

On Designing and Implementing Satisfiability Modulo Theory (SIMT) Solvers Summer School 2009, Nancy Verification Technology, Systems and Applications

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Linear Arithmetic

Many approaches

- Graph-based for difference logic: $a b \le 3$
- Fourier-Motzkin elimination:

 $t_1 \leq ax, \ bx \leq t_2 \ \Rightarrow \ bt_1 \leq at_2$

- Standard Simplex
- General Form Simplex



Difference Logic: $a - b \le 5$

Very useful in practice!

Most arithmetical constraints in software verification/analysis are in this fragment.





Job shop scheduling

$d_{i,j}$	Machine 1	Machine 2
Job 1	2	1
Job 2	3	1
Job 3	2	3
max = 8	3	

Solution

 $t_{1,1} = 5, t_{1,2} = 7, t_{2,1} = 2, t_{2,2} = 6, t_{3,1} = 0, t_{3,2} = 3$

Encoding

$$\begin{array}{l} (t_{1,1} \geq 0) \land (t_{1,2} \geq t_{1,1} + 2) \land (t_{1,2} + 1 \leq 8) \land \\ (t_{2,1} \geq 0) \land (t_{2,2} \geq t_{2,1} + 3) \land (t_{2,2} + 1 \leq 8) \land \\ (t_{3,1} \geq 0) \land (t_{3,2} \geq t_{3,1} + 2) \land (t_{3,2} + 3 \leq 8) \land \\ (t_{1,1} \geq t_{2,1} + 3) \lor (t_{2,1} \geq t_{1,1} + 2)) \land \\ ((t_{1,1} \geq t_{3,1} + 2) \lor (t_{3,1} \geq t_{1,1} + 2)) \land \\ ((t_{2,1} \geq t_{3,1} + 2) \lor (t_{3,1} \geq t_{2,1} + 3)) \land \\ ((t_{1,2} \geq t_{2,2} + 1) \lor (t_{2,2} \geq t_{1,2} + 1)) \land \\ ((t_{1,2} \geq t_{3,2} + 3) \lor (t_{3,2} \geq t_{1,2} + 1)) \land \\ ((t_{2,2} \geq t_{3,2} + 3) \lor (t_{3,2} \geq t_{2,2} + 1)) \end{array}$$



Difference Logic

Chasing negative cycles! Algorithms based on Bellman-Ford (O(mn)).





Many solvers (e.g., ICS, Simplify) are based on the Standard Simplex.



Many solvers (e.g., ICS, Simplify) are based on the Standard Simplex.

a - d + 2e = 3
b - d = 1
c + d - e = -1
a, b, c, d, e
$$\ge 0$$

 $100 - 12$
 $010 - 10$
 $0011 - 1$
d
e
 $Ax = b$ and $x > 0$.



Many solvers (e.g., ICS, Simplify) are based on the Standard Simplex.

a - d + 2e = 3 We say a,b,c are the **b** - d = 1 basic (or dependent) **c** + **d** - **e** = -1 variables a, b, c, d, $e \ge 0$ $\begin{vmatrix} a \\ b \\ 0 & 1 & 0 & -1 & 2 \\ 0 & 1 & 0 & -1 & 0 \\ 0 & 0 & 1 & 1 & -1 \\ \end{vmatrix} \begin{vmatrix} a \\ b \\ c \\ d \end{vmatrix} = \begin{vmatrix} 3 \\ 1 \\ -1 \\ \end{vmatrix}$ Microsoft* Ax = b and $x \ge 0$.

Many solvers (e.g., ICS, Simplify) are based on the Standard Simplex.

a - d + 2e = 3 We say a,b,c are the **b** - d = 1 basic (or dependent) = -1 variables **c** + d - e a, b, c, d, $e \ge 0$ $\begin{bmatrix} a \\ b \\ c \\ 0 \\ 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \\ 1 \\ -1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ c \\ -1 \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix}$ We say d,e are the non-basic (or nondependent) variables. Microsoft* Ax = b and $x \ge 0$.

- Incrementality: add/remove equations
- Slow backtracking
- No theory propagation



Fast Linear Arithmetic

- Simplex General Form
- Algorithm based on the dual simplex
- Non redundant proofs
- Efficient backtracking
- Efficient theory propagation
- Support for string inequalities: t > 0
- Preprocessing step
- Integer problems:

Gomory cuts, Branch & Bound, GCD test



General Form

General Form: Ax = 0 and $l_j \le x_j \le u_j$ Example:

$$x \ge 0, (x + y \le 2 \lor x + 2y \ge 6), (x + y = 2 \lor x + 2y > 4)$$

$$s_1 \equiv x + y, s_2 \equiv x + 2y,$$

$$x \ge 0, (s_1 \le 2 \lor s_2 \ge 6), (s_1 = 2 \lor s_2 > 4)$$

Only bounds (e.g., $s_1 \leq 2$) are asserted during the search.

Unconstrained variables can be eliminated before the beginning of the search.

$$s_1 \equiv x + y, \quad s_2 \equiv x + 2y$$



$$s_1 \equiv x + y, \quad s_2 \equiv x + 2y$$

 $s_1 \equiv x + y, \quad s_1 = x + y, \quad s_2 = x + 2y$



$$s_{1} \equiv x + y, \quad s_{2} \equiv x + 2y$$

$$s_{1} = x + y,$$

$$s_{2} = x + 2y$$

$$s_{1} - x - y = 0$$

$$s_{1} - x - y = 0$$

$$s_{2} - x - 2y = 0$$



$$s_1 \equiv x + y, \quad s_2 \equiv x + 2y$$

 $s_1 = x + y,$
 $s_2 = x + 2y$
 $s_1 - x - y = 0$
 s_1, s_2 are basic (dependent
 $s_2 - x - 2y = 0$
 x, y are non-basic

Research

A way to swap a basic with a non-basic variable!

It is just equational reasoning.

Key invariant: a basic variable occurs in only one equation. Example: swap s_1 and y

$$s_1 - x - y = 0$$

 $s_2 - x - 2y = 0$



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 $-s_1 + x + y = 0$
 $s_2 - 2s_1 + x = 0$



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$$s_1 - x - y = 0$$

 $s_2 - x - 2y = 0$
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 $s_2 - x - 2y = 0$
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Research

Definition:

An assignment (model) is a mapping from variables to values

A way to swap a basic with a non-basic variable!

It is just equational reasoning.

Key invariant: a basic variable occurs in only one equation. Example: swap s_1 and y

> $s_1 - x - y = 0$ $s_2 - x - 2y = 0$ $-s_1 + x + y = 0$ $s_2 - x - 2y = 0$ $-s_1 + x + y = 0$ $-s_1 + x + y = 0$ $s_2 - 2s_1 + x = 0$

It is just substituting equals by equals.

Key Property:

If an assignment satisfies the equations before a pivoting step, then it will also satisfy them after!

Definition:

An assignment (model) is a mapping from variables to values

A way to swap a basic with a non-basic variable!

It is just equational reasoning.

Key invariant: a basic variable occurs in only one equation. Example: swap s₂ and y

Example: M(x) = 1 M(y) = 1 $M(s_1) = 2$ $M(s_2) = 3$

	$\mathbf{s_1} - \mathbf{x} - \mathbf{y} = 0$
	$s_2 - x - 2y = 0$
1	
	$-s_1 + x + y = 0$
	$s_{2} - x - 2y = 0$
	$-s_1 + x + y = 0$

 $S_{2} - ZS_{1} + X = U$

It is just substituting equals by equals.

Key Property:

If an assignment satisfies the equations before a pivoting step, then it will also satisfy them after!

Equations + Bounds + Assignment

An assignment (model) is a mapping from variables to values.

We maintain an assignment that satisfies all equations and bounds.

The assignment of non dependent variables implies the assignment of dependent variables.

Equations + Bounds can be used to derive new bounds.

Example: $x = y - z, y \le 2, z \ge 3 \rightsquigarrow x \le -1$.

The new bound may be inconsistent with the already known bounds.

Example: $x \leq -1, x \geq 0$.

