

Satisfiability Modulo Theories and Network Verification

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Microsoft Research
Formal Methods and Networks Summer School
Ithaca, June 10-14 2013

Lectures

Wednesday 2:00pm-2:45pm:

An Introduction to SMT with Z3

Thursday 11:00am-11:45am

Algorithmic underpinnings of SAT/SMT

Friday 9:00am-9:45am

Theories, Solvers and **Applications**



Plan

1. Progress in automated reasoning
SAT, Automated Theorem Proving, SMT
1. An abstract account for SMT search (DPLL+T)
2. Integrating Theories

Takeaway: Theorem Proving is cool and beautiful

Symbolic Engines: SAT, FTP and SMT

SAT: Propositional Satisfiability.

$$(\text{Tie} \vee \text{Shirt}) \wedge (\neg \text{Tie} \vee \neg \text{Shirt}) \wedge (\neg \text{Tie} \vee \text{Shirt})$$

FTP: First-order Theorem Proving.

$$\forall X, Y, Z [X * (Y * Z) = (X * Y) * Z]$$

$$\forall X [X * \text{inv}(X) = e] \quad \forall X [X * e = e]$$

SMT: Satisfiability Modulo background Theories

$$b + 2 = c \wedge A[3] \neq A[c-b+1]$$

SAT - Milestones

Problems impossible 10 years ago are trivial today

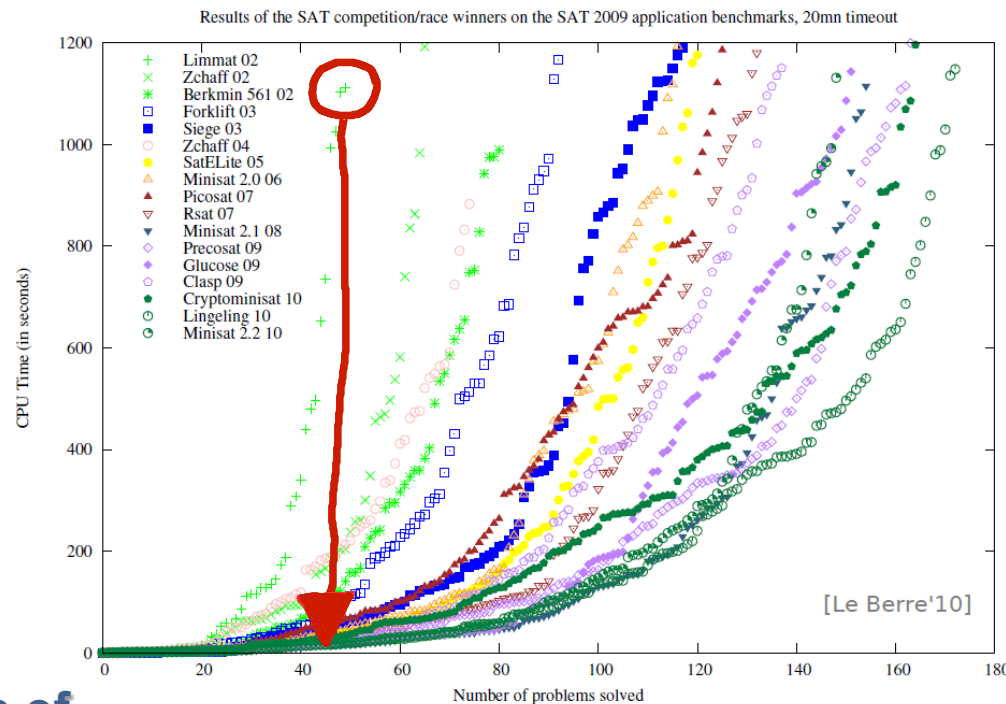
year	Milestone
1960	Davis-Putnam procedure
1962	Davis-Logeman-Loveland
1984	Binary Decision Diagrams
1992	DIMACS SAT challenge
1994	SATO: clause indexing
1997	GRASP: conflict clause learning
1998	Search Restarts
2001	zChaff: 2-watch literal, VSIDS
2005	Preprocessing techniques
2007	Phase caching
2008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

