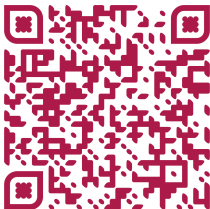


# Fourier-Motzkin Elimination using Saturation Matrix

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- 2 Double Description Method
- 3 Saturation Matrix
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$$\begin{array}{rcl}
 -2x_1 + 4x_2 - 3x_3 = 0 & & -2x_1 + 4x_2 - 3x_3 = 0 \\
 -13x_1 + 24x_2 - 20x_3 = 0 & \xrightarrow{1 \text{ step GE}} & 0x_1 - 2x_2 - \frac{1}{2}x_3 = 0 \\
 -26x_1 + 54x_2 - 39x_3 = 0 & & 0x_1 + 2x_2 - 0x_3 = 0
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$$\begin{array}{rcl}
 3x_1 - 2x_2 + 1x_3 \leq 7 & & \\
 -2x_1 + 2x_2 - 1x_3 \leq 12 & \xrightarrow{1 \text{ step FME}} & 0x_1 + 2x_2 - 1x_3 \leq 50 \\
 -4x_1 + 1x_2 - 3x_3 \leq 15 & & 0x_1 - 5x_2 - 13x_3 \leq 73
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# Example

Eliminating  $t_1$  from

$$A = \begin{cases} a_1 : 3t_1 - 2t_2 + t_3 \leq 7 \\ a_2 : -2t_1 + 2t_2 - t_3 \leq 12 \\ a_3 : -4t_1 + t_2 + 3t_3 \leq 15 \end{cases}$$

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$$\text{combine}(a_1, a_2) = \text{combine}(2a_1 + 3a_2) = 2t_2 - t_3 \leq 50$$

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$$A'' = \{-31t_3 \leq 396\}$$

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- Jing, Moreno-Maza, Xie and Yuan [JMY24] proposed a method using Saturation Matrix.

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- Users can access it using the following functions,
  - ① PolyhedralSets:-Project
  - ② RegularChains:-FMXelim
  - ③ RegularChains:-SemiAlgebraicSetTools:-LinearSolve

## Definition (H-representation)

A **polyhedral set**  $P$  is any  $\{\mathbf{x} \mid A\mathbf{x} \leq \mathbf{b}\}$ , where  $A \in \mathbb{Q}^{m \times n}$  and  $\mathbf{b} \in \mathbb{Q}^m$ . Such a linear system is called an **H-representation** of  $P$ .

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- $P$  is **pointed**, if  $A$  is full column rank.

**NOTE:** From now,  $P$  is full-dimensional and pointed.

## Definition

To **eliminate**  $x_1$  from two inequalities,  $a_1x_1 + \dots + a_nx_n \leq d_1$  and  $b_1x_1 + \dots + b_nx_n \leq d_2$  where  $a_1 > 0$  and  $b_1 < 0$ , we can multiply the first inequality by  $|b_1|$  and the second one by  $a_1$  and add:

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## Definition

Having a linear inequality system  $S$  with  $m$  inequalities and  $n$  variables of the form  $a_{i1}x_1 + \dots + a_{in}x_n \leq d_i$ , We can **partition** the inequalities in three groups with respect to  $x_1$ :

- $A^+$  set of inequalities with positive  $x_1$  coefficient.
- $A^-$  set of inequalities with negative  $x_1$  coefficient.
- $A^0$  set of inequalities with zero  $x_1$  coefficient.

## Idea

## Theorem

Let  $A'$  be the set formed by the combining each inequality in  $A^+$  with each inequality in  $A^-$  and including inequalities in  $A^0$  such that  $A'$  does not have  $x_1$  term. Then,

$$(x_2, \dots, x_n) \in \text{Sol}(A') \iff \exists x_1 (x_1, x_2, \dots, x_n) \in \text{Sol}(A)$$

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## Improve Complexity

- FME's complexity is **double exponential**.
- Most of these generated inequalities are **redundant**.
- Detecting and removing them can significantly improve the complexity.



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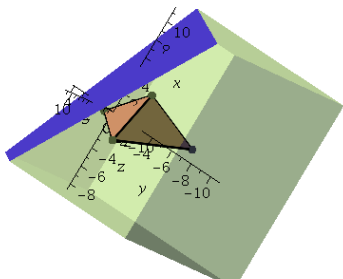
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- **Strongly redundant** if  $\mathbf{a}^t \mathbf{x} < \mathbf{b}$  for all  $\mathbf{x} \in P$ .
- **Weakly redundant** if  $\mathbf{a}^t \mathbf{x} = \mathbf{b}$  holds for some  $\mathbf{x} \in P$ .



