

Algorithms for SAT

Automated Program Verification (APV)
Fall 2019

Prof. Arie Gurfinkel



Syntax of Propositional Logic

An *atomic formula* has a form A_i , where $i = 1, 2, 3 \dots$

Formulas are defined inductively as follows:

- All atomic formulas are formulas
- For every formula F , $\neg F$ (called not F) is a formula
- For all formulas F and G , $F \wedge G$ (called and) and $F \vee G$ (called or) are formulas

Abbreviations

- use A, B, C, \dots instead of A_1, A_2, \dots
- use $F_1 \rightarrow F_2$ instead of $\neg F_1 \vee F_2$ (implication)
- use $F_1 \leftrightarrow F_2$ instead of $(F_1 \rightarrow F_2) \wedge (F_2 \rightarrow F_1)$ (iff)

Syntax of Propositional Logic (PL)

$\text{truth_symbol} ::= \top(\text{true}) \mid \perp(\text{false})$

$\text{variable} ::= p, q, r, \dots$

$\text{atom} ::= \text{truth_symbol} \mid \text{variable}$

$\text{literal} ::= \text{atom} \mid \neg \text{atom}$

$\text{formula} ::= \text{literal} \mid$

$\neg \text{formula} \mid$

$\text{formula} \wedge \text{formula} \mid$

$\text{formula} \vee \text{formula} \mid$

$\text{formula} \rightarrow \text{formula} \mid$

$\text{formula} \leftrightarrow \text{formula}$

Normal Forms: CNF and DNF

A *literal* is either an atomic proposition v or its negation $\sim v$

A *clause* is a disjunction of literals

- e.g., $(v1 \parallel \sim v2 \parallel v3)$

A formula is in *Conjunctive Normal Form* (CNF) if it is a conjunction of disjunctions of literals (i.e., a conjunction of clauses):

- e.g., $(v1 \parallel \sim v2) \&\& (v3 \parallel v2)$

$$\bigwedge_{i=1}^n \left(\bigvee_{j=1}^{m_i} L_{i,j} \right)$$

A formula is in *Disjunctive Normal Form* (DNF) if it is a disjunction of conjunctions of literals

$$\bigvee_{i=1}^n \left(\bigwedge_{j=1}^{m_i} L_{i,j} \right)$$

Boolean Satisfiability (CNF-SAT)

Let V be a set of variables

A *literal* is either a variable v in V or its negation $\sim v$

A *clause* is a disjunction of literals

- e.g., $(v1 \vee \sim v2 \vee v3)$

A Boolean formula in *Conjunctive Normal Form* (CNF) is a conjunction of clauses

- e.g., $(v1 \vee \sim v2) \wedge (v3 \vee v2)$

An *assignment* s of Boolean values to variables *satisfies* a clause c if it evaluates at least one literal in c to true

An assignment s *satisfies* a formula C in CNF if it satisfies every clause in C

Boolean Satisfiability Problem (CNF-SAT):

- determine whether a given CNF C is satisfiable

CNF Examples

CNF 1

- $\sim b$
- $\sim a \parallel \sim b \parallel \sim c$
- a
- sat: $s(a) = \text{True}; s(b) = \text{False}; s(c) = \text{False}$

CNF 2

- $\sim b$
- $\sim a \parallel b \parallel \sim c$
- a
- $\sim a \parallel c$
- unsat

Algorithms for SAT

SAT is NP-complete

- solution can be checked in polynomial time
- no polynomial algorithms for finding a solution are known

DPLL (Davis-Putnam-Logemman-Loveland, '60)

- smart enumeration of all possible SAT assignments
- worst-case EXPTIME
- alternate between deciding and propagating variable assignments

CDCL (GRASP '96, Chaff '01)

- conflict-driven clause learning
- extends DPLL with
 - smart data structures, backjumping, clause learning, heuristics, restarts...
- scales to millions of variables
- N. Een and N. Sörensson, "An Extensible SAT-solver", in SAT 2013.

Background Reading: SAT

← →

http://cacm.acm.org/magazines/2009/8/34498-boolean-satisfiability-from-theoretical-h

Boolean Satisfiability: From ... ×

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REVIEW ARTICLES








Boolean Satisfiability: From Theoretical Hardness to Practical Success


By Sharad Malik, Lintao Zhang
Communications of the ACM, Vol. 52 No. 8, Pages 76-82
10.1145/1536616.1536637
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There are many practical situations where we need to satisfy several potentially conflicting constraints. Simple examples of this abound in daily life, for example, determining a schedule for a series of games that resolves the availability of players and venues, or finding a seating assignment at dinner consistent with various rules the host would like to impose. This also applies to applications in computing, for example, ensuring that a hardware/software system functions correctly with its overall behavior constrained by the behavior of its components and their composition, or finding a plan for a robot to reach a goal that is

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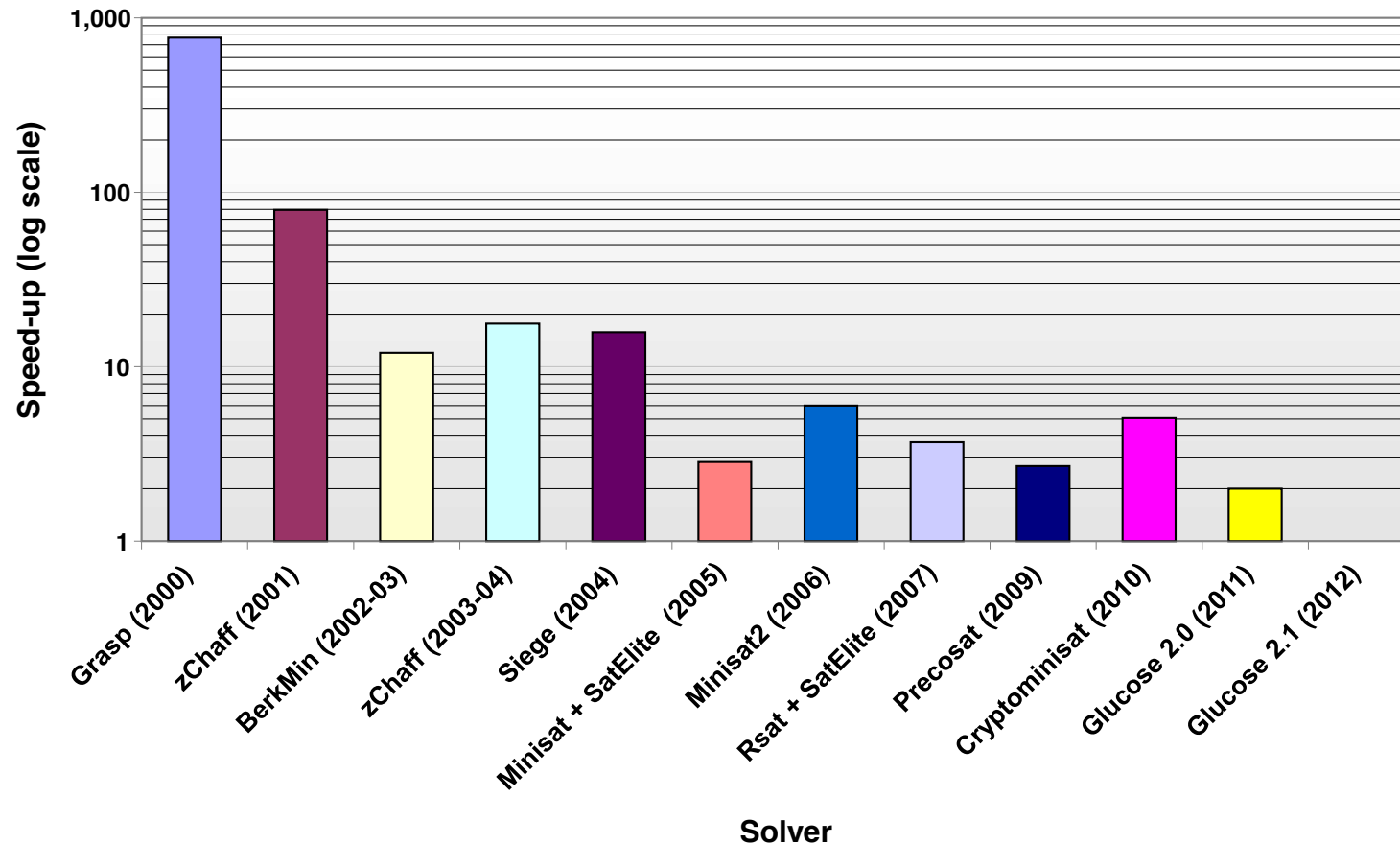
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[Theoretical hardness: SAT and NP Completeness](#)