Concept



2002

2010



Millions of
variables from
HW designs

Courtesy Daniel le Berre

FTP - Milestones

Year	Milestone	Who	Year	Milestone	Who
1930	Herbrand's theorem	Herbrand	1970	Completion and saturation procedures	many people and provers
1934	Sequent calculi	Gentzen	1970	Knuth-Bendix ordering	Knuth; Bendix
1934	Inverse method	Gentzen	1971	Selection function	Kowalski; Kuehner
1955	Semantic tableaux	Beth	1972	Built-in equational theories	Plotkin
	Herbrand-based theorem				
1960	proving	Wang Hao	1972	Prolog	Colmerauer
1960	Ordered resolution	Davis; Putnam	1974	Saturation algorithms	Overbeek
		Davis; Logemann; Loveland			
1962	DLL		1975	Completeness of paramodulation	Brand
1963	First-order inverse method	Maslov	1975	AC-unification	Stickel
1965	Unification	J. Robinson	1976	Resolution as a decision procedure	Joyner
1965	First-order resolution	J. Robinson	1979	Basic paramodulation	Degtyarev
1965	Subsumption	J. Robinson	1980	Lexicographic path orderings	Kamin; Levy
1967	Orderings	Slagle	1985	Theory resolution	Stickel
		Wos; G. Robinson; Carson; Shalla		Definitional clause form	
1967	Demodulation or rewriting		1986	transformation	Plaisted; Greenbaum
1968	Model elimination	Loveland	1988	Superposition	Zhang
1969	Paramodulation	G. Robinson; Wos	1988	Model construction	Zhang
			1989	Term indexing	Stickel; Overbeek
			1990	General theory of redundancy	Bachmair; Ganzinger
			1992	Basic superposition	Nieuwenhuis; Rubio
			1993	First instance-based methods	Billon; Plaisted
			1993	Discount saturation algorithm	Avenhaus; Denzinger
			1998	Finite model finding using SAT	McCune
			2000	First-order DPLL	Baumgartner
			2003	iProver method	Ganzinger; Korovin
			2008	Sine selection	Hoder

Some success stories:

- Open Problems (of 25 years):
XCB: $X \equiv ((X \equiv Y) \equiv (Z \equiv Y)) \equiv Z$
is a single axiom for equivalence
- Knowledge Ontologies
GBs of formulas

Courtesy Andrei Voronkov, U of Manchester

SMT - Milestones

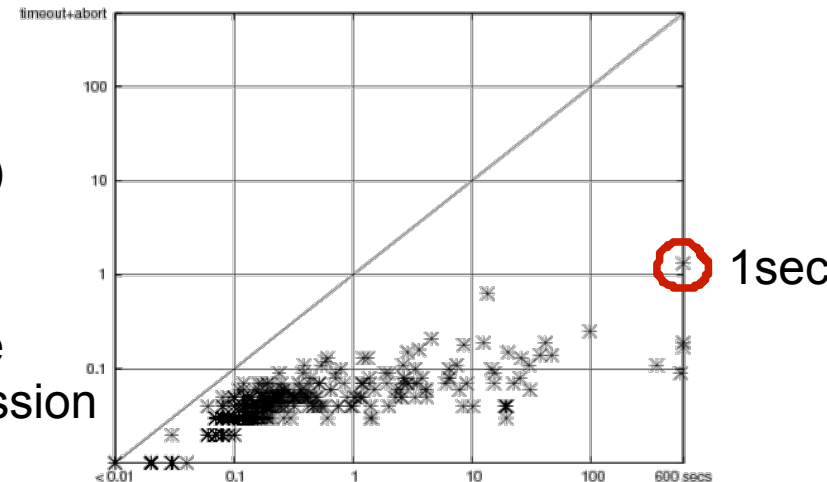
year	Milestone
1977	Efficient Equality Reasoning
1979	Theory Combination Foundations
1979	Arithmetic + Functions
1982	Combining Canonizing Solvers
1992-8	Systems: PVS, Simplify, STeP, SVC
2002	Theory Clause Learning
2005	SMT competition
2006	Efficient SAT + Simplex
2007	Efficient Equality Matching
2009	Combinatory Array Logic, ...

Includes progress from SAT:



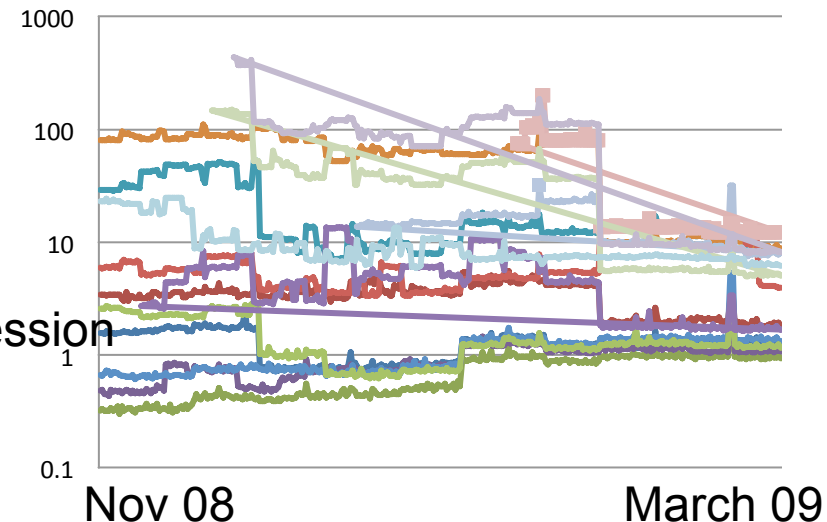
$$15\text{KLOC} + 285\text{KLOC} = \text{Z3}$$