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- The most efficient variant, proposed by Fukuda and Prodon in [FP96] is implemented in the CDD library [cdd].

Given an inequality  $A_i \mathbf{x} \geq 0$ , we partition the space  $\mathbb{Q}^d$  into three regions,

- $H_i^+ = \{\mathbf{x} \in \mathbb{Q}^d \mid A_i \mathbf{x} > 0\}$ .
- $H_i^- = \{\mathbf{x} \in \mathbb{Q}^d \mid A_i \mathbf{x} < 0\}$ .
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Let  $J$  be the set of column indices of  $R$ . The rays  $r_j$  ( $j \in J$ ) are then partitioned as follows,

- $J^+ = \{j \in J \mid \mathbf{r}_j \in H_i^+\}$ .
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- $J^0 = \{j \in J \mid \mathbf{r}_j \in H_i^0\}$ .

Given an inequality  $A_i \mathbf{x} \geq 0$ , we partition the space  $\mathbb{Q}^d$  into three regions,

- $H_i^+ = \{\mathbf{x} \in \mathbb{Q}^d \mid A_i \mathbf{x} > 0\}$ .
- $H_i^- = \{\mathbf{x} \in \mathbb{Q}^d \mid A_i \mathbf{x} < 0\}$ .
- $H_i^0 = \{\mathbf{x} \in \mathbb{Q}^d \mid A_i \mathbf{x} = 0\}$ .

Let  $J$  be the set of column indices of  $R$ . The rays  $r_j$  ( $j \in J$ ) are then partitioned as follows,

- $J^+ = \{j \in J \mid \mathbf{r}_j \in H_i^+\}$ .
- $J^- = \{j \in J \mid \mathbf{r}_j \in H_i^-\}$ .
- $J^0 = \{j \in J \mid \mathbf{r}_j \in H_i^0\}$ .

### Lemma

Let  $(A_K, R)$  be a DD pair and let  $i$  be a row index of  $A$  not in  $K$ . Then  $(A_{K+i}, R')$  is a DD pair, where  $R'$  is a  $d \times |J'|$  matrix with column vectors  $\mathbf{r}_j$  ( $j \in J'$ ) defined by,

$$J' = J^+ \cap J^0 \cap (J^+ \times J^-), \text{ and}$$

$$\mathbf{r}_{jj'} = (A_i \mathbf{r}_j) \mathbf{r}_{j'} - (A_i \mathbf{r}_{j'}) \mathbf{r}_j \text{ for each } (j, j') \in J^+ \times J^-.$$

Let  $P$  be an H-cone defined by  $P = \{\mathbf{x} \in \mathbb{R}^d \mid A\mathbf{x} \geq \mathbf{0}\}$ .

### Lemma (DD Pair Duality)

*For any  $A$  and  $R$ ,  $(A, R)$  is a DD pair  $\iff (R^T, A^T)$  is a DD pair.*

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### Definition

The **zero set** of  $\mathbf{u} \in P$ , denoted  $Z(A)$  is the set of row indices  $i$  such that  $A_i\mathbf{u} = 0$ , where  $A_i$  is the  $i$ -th row of  $A$ .



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### Lemma (Adjacency Test)

Two distinct rays  $r$  and  $r'$  of the polyhedral cone  $P$  are called **adjacent** if they span a 2-dimensional face of  $P$ , that is,

$$\text{Rank}(A_{Z(r) \cap Z(r')}) = d - 2.$$

## Algorithm 1 Double Description Method

**Require:** 1. a matrix  $A \in \mathbb{Q}^{m \times n}$  defining the H-representation of a polyhedral cone  $P$ ;

2.  $P$  is full-dimensional and pointed.

