





# **Constraint Solving**

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# **Definition (Equality Logic)**

terms are restricted to variables, no quantifiers:

$$\varphi ::= \varphi \land \varphi \mid \varphi \lor \varphi \mid \varphi \to \varphi \mid \neg \varphi \mid t = t$$

t ::= x

*T*-solver for conjunction  $\varphi$  of equality logic literals over set of variables *V* 

### **Definition**

equality graph is undirected graph  $G_{=}(\varphi) = (V, E_{=}, E_{\neq})$  with

- $E_{=}$  edges corresponding to positive (equality) literals in  $\varphi$
- $E_{\neq}$  edges corresponding to negative (inequality) literals in  $\varphi$

### Lemma

 $\varphi$  is satisfiable  $\iff$ 

 $G_{=}(\varphi)$  contains no simple contradictory cycles (with exactly one  $E_{\neq}$  edge)

# Outline

- 1. Summary of Previous Lecture
- 2. Difference Logic
- 3. Simplex Algorithm
- 4. Support of Strict Inequalities
- 5. Further Reading

# Quantifier-Free Fragment of Equality Logic with Uninterpreted Functions (EUF)

$$\varphi ::= \varphi \land \varphi \mid \varphi \lor \varphi \mid \varphi \rightarrow \varphi \mid \neg \varphi \mid t = t \qquad \qquad t ::= f(t, \dots, t)$$

$$t ::= f(t,\ldots,t)$$

# **T-Solver for Conjunctive Fragment via Congruence Closure**

set *E* of ground equations and ground equation  $s \approx t$ 

output: valid  $(E \models_T s = t)$  or invalid  $(E \not\models_T s = t)$ 

- build congruence classes
  - (a) put different subterms of terms in  $E \cup \{s = t\}$  in separate sets
  - **(b)** merge sets  $\{\ldots, t_1, \ldots\}$  and  $\{\ldots, t_2, \ldots\}$  for all  $t_1 = t_2$  in E
  - (c) repeatedly merge sets

$$\{\ldots, f(s_1, \ldots, s_n), \ldots\}$$
 and  $\{\ldots, f(t_1, \ldots, t_n), \ldots\}$ 

if  $s_i$  and  $t_i$  belong to same set for all  $1 \le i \le n$ 

2 if s and t belong to same set then return valid else return invalid

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# **Difference Logic**

atoms are constraints of the form

- $x y \leq c$
- x y < c

where *x* and *y* are variables and *c* is some constant of  $\mathbb{Z}$  or  $\mathbb{Q}$ 

### Remarks

- difference logic is fragment of linear arithmetic; advantage: faster decision procedure
- domains:  $\mathbb{Z}$  or  $\mathbb{Q}$  (*T*-solver in polynomial time)
- $x y = c \iff x y \leqslant c \land y x \leqslant -c$
- $x y \geqslant c \iff y x \leqslant -c$
- $x y > c \iff y x < -c$
- $x < c \iff x x_0 < c$  where  $x_0$  is fresh variable that must be assigned 0

## Example Job-Shop Scheduling

- m machines  $(M_1, \ldots, M_m)$  and n jobs  $(J_1, \ldots, J_n)$
- each job  $J_i$  is sequence  $(M_1^i, d_1^i), \dots, (M_n^i, d_n^i)$  of operations consisting of machine and duration (rational number;  $\tau(M, d) = d$ )
- O is multiset of all operations from all jobs
- schedule is function S that defines for each operation  $v \in O$  its starting time S(v) on machine specified by v
- schedule S is feasible if

 $S(v) \geqslant 0$ 

for all  $v \in O$ 

 $S(v_i) + \tau(v_i) \leqslant S(v_i)$ 

for all consecutive  $v_i, v_j$  in same job

 $S(v_i) + \tau(v_i) \leqslant S(v_i) \vee S(v_i) + \tau(v_i) \leqslant S(v_i)$ 

for every pair of different operations  $v_i$ ,  $v_i$  scheduled on same machine

• aim: minimize global duration gd; add constraints  $S(v) + \tau(v) \le gd$  for each  $v \in O$ 

# **Definition Inequality Graph**

conjunction  $\varphi$  of nonstrict difference constraints

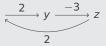
• inequality graph of  $\varphi$  contains edge from x to y with weight c for every constraint  $x - y \le c$ in  $\varphi$ 

### Theorem

conjunction  $\varphi$  of nonstrict difference constraints is satisfiable inequality graph of  $\varphi$  has no negative cycle

### **Example**

$$x-y \leqslant 2$$



satisfiable

### Theorem

conjunction  $\varphi$  of nonstrict difference constraints is satisfiable inequality graph of  $\varphi$  has no negative cycle

