

SS 2024 lecture 7



# **Constraint Solving**

René Thiemann and Fabian Mitterwallner based on a previous course by Aart Middeldorp

# Outline

- **1. Summary of Previous Lecture**
- 2. Complexity of Simplex Algorithm
- 3. Unsatisfiable Cores and Farkas' Lemma
- 4. Simplex Algorithm for DPLL(7)
- 5. Further Reading

#### **Difference Logic**

conjunction of constraints of the form  $x - y \leq c$  or x - y < c

#### **Definition Inequality Graph**

conjunction  $\varphi$  of nonstrict difference constraints

• inequality graph of  $\varphi$  contains edge from  $x \stackrel{c}{\longrightarrow} y$  for every constraint  $x - y \leq c$  in  $\varphi$ 

#### Theorem

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

#### **Bellman-Ford Algorithm**

computes distances in graphs from single source; detects negative cycles



#### Simplex - Representation

represent m inequalities using m slack variables  $s_i$  and bounds  $s_i \leq l \geq c$ 

matrix presentation

**basic** variables  $\rightarrow$   $\begin{array}{c} s_1 \\ s_2 \\ s_3 \end{array} \begin{pmatrix} -1 & 1 \\ 0 & 1 \\ -1 & -1 \\ 0 & 1 \end{pmatrix}$ meaning of rows:
equalities, e.g.,  $s_4 = 3x - 1y$  $x y \leftarrow$  **nonbasic** variables

#### Notation

- matrix is **tableau**, stored in combination with **bounds** x < / > c and **assignment**
- *B* is set of **basic variables** (in tableau listed vertically)
- *N* is set of **nonbasic variables** (in tableau listed horizontally)

#### $\mathbf{DPLL}(T)$ Simplex Algorithm

- **Input:** conjunction of LRA atoms  $\varphi$  without < **Output:** satisfiable assignment or unsatisfiable
  - 1 transform  $\varphi$  into tableau and bounds
  - 2 assign 0 to each variable
  - 3 if all basic variables satisfy their bounds then return current (satisfying) assignment
  - 4 let  $x_i \in B$  be variable that violates its bounds
  - search for suitable variable  $x_j \in N$  for pivoting with  $x_i$
  - 6 return unsatisfiable if search unsuccessful
  - **7** perform pivot operation on  $x_i$  and  $x_j$
  - 9 update assignment
  - 10 go to step 3

## $\mathbf{DPLL}(T)$ Simplex Algorithm

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

$$-\infty \leq l_i \leq x_i \leq u_i \leq +\infty$$
 (2)

#### Invariant

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

## Suitability

 for x<sub>i</sub> ∈ B violating lower or upper bound, find suitable non-basic variable x<sub>j</sub> such that increase (or decrease) of x<sub>j</sub> is possible w.r.t. bounds of x<sub>j</sub> and helps to solve violation of x<sub>i</sub>

# Pivoting

- swap basic  $x_i$  and nonbasic  $x_j$ , so  $i \in B$  and  $j \in N$
- reorder row *i* in tableau to obtain form  $x_j = ... (\star)$ , and substitute ( $\star$ ) in remaining tableau
- result afterwards: tableau A' where  $j \in B$  and  $i \in N$

# Update

- assignment of x<sub>i</sub> is updated to previously violated bound l<sub>i</sub> or u<sub>i</sub>,
- assignment of each  $x_k \in B$  is recomputed using A'



#### nonbasic $\vec{x}_N$ $\vec{x}_j$ $\vec{x}_i$ $\vec{x}_j$ $\vec{x}_$

#### $\mathbb{Q}_{\delta}$ : $\delta$ -Rationals

•  $\delta$ -rationals are used for supporting strict inequalities in LRA and difference logic

```
replace expr < c by expr \leq c - \delta
```

- $\delta$  represents some small positive rational number
- computation on  $\mathbb{Q}_\delta$  is done symbolically, e.g., in simplex algorithm
- after solution for  $\mathbb{Q}_{\delta}$  is detected, a concrete  $\delta$  can be computed (exercise)

# Outline

#### **1. Summary of Previous Lecture**

#### 2. Complexity of Simplex Algorithm

- 3. Unsatisfiable Cores and Farkas' Lemma
- 4. Simplex Algorithm for DPLL(T)
- 5. Further Reading

# Complexity of DPLL(T) Simplex Algorithm

• input: *m* inequalities using *n* problem variables

### Complexity of DPLL(T) Simplex Algorithm

- input: *m* inequalities using *n* problem variables
- switch to general form: *m* basic variables, *n* nonbasic variables

- input: *m* inequalities using *n* problem variables
- switch to general form: *m* basic variables, *n* nonbasic variables
- number of different tableaux:  $\binom{m+n}{n}$



- input: *m* inequalities using *n* problem variables
- switch to general form: *m* basic variables, *n* nonbasic variables
- number of different tableaux:  $\binom{m+n}{n}$
- number of different configurations:  $\binom{m+n}{n} \cdot 3^n$  (each nonbasic variable gets assigned 0, lower bound, or upper bound)



- input: *m* inequalities using *n* problem variables
- switch to general form: *m* basic variables, *n* nonbasic variables
- number of different tableaux:  $\binom{m+n}{n}$
- number of different configurations:  $\binom{m+n}{n} \cdot 3^n$  (each nonbasic variable gets assigned 0, lower bound, or upper bound)
- consequences



- input: *m* inequalities using *n* problem variables
- switch to general form: *m* basic variables, *n* nonbasic variables
- number of different tableaux:  $\binom{m+n}{n}$
- number of different configurations:  $\binom{m+n}{n} \cdot 3^n$  (each nonbasic variable gets assigned 0, lower bound, or upper bound)
- consequences
  - bad news 1: assuming termination, obtain exponential worst-case complexity

- input: *m* inequalities using *n* problem variables
- switch to general form: *m* basic variables, *n* nonbasic variables
- number of different tableaux:  $\binom{m+n}{n}$
- number of different configurations:  $\binom{m+n}{n} \cdot 3^n$  (each nonbasic variable gets assigned 0, lower bound, or upper bound)
- consequences
  - bad news 1: assuming termination, obtain exponential worst-case complexity
  - bad news 2: simplex algorithm does not terminate in general

- input: *m* inequalities using *n* problem variables
- switch to general form: *m* basic variables, *n* nonbasic variables
- number of different tableaux:  $\binom{m+n}{n}$
- number of different configurations:  $\binom{m+n}{n} \cdot 3^n$  (each nonbasic variable gets assigned 0, lower bound, or upper bound)
- consequences
  - bad news 1: assuming termination, obtain exponential worst-case complexity
  - bad news 2: simplex algorithm does not terminate in general
  - good news 1: simplex algorithm terminates using Bland's rule

- input: *m* inequalities using *n* problem variables
- switch to general form: *m* basic variables, *n* nonbasic variables
- number of different tableaux:  $\binom{m+n}{n}$
- number of different configurations:  $\binom{m+n}{n} \cdot 3^n$  (each nonbasic variable gets assigned 0, lower bound, or upper bound)
- consequences
  - bad news 1: assuming termination, obtain exponential worst-case complexity
  - bad news 2: simplex algorithm does not terminate in general
  - good news 1: simplex algorithm terminates using Bland's rule
  - good news 2: worst-case complexity rarely observed, often only  $\mathcal{O}(m)$  many iterations

- input: *m* inequalities using *n* problem variables
- switch to general form: *m* basic variables, *n* nonbasic variables
- number of different tableaux:  $\binom{m+n}{n}$
- number of different configurations:  $\binom{m+n}{n} \cdot 3^n$  (each nonbasic variable gets assigned 0, lower bound, or upper bound)
- consequences
  - bad news 1: assuming termination, obtain exponential worst-case complexity
  - bad news 2: simplex algorithm does not terminate in general
  - good news 1: simplex algorithm terminates using Bland's rule
  - good news 2: worst-case complexity rarely observed, often only  $\mathcal{O}(m)$  many iterations

#### **Bland's Rule**

 in pivoting pick lexicographically smallest (x<sub>i</sub>, x<sub>j</sub>) ∈ B × N such that x<sub>i</sub> and x<sub>j</sub> are suitable; assumes some fixed order on variables

$$\begin{array}{ccc} -1 \leqslant x_1 \leqslant 0 & -4 \leqslant x_2 \leqslant 0 & -5 \leqslant x_3 \leqslant -4 & -7 \leqslant x_4 \leqslant 1 \\ & x_1 & x_2 \\ x_3 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \end{array}$$

$$\begin{array}{cccc} -1 \leqslant x_1 \leqslant 0 & -4 \leqslant x_2 \leqslant 0 & -5 \leqslant x_3 \leqslant -4 & -7 \leqslant x_4 \leqslant 1 \\ x_3 & \begin{pmatrix} 1 & 2 \\ x_4 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} & \frac{x_1 & x_2 & x_3 & x_4}{0 & 0 & 0 & 0} \\ \end{array}$$

$$\begin{array}{cccc} -1 \leqslant x_1 \leqslant 0 & -4 \leqslant x_2 \leqslant 0 & -5 \leqslant x_3 \leqslant -4 & -7 \leqslant x_4 \leqslant 1 \\ x_3 & \begin{pmatrix} 1 & 2 \\ x_4 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} & \frac{x_1 & x_2 & x_3 & x_4}{0 & 0 & 0 & 0} \\ \end{array}$$



$$-1 \leqslant x_1 \leqslant 0$$
  $-4 \leqslant x_2 \leqslant 0$   $-5 \leqslant x_3 \leqslant -4$   $-7 \leqslant x_4 \leqslant 1$ 

$$-1 \leqslant x_1 \leqslant 0 \qquad \qquad -4 \leqslant x_2 \leqslant 0 \qquad \qquad -5 \leqslant x_3 \leqslant -4 \qquad \qquad -7 \leqslant x_4 \leqslant 1$$

$$\begin{array}{c} \begin{array}{c} x_1 & x_2 \\ x_3 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \\ & & \\ \end{array} \begin{array}{c} x_1 & x_2 & x_3 & x_4 \\ \hline 0 & 0 & 0 & 0 \end{array} \\ & & & \\ & & \\ x_3 & x_2 \\ \end{array} \begin{array}{c} x_1 \\ x_1 \\ x_4 \end{array} \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \\ \hline \begin{array}{c} x_1 & x_2 & x_3 & x_4 \\ \hline -4 & 0 & -4 & -8 \end{array}$$