If the assignment of a non-basic variable does not satisfy a bound, then fix it and propagate the change to all dependent variables.

a = c - d	a = c - d
b = c + d	<mark>b</mark> = c + d
M(a) = 0	M(a) = 1
M(b) = 0	M(b) = 1
M(c) = 0	M(c) = 1
M(d) = 0	M(d) = 0
$1 \le c$	1 ≤ c



If the assignment of a non-basic variable does not satisfy a bound, then fix it and propagate the change to all dependent variables. Of course, we may introduce new "problems".

a = c - d	a = c - d
b = c + d	<mark>b</mark> = c + d
M(a) = 0	M(a) = 1
M(b) = 0	M(b) = 1
M(c) = 0	M(c) = 1
M(d) = 0	M(d) = 0
$1 \le c$	$1 \le c$
$a \le 0$	a ≤ 0



If the assignment of a basic variable does not satisfy a bound, then pivot it, fix it, and propagate the change to its new dependent variables.

a = c - d	<mark>c</mark> = a + d	<mark>c</mark> = a + d
b = c + d	<mark>b</mark> = a + 2d	<mark>b</mark> = a + 2d
M(a) = 0	M(a) = 0	M(a) = 1
M(b) = 0	M(b) = 0	M(b) = 1
M(c) = 0	M(c) = 0	M(c) = 1
M(d) = 0	M(d) = 0	M(d) = 0
$1 \le a$	$1 \le a$	$1 \le a$



Sometimes, a model cannot be repaired. It is pointless to pivot.

a = b - c $a \le 0, 1 \le b, c \le 0$ M(a) = 1 M(b) = 1M(c) = 0 The value of M(a) is too big. We can reduce it by: - reducing M(b) not possible b is at lower bound - increasing M(c) not possible c is at upper bound



Extracting proof from failed repair attempts is easy.

```
\begin{split} s_1 &\equiv a + d, \ s_2 &\equiv c + d \\ a &= s_1 - s_2 + c \\ a &\leq 0, \ 1 \leq s_1, \ s_2 \leq 0, \ 0 \leq c \\ M(a) &= 1 \\ M(s_1) &= 1 \\ M(s_2) &= 0 \\ M(c) &= 0 \end{split}
```



Extracting proof from failed repair attempts is easy.

```
\begin{split} s_1 &\equiv a + d, \ s_2 &\equiv c + d \\ a &= s_1 - s_2 + c \\ a &\leq 0, \ 1 \leq s_1, \ s_2 \leq 0, \ 0 \leq c \\ M(a) &= 1 \\ M(s_1) &= 1 \\ M(s_2) &= 0 \\ M(c) &= 0 \end{split}
```

{ a \leq 0, 1 \leq s $_1$, s $_2$ \leq 0, 0 \leq c } is inconsistent



Extracting proof from failed repair attempts is easy.

```
\begin{split} s_1 &\equiv a + d, \ s_2 &\equiv c + d \\ a &= s_1 - s_2 + c \\ a &\leq 0, \ 1 \leq s_1, \ s_2 \leq 0, \ 0 \leq c \\ M(a) &= 1 \\ M(s_1) &= 1 \\ M(s_2) &= 0 \\ M(c) &= 0 \end{split}
```

{ a $\leq 0, 1 \leq s_1, s_2 \leq 0, 0 \leq c$ } is inconsistent

{ $a \le 0, 1 \le a + d, c + d \le 0, 0 \le c$ } is inconsistent



Strict Inequalities

The method described only handles non-strict inequalities (e.g., $x \leq 2$).

For integer problems, strict inequalities can be converted into non-strict inequalities. $x < 1 \rightsquigarrow x \leq 0$.

For rational/real problems, strict inequalities can be converted into non-strict inequalities using a small δ . $x < 1 \rightsquigarrow x \le 1 - \delta$.

We do not compute a δ , we treat it symbolically.

 δ is an infinitesimal parameter: $(c, k) = c + k\delta$



Initial state

$$s \ge 1, x \ge 0$$
$$(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$$

Model		Equa	ations	Bounds
M(x) =	0 <i>s</i>	=	x + y	
M(y) =	0 <i>u</i>	=	x + 2y	
M(s) =	0 v	=	x - y	
M(u) =	0			
M(v) =	0			



• Asserting $s \ge 1$

$$s \ge 1, x \ge 0$$

(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)

Model	Equations	Bounds
M(x) = 0	s = x + y	
M(y) = 0	u = x + 2y	
M(s) = 0	v = x - y	
M(u) = 0		
M(v) = 0		

Example

• Asserting $s \ge 1$ assignment does not satisfy new bound.

 $s \ge 1, x \ge 0$

 $(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$

Model	Equations	Bounds
M(x) = 0	s = x + y	$s \geq 1$
M(y) = 0	u = x + 2y	
M(s) = 0	v = x - y	
M(u) = 0		
M(v) = 0		

Example

Asserting $s \ge 1$ pivot s and x (s is a dependent variable).

 $s \ge 1, x \ge 0$ $(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$



Example

• Asserting $s \ge 1$ pivot s and x (s is a dependent variable).

 $s \ge 1, x \ge 0$ (y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)


Asserting $s \ge 1$ pivot s and x (s is a dependent variable).



• Asserting $s \ge 1$ update assignment.



• Asserting $s \ge 1$ update dependent variables assignment.





• Asserting $x \ge 0$

$$s \ge 1, x \ge 0$$
$$(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$$

Model		Equ	ations	В	ound	s
M(x) =	= 1 x	=	s-y	s	\geq	1
M(y) =	= 0 <u>u</u>	П	s + y			
M(s) =	= 1 v		s-2y			
M(u) =	- 1					
M(v) =	= 1					

• Asserting $x \ge 0$ assignment satisfies new bound.

 $s \ge 1, x \ge 0$ $(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$

ModelEquationsBoundsM(x) = 1x = s - y $s \ge 1$ M(y) = 0u = s + y $x \ge 0$ M(s) = 1v = s - 2yM(u) = 1M(v) = 1

• Case split $\neg y \leq 1$

$$s \ge 1, x \ge 0$$
$$(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$$

Model		Equa	tions	B	ound	IS
M(x) =	1 x	=	s-y	s	\geq	1
M(y) =	0 u	-	s + y	x	\geq	0
M(s) =	1 v	=	s-2y			
M(u) =	1					
M(v) =	1					

• Case split $\neg y \leq 1$ assignment does not satisfies new bound. $s \geq 1, x \geq 0$ $(y \leq 1 \lor v \geq 2), (v \leq -2 \lor v \geq 0), (v \leq -2 \lor u \leq -1)$

Model	Equations	Bounds
M(x) = 1	x = s - y	$s~\geq~1$
M(y) = 0	u = s + y	$x \geq 0$
M(s) = 1	v = s - 2y	y > 1
M(u) = 1		
M(v) = 1		

• Case split $\neg y \leq 1$ update assignment.

$$s \ge 1, x \ge 0$$

 $(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$

Mo	del	Equations	B	ound	Is
M(x) =	= 1	x = s - y	s	\geq	1
M(y) =	$= 1 + \delta$	u = s + y	x	\geq	0
M(s) =	= 1	v = s - 2y	y	>	1
M(u) =	= 1				

M(v) = 1

• Case split $\neg y \leq 1$ update dependent variables assignment.





Bound violation

$$s \ge 1, x \ge 0$$
$$(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$$

	Mod	lel		Equa	ations	B	ound	ls
M(x)	=	$-\delta$	x	<u> </u>	s-y	s	\geq	1
M(y)	=	$1 + \delta$	u	=	s + y	x	\geq	0
M(s)	=	1	v	=	s-2y	y	>	1
M(u)	=	$2 + \delta$						
M(v)	=	$-1-2\delta$						

Bound violation pivot x and s (x is a dependent variables).



Bound violation pivot x and s (x is a dependent variables).



Bound violation pivot x and s (x is a dependent variables).





Bound violation update assignment.

	Mode	el		Equa	ations	B	ound	s
M(x)	=	0	S	=	x + y	s	\geq	1
M(y)	=	$1 + \delta$	\overline{u}	=	x + 2y	x	\geq	0
M(s)	=	1	v	=	x - y	 y	>	1
M(u)	=	$2 + \delta$						
M(v)	=	$-1-2\delta$						

Bound violation update dependent variables assignment.



• Theory propagation $x \ge 0, y > 1 \rightsquigarrow u > 2$

M	odel		Equ	ations	B	ound	s
M(x) =	= 0	s	Ξ	x + y	s	\geq	1
M(y) =	$= 1 + \delta$	\overline{u}	=	x + 2y	x	\geq	0
M(s) =	$= 1 + \delta$	v	=	x - y	y	>	1
M(u) =	$= 2 + 2\delta$						
M(v) =	$= -1 - \delta$						

▶ Theory propagation $u > 2 \rightsquigarrow \neg u \leq -1$

	Mode	el		Equ	ations	В	ound	Is
M(x)	=	0	s	=	x + y	S	\geq	1
M(y)	=	$1+\delta$	u	=	x + 2y	x	\geq	0
M(s)	=	$1+\delta$	v	=	x - y	\overline{y}	>	1
M(u)	=	$2+2\delta$				u	>	2
M(v)	=	$-1 - \delta$						

▶ Boolean propagation $\neg y \le 1 \rightsquigarrow v \ge 2$ $s \ge 1, x \ge 0$ $(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$

Model		Equations	B	ound	Is
M(x) = 0) s	= x + y	s	\geq	1
M(y) = 1 +	$-\delta$ u	= x + 2y	x	\geq	0
M(s) = 1 +	$-\delta$ v	= x - y	y	>	1
M(u) = 2 +	-2δ		\overline{u}	>	2
M(v) = -1	$-\delta$				

• Theory propagation $v \ge 2 \leadsto \neg v \le -2$

Model	Equations	Bounds
M(x) = 0	s = x + y	$s \geq 1$
$M(y) = 1 + \delta$	u = x + 2y	$x \geq 0$
$M(s) = 1 + \delta$	v = x - y	y > 1
$M(u) = 2 + 2\delta$		u > 2
$M(v) = -1 - \delta$		



Conflict empty clause

$$s \ge 1, x \ge 0$$

 $(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$

	Mode	el		Equa	ations		B	ound	IS
M(x)	=	0	s	=	x + y		S	\geq	1
M(y)	=	$1 + \delta$	u	=	x + 2y		x	\geq	0
M(s)	=	$1 + \delta$	v	=	x - y	-	y	>	1
M(u)	=	$2+2\delta$					\overline{u}	>	2
M(v)	=	$-1 - \delta$							



Backtracking

$$s \ge 1, x \ge 0$$
$$(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$$

Model	Equations	Bounds
M(x) = 0	s = x + y	$s \geq 1$
$M(y) = 1 + \delta$	u = x + 2y	$x \geq 0$
$M(s) = 1 + \delta$	v = x - y	
$M(u) = 2 + 2\delta$		
$M(v) = -1 - \delta$		



• Asserting $y \leq 1$

$$s \ge 1, x \ge 0$$
$$(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$$

Model	Equations	Bounds
M(x) = 0	s = x + y	$s \geq 1$
$M(y) = 1 + \delta$	u = x + 2y	$x \geq 0$
$M(s) = 1 + \delta$	v = x - y	
$M(u) = 2 + 2\delta$		
$M(v) = -1 - \delta$		

• Asserting $y \leq 1$ assignment does not satisfy new bound.