**Ensure:** a matrix  $R$  defining the V-representation of  $P$ .

```

1: Let  $K$  be the set of the indices of  $A$ 's independent rows;
2:  $R' := (A_K)^{-1}$ ;
3: Let  $J$  be the set of the columns of  $R'$ ;
4: while  $K \neq \{1, \dots, m\}$  do
5:   Select a  $A$ -row index  $i \notin K$ ;
6:   Set  $R'$  to empty matrix;
7:    $J^+, J^-, J^0 := \text{Partition}(J, A_i)$ ;
8:   Append  $J^+$  and  $J^0$  as columns in  $R'$ ;
9:   for  $p \in J^+$  do
10:    for  $n \in J^-$  do
11:     if  $\text{AdjacencyTest}(A_K, r_p, r_n)$  then
12:       $r_{\text{new}} := (A_i r_p) r_n - (A_i r_n) r_p$ ;
13:      Append  $r_{\text{new}}$  as a column to  $R'$ ;
14:     end if
15:    end for
16:  end for
17:  Let  $J$  be the set of the columns of  $R'$ ;
18:   $K = K \cup \{i\}$ ;
19: end while
20: Let  $R$  be the matrix created by the vectors in  $J$  as its columns;
21: return  $R$ ;
```

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# Saturation Matrix

## Definition

- A vertex  $\mathbf{v} \in V$  of  $P$  *saturates* an inequality  $\ell$  if  $\mathbf{v}$  lies on the hyperplane  $\mathcal{H}_\ell$ , that is, if  $\mathbf{a}^t \mathbf{v} = b$  holds.
- A ray  $\mathbf{r} \in R$  of  $P$  *saturates* an inequality  $\ell$  if  $\mathbf{r}$  is parallel to the hyperplane  $\mathcal{H}_\ell$ , that is, if  $\mathbf{a}^t \mathbf{r} = 0$  holds.

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- $S^{\mathcal{H}}(\mathbf{u})$ : all hyperplanes that  $\mathbf{u}$  saturates.
- $S^{\mathcal{H}}(S^{\mathcal{VR}}(\ell)) = \bigcap_{\mathbf{u} \in S^{\mathcal{VR}}(\ell)} S^{\mathcal{H}}(\mathbf{u})$ : inequalities saturated by all vertices or rays saturating  $\ell$ .



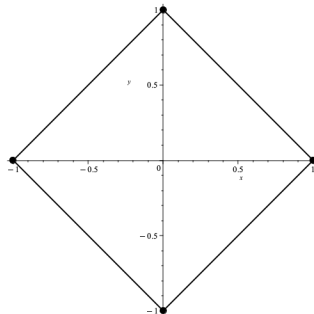
## Definition

The *saturation matrix* of  $F$  is the boolean matrix  $\text{satM}(F) \in \mathbb{Q}^{m \times k}$ , where each entry  $(i, j)$  is defined as follows:

- 1 if the  $j$ -th element of  $\mathcal{VR}(F)$  saturates the  $i$ -th inequality of  $F$ .
- 0 otherwise.

## Example

$F$	$\mathcal{VR}(F)$	$\text{satM}(F)$				
$l_1 : x + y \leq 1$	$\mathbf{v}_1 : (0, 1)$	$\mathbf{v}_1$	$\mathbf{v}_2$	$\mathbf{v}_3$	$\mathbf{v}_4$	
$l_2 : -x - y \leq 1$	$\mathbf{v}_2 : (1, 0)$	$l_1$	1	1	0	0
$l_3 : x - y \leq 1$	$\mathbf{v}_3 : (-1, 0)$	$l_2$	0	0	1	1
$l_4 : -x + y \leq 1$	$\mathbf{v}_4 : (0, -1)$	$l_3$	0	1	0	1
		$l_4$	1	0	1	0



From the saturation matrix  $\text{satM}(F) = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix}$ , it is easy to obtain

the following identities:

$$\mathcal{S}^{\mathcal{VR}}(l_1) = \{\mathbf{v}_1, \mathbf{v}_2\} \quad \mathcal{S}^{\mathcal{H}}(\mathbf{v}_1) = \{l_1, l_4\}$$

$$\mathcal{S}^{\mathcal{VR}}(l_2) = \{\mathbf{v}_3, \mathbf{v}_4\} \quad \mathcal{S}^{\mathcal{H}}(\mathbf{v}_2) = \{l_1, l_3\}$$

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$$\mathcal{S}^{\mathcal{VR}}(l_4) = \{\mathbf{v}_1, \mathbf{v}_3\} \quad \mathcal{S}^{\mathcal{H}}(\mathbf{v}_4) = \{l_2, l_3\}$$

# Updating the Saturation Matrix

The saturation matrix is processed in two ways:

- Row-wise: to compute **bit-wise AND**.
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  - Compute the bit-wise OR of the columns (regarded as bit-vectors) of  $\text{satM}(F)$  indexed by  $u_1, \dots, u_e$ .