Example (Felgenhauer and Middeldorp)			
$-1\leqslant x_1\leqslant 0$	$-4 \leqslant x_2 \leqslant 0$	$-5 \leqslant x_3 \leqslant -4$	$-7\leqslant x_4\leqslant 1$
$\begin{array}{c} x_1  x_2 \\ x_3  \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix}$	$\frac{x_1  x_2  x_3  x_4}{0  0  0  0}$		
$\begin{array}{c} x_3  x_2 \\ x_1  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		
$\begin{array}{c} x_{3} & x_{4} \\ x_{1} & \begin{pmatrix} -\frac{1}{3} & \frac{2}{3} \\ \frac{2}{3} & -\frac{1}{3} \end{pmatrix} \\ x_{2} & \begin{pmatrix} \frac{2}{3} & -\frac{1}{3} \end{pmatrix} \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		

Example (Felgenhauer	and Middeldorp)		
$-1\leqslant x_1\leqslant 0$	$-4 \leqslant x_2 \leqslant 0$	$-5 \leqslant x_3 \leqslant -4$	$-7\leqslant x_4\leqslant 1$
	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		
$\begin{array}{c} x_3  x_2 \\ x_1  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		
$\begin{array}{c} x_{3} & x_{4} \\ x_{1} & \left(-\frac{1}{3} & \frac{2}{3} \\ x_{2} & \left(\frac{2}{3} & -\frac{1}{3}\right) \end{array}\right)$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		

Example (Felgenhauer and Middeldorp)		
$-1\leqslant x_1\leqslant 0$ $-4\leqslant x_2\leqslant 0$	$-5 \leqslant x_3 \leqslant -4$	$-7\leqslant x_{4}\leqslant 1$
$\begin{array}{c} x_1 & x_2 \\ x_3 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \\ x_4 & \begin{pmatrix} 2 & 1 \end{pmatrix} \end{array} \xrightarrow{\begin{array}{c} x_1 & x_2 & x_3 & x_4 \\ \hline 0 & 0 & 0 & 0 \end{array}}$		
$\begin{array}{c} x_{3} & x_{2} \\ x_{1} & \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} & \begin{array}{c} x_{1} & x_{2} & x_{3} & x_{4} \\ \hline -4 & 0 & -4 & -8 \end{array}$		
$\begin{array}{c} x_{3} & x_{4} \\ x_{1} & \left(-\frac{1}{3} & \frac{2}{3} \\ x_{2} & \left(\frac{2}{3} & -\frac{1}{3}\right) \end{array}\right) \frac{x_{1} & x_{2} & x_{3} & x_{4} \\ -\frac{10}{3} & -\frac{1}{3} & -4 & -7 \end{array}$		
$\begin{array}{c} \downarrow \\ x_1 & x_4 \\ x_3 & \begin{pmatrix} -3 & 2 \\ -2 & 1 \end{pmatrix} & \frac{x_1 & x_2 & x_3 & x_4}{-1 & -5 & -11 & -7} \end{array}$		

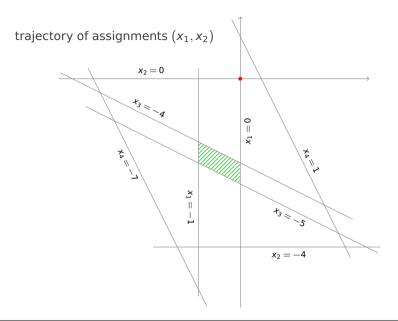
Example (Felgenhauer	and Middeldorp)		
$-1\leqslant x_1\leqslant 0$	$-4 \leqslant x_2 \leqslant 0$	$-5 \leqslant x_3 \leqslant -4$	$-7\leqslant x_4\leqslant 1$
$\begin{array}{c} x_1  x_2 \\ x_3  \left(\begin{array}{cc} 1 & 2 \\ 2 & 1 \end{array}\right) \end{array}$	$\frac{x_1  x_2  x_3  x_4}{0  0  0  0}$		
$\begin{array}{c} x_3  x_2 \\ x_1  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \end{array}$	$\frac{x_1  x_2  x_3  x_4}{-4  0  -4  -8}$		
$ \begin{array}{ccc}                                   $	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		
$\begin{array}{c} x_1  x_4 \\ x_3  \begin{pmatrix} -3 & 2 \\ -2 & 1 \end{pmatrix} \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c} x_1 & x_2 \\ \rightarrow & x_3 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \end{array} $	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

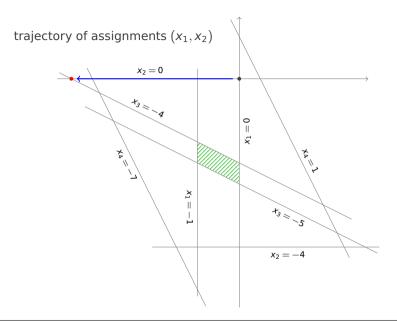
Example (Felgenhauer	and Middeldorp)		
$-1\leqslant x_1\leqslant 0$	$-4 \leqslant x_2 \leqslant 0$	$-5 \leqslant x_3 \leqslant -4$	$-7 \leqslant x_4 \leqslant 1$
	$\frac{x_1 \ x_2 \ x_3 \ x_4}{0 \ 0 \ 0 \ 0}$		
$\begin{array}{c} x_3  x_2 \\ x_1  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \end{array}$	$\frac{x_1  x_2  x_3  x_4}{-4  0  -4  -8}$		
		$\begin{array}{c} x_3  x_2 \\ x_1  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix}  \xrightarrow{x} \\ \end{array}$	
$\begin{array}{c} x_1  x_4 \\ x_3  \begin{pmatrix} -3 & 2 \\ -2 & 1 \end{pmatrix} \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\rightarrow \begin{array}{c} x_1 & x_2 \\ x_1 & x_2 \\ x_4 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \end{array} \begin{array}{c} x \\ - \end{array}$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$

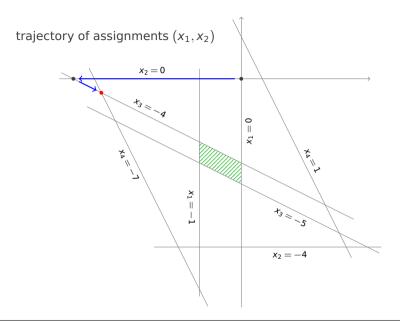
Example (Felgenhauer and Middeldorp)			
$-1\leqslant x_1\leqslant 0$	$-4 \leqslant x_2 \leqslant 0$	$-5 \leqslant x_3 \leqslant -4$	$-7\leqslant x_{4}\leqslant 1$
	$\begin{array}{cccccccccccccccccccccccccccccccccccc$		
	$     \frac{x_1  x_2  x_3  x_4}{-4  0  -4  -8} $	$\begin{array}{c} x_3  x_4 \\ x_1  \left(-\frac{1}{3}  \frac{2}{3} \\ x_2  \left(\frac{2}{3}  -\frac{1}{3}\right) \end{array} \xrightarrow{X}$	$\frac{x_1}{3}$ $\frac{x_2}{-\frac{11}{3}}$ $\frac{x_3}{-5}$ $\frac{x_4}{1}$
	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	A	
$\begin{array}{c} x_1  x_4 \\ x_3  \begin{pmatrix} -3 & 2 \\ -2 & 1 \end{pmatrix} \end{array}$	$\frac{x_1  x_2  x_3  x_4}{-1  -5  -11  -7}  -$	$\rightarrow \begin{array}{c} x_1 & x_2 \\ x_1 & x_2 \\ x_4 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \end{array} \xrightarrow{x}_{-}$	$x_1  x_2  x_3  x_4$ -1 -4 -9 -6

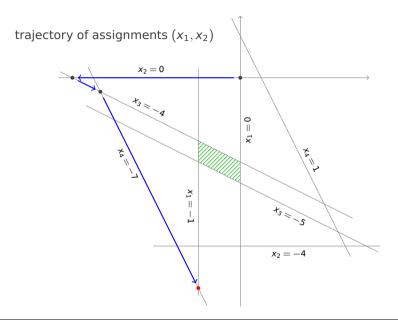
Example (Felgenhauer	and Middeldorp)		
$-1\leqslant x_1\leqslant 0$	$-4 \leqslant x_2 \leqslant 0$	$-5 \leqslant x_3 \leqslant -4$	$-7\leqslant x_4\leqslant 1$
$\begin{array}{c} x_1  x_2 \\ x_3  \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix}$	$\frac{x_1  x_2  x_3  x_4}{0  0  0  0}$	$\begin{array}{c} x_1  x_4 \\ x_3  \begin{pmatrix} -3 & 2 \\ -2 & 1 \end{pmatrix}  \frac{x_1}{0} \\ \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$
$\begin{array}{c} x_3  x_2 \\ x_1  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c} x_{3} & x_{4} \\ x_{1} & \left(-\frac{1}{3} & \frac{2}{3} \\ x_{2} & \left(\frac{2}{3} & -\frac{1}{3}\right) & \frac{x_{1}}{\frac{7}{3}} \end{array}\right)$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
$\begin{array}{c} x_3  x_4 \\ x_1  \begin{pmatrix} -\frac{1}{3} & \frac{2}{3} \\ x_2  \begin{pmatrix} \frac{2}{3} & -\frac{1}{3} \end{pmatrix} \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c} x_3  x_2 \\ x_1  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix}  \frac{x_1}{3} \\ \uparrow$	$x_2 x_3 x_4 -4 -5 2$
$\begin{array}{c} x_1  x_4 \\ x_3  \begin{pmatrix} -3 & 2 \\ -2 & 1 \end{pmatrix} \end{array}$	$\frac{x_1  x_2  x_3  x_4}{-1  -5  -11  -7}  -$	$\rightarrow \begin{array}{c} x_1 & x_2 \\ x_3 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \end{array} \begin{array}{c} x_1 \\ - x_2 \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