• Asserting $y \leq 1$ update assignment.

Mo	odel	Equations	Bounds
M(x) =	= 0	s = x + y	$s \geq 1$
M(y) =	- 1	u = x + 2y	$x \geq 0$
M(s) =	$= 1 + \delta$	v = x - y	$y \leq 1$
M(u) =	$= 2 + 2\delta$		
M(v) =	$= -1 - \delta$		

M(v) = -1

• Asserting $y \leq 1$ update dependent variables assignment.

Model			Equ	ations	B	ounc	ls
M(x) =	0	s	=	x + y	s	\geq	1
M(y) =	1	u	Ξ	x + 2y	x	\geq	0
M(s) =	1	v	Ξ	x - y	y	\leq	1
M(u) =	2						

• Theory propagation $s \ge 1, y \le 1 \rightsquigarrow v \ge -1$ $s \ge 1, x \ge 0$ $(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$

Mo	odel			Equa	ations	Bo	ounc	s
M(x)	=	0	x	=	s - y	s	\geq	1
M(y)	=	1	\overline{u}	=	s + y	x	\geq	0
M(s)	<u>—</u> :	1	v	=	s-2y	y	\leq	1
M(u)	=	2						
M(v)	=	-1						

• Theory propagation $v \ge -1 \rightsquigarrow \neg v \le -2$ $s \ge 1, x \ge 0$ $(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$

Mo	odel				Equa	ations	E	Boun	ds
M(x)	=	0		x	=	s - y	s	\geq	1
M(y)	=	1	1	u	=	s + y	x	\geq	0
M(s)	=	1		v	=	s - 2y	y	\leq	1
M(u)	=	2					v	\geq	-1
M(v)	=	$^{-1}$							

▶ Boolean propagation $\neg v \leq -2 \rightsquigarrow v \geq 0$ $s \geq 1, x \geq 0$ $(y \leq 1 \lor v \geq 2), (v \leq -2 \lor v \geq 0), (v \leq -2 \lor u \leq -1)$

Мо	del			Equa	ations		E	Boun	ds
M(x)	=	0	x	-	s - y		s	\geq	1
M(y)	=	1	u	े 	s + y		x	\geq	0
M(s)	=	1	v	-	s - 2y	_	y	\leq	1
M(u)	=	2					v	\geq	-1
M(v)	=	-1							

Bound violation assignment does not satisfy new bound.

Model			Equa	ations	Bo	ound	s
M(x) =	0	x	·==	s - y	s	\geq	1
M(y) =	1	u	=	s + y	x	\geq	0
M(s) =	1	v	-	s-2y	y	\leq	1
M(u) =	2				v	\geq	0
M(v) =	-1						

Bound violation pivot u and s (u is a dependent variable).

Mo	odel			Equa	ations	Bo	ound	s
M(x)	=	0	x	=	s - y	S	\geq	1
M(y)	=	1	u	=	s + y	x	\geq	0
M(s)	=	1	v	=	s - 2y	y	\leq	1
M(u)	=	2				v	\geq	0
M(v)	=	-1						

• Bound violation pivot u and s (u is a dependent variable).

Model			Equa	ations		Bounds				
M(x) =	0	x	-	s - y		S	\geq	1		
M(y) =	1	\overline{u}		s + y		r	\geq	0		
M(s) =	1	S	0 <u>—9</u>	v + 2y		y	\leq	1		
M(u) =	2				1	U	\geq	0		
M(v) =	-1									

• Bound violation pivot u and s (u is a dependent variable).

Moo	del			Equa	ations	Bo	ound	s
M(x)	. <u> </u>	0	x	=	v + y	s	\geq	1
M(y)		1	\overline{u}		v + 3y	x	\geq	0
M(s)	-	1	s	=	v + 2y	y	\leq	1
M(u)	_	2				v	\geq	0
M(v)	=	-1						



Bound violation update assignment.

Model		Equations	Bo	ound	S
M(x) =	$0 \qquad x$	= v + y	s	\geq	1
M(y) =	1 u	= v + 3y	x	\geq	0
M(s) =	1 8	= v + 2y	\overline{y}	\leq	1
M(u) =	2		v	\geq	0
M(v) =	0				

Bound violation update dependent variables assignment.

 $s \ge 1, x \ge 0$

Model		Equa	ations	B	ound	Is
M(x) =	1 x	=	v + y	s	\geq	1
M(y) =	1 u	=	v + 3y	x	\geq	0
M(s) =	2 8	=	v + 2y	y	\leq	1
M(u) =	3			v	\geq	0
M(v) =	0					

• Boolean propagation $\neg v \leq -2 \rightsquigarrow u \leq -1$ $s \geq 1, x \geq 0$ $(y \leq 1 \lor v \geq 2), (v \leq -2 \lor v \geq 0), (v \leq -2 \lor u \leq -1)$

Model		Equ	ations	B	ounc	IS
M(x) =	1 <i>x</i>		v + y	s	\geq	1
M(y) =	1 u		v + 3y	x	\geq	0
M(s) =	2 s	:=:	v + 2y	\boldsymbol{y}	\leq	1
M(u) =	3			v	\geq	0
M(v) =	0					

Bound violation assignment does not satisfy new bound.

 $s \ge 1, x \ge 0$

Model	Equations	Bounds
M(x) = 1	x = v + y	$s \geq 1$
M(y) = 1	u = v + 3y	$x \geq 0$
M(s) = 2	s = v + 2y	$y \leq 1$
M(u) = 3		$v \geq 0$
M(v) = 0		$u \leq -1$
• Bound violation pivot u and y (u is a dependent variable).

Model		Equa	ations	E	Boun	ds
M(x) =	1 x		v + y	s	\geq	1
M(y) ~=~	1 <mark>u</mark>		v + 3y	x	\geq	0
M(s) =	2 s		v + 2y	y	\leq	1
M(u) =	3			v	\geq	0
$M(v) \ = \ $	0			u	\leq	-1

Bound violation pivot u and y (u is a dependent variable).

Model		Equ	ations	E	Boun	ds
M(x) =	1 x	=	v + y	S	\geq	1
M(y) =	1 y	=	$\frac{1}{3}u - \frac{1}{3}v$	x	\geq	0
M(s) =	2 s	=	v + 2y	y	\leq	1
M(u) =	3			v	\geq	0
M(v) =	0			\overline{u}	\leq	-1

Bound violation pivot u and y (u is a dependent variable).

Mod	del			Equ	ations		E	Boun	ds
M(x)	-	1	x	=	$\frac{1}{3}u + \frac{2}{3}v$		\mathbf{S}	\geq	1
M(y)	=	1	y	=	$\frac{1}{3}u - \frac{1}{3}v$	-	r	\geq	0
M(s)	=	2	s	=	$\frac{2}{3}u + \frac{1}{3}v$		y	\leq	1
M(u)	=	3				1	v	\geq	0
M(v)	=	0				1	u	\leq	-1



Bound violation update assignment.

Model		Equ	uations	E	Boun	ds
M(x) =	1 x	=	$\frac{1}{3}u + \frac{2}{3}v$	S	\geq	1
M(y) =	1 <i>y</i>	=	$\frac{1}{3}u - \frac{1}{3}v$	x	\geq	0
M(s) =	2 s	Ξ	$\frac{2}{3}u + \frac{1}{3}v$	y	\leq	1
M(u) =	-1			v	\geq	0
M(v) =	0			\overline{u}	\leq	-1

Bound violation update dependent variables assignment.

Model		Equations			Bounds			
M(x)	=	$-\frac{1}{3}$	x		$\frac{1}{3}u + \frac{2}{3}v$	s	\geq	1
M(y)	:=:	$-\frac{1}{3}$	y	:=:	$\frac{1}{3}u - \frac{1}{3}v$	x	\geq	0
M(s)	=	$-\frac{2}{3}$	s	=	$\frac{2}{3}u + \frac{1}{3}v$	y	\leq	1
M(u)	=	-1				v	\geq	0
M(v)	=	0				\overline{u}	\leq	-1



Bound violations

$$s \ge 1, x \ge 0$$
$$(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$$

Mo	odel			Equ	ations		E	Boun	ds
M(x)	=	$-\frac{1}{3}$	x	=	$\frac{1}{3}u + \frac{2}{3}$	v	s	\geq	1
M(y)	=	$-\frac{1}{3}$	y		$\frac{1}{3}u - \frac{1}{3}$	v	x	\geq	0
M(s)	:=:	$-\frac{2}{3}$	S	:=:	$\frac{2}{3}u + \frac{1}{3}$	v	\boldsymbol{y}	\leq	1
M(u)	:=:	-1					v	\geq	0
M(v)	2 — 3	0					u	\leq	-1

Bound violations pivot s and v (s is a dependent variable).

