## Proof Complexity and SAT Solving

#### Jakob Nordström

#### University of Copenhagen and Lund University

#### Dagstuhl Workshop 22411 "Theory and Practice of SAT and Combinatorial Solving" October 10, 2022

# The Boolean Satisfiability (SAT) Problem

#### Sat

Given a propositional logic formula F, is there a satisfying assignment for F?

$$(x \lor z) \land (y \lor \neg z) \land (x \lor \neg y \lor u) \land (\neg y \lor \neg u)$$
  
 $\land (u \lor v) \land (\neg x \lor \neg v) \land (\neg u \lor w) \land (\neg x \lor \neg u \lor \neg w)$ 

- Variables should be set to true or false
- Constraint  $(x \lor \neg y \lor z)$ : means x or z should be true or y false
- $\bullet~\wedge$  means all constraints should hold simultaneously
- Is there a truth value assignment satisfying all constraints?

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#### Can we use computers to solve this problem efficiently?

Jakob Nordström (UCPH & LU)

Proof Complexity and SAT Solving

$$\begin{array}{l} (x \lor z) \land (y \lor \neg z) \land (x \lor \neg y \lor u) \land (\neg y \lor \neg u) \\ \land (u \lor v) \land (\neg x \lor \neg v) \land (\neg u \lor w) \land (\neg x \lor \neg u \lor \neg w) \end{array}$$

$$\begin{aligned} & (x \lor z) \land (y \lor \neg z) \land (x \lor \neg y \lor u) \land (\neg y \lor \neg u) \\ \land & (u \lor v) \land (\neg x \lor \neg v) \land (\neg u \lor w) \land (\neg x \lor \neg u \lor \neg w) \end{aligned}$$

$$(1-x)(1-z) = 0$$
  
(1-y)z = 0  
(1-x)y(1-u) = 0  
yu = 0  
(1-u)(1-v) = 0  
xv = 0  
u(1-w) = 0  
xuw = 0

$$\begin{array}{l} (x \lor z) \land (y \lor \neg z) \land (x \lor \neg y \lor u) \land (\neg y \lor \neg u) \\ \land (u \lor v) \land (\neg x \lor \neg v) \land (\neg u \lor w) \land (\neg x \lor \neg u \lor \neg w) \end{array}$$

1 - x - z + xz = 0z - yz = 0y - xy - yu + xyu = 0yu = 01 - u - v + uv = 0xv = 0u - uw = 0xuw = 0

$$\begin{aligned} (x \lor z) \land (y \lor \neg z) \land (x \lor \neg y \lor u) \land (\neg y \lor \neg u) \\ \land (u \lor v) \land (\neg x \lor \neg v) \land (\neg u \lor w) \land (\neg x \lor \neg u \lor \neg w) \end{aligned}$$

1 - x - z + xz = 0	$x + z \ge 1$
z - yz = 0	$y + (1 - z) \ge 1$
y - xy - yu + xyu = 0	$x + (1 - y) + u \ge 1$
yu = 0	$(1-y) + (1-u) \ge 1$
1 - u - v + uv = 0	$u+v \ge 1$
xv = 0	$(1-x) + (1-v) \ge 1$
u - uw = 0	$(1-u) + w \ge 1$
xuw = 0	$(1-x) + (1-u) + (1-w) \ge 1$

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1 - x - z + xz = 0	$x+z \ge 1$
z - yz = 0	$y-z \ge 0$
y - xy - yu + xyu = 0	$x - y + u \ge 0$
yu = 0	$-y-u \ge -1$
1 - u - v + uv = 0	$u+v \ge 1$
xv = 0	$-x - v \ge -1$
u - uw = 0	$-u+w \ge 0$
xuw = 0	$-x - u - w \ge -2$

## Solving SAT in Theory and Practice

- Problem mentioned in Gödel's letter in 1956 to von Neumann
- Topic of intense research in computer science ever since 1960s
- NP-complete, so probably very hard worst case [Coo71, Lev73]
- But enormous progress last 20–25 years on conflict-driven clause learning (CDCL) SAT solvers [BS97, MS99, MMZ<sup>+</sup>01]
- Today large-scale real-world problems with hundreds of thousands or millions of variables solved routinely
- But. . . There are also small formulas (just  $\sim$ 100 variables) that are completely beyond reach for even the very best SAT solvers

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#### How can we rigorously analyse SAT solving algorithms?

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#### How can we rigorously analyse SAT solving algorithms? This talk: Use proof complexity (not only conceivable answer)

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- **()** Is there a short proof deciding *F* using rules in this proof system?
- ② Can short proofs in the proof system be found efficiently?

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**Focus of this talk:** Question 1 for different proof systems/algorithms Study unsatisfiable formulas — proof of satisfiability easy

# Outline

#### DPLL, CDCL, and Resolution

- Davis-Putnam-Logemann-Loveland (DPLL) Method
- Conflict-Driven Clause Learning (CDCL)
- Resolution Proof System

#### 2 Algebraic and Semi-algebraic Approaches

- Nullstellensatz
- Polynomial Calculus and Gröbner Bases
- Cutting Planes and Pseudo-Boolean Solving
- Some Proof Systems We Won't Have Time for
  - Sherali-Adams and Sums of Squares
  - Stabbing Planes
  - Extended Resolution

Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

## Formal Description of SAT Problem

- Variable x: takes value true (=1) or false (=0)
- Literal  $\ell$ : variable x or its negation  $\overline{x}$  (write  $\overline{x}$  instead of  $\neg x$ )
- Clause C = ℓ<sub>1</sub> ∨ · · · ∨ ℓ<sub>k</sub>: disjunction of literals (Consider as sets, so no repetitions and order irrelevant)
- Conjunctive normal form (CNF) formula  $F = C_1 \land \cdots \land C_m$ : conjunction of clauses

The SATISFIABILITY (or just SAT) Problem

Given a CNF formula F, is it satisfiable?

Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

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For instance, what about our example formula?

