

Proof Complexity and Its Relations to SAT-Solving

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PART I: PROOF COMPLEXITY AND SAT

1. Propositional Logic
2. SAT-Solvers
3. Frege Systems
4. Cut-Free and Cut-Only Proofs

PART II: COMPLEXITY OF PROOF SEARCH

1. Proof Search and Automatability
2. Proof of NP-hardness for Resolution
3. An Open Problem

Part I

PROOF COMPLEXITY AND SAT

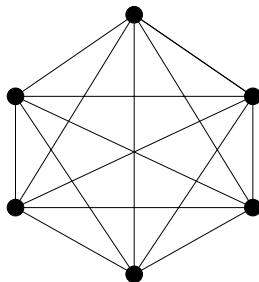
Satisfiability

Example 1: 15 variables and $40 = 20 + 20$ clauses

$x_1 \vee x_2 \vee x_6$	$x_1 \vee x_3 \vee x_7$	$x_1 \vee x_4 \vee x_8$	$x_1 \vee x_5 \vee x_9$
$x_2 \vee x_3 \vee x_{10}$	$x_2 \vee x_4 \vee x_{11}$	$x_2 \vee x_5 \vee x_{12}$	$x_3 \vee x_4 \vee x_{13}$
$x_3 \vee x_5 \vee x_{14}$	$x_4 \vee x_5 \vee x_{15}$	$x_6 \vee x_7 \vee x_{10}$	$x_6 \vee x_8 \vee x_{11}$
$x_6 \vee x_9 \vee x_{12}$	$x_7 \vee x_8 \vee x_{13}$	$x_7 \vee x_9 \vee x_{14}$	$x_8 \vee x_9 \vee x_{15}$
$x_{10} \vee x_{11} \vee x_{13}$	$x_{10} \vee x_{12} \vee x_{14}$	$x_{11} \vee x_{12} \vee x_{15}$	$x_{13} \vee x_{14} \vee x_{15}$
$\overline{x_1} \vee \overline{x_2} \vee \overline{x_6}$	$\overline{x_1} \vee \overline{x_3} \vee \overline{x_7}$	$\overline{x_1} \vee \overline{x_4} \vee \overline{x_8}$	$\overline{x_1} \vee \overline{x_5} \vee \overline{x_9}$
$\overline{x_2} \vee \overline{x_3} \vee \overline{x_{10}}$	$\overline{x_2} \vee \overline{x_4} \vee \overline{x_{11}}$	$\overline{x_2} \vee \overline{x_5} \vee \overline{x_{12}}$	$\overline{x_3} \vee \overline{x_4} \vee \overline{x_{13}}$
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Diagonal Ramsey Numbers $R(k, k)$

$$R(3, 3) \leq 6$$



In every party of six,
either three of them are mutual friends,
or three of them are mutual strangers.

Ramsey Numbers, Erdős, and the Aliens

Erdős asks us to imagine an alien force, vastly more powerful than us, landing on Earth and demanding the value of $R(5, 5)$ or they will destroy our planet. In that case, he claims, we should marshal all our computers and all our mathematicians and attempt to find the value. But suppose, instead, that they ask for $R(6, 6)$. In that case, he believes, we should attempt to destroy the aliens.

Joel Spencer, Ten Lectures on the Probabilistic Method, 1994.

Encodings Can Be Subtle

Different encoding: n^k vs $k^2 n^2$.

$b_{u,v}$: “the pair $\{u, v\}$ is colored blue (else red)”

$x_{i,u}$: “ u is the i -th vertex of a blue k -clique”

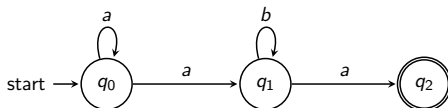
$y_{i,v}$: “ v is the i -th vertex of a red k -clique”

$x_{i,1} \vee \cdots \vee x_{i,n}$ for all i ,
 $\overline{x_{i,u}} \vee \overline{x_{j,u}}$ for all $i \neq j$ and all u ,
 $\overline{x_{i,u}} \vee \overline{x_{j,v}} \vee b_{u,v}$ for all $i \neq j$ and all $u \neq v$,

$y_{i,1} \vee \cdots \vee y_{i,n}$ for all i ,
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More satisfiability

Example 2: Automaton accepts some n -symbol word.



x_i : “the i -th symbol in word is a (else b)”

$s_{t,q}$: “after reading t symbols the state is q ”

$$\overline{s_{0,q_0}} \vee \overline{x_t} \vee s_{t+1,q_0} \vee s_{t+1,q_1} \quad \text{for } t = 0, 1, \dots, n$$

$$\overline{s_{t,q_0}} \vee \overline{x_t} \vee \overline{s_{t+1,q_2}} \quad \text{for } t = 0, 1, \dots, n$$

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...

$$s_{n,q_2}$$

Cook-Levin and Fagin Theorems

Theorem [Cook-Levin 1971] SAT is NP-complete.

A is in NP

iff

A can be reduced to SAT

by polynomial-time reductions.

Theorem [Fagin 1974] $NP = ESO$.

A is in NP

iff

A is a satisfiability problem itself, i.e.,

iff

A is the set of finite models of
a formula of the existential fragment
of second-order logic $\exists \bar{R} \forall \bar{x} \exists \bar{y} \varphi$

An algorithm which:

Given a set of clauses F , finds:

either a satisfying assignment
or a proof of unsatisfiability

Caution:

For formulas with 1000 variables,
the search space is ridiculously HUGE!