M	odel			Equ	ations	E	Boun	ds
M(x)	=	$-\frac{1}{3}$	x	=	$\frac{1}{3}u + \frac{2}{3}v$	S	\geq	1
M(y)	=	$-\frac{1}{3}$	y	=	$\frac{1}{3}u - \frac{1}{3}v$	x	\geq	0
M(s)	=	$-\frac{2}{3}$	s	=	$\frac{2}{3}u + \frac{1}{3}v$	y	\leq	1
M(u)	=	-1				v	\geq	0
M(v)	=	0				u	\leq	-1

• Bound violations pivot s and v (s is a dependent variable).



Bound violations pivot s and v (s is a dependent variable).

Mo	odel			Equ	ations		E	Boun	ds
M(x)	=	$-\frac{1}{3}$	x		2s-u	0	s	\geq	1
M(y)	Ξ	$-\frac{1}{3}$	y	2 — 2	-s+u	4	r	\geq	0
M(s)	=	$-\frac{2}{3}$	v	:=:	3s - 2u		y	\leq	1
M(u)	=	-1					v	\geq	0
M(v)	=	0				1	u	\leq	-1



Bound violations update assignment.

Mo	odel			Equ	lations		В	oun	ds
M(x)	=	$-\frac{1}{3}$	x		2s-u	S	3	\geq	1
M(y)	=	$-\frac{1}{3}$	y	=	-s+u	1	2	\geq	0
M(s)	=	1	v		3s - 2u	3	1	\leq	1
M(u)	=	-1				ι	,	\geq	0
M(v)	_	0				U	l	\leq	-1

Bound violations update dependent variables assignment.

Model		Equations			Bounds			
M(x)	=	3	x	=	2s - u	s	\geq	1
M(y)	Ξ	-2	y	Ξ	-s + u	x	\geq	0
M(s)	=	1	v	=	3s - 2u	y	\leq	1
M(u)	=	-1				v	\geq	0
M(v)	=	5				u	\leq	-1

Found satisfying assignment

$$s \ge 1, x \ge 0$$
$$(y \le 1 \lor v \ge 2), (v \le -2 \lor v \ge 0), (v \le -2 \lor u \le -1)$$

M	odel			Equ	ations	E	Boun	ds
M(x)	=	3	x	=	2s - u	S	\geq	1
M(y)		-2	y	Ξ	-s+u	x	\geq	0
M(s)	=	1	v	=	3s - 2u	y	\leq	1
M(u)	=	-1				v	\geq	0
M(v)		5				u	\leq	-1

Correctness

Completeness: trivial

Soundness: also trivial

Termination: non trivial.

We cannot choose arbitrary variable to pivot.

Assume the variables are ordered.

Bland's rule: select the smallest basic variable **c** that does not satisfy its bounds, then select the smallest non-basic in the row of **c** that can be used for pivoting.

Too technical.

Uses the fact that a tableau has a finite number of configurations. Then, any infinite trace will have cycles.



Data-structures

Array of rows (equations).

Each row is a dynamic array of tuples:

(coefficient, variable, pos_in_occs, is_dead)

Each variable x has a "set" (dynamic array) of occurrences:

(row_idx, pos_in_row, is_dead)

Each variable x has a "field" row[x]

row[x] is -1 if x is non basic

otherwise, row[x] contains the idx of the row containing x Each variable x has "fields": lower[x], upper[x], and value[x]



Data-structures

rows: array of rows (equations).

Each row is a dynamic array of tuples:

(coefficient, variable, pos_in_occs, is_dead)

occs[x]: Each variable x has a "set" (dynamic array) of occurrences:

(row_idx, pos_in_row, is_dead)

row[x]:

row[x] is -1 if x is non basic

otherwise, row[x] contains the idx of the row containing x Other "fields": lower[x], upper[x], and value[x] atoms[x]: atoms (assigned/unassigned) that contains x



Data-structures

```
s_1 \equiv a + b, s_2 \equiv c - b
p_1 \equiv a \leq 0, p_2 \equiv 1 \leq s_1, p_3 \equiv 1 \leq s_2
p_1, p_2 were already assigned
a - s_1 + s_2 + c = 0
b- c + s_2 = 0
a \le 0, 1 \le s_1
M(a) = 0 value[a] = 0
M(b) = -1 value[a] = -1
M(c) = 0 value[c] = 0
M(s_1) = 1 value[s_1] = 1
M(s_2) = 1
              value[s_2] = 1
```

```
rows = [

[(1, a, 0, t), (-1, s_1, 0, t), (1, s_2, 1, t), (1, c, 0, t)],

[(1,b, 0, t), (-1, c, 1, t), (1, s_2, 2, t)]]
```

```
occs[a] = [(0, 0, f)]
occs[b] = [(1,0,f)]
occs[c] = [(0,3,f), (1,1,f)]
occs[s<sub>1</sub>] = [(0,1,f)]
occs[s<sub>2</sub>] = [(0,0,t), (0,2,f), (1,2,f)]
```

```
row[a] = 0, row[b] = 1, row[c] = -1, ...
upper[a] = 0, lower[s<sub>1</sub>] = 1
atoms[a] = {p<sub>1</sub>}, atoms[s<sub>1</sub>] = {p<sub>2</sub>}, ...
```



Combining Theories

In practice, we need a combination of theories.

b + 2 = c and $f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

A theory is a set (potentially infinite) of first-order sentences.

Main questions:

Is the union of two theories T1 \cup T2 consistent? Given a solvers for T1 and T2, how can we build a solver for T1 \cup T2?



Disjoint Theories

Two theories are disjoint if they do not share function/constant and predicate symbols.

= is the only exception.

Example: The theories of arithmetic and arrays are disjoint.

Arithmetic symbols: $\{0, -1, 1, -2, 2, ..., +, -, *, >, <, \ge, \le\}$ Array symbols: $\{$ read, write $\}$

Research

Purification

It is a different name for our "naming" subterms procedure.

 $b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

b + 2 = c, v₆ ≠ v₇ v₁ ≡ 3, v₂ ≡ write(a, b, v₁), v₃ ≡ c-2, v₄ ≡ read(v₂, v₃), v₅ ≡ c-b+1, v₆ ≡ f(v₄), v₇ ≡ f(v₅)



Purification

It is a different name for our "naming" subterms procedure.

 $b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

 $b + 2 = c, v_{6} \neq v_{7}$ $v_{1} \equiv 3, v_{2} \equiv write(a, b, v_{1}), v_{3} \equiv c-2, v_{4} \equiv read(v_{2}, v_{3}),$ $v_{5} \equiv c-b+1, v_{6} \equiv f(v_{4}), v_{7} \equiv f(v_{5})$ $b + 2 = c, v_{1} \equiv 3, v_{3} \equiv c-2, v_{5} \equiv c-b+1,$ $v_{2} \equiv write(a, b, v_{1}), v_{4} \equiv read(v_{2}, v_{3}),$ $v_{6} \equiv f(v_{4}), v_{7} \equiv f(v_{5}), v_{6} \neq v_{7}$

Research

Stably Infinite Theories

A theory is stably infinite if every satisfiable QFF is satisfiable in an infinite model.

EUF and arithmetic are stably infinite.

Bit-vectors are not.



Important Result

The union of two consistent, disjoint, stably infinite theories is consistent.



Convexity

```
A theory T is convex iff
for all finite sets S of literals and
for all a_1 = b_1 \lor ... \lor a_n = b_n
S implies a_1 = b_1 \lor ... \lor a_n = b_n
iff
S implies a_i = b_i for some 1 \le i \le n
```



Convexity: Results

Every convex theory with non trivial models is stably infinite.

All Horn equational theories are convex. formulas of the form $s_1 \neq r_1 \lor ... \lor s_n \neq r_n \lor t = t'$

Linear rational arithmetic is convex.



Convexity: Negative Results

Linear integer arithmetic is not convex

$$1 \le a \le 2$$
, b = 1, c = 2 implies a = b \lor a = c

Nonlinear arithmetic

$$a^2 = 1, b = 1, c = -1$$
 implies $a = b \lor a = c$

Theory of bit-vectors

Theory of arrays $c_1 = read(write(a, i, c_2), j), c_3 = read(a, j)$ implies $c_1 = c_2 \lor c_1 = c_3$



Combination of non-convex theories

EUF is convex (O(n log n)) IDL is non-convex (O(nm))

EUF \cup IDL is NP-CompleteReduce 3CNF to EUF \cup IDLFor each boolean variable p_i add $0 \le a_i \le 1$ For each clause $p_1 \lor \neg p_2 \lor p_3$ add $f(a_1, a_2, a_3) \ne f(0, 1, 0)$



Combination of non-convex theories

EUF is convex (O(n log n)) IDL is non-convex (O(nm))

EUF \cup IDL is NP-CompleteReduce 3CNF to EUF \cup IDLFor each boolean variable p_i add $0 \le a_i \le 1$ For each clause $p_1 \lor \neg p_2 \lor p_3$ add $f(a_1, a_2, a_3) \ne f(0, 1, 0)$ Implies $a_1 \ne 0 \lor a_2 \ne 1 \lor a_3 \ne 0$



Nelson-Oppen Combination

Let \mathcal{T}_1 and \mathcal{T}_2 be consistent, stably infinite theories over disjoint (countable) signatures. Assume satisfiability of conjunction of literals can decided in $O(T_1(n))$ and $O(T_2(n))$ time respectively. Then,

- 1. The combined theory ${\mathcal T}$ is consistent and stably infinite.
- 2. Satisfiability of quantifier free conjunction of literals in T can be decided in $O(2^{n^2} \times (T_1(n) + T_2(n)))$.
- 3. If \mathcal{T}_1 and \mathcal{T}_2 are convex, then so is \mathcal{T} and satisfiability in \mathcal{T} is in $O(n^3 \times (T_1(n) + T_2(n)))$.