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Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

### **DPLL:** Attempting Smart Case Analysis

The foundation of state-of-the-art SAT solvers is the DPLL method developed by Davis, Putnam, Logemann & Loveland [DP60, DLL62]

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DPLL (somewhat simplified description)

If F contains empty clause (without literals), report "unsatisfiable" and return — refer to as conflict

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- Set x = 0, simplify F and make recursive call

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- Set x = 1, simplify F and make recursive call

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- If F contains empty clause (without literals), report "unsatisfiable" and return — refer to as conflict
- 2 If F contains no clauses, report "satisfiable" and terminate
- **③** Otherwise pick some variable x in F
- **④** Set x = 0, simplify F and make recursive call
- Set x = 1, simplify F and make recursive call
- If result in both cases "unsatisfiable", then report "unsatisfiable" and return

Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

## A DPLL Toy Example

$$F = (x \lor z) \land (y \lor \overline{z}) \land (x \lor \overline{y} \lor u) \land (\overline{y} \lor \overline{u})$$
$$\land (u \lor v) \land (\overline{x} \lor \overline{v}) \land (\overline{u} \lor w) \land (\overline{x} \lor \overline{u} \lor \overline{w})$$

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Visualize execution of DPLL algorithm as search tree

Pick variables in internal nodes; terminate in leaves when falsified clause found (i.e., when conflict reached)

- satisfied clauses
- falsified literals

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x

- satisfied clauses
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$$F = (z) \land (y \lor \overline{z}) \land (\overline{y} \lor u) \land (\overline{y} \lor \overline{u}) \\ \land (u \lor v) \land (\overline{x} \lor \overline{v}) \land (\overline{u} \lor w) \land (\overline{x} \lor \overline{u} \lor \overline{w})$$

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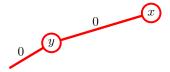
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$$F = (z) \land (\overline{z}) \land (\overline{y} \lor u) \land (\overline{y} \lor \overline{u}) \\ \land (u \lor v) \land (\overline{x} \lor \overline{v}) \land (\overline{u} \lor w) \land (\overline{x} \lor \overline{u} \lor \overline{w})$$

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Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

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$$F = (x \lor z) \land (\overline{z}) \land (\overline{y} \lor u) \land (\overline{y} \lor \overline{u}) \\ \land (u \lor v) \land (\overline{x} \lor \overline{v}) \land (\overline{u} \lor w) \land (\overline{x} \lor \overline{u} \lor \overline{w})$$

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$$0$$
  $y$   $0$   $x$   
 $x \lor z$ 

Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

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$$F = (z) \land (\underline{y} \lor \overline{z}) \land (\overline{y} \lor u) \land (\overline{y} \lor \overline{u}) \\ \land (u \lor v) \land (\overline{x} \lor \overline{v}) \land (\overline{u} \lor w) \land (\overline{x} \lor \overline{u} \lor \overline{w})$$

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$$0 \qquad x \\ 0 \qquad y \qquad 0 \qquad x \\ x \lor z \qquad y \lor \overline{z}$$

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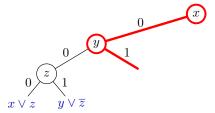
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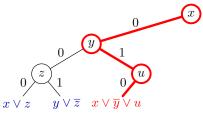
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$$F = (z) \land (y \lor \overline{z}) \land (x \lor \overline{y} \lor u) \land (\overline{u})$$
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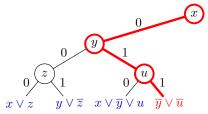
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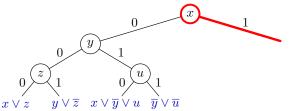
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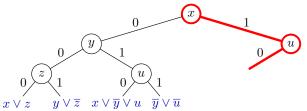
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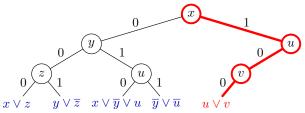
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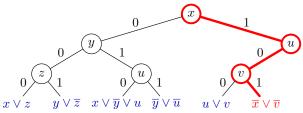
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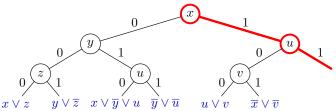
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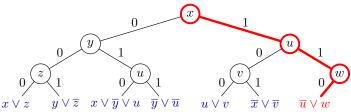
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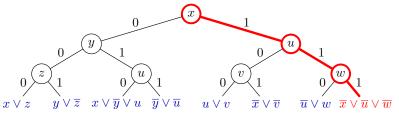
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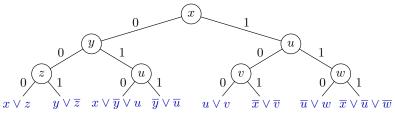
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Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

## State-of-the-art SAT solvers: Ingredients

Many more ingredients in modern conflict-driven clause learning (CDCL) SAT solvers (as pioneered in [BS97, MS99, MMZ<sup>+</sup>01]), e.g.:

- Branching or decision heuristic (choice of pivot variables crucial)
- When reaching leaf, compute explanation for conflict and add to formula as new clause (clause learning)
- Every once in a while, restart from beginning (but save computed info)

Let us briefly discuss some of these ingredients

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# Variable Assignment Heuristics

#### Unit propagation

- Suppose current assignment  $\rho$  falsifies all literals in  $C = \ell_1 \lor \ell_2 \lor \cdots \lor \ell_k$  except one (say  $\ell_k$ ) — C is unit under  $\rho$
- Then  $\ell_k$  has to be true, so set it to true
- Known as unit progagation or Boolean constraint progagation
- Always propagate if possible in modern solvers aim for 99% of assignments being unit propagations

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### VSIDS (Variable state independent decaying sum)

- $\bullet$  When backtracking, score +1 for variables "causing conflict"
- Also multiply all scores with factor  $\kappa < 1$  exponential filter rewarding variables involved in recent conflicts
- When no propagations, decide on variable with highest score

# Clause Learning

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• At conflict, want to add clause avoiding same part of search tree being explored again

# **Clause Learning**

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# **Clause Learning**

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- In practice, more advanced learning schemes

# **Clause Learning**

Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

- At conflict, want to add clause avoiding same part of search tree being explored again
- Suppose we can compute that decisions x = 1, y = 0, z = 1 responsible for conflict
- Then can add  $\overline{x} \lor y \lor \overline{z}$  to avoid these decisions being made again decision learning scheme
- In practice, more advanced learning schemes
- Derive new clause from clauses unit propagating on the way to conflict

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# Decisions, Unit Propagations, and Conflict

Two kinds of assignments — illustrate on example formula:

 $(p \vee \overline{u}) \wedge (q \vee r) \wedge (\overline{r} \vee w) \wedge (u \vee x \vee y) \wedge (x \vee \overline{y} \vee z) \wedge (\overline{x} \vee z) \wedge (\overline{y} \vee \overline{z}) \wedge (\overline{x} \vee \overline{z}) \wedge (\overline{p} \vee \overline{u})$ 

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### Decisions, Unit Propagations, and Conflict

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**Decision** Free choice to assign value to variable Notation  $p \stackrel{d}{=} 0$ 

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#### Decision

Free choice to assign value to variable

Notation  $p \stackrel{\mathsf{d}}{=} 0$ 

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### Decisions, Unit Propagations, and Conflict

Two kinds of assignments — illustrate on example formula:

 $(p \vee \overline{u}) \land (q \vee r) \land (\overline{r} \lor w) \land (u \lor x \lor y) \land (x \lor \overline{y} \lor z) \land (\overline{x} \lor z) \land (\overline{y} \lor \overline{z}) \land (\overline{x} \lor \overline{z}) \land (\overline{p} \lor \overline{u})$ 



#### Decision

Free choice to assign value to variable

Notation  $p \stackrel{\mathsf{d}}{=} 0$ 

#### Unit propagation

Forced choice to avoid falsifying clause Given p = 0, clause  $p \lor \overline{u}$  forces u = 0

Notation  $u \stackrel{p \lor \overline{u}}{=} 0$  ( $p \lor \overline{u}$  is reason clause)

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#### Decision

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Always propagate if possible, else decide Add to assignment trail Until satisfying assignment or conflict

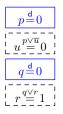
Proof Complexity and SAT Solving

Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

## Decisions, Unit Propagations, and Conflict

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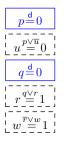
Proof Complexity and SAT Solving

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### Decisions, Unit Propagations, and Conflict

Two kinds of assignments — illustrate on example formula:

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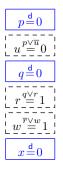
Proof Complexity and SAT Solving

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## Decisions, Unit Propagations, and Conflict

Two kinds of assignments — illustrate on example formula:

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#### Decision

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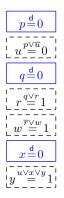
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### Decisions, Unit Propagations, and Conflict

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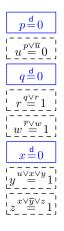
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### Decisions, Unit Propagations, and Conflict

Two kinds of assignments — illustrate on example formula:

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#### Decision

Free choice to assign value to variable

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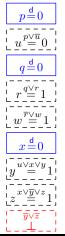
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## Decisions, Unit Propagations, and Conflict

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#### Decision

Free choice to assign value to variable

Notation  $p \stackrel{d}{=} 0$ 

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Forced choice to avoid falsifying clause Given p = 0, clause  $p \lor \overline{u}$  forces u = 0

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Always propagate if possible, else decide Add to assignment trail

Until satisfying assignment or conflict

Proof Complexity and SAT Solving

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decision

decision

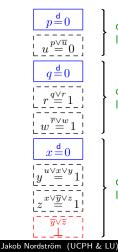
level 2

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## Decisions, Unit Propagations, and Conflict

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Decision

level 1 Free choice to assign value to variable Notation  $p \stackrel{d}{=} 0$ 

### Unit propagation

Forced choice to avoid falsifying clause Given p = 0, clause  $p \lor \overline{u}$  forces u = 0

Notation  $u \stackrel{p \lor \overline{u}}{=} 0$  ( $p \lor \overline{u}$  is reason clause)

#### decision level 3

<sup>1</sup> Always propagate if possible, else decide Add to assignment trail Until satisfying assignment or conflict

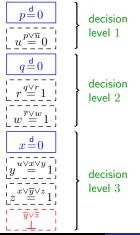
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# **Conflict Analysis**

Time to analyse this conflict and learn from it!

 $(p \lor \overline{u}) \land (q \lor r) \land (\overline{r} \lor w) \land (u \lor x \lor y) \land (x \lor \overline{y} \lor z) \land (\overline{x} \lor z) \land (\overline{y} \lor \overline{z}) \land (\overline{x} \lor \overline{z}) \land (\overline{p} \lor \overline{u})$ 

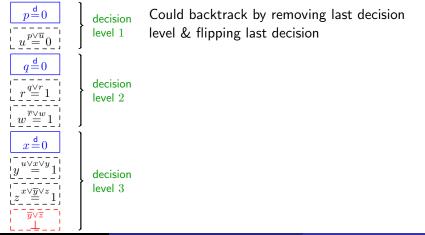


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# **Conflict Analysis**

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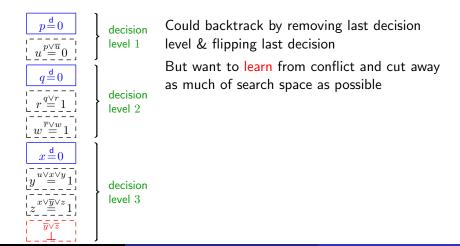
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Proof Complexity and SAT Solving

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# **Conflict Analysis**

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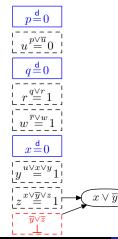


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# **Conflict Analysis**

 $\begin{array}{l} \text{Time to analyse this conflict and learn from it!} \\ (p \lor \overline{u}) \land (q \lor r) \land (\overline{r} \lor w) \land (u \lor x \lor y) \land (x \lor \overline{y} \lor z) \land (\overline{x} \lor z) \land (\overline{y} \lor \overline{z}) \land (\overline{x} \lor \overline{z}) \land (\overline{p} \lor \overline{u}) \end{array}$ 



Could backtrack by removing last decision level & flipping last decision

But want to learn from conflict and cut away as much of search space as possible

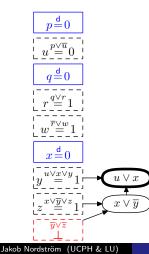
Case analysis over z for last two clauses:

- $x \lor \overline{y} \lor z$  wants z = 1
- $\overline{y} \vee \overline{z}$  wants z = 0
- Resolve clauses by merging them & removing z must satisfy x ∨ ȳ

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# **Conflict Analysis**

Time to analyse this conflict and learn from it!  $(p \lor \overline{u}) \land (q \lor r) \land (\overline{r} \lor w) \land (u \lor x \lor y) \land (x \lor \overline{y} \lor z) \land (\overline{x} \lor z) \land (\overline{y} \lor \overline{z}) \land (\overline{x} \lor \overline{z}) \land (\overline{p} \lor \overline{u})$ 



Could backtrack by removing last decision level & flipping last decision

But want to learn from conflict and cut away as much of search space as possible

Case analysis over z for last two clauses:

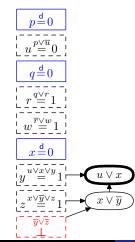
- $x \lor \overline{y} \lor z$  wants z = 1
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- Resolve clauses by merging them & removing z must satisfy x ∨ ȳ

Repeat until UIP clause with only 1 variable after last decision — learn and backjump Proof Complexity and SAT Solving Oct 10, 2022 14/53

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## Complete Example of CDCL Execution

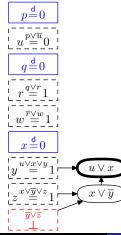
Backjump: undo max #decisions while learned clause propagates  $(p \lor \overline{u}) \land (q \lor r) \land (\overline{r} \lor w) \land (u \lor x \lor y) \land (x \lor \overline{y} \lor z) \land (\overline{x} \lor z) \land (\overline{y} \lor \overline{z}) \land (\overline{x} \lor \overline{z}) \land (\overline{p} \lor \overline{u})$ 