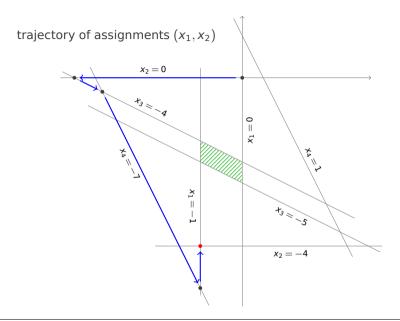
<b>Example (Felgenhauer and Middeldorp</b>	)
$-1 \leqslant x_1 \leqslant 0$ $-4 \leqslant x_2 \leqslant 0$	$-5 \leqslant x_3 \leqslant -4$ $-7 \leqslant x_4 \leqslant 1$
$\begin{array}{c} x_1 & x_2 \\ x_3 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \\ x_4 & \begin{pmatrix} 2 & 1 \end{pmatrix} \end{array} \xrightarrow{\begin{array}{c} x_1 & x_2 & x_3 & x_4 \\ \hline 0 & 0 & 0 & 0 \end{array}}$	$\leftarrow \begin{array}{c} x_{1} & x_{4} \\ x_{3} & \begin{pmatrix} -3 & 2 \\ -2 & 1 \end{pmatrix} \\ \end{array} \begin{array}{c} x_{1} & x_{2} & x_{3} & x_{4} \\ \hline 0 & 1 & 2 & 1 \end{array}$
$\begin{array}{c} x_{3}  x_{2} \\ x_{1}  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \\ x_{4}  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \\ \begin{array}{c} x_{1}  x_{2}  x_{3}  x_{4} \\ \hline -4  0  -4  -8 \end{array}$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$
$\begin{array}{c} x_{3} & x_{4} \\ x_{1} & \begin{pmatrix} -\frac{1}{3} & \frac{2}{3} \\ x_{2} & \begin{pmatrix} \frac{2}{3} & -\frac{1}{3} \end{pmatrix} \end{pmatrix} \xrightarrow{\begin{array}{c} x_{1} & x_{2} & x_{3} & x_{4} \\ \hline -\frac{10}{3} & -\frac{1}{3} & -4 & -7 \end{array}$	$\begin{array}{c} x_{3}  x_{2} \\ x_{1}  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix}  \frac{x_{1}  x_{2}  x_{3}  x_{4}}{3  -4  -5  2} \\ \end{array}$
$\begin{array}{c} & & \\ x_1 & x_4 \\ x_3 & \begin{pmatrix} -3 & 2 \\ -2 & 1 \end{pmatrix} \\ \end{array} \begin{array}{c} x_1 & x_2 & x_3 & x_4 \\ \hline & -1 & -5 & -11 & -7 \end{array}$	$ \xrightarrow{x_1 \ x_2} \xrightarrow{x_1 \ x_2} \frac{x_1 \ x_2}{x_4} \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \frac{x_1 \ x_2 \ x_3 \ x_4}{-1 \ -4 \ -9 \ -6} $

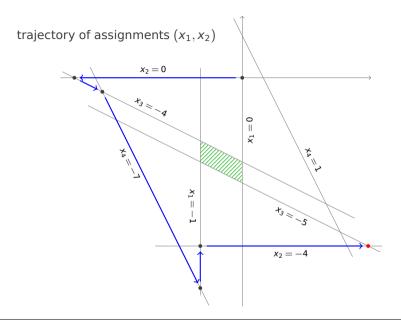


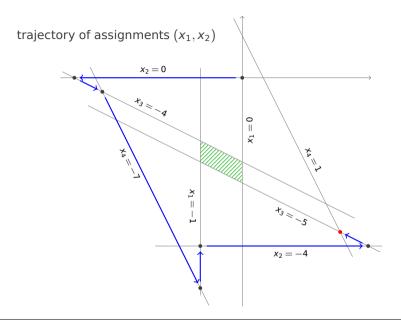


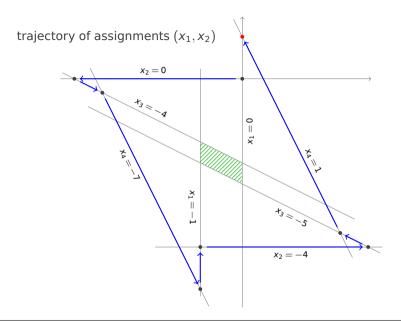


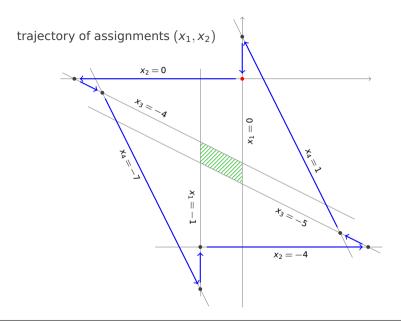












Example (Felgenhauer and Middeldorp)					
$-1\leqslant x_1\leqslant 0$	$-4 \leqslant x_2 \leqslant 0$	$-5 \leqslant x_3 \leqslant -4$	$-7 \leqslant x_4 \leqslant 1$		
· · · · · ·	$     \frac{x_1  x_2  x_3  x_4}{0  0  0  0} $				
$\begin{array}{c} x_3  x_2 \\ x_1  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \\ \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	violation of Bland's rule			
$\begin{array}{c} x_3  x_4 \\ x_1  \begin{pmatrix} -\frac{1}{3}  \frac{2}{3} \\ x_2  \begin{pmatrix} \frac{2}{3}  -\frac{1}{3} \end{pmatrix} \end{array}$	$\frac{x_1  x_2  x_3  x_4}{-\frac{10}{3}  -\frac{1}{3}  -4  -7}$				

#### Example (Felgenhauer and Middeldorp)

$$-1 \leqslant x_1 \leqslant 0$$
  $-4 \leqslant x_2 \leqslant 0$   $-5 \leqslant x_3 \leqslant -4$   $-7 \leqslant x_4 \leqslant 1$ 

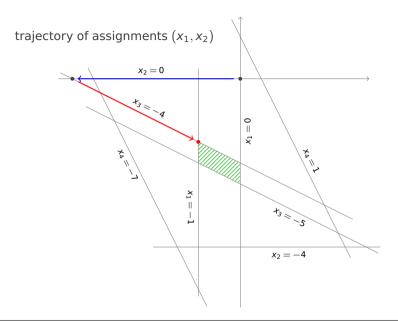
$$\begin{array}{c} \begin{array}{c} x_1 & x_2 \\ x_3 & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \\ & & \\ \end{array} \begin{array}{c} x_1 & x_2 & x_3 & x_4 \\ \hline 0 & 0 & 0 & 0 \end{array} \\ & & & \\ & & \\ x_3 & x_2 \\ \end{array} \begin{array}{c} x_1 & x_2 & x_3 & x_4 \\ & & \\ x_1 & \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \end{array} \begin{array}{c} \begin{array}{c} x_1 & x_2 & x_3 & x_4 \\ \hline -4 & 0 & -4 & -8 \end{array}$$

#### Example (Felgenhauer and Middeldorp)

$$-1 \leqslant x_1 \leqslant 0$$
  $-4 \leqslant x_2 \leqslant 0$   $-5 \leqslant x_3 \leqslant -4$   $-7 \leqslant x_4 \leqslant 1$ 

$$\begin{array}{c} \begin{array}{c} x_{1} & x_{2} \\ x_{3} & \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix} \\ \hline \begin{array}{c} x_{1} & x_{2} & x_{3} & x_{4} \\ \hline 0 & 0 & 0 & 0 \end{array} \\ & & \downarrow \\ x_{3} & x_{2} \\ x_{1} & \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \\ \hline \begin{array}{c} x_{1} & x_{2} & x_{3} & x_{4} \\ \hline -4 & 0 & -4 & -8 \end{array} \\ & & \downarrow \\ x_{3} & x_{1} \\ x_{4} & \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{1}{2} & \frac{3}{2} \end{pmatrix} \\ \hline \begin{array}{c} x_{1} & x_{2} & x_{3} & x_{4} \\ \hline -1 & -\frac{3}{2} & -4 & -\frac{7}{2} \end{array} \end{array}$$

Example (Felgenhauer and Middeldorp)					
$-1\leqslant x_1\leqslant 0$	$-4 \leqslant x_2 \leqslant 0$	$-5 \leqslant x_3 \leqslant -4$	$-7 \leqslant x_4 \leqslant 1$		
$\begin{array}{c} x_1  x_2 \\ x_3  \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix}$	$\frac{x_1  x_2  x_3  x_4}{0  0  0  0}$				
$\begin{array}{c} x_3  x_2 \\ x_1  \begin{pmatrix} 1 & -2 \\ 2 & -3 \end{pmatrix} \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				
$\begin{array}{c} X_3  X_1 \\ X_2  \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{1}{2} & \frac{3}{2} \end{pmatrix} \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	satisfying assignment			



# Outline

- **1. Summary of Previous Lecture**
- 2. Complexity of Simplex Algorithm

#### 3. Unsatisfiable Cores and Farkas' Lemma

- 4. Simplex Algorithm for DPLL(T)
- 5. Further Reading

• recall: for DPLL(T) it is beneficial if theory solvers produce small unsatisfiable cores



- recall: for DPLL(T) it is beneficial if theory solvers produce small unsatisfiable cores
- simplex algorithm can easily identify unsatisfiable cores

- recall: for DPLL(T) it is beneficial if theory solvers produce small unsatisfiable cores
- simplex algorithm can easily identify unsatisfiable cores
- in detail: consider that unsatisfiability is detected via basic variable x<sub>i</sub>

- recall: for DPLL(T) it is beneficial if theory solvers produce small unsatisfiable cores
- simplex algorithm can easily identify unsatisfiable cores
- in detail: consider that unsatisfiability is detected via basic variable x<sub>i</sub>
  - w.l.o.g. we only consider the case  $v(x_i) < I_i$  (the other case is symmetric)

- recall: for DPLL(T) it is beneficial if theory solvers produce small unsatisfiable cores
- simplex algorithm can easily identify unsatisfiable cores
- in detail: consider that unsatisfiability is detected via basic variable x<sub>i</sub>
  - w.l.o.g. we only consider the case  $v(x_i) < I_i$  (the other case is symmetric)
  - in this case tableau contains equation

$$\mathbf{x}_i = \sum_{j \in N_{pos}} \mathbf{A}_{ij} \mathbf{x}_j + \sum_{k \in \mathbf{N}_{neg}} \mathbf{A}_{ik} \mathbf{x}_k$$

such that  $A_{ij} > 0 \land v(x_j) = u_j$  for all  $j \in N_{pos}$  and  $A_{ik} < 0 \land v(x_k) = I_k$  for all  $k \in N_{neg}$ 

- recall: for DPLL(T) it is beneficial if theory solvers produce small unsatisfiable cores
- simplex algorithm can easily identify unsatisfiable cores
- in detail: consider that unsatisfiability is detected via basic variable x<sub>i</sub>
  - w.l.o.g. we only consider the case  $v(x_i) < I_i$  (the other case is symmetric)
  - in this case tableau contains equation

$$\mathbf{x}_i = \sum_{j \in N_{pos}} \mathbf{A}_{ij} \mathbf{x}_j + \sum_{k \in \mathbf{N}_{neg}} \mathbf{A}_{ik} \mathbf{x}_k$$

such that  $A_{ij} > 0 \land v(x_j) = u_j$  for all  $j \in N_{pos}$  and  $A_{ik} < 0 \land v(x_k) = I_k$  for all  $k \in N_{neg}$ 