“200 TB maths proof is largest ever” [Nature 2016]

Theorem [Heule-Kullmann-Marek 2016]

The numbers $1, \dots, 7825$ **cannot be partitioned** into two parts each **without** Pythagorean triples.

But the numbers $1, \dots, 7824$, **can**.

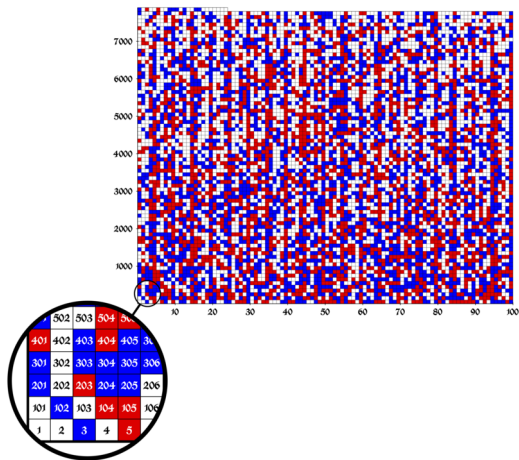
$$a^2 + b^2 = c^2$$

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The Coloring of $1, \dots, 7824$

$$a^2 + b^2 \neq c^2$$

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Source of image: Wikipedia

Recall:

Given a set of clauses F , algorithm finds:

either a satisfying assignment
or a proof of unsatisfiability

An annoying asymmetry:

Satisfying assignments are always small.

Proofs of unsatisfiability tend to be exponentially bigger.

This, among other reasons, motivates the study of
propositional proof complexity.

Frege Systems, aka Hilbert-style Proof Systems

Language:

\rightarrow, \neg

Modus ponens:

$$\frac{A \quad A \rightarrow B}{B}$$

Axioms:

$$A \rightarrow (B \rightarrow A)$$

$$(C \rightarrow (B \rightarrow A)) \rightarrow ((C \rightarrow B) \rightarrow (C \rightarrow A))$$

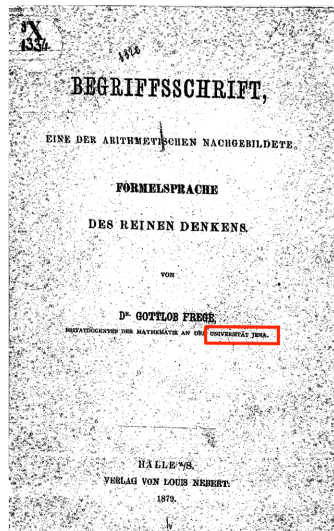
$$(D \rightarrow (B \rightarrow A)) \rightarrow (B \rightarrow (D \rightarrow A))$$

$$(B \rightarrow A) \rightarrow (\neg A \rightarrow \neg B)$$

$$\neg\neg A \rightarrow A$$

$$A \rightarrow \neg\neg A$$

Gottlob Frege, Begriffsschrift, Universität Jena, 1879



Source: Wikipedia
Guus Hoekman

Cook-Reckhow Theorem: Birth of Proof Complexity

Theorem [Cook-Reckhow'1979]

Any two Frege systems **polynomially simulate** each other.

Notes:

- Polynomial simulation \equiv polynomial time **translations** exist.
- Also for “Extended Frege Systems”: **abbreviations** allowed.
- Mild conditions apply: soundness, implicational completeness, complete basis of connectives.

Tait Style Systems

Language: $\wedge, \vee, x_i, \overline{x_i}$ (Negation Normal Form: A and \overline{A})

Rules: Axiom, Weakening, Conjunction, Cut

$$\frac{}{A \vee \overline{A}} \quad \frac{A}{A \vee B} \quad \frac{A \vee C \quad B \vee D}{A \vee B \vee (C \wedge D)} \quad \frac{A \vee C \quad B \vee \overline{C}}{A \vee B}$$

Soundness: Obvious

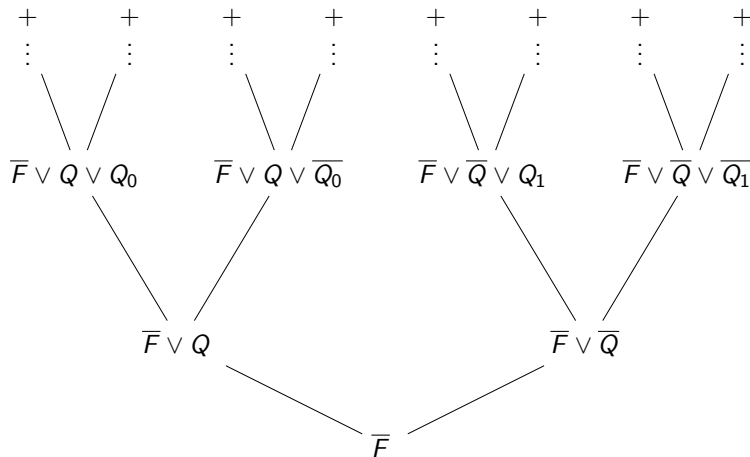
Completeness: Also almost obvious; even **cut-free**!