### $\longrightarrow$

### **Proof**

- ⇒ negative cycle
- $X_1 \xrightarrow{k_1} X_2 \xrightarrow{k_2} X_2 \longrightarrow \cdots \longrightarrow X_n \xrightarrow{k_n} X_1$

in inequality graph of  $\varphi$  corresponds to conjuction

$$x_1 - x_2 \leqslant k_1 \wedge x_2 - x_3 \leqslant k_2 \wedge \cdots \wedge x_n - x_1 \leqslant k_n$$

adding these literals gives

$$0 \leqslant k_1 + k_2 + \cdots + k_n$$

with 
$$k_1 + k_2 + \cdots + k_n < 0$$

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### Theorem

conjunction  $\varphi$  of nonstrict difference constraints is satisfiable inequality graph of  $\varphi$  has no negative cycle

### **Proof**

- $\Leftarrow$  assume inequality graph of  $\varphi$  has no negative cycle construct satisfying assignment for  $\varphi$  as follows
  - add additional starting node s in graph, add edges  $s \to x$  with weight 0 for all variables x
  - define v(x) = -distance(s, x); well-defined, since there are no negative cycles
  - v satisfies  $\varphi$

### Example



$$v(x) = 1, v(y) = 0, v(z) = 3$$

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## Algorithms for Distance Computation and Negative Cycle Detection

- Dijkstra
  - computes distances from a single source to all other nodes
  - complexity:  $\mathcal{O}(|V| \cdot log(|V|) + |E|)$
  - restriction: no negative cycles allowed
- Bellman–Ford
  - computes distances from a single source to all other nodes
  - complexity:  $\mathcal{O}(|V| \cdot |E|)$
  - can also detect negative cycles
- Floyd–Warshall
- computes distances between all nodes
- complexity:  $\mathcal{O}(|V|^3)$
- can also detect negative cycles
- ⇒ use Bellman–Ford algorithm for difference logic

# **Bellman-Ford Algorithm for Inequality Graphs**

**Input** inequality graph (V, E, w) with fresh starting node s

**Output** " $\exists$  negative cycle" or distances to node s

**1** distance[v] := 0 for all nodes  $v \in V$ 

(this step is special for inequality graphs)

2 repeat |V| - 1 times

for all  $(u, v) \in E$  do

if distance[v] > distance[u] + w(u, v) then

distance[v] := distance[u] + w(u, v)

predecessor[v] := u

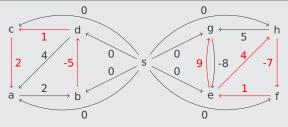
if distance[v] > distance[u] + w(u, v) then

return "∃ negative cycle"

which can be reconstructed using predecessor array

4 return distance array, shortest paths available via predecessor array

## **Example Bellman-Ford in Action**



teration	а	b	С	d	е	f	g	h
0	0	0	0	0	0	0	0	0
1	0	0	0	-5	-8	-7	0	0
2	-1	0	-4	-5	-8	-7	0	-4
3	-2	0	-4	-5	-8	-11	0	-4
4	-2	0	-4	-5	-10	-11	0	-4
5	-2	0	-4	-5	-10	-11	-1	-6
. 2 more iterations, then negative cycle is detect								

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Relevance of Linear Arithmetic

• component configuration problems

planning problems

scheduling problems

LRA and LIA admit more natural and succinct encodings of

## **Definition (Theory of Linear Arithmetic over** *D***)**

• for variables  $x_1, \ldots, x_n$ , built quantifier-free formulas according to grammar

$$\varphi ::= \neg \varphi \mid \varphi \lor \varphi \mid \varphi \land \varphi \mid t < t \mid t \le t$$

$$t ::= a_1 x_1 + \dots + a_n x_n + b$$

s = t is encoded as  $s < t \land t < s$ for  $a_1, \ldots, a_n, b \in \text{in domain } D$ 

• **solution** assigns values in D to  $x_1, \ldots, x_n$ 

### Definitions

- Linear Real Arithmetic (LRA) uses domain  $D = \mathbb{R}$
- Linear Integer Arithmetic (LIA) uses domain  $D = \mathbb{Z}$

### Example

- $x + y + z = 2 \land z > y \land y > -1$ is satisfiable in LRA and LIA, e.g. with v(x) = v(y) = 0 and v(z) = 2
- $x < 3 \land 2x > 4$ is unsatisfiable in LIA but satisfiable in LRA, e.g. with v(x) = 2.5

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• ...

everything with cardinality constraints: n-queens, Sudoku, Minesweeper, . . .