• then the set of (original) constraints (corresponding to)

$$egin{aligned} & x_i \geq l_i \ & x_j \leq u_j \ & x_k \geq l_k \end{aligned}$$
 for all  $j \in N_{pos}$  for all  $k \in N_{neg}$ 

#### is an unsatisfiable core

- recall: for DPLL(T) it is beneficial if theory solvers produce small unsatisfiable cores
- simplex algorithm can easily identify unsatisfiable cores
- in detail: consider that unsatisfiability is detected via basic variable x<sub>i</sub>
  - w.l.o.g. we only consider the case  $v(x_i) < I_i$  (the other case is symmetric)
  - in this case tableau contains equation

$$\mathbf{x}_i = \sum_{j \in N_{pos}} \mathbf{A}_{ij} \mathbf{x}_j + \sum_{k \in \mathbf{N}_{neg}} \mathbf{A}_{ik} \mathbf{x}_k$$

such that  $A_{ij} > 0 \land v(x_j) = u_j$  for all  $j \in N_{pos}$  and  $A_{ik} < 0 \land v(x_k) = I_k$  for all  $k \in N_{neg}$ 

• then the set of (original) constraints (corresponding to)

$$egin{aligned} & x_i \geq I_i \ & x_j \leq u_j \ & ext{for all } j \in N_{ ext{pos}} \ & ext{x}_k \geq I_k \end{aligned}$$
 for all  $k \in N_{ ext{neg}}$ 

is an unsatisfiable core

• this core is minimal w.r.t. the subset-relation

- consider  $\leq$ -constraints  $\underbrace{-x \leq -5}_{\ell_1 \leq r_1} \land \underbrace{2x + y \leq 12}_{\ell_2 \leq r_2} \land \underbrace{-y \leq -3}_{\ell_3 \leq r_3} \land \underbrace{x 3y \leq 2}_{\ell_4 \leq r_4}$
- alternative way to prove unsatisfiability of constraints  $\ell_1 \leq r_1, \ell_2 \leq r_2, \dots$



• consider  $\leq$ -constraints  $\underline{-x \leq -5} \land \underline{2x + y \leq 12} \land \underline{-y \leq -3} \land \underline{x - 3y \leq 2}$  $\ell_2 \leq r_2$  $\ell_3 \leq r_3$  $\ell_4 < r_4$ 

 $\ell_1 \leq r_1$ 

- alternative way to prove unsatisfiability of constraints  $\ell_1 < r_1, \ell_2 < r_2, \ldots$ 
  - find Farkas' coefficients, i.e., non-negative coefficients c1, c2,... such that

$$\mathbb{Q} \ni \sum_i c_i \ell_i > \sum_i c_i r_i \in \mathbb{Q}$$

- consider  $\leq$ -constraints  $\underbrace{-x \leq -5}_{\ell_1 \leq r_1} \land \underbrace{2x + y \leq 12}_{\ell_2 \leq r_2} \land \underbrace{-y \leq -3}_{\ell_3 < r_3} \land \underbrace{x 3y \leq 2}_{\ell_4 < r_4}$
- alternative way to prove unsatisfiability of constraints  $\ell_1 \leq r_1, \ell_2 \leq r_2, \dots$ 
  - find Farkas' coefficients, i.e., non-negative coefficients  $c_1, c_2, \ldots$  such that

$$\mathbb{Q} \ni \sum_i c_i \ell_i > \sum_i c_i r_i \in \mathbb{Q}$$

• example: choose  $c_1 = 2$ ,  $c_2 = c_3 = 1$ ,  $c_4 = 0$ 

 $2 \cdot (-x) + 1 \cdot (2x + y) + 1 \cdot (-y) + 0 \cdot (x - 3y) = 0 > -1 = 2 \cdot (-5) + 1 \cdot 12 + 1 \cdot (-3) + 0 \cdot 2$ 

- consider  $\leq$ -constraints  $\underbrace{-x \leq -5}_{\ell_1 \leq r_1} \land \underbrace{2x + y \leq 12}_{\ell_2 \leq r_2} \land \underbrace{-y \leq -3}_{\ell_3 \leq r_3} \land \underbrace{x 3y \leq 2}_{\ell_4 \leq r_4}$
- alternative way to prove unsatisfiability of constraints  $\ell_1 \leq r_1, \ell_2 \leq r_2, \dots$ 
  - find Farkas' coefficients, i.e., non-negative coefficients  $c_1, c_2, \ldots$  such that

$$\mathbb{Q} \ni \sum_i c_i \ell_i > \sum_i c_i r_i \in \mathbb{Q}$$

• example: choose  $c_1 = 2$ ,  $c_2 = c_3 = 1$ ,  $c_4 = 0$ 

 $2 \cdot (-x) + 1 \cdot (2x + y) + 1 \cdot (-y) + 0 \cdot (x - 3y) = 0 > -1 = 2 \cdot (-5) + 1 \cdot 12 + 1 \cdot (-3) + 0 \cdot 2$ 

● Farkas' Lemma: finite set of ≤-constraints is unsatisfiable iff Farkas' coefficients exists

- consider  $\leq$ -constraints  $\underbrace{-x \leq -5}_{\ell_1 \leq r_1} \land \underbrace{2x + y \leq 12}_{\ell_2 \leq r_2} \land \underbrace{-y \leq -3}_{\ell_3 \leq r_3} \land \underbrace{x 3y \leq 2}_{\ell_4 \leq r_4}$
- alternative way to prove unsatisfiability of constraints  $\ell_1 \leq r_1, \ell_2 \leq r_2, \dots$ 
  - find Farkas' coefficients, i.e., non-negative coefficients  $c_1, c_2, \ldots$  such that

$$\mathbb{Q} \ni \sum_i c_i \ell_i > \sum_i c_i r_i \in \mathbb{Q}$$

• example: choose  $c_1 = 2$ ,  $c_2 = c_3 = 1$ ,  $c_4 = 0$ 

 $2 \cdot (-x) + 1 \cdot (2x + y) + 1 \cdot (-y) + 0 \cdot (x - 3y) = 0 > -1 = 2 \cdot (-5) + 1 \cdot 12 + 1 \cdot (-3) + 0 \cdot 2$ 

- Farkas' Lemma: finite set of  $\leq$ -constraints is unsatisfiable iff Farkas' coefficients exists
  - soundness: existence of Farkas' coefficients obviously shows unsatisfiability

- consider  $\leq$ -constraints  $\underbrace{-x \leq -5}_{\ell_1 \leq r_1} \land \underbrace{2x + y \leq 12}_{\ell_2 < r_2} \land \underbrace{-y \leq -3}_{\ell_3 < r_3} \land \underbrace{x 3y \leq 2}_{\ell_4 < r_4}$
- alternative way to prove unsatisfiability of constraints  $\ell_1 \leq r_1, \ell_2 \leq r_2, \dots$ 
  - find Farkas' coefficients, i.e., non-negative coefficients  $c_1, c_2, \ldots$  such that

$$\mathbb{Q} \ni \sum_i c_i \ell_i > \sum_i c_i r_i \in \mathbb{Q}$$

• example: choose  $c_1 = 2$ ,  $c_2 = c_3 = 1$ ,  $c_4 = 0$ 

 $2 \cdot (-x) + 1 \cdot (2x + y) + 1 \cdot (-y) + 0 \cdot (x - 3y) = 0 > -1 = 2 \cdot (-5) + 1 \cdot 12 + 1 \cdot (-3) + 0 \cdot 2$ 

- Farkas' Lemma: finite set of  $\leq$ -constraints is unsatisfiable iff Farkas' coefficients exists
  - soundness: existence of Farkas' coefficients obviously shows unsatisfiability
  - completeness: if constraints are unsatisfiable, then simplex will detect this; whenever unsatisfiability is detected in simplex algorithm, one can extract Farkas' coefficients from the tableau equation (similar to the detection of unsatisfiable cores, but with finer analysis)

## Example (Application of Linear Arithmetic: Termination Proving)

consider program

```
factorial(n) {
    i = 1;
    r = 1;
    while (i <= n) {
        r = r * i;
        i = i + 1; }
    return r;</pre>
```

## Example (Application of Linear Arithmetic: Termination Proving)

consider program

```
factorial(n) {
    i = 1;
    r = 1;
    while (i <= n) {
        r = r * i;
        i = i + 1; }
    return r; }
</pre>
```

•  $\varphi$  describes one iteration of loop (primed variables store values after iteration)

$$\varphi := i \le n \land i' = i + \mathbf{1} \land r' = r \cdot i \land n' = n$$

## Example (Application of Linear Arithmetic: Termination Proving)

consider program

```
factorial(n) {
    i = 1;
    r = 1;
    while (i <= n) {
        r = r * i;
        i = i + 1; }
    return r; }
</pre>
```

• arphi describes one iteration of loop (primed variables store values after iteration)

$$\varphi := i \le n \land i' = i + 1 \land r' = r \cdot i \land n' = n$$

- proving termination: find linear ranking function, i.e., linear expression e(i, n, r), decrease factor d with  $0 < d \in \mathbb{Q}$ , and bound  $f \in \mathbb{Q}$  such that
  - $\varphi \rightarrow e(i, n, r) \ge e(i', n', r') + d$  (expression decreases in every iteration by at least d) •  $\varphi \rightarrow e(i, n, r) \ge f$  (expression is bounded from below by f)

- loop iteration  $\varphi := i \le n \land i' = i + 1 \land r' = r \cdot i \land n' = n$
- proving termination by validity of formulas

$$arphi 
ightarrow \mathbf{e}(i,n,r) \ge \mathbf{e}(i',n',r') + d \qquad \qquad arphi 
ightarrow \mathbf{e}(i,n,r) \ge f$$



- loop iteration  $\varphi := i \le n \land i' = i + 1 \land r' = r \cdot i \land n' = n$
- proving termination by validity of formulas

$$arphi 
ightarrow {f e}(i,n,r) \geq {f e}(i',n',r') + d \qquad \qquad arphi 
ightarrow {f e}(i,n,r) \geq f$$

is equivalent to unsatisfiability of negated formulas

$$\varphi \wedge \mathbf{e}(i,n,r) < \mathbf{e}(i',n',r') + d$$
  $\varphi \wedge \mathbf{e}(i,n,r) < f$ 