Some Experience with SAT Solving

Speed-up of 2012 solver over other solvers



from M. Vardi, <https://www.cs.rice.edu/~vardi/papers/highlights15.pdf>

SAT - Milestones

Problems impossible 10 years ago are trivial today

year	Milestone
1960	Davis-Putnam procedure
1962	Davis-Logeman-Loveland
1984	Binary Decision Diagrams
1992	DIMACS SAT challenge
1994	SATO: clause indexing
1997	GRASP: conflict clause learning
1998	Search Restarts
2001	zChaff: 2-watch literal, VSIDS
2005	Preprocessing techniques
2007	Phase caching
2008	Cache optimized indexing
2009	In-processing, clause management
2010	Blocked clause elimination

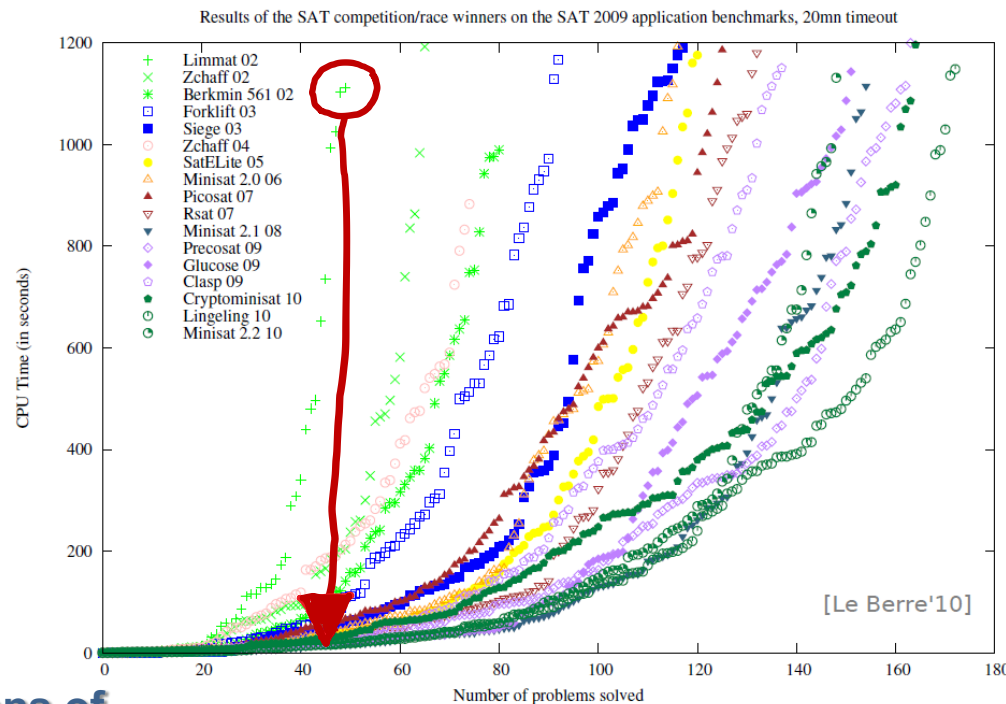
Concept



Millions of
variables from
HW designs

2002

2010

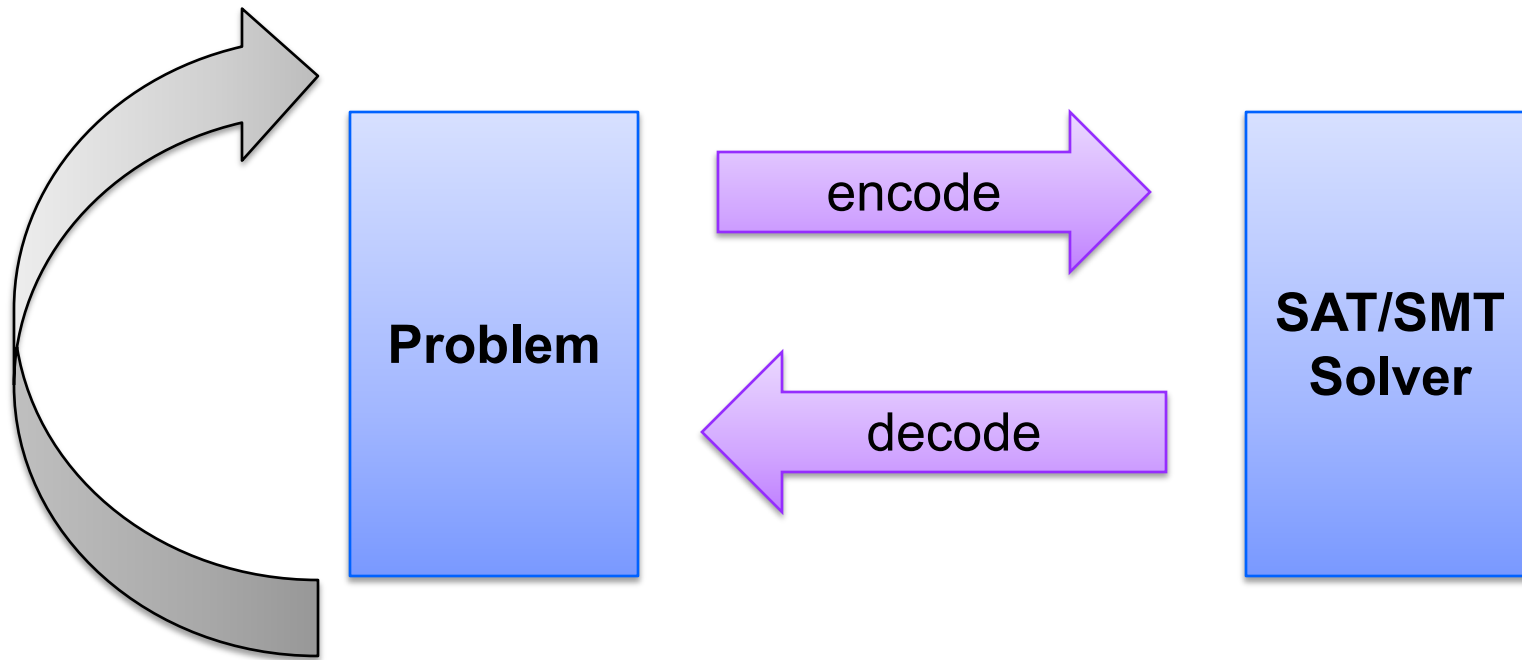


Courtesy Daniel le Berre

NP is the new P!

Solve any computational problem by effective reduction to SAT/SMT

- iterate as necessary



Graph k-Coloring

Given a graph $G = (V, E)$, and a natural number $k > 0$ is it possible to assign colors to vertices of G such that no two adjacent vertices have the same color.

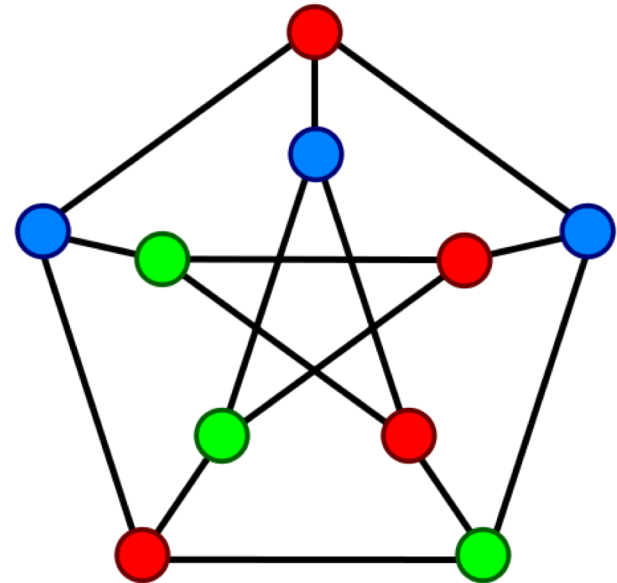
Formally:

- does there exist a function $f : V \rightarrow [0..k)$ such that
- for every edge (u, v) in E , $f(u) \neq f(v)$