Nelson-Oppen Combination

The combination procedure:

- **Initial State:** ϕ is a conjunction of literals over $\Sigma_1 \cup \Sigma_2$.
- **Purification:** Preserving satisfiability transform ϕ into $\phi_1 \wedge \phi_2$, such that, $\phi_i \in \Sigma_i$.
- Interaction: Guess a partition of $\mathcal{V}(\phi_1) \cap \mathcal{V}(\phi_2)$ into disjoint subsets. Express it as conjunction of literals ψ . Example. The partition $\{x_1\}, \{x_2, x_3\}, \{x_4\}$ is represented as $x_1 \neq x_2, x_1 \neq x_4, x_2 \neq x_4, x_2 = x_3$.
- Component Procedures : Use individual procedures to decide

whether $\phi_i \wedge \psi$ is satisfiable.

Return: If both return yes, return yes. No, otherwise.



Soundness

Each step is satisfiability preserving.

Say ϕ is satisfiable (in the combination).

- Purification: $\phi_1 \wedge \phi_2$ is satisfiable.
- Iteration: for some partition ψ , $\phi_1 \wedge \phi_2 \wedge \psi$ is satisfiable.
- Component procedures: $\phi_1 \wedge \psi$ and $\phi_2 \wedge \psi$ are both satisfiable in component theories.
- Therefore, if the procedure return unsatisfiable, then ϕ is unsatisfiable.



Completeness

Suppose the procedure returns satisfiable.

- Let ψ be the partition and A and B be models of $\mathcal{T}_1 \wedge \phi_1 \wedge \psi$ and $\mathcal{T}_2 \wedge \phi_2 \wedge \psi$.
- The component theories are stably infinite. So, assume the models are infinite (of same cardinality).
- Let h be a bijection between |A| and |B| such that h(A(x)) = B(x) for each shared variable.
- Extend B to \overline{B} by interpretations of symbols in Σ_1 : $\overline{B}(f)(b_1, \ldots, b_n) = h(A(f)(h^{-1}(b_1), \ldots, h^{-1}(b_n)))$
- \bar{B} is a model of:

 $\mathcal{T}_1 \wedge \phi_1 \wedge \mathcal{T}_2 \wedge \phi_2 \wedge \psi$



NO deterministic procedure (for convex theories)

Instead of guessing, we can deduce the equalities to be shared.

Purification: no changes.

Interaction: Deduce an equality x = y:

$$\mathcal{T}_1 \vdash (\phi_1 \Rightarrow x = y)$$

Update $\phi_2 := \phi_2 \wedge x = y$. And vice-versa. Repeat until no further changes.

Component Procedures : Use individual procedures to decide whether ϕ_i is satisfiable.

Remark: $\mathcal{T}_i \vdash (\phi_i \Rightarrow x = y)$ iff $\phi_i \land x \neq y$ is not satisfiable in \mathcal{T}_i .



NO deterministic procedure Completeness

Assume the theories are convex.

- Suppose ϕ_i is satisfiable.
- Let *E* be the set of equalities $x_j = x_k$ ($j \neq k$) such that, $\mathcal{T}_i \not\vdash \phi_i \Rightarrow x_j = x_k$.
- By convexity, $\mathcal{T}_i \not\vdash \phi_i \Rightarrow \bigvee_E x_j = x_k$.
- $\phi_i \wedge \bigwedge_E x_j \neq x_k$ is satisfiable.
- The proof now is identical to the nondeterministic case.
- Sharing equalities is sufficient, because a theory T₁ can assume that x^B ≠ y^B whenever x = y is not implied by T₂ and vice versa.



NO procedure: Example

 $b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

ArithmeticArraysEUFb + 2 = c, $v_2 \equiv write(a, b, v_1)$, $v_6 \equiv f(v_4)$, $v_1 \equiv 3$, $v_4 \equiv read(v_2, v_3)$ $v_7 \equiv f(v_5)$, $v_3 \equiv c-2$, $v_6 \neq v_7$ $v_5 \equiv c-b+1$ $v_5 \equiv c-b+1$



NO procedure: Example

 $b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

Arithmetic	Arrays	EUF
b + 2 = c ,	$v_2 \equiv write(a, b, v_1),$	$v_6 \equiv f(v_4),$
$v_1 \equiv 3$,	$v_4 \equiv read(v_2, v_3)$	$v_7 \equiv f(v_5),$
$v_3 \equiv c-2,$		$v_6 \neq v_7$
$v_5 \equiv c-b+1$		

Substituting c



NO procedure: Example

 $b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

ArithmeticArraysEUFb + 2 = c, $v_2 \equiv write(a, b, v_1)$, $v_6 \equiv f(v_4)$, $v_1 \equiv 3$, $v_4 \equiv read(v_2, v_3)$, $v_7 \equiv f(v_5)$, $v_3 \equiv b$, $v_6 \neq v_7$ $v_5 \equiv 3$ $v_5 \equiv 3$

Propagating $v_3 = b$


$b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

ArithmeticArraysEUFb + 2 = c, $v_2 \equiv write(a, b, v_1)$, $v_6 \equiv f(v_4)$, $v_1 \equiv 3$, $v_4 \equiv read(v_2, v_3)$, $v_7 \equiv f(v_5)$, $v_3 \equiv b$, $v_3 = b$ $v_6 \neq v_7$, $v_5 \equiv 3$ $v_5 \equiv b$ $v_8 = b$

Deducing $v_4 = v_1$



 $b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

Arithmetic	Arrays	EUF
b + 2 = c,	$v_2 \equiv write(a, b, v_1),$	$v_6 \equiv f(v_4),$
$v_1 \equiv 3$,	$v_4 \equiv read(v_2, v_3),$	$v_7 \equiv f(v_5),$
$v_3 \equiv b$,	v ₃ = b,	v ₆ ≠ v ₇ ,
$v_5 \equiv 3$	$v_4 = v_1$	v ₃ = b

Propagating $v_4 = v_1$



 $b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

Arithmetic	Arrays	EUF
b + 2 = c,	$v_2 \equiv write(a, b, v_1),$	$v_6 \equiv f(v_4),$
$v_1 \equiv 3,$	$v_4 \equiv read(v_2, v_3),$	$v_7 \equiv f(v_5),$
$v_3 \equiv b$,	v ₃ = b,	v ₆ ≠ v ₇ ,
$v_5 \equiv 3,$	$v_4 = v_1$	v ₃ = b,
$v_4 = v_1$		$v_4 = v_1$

Propagating $v_5 = v_1$



 $b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

Arithmetic Arrays EUF b + 2 = c, $v_2 \equiv write(a, b, v_1),$ $\mathbf{v}_6 \equiv \mathbf{f}(\mathbf{v}_4),$ $v_4 \equiv read(v_2, v_3),$ $v_7 \equiv f(v_5),$ $v_1 \equiv 3$, $v_{3} = b,$ $v_3 \equiv b$, $V_6 \neq V_7$, $v_4 = v_1$ $v_5 \equiv 3$, $v_3 = b$, $V_4 = V_1$ $V_4 = V_{1}$ $v_{5} = v_{1}$

Congruence: $v_6 = v_7$



 $b + 2 = c, f(read(write(a,b,3), c-2)) \neq f(c-b+1)$

Arithmetic	Arrays	EUF
b + 2 = c,	$v_2 \equiv write(a, b, v_1),$	$v_6 \equiv f(v_4),$
$v_1 \equiv 3$,	$v_4 \equiv read(v_2, v_3),$	$v_7 \equiv f(v_5),$
$v_3 \equiv b$,	v ₃ = b,	v ₆ ≠ v ₇ ,
$v_5 \equiv 3$,	$v_4 = v_1$	v ₃ = b,
$v_4 = v_1$		$v_4 = v_1$,
		$v_{5} = v_{1}$,

Unsatisfiable



 $v_6 = v_7$

NO deterministic procedure

Deterministic procedure may fail for non-convex theories.

```
0 \le a \le 1, 0 \le b \le 1, 0 \le c \le 1,
f(a) \ne f(b),
f(a) \ne f(c),
f(b) \ne f(c)
```



Combining Procedures in Practice

Propagate all implied equalities.

- Deterministic Nelson-Oppen.
- Complete only for convex theories.
- It may be expensive for some theories.

Delayed Theory Combination.

- Nondeterministic Nelson-Oppen.
- Create set of interface equalities (x = y) between shared variables.
- Use SAT solver to guess the partition.
- Disadvantage: the number of additional equality literals is quadratic in the number of shared variables.



Combining Procedures in Practice

Common to these methods is that they are pessimistic about which equalities are propagated.

Model-based Theory Combination

> Optimistic approach.