Z3
(of '07)
Time
On
Boogie
Regression



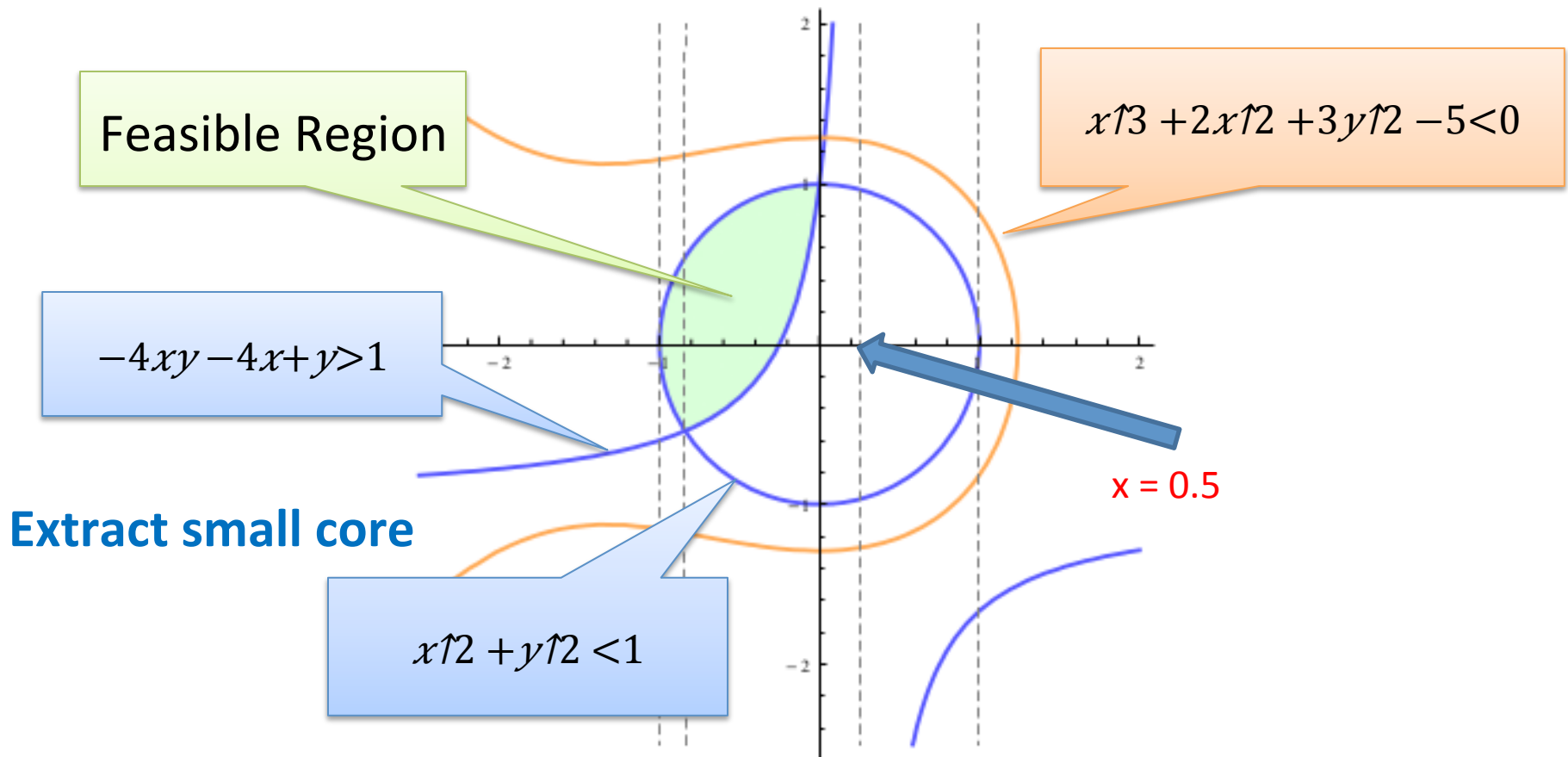
Simplify (of '01) time

Z3
Time
On
VCC
Regression



Z3 News: Solving $\exists R$ Efficiently

A key idea: Use partial solution to guide the search



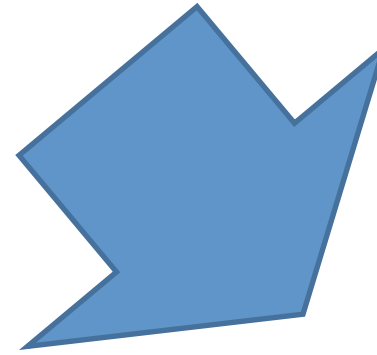
Z3

News: Horn Clause Satisfiability

mc(x) = x-10 if x > 100

mc(x) = **mc**(**mc**(x+11)) if x ≤ 100

assert (x ≤ 101 ⇒ **mc**(x) = 91)