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  - Compute the bit-wise OR of the columns (regarded as bit-vectors) of  $\text{satM}(F)$  indexed by  $u_1, \dots, u_e$ .
  - Replace these columns with results of this bit-wise OR.

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## Algorithm 2 CheckRedundancy

---

**Require:** 1. the inequality system  $F$  with  $m$  inequalities;  
 2. the saturation matrix  $\text{satM}$ .

**Ensure:** the minimal system  $F_{\text{irred}}$  and the corresponding saturation matrix  $\text{satM}_{\text{irred}}$ .

```

1: Irredundant := {seq( $i, i = 1..m$ )};
2: for  $i$  from 1 to  $m$  do
3:   if the number of nonzero elements in  $\text{satM}[i]$  is less than  $n$  then
4:     Irredundant := Irredundant \ { $i$ };
5:   next;
6:   end if
7:   for  $j$  in Irredundant \ { $i$ } do
8:     if  $\text{satM}[i] = \text{satM}[i] \text{ AND } \text{satM}[j]$  then
9:       Irredundant := Irredundant \ { $i$ };
10:      break;
11:     end if
12:   end for
13: end for
14:  $F_{\text{irred}}$  := [seq( $F[i], i$  in Irredundant)] and  $\text{satM}_{\text{irred}}$  := [seq( $\text{satM}[i], i$  in Irredundant)];
15: return  $F_{\text{irred}}$  and  $\text{satM}_{\text{irred}}$ ;

```

---

### Algorithm 3 Minimal projected representation

**Require:** 1. an inequality system  $F$ ;

2. a variable order  $x_1 > x_2 > \dots > x_n$ .

**Ensure:** the minimal projected representation  $res$  of  $F$ .

- 1: **Compute the V-representation**  $V$  of  $F$  by DD method;
- 2: Set  $res := table()$ ;
- 3: Sort the elements in  $V$  w.r.t. the reverse lexicographic order;
- 4: Compute the saturation matrix  $satM$ ;
- 5:  $F, satM := CheckRedundancy(F, satM(F))$ ;
- 6:  $res[x_1] := F^{x_1}$ ;
- 7: **for**  $i$  from 1 to  $n - 1$  **do**
- 8:    $(F^p, F^n, F^0) := partition(F)$ ;
- 9:    $V_{new} := proj(V, \{x_i\})$ ;
- 10:   Merging:  $satM := Merge(satM)$ ;
- 11:   Let  $F_{new} := F^0$  and  $satM_{new} := satM[F^0]$ ;
- 12:   **for** each  $f_p \in F^p$  and  $f_n \in F^n$  **do**
- 13:     Append  $proj((f_p, f_n), \{x_i\})$  to  $F_{new}$ ;
- 14:     Append  $satM[f_p] AND satM[f_n]$  to  $satM_{new}$ ;
- 15:   **end for**
- 16:    $F, satM := CheckRedundancy(F_{new}, satM_{new})$ ;
- 17:    $V := V_{new}$  and  $res[x_{i+1}] := F^{x_{i+1}}$ ;
- 18: **end for**
- 19: **return**  $res$ ;

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# Complexity

Given a H-representation  $(A, \mathbf{b})$  with  $A \in \mathbb{Q}^{m \times n}$ ,  $\mathbf{b} \in \mathbb{Q}^m$  and  $\text{height}([A, \mathbf{b}]) = h$ .

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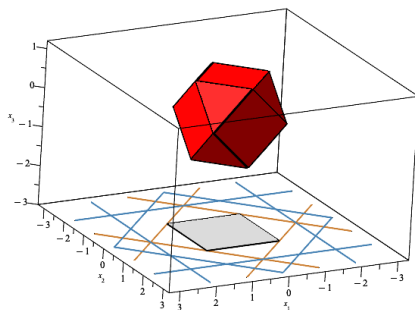
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  - For each inequality  $\ell$  in  $F$ , find the index set  $I$  of all the 1's in  $\text{satM}[\ell]$ .
  - Apply bit-wise AND on column of  $\text{satM}[1..-1, I]$  requiring  $m \cdot |I|$  bit operations, where  $|I| < k$ .