Use a candidate model M_i for one of the theories T_i and propagate all equalities implied by the candidate model, hedging that other theories will agree.

if $M_i \models \mathcal{T}_i \cup \Gamma_i \cup \{u = v\}$ then propagate u = v.

- If not, use backtracking to fix the model.
- It is cheaper to enumerate equalities that are implied in a particular model than of all models.



$x=f(\underline{y-1}), f(x)\neq f(y), 0\leq x\leq 1, 0\leq y\leq 1$

Purifying



$x = f(z), f(x) \neq f(y), 0 \le x \le 1, 0 \le y \le 1, z = y - 1$



	${\cal T}_E$		7	$\lceil_A \rceil$
Literals	Eq. Classes	Model	Literals	Model
x = f(z)	$\{x, f(z)\}$	$E(x) = *_1$	$0 \le x \le 1$	A(x) = 0
$f(x) \neq f(y)$	$\{y\}$	$E(y) = *_2$	$0 \leq y \leq 1$	A(y) = 0
	$\{z\}$	$E(z) = *_3$	z = y - 1	A(z) = -1
	$\{f(x)\}$	$E(f) = \{ *_1 \mapsto *_4,$		
	$\{f(y)\}$	$*_2 \mapsto *_5,$		
		$*_3\mapsto *_1,$		
		else $\mapsto *_6$ }		

Assume x = y

	${\cal T}_E$		7	Γ_A
Literals	Eq. Classes	Model	Literals	Model
x = f(z)	$\{x, y, f(z)\}$	$E(x) = *_1$	$0 \leq x \leq 1$	A(x) = 0
$f(x) \neq f(y)$	$\{z\}$	$E(y) = *_1$	$0 \leq y \leq 1$	A(y) = 0
x = y	$\{f(x), f(y)\}$	$E(z) = *_2$	z = y - 1	A(z) = -1
		$E(f) = \{ *_1 \mapsto *_3,$	x = y	
		$*_2 \mapsto *_1,$		
		$\textit{else} \mapsto *_4 \}$		

Unsatisfiable

	${\cal T}_E$		7	Г _А
Literals	Eq. Classes	Model	Literals	Model
x = f(z)	$\{x, f(z)\}$	$E(x) = *_1$	$0 \le x \le 1$	A(x) = 0
$f(x) \neq f(y)$	$\{y\}$	$E(y) = *_2$	$0 \le y \le 1$	A(y) = 0
$x \neq y$	$\{z\}$	$E(z) = *_3$	z = y - 1	A(z) = -1
	$\{f(x)\}$	$E(f) = \{ *_1 \mapsto *_4, $	$x \neq y$	
	$\{f(y)\}$	$*_2 \mapsto *_5,$		
		$*_3 \mapsto *_1,$		
		$\textit{else} \mapsto \ast_6 \}$		

Backtrack, and assert $x \neq y$. \mathcal{T}_A model need to be fixed.

${\mathcal T}_E$			T	A
Literals	Eq. Classes	Model	Literals	Model
x = f(z)	$\{x, f(z)\}$	$E(x) = *_1$	$0 \le x \le 1$	A(x) = 0
$f(x) \neq f(y)$	$\{y\}$	$E(y) = *_2$	$0 \leq y \leq 1$	A(y) = 1
$x \neq y$	$\{z\}$	$E(z) = *_3$	z = y - 1	A(z) = 0
	$\{f(x)\}$	$E(f) = \{*_1 \mapsto *_4,$	$x \neq y$	
	$\{f(y)\}$	$*_2 \mapsto *_5,$		
		$*_3 \mapsto *_1,$		
		else $\mapsto *_6 \}$		

Assume x = z

${\cal T}_E$			\mathcal{T}_{i}	A
Literals	Eq. Classes	Model	Literals	Model
x = f(z)	$\{x, z,$	$E(x) = *_1$	$0 \le x \le 1$	A(x) = 0
$f(x) \neq f(y)$	$f(x), f(z)\}$	$E(y) = *_2$	$0 \leq y \leq 1$	A(y)=1
$x \neq y$	$\{y\}$	$E(z) = *_1$	z = y - 1	A(z) = 0
x = z	$\{f(y)\}$	$E(f) = \{ *_1 \mapsto *_1, $	$x \neq y$	
		$*_2 \mapsto *_3,$	x = z	
		$\textit{else}\mapsto *_4\bigr\}$		

Satisfiable

	${\cal T}_E$		T	A
Literals	Eq. Classes	Model	Literals	Model
x = f(z)	$\{x, z,$	$E(x) = *_1$	$0 \le x \le 1$	A(x) = 0
$f(x) \neq f(y)$	f(x), f(z)	$E(y) = *_2$	$0 \leq y \leq 1$	A(y) = 1
$x \neq y$	$\{y\}$	$E(z) = *_1$	z = y - 1	A(z) = 0
x = z	$\{f(y)\}$	$E(f) = \{ *_1 \mapsto *_1,$	$x \neq y$	
		$*_2 \mapsto *_3,$	x = z	
		else $\mapsto *_4 \}$		

Let h be the bijection between |E| and |A|.

 $h = \{ *_1 \mapsto 0, *_2 \mapsto 1, *_3 \mapsto -1, *_4 \mapsto 2, \ldots \}$

	${\mathcal T}_E$		\mathcal{T}_A
Literals	Model	Literals	Model
x = f(z)	$E(x) = *_1$	$0 \le x \le 1$	A(x) = 0
$f(x) \neq f(y)$	$E(y) = *_2$	$0 \leq y \leq 1$	A(y) = 1
$x \neq y$	$E(z) = *_1$	z = y - 1	A(z) = 0
x = z	$E(f) = \{ *_1 \mapsto *_1, $	$x \neq y$	$A(f) = \{0 \mapsto 0$
	$*_2 \mapsto *_3,$	x = z	$1\mapsto -1$
	$\textit{else} \mapsto \ast_4 \}$		$\textit{else}\mapsto 2\}$

Extending A using h.

 $h = \{*_1 \mapsto 0, *_2 \mapsto 1, *_3 \mapsto -1, *_4 \mapsto 2, \ldots\}$

Model Mutation

Sometimes M(x) = M(y) by accident.

$$\bigwedge_{i=1}^{N} f(x_i) \ge 0 \ \land \ x_i \ge 0$$

Model mutation: diversify the current model.

Freedom Intervals

Model mutation without pivoting

For each non basic variable x_i compute $[L_i, U_i]$

Each row containing x_j enforces a limit on how much it can be increase and/or decreased without violating the bounds of the basic variable in the row.

Opportunistic Equality Propagation

We say a variable is fixed if the lower and upper bound are the same. $1 \le x \le 1$

A polynomial P is fixed if all its variables are fixed.

Given a fixed polynomial P of the forma $2x_1 + x_2$, we use M(P) to denote $2M(x_1) + M(x_2)$

Opportunistic Equality Propagation

FixedEq

$$l_i \leq x_i \leq u_i, \ l_j \leq x_j \leq u_j \Longrightarrow \ x_i = x_j \ \text{if} \ l_i = u_i = l_j = u_j$$

EqRow

 $x_i = x_j + P \qquad \qquad \Longrightarrow \quad x_i = x_j \quad \text{if} \quad P \text{ is fixed, and } \mathsf{M}(P) = 0$

EqOffsetRows

$$\begin{array}{ll} x_i = x_k + P_1 \\ x_j = x_k + P_2 \end{array} \qquad \qquad \Longrightarrow \quad x_i = x_j \quad \text{if} \quad \left\{ \begin{array}{l} P_1 \text{ and } P_2 \text{ are fixed, and} \\ \mathsf{M}(P_1) = \mathsf{M}(P_2) \end{array} \right. \end{array}$$

EqRows

$$\begin{array}{ll} x_i = P + P_1 \\ x_j = P + P_2 \end{array} & \implies x_i = x_j \ \ \mbox{if} \ \ \begin{cases} P_1 \ \mbox{and} \ P_2 \ \mbox{are fixed, and} \\ M(P_1) = M(P_2) \end{cases} \\ \end{array}$$

.

Non-stably infinite theories in practice

Bit-vector theory is not stably-infinite.

How can we support it?

Solution: add a predicate is-bv(x) to the bit-vector theory (intuition: is-bv(x) is true iff x is a bitvector).

The result of the bit-vector operation op(x, y) is not specified if $\neg is-bv(x)$ or $\neg is-bv(y)$.

The new bit-vector theory is stably-infinite.

Reduction Functions

A reduction function reduces the satifiability problem for a complex theory into the satisfiability problem of a simpler theory.

Ackermannization is a reduction function.

Reduction Functions

Theory of commutative functions.

- $\blacktriangleright \forall x, y. f(x, y) = f(y, x)$
- Reduction to EUF
- For every f(a, b) in ϕ , do $\phi := \phi \wedge f(a, b) = f(b, a)$.