Graph coloring for $k > 2$ is NP-complete

Problem: Encode k-coloring of G into CNF

- construct CNF C such that C is SAT iff G is k-colorable



***k*-coloring as CNF**

Let a Boolean variable $f_{v,i}$ denote that vertex v has color i

- if $f_{v,i}$ is true if and only if $f(v) = i$

Every vertex has at least one color

$$\bigvee_{0 \leq i < k} f_{v,i} \quad (v \in V)$$

No vertex is assigned two colors

$$\bigwedge_{0 \leq i < j < k} (\neg f_{v,i} \vee \neg f_{v,j}) \quad (v \in V)$$

No two adjacent vertices have the same color

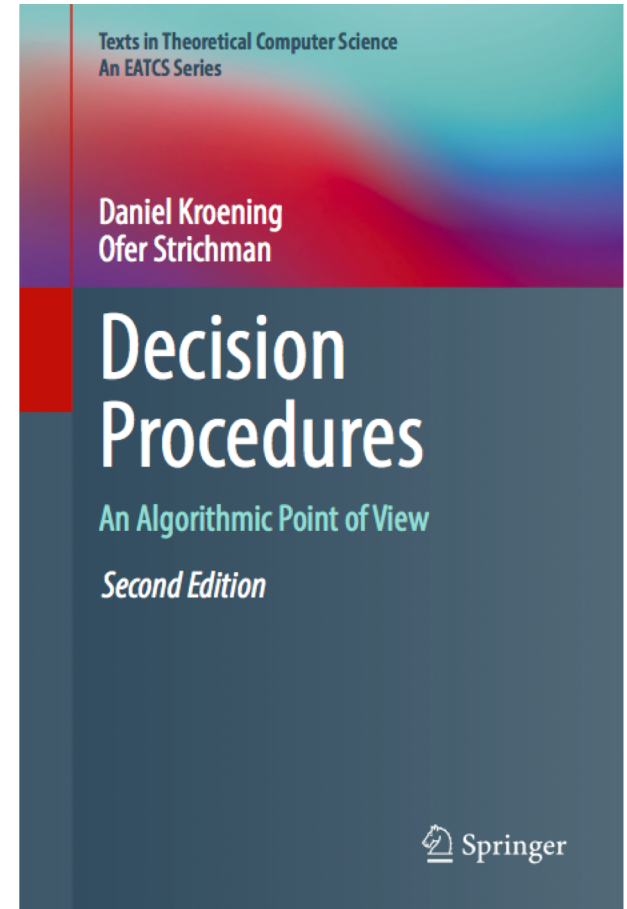
$$\bigwedge_{0 \leq i < k} (\neg f_{v,i} \vee \neg f_{u,i}) \quad ((v, u) \in E)$$

Davis Putnam Logemann Loveland

DPLL PROCEDURE

References

Chapter 2: Decision Procedures for Propositional Logic



<https://link.springer.com/book/10.1007%2F978-3-540-74105-3>

Decision Procedure for Satisfiability

Algorithm that in some finite amount of computation decides if a given propositional logic (PL) formula F is satisfiable

- NP-complete problem

Modern decision procedures for PL formulae are called SAT solvers

Naïve approach

- Enumerate models (i.e., truth tables)
- Enumerate resolution proofs

Modern SAT solvers

- DPLL algorithm
 - Davis-Putnam-Logemann-Loveland
- Combines model- and proof-based search
- Operates on Conjunctive Normal Form (CNF)

Propositional Resolution

Pivot

$C \vee p$

$D \vee \neg p$

$C \vee D$

Resolvent

$$\text{Res}(\{C, p\}, \{D, \neg p\}) = \{C, D\}$$

Given two clauses $\{C, p\}$ and $\{D, \neg p\}$ that contain a literal p of different polarity, create a new clause by taking the union of literals in C and D

Resolution Lemma

Lemma:

Let F be a CNF formula. Let R be a resolvent of two clauses X and Y in F . Then, $F \cup \{R\}$ is equivalent to F

Resolution Theorem

Let F be a set of clauses

$$Res(F) = F \cup \{R \mid R \text{ is a resolvent of two clauses in } F\}$$

$$Res^0(F) = F$$

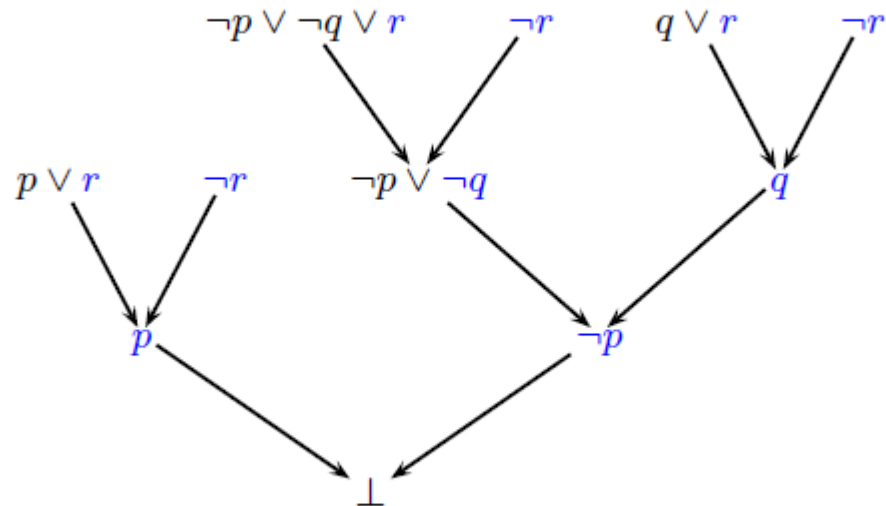
$$Res^{n+1}(F) = Res(Res^n(F)), \text{ for } n \geq 0$$

$$Res^*(F) = \bigcup_{n \geq 0} Res^n(F)$$

Theorem: A CNF F is UNAT iff $Res^*(F)$ contains an empty clause

Example of a resolution proof

A refutation of $\neg p \vee \neg q \vee r, p \vee r, q \vee r, \neg r$:



Resolution Proof Example

Show by resolution that the following CNF is UNSAT

$$\neg b \wedge (\neg a \vee b \vee \neg c) \wedge a \wedge (\neg a \vee c)$$

$$\begin{array}{c} \frac{\neg a \vee b \vee \neg c \quad a}{b \vee \neg c} \quad b \quad \frac{a \quad \neg a \vee c}{c} \\ \hline \neg c \quad c \\ \hline \perp \end{array}$$

Proof of the Resolution Theorem

(Soundness) By Resolution Lemma, F is equivalent to $\text{Res}^i(F)$ for any i . Let n be such that $\text{Res}^{n+1}(F)$ contains an empty clause, but $\text{Res}^n(F)$ does not. Then $\text{Res}^n(F)$ must contain two unit clauses L and $\neg L$. Hence, it is UNSAT.

(Completeness) By induction on the number of different atomic propositions in F .

Base case is trivial: F contains an empty clause.

IH: Assume F has atomic propositions A_1, \dots, A_{n+1}

Let F_0 be the result of replacing A_{n+1} by 0

Let F_1 be the result of replacing A_{n+1} by 1

Apply IH to F_0 and F_1 . Restore replaced literals. Combine the two resolutions.

Proof System

$$P_1, \dots, P_n \vdash C$$

An inference rule is a tuple (P_1, \dots, P_n, C)

- where, P_1, \dots, P_n, C are formulas
- P_i are called **premises** and C is called a **conclusion**
- intuitively, the rule says that the conclusion is true if the premises are

A proof system P is a collection of inference rules

A proof in a proof system P is a tree (or a DAG) such that

- nodes are labeled by formulas
- for each node n , $(\text{parents}(n), n)$ is an inference rule in P

Propositional Resolution

$$\frac{C \vee p \qquad D \vee \neg p}{C \vee D}$$

Propositional resolution is a sound inference rule

Proposition resolution system consists of a single propositional resolution rule

DP Procedure: SAT solving by resolution

Assume that input formula F is in CNF

1. Pick two clauses C_1 and C_2 in F that can be resolved
2. If the resolvent C is an empty clause, return UNSAT
3. Otherwise, add C to F and go to step 1
4. If no new clauses can be resolved, return SAT

Termination: finitely many derived clauses

DPLL: David Putnam Logemann Loveland

Combines pure resolution-based search with case splitting on decisions

Proof search is restricted to unit resolution

- can be done very efficiently (polynomial time)

Case split restores completeness

DPLL can be described by the following two rules

- F is the input formula in CNF

$$\frac{F}{F, p \quad | \quad F, \neg p} \text{ split} \quad p \text{ and } \neg p \text{ are not in } F$$

$$\frac{F, C \vee \ell, \neg \ell}{F, C, \neg \ell} \text{ unit}$$

Davis, Martin; Logemann, George; Loveland, Donald (1962).