### T-Solver for Conjunctions of Linear Arithmetic Inequalities

• integers (LIA): **NP-complete** 

reals or rationals (LRA): polynomial Simplex algorithm

### exponential worst-case complexity

### **Some History**

**1947 Danzig** proposed Simplex algorithm to solve **optimization** problem:

maximize 
$$c(\vec{x})$$
 such that  $A\vec{x} \leq b$  and  $\vec{x} \geq 0$ 

for linear objective function c, matrix A, vector b, and vector of variables  $\vec{x}$ 

- also known as linear programming
- **1979 Khachiyan** proposed polynomial version based on ellipsoid method
- 1984 Karmakar proposed polynomial version based on interior points method
- **2000-** T-solver version of simplex algorithm to solve satisfiability problem

$$A\vec{x} \leq b$$

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### Problem Input (General Form)

m equalities

 $a_1x_1+\cdots+a_nx_n=0$ 

slack variables

• (optional) lower and upper bounds on variables

# $I_i < x_i < u_i$

### Lemma

any conjunctive LRA problem without < can be turned into equisatisfiable general form

### **Example**

$$x - y \ge -1$$
  $-x + y - s_1 = 0$   $s_1 \le 1$ 

$$y \leq 4$$
  $y - s_2 = 0$   $s_2 \leq 4$ 

$$x + y \ge 6$$
  $-x - y - s_3 = 0$   $s_3 \le -6$ 

- $3x y \le 7$  $3x - y - s_4 = 0$   $s_4 < 7$
- $s_1, s_2, s_3, s_4$  are slack variables x, y are problem variables

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# Representation

represent equalities

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

$$y - s_2 = 0$$

$$-x - y - s_3 = 0$$

$$3x - y - s_4 = 0$$

via  $m \times n$  matrix presentation

← **nonbasic** variables

**basic** variables  $\rightarrow$ 

### **Notation**

- matrix is tableau
- B is set of **basic variables** (in tableau listed vertically)
- N is set of nonbasic variables (in tableau listed horizontally)

# Simplex Algorithm as T-solver

Input: conjunction of LRA atoms  $\varphi$  without <satisfiable assignment or unsatisfiable Output:

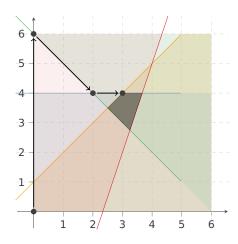
- 1 transform  $\varphi$  into general form and construct tableau
- 2 fix order on variables and assign 0 to each variable
- 3 if all basic variables satisfy their bounds then return current (satisfying) assignment
- let  $x_i \in B$  be variable that violates its bounds
- search for suitable variable  $x_i \in N$  for pivoting with  $x_i$
- return **unsatisfiable** if search unsuccessful
- perform **pivot** operation on  $x_i$  and  $x_i$
- 9 update assignment
- 10 go to step 3

# Simplex, Visually

x - y > -1constraints

$$x + y \ge 6$$
$$3x - y \le 7$$

- solution space
- Simplex solution search





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3. Simplex Algorithm

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nonbasic  $\vec{x}_N$ 

### **Example**

tableau bounds

assignment

$$s_2$$
  $s_1$ 

$$\begin{array}{ccc}
s_3 \\
x \\
y \\
\end{array}
\left(
\begin{array}{ccc}
-2 & 1 \\
1 & -1 \\
0 & s_2 \leqslant 4 \\
s_3 \leqslant -3 \\
\end{array}
\right)$$

### 3 Iteration 3

- s<sub>1</sub> violates its bounds
- decreasing  $s_1$  requires to decrease  $s_2$  or  $s_3$  (both suitable since they have no lower bound)

• pivot 
$$s_1$$
 with  $s_3$ :

$$s_3 = s_1 - 2s_2$$
  
 $v = s_2$ 

$$x = -s_1 + s_2 s_4 = -3s_1 + 2s_2$$

update assignment

$$s_1 := 1$$
  
 $s_3 := -7$ 

$$s_2 = 4$$
  
  $x := 3$ 

$$y := 4$$
  $s_4 := 5$ 

# Simplex Algorithm as T-solver

$$A\vec{x}_N = \vec{x}_B \tag{1}$$

### $-\infty \le I_i \le x_i \le u_i \le +\infty$ (2)

## **Invariant**

• (1) is satisfied and (2) holds for all nonbasic variables

## **Pivoting**

• swap basic  $x_i$  and nonbasic  $x_i$ , so  $i \in B$  and  $j \in N$ 

$$x_i = \sum_{k \in N} A_{ik} x_k \implies x_j = \frac{1}{A_{ij}} \left( x_i - \sum_{k \in N - \{j\}} A_{ik} x_k \right)$$
 (\*

• new tableau A' consists of (\*) and  $A_{B-\{i\}}\vec{x}_N = \vec{x}_{B-\{i\}}$  with (\*) substituted