Verifying Compilers



pre/post conditions invariants and other annotations



Verification conditions: Structure



- Quantifiers, quantifiers, quantifiers, ...
- Modeling the runtime
 - ∀ h,o,f:
 IsHeap(h) ∧ o ≠ null ∧ read(h, o, alloc) = t
 ⇒
 read(h,o, f) = null ∨ read(h, read(h,o,f),alloc) = t



- Quantifiers, quantifiers, quantifiers, ...
- Modeling the runtime
- Frame axioms
 - \forall o, f:
 - o ≠ null ∧ read(h₀, o, alloc) = t ⇒ read(h₁, o, f) = read(h₀, o, f) ∨ (o, f) ∈ M



- Quantifiers, quantifiers, quantifiers, ...
- Modeling the runtime
- Frame axioms
- User provided assertions
 ∀ i,j: i ≤ j ⇒ read(a,i) ≤ read(b,j)



- Quantifiers, quantifiers, quantifiers, ...
- Modeling the runtime
- Frame axioms
- User provided assertions
- Theories
 - ∀ x: p(x,x)
 - $\forall x,y,z: p(x,y), p(y,z) \Longrightarrow p(x,z)$
 - $\forall x,y: p(x,y), p(y,x) \Longrightarrow x = y$



- Quantifiers, quantifiers, quantifiers, ...
- Modeling the runtime
- Frame axioms
- User provided assertions
- Theories
- Solver must be fast in satisfiable instances.



We want to find bugs!



Some statistics

- Grand challenge: Microsoft Hypervisor
- 70k lines of dense C code
- VCs have several Mb
- Thousands of non ground clauses
- Developers are willing to wait at most 5 min per VC



Many Approaches

Heuristic quantifier instantiation

Combining SMT with Saturation provers

Complete quantifier instantiation

Decidable fragments

Model based quantifier instantiation



E-matching & Quantifier instantiation

- SMT solvers use heuristic quantifier instantiation.
- E-matching (matching modulo equalities).

Example:

 $\forall x: f(g(x)) = x \{ f(g(x)) \}$ a = g(b), b = c, f(a) \neq c Trigger





E-matching & Quantifier instantiation

- SMT solvers use heuristic quantifier instantiation.
- E-matching (matching modulo equalities).
- Example:





E-matching: why do we use it?

- Integrates smoothly with DPLL.
- Software verification problems are big & shallow.
- Decides useful theories:
 - Arrays
 - Partial orders
 - ⊜ ...


Efficient E-matching

- E-matching is NP-Hard.
- In practice

Problem	Indexing Technique
Fast retrieval	E-matching code trees
Incremental E-Matching	Inverted path index



E-matching code trees



f(x1, g(x1, a), h(x2), b)

Compiler

Similar triggers share several instructions.

Combine code sequences in a code tree

Instructions:

- 1. init(f, 2)
- 2. check(r4, b, 3)
- 3. bind(r2, g, r5, 4)
- 4. compare(r1, r5, 5)
- 5. check(r6, a, 6)
- 6. bind(r3, h, r7, 7)
- 7. yield(r1, r7)



- E-matching needs ground seeds.
 - ∀x: p(x),
 - $\forall x: not p(x)$



- E-matching needs ground seeds.
- Bad user provided triggers: $\forall x: f(g(x)) = x \{ f(g(x)) \}$ g(a) = c, g(b) = c, $a \neq b$

Trigger is too restrictive



- E-matching needs ground seeds.
- Bad user provided triggers:
 - $\forall x: f(g(x))=x \{ g(x) \}$ g(a) = c, g(b) = c, $a \neq b$

More "liberal" trigger



- E-matching needs ground seeds.
- Bad user provided triggers:
 - $\forall x: f(g(x))=x \{ g(x) \}$ g(a) = c, g(b) = c, $a \neq b,$ f(g(a)) = a,f(g(b)) = b a=b



- E-matching needs ground seeds.
- Bad user provided triggers.
- It is not refutationally complete.









Tight integration: DPLL + Saturation solver.







Inference rule:

$$\frac{C_1 \quad \dots \quad C_n}{C}$$

- DPLL(Γ) is parametric.
- Examples:
 - Resolution
 - Superposition calculus
 - ⊜ ...









DPLL(Γ): Deduce I

p(a) | p(a) \lor q(a), \forall x: \neg p(x) \lor r(x), \forall x: p(x) \lor s(x)



DPLL(Γ): Deduce I

p(a) | p(a) \lor q(a), \neg p(x) \lor r(x), p(x) \lor s(x)



DPLL(Γ): Deduce I

$p(a) \mid p(a) \lor q(a), \neg p(x) \lor r(x), p(x) \lor s(x)$

Resolution

$p(a) \mid p(a) \lor q(a), \neg p(x) \lor r(x), p(x) \lor s(x), r(x) \lor s(x)$



DPLL(Γ): Deduce II

• Using ground atoms from M:

- Main issue: backtracking.
- Hypothetical clauses:

Η

Track literals from M used to derive C

(hypothesis) Ground literals

(regular) Clause

M | F



DPLL(Γ): Deduce II





DPLL(Γ): Backtracking

p(a), r(a) | p(a)∨q(a), ¬p(a)∨¬r(a), p(a)▷r(a), ...



DPLL(Γ): Backtracking

p(a), r(a) | p(a)∨q(a), ¬p(a)∨¬r(a), p()) (a), ...

p(a) is removed from M

¬p(a) | p(a)∨q(a), ¬p(a)∨¬r(a), ...



DPLL(\Gamma): Improvement

 Saturation solver ignores non-unit ground clauses.

p(a) | p() (a), ¬p(x)∨r(x)



DPLL(\Gamma): Improvement

- Saturation solver ignores non-unit ground clauses.
- It is still refutanionally complete if:
 - Γ has the reduction property.



DPLL(\Gamma): Improvement

- Saturation solver ignores non-unit ground clauses.
- It is still refutanionally complete if:
 - Γ has the reduction property.





$DPLL(\Gamma)$: Problem

- Interpreted symtbols $\neg(f(a) > 2), f(x) > 5$
- It is refutationally complete if
 - Interpreted symbols only occur in ground clauses
 - Non ground clauses are variable inactive
 - "Good" ordering is used



Notation Remainder

$$\forall x_1, x_2: \neg p(x_1, x_2) \lor f(x_1) = f(x_2) + 1,$$

p(a,b), a < b + 1



Notation Remainder

$$\neg p(x_1, x_2) \lor f(x_1) = f(x_2) + 1,$$

p(a,b), a < b + 1



Essentially uninterpreted fragment

 Variables appear only as arguments of uninterpreted symbols.

$$f(g(x_1) + a) < g(x_1) \lor h(f(x_1), x_2) = 0$$

$$f(x_1 + x_2) \le f(x_1) + f(x_2)$$





```
Given a set of formulas F, build an equisatisfiable set of quantifier-free formulas F*
```

"Domain" of f is the set of ground terms A_f t $\in A_f$ if there is a ground term f(t)

Suppose

- 1. We have a clause C[f(x)] containing f(x).
- 2. We have f(t).

→ Instantiato v

Instantiate x with t: C[f(t)].



F $g(x_1, x_2) = 0 \lor h(x_2) = 0,$ $g(f(x_1),b) + 1 \le f(x_1),$ h(c) = 1,f(a) = 0



F

$$F^*$$
 $g(x_1, x_2) = 0 \lor h(x_2) = 0,$
 $h(c) = 1,$
 $g(f(x_1), b) + 1 \le f(x_1),$
 $f(a) = 0$
 $h(c) = 1,$
 $f(a) = 0$
 $h(c) = 1,$
 $f(a) = 0$

Copy quantifier-free formulas

"Domains": A_f: { a } A_g: { } A_h: { c }

F* F $g(x_1, x_2) = 0 \lor h(x_2) = 0$, h(c) = 1,f(a) = 0, $g(f(x_1),b) + 1 \le f(x_1),$ h(c) = 1, f(a) = 0

"Domains": A_f: { a } A_g: { } A_h: { c }

F $g(x_1, x_2) = 0 \lor h(x_2) = 0$, $g(f(x_1),b) + 1 \le f(x_1),$ h(c) = 1, f(a) = 0

F*
h(c) = 1,
f(a) = 0,
g(f(a),b) + 1
$$\leq$$
 f(a)

"Domains": A_f: { a } A_g: { [f(a), b] } A_h: { c }

F $g(x_1, x_2) = 0 \lor h(x_2) = 0$, $g(f(x_1),b) + 1 \le f(x_1),$ h(c) = 1, f(a) = 0

F* h(c) = 1,f(a) = 0, $g(f(a),b) + 1 \le f(a),$

"Domains": A_f: { a } A_g: { [f(a), b] } A_h: { c }

F $g(x_1, x_2) = 0 \lor h(x_2) = 0$, $g(f(x_1),b) + 1 \le f(x_1),$ h(c) = 1, f(a) = 0

```
F*
h(c) = 1,
f(a) = 0,
g(f(a),b) + 1 \leq f(a),
g(f(a), b) = 0 \vee h(b) = 0
```

```
"Domains":
A<sub>f</sub>: { a }
A<sub>g</sub>: { [f(a), b] }
A<sub>h</sub>: { c, b }
```

F

$$g(x_1, x_2) = 0 \lor h(x_2) = 0,$$

 $g(f(x_1),b) + 1 \le f(x_1),$
 $h(c) = 1,$
 $f(a) = 0$

F*
h(c) = 1,
f(a) = 0,
g(f(a),b) + 1
$$\leq$$
 f(a),
g(f(a), b) = 0 \vee h(b) = 0