Quantitative completeness:

$$2^{\#\text{vars}(F)} \cdot \#\text{gates}(F).$$

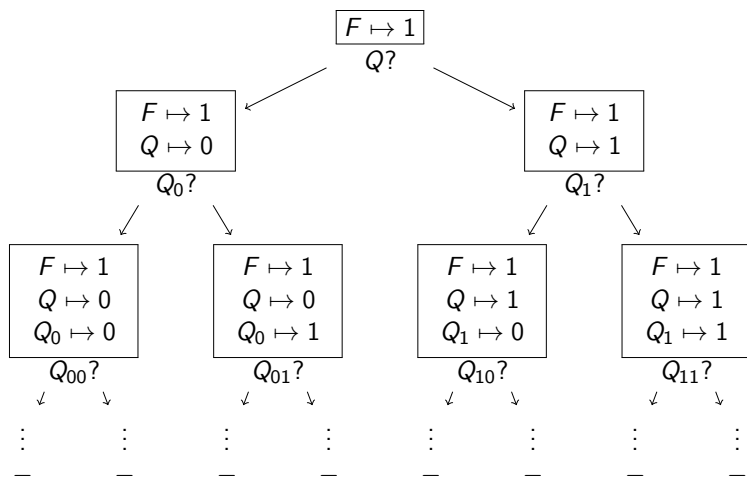
Resolution $\stackrel{\text{def}}{=} \text{cut-only}$ proofs from clauses to clauses.

Goal: Prove F is unsatisfiable. **Means:** Build up \overline{F} from axioms.



Decision Trees

Goal: Prove F is unsatisfiable. **Means:** Reduce F to $\overline{\text{axioms}}$



Quantitative Equivalence (With a But)

Theorem [Buss-Pudlak'1995]

1. If there is a decision tree proof of \overline{F} with L nodes,
then there is a proof of \overline{F} with $\text{poly}(L)$ lines.
2. If there is a proof of \overline{F} with L lines,
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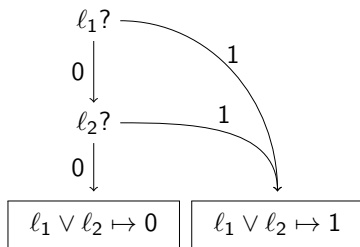
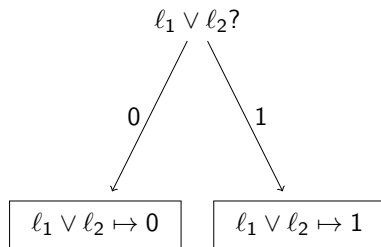
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Separation: Pebbling Formulas [Ben-Sasson-Wigderson'99].

Solution: Decision DAGs



Resolution

Definition Given $F = C_1 \wedge \dots \wedge C_m$ with each C_i a clause, a Resolution refutation of F is a **cut-only proof**

$$C_1, \dots, C_m, D_1, D_2, \dots, D_L = \emptyset$$

of the \emptyset from the C_i .

Proposition

Up to multiplicative constants, the following are the same:

1. Decision **trees** with **clause-queries** and L nodes.
2. Decision **dags** with **literal-queries** and L nodes.
3. **Tree-like DNF-proofs** of length L .
4. **Dag-like clause-proofs** of length L .
5. Resolution refutations of length L .

Back to SAT-Solvers

DPLL: Searches for **tree-like** Resolution proofs

CDCL: Searches for **dag-like** Resolution proofs

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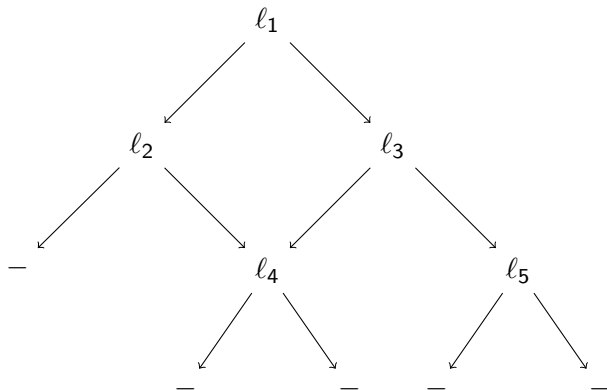
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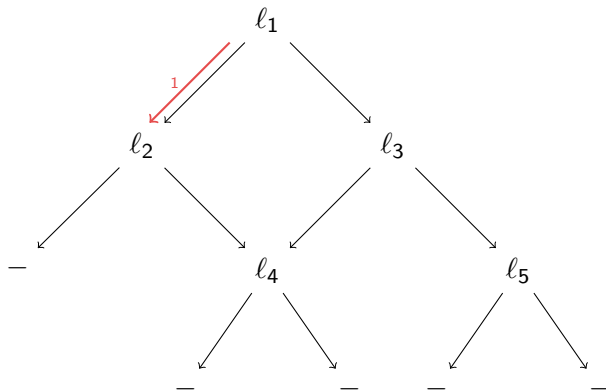
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9. Preprocessing and inprocessing
10. Symmetry breaking
11. ...

Execution Trace of CDCL-Based SAT-Solvers



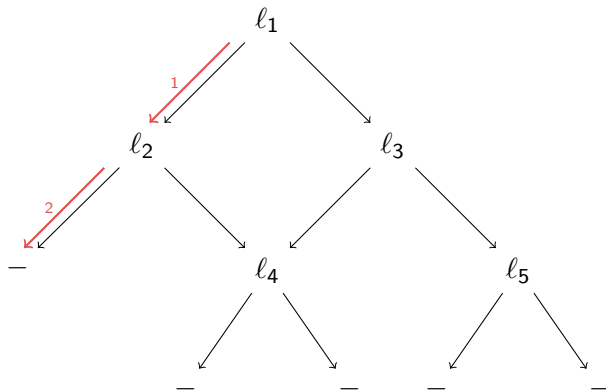
Execution Trace of CDCL-Based SAT-Solvers