- loop iteration  $\varphi := i \le n \land i' = i + 1 \land r' = r \cdot i \land n' = n$
- proving termination by validity of formulas

$$arphi 
ightarrow \mathbf{e}(i,n,r) \geq \mathbf{e}(i',n',r') + d \qquad \qquad arphi 
ightarrow \mathbf{e}(i,n,r) \geq f$$

is equivalent to unsatisfiability of negated formulas

$$\varphi \wedge e(i,n,r) < e(i',n',r') + d$$
  $\varphi \wedge e(i,n,r) < f$ 

- choose linear ranking function e(i, n, r) := n i and d := 1 and f = -1, and drop all non-linear constraints to get two linear problems:
  - $i < n \land i' = i + 1 \land n' = n \land n i < n' i' + 1$  (violate decrease) •  $i < n \land i' = i + 1 \land n' = n \land n - i < -1$  (violate boundedness)

- loop iteration  $\varphi := i \le n \land i' = i + 1 \land r' = r \cdot i \land n' = n$
- proving termination by validity of formulas

$$arphi 
ightarrow \mathbf{e}(i,n,r) \geq \mathbf{e}(i',n',r') + d \qquad \qquad arphi 
ightarrow \mathbf{e}(i,n,r) \geq f$$

is equivalent to unsatisfiability of negated formulas

$$\varphi \wedge e(i,n,r) < e(i',n',r') + d$$
  $\varphi \wedge e(i,n,r) < f$ 

- choose linear ranking function e(i, n, r) := n i and d := 1 and f = -1, and drop all non-linear constraints to get two linear problems:
  - $i < n \land i' = i + 1 \land n' = n \land n i < n' i' + 1$  (violate decrease) •  $i < n \land i' = i + 1 \land n' = n \land n - i < -1$  (violate boundedness)

both problems are unsatisfiable over  ${\mathbb Q}$  (just run simplex), so termination is proved

- loop iteration  $\varphi := i \le n \land i' = i + 1 \land r' = r \cdot i \land n' = n$
- proving termination by validity of formulas

$$arphi 
ightarrow \mathbf{e}(i,n,r) \geq \mathbf{e}(i',n',r') + d \qquad \qquad arphi 
ightarrow \mathbf{e}(i,n,r) \geq f$$

is equivalent to unsatisfiability of negated formulas

$$\varphi \wedge e(i,n,r) < e(i',n',r') + d$$
  $\varphi \wedge e(i,n,r) < f$ 

- choose linear ranking function e(i, n, r) := n i and d := 1 and f = -1, and drop all non-linear constraints to get two linear problems:
  - $i < n \land i' = i + 1 \land n' = n \land n i < n' i' + 1$  (violate decrease)

• 
$$i < n \land i' = i + 1 \land n' = n \land n - i < -1$$
 (violate boundedness)

both problems are unsatisfiable over  ${\mathbb Q}$  (just run simplex), so termination is proved

problem: how to find linear expression e(i, n, r) and constants d and f?

- loop iteration  $\varphi := i \le n \land i' = i + 1 \land r' = r \cdot i \land n' = n$
- proving termination by validity of formulas

$$arphi 
ightarrow \mathbf{e}(i,n,r) \geq \mathbf{e}(i',n',r') + d \qquad \qquad arphi 
ightarrow \mathbf{e}(i,n,r) \geq f$$

is equivalent to unsatisfiability of negated formulas

$$\varphi \wedge e(i,n,r) < e(i',n',r') + d$$
  $\varphi \wedge e(i,n,r) < f$ 

- choose linear ranking function e(i, n, r) := n i and d := 1 and f = -1, and drop all non-linear constraints to get two linear problems:
  - $i < n \land i' = i + 1 \land n' = n \land n i < n' i' + 1$  (violate decrease)

• 
$$i < n \land i' = i + 1 \land n' = n \land n - i < -1$$
 (violate boundedness)

both problems are unsatisfiable over  ${\mathbb Q}$  (just run simplex), so termination is proved

- problem: how to find linear expression e(i, n, r) and constants d and f?
- solution: combined search for e(i, n, r), d and f and Farkas' coefficients

#### **Towards Algorithm to Synthesize Linear Ranking Function**

• assume loop is given as transition formula in the form of linear inequalities  $A\vec{x} + A'\vec{x'} \le \vec{b}$  between primed and unprimed variables



## **Towards Algorithm to Synthesize Linear Ranking Function**

- assume loop is given as transition formula in the form of linear inequalities  $A\vec{x} + A'\vec{x'} \le \vec{b}$  between primed and unprimed variables
- example

$$\underbrace{\begin{pmatrix} 1 & -1 \\ 0 & 1 \\ 0 & -1 \\ 1 & 0 \\ -1 & 0 \end{pmatrix}}_{A} \cdot \begin{pmatrix} i \\ n \end{pmatrix} + \underbrace{\begin{pmatrix} 0 & 0 \\ 0 & -1 \\ 0 & 1 \\ -1 & 0 \\ 1 & 0 \end{pmatrix}}_{A'} \cdot \begin{pmatrix} i' \\ n' \end{pmatrix} \leq \underbrace{\begin{pmatrix} 0 \\ 0 \\ 0 \\ -1 \\ 1 \end{pmatrix}}_{\vec{b}}$$

encodes transition formula  $i \le n \land n' = n \land i' = i + 1$ (formula  $\varphi$  after removal of non-linear part)

## Algorithm to Synthesize Linear Ranking Function [Podelski, Rybalschenko]

- assume loop is given as transition formula in the form of linear inequalities  $A\vec{x} + A'\vec{x'} \le \vec{b}$  between primed and unprimed variables
- idea: find parameters of ranking function and Farkas' coefficients in one go



## Algorithm to Synthesize Linear Ranking Function [Podelski, Rybalschenko]

- assume loop is given as transition formula in the form of linear inequalities  $A\vec{x} + A'\vec{x'} \le \vec{b}$  between primed and unprimed variables
- idea: find parameters of ranking function and Farkas' coefficients in one go
- algorithm: encode the following constraints for row vectors  $\vec{c_1}, \vec{c_2}$  of variables
  - $ec{c_1} \geq ec{0}$ ,  $ec{c_2} \geq ec{0}$
  - $\vec{c_1}A' = 0$
  - $\vec{c_1}A = \vec{c_2}A$
  - $\vec{c_2}A = -\vec{c_2}A'$
  - $\vec{c_2}\vec{b} < 0$

# Algorithm to Synthesize Linear Ranking Function [Podelski, Rybalschenko]

- assume loop is given as transition formula in the form of linear inequalities  $A\vec{x} + A'\vec{x'} \le \vec{b}$  between primed and unprimed variables
- idea: find parameters of ranking function and Farkas' coefficients in one go
- algorithm: encode the following constraints for row vectors  $\vec{c_1}, \vec{c_2}$  of variables
  - $ec{c_1} \geq ec{0}$ ,  $ec{c_2} \geq ec{0}$
  - $\vec{c_1}A' = 0$
  - $\vec{c_1}A = \vec{c_2}A$
  - $\vec{c_2}A = -\vec{c_2}A'$
  - $\vec{c_2}\vec{b} < 0$

and return "linear ranking function exists" iff constraints are satisfiable



# Algorithm to Synthesize Linear Ranking Function [Podelski, Rybalschenko]

- assume loop is given as transition formula in the form of linear inequalities  $A\vec{x} + A'\vec{x'} \le \vec{b}$  between primed and unprimed variables
- idea: find parameters of ranking function and Farkas' coefficients in one go
- algorithm: encode the following constraints for row vectors  $\vec{c_1}, \vec{c_2}$  of variables
  - $ec{c_1} \geq ec{0}$ ,  $ec{c_2} \geq ec{0}$
  - $\vec{c_1}A' = 0$
  - $\vec{c_1}A = \vec{c_2}A$
  - $\vec{c_2}A = -\vec{c_2}A'$
  - $\vec{c_2}\vec{b} < 0$

and return "linear ranking function exists" iff constraints are satisfiable

• completeness is based on Farkas' lemma (assumes satisfiable transition formula)

# Algorithm to Synthesize Linear Ranking Function [Podelski, Rybalschenko]

- assume loop is given as transition formula in the form of linear inequalities  $A\vec{x} + A'\vec{x'} \le \vec{b}$  between primed and unprimed variables
- idea: find parameters of ranking function and Farkas' coefficients in one go
- algorithm: encode the following constraints for row vectors  $\vec{c_1}, \vec{c_2}$  of variables
  - $ec{c_1} \geq ec{0}$ ,  $ec{c_2} \geq ec{0}$
  - $\vec{c_1}A' = 0$
  - $\vec{c_1}A = \vec{c_2}A$
  - $\vec{c_2}A = -\vec{c_2}A'$
  - $\vec{c_2}\vec{b} < 0$

and return "linear ranking function exists" iff constraints are satisfiable

- completeness is based on Farkas' lemma (assumes satisfiable transition formula)
- soundness: extract parameters of ranking function from concrete solution  $\vec{c_1}, \vec{c_2}$

$$e(\vec{x}) = \vec{c_2}A'\vec{x}$$
  $d = -\vec{c_2}\vec{b}$   $f = -\vec{c_1}\vec{b}$ 

# **Example Application (Continue in Termination Proof)**

• 
$$(c_1 \ c_2 \ c_3 \ c_4 \ c_5) \ge (0 \ 0 \ 0 \ 0), (c_6 \ c_7 \ c_8 \ c_9 \ c_{10}) \ge (0 \ \dots \ 0)$$
  
•  $(-c_4 + c_5 \ -c_2 + c_3) = (0 \ 0)$   
•  $(c_1 + c_4 - c_5 \ -c_1 + c_2 - c_3) = (c_6 + c_9 - c_{10} \ -c_6 + c_7 - c_8)$   
•  $(c_6 + c_9 - c_{10} \ -c_6 + c_7 - c_8) = -(-c_9 + c_{10} \ -c_7 + c_8)$   
•  $c_{10} - c_9 < 0$ 

# **Example Application (Continue in Termination Proof)**

• 
$$(c_1 \ c_2 \ c_3 \ c_4 \ c_5) \ge (0 \ 0 \ 0 \ 0), (c_6 \ c_7 \ c_8 \ c_9 \ c_{10}) \ge (0 \ \dots \ 0)$$
  