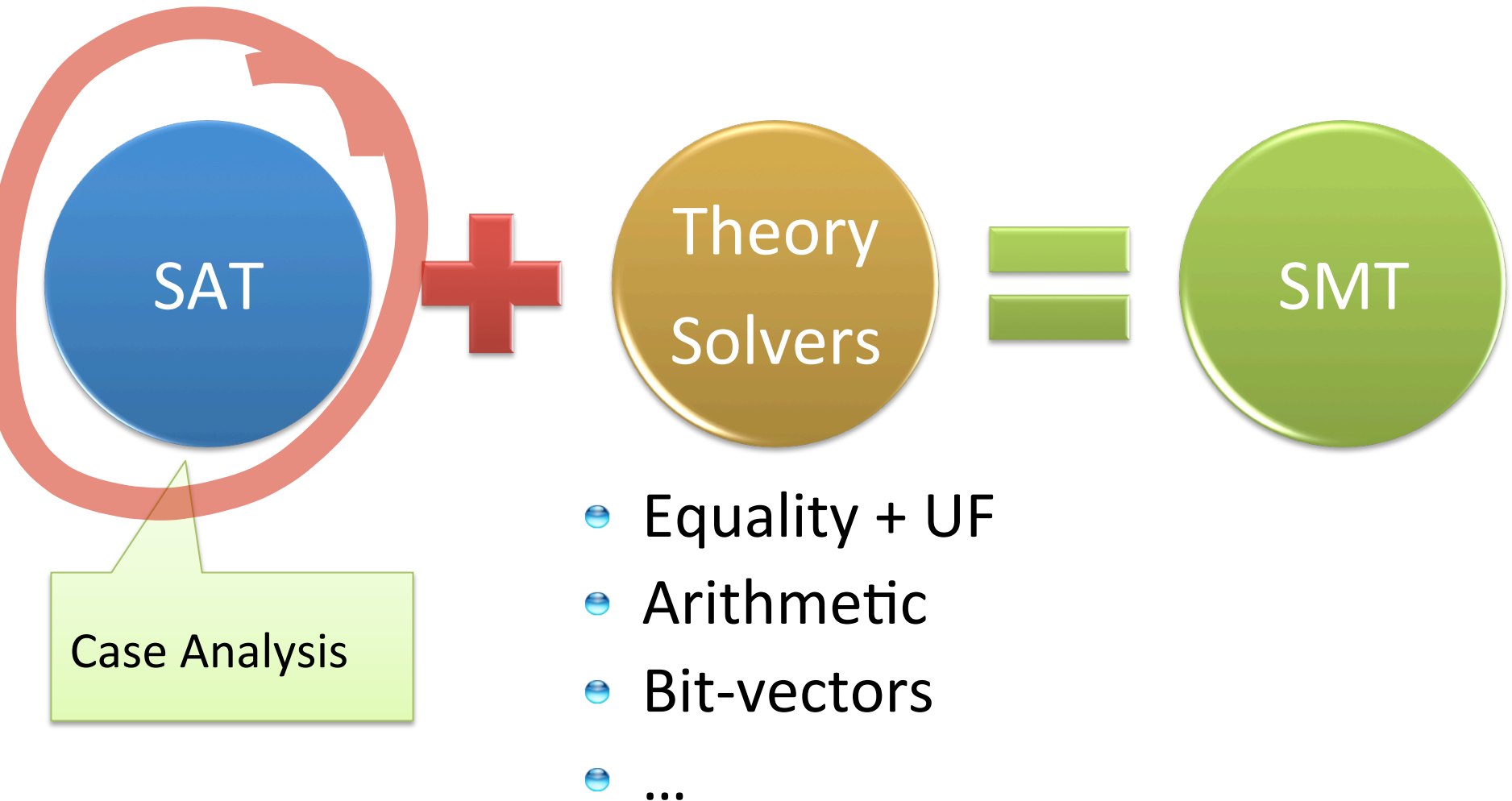
$\forall X. X > 100 \rightarrow \text{mc}(X, X-10)$

$\forall X, Y, R. X \leq 100 \wedge \text{mc}(X+11, Y) \wedge \text{mc}(Y, R) \rightarrow$
 $\text{mc}(X, R)$

$\forall X, R. \text{mc}(X, R) \wedge X \leq 101 \rightarrow R = 91$

SMT SOLVING

SMT : Basic Architecture



SAT + Theory solvers

Basic Idea

$$x \geq 0, y = x + 1, (y > 2 \vee y < 1)$$



Abstract (aka “naming” atoms)

$$p_1, p_2, (p_3 \vee p_4) \quad \begin{array}{l} p_1 \equiv (x \geq 0), p_2 \equiv (y = x + 1), \\ p_3 \equiv (y > 2), p_4 \equiv (y < 1) \end{array}$$

SAT + Theory solvers

Basic Idea

$$x \geq 0, y = x + 1, (y > 2 \vee y < 1)$$



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SAT
Solver

SAT + Theory solvers

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SAT
Solver



Assignment

$p_1, p_2, \neg p_3, p_4$

SAT + Theory solvers

Basic Idea

$$x \geq 0, y = x + 1, (y > 2 \vee y < 1)$$



Abstract (aka “naming” atoms)

$$p_1, p_2, (p_3 \vee p_4)$$



SAT
Solver



Assignment

$$p_1, p_2, \neg p_3, p_4$$



$$\begin{aligned} p_1 &\equiv (x \geq 0), p_2 \equiv (y = x + 1), \\ p_3 &\equiv (y > 2), p_4 \equiv (y < 1) \end{aligned}$$



$$\begin{aligned} x &\geq 0, y = x + 1, \\ \neg(y > 2), y &< 1 \end{aligned}$$

SAT + Theory solvers

Basic Idea

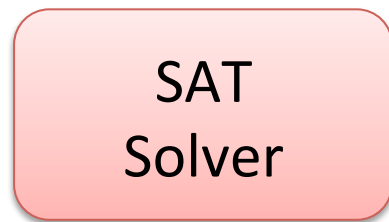
$$x \geq 0, y = x + 1, (y > 2 \vee y < 1)$$