"A Machine Program for Theorem Proving".

C. ACM. 5 (7): 394–397. doi:[10.1145/368273.368557](https://doi.org/10.1145/368273.368557)

The original DPLL procedure

Incrementally **builds** a satisfying truth assignment M for the input CNF formula F

M is grown by

- **deducing** the truth value of a literal from M and F , or
- **guessing** a truth value

If a wrong guess for a literal leads to an inconsistency, the procedure **backtracks** and tries the opposite value

DPLL: Illustration

M | F

Partial model

Set of clauses

DPLL: Decide

Guessing (Decide)

$$p \mid p \vee q, \neg q \vee r$$



$$p, \neg q \mid p \vee q, \neg q \vee r$$

DPLL: Boolean Constraint Propagation

Deducing (Unit Propagation or BCP)

$$p \mid p \vee q, \neg p \vee s$$



$$p, s \mid p \vee q, \neg p \vee s$$

DPLL: Backtracking

Backtracking

$p, \neg s, q \mid p \vee q, s \vee q, \neg p \vee \neg q$



$p, s \mid p \vee q, s \vee q, \neg p \vee \neg q$

Pure Literals

A literal is **pure** if only occurs positively or negatively.

Example :

$$\varphi = (\neg x_1 \vee x_2) \wedge (x_3 \vee \neg x_2) \wedge (x_4 \vee \neg x_5) \wedge (x_5 \vee \neg x_4)$$

$\neg x_1$ and x_3 are pure literals

Pure literal rule :

Clauses containing pure literals can be removed from the formula (i.e. just satisfy those pure literals)

$$\varphi_{\neg x_1, x_3} = (x_4 \vee \neg x_5) \wedge (x_5 \vee \neg x_4)$$

Preserve satisfiability, not logical equivalency !

DPLL Procedure

- ▶ Standard backtrack search
- ▶ DPLL(F) :
 - ▶ Apply unit propagation
 - ▶ If conflict identified, return UNSAT
 - ▶ Apply the pure literal rule
 - ▶ If F is satisfied (empty), return SAT
 - ▶ Select decision variable x
 - ▶ If $\text{DPLL}(F \wedge x) = \text{SAT}$ return SAT
 - ▶ return $\text{DPLL}(F \wedge \neg x)$

The Original DPLL Procedure – Example

assign	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Deduce 1	
1	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Deduce $\neg 2$	
1, 2	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Guess 3	
1, 2, 3	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Deduce 4	
1, 2, 3, 4	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Conflict	

The Original DPLL Procedure – Example

assign	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Deduce 1	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
1	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Deduce $\neg 2$	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
1, 2	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Guess 3	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
1, 2, 3	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Deduce 4	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
1, 2, 3, 4	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Undo 3	

The Original DPLL Procedure – Example

assign	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Deduce 1	
1	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Deduce $\neg 2$	
1, 2	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Guess $\neg 3$	
1, 2, 3	$1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$
Model Found	

An Abstract Framework for DPLL

The DPLL procedure can be described declaratively by simple sequent-style calculi

Such calculi, however, cannot model meta-logical features such as backtracking, learning, and restarts

We model DPLL and its enhancements as transition systems instead

A transition system is a binary relation over states, induced by a set of conditional transition rules

An Abstract Framework for DPLL

State

- **fail** or $M \parallel F$
- where
 - F is a CNF formula, a set of clauses, and
 - M is a sequence of annotated literals denoting a partial truth assignment

Initial State

- $\emptyset \parallel F$, where F is to be checked for satisfiability

Expected final states:

- **fail** if F is unsatisfiable
- $M \parallel G$
where
 - M is a model of G
 - G is logically equivalent to F

Transition Rules for DPLL

Extending the assignment:

$$\begin{array}{ll} \text{UnitProp} & M \parallel F, C \vee I \rightarrow M I \parallel F, C \vee I \quad \left\{ \begin{array}{l} M \models \neg C \\ I \text{ is undefined in } M \end{array} \right. \\ \\ \text{Decide} & M \parallel F, C \rightarrow M I^d \parallel F, C \quad \left\{ \begin{array}{l} I \text{ or } \neg I \text{ occur in } C \\ I \text{ is undefined in } M \end{array} \right. \end{array}$$

Notation: I^d is a decision literal

Transition Rules for DPLL

Repairing the assignment:

Fail

$M \parallel F, C \rightarrow \text{fail}$

$M \models \neg C$

M does not contain
decision literals

Backtrack $M \models N \parallel F, C \rightarrow M \neg I \parallel F, C$

$M \models N \models \neg C$

I is the last decision
literal

Transition Rules DPLL – Example

$$\emptyset \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

UnitProp
1

$$1 \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

UnitProp
¬2

$$1, 2 \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

Decide 3

$$1, 2, 3^d \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

UnitProp
4

$$1, 2, 3^d, 4 \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

Backtrac
k 3

Transition Rules DPLL – Example

$$\emptyset \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

UnitProp
1

$$1 \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

UnitProp
 $\neg 2$

$$1, 2 \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

Decide 3

$$1, 2, 3^d \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

UnitProp
4

$$1, 2, 3 \parallel 1 \vee 2, 2 \vee \neg 3 \vee 4, \neg 1 \vee \neg 2, \neg 1 \vee \neg 3 \vee \neg 4, 1$$

Backtrac
k 3

Transition Rules for DPLL (on one slide)

UnitProp $M \parallel F, C \vee I \rightarrow M I \parallel F, C \vee I$ $\left\{ \begin{array}{l} M \models \neg C \\ I \text{ is undefined in } M \end{array} \right.$

Decide $M \parallel F, C \rightarrow M I^d \parallel F, C$ $\left\{ \begin{array}{l} I \text{ or } \neg I \text{ occur in } C \\ I \text{ is undefined in } M \end{array} \right.$

Fail $M \parallel F, C \rightarrow \text{fail}$ $\left\{ \begin{array}{l} M \models \neg C \\ M \text{ does not contain} \\ \text{decision literals} \end{array} \right.$

Backtrack $M I^d N \parallel F, C \rightarrow M \neg I \parallel F, C$ $\left\{ \begin{array}{l} M I^d N \models \neg C \\ I \text{ is the last decision literal} \end{array} \right.$

The DPLL System – Correctness

Some terminology

- Irreducible state: state to which no transition rule applies.
- Execution: sequence of transitions allowed by the rules and starting with states of the form $\emptyset \parallel F$.
- Exhausted execution: execution ending in an irreducible state

Proposition (Strong Termination) Every execution in DPLL is finite

Proposition (Soundness) For every exhausted execution starting with $\emptyset \parallel F$ and ending in $M \parallel F$, $M \models F$

Proposition (Completeness) If F is unsatisfiable, every exhausted execution starting with $\emptyset \parallel F$ ends with fail

Maintained in more general rules + theories

Modern DPLL: CDCL

Conflict Driven Clause Learning

- two watched literals – efficient index to find clauses that can be used in unit resolution
- periodically restart backtrack search
- activity-based decision heuristic to choose decision variable
- **conflict resolution via clausal learning**

We will briefly look at clausal learning

More details on CDCL are available in

- Chapter 2 of Decision Procedures book
- ECE750 with Vijay Ganesh

Conflict Directed Clause Learning

Lemma learning

$$\neg t, p, q, s \mid t \vee \neg p \vee q, \neg q \vee s, \neg p \vee \neg s$$



$$\neg t, p, q, s \mid t \vee \neg p \vee q, \neg q \vee s, \neg p \vee \neg s \mid \neg p \vee \neg s$$



$$\neg t, p, q, s \mid t \vee \neg p \vee q, \neg q \vee s, \neg p \vee \neg s \mid \neg p \vee \neg q$$



$$\neg t, p, q, s \mid t \vee \neg p \vee q, \neg q \vee s, \neg p \vee \neg s \mid \neg p \vee t$$

