

## An Existence Theorem for Systems of Linear Equations

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Given is a constructive proof of the following theorem: A system of linear equations has a [nonnegative] solution if and only if each system constructed by replacing each equation by one of the two associated inequalities has a [nonnegative] solution.

Let

$$Ax = b \quad (S)$$

be a system of linear equations with an  $m \times n$  matrix  $A$ . Denote  $Y_m = \{y \in R^m; |y_i| = 1 \text{ for each } i\}$ , so that  $Y_m$  consists of  $2^m$  elements, and for each  $y \in Y_m$  let  $D_y = \text{diag}\{y_1, \dots, y_m\}$  (i.e.  $(D_y)_{ii} = y_i$  for each  $i$  and  $(D_y)_{ij} = 0$  for  $i \neq j$ ). Together with (S), we shall consider the family of systems of linear inequalities of the form

$$D_y Ax \leq D_y b \quad (S_y)$$

for all  $y \in Y_m$ . Obviously, the  $i$ th inequality in  $(S_y)$  has the form  $(Ax)_i \leq b_i$  if  $y_i = 1$  and is equivalent to  $(Ax)_i \geq b_i$  if  $y_i = -1$ . It is the purpose of this paper to give a constructive proof of this theorem:

**THEOREM 1** *The system (S) has a [nonnegative] solution if and only if  $(S_y)$  has a [nonnegative] solution for each  $y \in Y_m$ .*

The “only if” part is obvious since each solution of (S) also satisfies  $(S_y)$  for each  $y \in Y_m$ . The “if” part is a consequence of the following theorem, which gives a little more:

**THEOREM 2** *Let  $(S_y)$  have a solution  $x_y$  for each  $y \in Y_m$ . Then (S) has a solution which is a convex combination of the  $x_y$ 's.*

If all the  $x_y$ 's are nonnegative, then their convex combination is also a nonnegative vector; this provides for the respective part of Theorem 1. Theorem 2 was proved in [2] in a nonconstructive way using Farkas lemma [1]. We shall show here that a solution to (S) can be constructed from the  $x_y$ 's algorithmically, although the algorithm itself is not too much efficient, which is no surprise since it must handle  $2^m$  vectors  $x_y$  at the outset.

For the description of the algorithm we shall need a special order of elements in  $Y_m$  which is defined inductively via the sets  $Y_j$ ,  $j = 1, \dots, m-1$ , in the following way:

- (a) the order of  $Y_1$  is  $-1, 1$ ;
- (b) if  $y_1, \dots, y_{2^j}$  is the order of  $Y_j$ , then  $(y_1, -1), \dots, (y_{2^j}, -1), (y_1, 1), \dots, (y_{2^j}, 1)$  is the order of  $Y_{j+1}$ .

We additionally define  $Y_0 = \{1\}$ . Further, for any sequence  $s_1, \dots, s_{2^h}$  with an even number of elements, each pair  $s_j, s_{j+h}$  is called a conjugate pair,  $j = 1, \dots, h$ .

We may now formulate the following "cancellation algorithm" for finding a solution to  $(S)$  from known solutions  $x_y$  to  $(S_y)$ ,  $y \in Y_m$ :

### Algorithm

STEP 0 Form a sequence of vectors  $(x_y^T, (Ax_y - b)^T)^T$  ordered in the order of  $Y_m$ .

STEP 1 For each conjugate pair  $x, x'$  in the current sequence compute

$$\lambda = \frac{x'_k}{x'_k - x_k} \quad \text{if } x'_k \neq x_k$$

$$\lambda = 1 \quad \text{otherwise}$$

where  $k$  is the index of the current last entry and set

$$x := \lambda x + (1 - \lambda)x'$$

STEP 2 Cancel the second part of the sequence and in the remaining part delete the last entry of each vector.

STEP 3 If there remains a single vector  $x$ , terminate. Otherwise go to Step 1.