1. decide



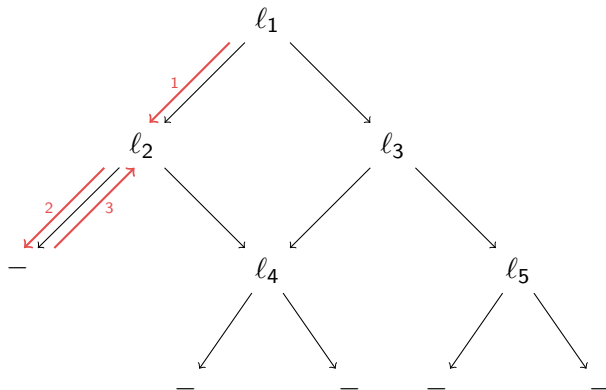
Execution Trace of CDCL-Based SAT-Solvers

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2. decide



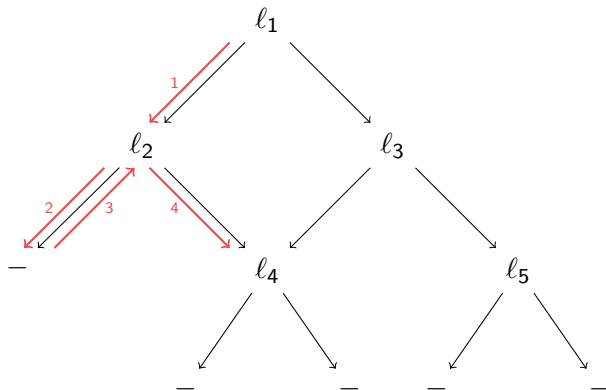
Execution Trace of CDCL-Based SAT-Solvers

1. decide
2. decide
3. conflict / learn



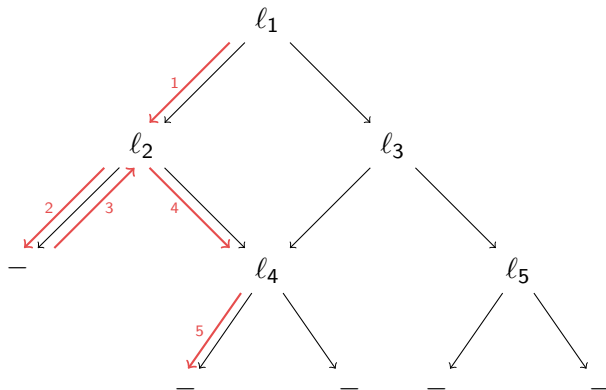
Execution Trace of CDCL-Based SAT-Solvers

1. decide
2. decide
3. conflict / learn
4. propagate



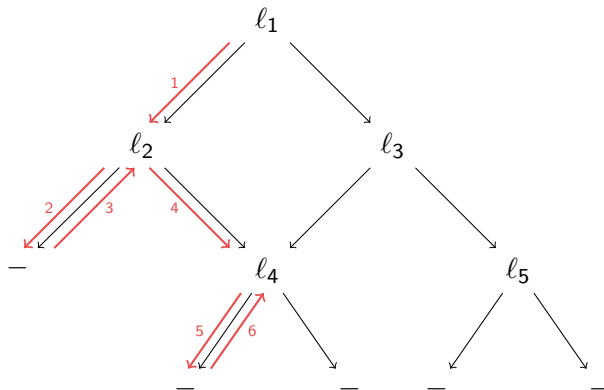
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4. propagate
5. decide



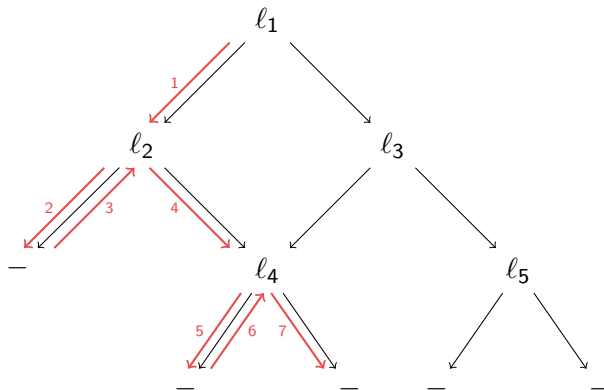
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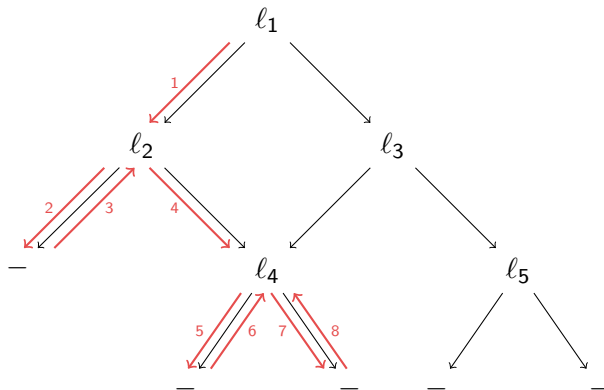
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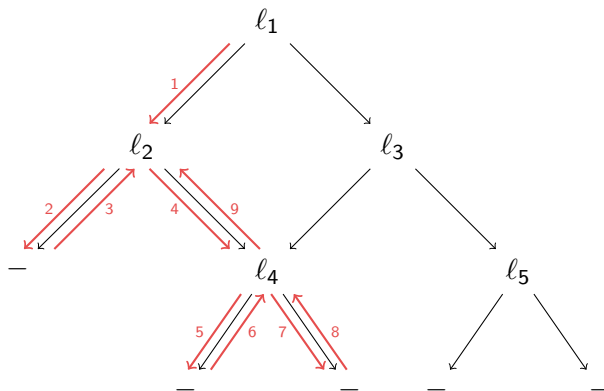
Execution Trace of CDCL-Based SAT-Solvers