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- Redundancy detection in the initial input system: :  $\mathcal{O}(m^{n+2})$  bit operations.
  - For each inequality  $\ell$  in  $F$ , find the index set  $I$  of all the 1's in  $\text{satM}[\ell]$ .
  - Apply bit-wise AND on column of  $\text{satM}[1..-1, I]$  requiring  $m \cdot |I|$  bit operations, where  $|I| < k$ .
  - Detecting redundancy for one inequality requires  $m^{n+1}$ ; for all inequalities:  $m^{n+2}$  bit operations.

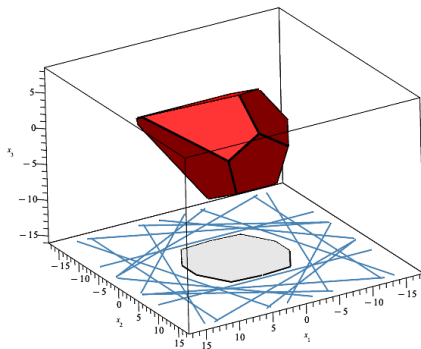
# Cuboctahedron



- 1 strongly redundant inequalities
- 2 weakly redundant inequalities eliminated by cardinality
- 3 weakly redundant inequalities eliminated by containment

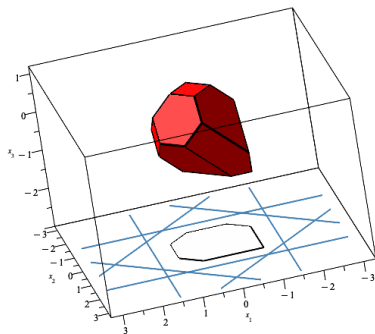


# Snub disphenoid (triangular dodecahedron)



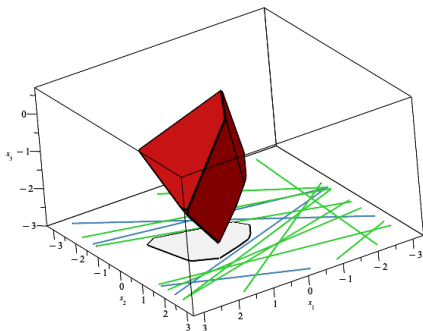
- 1 strongly redundant inequalities
- 2 weakly redundant inequalities eliminated by cardinality
- 3 weakly redundant inequalities eliminated by containment

# Truncated octahedron



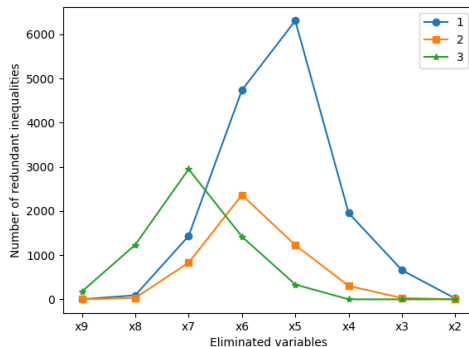
- 1 strongly redundant inequalities
- 2 weakly redundant inequalities eliminated by cardinality
- 3 weakly redundant inequalities eliminated by containment

# Random 3D polyhedron



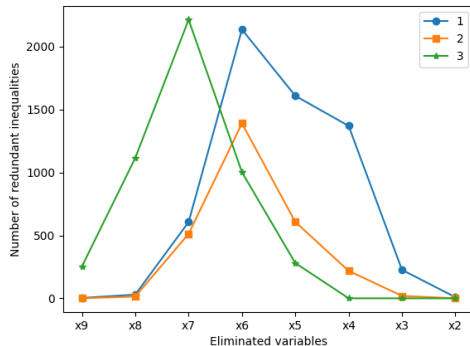
- 1 strongly redundant inequalities
- 2 weakly redundant inequalities eliminated by cardinality
- 3 weakly redundant inequalities eliminated by containment

# Random 10D polyhedron



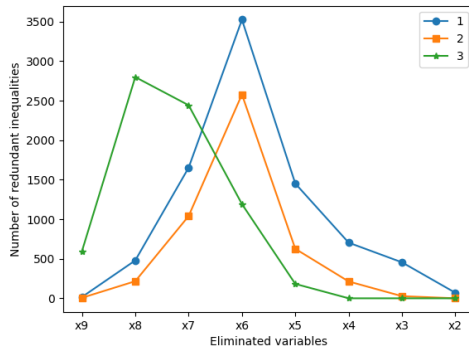
- 1 strongly redundant inequalities
- 2 weakly redundant inequalities eliminated by cardinality
- 3 weakly redundancies inequalities eliminated by containment