Learned Clause by Resolution

A new clause is learned by resolving the conflict clause with clauses deduced from the last decision

$$\neg t, p, q, s \mid t \vee \neg p \vee q, \neg q \vee s, \neg p \vee \neg s$$

$$\begin{array}{rcc} \neg p \vee \neg s & & \neg q \vee s \\ \hline & \neg p \vee \neg q & t \vee \neg p \vee q \\ & \hline & t \vee \neg p \end{array}$$

Trivial Resolution: at every resolution step, at least one clause is an input clause

Modern CDCL: Abstract Rules

Initialize $\epsilon \mid F$ F is a set of clauses

Decide $M \mid F \Rightarrow M, \ell \mid F$ ℓ is unassigned

Propagate $M \mid F, C \vee \ell \Rightarrow M, \ell^{C \vee \ell} \mid F, C \vee \ell$ C is false under M

Sat $M \mid F \Rightarrow M$ F true under M

Conflict $M \mid F, C \Rightarrow M \mid F, C \mid C$ C is false under M

Learn $M \mid F \mid C \Rightarrow M \mid F, C \mid C$

Unsat $M \mid F \mid \emptyset \Rightarrow \text{Unsat}$

Backjump $MM' \mid F \mid C \vee \ell \Rightarrow M \ell^{C \vee \ell} \mid F$ $\bar{C} \subseteq M, \neg \ell \in M'$

Resolve $M \mid F \mid C' \vee \neg \ell \Rightarrow M \mid F \mid C' \vee C$ $\ell^{C \vee \ell} \in M$

Forget $M \mid F, C \Rightarrow M \mid F$ C is a learned clause

Restart $M \mid F \Rightarrow \epsilon \mid F$

[Nieuwenhuis, Oliveras, Tinelli J.ACM 06] customized

Conjunctive Normal Form

$\varphi \leftrightarrow \psi$	$\Rightarrow \text{CNF}$	$\varphi \rightarrow \psi \wedge \psi \rightarrow \varphi$
$\varphi \rightarrow \psi$	$\Rightarrow \text{CNF}$	$\neg \varphi \vee \psi$
$\neg(\varphi \vee \psi)$	$\Rightarrow \text{CNF}$	$\neg \varphi \wedge \neg \psi$
$\neg(\varphi \wedge \psi)$	$\Rightarrow \text{CNF}$	$\neg \varphi \vee \neg \psi$
$\neg \neg \varphi$	$\Rightarrow \text{CNF}$	φ
$(\varphi \wedge \psi) \vee \xi$	$\Rightarrow \text{CNF}$	$(\varphi \vee \xi) \wedge (\psi \vee \xi)$

Every propositional formula can be put in CNF

PROBLEM: (potential) exponential blowup of the resulting formula

Tseitin Transformation – Main Idea

Introduce a fresh variable e_i for every subformula G_i of F

- intuitively, e_i represents the truth value of G_i

Assert that every e_i and G_i pair are equivalent

- $e_i \leftrightarrow G_i$
- and express the assertion as CNF

Conjoin all such assertions in the end

Formula to CNF Conversion

```
def cnf ( $\phi$ ):  
    p, F = cnf_rec ( $\phi$ )  
    return p  $\wedge$  F
```

mk_fresh_var() returns a fresh variable not used anywhere before

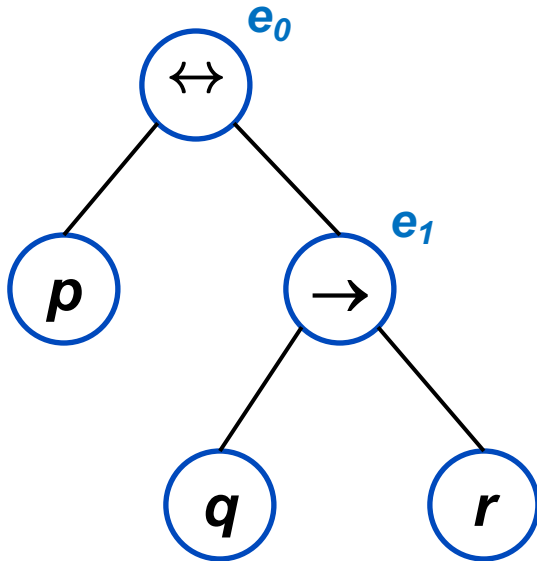
```
def cnf_rec ( $\phi$ ):  
    if is_atomic ( $\phi$ ): return ( $\phi$ , True)  
    elif  $\phi == \psi \wedge \xi$ :  
        q, F1 = cnf_rec ( $\psi$ )  
        r, F2 = cnf_rec ( $\xi$ )  
  
        p = mk_fresh_var ()  
        # C is CNF for  $p \leftrightarrow (q \wedge r)$   
        C = ( $\neg p \vee q$ )  $\wedge$  ( $\neg p \vee r$ )  $\wedge$  ( $p \vee \neg q \vee \neg r$ )  
        return (p, F1  $\wedge$  F2  $\wedge$  C)  
    elif  $\phi == \psi \vee \xi$ :  
        ...
```

Exercise: Complete cases for

$\phi == \psi \vee \xi$, $\phi == \neg \psi$, $\phi == \psi \leftrightarrow \xi$

Tseitin Transformation: Example

$$G : p \leftrightarrow (q \rightarrow r)$$

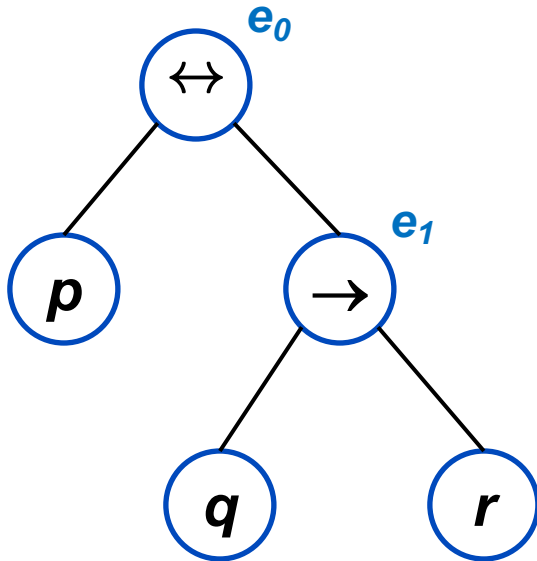


$$G : e_0 \wedge (e_0 \leftrightarrow (p \leftrightarrow e_1)) \wedge (e_1 \leftrightarrow (q \rightarrow r))$$

$$\begin{aligned} & e_1 \leftrightarrow (q \rightarrow r) \\ = & (e_1 \rightarrow (q \rightarrow r)) \wedge ((q \rightarrow r) \rightarrow e_1) \\ = & (\neg e_1 \vee \neg q \vee r) \wedge ((\neg q \vee r) \rightarrow e_1) \\ = & (\neg e_1 \vee \neg q \vee r) \wedge (\neg q \rightarrow e_1) \wedge (r \rightarrow e_1) \\ = & (\neg e_1 \vee \neg q \vee r) \wedge (q \vee e_1) \wedge (\neg r \vee e_1) \end{aligned}$$

Tseitin Transformation: Example

$$G : p \leftrightarrow (q \rightarrow r)$$

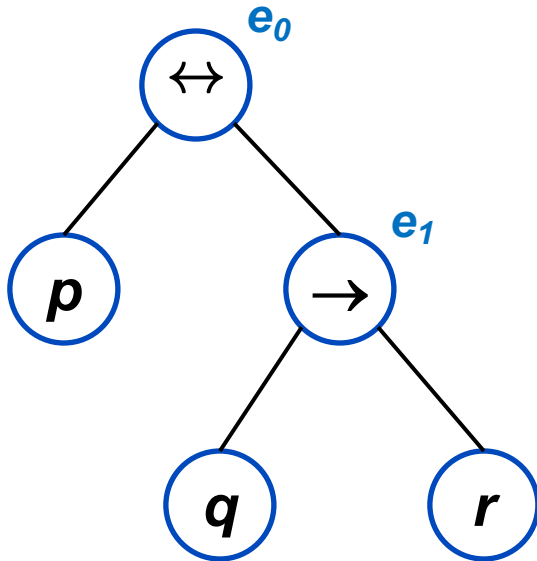


$$G : e_0 \wedge (e_0 \leftrightarrow (p \leftrightarrow e_1)) \wedge (e_1 \leftrightarrow (q \rightarrow r))$$

$$\begin{aligned}
 & e_0 \leftrightarrow (p \leftrightarrow e_1) \\
 = & (e_0 \rightarrow (p \leftrightarrow e_1)) \wedge ((p \leftrightarrow e_1) \rightarrow e_0) \\
 = & (e_0 \rightarrow (p \rightarrow e_1)) \wedge (e_0 \rightarrow (e_1 \rightarrow p)) \wedge \\
 & (((p \wedge e_1) \vee (\neg p \wedge \neg e_1)) \rightarrow e_0) \\
 = & (\neg e_0 \vee \neg p \vee e_1) \wedge (\neg e_0 \vee \neg e_1 \vee p) \wedge \\
 & (\neg p \vee \neg e_1 \vee e_0) \wedge (p \vee e_1 \vee e_0)
 \end{aligned}$$