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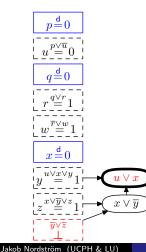


Assertion level 1 (max for non-UIP literal in learned clause) — keep trail to that level

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# Complete Example of CDCL Execution

Backjump: undo max #decisions while learned clause propagates  $(p \lor \overline{u}) \land (q \lor r) \land (\overline{r} \lor w) \land (u \lor x \lor y) \land (x \lor \overline{y} \lor z) \land (\overline{x} \lor z) \land (\overline{y} \lor \overline{z}) \land (\overline{x} \lor \overline{z}) \land (\overline{p} \lor \overline{u})$ 



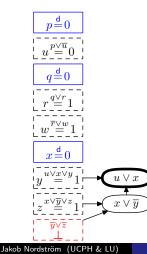


Assertion level 1 (max for non-UIP literal in learned clause) — keep trail to that level Now UIP literal guaranteed to flip (assert) but this is a propagation, not a decision

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# Complete Example of CDCL Execution

Backjump: undo max #decisions while learned clause propagates  $(p \lor \overline{u}) \land (q \lor r) \land (\overline{r} \lor w) \land (u \lor x \lor y) \land (x \lor \overline{y} \lor z) \land (\overline{x} \lor z) \land (\overline{y} \lor \overline{z}) \land (\overline{x} \lor \overline{z}) \land (\overline{p} \lor \overline{u})$ 





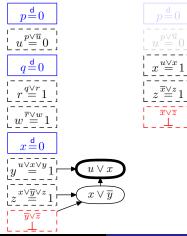
Assertion level 1 (max for non-UIP literal in learned clause) — keep trail to that level Now UIP literal guaranteed to flip (assert) but this is a propagation, not a decision

Then continue as before...

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# Complete Example of CDCL Execution

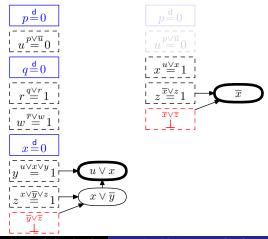
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Backjump: undo max #decisions while learned clause propagates  $(p \lor \overline{u}) \land (q \lor r) \land (\overline{r} \lor w) \land (u \lor x \lor y) \land (x \lor \overline{y} \lor z) \land (\overline{x} \lor z) \land (\overline{y} \lor \overline{z}) \land (\overline{x} \lor \overline{z}) \land (\overline{p} \lor \overline{u})$ 

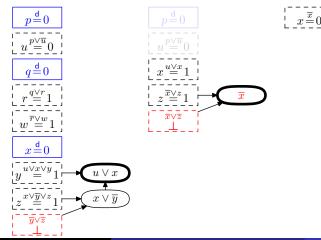


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Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

# Complete Example of CDCL Execution

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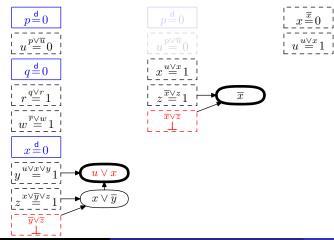


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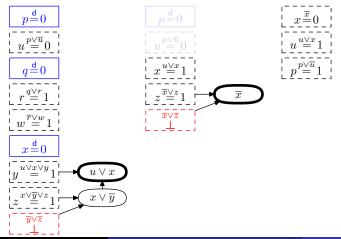
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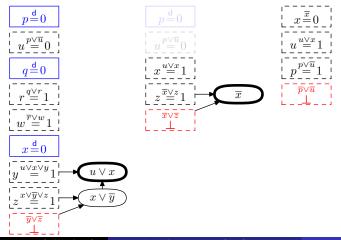
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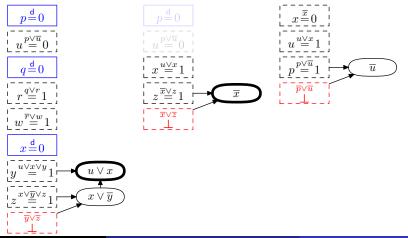


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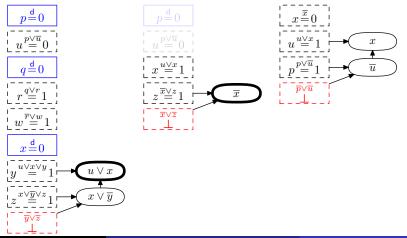


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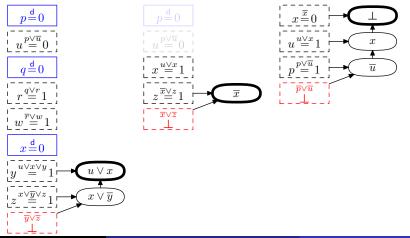
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SAT Solver Analysis and the Resolution Proof System

How to make rigorous analysis of SAT solver performance? Many intricate, hard-to-understand heuristics So focus instead on underlying method of reasoning

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#### SAT Solver Analysis and the Resolution Proof System

How to make rigorous analysis of SAT solver performance? Many intricate, hard-to-understand heuristics So focus instead on underlying method of reasoning

#### Resolution proof system [Bla37, Rob65]

- Start with clauses of CNF formula (axioms)
- Derive new clauses by resolution rule

$$\frac{C_1 \lor x \qquad C_2 \lor \overline{x}}{C_1 \lor C_2}$$

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# Resolution Proofs by Contradction

#### Resolution rule:

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#### Observation

If F is a satisfiable CNF formula and D is derived from clauses  $D_1, D_2 \in F$  by the resolution rule, then  $F \wedge D$  is satisfiable.