Abstract (aka “naming” atoms)

$$p_1, p_2, (p_3 \vee p_4)$$

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Assignment

$$p_1, p_2, \neg p_3, p_4$$

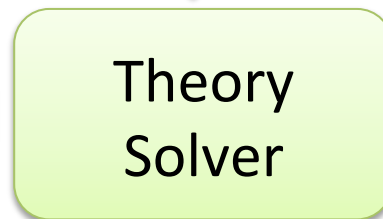


$$x \geq 0, y = x + 1, \\ \neg(y > 2), y < 1$$



Unsatisfiable

$$x \geq 0, y = x + 1, y < 1$$



SAT + Theory solvers

Basic Idea

$$x \geq 0, y = x + 1, (y > 2 \vee y < 1)$$



Abstract (aka “naming” atoms)

$$p_1, p_2, (p_3 \vee p_4)$$

$$p_1 \equiv (x \geq 0), p_2 \equiv (y = x + 1), \\ p_3 \equiv (y > 2), p_4 \equiv (y < 1)$$



SAT
Solver



Assignment

$$p_1, p_2, \neg p_3, p_4$$



$$x \geq 0, y = x + 1, \\ \neg(y > 2), y < 1$$



Theory
Solver

Unsatisfiable

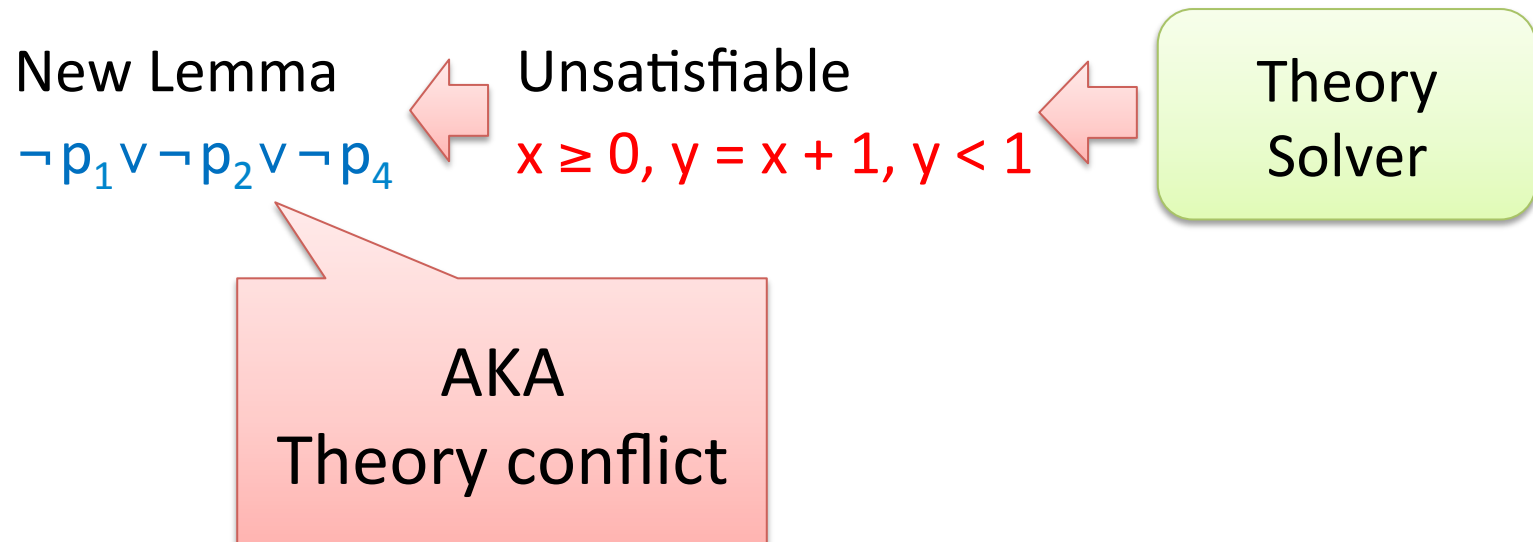
$$x \geq 0, y = x + 1, y < 1$$



New Lemma

$$\neg p_1 \vee \neg p_2 \vee \neg p_4$$

SAT + Theory solvers



SAT/SMT SOLVING USING DPLL(T)