# Random 10D polyhedron



- ① strongly redundant inequalities
- ② weakly redundant inequalities eliminated by cardinality
- ③ weakly redundancies inequalities eliminated by containment

# Random 10D polyhedron



- ① strongly redundant inequalities
- ② weakly redundant inequalities eliminated by cardinality
- ③ weakly redundancies inequalities eliminated by containment

# Comparative experimentation

- **FME and mpr** (this algorithm by Jing, Moreno-Maza, Xie and Yuan [JMY24]): Eliminates variables sequentially, uses both the  $H$ - and  $V$ -representations, with redundancy check via the saturation matrix.

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- **polylib**(by Loechner [Lo99]): Eliminates multiple variables, works with  $V$ -representation, can convert between  $H$ - and  $V$ -representation as needed.

Each test case is associated with a triple  $(n, m, k)$  where  $n$  and  $m$  are the number of variables and inequalities in the input inequality system, while  $k$  is the number of vertices and rays.

test case	$(n, m, k)$	FME C	RTC	FME DD	FME VR	mpr	BPAS	cdd	polylib
32hedron	(6, 32, 11)	8.00	849.00	363.00	14576.00	6.54	16.80	4183.08	1.92
64hedron	(7,64,13)	25.00	3211.00	764.00	218833.00	13.05	52.42	>5min	1.67
francois	(13,27,2304)	2.00	101.00	48.00	65.00	499.92	253.66	388.36	> 5min
francois2	(13,31,384)	2.00	99.00	57.00	89.00	41.80	140.34	55.17	80.63
xavi	(2,7,5)	1.00	29.00	27.00	31.00	0.92	2.91	2.66	0.57
c6.in	(11,17,31)	6.00	29.00	903.00	>5min	9.85	12.72	84.11	5.56
c9.in	(16,18,140)	8.00	701.00	1685.00	>5min	25.08	65.54	151.17	131.53
c10.in	(18,20,142)	9.00	722.00	2038.00	>5min	22.10	98.68	249.02	16.06
e2.in	(6,9,8)	2.00	96.00	128.00	914.00	2.71	4.60	14.42	1.79
e7.in	(4,7,5)	1.00	28.00	46.00	75.00	1.92	3.12	5.24	1.09
e8.in	(3,6,4)	1.00	14.00	69.00	99.00	2.51	2.30	2.56	0.84
e13.in	(6,9,18)	2.00	91.00	133.00	962.00	4.30	3.74	13.13	1.35
e14.in	(5,7,10)	1.00	32.00	153.00	360.00	2.20	1.58	9.91	1.42
S24	(24, 25,25)	1802.00	1996.00	560.00	>5min	23.50	58.80	748.67	17.47
cube	(10, 20,1024)	1.00	63.00	50.00	70.00	81.33	201.92	125.900	161.06
C56	(5, 6,6)	2.00	216.00	91.00	1399.00	3.67	4.09	11.81	0.79
C68	(6, 16,8)	1.00	132.00	50.00	82.00	4.18	10.13	505.00	1.86
C1011	(10, 11,11)	13.00	>5min	920.00	>5min	24.99	115.68	1716.25	9.99
C510	(5, 42,10)	14.00	314.00	355.00	188.00	12.00	40.01	>5min	4.42
T1	(5, 10,38)	3.00	655.00	216.00	2819.00	5.61	16.44	27.42	8.81
T3	(10,12,29)	18.00	>5min	1943.00	>5min	21.29	141.64	288.07	12.07
T5	(5, 10,36)	4.00	1088.00	411.00	3812.00	8.12	15.62	22.92	4.76
T6	(10,20,390)	44901.00	>5min	>5min	>5min	1142.9	23800.11	14937.61	>5min
T7	(5, 8,26)	2.00	670.00	262.00	3559.00	5.81	10.79	13.96	4.00
T9	(10,12,36)	21.00	>5min	2501.00	>5min	36.56	414.53	479.18	100.34
T10	(6, 8,24)	6.00	1228.00	263.00	7190.00	4.58	13.65	18.39	5.27
T12	(5, 11,42)	9.00	959.00	1144.00	8950.00	8.52	19.03	38.65	8.60
R_15_20	(15, 20,1328)	27800.00	>5min	>5min	>5min	28430.40	336035.00	38037.21	>5min

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- 3 Saturation Matrix
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# References I



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