•  $(-c_4 + c_5 \ -c_2 + c_3) = (0 \ 0)$   
•  $(c_1 + c_4 - c_5 \ -c_1 + c_2 - c_3) = (c_6 + c_9 - c_{10} \ -c_6 + c_7 - c_8)$   
•  $(c_6 + c_9 - c_{10} \ -c_6 + c_7 - c_8) = -(-c_9 + c_{10} \ -c_7 + c_8)$   
•  $c_{10} - c_9 < 0$ 

• find solution 
$$c_1=c_8=c_9=1$$
,  $c_i=0$  for  $i\notin\{1,8,9\}$ 

# Example Application (Continue in Termination Proof)

• 
$$(c_1 \ c_2 \ c_3 \ c_4 \ c_5) \ge (0 \ 0 \ 0 \ 0), \ (c_6 \ c_7 \ c_8 \ c_9 \ c_{10}) \ge (0 \ \dots \ 0)$$
  
•  $(-c_4 + c_5 \ -c_2 + c_3) = (0 \ 0)$   
•  $(c_1 + c_4 - c_5 \ -c_1 + c_2 - c_3) = (c_6 + c_9 - c_{10} \ -c_6 + c_7 - c_8)$ 

• 
$$(c_6 + c_9 - c_{10} - c_6 + c_7 - c_8) = -(-c_9 + c_{10} - c_7 + c_8)$$

• 
$$c_{10} - c_9 < 0$$

- find solution  $c_1 = c_8 = c_9 = 1$ ,  $c_i = 0$  for  $i \notin \{1, 8, 9\}$
- extract ranking function parameters

• 
$$e(i,n) = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 \end{pmatrix} A' \begin{pmatrix} i \\ n \end{pmatrix} = n - b$$
  
•  $d = -\begin{pmatrix} 0 & 0 & 1 & 1 & 0 \end{pmatrix} \vec{b} = 1$   
•  $f = -\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \end{pmatrix} \vec{b} = 0$ 

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of  $d: d = -\vec{c_2}\vec{b} > 0$
- boundedness

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$
- boundedness
  - assume  $\vec{x}$  and  $\vec{x'}$  satisfy loop transition formula

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$
- boundedness
  - assume  $\vec{x}$  and  $\vec{x'}$  satisfy loop transition formula
  - hence  $\vec{c_1}(A\vec{x} + A'\vec{x'}) \leq \vec{c_1}\vec{b}$

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$
- boundedness
  - assume  $\vec{x}$  and  $\vec{x'}$  satisfy loop transition formula
  - hence  $\vec{c_1}(A\vec{x} + A'\vec{x'}) \leq \vec{c_1}\vec{b}$
  - hence  $\vec{c_1} A \vec{x} + \vec{c_1} A' \vec{x'} \le \vec{c_1} \vec{b}$

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$
- boundedness
  - assume  $\vec{x}$  and  $\vec{x'}$  satisfy loop transition formula
  - hence  $\vec{c_1}(A\vec{x} + A'\vec{x'}) \leq \vec{c_1}\vec{b}$
  - hence  $\vec{c_1} A \vec{x} + \vec{c_1} A' \vec{x'} \le \vec{c_1} \vec{b}$
  - hence  $\vec{c_1} A \vec{x} \leq \vec{c_1} \vec{b}$

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$
- boundedness
  - assume  $\vec{x}$  and  $\vec{x'}$  satisfy loop transition formula
  - hence  $\vec{c_1}(A\vec{x} + A'\vec{x'}) \leq \vec{c_1}\vec{b}$
  - hence  $\vec{c_1} A \vec{x} + \vec{c_1} A' \vec{x'} \le \vec{c_1} \vec{b}$
  - hence  $\vec{c_1} A \vec{x} \leq \vec{c_1} \vec{b}$
  - hence  $\vec{c_2} A \vec{x} \leq \vec{c_1} \vec{b}$

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$
- boundedness
  - assume  $\vec{x}$  and  $\vec{x'}$  satisfy loop transition formula
  - hence  $\vec{c_1}(A\vec{x} + A'\vec{x'}) \leq \vec{c_1}\vec{b}$
  - hence  $\vec{c_1} A \vec{x} + \vec{c_1} A' \vec{x'} \le \vec{c_1} \vec{b}$
  - hence  $\vec{c_1} A \vec{x} \leq \vec{c_1} \vec{b}$
  - hence  $\vec{c_2} A \vec{x} \leq \vec{c_1} \vec{b}$
  - hence  $-\vec{c_2}A'\vec{x} \leq \vec{c_1}\vec{b}$

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$
- boundedness
  - assume  $\vec{x}$  and  $\vec{x'}$  satisfy loop transition formula
  - hence  $\vec{c_1}(A\vec{x} + A'\vec{x'}) \leq \vec{c_1}\vec{b}$
  - hence  $\vec{c_1} A \vec{x} + \vec{c_1} A' \vec{x'} \le \vec{c_1} \vec{b}$
  - hence  $\vec{c_1} A \vec{x} \leq \vec{c_1} \vec{b}$
  - hence  $\vec{c_2} A \vec{x} \leq \vec{c_1} \vec{b}$
  - hence  $-\vec{c_2}A'\vec{x} \leq \vec{c_1}\vec{b}$
  - hence  $-e(\vec{x}) \leq -f$

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$
- boundedness
  - assume  $\vec{x}$  and  $\vec{x'}$  satisfy loop transition formula
  - hence  $\vec{c_1}(A\vec{x} + A'\vec{x'}) \leq \vec{c_1}\vec{b}$
  - hence  $\vec{c_1} A \vec{x} + \vec{c_1} A' \vec{x'} \le \vec{c_1} \vec{b}$
  - hence  $\vec{c_1} A \vec{x} \leq \vec{c_1} \vec{b}$
  - hence  $\vec{c_2} A \vec{x} \leq \vec{c_1} \vec{b}$
  - hence  $-\vec{c_2}A'\vec{x} \leq \vec{c_1}\vec{b}$
  - hence  $-e(\vec{x}) \leq -f$
  - hence  $e(\vec{x}) \ge f$

- loop transition formula:  $A\vec{x} + A'\vec{x'} \le \vec{b}$
- constraints:  $\vec{c_1} \ge \vec{0}$ ,  $\vec{c_2} \ge \vec{0}$ ,  $\vec{c_1}A' = 0$ ,  $\vec{c_1}A = \vec{c_2}A$ ,  $\vec{c_2}A = -\vec{c_2}A'$ , and  $\vec{c_2}\vec{b} < 0$
- ranking function parameters:  $e(\vec{x}) = \vec{c_2}A'\vec{x}$ ,  $d = -\vec{c_2}\vec{b}$ , and  $f = -\vec{c_1}\vec{b}$
- choice of d:  $d = -\vec{c_2}\vec{b} > 0$
- boundedness
  - assume  $\vec{x}$  and  $\vec{x'}$  satisfy loop transition formula
  - hence  $\vec{c_1}(A\vec{x} + A'\vec{x'}) \leq \vec{c_1}\vec{b}$
  - hence  $\vec{c_1} A \vec{x} + \vec{c_1} A' \vec{x'} \le \vec{c_1} \vec{b}$
  - hence  $\vec{c_1} A \vec{x} \leq \vec{c_1} \vec{b}$
  - hence  $\vec{c_2} A \vec{x} \leq \vec{c_1} \vec{b}$
  - hence  $-\vec{c_2}A'\vec{x} \leq \vec{c_1}\vec{b}$
  - hence  $-e(\vec{x}) \leq -f$
  - hence  $e(\vec{x}) \ge f$
- decrease  $e(\vec{x}) \ge e(\vec{x'}) + d$ : similar to boundedness

# Outline

- **1. Summary of Previous Lecture**
- 2. Complexity of Simplex Algorithm
- 3. Unsatisfiable Cores and Farkas' Lemma
- 4. Simplex Algorithm for DPLL(T)
- 5. Further Reading

situation

- situation
  - solving LRA problems is in P (interior point method, ...)

- situation
  - solving LRA problems is in P (interior point method, ...)
  - simplex algorithm has exponential worst-case time complexity



- situation
  - solving LRA problems is in P (interior point method, ...)
  - simplex algorithm has exponential worst-case time complexity
- simplex algorithm is still popular



- situation
  - solving LRA problems is in P (interior point method, ...)
  - simplex algorithm has exponential worst-case time complexity
- simplex algorithm is still popular
  - exponential behaviour rarely triggered, only on artificial examples



- situation
  - solving LRA problems is in P (interior point method, ...)
  - simplex algorithm has exponential worst-case time complexity
- simplex algorithm is still popular
  - exponential behaviour rarely triggered, only on artificial examples
  - simplex can be used incrementally

- situation
  - solving LRA problems is in P (interior point method, ...)
  - simplex algorithm has exponential worst-case time complexity
- simplex algorithm is still popular
  - exponential behaviour rarely triggered, only on artificial examples
  - simplex can be used incrementally
- incrementality

- situation
  - solving LRA problems is in P (interior point method, ...)
  - simplex algorithm has exponential worst-case time complexity
- simplex algorithm is still popular
  - exponential behaviour rarely triggered, only on artificial examples
  - simplex can be used incrementally
- incrementality
  - simplex can be used as theory solver for DPLL(T), where often constraints are activated and deactivated

- situation
  - solving LRA problems is in P (interior point method, ...)
  - simplex algorithm has exponential worst-case time complexity
- simplex algorithm is still popular
  - exponential behaviour rarely triggered, only on artificial examples
  - simplex can be used incrementally
- incrementality
  - simplex can be used as theory solver for DPLL(T), where often constraints are activated and deactivated
  - simplex can be used as **backend for LIA solver** (next lecture), where new constraints are added on-the-fly

- situation
  - solving LRA problems is in P (interior point method, ...)
  - simplex algorithm has exponential worst-case time complexity
- simplex algorithm is still popular
  - exponential behaviour rarely triggered, only on artificial examples
  - simplex can be used incrementally
- incrementality
  - simplex can be used as theory solver for DPLL(T), where often constraints are activated and deactivated
  - simplex can be used as **backend for LIA solver** (next lecture), where new constraints are added on-the-fly
  - aim: do not restart simplex from scratch when slightly modifying constraints

 make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds



- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored



- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive
- activation of a constraint

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive
- activation of a constraint
  - activate corresponding lower or upper bound  $s_i \leq c$  or  $c \leq s_i$  for slack variable  $s_i$

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive
- activation of a constraint
  - activate corresponding lower or upper bound  $s_i \leq c$  or  $c \leq s_i$  for slack variable  $s_i$
  - if new bound gives rise to a conflict  $u_i < l_i$  then report unsatisfiable