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Such proof by contradiction also called resolution refutation

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## DPLL and Resolution Proofs

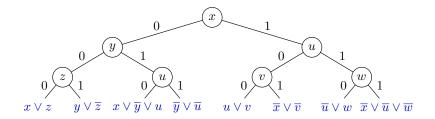
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Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

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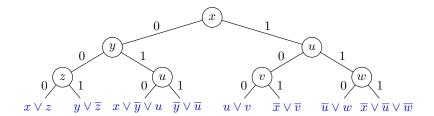


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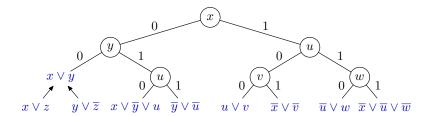


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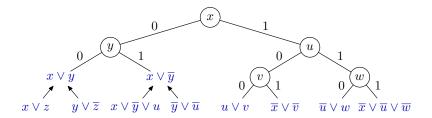


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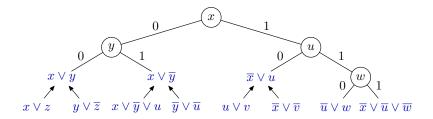


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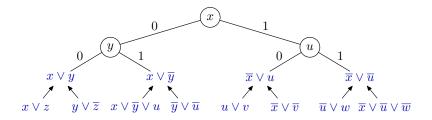


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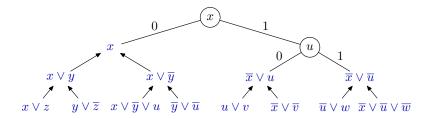


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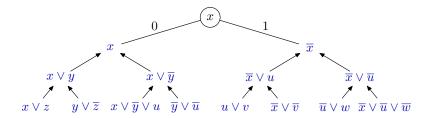


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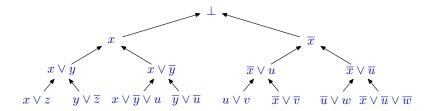


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Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

DPLL Running Time and Tree-Like Resolution Proof Size

• Can extract resolution proof from any DPLL execution

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- Conflict-driven clause learning adds "shortcut edges" in tree, but still yields resolution proof

Davis-Putnam-Logemann-Loveland (DPLL) Method Conflict-Driven Clause Learning (CDCL) Resolution Proof System

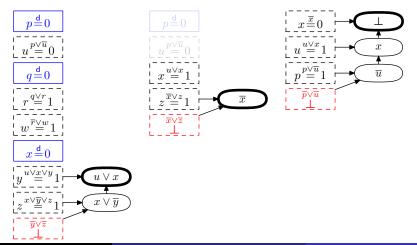
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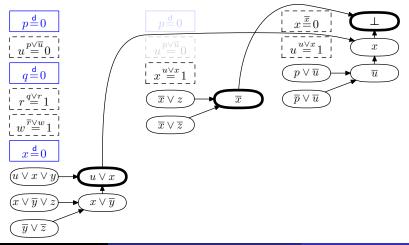


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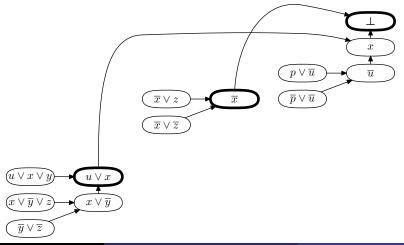
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(\*) Except for some preprocessing techniques, which is an important omission, but this gets complicated and we don't have time to go into details. .

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## Current State of Affairs in SAT Solving

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- Paradox: resolution quite weak proof system; many strong proof complexity lower bounds for (seemingly) "obvious" formulas

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## Examples of Hard Formulas For Resolution (1/3)

# **Pigeonhole principle (PHP) formulas** [Hak85] "n + 1 pigeons don't fit into n holes"

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Variables  $p_{i,j} =$  "pigeon  $i \rightarrow$  hole j";  $1 \le i \le n+1$ ;  $1 \le j \le n$ 

 $\begin{array}{ll} p_{i,1} \lor p_{i,2} \lor \cdots \lor p_{i,n} & \mbox{every pigeon } i \mbox{ gets a hole} \\ \hline p_{i,j} \lor \overline{p}_{i',j} & \mbox{no hole } j \mbox{ gets two pigeons } i \neq i' \end{array}$ 

Can also add "functionality" and "onto" axioms

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Even onto functional PHP hard — "resolution cannot count"

Resolution proof requires  $\exp(\Omega(n)) = \exp(\Omega(\sqrt[3]{N}))$  clauses (measured in terms of formula size N)

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#### **Tseitin formulas** [Urq87] "Sum of degrees of vertices in graph is even"

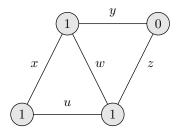
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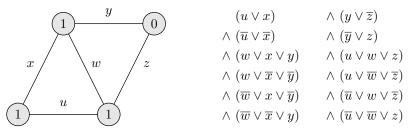
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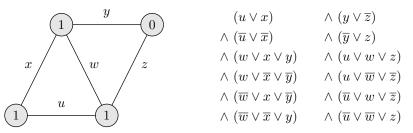
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Requires proof size  $\exp(\Omega(N))$  on well-connected so-called expander graphs — "resolution cannot count mod 2"

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Proof Complexity and SAT Solving

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#### **Random** *k*-**CNF formulas** [CS88]

 $\Delta n$  randomly sampled k-clauses over n variables

( $\Delta\gtrsim4.5$  sufficient to get unsatisfiable 3-CNF almost surely)

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#### And more...

- COLOURING [BCMM05]
- Zero-one designs [Spe10, VS10, MN14]
- Et cetera... (See, e.g., [BN21] for overview)

Nullstellensatz

Polynomial Calculus and Gröbner Bases Cutting Planes and Pseudo-Boolean Solving

### SAT as System of Polynomial Equations

• Given CNF formula  $F = \bigwedge_{i=1}^{m} C_i$ 

Nullstellensatz Polynomial Calculus and Gröbner Bases Cutting Planes and Besuda Baslan Salu

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Nullstellensatz Polynomial Calculus and Gröbner Bases Cutting Planes and Pseudo-Boolean Solvi

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Add Boolean axioms

$$x_j^2 - x_j = 0$$

for all variables

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Nullstellensatz Polynomial Calculus and Gröbner Bases Cutting Planes and Pseudo-Boolean Solving

#### Hilbert's Nullstellensatz

Consider any system of polynomial equations

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#### Hilbert's Nullstellensatz

System infeasible  $\Leftrightarrow$  exist  $q_i, r_j \in \mathbb{F}[x_1, \dots, x_n]$  such that

$$\sum_{i=1}^{m} q_i(x_1, \dots, x_n) \cdot p_i(x_1, \dots, x_n) + \sum_{j=1}^{n} r_j(x_1, \dots, x_n) \cdot (x_j^2 - x_j) = 1$$

Nullstellensatz Polynomial Calculus and Gröbner Bases

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### Nullstellensatz Proof System [BIK<sup>+</sup>94]

Nullstellensatz refutation of

$$p_i(x_1, \dots, x_n) = 0 \qquad \qquad i \in [m]$$
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#### is (syntactic) equality

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Complexity measures of refutations:

- Size: number of monomials (when all polynomials expanded out)
- Degree: highest total degree of any polynomial

Nullstellensatz

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$$\begin{array}{l} (x \lor z) \land (y \lor \neg z) \land (x \lor \neg y \lor u) \land (\neg y \lor \neg u) \\ \land (u \lor v) \land (\neg x \lor \neg v) \land (\neg u \lor w) \land (\neg x \lor \neg u \lor \neg w) \end{array}$$