1. decide
2. decide
3. conflict / learn
4. propagate
5. decide
6. conflict / learn
7. propagate
8. conflict / analysis



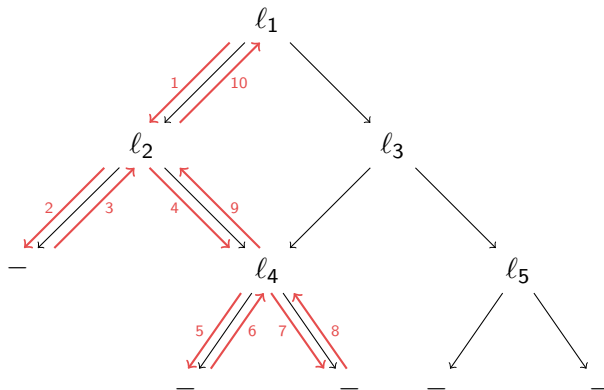
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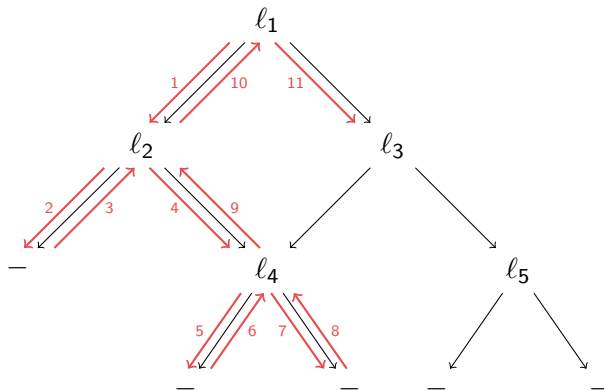
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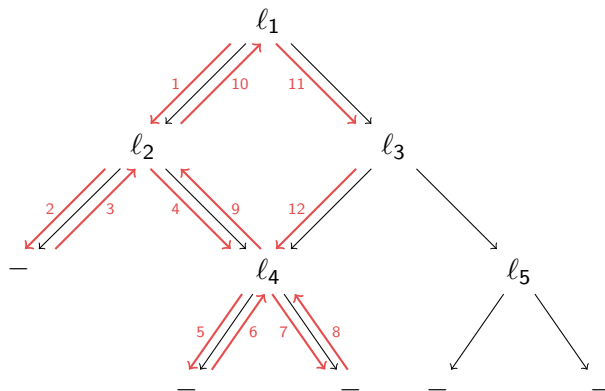


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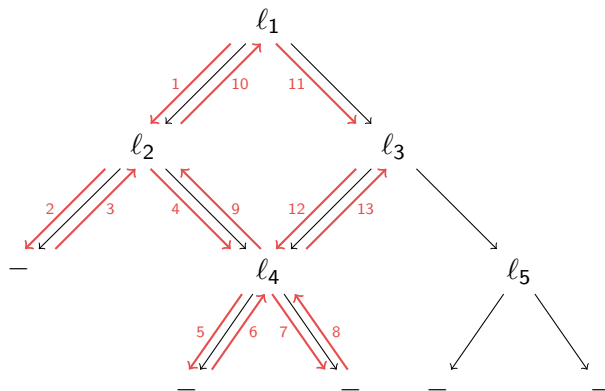
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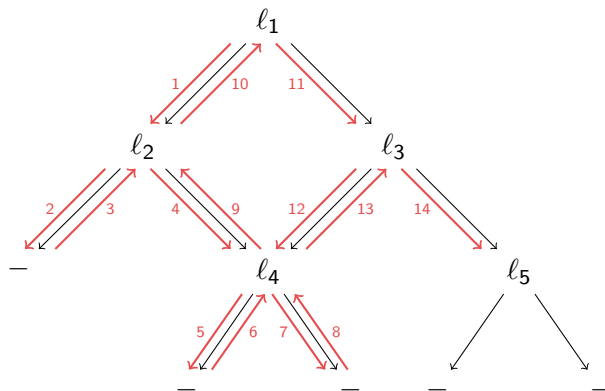


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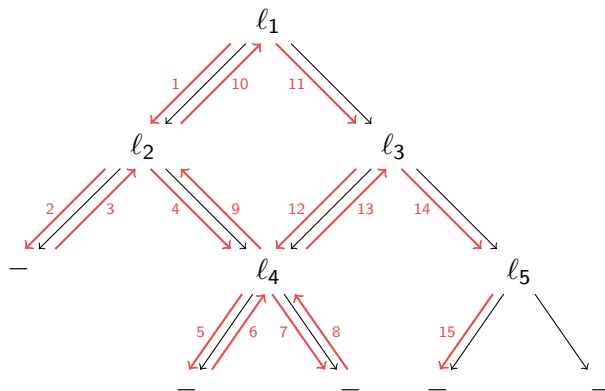


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7. propagate
8. conflict / analysis
9. conflict / analysis
10. conflict / learn
11. propagate
12. decide
13. conflict with **learned** / learn