**[DAVIS PUTNAM LOGEMAN LOVELAND
MODULO THEORIES]**

Resolution

Formula must be in CNF

Resolution rule: $C \vee p \quad D \vee \neg p / C \vee D$

Example: $q \vee t \vee p \quad q \vee r \vee \neg p / q \vee t \vee r$

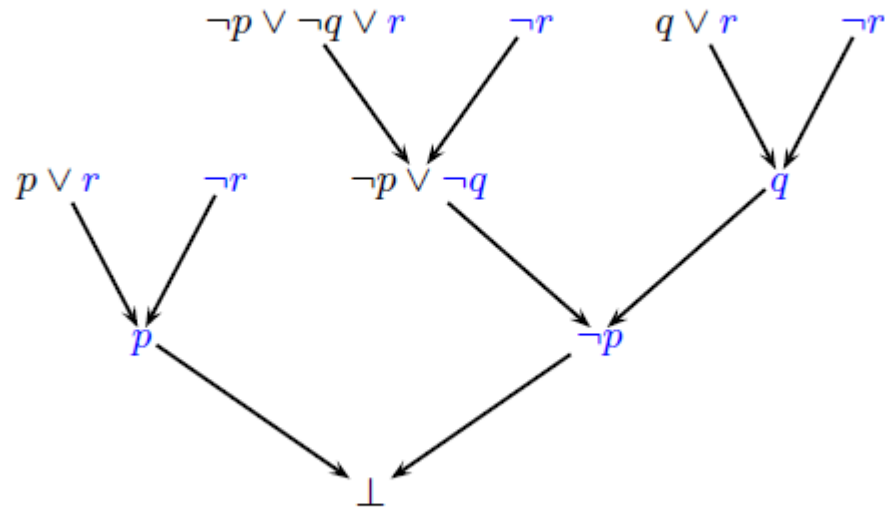
The result of resolution is the resolvent (clause).
Original clauses are kept (not deleted).
Duplicate literals are deleted from the resolvent.

Note: No branching.

Termination: Only finite number of possible derived clauses.

Resolution (example)

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



Ex: Implement a naïve resolution procedure.

Unit & Input Resolution

Unit resolution: $C \vee \ell \quad \neg \ell / C \quad \neg \ell$ ($C \vee \ell$ is subsumed by C)

Input resolution: $C \vee \ell \quad D \vee \neg \ell / C \vee D$ ($C \vee \ell$ member of input F).

Exercise:

Set of clauses F :

F has an input refutation iff F has a unit refutation.

DPLL

DPLL: David Putnam Logeman Loveland = Unit resolution + split rule.

$F/F, p \mid F, \neg p$ **split** *p and $\neg p$ are not in F*

$F, C \vee \ell, \neg \ell / F, C, \neg \ell$ **unit**

Ingredient of most efficient SAT solvers

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 (as a 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 $\text{DPLL}(F \wedge \neg x)$

DPLL

$M \mid F$

Partial model

Set of clauses

DPLL

Guessing

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



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

DPLL

Deducing

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



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

DPLL

Backtracking

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



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

Modern DPLL

- Non-chronological backtracking (backjumping)
- Lemma learning

and

- Efficient indexing (two-watch literal)
- ...

CDCL – Conflict Directed Clause Learning

Lemma learning

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



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



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



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

Core Engine in Z3: Modern DPLL/CDCL

Initialize $\epsilon \mid F$

Decide $M \mid F \Rightarrow M, \ell \mid F$

Propagate $M \mid F, C \vee \ell \Rightarrow M, \ell \uparrow C \vee \ell \mid F, C \vee \ell$

Sat $M \mid F \Rightarrow M$

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

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

$\Rightarrow \text{Unsat}$

$M \mid F, C \vee \ell \Rightarrow M \mid F, C \vee \ell \mid F$

$\mid C \vee \neg \ell \Rightarrow M \mid F \mid C \vee C$

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

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

“It took me a year to understand the Mini-SAT FUIP code”
Mate Soos to Niklas Sörenson over ice-cream in Trento

