{L = 1\}$  to  $\alpha$                                 // Unit Propagation
3 if a literal is assigned both 0 and 1 in  $\alpha$  then
4   |   return false                                        // Conflict
5 if all literals assigned then
6   |   return true                                        // Assignment found
7 choose a literal  $L$  not assigned in  $\alpha$  occurring in  $S$  // Case Splitting
8 if trailDPLL( $S, \alpha \cup \{\{L = 1\}\}$ ) then
9   |   return true                                        // first branch
10 else if trailDPLL( $S, \alpha \cup \{\{L = 0\}\}$ ) then
11   |   return true                                        // second branch
12 else return false
  
```

DPLL Algorithm

Properties

- DPLL *always terminates*
 - Each recursion eliminates one variable
 - Worst case: *binary tree search* of depth $|V|$
- DPLL is *sound and complete*
 - If clause set S is *SAT*, we eventually find a satisfying α
 - If clause set S is *UNSAT*, the entire space of (partial) variable assignments is searched (but *variable selection still matters!*)
- Space complexity: *linear!*
 - systematic search avoids blowup of “*unfocused*” DP

Recap

Elementary Algorithms

- Local Search
 - Examples: GSAT, WalkSAT
 - Terminology: breakcount, makecount, diffscore
- Resolution
 - Soundness and Completeness
 - Saturation Algorithm (Exponential Complexity)
- DP Algorithm
 - Systematized Resolution
 - Improved Average Time Complexity
- DPLL Algorithm
 - Case Splitting and Unit Propagation
 - Linear Space Complexity

Next Steps

Coming Lectures

- How can we implement unit propagation efficiently?
- Which literal L to use for case splitting?
- How can we efficiently implement the case splitting step?