Tseitin Transformation: Example

$$G : p \leftrightarrow (q \rightarrow r)$$



$$G : e_0 \wedge (e_0 \leftrightarrow (p \leftrightarrow e_1)) \wedge (e_1 \leftrightarrow (q \rightarrow r))$$

$$G : e_0 \wedge (\neg e_0 \vee \neg p \vee e_1) \wedge (\neg e_0 \vee p \vee \neg e_1) \wedge (e_0 \vee p \vee e_1) \wedge (e_0 \vee \neg p \vee \neg e_1) \wedge (\neg e_1 \vee \neg q \vee r) \wedge (e_1 \vee q) \wedge (e_1 \vee \neg r)$$

Tseitin Transformation [1968]

Used in practice

- No exponential blow-up
- CNF formula size is linear with respect to the original formula

Does not produce an equivalent CNF

However, given F , the following holds for the computed CNF F' :

- F' is equisatisfiable to F
- Every model of F' can be translated (i.e., projected) to a model of F
- Every model of F can be translated (i.e., completed) to a model of F'

No model is lost or added in the conversion

DIMACS CNF File Format

Textual format to represent CNF-SAT problems

c start with comments

c

c

p cnf 5 3

1 -5 4 0

-1 5 3 4 0

-3 -4 0

Format details

- comments start with c
- header line: p cnf nbvar nbclauses
 - nbvar is # of variables, nbclauses is # of clauses
- each clause is a sequence of distinct numbers terminating with 0
 - positive numbers are variables, negative numbers are negations

BOUNDED MODEL CHECKING

SAT-based Model Checking

Main idea

Translate the model and the specification to
propositional formulas

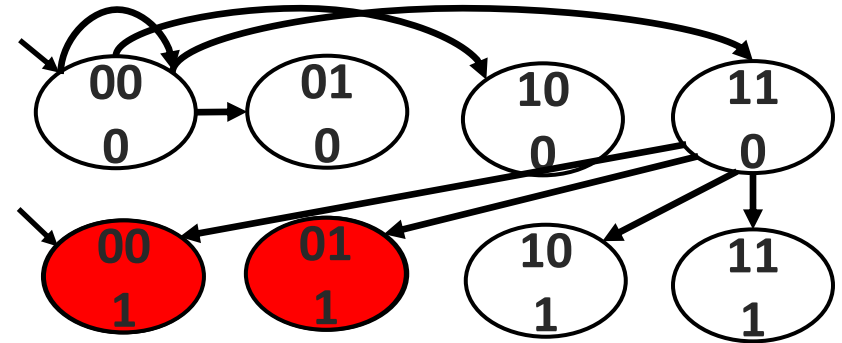
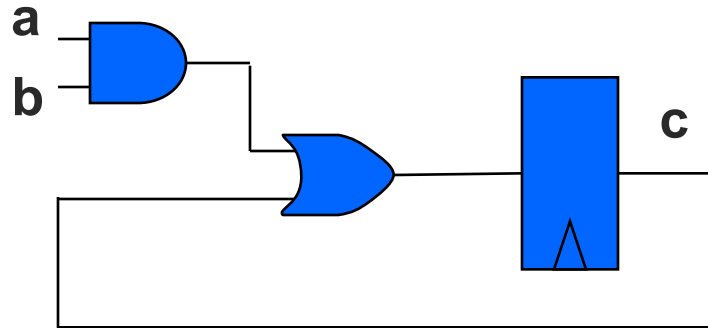
$(p, \neg p, p \vee q, p \wedge q, p \rightarrow q \dots)$

Reduce the model checking problem to **satisfiability**
of propositional formulas



Use efficient tools (**SAT solvers**) for solving the
satisfiability problem

Modeling with Propositional Formulas



Finite-State System is modeled as (V, INIT, T) :

- **V** – finite set of Boolean **variables**
 - Boolean variables: **a b c** \rightarrow 8 states: 000,001,...
- **INIT(V)** – describes the set of initial states
 - $\text{INIT} = \neg a \wedge \neg b$
- **T(V,V')** – describes the set of transitions
 - $T(a,b,c,a',b',c') = (c' \leftrightarrow (a \wedge b) \vee c)$

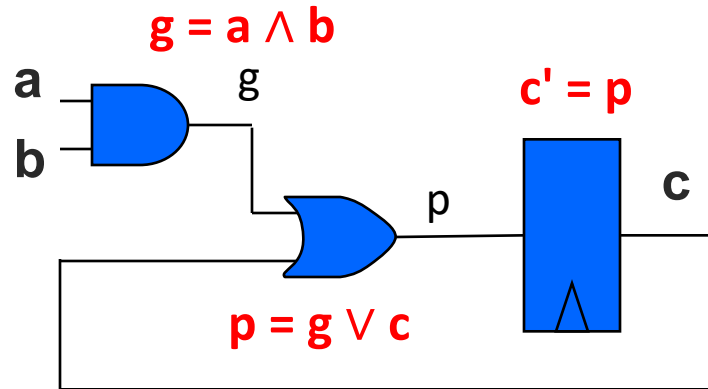
state =
valuation to
variables

note: $c = c_t$ and $c' = c_{t+1}$

Property:

- **p(V)** - describes the set of states satisfying p
 - $p = a \vee \neg c$ (Bad = $\neg p = \neg a \wedge c$)

Modeling in CNF (Tseitin encoding)



$$T(a,b,c,g,p,a',b',c') =$$

$$g \leftrightarrow a \wedge b,$$

$$p \leftrightarrow g \vee c,$$

$$c' \leftrightarrow p$$

Each circuit element is a constraint

Bounded model checking (**BMC**) for checking **AGp**

Given

- A finite transition **system** $M = (V, \text{INIT}(V), T(V, V'))$
- A **safety property** $\text{AG } p$, where $p = p(V)$
- A **bound** k

Determine

- Does M contain a counterexample to p of *k transitions (or fewer) ?*

* BMC can handle all of **LTL** formulas

A. Biere, A. Cimatti, E. M. Clarke, M. Fujita, Y. Zhu, DAC'99

Bounded model checking for checking AGp

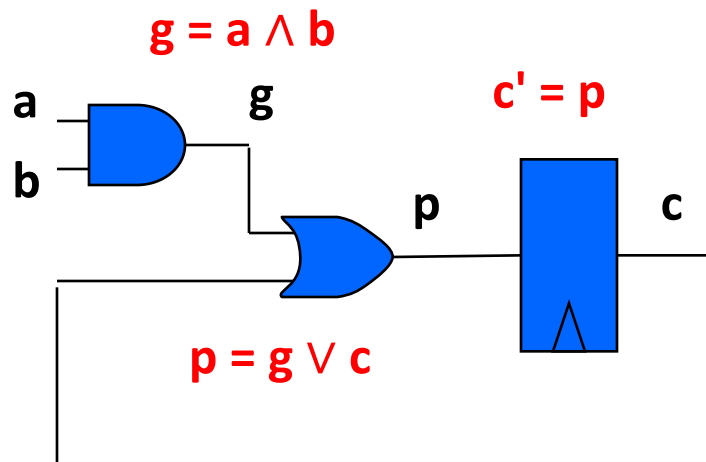
Unwind the model for k levels, i.e., construct all computations of length k
If a state satisfying $\neg p$ is encountered, then produce a counterexample

The method is suitable for **falsification**, not verification

Can be translated to a SAT problem

Bounded model checking with SAT

Construct a formula $f_{M,k}$ describing all possible computations of M of length k