Execution Trace of CDCL-Based SAT-Solvers

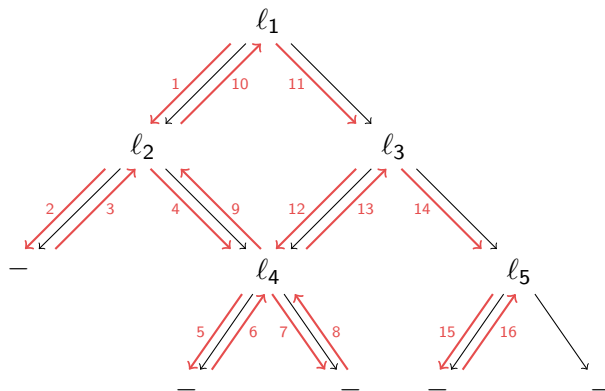


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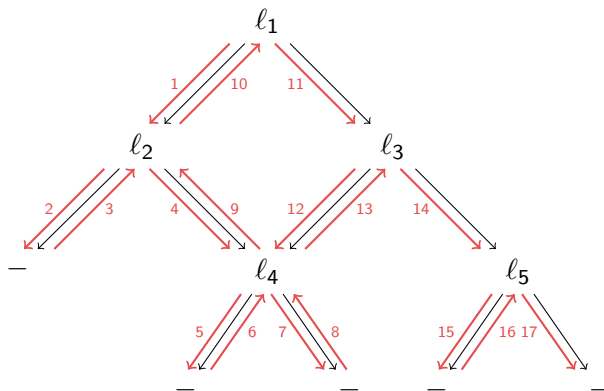
1. decide
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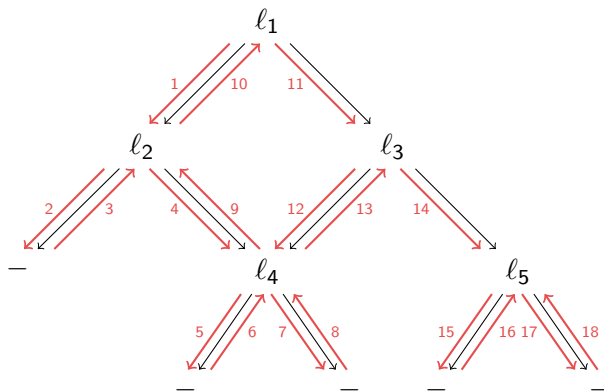
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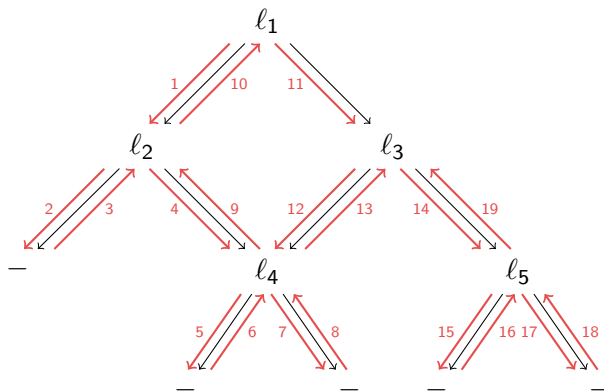
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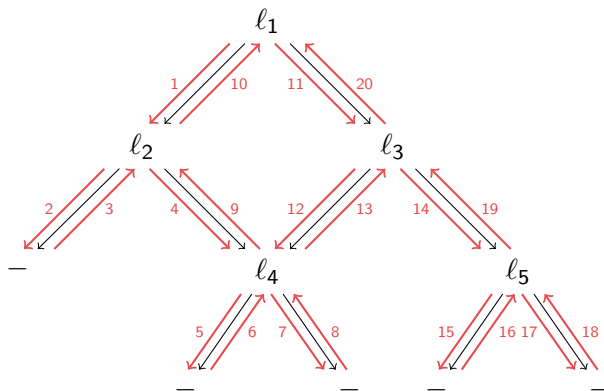
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20. conflict / learn **empty** clause

Comparison with Resolution

Theorem [Beame-Kautz-Sabharwal'2004]

If a CNF F with n variables has a Resolution refutation of length L , then there is a sequence of non-deterministic **ideal choices** for CDCL with **restarts**, **rebranching**, and any **non-redundant learning scheme** that learns the empty clause in $O(nL)$ steps.

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- Later removed at cost $O(n^4L)$ [Pipatsrisawat-Darwiche'09]
- Is non-determinism essential? ... now answered (next lecture)
- For bounded width Resolution (e.g., 2-SAT, bounded tree-width), randomness suffices to ensure $n^{O(\text{width})}$ steps [Atserias-Fichte-Thurley'09]

Lower Bounds for Resolution

Theorem [Haken'1986]

Every Resolution refutation of the Pigeonhole Principle formulas PHP_n^{n+1} must have length $2^{\Omega(n)}$.

Pigeonhole Principle Formulas PHP_n^{n+1} :

$p_{u,j}$: “pigeon $u \in \{1, \dots, n+1\}$ flies to hole $j \in \{1, \dots, n\}$ ”

$p_{u,1} \vee \dots \vee p_{u,n}$ for all u

$\overline{p_{u,j}} \vee \overline{p_{v,j}}$ for all $u \neq v$ and all j

Random Restriction Method in Three Steps: I

STEP I: Choose a suitable collection H of **partial assignments** α , so that the restricted formula $\text{PHP}_n^{n+1}|_\alpha$ is isomorphic to a smaller instance PHP_m^{m+1} of itself.

Here:

Let H be the set of partial assignments α that describe **partial matchings** of $n - m$ pigeons to $n - m$ holes.

$$\begin{array}{ll} \alpha(p_{u,j}) = 1 & \text{if } u \text{ is matched to } j \\ \alpha(p_{u,j}) = 0 & \text{if } u \text{ is matched to } j' \neq j \\ \alpha(p_{u,j}) = 0 & \text{if } u \text{ is not matched and } j \text{ is matched} \\ \alpha(p_{u,j}) = p_{u,j} & \text{if } u \text{ is not matched and } j \text{ is not matched.} \end{array}$$

We will choose $m = n/2$.