C is false under M

Proof

Conflict Resolution

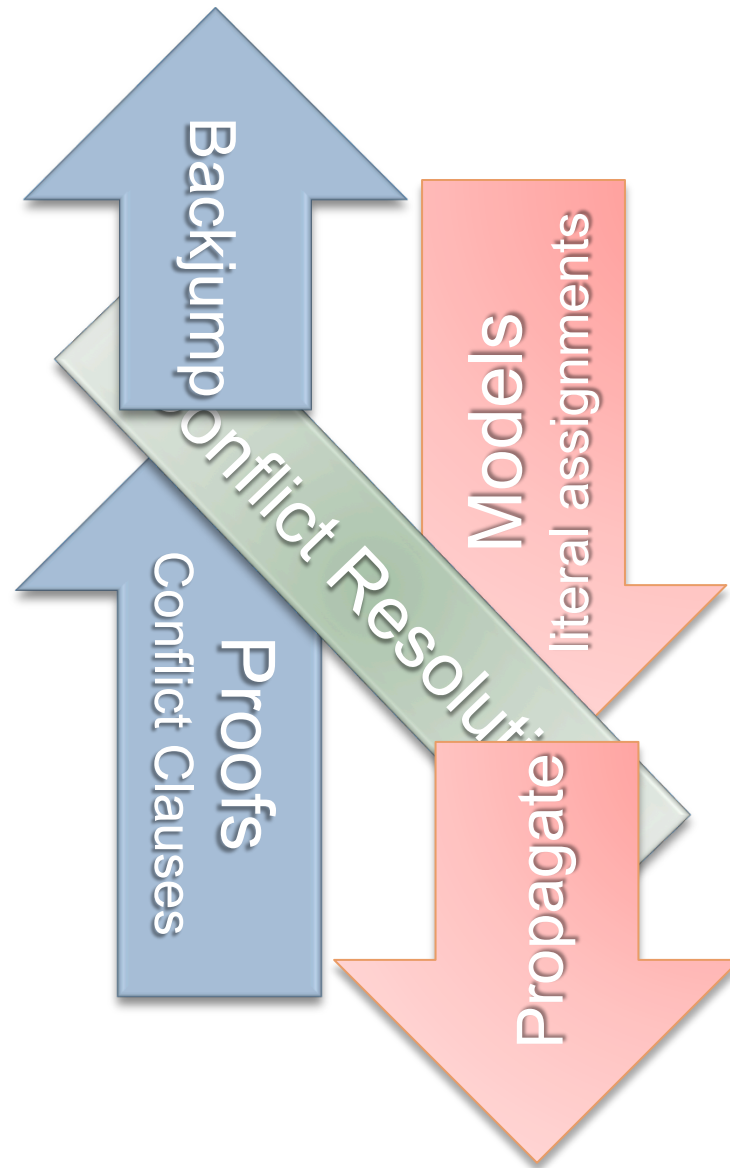
$C \subseteq M, \neg \ell \in M'$

$\ell \uparrow C \vee \ell \in M$

C is a learned clause

We will **now** motivate the CDCL algorithm as a cooperative procedure between model and proof search

Mile High: Modern SAT/SMT search



The Farkas Lemma Dichotomy

1. There is an x such that: $Ax=b \wedge x \geq 0$
2. There is a y such that: $yA \geq 0 \wedge yb < 0$

For every matrix A , vector b it is the case that either (1) or (2) holds (and not both).

A Dichotomy of Models and Proofs

1. There is a model M such that $M \models F$
2. There is a proof Π such that $F \vdash \bot \Pi \emptyset$

For every formula F (set of clauses) it is the case that either (1) or (2) holds (and not both).

A Dichotomy of Models and Proofs

1. There is $M' \supseteq M$ such that $M' \models F$
2. There is $M' \subseteq M$ and proof Π such that $F \vdash \downarrow \Pi M'$

For every formula F (set of clauses) and partial model M it is the case that either (1) or (2) holds (and not both).

A Dichotomy of Models and Proofs

1. There is $M' \supseteq M$ such that $M' \models F$
2. There is $M' \subseteq M$ and proof Π such that $F \vdash \downarrow \Pi M'$

Given M can it be extended to M' to satisfy (1)?
If not, find subset M' to establish (2).
(that is inconsistent with F)

A Dichotomy of Models and Proofs

Corollary:

If $F \vdash \perp \Pi \mathcal{C}$ then it is not possible to extend \mathcal{C} to satisfy F

Corollary:

If $M \models \neg F$ then

- $\mathcal{C}, \ell \subseteq M$ for some $F \vdash \mathcal{C} \vee \ell$ (or F contains \emptyset)
- for every D , where
 - $D, \mathcal{C} \subseteq M' \subseteq M$,
 - $M' \vdash (D \vee \neg \ell)$

it is not possible to extend M' to satisfy F

CDCL Search – Data structures

Partial Model:

Sequence of literals

Decision lits:

case splits

Propagation lits:

only one case
makes sense.

$M \mid F$

Formula:

set of clauses



Proof: Implicit

Consequences added to F

Invariant:

For state $M \mid F \mid C$:

$$C \subseteq M \quad F \vdash C$$

Invariant:

For states $M \mid F$ and $M \mid F \mid D$ where $M = M \downarrow 1 \ell \uparrow C \vee \ell M \downarrow 2$:

$$C \subseteq M \downarrow 1 \quad F \vdash C \vee \ell$$

CDCL steps

Initialize $\epsilon \models F$

F is a set of clauses

No model candidate has been fixed

CDCL steps

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

Case split on ℓ

If M can be extended to satisfy F ,
then the extension contains M, p or $M, \neg p$

CDCL steps

Propagate $M \mid F, C \vee \ell \Rightarrow M, \ell \uparrow C \vee \ell \quad \mid F, C \vee \ell$ *C is false under M*

ℓ must be true if M has any chance
of being a model for $F, C \vee \ell$

CDCL steps

Sat	$M \mid F \Rightarrow M$	F true under M
Unsat	$M \mid F \mid \emptyset \Rightarrow \text{Unsat}$	

CDCL steps

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

C is a **sufficient** explanation why M is not a model of F

CDCL steps

Resolve $M \mid F \mid C \vee \neg \ell \Rightarrow M \mid F \mid C \vee D$ $\ell \uparrow D \vee \ell \in M$

Recall

Corollary:

If $M \models \neg F$ then

- $C, \ell \subseteq M$ for some $F \vdash C \vee \ell$

(or F contains \emptyset)

- for every D , where

- $D, C \subseteq M' \subseteq M$,

- $M' \vdash (D \vee \neg \ell)$

it is not possible to extend M' to satisfy F

$C \vee D$ is a sufficient and **earlier** explanation
why M is not a model of F

CDCL steps

Backjump $MM' \mid F \mid C \vee \ell \Rightarrow M \ell \uparrow C \vee \ell \mid F$ $C \subseteq M, \neg \ell \in M'$

- $C \vee \ell$ is a sufficient explanation why M is not a model of F
- Prefixes of MM' that contain $\neg \ell$ cannot become a model of F

FUIP *First Unique Implication Point* strategy when # of decision literals in M is minimal.