#### Nullstellensatz

Polynomial Calculus and Gröbner Bases Cutting Planes and Pseudo-Boolean Solving

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$$(1 - x)(1 - z) (1 - y)z (1 - x)y(1 - u) yu (1 - u)(1 - v) xv u(1 - w) xuw$$

Nullstellensatz

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$$(1 - y) \cdot (1 - x)(1 - z) + (1 - x) \cdot (1 - y)z + 1 \cdot (1 - x)y(1 - u) + (1 - x) \cdot yu + x \cdot (1 - u)(1 - v) + (1 - u) \cdot xv + x \cdot u(1 - w) + 1 \cdot xuw$$

#### Nullstellensatz

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Nullstellensatz

Polynomial Calculus and Gröbner Bases

#### Nullstellensatz Example (Not Expanded out)

$$\begin{aligned} (x \lor z) \land (y \lor \neg z) \land (x \lor \neg y \lor u) \land (\neg y \lor \neg u) \\ \land (u \lor v) \land (\neg x \lor \neg v) \land (\neg u \lor w) \land (\neg x \lor \neg u \lor \neg w) \end{aligned}$$

$$(1 - y) \cdot (1 - x)(1 - z) + (1 - x) \cdot (1 - y)z + 1 \cdot (1 - x)y(1 - u) + (1 - x) \cdot yu Size 27 + x \cdot (1 - u)(1 - v) Degree 3 (No use of Boolean axioms) + x \cdot u(1 - w) + 1 \cdot xuw = 1$$

\_

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## Nullstellensatz Proof Search

- Solve linear system of equations with coefficients of polynomials  $q_i$ ,  $r_j$  as unknowns
- Used successfully to solve, e.g., graph colouring problems [DLMM08, DLMO09, DLMM11]
- Running time grows exponentially with degree, though high-degree refutations can be very small [BCIP02, dRMNR21]

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#### • Annoying problem: $x_1 \lor x_2 \lor x_3$ translates to polynomial

 $(1-x_1)(1-x_2)(1-x_3) = 1-x_1-x_2-x_3+x_1x_2+x_1x_3+x_2x_3-x_1x_2x_3$ 

**Dual Variables** 

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$$\prod_{i\in\mathcal{P}} x_i' \cdot \prod_{j\in\mathcal{N}} x_j = 0$$

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$$\prod_{i\in\mathcal{P}} x'_i \cdot \prod_{j\in\mathcal{N}} x_j = 0$$

 Doesn't affect degree (obviously), but can decrease size exponentially [dRLNS21] (also for other algebraic proof systems)

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## Polynomial Calculus [CEI96, ABRW02]

#### Nullstellensatz again

Infeasibility of

$$p_i(x_1, \dots, x_n) = 0 \qquad i \in [m]$$

$$x_j^2 - x_j = 0 \qquad j \in [n]$$

$$x_j + x'_j - 1 = 0 \qquad j \in [n]$$

$$\uparrow$$

1 lies in polynomial ideal generated by these polynomials

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 $\bullet$  Compute polynomials in this ideal  ${\mathcal I}$  step by step

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• 
$$p_i \in \mathcal{I}$$
,  $x_j^2 - x_j \in \mathcal{I}$ , and  $x_j + x_j' - 1 \in \mathcal{I}$  for all  $i \in [m]$ ,  $j \in [n]$ 

Nullstellensatz Polynomial Calculus and Gröbner Bases Cutting Planes and Pseudo-Boolean Solving

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#### Nullstellensatz again

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$$p_i(x_1, \dots, x_n) = 0 \qquad i \in [m]$$

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• 
$$p_i \in \mathcal{I}, x_j^2 - x_j \in \mathcal{I}$$
, and  $x_j + x_j' - 1 \in \mathcal{I}$  for all  $i \in [m], j \in [n]$   
• If  $p, q \in \mathcal{I}$ , then  $\alpha p + \beta q \in \mathcal{I}$  for any  $\alpha, \beta \in \mathbb{F}$ 

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# Polynomial Calculus [CEI96, ABRW02]

#### Nullstellensatz again

Infeasibility of

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- If  $p,q\in\mathcal{I}$ , then  $\alpha p+\beta q\in\mathcal{I}$  for any  $\alpha,\beta\in\mathbb{F}$
- If  $p \in \mathcal{I}$ , then  $m \cdot p \in \mathcal{I}$  for any monomial  $m = \prod_j x_j$

## Polynomial Calculus Derivations and Refutations

- A polynomial calculus derivation is a sequence of polynomials in the ideal generated by  $p_i$ ,  $x_j^2 x_j$ , and  $x_j + x'_j 1$
- Derivation rules (from previous slide):
  - Axioms  $p_i$ ,  $x_j^2 x_j$ , and  $x_j + x_j' 1$
  - Linear combination  $p, q \Rightarrow \alpha p + \beta q$
  - Monomial multiplication  $p \Rightarrow m \cdot p$
- $\bullet\,$  A refutation ends with the polynomial 1
- Complexity measures:
  - Size: total number of monomials in all polynomials in sequence expanded out
  - Degree: highest total degree of any polynomial
- Polynomial calculus (much) stronger than Nullstellensatz w.r.t. both size and degree

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## Polynomial Calculus Can Simulate Resolution

Polynomial calculus can always simulate resolution proofs efficiently step by step

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Example: Resolution step

 $\begin{array}{ccc} x \lor \overline{y} \lor z & \overline{y} \lor \overline{z} \\ \\ \hline x \lor \overline{y} \end{array}$ 

## Polynomial Calculus Can Simulate Resolution

Polynomial calculus can always simulate resolution proofs efficiently step by step

Example: Resolution step

 $\frac{x \vee \overline{y} \vee z}{x \vee \overline{y}}$ 

simulated by polynomial calculus derivation

$$\begin{array}{c|c} yz & z+z'-1 \\ \hline x'yz & x'yz+x'yz'-x'y \\ \hline x'yz' & -x'yz'+x'y \\ \hline \hline x'y \end{array}$$

### Polynomial Calculus is Strictly Stronger than Resolution

Polynomial calculus can be exponentially stronger than resolution

For instance:

- Tseitin formulas on expander graphs if  $\mathbb{F} = GF(2)$
- Onto functional pigeonhole principle over any field [Rii93]

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- But other versions of pigeonhole principle formulas remain hard:
  - "vanilla" PHP [Raz98, AR03]
  - onto PHP [AR03]
  - functional PHP [MN15]

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  - onto PHP [AR03]
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Other hard formulas:

- Tseitin-like formulas for counting mod p if  $p \neq$  field characteristic [BGIP01]
- Random *k*-CNF formulas
  - all characteristics except 2 [BI99]
  - all characteristics [AR03]

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Gröbner Bases: Admissible Orderings and Leading Terms

Admissible ordering  $\leq$  on monomials m, m', t:

 $m \preceq m' \Rightarrow t \cdot m \preceq t \cdot m'$ 

$$2 m \preceq t \cdot m$$

Examples:

- Lexicographic
- Degree-lexicographic

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Can write  $p = \operatorname{lt}(p) + p'$  for  $\operatorname{lt}(p)$  leading term (largest w.r.t.  $\preceq$ )

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Can write  $p = \operatorname{lt}(p) + p'$  for  $\operatorname{lt}(p)$  leading term (largest w.r.t.  $\preceq$ )

If  $\operatorname{lt}(p) = t \cdot \operatorname{lt}(q)$ , can reduce  $p \mod q$  by computing  $p - t \cdot q$ 

"Multivariate division": Reduce p modulo all q in set of polynomials G until no further reductions possible

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## Gröbner Bases: Buchberger's Algorithm

#### Buchberger's algorithm (very rough)

- Let  $\mathcal{G} := all axioms$
- **2** Pick unprocessed pair  $p, q \in \mathcal{G}$  or terminate if none exists
- $\textbf{O} \quad \text{Compute } p' = t_p \cdot p \text{ and } q' = t_q \cdot q \text{ to make leading terms cancel}$
- Set S := p' q'; reduce S mod G with multivariate division; add result to G if non-zero
- 5 Go to 2

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5 Go to 2

#### Computes so-called Gröbner basis

**Fact:** At termination,  $1 \in \mathcal{G} \Leftrightarrow$  polynomial equations infeasible

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#### Gröbner bases: Some Problems and Questions

Buchberger not a great SAT solving algorithm Slow and memory-intensive, and computes too much info Possible to use conflict-driven paradigm?!

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- Oual variables increase reasoning power exponentially [dRLNS21] But are immediately eliminated by multivariate division Possible to design dual-variable-aware Buchberger?!
- Analysis of polynomial calculus uses degree-lexicographic ordering In computational algebra, many other orderings used Prove proof complexity separation results for different orderings?

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## What About Algebraic SAT Solvers?

- Excitement about Gröbner basis approach after [CEI96]
- Promise of performance improvement failed to deliver
- Meanwhile: the CDCL revolution in late 1990s...

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- Some current SAT solvers do Gaussian elimination, but this is only very limited form of polynomial calculus
- Is it harder to build good algebraic SAT solvers, or is it just that too little work has been done (or both)?
- But very successful work on circuit verification in [KFB20, KB20, KBK20a, KBK20b, KB21, KBBN22]

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#### SAT as System of 0-1 Integer Linear Inequalities

• Given CNF formula  $F = \bigwedge_{i=1}^{m} C_i$ 

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### SAT as System of 0-1 Integer Linear Inequalities

- Given CNF formula  $F = \bigwedge_{i=1}^{m} C_i$
- Translate clauses

$$C = \bigvee_{i \in \mathcal{P}} x_i \lor \bigvee_{j \in \mathcal{N}} \overline{x}_j$$

to 0-1 integer linear inequalities

$$\sum_{i \in \mathcal{P}} x_i + \sum_{j \in \mathcal{N}} (1 - x_j) \ge 1$$

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$$\sum_{i \in \mathcal{P}} x_i + \sum_{j \in \mathcal{N}} (1 - x_j) \ge 1$$

Add variable axioms

$$x_j \ge 0$$
$$-x_j \ge -1$$

for all variables

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## Cutting Planes Proof System [CCT87]

Cutting planes introduced in [CCT87] to model integer linear programming algorithm in [Gom63, Chv73]

Can be applied to any system of 0-1 integer linear inequalities

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#### Cutting planes derivation rules

$$\begin{aligned} & \text{Multiplication} \ \frac{\sum a_i x_i \ge A}{\sum c a_i x_i \ge cA} \quad c \in \mathbb{N}^+ \\ & \text{Addition} \ \frac{\sum a_i x_i \ge A}{\sum (a_i + b_i) x_i \ge A + B} \\ & \text{Division} \ \frac{\sum c a_i x_i \ge A}{\sum a_i x_i \ge [A/c]} \quad c \in \mathbb{N}^+ \end{aligned}$$

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## Cutting Planes Derivations and Refutations

- A cutting planes derivation is a sequence of 0-1 integer linear inequalities derived from
  - Axioms (clauses and variable bounds)
  - Multiplication  $\sum a_i x_i \ge A \Rightarrow \sum c a_i x_i \ge c A$
  - Addition  $\sum a_i x_i \ge A$ ,  $\sum b_i x_i \ge B \Rightarrow \sum (a_i + b_i) x_i \ge A + B$
  - Division  $\sum ca_i x_i \ge A \Rightarrow \sum a_i x_i \ge \lceil A/c \rceil$
- A refutation ends with the inequality  $0\geq 1$
- Complexity measures:
  - Length: # inequalities
  - Size: Count also bit size of representing all coefficients

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## Cutting Planes vs. Resolution

• Cutting planes can simulate resolution reasoning efficiently and can be exponentially stronger

(e.g., for PHP, just count and argue that #pigeons > #holes)

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## Cutting Planes vs. Resolution

- Cutting planes can simulate resolution reasoning efficiently and can be exponentially stronger (e.g., for PHP, just count and argue that #pigeons > #holes)
- And 0-1 linear inequalities are similar to but much more concise than CNF

Compare $x_1 + x_2 + x_3 + x_4 + x_5 + x_6 > 3$
and
$(x_1 \lor x_2 \lor x_3 \lor x_4) \land (x_1 \lor x_2 \lor x_3 \lor x_5) \land (x_1 \lor x_2 \lor x_3 \lor x_6)$
$\wedge (x_1 \vee x_2 \vee x_4 \vee x_5) \wedge (x_1 \vee x_2 \vee x_4 \vee x_6) \wedge (x_1 \vee x_2 \vee x_5 \vee x_6)$
$\wedge (x_1 \vee x_3 \vee x_4 \vee x_5) \wedge (x_1 \vee x_3 \vee x_4 \vee x_6) \wedge (x_1 \vee x_3 \vee x_5 \vee x_6)$
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$\wedge (x_2 \vee x_3 \vee x_5 \vee x_6) \wedge (x_2 \vee x_4 \vee x_5 \vee x_6) \wedge (x_3 \vee x_4 \vee x_5 \vee x_6)$

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#### Hard Formulas for Cutting Planes