Random Restriction Method in Three Steps: II

STEP II: Define a suitable notion of **weak clause** that is **very likely true** under a random partial assignment from H .

Here:

A pigeon u is **n -weak in the clause** if the clause has

- $n/2$ positive literals $p_{u,j_1}, \dots, p_{u,j_{n/2}}$ of pigeon u , or
- a negative literal $\overline{p_{u,j}}$ of pigeon u .

A clause is **n -weak** if there are $n/2$ many n -weak pigeons in it.

Rough estimation of probability:

- Fix a weak clause C ; choose $\alpha \in H$ at random.
- Roughly $(n - m)/2 = n/4$ of the matched pigeons are weak.
- Roughly $1/2$ of the positive ones satisfy C .
- Roughly $1 - 1/(n - m) \geq 1/2$ of the negative ones satisfy C .

$$\Pr_{\alpha \in H}[C|_{\alpha} \neq 1] \lesssim (1/2)^{n/4}$$

Random Restriction Method in Three Steps: III

STEP III: Show that every Resolution refutation of PHP_m^{m+1} **must** contain at least one n -weak clause.

Here:

- For contradiction, fix a refutation without n -weak clauses.
- By $m = n/2$, in all clauses, not all pigeons are n -weak.
- **Walking up the dag** from the empty clause to the axioms, do:
- Sustain a partial matching from m pigeons to m holes.
- The partial matching will falsify the current clause.
- And the **unmatched pigeon** will **not** be **weak** in current clause.
- Initially: any matching works since all falsify the empty clause.
- At an inference step resolving on $p_{u,j}$:
- **Follow the falsified clause.**
- If unmatched pigeon became weak, exchange with non-weak.
- Eventually we reach a clause of PHP_m^{m+1} .
- Contradiction: our partial matchings do not falsify those.

QED

Part II

COMPLEXITY OF PROOF SEARCH

Automatability : Searching for *Short* Proofs

Definition [Bonet-Pitassi-Raz'1999]

A proof system P is **automatable in time $T(s)$** if there is an algorithm that **given a tautology F finds a P -proof** of F in time $T(s^*)$, where s^* is the size of the smallest P -proof of F .

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A Fundamental Question

Which proof systems are automatable in non-trivial time?

An Early Lower Bound:

Theorem [Krajicek-Pudlak'1994]

Extended Frege systems are **not automatable** in time $T(s)$,
unless n -bit RSA cryptosystem can be broken in time $T(\text{poly}(n))$.

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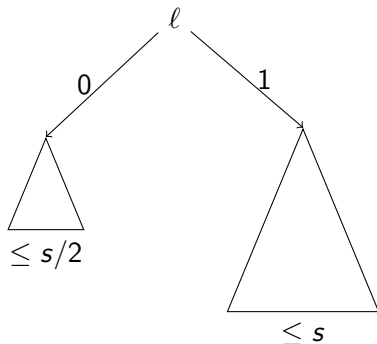
An Early Upper Bound:

Theorem [Beame-Pitassi'1998]

Tree-like Resolution **is automatable** in time $T(s) = s^{O(\log s)}$.

Beame-Pitassi Algorithm

1. **guess** the root literal ℓ
($2n$ choices only)
2. **recurse** with parameter $s/2$
(abort the branch if it fails)
3. **recurse** with parameter s
(it must succeed; subtle
because the chosen ℓ
need not be optimal).



$$T(n, s) \leq 2nT(n-1, s/2) + T(n-1, s)$$

$$T(n, s) = n^{O(\log s)} \leq s^{O(\log s)}.$$

Non-Automatability of Resolution

Theorem [Atserias-Müller'2019]

Resolution is **not automatable** in time $T(s)$, [poly-time]
unless n -variable SAT is solvable in time $T(\text{poly}(n))$ [$P = NP$].

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Notes:

- Compare with Beame-Pitassi algorithm!
- Improved earlier results of [Alekhovich-Razborov'2001]
- Introduced a **new method** for proving non-automatability
- Correctness of the reduction involves proving a lower bound!

Proof Strategy for NP-Hardness

We want a polynomial-time reduction:

from n -variable SAT
to min proof-size approximation for Resolution (R).

$$F \xrightarrow{\text{poly}(n) \text{ time}} G_F$$

Requirements:

1. If F is **satisfiable**, then $\text{SIZE}_R(G_F) \leq \text{poly}(n)$.
2. If F is **unsatisfiable**, then $\text{SIZE}_R(G_F) \not\leq \exp(\Omega(n))$.

Choice of the Formula G_F : the REF Formulas

$\text{REF}_{F,s}$ = “the CNF formula F has an R-refutation of length s ”

Variables:

- $D_{u,i,b}$: “line u contains variable x_i with sign $b \in \{0, 1\}$ ”
- $I_{u,j}$: “line u is an **initial** assumption; the j -th clause of F ”
- $V_{u,i}$: “line u is derived by resolving on **variable** x_i ”
- $L_{u,v}$: “line u is derived using v as **left** assumption”
- $R_{u,v}$: “line u is derived using v as **right** assumption”
- A_u : “line u is **active**; i.e., actually used in the proof”

Clauses (a sample):

$$\begin{array}{ccc} \overline{A_u} \vee \overline{V_{u,i}} \vee \overline{L_{u,v}} \vee D_{v,i,1} & \overline{A_u} \vee \overline{V_{u,i}} \vee \overline{R_{u,v}} \vee D_{v,i,0} & \overline{D_{s,i,b}} \\ \overline{A_u} \vee \overline{V_{u,i}} \vee \overline{L_{u,v}} \vee A_v & \overline{A_u} \vee \overline{V_{u,i}} \vee \overline{R_{u,v}} \vee A_v & A_s \\ \dots & & \end{array}$$

Requirement 1 : The Upper Bound

If F is **satisfiable**, then $\text{SIZE}_R(\text{REF}_{F,n^c}) \leq \text{poly}(n)$.