Why is **FUIP** better?

- Minimizes # of backtracking points before learned fact $\ell \uparrow C \vee \ell$
- What if $\ell \uparrow C \vee \ell$ implies negation of removed backtracking point?
 - We would *forget* the learned fact $\ell \uparrow C \vee \ell$ during backjumping.
 - ... only to then re-learn it.

CDCL steps

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

Re-use proof step for later: build DAG proof instead of TREE proof

CDCL steps

Forget

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

C is a learned clause

News: glucose 2.1 won the SAT Competition 2012 Applications Track

All about the Glucose Solver

Gilles and I at SAT'2011

Overview of glucose results

Glucose 2.1 was ranked 1st at the 2012 SAT competition on Applications (SAT+UNSAT) problems and was in good positions in other tracks

Glucose 2.0 was ranked 1st at the 2011 SAT competition on Applications (SAT+UNSAT) problems and was in good positions in other tracks

Glucose 1.0 was ranked 1st at the 2009 SAT competition on SAT+UNSAT category, but was ranked 2nd, due to tie-break

short analysis of glucose 2: Learning was firstly introduced in the SAT competition. Glucose 2 learnt 973,461 clauses and removed 909,123,525 of them, i.e. more than 93% of the learned clauses are removed. This view is really new and contradicts the common belief that one of the performance keys of our solver is not only to keep learned clauses, but also on the removal of those clauses. In the CDCL incompleteness (keeping learnt clauses is essential for the SAT 2011 competition beside the fact that it allows to find a shortest proof as possible. In parallel track in the SAT 2011 competition beside the fact that it allows to find a shortest proof as possible. In parallel track in the SAT 2011 competition beside the fact that it allows to find a shortest proof as possible.

Don't forget to forget:

- Learned clauses could turn out to be useless.
- They could hog resources

Blocked Clause Elimination:

- Remove clauses that will not be used in proofs

all Glucose 2's traces of the last competition, phase 2, in the SAT competition. Glucose 2 learnt 973,461 clauses but removed 909,123,525 of them, i.e. more than 93% of the learned clauses are removed. This view is really new and contradicts the common belief that one of the performance keys of our solver is not only to keep learned clauses, but also on the removal of those clauses. In the CDCL incompleteness (keeping learnt clauses is essential for the SAT 2011 competition beside the fact that it allows to find a shortest proof as possible. In parallel track in the SAT 2011 competition beside the fact that it allows to find a shortest proof as possible. In parallel track in the SAT 2011 competition beside the fact that it allows to find a shortest proof as possible.

CDCL steps

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

Avoid getting trapped in one part of search space

$S \downarrow 1, S \downarrow 2, \dots = 1, 1, 2, 1, 1, 2, 4, 1, 1, 2, 1, 1, 2, 4, 8, 1, 1, 2, 1, 1, 2, 4, 1, 1, 2, 4, 8, 1, \dots$

[Reluctant doubling sequence: Luby, Sinclair, Zuckerman, IPL 47]



Donald E. Knuth (高德纳), Professor Emeritus of [The Art of Computer Programming](#) at [Stanford University](#), welcomes you to his home page.

$(u \downarrow n + 1, v \downarrow n + 1) = (u \downarrow n \ \& \ -u \downarrow n ? (u \downarrow n + 1, 1) : (u \downarrow n, 2v \downarrow n))$.

Generating
function
[fasc6a
draft chapter
on SAT]

Modern DPLL - tuning

- Restart frequency
 - Why is restarting good?
 - Efficient replay trick for frequent restart
- Which variable to split on
- Which branch to explore first
- Which lemmas to learn
- Blocked clause elimination
- Cache binary propagations
 - This is just scratching the surface

DPLL(\mathcal{T}) solver interaction

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

T- Conflict $M \mid F \Rightarrow M \mid F \mid \neg M'$ $M' \subseteq M$ and M' is false under T

T- Propagate $a > b, b > c \mid F, a \leq c \vee b \leq d \Rightarrow$
 $a > b, b > c, b \leq d^{a \leq c \vee b \leq d} \mid F, a \leq c \vee b \leq d$

T- Conflict $M \mid F \Rightarrow M \mid F, a \leq b \vee b \leq c \vee c < a$
 where $a > b, b > c, a \leq c \subseteq M$

Model based Theory Combination

Challenge:

- Solvers need to exchange what is equal.
- Computing all implied equalities is expensive.

Idea:

- Have solvers produce models.
- Use models to introduce equalities on demand.
If then guess

Summary

1. Progress in automated reasoning
SAT, Automated Theorem Proving, SMT
1. An abstract account for SMT search (DPLL+T)
2. Integrating Theories

Takeaway: Theorem Proving is cool and beautiful