$T(a,b,c,a',b',c') =$

$$g \leftrightarrow a \wedge b,$$

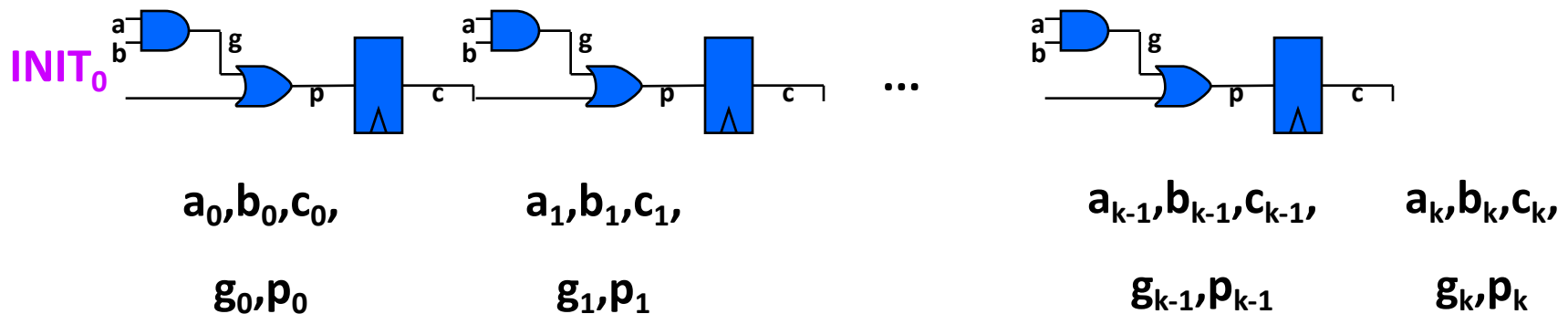
$$p \leftrightarrow g \vee c,$$

$$c' \leftrightarrow p$$

Bounded model checking with SAT

Construct a formula $f_{M,k}$ describing all possible computations of M of length k

$$f_{M,k} = \text{INIT}_0 \wedge T_0 \wedge T_1 \wedge \dots \wedge T_{k-1}$$



$$\text{INIT}_0 = \text{INIT}(V_0)$$

$$T_i = T(V_i, V_{i+1})$$

Bounded model checking with SAT

Construct a formula $f_{M,k}$ describing all possible computations of M of length k

Construct a formula $f_{\phi,k}$ expressing that $\phi = EF \neg p$ holds within k computation steps

$$f_{\phi,k} = \bigvee_{i=0,\dots,k} (\neg p_i) \quad [\text{Sometimes } f_{\phi,k} = \neg p_k]$$

$$p_i = p(V_i)$$

Bounded model checking with SAT

Construct a formula $f_{M,k}$ describing all possible computations of M of length k

Construct a formula $f_{\varphi,k}$ expressing that $\varphi = \text{EF} \neg p$ holds within k computation steps

Check whether $f = f_{M,k} \wedge f_{\varphi,k}$ is satisfiable

If f is satisfiable then $M \not\models \text{AG}p$

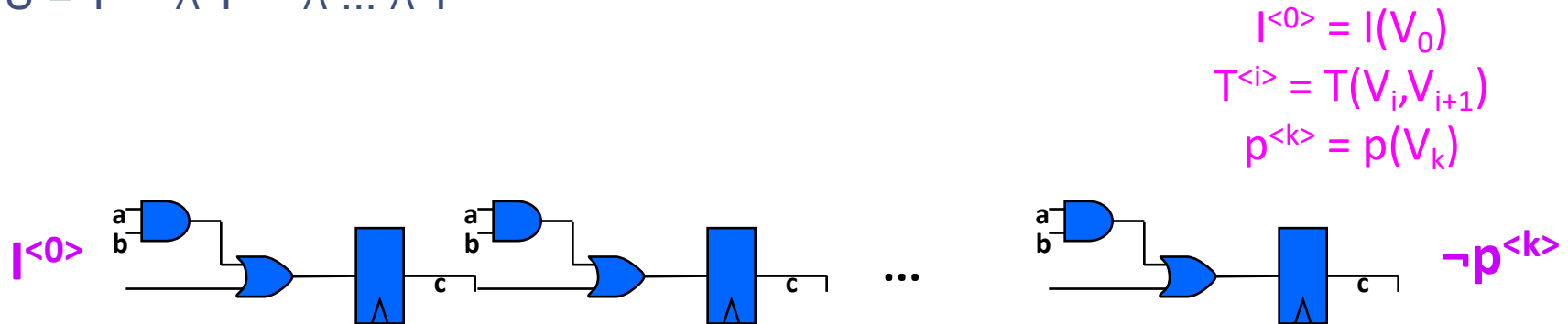
The satisfying assignment is a **counterexample**

BMC for checking AG p with SAT

Unfold the model k times:

- $U = T^{<0>} \wedge T^{<1>} \wedge \dots \wedge T^{<k-1>}$

Biere, et al. TACAS99



- Use SAT solver to check satisfiability of

$$I^{<0>} \wedge U \wedge \neg p^{<k>}$$

- If **satisfiable**: the satisfying assignment describes a counterexample of length k
- If **unsatisfiable**: property has no counterexample of length k

Example – shift register

Shift register of 3 bits: $\langle x, y, z \rangle$

Transition relation:

$$T(x, y, z, x', y', z') = x' \leftrightarrow y \wedge y' \leftrightarrow z \wedge z' = 1$$

|_____|
error

Initial condition:

$$\text{INIT}(x, y, z) = x=0 \vee y=0 \vee z=0$$

Specification: $\text{AG} (x=0 \vee y=0 \vee z=0)$

Propositional formula for k=2

$$f_{M,2} = (x_0=0 \vee y_0=0 \vee z_0=0) \wedge \\ (x_1 \leftrightarrow y_0 \wedge y_1 \leftrightarrow z_0 \wedge z_1=1) \wedge \\ (x_2 \leftrightarrow y_1 \wedge y_2 \leftrightarrow z_1 \wedge z_2=1)$$

$$\text{INIT} = x=0 \vee y=0 \vee z=0$$

$$T = x' \leftrightarrow y \wedge y' \leftrightarrow z \wedge z'=1$$

$$f_{\varphi,2} = \bigvee_{i=0,\dots,2} (x_i=1 \wedge y_i=1 \wedge z_i=1)$$

$$P = x=0 \vee y=0 \vee z=0$$

Satisfying assignment: 101 011 111

This is a counterexample!

A remark

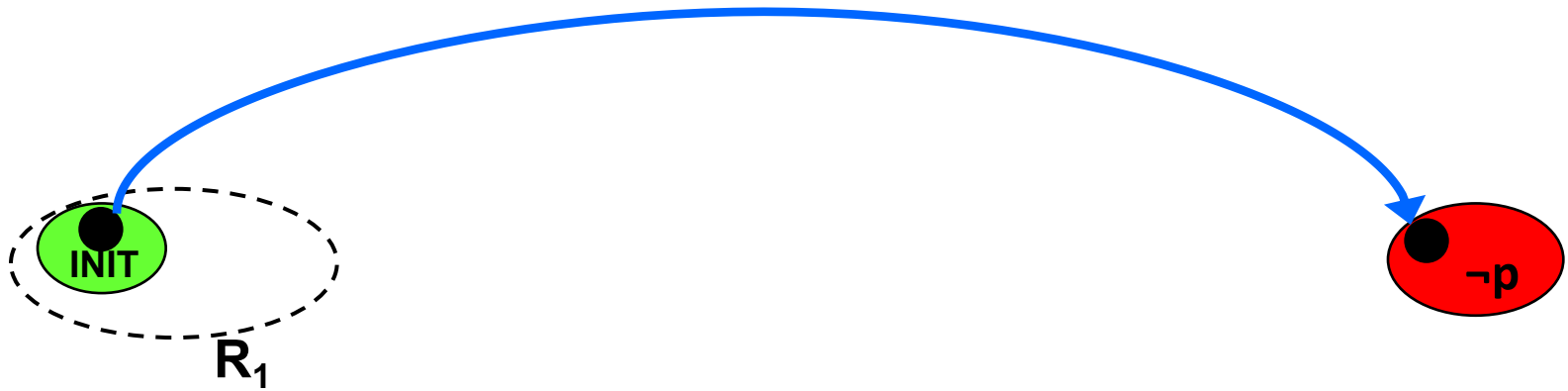
In order to describe a computation of length k by a propositional formula we need $k+1$ copies of the state variables.

With BDDs we use only two copies: for current and next states.