F

$$g(x_1, x_2) = 0 \lor h(x_2) = 0,$$

 $g(f(x_1),b) + 1 \le f(x_1),$
 $h(c) = 1,$
 $f(a) = 0$

F*

$$h(c) = 1,$$

 $f(a) = 0,$
 $g(f(a),b) + 1 \le f(a),$
 $g(f(a),b) = 0 \lor h(b) = 0,$
 $g(f(a),c) = 0 \lor h(c) = 0$

"Domains":
A_f: { a }
A_g: { [f(a), b], [f(a), c] }
A_h: { c, b }

```
F

g(x_1, x_2) = 0 \lor h(x_2) = 0,

g(f(x_1),b) + 1 \le f(x_1),

h(c) = 1,

f(a) = 0
```

F* h(c) = 1,f(a) = 0, $g(f(a),b) + 1 \le f(a),$ $g(f(a), b) = 0 \vee h(b) = 0$, $g(f(a), c) = 0 \lor h(c) = 0$ M $a \rightarrow 2, b \rightarrow 2, c \rightarrow 3$ $f \rightarrow \{2 \rightarrow 0, ...\}$ $h \rightarrow \{2 \rightarrow 0, 3 \rightarrow 1, ...\}$ $g \rightarrow \{ [0,2] \rightarrow -1, [0,3] \rightarrow 0, ... \}$ Microsoft^{*} Research

Basic Idea (cont.)

```
Given a model M for F^*,
Build a model M<sup>\pi</sup> for F
```

Define a projection function π_f s.t. range of π_f is M(A_f), and π_f (v) = v if v \in M(A_f)

Then, $M^{\pi}(f)(v) = M(f)(\pi_f(v))$



Basic Idea (cont.)




Basic Idea (cont.)

Given a model M for F^* , Build a model M^{π} for F

In our example, we have: h(b) and $h(c) \rightarrow A_h = \{ b, c \}$, and $M(A_h) = \{ 2, 3 \}$

$$\pi_{h} = \{ 2 \rightarrow 2, 3 \rightarrow 3, \text{else} \rightarrow 3 \}$$

 $M^{\pi}(h) = \lambda x. \text{ if}(x=2, 0, 1)$

Research

Example

F* $g(x_1, x_2) = 0 \lor h(x_2) = 0$, h(c) = 1, $g(f(x_1),b) + 1 \le f(x_1),$ f(a) = 0,h(c) = 1, $g(f(a),b) + 1 \le f(a),$ f(a) = 0 $g(f(a), b) = 0 \lor h(b) = 0,$ $g(f(a), c) = 0 \lor h(c) = 0$ M Mπ $a \rightarrow 2, b \rightarrow 2, c \rightarrow 3$ $a \rightarrow 2, b \rightarrow 2, c \rightarrow 3$ $f \rightarrow \{2 \rightarrow 0, ...\}$ $f \rightarrow \lambda x. 2$ $h \rightarrow \{2 \rightarrow 0, 3 \rightarrow 1, ...\}$ $h \rightarrow \lambda x. \text{ if}(x=2, 0, 1)$ $g \rightarrow \{ [0,2] \rightarrow -1, [0,3] \rightarrow 0, ... \}$ $g \rightarrow \lambda x, y$. if (x=0 \wedge y=2,-1, 0) Microsoft^{*} Research

Example: Model Checking

Μπ $a \rightarrow 2, b \rightarrow 2, c \rightarrow 3$ Does M^{π} satisfies? $f \rightarrow \lambda x. 2$ $\forall x_1, x_2 : g(x_1, x_2) = 0 \lor h(x_2) = 0$ $h \rightarrow \lambda x. \text{ if}(x=2, 0, 1)$ $g \rightarrow \lambda x, y$. if (x=0 \wedge y=2,-1, 0) $\forall x_1, x_2$: if $(x_1=0 \land x_2=2,-1,0) = 0 \lor if(x_2=2,0,1) = 0$ is valid $\exists x_1, x_2: if(x_1=0 \land x_2=2,-1,0) \neq 0 \land if(x_2=2,0,1) \neq 0$ is unsat if $(s_1=0 \land s_2=2,-1,0) \neq 0 \land if(s_2=2,0,1) \neq 0$ is unsat



Why does it work?

Suppose M^{π} does not satisfy C[f(x)].

Then for some value v, $M^{\pi}{x \rightarrow v}$ falsifies C[f(x)].

 $M^{\pi}{x \rightarrow \pi_{f}(v)}$ also falsifies C[f(x)].

But, there is a term $t \in A_f$ s.t. $M(t) = \pi_f(v)$ Moreover, we instantiated C[f(x)] with t.

So, M must not satisfy C[f(t)]. Contradiction: M is a model for F*.



Refinement 1: Lazy construction

- F* may be very big (or infinite).
- Lazy-construction
 - Build F* incrementally, F* is the limit of the sequence $F^0 \subset F^1 \subset ... \subset F^k \subset ...$
 - If F^k is unsat then F is unsat.
 - If F^k is sat, then build (candidate) M^{π}
 - If M^{π} satisfies all quantifiers in F then return sat.



Refinement 2: Model-based instantiation

Suppose M^{π} does not satisfy a clause C[f(x)] in F.

Add an instance C[f(t)] which "blocks" this spurious model. Issue: how to find t?

Use model checking, and the "inverse" mapping π_f^{-1} from values to terms (in A_f). $\pi_f^{-1}(v) = t$ if $M^{\pi}(t) = \pi_f(v)$



Model-based instantiation: Example



Infinite F*

- Is our procedure refutationally complete?
- FOL Compactness

 A set of sentences is unsatisfiable iff
 it contains an unsatisfiable finite subset.
- A theory T is a set of sentences, then apply compactness to F*UT



Infinite F*: Example

F

 $\forall x_1: f(x_1) < f(f(x_1)),$ $\forall x_1: f(x_1) < a,$ 1 < f(0).



F^* f(0) < f(f(0)), f(f(0)) < f(f(f(0))), ... f(0) < a, f(f(0)) < a, ... F(f(0) < a, ...) F(f(0) < a, ...) F(f(0) < a, ...) F(f(0) < a, ...) F(f(0) < a,) <



Infinite F*: What is wrong?

- Theory of linear arithmetic T_z is the set of all first-order sentences that are true in the standard structure Z.
- T_z has non-standard models.
- F and F* are satisfiable in a non-standard model.
- Alternative: a theory is a class of structures.
- Compactness does not hold.
- F and F* are still equisatisfiable.



$\Delta_{\rm F}$ and Set Constraints

Given a clause C_k[x₁, ..., x_n]

Let

 ${\color{black}S_{k,i}}$ be the set of ground terms used to instantiate ${\color{black}x_i}$ in clause ${\color{black}C_k}[{\color{black}x_1},...,{\color{black}x_n}]$

How to characterize $S_{k,i}$?

F j-th argument of f in C _k	$\Delta_{\rm F}$ system of set constraints
a ground term t	$t\inA_{f,j}$
t[x ₁ ,, x _n]	$t[S_{k,1},,S_{k,n}] \subseteq A_{f,j}$
x _i	$S_{k,i} = A_{f,j}$



$\Delta_{\rm F}$: Example



Complexity

• $\Delta_{\rm F}$ is stratified then the least solution (and F*) is finite

$t[S_{k,1}^{}\text{,, }S_{k,n}^{}] \subseteq A_{f,j}^{}$	$ evel(S_{k,i}) < level(A_{f,j})$
$S_{k,i} = A_{f,j}$	$level(S_{k,i}) = level(A_{f,j})$

- New decidable fragment: NEXPTIME-Hard.
- The least solution of Δ_F is exponential in the worst case. $a \in S_1, b \in S_1, f_1(S_1, S_1) \subseteq S_2, ..., f_n(S_n, S_n) \subseteq S_{n+1}$
- F* can be doubly exponential in the size of F.



Extensions

• Arithmetical literals: π_f must be monotonic.

Literal of C _k	Δ_{F}
–¬(x _i ≤x _j)	$S_{k,i} = S_{k,j}$
$\neg(x_i \leq t), \neg(t \leq x_i)$	$t\in S_{k,i}$
$x_i = t$	$\{t+1, t-1\} \subseteq S_{k,i}$

• Offsets:

j-th argument of f in C _k	Δ_{F}
x _i +r	$egin{array}{llllllllllllllllllllllllllllllllllll$



Extensions: Example

Shifting

$$\neg (0 \leq x_1) \lor \neg (x_1 \leq n) \lor f(x_1) = g(x_1+2)$$



More Extensions

- Many-sorted logic
- Pseudo-Macros

 $\begin{array}{l} 0 \leq g(x_{1}) \lor f(g(x_{1})) = x_{1}, \\ 0 \leq g(x_{1}) \lor h(g(x_{1})) = 2x_{1}, \\ g(a) < 0 \end{array}$



Conclusion

Powerful, mature, and versatile tools like SMT solvers can now be exploited in very useful ways.

The construction and application of satisfiability procedures is an active research area with exciting challenges.

SMT is hot at Microsoft.

Z3 is a new SMT solver.

Main applications:

- Test-case generation.
- Verifying compiler.
- Model Checking & Predicate Abstraction.



Books

- Bradley & Manna: The Calculus of Computation
- Kroening & Strichman: Decision Procedures, An Algorithmic Point of View
- Chapter in the Handbook of Satisfiability



Web Links

Z3:

http://research.microsoft.com/projects/z3
http://research.microsoft.com/~leonardo

Slides & Papers

http://www.smtlib.org

http://www.smtcomp.org



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