

Satisfiability Modulo Theories (SMT): ideas and applications Università Degli Studi Di Milano Scuola di Dottorato in Informatica, 2010

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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.

$$a - d + 2e = 3$$

$$b - d = 1$$

$$c + d - e = -1$$

$$a, b, c, d, e \ge 0$$

$$100 - 12 = \begin{bmatrix} a \\ b \\ c \\ 010 - 10 \\ 0011 - 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ e \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix}$$

$$Ax = b$$
 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) **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 $x \ge 0$. Kecear

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

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



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



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 s₁ and y

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

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

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

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

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

$$s_{2} - 2s_{1} + x = 0$$
Microsoft
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 s₁ 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	
	$-s_1 + x + y = 0$
	<mark>s₂</mark> - x - 2y = 0 🧹
	$-s_1 + x + y = 0$
	s - 2s + y = 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!

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

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





• Asserting $s \ge 1$

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





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

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



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 $x \ge 0$

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





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





• Case split $\neg y \leq 1$

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

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





• Case split $\neg y \leq 1$ assignment does not satisfies new bound.





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





• 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)





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.





Bound violation update dependent variables assignment.



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



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





▶ Boolean propagation $\neg y \leq 1 \rightsquigarrow v \geq 2$



 \blacktriangleright Theory propagation $v\geq 2 \leadsto \neg v \leq -2$





Conflict empty clause





Backtracking

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





• Asserting $y \leq 1$

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





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





• Asserting $y \leq 1$ update assignment.





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



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



▶ Theory propagation $v \ge -1 \rightsquigarrow \neg v \le -2$



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





Bound violation assignment does not satisfy new bound.





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

Model	Equations	Bounds
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	Equations	Bounds
M(x) = 0	x = s - y	$s \geq 1$
M(y) = 1	u = s + y	$x \geq 0$
M(s) = 1	s = v + 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		Equations	Bounds	
M(x) =	0 x	= v + y	$s \geq 1$	
M(y) =	1 u	= v + 3y	$x \geq 0$)
M(s) =	1 <i>s</i>	= v + 2y	$y \leq 1$	
M(u) =	2		$v \geq 0$)
M(v) = -	-1			



Bound violation update assignment.

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



Bound violation update dependent variables assignment.

 $s \ge 1, x \ge 0$

Model	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		

▶ 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	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		



Bound violation assignment does not satisfy new bound.

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	Eq	luations	Bo	ound	ls
M(x) =	1 x =	v + y	s	\geq	1
M(y) ~=~	1 <i>u</i> =	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).





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





Bound violation update assignment.

Mod	lel		Equ	ations	E	Bound	ds
M(x) =	= 1 :	x	=	$\frac{1}{3}u + \frac{2}{3}v$	s	\geq	1
M(y) :	= 1 🥊	y	=	$\frac{1}{3}u - \frac{1}{3}v$	x	\geq	0
M(s) :	= 2	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 violation update dependent variables assignment.





Bound violations

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

Model			Equ	ations	E	Bound	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).





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





Bound violations update assignment.





Bound violations update dependent variables assignment.





Found satisfying assignment

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

Model		Equa	ations	E	Bound	ds
M(x) =	3 <i>x</i>	=	2s-u	s	\geq	1
M(y) = -	-2 y	=	-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 $\}$



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 $f(a_1, a_2, a_3) \ne f(0, 1, 0)$ \bigcup implies $a_1 \ne 0 \lor a_2 \ne 1 \lor a_3 \ne 0$

Research

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 T_1 and T_2 are convex, then so is T and satisfiability in 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, $v_2 \equiv write(a, b, v_1),$ $\mathbf{v}_6 \equiv \mathbf{f}(\mathbf{v}_4),$ $v_4 \equiv read(v_2, v_3),$ $\mathbf{v}_7 \equiv \mathbf{f}(\mathbf{v}_5),$ $v_1 \equiv 3$, $v_3 = b$, $v_3 \equiv b$, $V_6 \neq V_7$ $v_4 = v_1$ $v_{3} = b$, $v_5 \equiv 3$, $V_4 = V_1$ $V_4 = V_{1}$ $v_{5} = v_{1}$

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,
$v_4 = v_1$		$v_4 = v_1$,
1 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.

Research



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

Purifying





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



Example

${\cal T}_E$			${\cal T}_A$	
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) = 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	Г _А
Literals	Eq. Classes	Model	Literals	Model
x = f(z)	$\{x, y, f(z)\}$	$E(x) = *_1$	$0 \le x \le 1$	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	
		$*_2 \mapsto *_1,$		
		$\textit{else}\mapsto *_4 \bigr\}$		

Unsatisfiable



${\cal T}_E$			${\mathcal T}_A$	
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) = 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.



${\cal T}_E$			${\mathcal T}_A$	
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

Example

${\cal T}_E$			\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	
		$\textit{else} \mapsto *_4 \bigr\}$		

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

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

Example

	${\cal T}_E$		${\mathcal T}_A$
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	$1\mapsto -1$
	$\textit{else}\mapsto *_4 \bigr\}$		$\textit{else}\mapsto 2\}$

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

$$x_i = x_j + P \implies x_i = x_j \text{ if } P \text{ is fixed, and } \mathbf{M}(P) = 0$$

EqOffsetRows

EqRows

$$\begin{array}{ll} x_i = P + P_1 \\ x_j = P + P_2 \end{array} & \implies x_i = x_j \ \ \mbox{if} \ \ \left\{ \begin{array}{l} P_1 \ \mbox{and} \ P_2 \ \mbox{are fixed, and} \\ \ \ \mbox{M}(P_1) = \mbox{M}(P_2) \end{array} \right. \label{eq:constraint}$$

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.

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