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive
- activation of a constraint
  - activate corresponding lower or upper bound  $s_i \leq c$  or  $c \leq s_i$  for slack variable  $s_i$
  - if new bound gives rise to a conflict  $u_i < I_i$  then report unsatisfiable
  - otherwise, if  $s_i \in N$  and  $s_i$  violates bound, then update assignment of  $s_i$  to c (at this point, invariants (1) and (2) are established for the active bounds)

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive
- activation of a constraint
  - activate corresponding lower or upper bound  $s_i \leq c$  or  $c \leq s_i$  for slack variable  $s_i$
  - if new bound gives rise to a conflict  $u_i < l_i$  then report unsatisfiable
  - otherwise, if  $s_i \in N$  and  $s_i$  violates bound, then update assignment of  $s_i$  to c (at this point, invariants (1) and (2) are established for the active bounds)
  - run simplex on current tableau and assignment to determine satisfiability

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive
- activation of a constraint
  - activate corresponding lower or upper bound  $s_i \leq c$  or  $c \leq s_i$  for slack variable  $s_i$
  - if new bound gives rise to a conflict  $u_i < I_i$  then report unsatisfiable
  - otherwise, if  $s_i \in N$  and  $s_i$  violates bound, then update assignment of  $s_i$  to c (at this point, invariants (1) and (2) are established for the active bounds)
  - run simplex on current tableau and assignment to determine satisfiability
- deactivation of a constraint

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive
- activation of a constraint
  - activate corresponding lower or upper bound  $s_i \leq c$  or  $c \leq s_i$  for slack variable  $s_i$
  - if new bound gives rise to a conflict  $u_i < l_i$  then report unsatisfiable
  - otherwise, if  $s_i \in N$  and  $s_i$  violates bound, then update assignment of  $s_i$  to c (at this point, invariants (1) and (2) are established for the active bounds)
  - run simplex on current tableau and assignment to determine satisfiability
- deactivation of a constraint
  - deactivate corresponding lower or upper bound

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive
- activation of a constraint
  - activate corresponding lower or upper bound  $s_i \leq c$  or  $c \leq s_i$  for slack variable  $s_i$
  - if new bound gives rise to a conflict  $u_i < l_i$  then report unsatisfiable
  - otherwise, if  $s_i \in N$  and  $s_i$  violates bound, then update assignment of  $s_i$  to c (at this point, invariants (1) and (2) are established for the active bounds)
  - run simplex on current tableau and assignment to determine satisfiability
- deactivation of a constraint
  - deactivate corresponding lower or upper bound
  - usually occurs after a conflict has been detected

- make all constraints available to simplex at the beginning of the algorithm, ignoring Boolean structure => obtain global tableau for all constraints
- modify simplex algorithm by adding active-flags for upper and lower bounds
- when executing simplex, all inactive bounds are ignored
- initially all bounds are inactive
- activation of a constraint
  - activate corresponding lower or upper bound  $s_i \leq c$  or  $c \leq s_i$  for slack variable  $s_i$
  - if new bound gives rise to a conflict  $u_i < l_i$  then report unsatisfiable
  - otherwise, if  $s_i \in N$  and  $s_i$  violates bound, then update assignment of  $s_i$  to c (at this point, invariants (1) and (2) are established for the active bounds)
  - run simplex on current tableau and assignment to determine satisfiability
- deactivation of a constraint
  - deactivate corresponding lower or upper bound
  - usually occurs after a conflict has been detected
  - tableau and assignment can be reused from before: they satisfy invariants (1) and (2)

• input is formula  $\varphi$ 

$$(c_1 \lor c_5) \land (c_6 \lor \neg c_3) \land (c_4 \lor c_5) \land (c_2 \lor c_7 \lor \neg c_8) \land \ldots$$

$$x \geq 5 \atop c_1$$
  $2x + y \leq 12 \atop c_2$   $y < 3 \atop c_3$   $x - 3y \leq 2 \atop c_4$  ...

- example execution (without theory propagation)
  - start simplex with tableau for all atoms and negated atoms within  $\varphi$ , but no activated bounds (obtain tableau  $T_0$ , assignment  $v_0(x) = 0$ )

• input is formula  $\varphi$ 

$$(c_1 \lor c_5) \land (c_6 \lor \neg c_3) \land (c_4 \lor c_5) \land (c_2 \lor c_7 \lor \neg c_8) \land \ldots$$

$$x \geq 5 \atop c_1$$
  $2x + y \leq 12 \atop c_2$   $y < 3 \atop c_3$   $x - 3y \leq 2 \atop c_4$  ...

example execution (without theory propagation)

- start simplex with tableau for all atoms and negated atoms within  $\varphi$ , but no activated bounds (obtain tableau  $T_0$ , assignment  $v_0(x) = 0$ )
- assume partial Boolean assignment  $c_1, \neg c_3, c_4$  from Boolean solver  $\implies$  activate the bounds, execute simplex on  $T_0$  and  $v_0$  to obtain  $T_1$  and  $v_1$

• input is formula  $\varphi$ 

$$(c_1 \lor c_5) \land (c_6 \lor \neg c_3) \land (c_4 \lor c_5) \land (c_2 \lor c_7 \lor \neg c_8) \land \ldots$$

$$x \geq 5$$
  
 $c_1$   $2x + y \leq 12$   $y < 3$   $x - 3y \leq 2$   $\dots$ 

example execution (without theory propagation)

- start simplex with tableau for all atoms and negated atoms within  $\varphi$ , but no activated bounds (obtain tableau  $T_0$ , assignment  $v_0(x) = 0$ )
- assume partial Boolean assignment  $c_1, \neg c_3, c_4$  from Boolean solver  $\implies$  activate the bounds, execute simplex on  $T_0$  and  $v_0$  to obtain  $T_1$  and  $v_1$
- all bounds are satisfied, so detect LRA-consistency

• input is formula  $\varphi$ 

$$(c_1 \lor c_5) \land (c_6 \lor \neg c_3) \land (c_4 \lor c_5) \land (c_2 \lor c_7 \lor \neg c_8) \land \ldots$$

$$x \geq 5$$
  
 $c_1$   $2x + y \leq 12$   $y < 3$   $x - 3y \leq 2$   $\dots$ 

example execution (without theory propagation)

- start simplex with tableau for all atoms and negated atoms within  $\varphi$ , but no activated bounds (obtain tableau  $T_0$ , assignment  $v_0(x) = 0$ )
- assume partial Boolean assignment  $c_1, \neg c_3, c_4$  from Boolean solver  $\implies$  activate the bounds, execute simplex on  $T_0$  and  $v_0$  to obtain  $T_1$  and  $v_1$
- all bounds are satisfied, so detect LRA-consistency
- extend to  $c_1$ ,  $\neg c_3$ ,  $c_4$ ,  $c_2$ , activate bound, execute simplex on  $T_1$  and  $v_1$  to obtain  $T_2$  and  $v_2$

• input is formula  $\varphi$ 

$$(c_1 \lor c_5) \land (c_6 \lor \neg c_3) \land (c_4 \lor c_5) \land (c_2 \lor c_7 \lor \neg c_8) \land \ldots$$

$$x \geq 5$$
  
 $c_1$   $2x + y \leq 12$   $y < 3$   $x - 3y \leq 2$   $\dots$ 

- example execution (without theory propagation)
  - start simplex with tableau for all atoms and negated atoms within  $\varphi$ , but no activated bounds (obtain tableau  $T_0$ , assignment  $v_0(x) = 0$ )
  - assume partial Boolean assignment  $c_1, \neg c_3, c_4$  from Boolean solver  $\implies$  activate the bounds, execute simplex on  $T_0$  and  $v_0$  to obtain  $T_1$  and  $v_1$
  - all bounds are satisfied, so detect LRA-consistency
  - extend to  $c_1$ ,  $\neg c_3$ ,  $c_4$ ,  $c_2$ , activate bound, execute simplex on  $T_1$  and  $v_1$  to obtain  $T_2$  and  $v_2$
  - detect unsatisfiable core  $c_1$ ,  $\neg c_3$ ,  $c_2$ , so learn  $\neg c_1 \lor c_3 \lor \neg c_2$

• input is formula  $\varphi$ 

$$(c_1 \lor c_5) \land (c_6 \lor \neg c_3) \land (c_4 \lor c_5) \land (c_2 \lor c_7 \lor \neg c_8) \land \ldots$$

$$x \geq 5$$
  
 $c_1$   $2x + y \leq 12$   $y < 3$   $x - 3y \leq 2$   $\dots$ 

- example execution (without theory propagation)
  - start simplex with tableau for all atoms and negated atoms within  $\varphi$ , but no activated bounds (obtain tableau  $T_0$ , assignment  $v_0(x) = 0$ )
  - assume partial Boolean assignment  $c_1, \neg c_3, c_4$  from Boolean solver  $\implies$  activate the bounds, execute simplex on  $T_0$  and  $v_0$  to obtain  $T_1$  and  $v_1$
  - all bounds are satisfied, so detect LRA-consistency
  - extend to  $c_1$ ,  $\neg c_3$ ,  $c_4$ ,  $c_2$ , activate bound, execute simplex on  $T_1$  and  $v_1$  to obtain  $T_2$  and  $v_2$
  - detect unsatisfiable core  $c_1$ ,  $\neg c_3$ ,  $c_2$ , so learn  $\neg c_1 \lor c_3 \lor \neg c_2$
  - ... next simplex invocation starting from  $T_2$  and  $v_2$  ...