Proof idea:

Use a satisfying assignment α of F to **nail down** the refutation!

Proof sketch:

- Prove that every active line contains a literal satisfied by α .
- Concretely, derive the clauses

$$T_u := \overline{A_u} \vee \bigvee_{i=1}^n D_{u,i,\alpha(i)} \quad \text{for } u = 1, 2, \dots, L.$$

- Produce empty clause by resolving T_s with A_s and the $\overline{D_{s,i,b}}$.

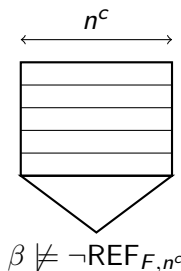
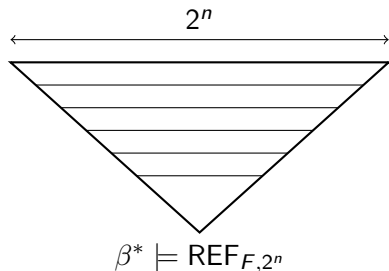
QED

Requirement 2 : The Lower Bound

If F is **unsatisfiable**, then $\text{SIZE}_R(\text{REF}_{F,n^c}) \not\leq \exp(\Omega(n))$.

Proof idea:

Use a **model** β^* of $\text{REF}_{F,2^n}$ to construct
a collection of “**pseudo-models**” β for REF_{F,n^c} .



The Lower Bound in Three Steps

- Identify a set H of α such that $\text{REF}_{F,s}|_{\alpha} \cong \text{REF}_{F,s/2}$.
- Here: let α set $1/2$ of all lines as inactive (but not the last).
- And let α also set all other variables of those lines.
- Identify a notion of **weak** clause made likely true by random α .
- Here: the clauses that **mention** more than $n/2$ lines.
- Calculation: $\Pr_{\alpha \in H}[C|_{\alpha} \neq 1] \leq (3/4)^{n/2}$.
- Prove that refutations of $\text{REF}_{F,s/2}$ must contain weak clauses.
- Walk up the dag from empty clause to axioms, and do:
- Sustain a **matching** between **active lines** and the **lines in β^*** .
- The corresponding assignments are the “**pseudo-models**” β .

QED

Reminder

Theorem

Resolution is **not automatable** in time $T(s)$, [poly-time]
unless n -variable SAT is solvable in time $T(\text{poly}(n))$ [P = NP].



Theorem

Tree-Like Resolution is **not automatable** in time $T(s) = s^{o(\log s)}$,
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The Tree-Like Case

We want a reduction:

from n -variable SAT

to min proof-size approximation for tree-like R (called R^*).

$$F \xrightarrow{\exp(o(n)) \text{ time}} G_F$$

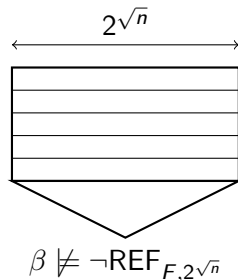
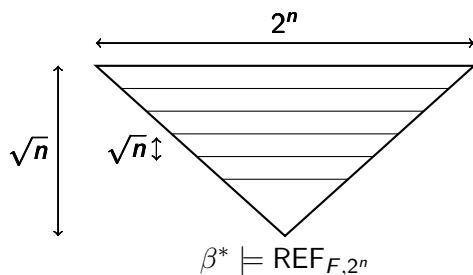
Requirements:

1. If F is **satisfiable**, then $\text{SIZE}_{R^*}(G_F) \leq \exp(O(\sqrt{n}))$.
2. If F is **unsatisfiable**, then $\text{SIZE}_{R^*}(G_F) \not\leq \exp(\Omega(n))$.

Modification of the Formula G_F : Shallow REF

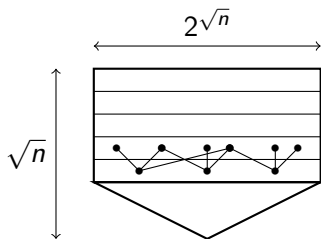
Key Observation:

In the “ F is **unsatisfiable**” case,
the model β^* of $\text{REF}_{F,2^n}$ happens to be:
tree-like and **layered**, and have **depth** n .



Modification of the Formula in More Details

- Modify the formula G_F ; now $\text{REF}_{F,s}|_\gamma$ with $s = 2\sqrt{n}$.
- The γ restricts A, D, I, V, L, R in a way **compatible** with β^* :
- Instead of arbitrary dag-depth, impose **depth n** .
- Instead of arbitrary structure, impose \sqrt{n} **layers** of depth \sqrt{n} .
- Instead of $\text{poly}(n)$ -size layers, allow layers of **size $2\sqrt{n}$** .
- Instead of full connectivity between layers, place **expanders**.
- Their bounded degree d ensures tree-like size $d^{\sqrt{n}} = 2^{O(\sqrt{n})}$.
- Their expansion property ensures matchability with β^* .



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- For Resolution, the problem is PARITY GAMES hard [BPT].
- For (Extended) Frege, the problem is RSA-hard [KP,BPR].

THE END