### **Update**

- assignment of  $x_i$  is updated to previously violated bound  $l_i$  or  $u_i$ ,
- assignment of  $x_k$  is recomputed using A' for all  $k \in B \{i\} \cup \{j\}$

# Simplex Algorithm as T-solver

$$A\vec{X}_N = \vec{X}_B \tag{1}$$

$$\forall i \in \mathbb{N}. \ -\infty \le I_i \le x_i \le u_i \le +\infty \tag{2}$$

### Suitability

- basic variable  $x_i$  violates lower or upper bound
- pick nonbasic variable  $x_i$  such that
  - if  $u_i < l_i$ : problem is trivially unsatisfiable and no suitable  $x_i$  exists
  - if  $x_i < l_i$ :  $A_{ii} > 0$  and  $x_i < u_i$  or  $A_{ii} < 0$  and  $x_i > l_i$
  - if  $x_i > u_i$ :  $A_{ii} > 0$  and  $x_i > I_i$  or  $A_{ii} < 0$  and  $x_i < u_i$

### Observation

• problem is unsatisfiable if no suitable pivot exists

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### Motivation

strict inequalities naturally arise, e.g., as negated non-strict inequalities in DPLL(T)

$$\neg(x+3\leq 5y) \leftrightarrow x+3>5y$$

### **How to Treat Strict Inequalities**

replace in conjunction of inequalities C every strict inequality

$$a_1x_1 + \cdots + a_nx_n > b$$

$$a_1x_1 + \cdots + a_nx_n < b$$

by non-strict inequality

$$a_1x_1 + \cdots + a_nx_n \ge b + \delta$$
  $a_1x_1 + \cdots + a_nx_n \le b - \delta$ 

$$1x_1 + \cdots + a_n x_n < b - \delta$$

to obtain constraints  $C_{\delta}$  in LRA without > and <, and treat  $\delta$  symbolically during simplex ( $\delta$  represents small positive rational number) algorithm

### Lemma

C is satisfiable

 $\iff$   $\exists$  rational number  $\delta > 0$  such that  $C_{\delta}$  is satisfiable

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4. Support of Strict Inequalities

# Symbolical computation with $\delta$

- $\delta$  represents small positive rational number, i.e., smaller than every concrete rational number that occurs during the computations of the simplex algorithm
- treat  $\delta$  symbolically:  $\mathbb{Q}_{\delta} = \{(c, k) \mid c, k \in \mathbb{Q}\}$  with (c, k) representing  $c + k\delta$
- operations for all  $a, c_1, k_1, c_2, k_2 \in \mathbb{Q}$ 
  - addition:  $(c_1, k_1) + (c_2, k_2) = (c_1 + c_2, k_1 + k_2)$
  - multiplication:  $a \cdot (c_1, k_1) = (ac_1, ak_1)$
  - $(c_1, k_1) = (c_2, k_2) \leftrightarrow c_1 = c_2 \land k_1 = k_2$ equality:
  - $(c_1, k_1) < (c_2, k_2) \quad \leftrightarrow \quad c_1 < c_2 \lor c_1 = c_2 \land k_1 < k_2$ comparison:  $(c_1, k_1) \leq (c_2, k_2) \quad \leftrightarrow \quad c_1 < c_2 \lor c_1 = c_2 \land k_1 \leq k_2$
- multiplication of two  $\mathbb{Q}_{\delta}$ -numbers is not defined, but also not required for the simplex algorithm
- coefficients in the tableau stay in ①
- only bounds and assignment require  $\mathbb{O}_{\delta}$

## Example

tableau

constraints

assignment

$$s_1$$
  $y$ 

$$\frac{x}{(2,1)}$$
  $\frac{y}{(0,1)}$ 

$$\frac{s_2}{1}$$
  $\frac{s_3}{(4,2)}$   $\frac{s_3}{(-2,-1)}$ 

$$s_3 \setminus -1 \quad 3 / \quad (1,0) \leqslant s$$

• pivot 
$$s_1$$
 with  $x \implies x = s_1 - y$ 

$$s_2 = 2(s_1 - y) - y = 2s_1 - 3y$$

$$s_3 = -(s_1 - y) + 2y = -s_1 + 3y$$

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## Kröning and Strichmann

• Sections 5.1, 5.2 and 5.7

# **Further Reading**



Bruno Dutertre and Leonardo de Moura. A Fast Linear-Arithmetic Solver for DPLL(T)

In Proc. of International Conference on Computer Aided Verification, pp. 81–94, 2006.

# **Important Concepts**

basic and nonbasic variables

Bellman–Ford algorithm

ullet  $\mathbb{Q}_{\delta}$ 

pivoting

difference logic

simplex algorithm

linear arithmetic (LRA and LIA)

suitable pair of variables

negative cycles

tableau

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