• initSimplex: takes list of indexed constraints, initially all inactive

- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core

- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core
- check: check if currently activated constraints are satisfiable, may detect unsat core



- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core
- check: check if currently activated constraints are satisfiable, may detect unsat core
- solution: after successful check, deliver satisfying assignment

- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core
- check: check if currently activated constraints are satisfiable, may detect unsat core
- solution: after successful check, deliver satisfying assignment
- checkpoint: after successful check, get checkpoint information to return to this state

- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core
- check: check if currently activated constraints are satisfiable, may detect unsat core
- solution: after successful check, deliver satisfying assignment
- checkpoint: after successful check, get checkpoint information to return to this state
- backtrack cp: return to previous checkpoint cp, where subset of constraints has been asserted

- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core
- check: check if currently activated constraints are satisfiable, may detect unsat core
- solution: after successful check, deliver satisfying assignment
- checkpoint: after successful check, get checkpoint information to return to this state
- backtrack cp: return to previous checkpoint cp, where subset of constraints has been asserted

## **Haskell Implementation**

 available under http://cl-informatik.uibk.ac.at/teaching/ss24/cs/simplex.tgz

- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core
- check: check if currently activated constraints are satisfiable, may detect unsat core
- solution: after successful check, deliver satisfying assignment
- checkpoint: after successful check, get checkpoint information to return to this state
- backtrack cp: return to previous checkpoint cp, where subset of constraints has been asserted

## **Haskell Implementation**

- available under http://cl-informatik.uibk.ac.at/teaching/ss24/cs/simplex.tgz
- SimplexInternals.hs verified simplex implementation

- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core
- check: check if currently activated constraints are satisfiable, may detect unsat core
- solution: after successful check, deliver satisfying assignment
- checkpoint: after successful check, get checkpoint information to return to this state
- backtrack cp: return to previous checkpoint cp, where subset of constraints has been asserted

## **Haskell Implementation**

- available under http://cl-informatik.uibk.ac.at/teaching/ss24/cs/simplex.tgz
- SimplexInternals.hs verified simplex implementation
- SimplexCommon.hs common interface to access verified types

- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core
- check: check if currently activated constraints are satisfiable, may detect unsat core
- solution: after successful check, deliver satisfying assignment
- checkpoint: after successful check, get checkpoint information to return to this state
- backtrack cp: return to previous checkpoint cp, where subset of constraints has been asserted

# **Haskell Implementation**

available under

http://cl-informatik.uibk.ac.at/teaching/ss24/cs/simplex.tgz

- SimplexInternals.hs verified simplex implementation
- SimplexCommon.hs common interface to access verified types
- SimplexInterface.hs wrapper for non-incremental simplex algorithm + example

- initSimplex: takes list of indexed constraints, initially all inactive
- assert i: activates constraint with index i, may detect unsat core
- check: check if currently activated constraints are satisfiable, may detect unsat core
- solution: after successful check, deliver satisfying assignment
- checkpoint: after successful check, get checkpoint information to return to this state
- backtrack cp: return to previous checkpoint cp, where subset of constraints has been asserted

## **Haskell Implementation**

available under

http://cl-informatik.uibk.ac.at/teaching/ss24/cs/simplex.tgz

- SimplexInternals.hs verified simplex implementation
- SimplexCommon.hs common interface to access verified types
- SimplexInterface.hs wrapper for non-incremental simplex algorithm + example
- SimplexIOInterface.hs wrapper for incremental simplex algorithm + example

ghci SimplexIOInterface.hs



ghci SimplexIOInterface.hs
ghci>

ghci SimplexIOInterface.hs
ghci> initSimplex exampleSlidesInput

```
ghci SimplexIOInterface.hs
ghci> initSimplex exampleSlidesInput
Okay <state 0, asserted: []>
ghci>
```

```
ghci SimplexIOInterface.hs
ghci> initSimplex exampleSlidesInput
Okay <state 0, asserted: []>
ghci> assert 1
Okay <state 1, asserted: [1]>
ghci>
```

```
ghci SimplexIOInterface.hs
ghci> initSimplex exampleSlidesInput
Okay <state 0, asserted: []>
ghci> assert 1
Okay <state 1, asserted: [1]>
ghci> assert (-3)
Okay <state 2, asserted: [-3,1]>
ghci> assert 4
Okay <state 3, asserted: [4,-3,1]>
ghci>
```

```
ghci SimplexIOInterface.hs
ghci> initSimplex exampleSlidesInput
Okay <state 0, asserted: []>
ghci> assert 1
Okay <state 1, asserted: [1]>
ghci> assert (-3)
Okay <state 2, asserted: [-3,1]>
ghci> assert 4
Okay <state 3, asserted: [4, -3, 1] >
ghci> check
Okay <state 4, asserted: [4,-3,1]>
ghci>
```

```
ghci SimplexIOInterface.hs
ghci> initSimplex exampleSlidesInput
Okav <state 0. asserted: []>
ghci> assert 1
Okay <state 1, asserted: [1]>
ghci> assert (-3)
Okay <state 2, asserted: [-3,1]>
ghci> assert 4
Okay <state 3, asserted: [4, -3, 1] >
ghci> check
Okay <state 4, asserted: [4,-3,1]>
ghci> checkpoint
checkpoint "cp5" created
Okay <state 5, asserted: [4.-3.1]>
ghci>
```

```
ghci SimplexIOInterface.hs
ghci> initSimplex exampleSlidesInput
Okav <state 0. asserted: []>
ghci> assert 1
Okav <state 1. asserted: [1]>
ghci> assert (-3)
Okay <state 2, asserted: [-3,1]>
ghci> assert 4
Okay <state 3, asserted: [4, -3, 1] >
ghci> check
Okay <state 4, asserted: [4,-3,1]>
ghci> checkpoint
checkpoint "cp5" created
Okay <state 5, asserted: [4, -3, 1]>
ghci> assert 2
Okay <state 6, asserted: [2.4.-3.1]>
ghci> check
unsat-core [2,1,-3] detected, use backtrack to one of ["cp5"]
ghci>
```

```
ghci SimplexIOInterface.hs
ghci> initSimplex exampleSlidesInput
Okav <state 0. asserted: []>
ghci> assert 1
Okav <state 1. asserted: [1]>
ghci> assert (-3)
Okay <state 2, asserted: [-3,1]>
ghci> assert 4
Okay <state 3, asserted: [4, -3, 1] >
ghci> check
Okay <state 4, asserted: [4,-3,1]>
ghci> checkpoint
checkpoint "cp5" created
Okay <state 5, asserted: [4, -3, 1]>
ghci> assert 2
Okay <state 6, asserted: [2,4,-3,1]>
ghci> check
unsat-core [2,1,-3] detected, use backtrack to one of ["cp5"]
ghci> backtrack "cp5"
Okay <state 7, asserted: [4,-3,1]>
```

• linear programming: find solution in  $\mathbb Q$  of linear constraints  $\varphi$  that maximizes linear function f



- linear programming: find solution in  $\mathbb Q$  of linear constraints  $\varphi$  that maximizes linear function f
- potential implementation



- linear programming: find solution in  $\mathbb Q$  of linear constraints  $\varphi$  that maximizes linear function f
- potential implementation
  - perform standard setup for running simplex on  $\varphi$



- linear programming: find solution in  $\mathbb Q$  of linear constraints  $\varphi$  that maximizes linear function f
- potential implementation
  - perform standard setup for running simplex on arphi
  - add additional slack variable s with tableau equality s = f, then start simplex



- linear programming: find solution in  $\mathbb Q$  of linear constraints  $\varphi$  that maximizes linear function f
- potential implementation
  - perform standard setup for running simplex on  $\varphi$
  - add additional slack variable s with tableau equality s = f, then start simplex
  - once solution v has been detected, compute f(v) and change bound of s to  $s \ge f(v) + \delta$



- linear programming: find solution in  $\mathbb Q$  of linear constraints  $\varphi$  that maximizes linear function f
- potential implementation
  - perform standard setup for running simplex on  $\varphi$
  - add additional slack variable s with tableau equality s = f, then start simplex
  - once solution v has been detected, compute f(v) and change bound of s to  $s \ge f(v) + \delta$
  - iterate to find better solution, or detect optimality if unsat is returned

- linear programming: find solution in  $\mathbb Q$  of linear constraints  $\varphi$  that maximizes linear function f
- potential implementation
  - perform standard setup for running simplex on  $\varphi$
  - add additional slack variable s with tableau equality s = f, then start simplex
  - once solution v has been detected, compute f(v) and change bound of s to  $s \ge f(v) + \delta$
  - iterate to find better solution, or detect optimality if unsat is returned
- problem: algorithm does not terminate if f can be increased arbitrarily

- linear programming: find solution in  $\mathbb Q$  of linear constraints  $\varphi$  that maximizes linear function f
- potential implementation
  - perform standard setup for running simplex on  $\varphi$
  - add additional slack variable s with tableau equality s = f, then start simplex
  - once solution v has been detected, compute f(v) and change bound of s to  $s \ge f(v) + \delta$
  - iterate to find better solution, or detect optimality if unsat is returned
- problem: algorithm does not terminate if *f* can be increased arbitrarily
- solution: use standard simplex algorithm for linear programming,<sup>a</sup> and not the DPLL(T)-variant of simplex for decidability that was presented here

- linear programming: find solution in  $\mathbb Q$  of linear constraints  $\varphi$  that maximizes linear function f
- potential implementation
  - perform standard setup for running simplex on  $\varphi$
  - add additional slack variable s with tableau equality s = f, then start simplex
  - once solution v has been detected, compute f(v) and change bound of s to  $s \ge f(v) + \delta$
  - iterate to find better solution, or detect optimality if unsat is returned
- problem: algorithm does not terminate if *f* can be increased arbitrarily
- solution: use standard simplex algorithm for linear programming,<sup>a</sup> and not the DPLL(T)-variant of simplex for decidability that was presented here
  - at least one difference: solving  $A\vec{x} \leq \vec{b}$  is formulated via slack variables  $\vec{s} \geq \vec{0}$  as tableau  $A\vec{x} + \vec{s} = \vec{b}$  so the tableau equations can have non-zero constants

# Outline

- **1. Summary of Previous Lecture**
- 2. Complexity of Simplex Algorithm
- 3. Unsatisfiable Cores and Farkas' Lemma
- 4. Simplex Algorithm for DPLL(T)

#### 5. Further Reading

#### **Kröning and Strichmann**

Sections 5.1 and 5.2

#### **Further Reading**



Bruno Dutertre and Leonardo de Moura. A Fast Linear-Arithmetic Solver for DPLL(T) In Proc. CAV, LNCS 4144, pp. 81–94, 2006.



Bertram Felgenhauer and Aart Middeldorp Constructing Cycles in the Simplex Method for DPLL(T) Proc. 14th ICTAC, LNCS 10580, pp. 213–228, 2017



- Andreas Podelski and Andrey Rybalchenko A Complete Method for the Synthesis of Linear Ranking Functions Proc. VMCAI 2004, LNCS 2937, pp. 239–251, 2004
- Ralph Bottesch, Max W. Haslbeck, and René Thiemann Verifying an Incremental Theory Solver for Linear Arithmetic in Isabelle/HOL In Proc. FroCoS, LNAI 11715, pp. 223—239, 2019.

#### **Important Concepts**

- active and inactive bounds
- Bland's selection rule
- Farkas' coefficients
- Farkas' lemma
- incremental simplex algorithm
- linear programming
- linear ranking function
- unsatisfiable core