BMC for checking $\varphi = \text{AG}p$

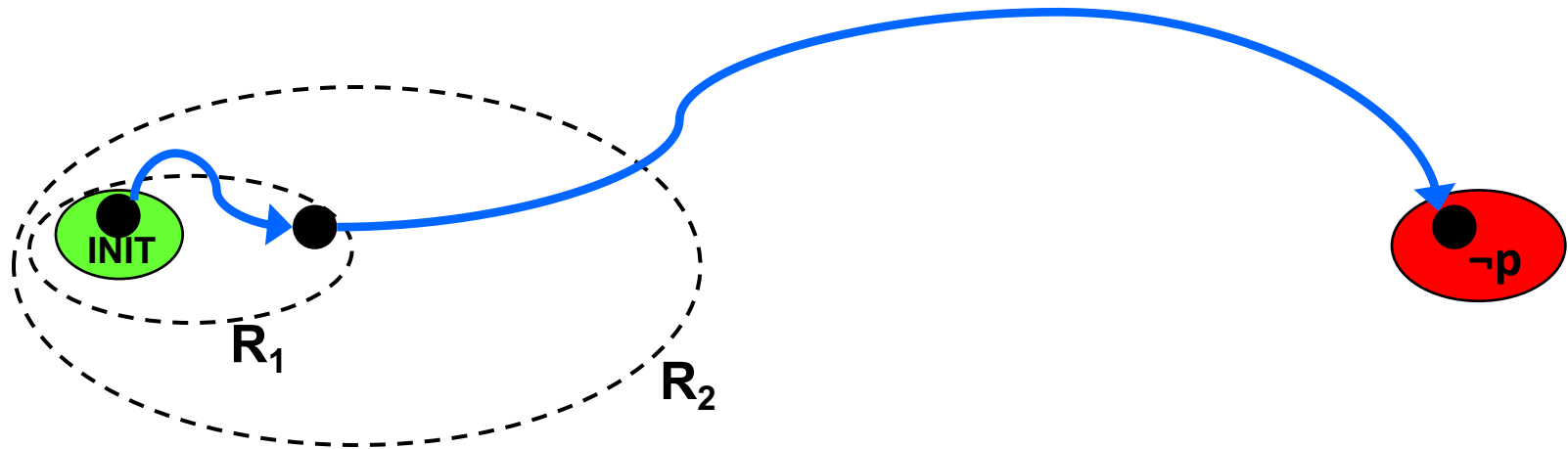
1. $k=1$
2. Build a propositional formula f_M^k describing all prefixes of length k of paths of M from an initial state
3. Build a propositional formula f_φ^k describing all prefixes of length k of paths satisfying $F \neg p$
4. If $(f_M^k \wedge f_\varphi^k)$ is **satisfiable**,
return the satisfying assignment as a **counterexample**
5. Otherwise, increase k and return to 2.

Bounded Model Checking



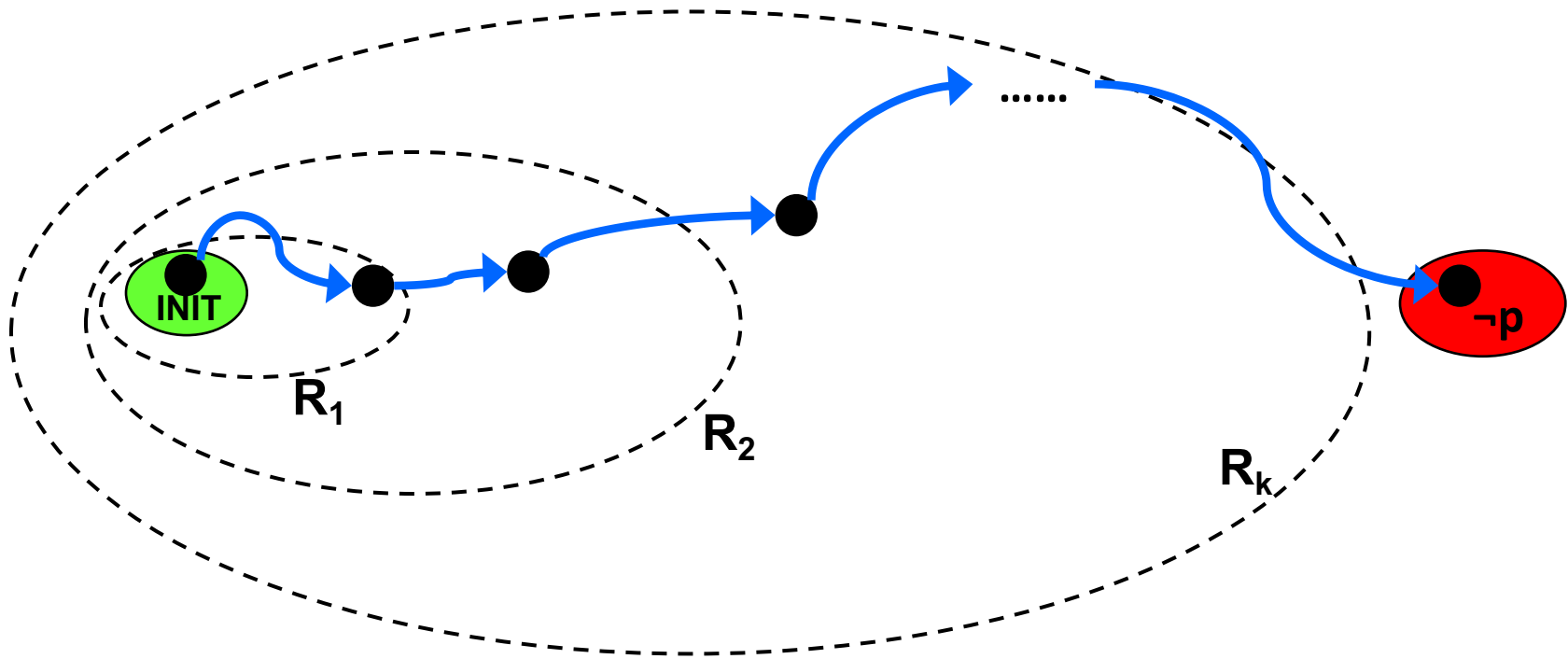
$$\text{INIT}(V^0) \wedge T(V^0, V^1) \wedge \neg p(V^1)$$

Bounded Model Checking



$$\text{INIT}(V^0) \wedge T(V^0, V^1) \wedge T(V^1, V^2) \wedge \neg p(V^2)$$

Bounded Model Checking



$$\text{INIT}(V^0) \wedge T(V^0, V^1) \wedge \dots \wedge T(V^{k-1}, V^k) \wedge \neg p(V^k)$$

BMC for checking AFp ($\varphi = EG\neg p$)

Is there an **infinite** path in M

- From an initial state
- all of its states satisfying $\neg p$
- Over **$k+1$ states** ?

If exists, there must also exist a lasso

BMC for checking AFp ($\varphi = \text{EG} \neg p$)

An **infinite** path in M , from an initial state, over **$k+1$** states, **all** satisfying $\neg p$:

$$f_M^k(V_0, \dots, V_k) = \text{INIT}(V_0) \wedge \bigwedge_{i=0, \dots, k-1} T(V_i, V_{i+1}) \wedge \bigwedge_{i=0, \dots, k-1} (V_k = V_i)$$

- $V_k = V_i$ means bitwise equality: $\bigwedge_{j=0, \dots, n} (v_{kj} \leftrightarrow v_{ij})$

$$f_\varphi^k(V_0, \dots, V_k) = \bigwedge_{i=0, \dots, k} \neg p(V_i)$$

Remark: BMC can handle all of LTL formulas

Bounded model checking

Can handle all of **LTL** formulas

Can be used for **verification** by choosing k which is large enough

- Need bound on length of the shortest counterexample.
 - *diameter* bound. The diameter is the maximum length of the shortest path between any two states.

Using such k is often **not practical** due to the size of the model

- Worst case diameter is exponential. Obtaining better bounds is sometimes possible, but generally intractable.

Bounded Model Checking

Terminates

- with a counterexample or
- with time- or memory-out

=> The method is suitable for **falsification**, not verification

Can be used for **verification** by choosing k which is large enough

- Need bound on length of the shortest counterexample.
 - *diameter* bound. The diameter is the maximum length of the shortest path between any two states.

Using such k is often **not practical**

- Worst case diameter is exponential. Obtaining better bounds is sometimes possible, but generally intractable.