#### **Clique-colouring formulas** [Pud97] "A graph with an *m*-clique is not (m - 1)-colourable"

Nullstellensatz Polynomial Calculus and Gröbner Bases Cutting Planes and Pseudo-Boolean Solving

## Hard Formulas for Cutting Planes

**Clique-colouring formulas** [Pud97] "A graph with an *m*-clique is not (m - 1)-colourable"

Variables

- $p_{i,j}$  indicators of the edges in graph;  $1 \le i < j \le n$
- $q_{k,i}$  identify members of *m*-clique;  $1 \le k \le m$ ,  $1 \le i \le n$
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$q_{k,1} \lor q_{k,2} \lor \cdots \lor q_{k,n}$	some vertex is the $k$ th member of clique
$\overline{q}_{k,i} \vee \overline{q}_{k',i}$	clique members are uniquely defined ( $k \neq k'$ )
$p_{i,j} \vee \overline{q}_{k,i} \vee \overline{q}_{k',j}$	clique members are connected by edges
$r_{i,1} \vee r_{i,2} \vee \cdots \vee r_{i,m-1}$	every vertex $i$ has a colour
$\overline{p}_{i,j} \vee \overline{r}_{i,\ell} \vee \overline{r}_{j,\ell}$	neighbours have distinct colours

## More Hard Formulas for Cutting Planes?

Lower bound for clique-colouring formulas uses interpolation and circuit complexity

- From small cutting planes proof, build small circuit of special type that can decide whether graph has clique
- Prove separately that no such small circuits can exist
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Cutting planes not well understood at all Clear need for development of new analysis methods Some exciting contributions in [HP17, FPPR22, GGKS20]

Surprisingly, Tseitin formulas are at most quasi-polynomially hard for cutting planes [DT20]!

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## SAT Solvers Based on Cutting Planes?

So-called pseudo-Boolean (PB) solvers using (subset of) cutting planes reasoning developed in, e.g., [CK05, SS06, LP10, EN18]

Perhaps counter-intuitively, hard to make competitive with CDCL

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### Challenge 1: Conjunctive normal form

- Pseudo-Boolean solvers terrible for CNF input
- Solvers can rewrite CNF to more helpful 0-1 linear inequalities [BLLM14, EN20], but this doesn't work so well in practice
- $\bullet\,$  Better to encode problem with  $0\mathchar`-1$  inequalities from the start

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Is it truly harder to build good pseudo-Boolean solvers? Or has just so much more work has been put into CDCL solvers?

Jakob Nordström (UCPH & LU)

Sherali-Adams and Sums of Squares Stabbing Planes Extended Resolution

Sherali-Adams (SA) and Sums of Squares (SoS)

Refutation of 
$$p_i \in \mathbb{R}[x_1, \dots, x_n]$$
,  $i \in [m]$ , and  $x_j^2 - x_j$ ,  $j \in [n]$ 

#### Nullstellensatz

$$\sum_{i=1}^{m} q_i \cdot p_i + \sum_{j=1}^{n} r_j \cdot (x_j^2 - x_j) = 1$$

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$$\sum_{i=1}^{m} q_i \cdot p_i + \sum_{j=1}^{n} r_j \cdot (x_j^2 - x_j) + \sum_{k=1}^{t} \alpha_k \prod_{i \in \mathcal{P}_t} (1 - x_i) \cdot \prod_{j \in \mathcal{N}_t} x_j = -1$$

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Sums of squares (SoS)  $(s_k \in \mathbb{R}[x_1, \dots, x_n])$ 

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Sherali-Adams and Sums of Squares Stabbing Planes Extended Resolution

# SA, SoS, and Other Proof Systems

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Strict hierarchy (over  $\mathbb{R}$ ):

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- Sherali-Adams
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Sums of squares is strictly stronger than polynomial calculus (over  $\mathbb{R}$ ) while Sherali-Adams and polynomial calculus are incomparable [Ber18]

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Sums of squares very strong proof system, except it cannot do parity reasoning efficiently [GV01, Gri01]

Survey [FKP19] is recommended for more reading

Sherali-Adams and Sums of Squares Stabbing Planes Extended Resolution

# Stabbing Planes [BFI<sup>+</sup>18]

#### Intended to model modern 0-1 integer linear programming

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Stabbing planes refutation of set of 0-1 integer linear inequalities  $\mathcal S$ 

 $\textbf{0} \ \ \text{If polytope } \mathcal{S} \ \text{is empty over } \mathbb{R}, \ \text{terminate this branch}$ 

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- Some constant  $\mathcal{S} := \mathcal{S} \cup \{\sum_i a_i \ell_i \ge A\}$

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- Solution Recurse with  $S := S \cup \{\sum_i a_i \ell_i \ge A\}$

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Stabbing planes with polynomial-size coefficient can be simulated by cutting planes with quasi-polynomial overhead  $[DT20, FGI^+21]$ 

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Sherali-Adams and Sums of Squares Stabbing Planes Extended Resolution

# Extended Resolution [Tse68]

#### **Resolution rule**

$$\frac{C_1 \lor x \qquad C_2 \lor \overline{x}}{C_1 \lor C_2}$$

#### Extension rule introducing clauses

$$a \lor \overline{x} \lor \overline{y} \qquad \overline{a} \lor x \qquad \overline{a} \lor y$$

#### for fresh variable a (encoding that $a \leftrightarrow (x \wedge y)$ must hold)

Sherali-Adams and Sums of Squares Stabbing Planes Extended Resolution

# Extended Resolution and SAT Solving

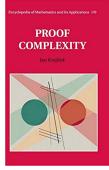
- Closely related (and equivalent) to *DRAT* proof system used to justify correctness of some preprocessing techniques [JHB12]
- DRAT also used for SAT solver proof logging
- Attempts to combine extended resolution with CDCL in, e.g., [AKS10, Hua10]
- Without restrictions, corresponds to extremely strong extended Frege system [CR79] — pretty much no lower bounds known
- To analyse solvers using extended resolution, would need to:
  - Describe heuristics/rules actually used
  - See if possible to reason about such restricted proof system

#### Handbook of Satisfiability

(Especially chapter 7 ©)



#### Proof Complexity by Jan Krajíček



[Kra19]

Overview of some proof systems used in combinatorial solving:

- Resolution  $\longleftrightarrow$  DPLL and CDCL
- Nullstellensatz and polynomial calculus  $\longleftrightarrow$  Gröbner bases
- Cutting planes  $\longleftrightarrow$  pseudo-Boolean solving

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Very brief discussion of some other proof systems:

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Proof complexity can

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- Be a fun playground for theory-practice interaction!

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# Thank you for your attention!

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