Now, both the algorithm and the preceding theorems are justified by this result:

**THEOREM 3** *The vector  $x$  obtained in Step 3 of the algorithm satisfies  $Ax = b$  and  $x \in \text{Conv}\{x_y; y \in Y_m\}$ .*

*Proof* The algorithm starts with  $2^m$  vectors of dimension  $n + m$  and proceeds by halving the sequence and deleting the last entry, hence it is finite and at the end gives a single  $n$ -dimensional vector  $x$ . Consider an  $(n + j)$ -dimensional vector  $\tilde{x}$  in a current step of the algorithm before updating (there are  $2^j$  such vectors) and let  $y, y \in Y_j$ , be a vector which occupies the same position in the order of  $Y_j$  as  $\tilde{x}$  in the current sequence. Denote  $x_y^j = (\tilde{x}_1, \dots, \tilde{x}_n)^T$  and  $r_y^j = (\tilde{x}_{n+1}, \dots, \tilde{x}_{n+j})^T$ . We shall prove that for each  $j = m, \dots, 1, 0$  and each  $y \in Y_j$  there holds

$$y_i(Ax_y^j)_i \leq y_i b_i \quad (i = 1, \dots, j) \quad (1.1)$$

$$(Ax_y^j)_i = b_i \quad (i = j + 1, \dots, m) \quad (1.2)$$

$$(r_y^j)_i = (Ax_y^j - b)_i \quad (i = 1, \dots, j) \quad (1.3)$$

$$x_y^j \in X, \quad (1.4)$$

where  $X = \text{Conv}\{x_y; y \in Y_m\}$ . The proof proceeds by induction on  $j = m, \dots, 0$ . The case  $j = m$  is trivial since  $x_y^m = x_y$  for each  $y \in Y_m$ , hence (1.1) is equivalent to  $(S_y)$  and (1.3) follows from the initial construction in Step 0. So assume (1.1)–(1.4) to hold for some  $j \in \{1, \dots, m\}$  and each  $y \in Y_j$ . Let  $y \in Y_{j-1}$ . Since, by the order of  $Y_j$ , any two conjugate vectors in  $Y_j$  differ only in the  $j$ th entry,  $x_y^{j-1}$  was constructed in Step 1 by

$$x_y^{j-1} = \lambda x_{(y,-1)}^j + (1 - \lambda)x_{(y,1)}^j$$

where

$$\lambda = \frac{(r_{(y,1)}^j)_j}{(r_{(y,1)}^j)_j - (r_{(y,-1)}^j)_j} = \frac{(Ax_{(y,1)}^j - b)_j}{(Ax_{(y,1)}^j - b)_j - (Ax_{(y,-1)}^j - b)_j} \in [0, 1] \quad (2)$$

since  $(Ax_{(y,1)}^j - b)_j \leq 0$  and  $(Ax_{(y,-1)}^j - b)_j \geq 0$  due to (1.1). Hence we have

$$\begin{aligned} y_i(Ax_y^{j-1})_i &\leq y_i b_i & (i = 1, \dots, j-1) \\ (Ax_y^{j-1})_i &= b_i & (i = j+1, \dots, m) \end{aligned}$$

since (1.1) and (1.2), being satisfied by  $x_{(y,-1)}^j$  and  $x_{(y,1)}^j$ , are also satisfied by their convex combination  $x_y^{j-1}$ . From (2) we obtain  $(Ax_y^{j-1} - b)_j = \lambda(Ax_{(y,-1)}^j - b)_j + (1 - \lambda)(Ax_{(y,1)}^j - b)_j = 0$ , hence

$$(Ax_y^{j-1})_j = b_j \quad (3)$$

holds provided the denominator in (2) is nonzero. If  $(Ax_{(y,-1)}^j - b)_j = (Ax_{(y,1)}^j - b)_j$ , then the common value is both nonnegative and nonpositive, so that  $(Ax_{(y,-1)}^j)_j = b_j = (Ax_{(y,1)}^j)_j$  and (3) again holds. From the updating formula in Step 1 we see that  $(r_y^{j-1})_i = \lambda(r_{(y,-1)}^j)_i + (1 - \lambda)(r_{(y,1)}^j)_i = \lambda(Ax_{(y,-1)}^j - b)_i + (1 - \lambda)(Ax_{(y,1)}^j - b)_i = (Ax_y^{j-1} - b)_i$ , so that (1.3) also holds for  $j-1$ . Since  $x_{(y,-1)}^j \in X$ ,  $x_{(y,1)}^j \in X$  and  $X$  is convex, we get that  $x_y^{j-1} \in X$ , thus completing the induction.

So for  $j = 0$  we obtain from (1.2), (1.4) that  $Ax_y^0 = b$ ,  $x_y^0 \in X$  holds for the single remaining  $n$ -dimensional vector  $x_y^0$ , which is equal to the above  $x$  from Step 3. This concludes the proof. ■

To illustrate the algorithm, consider a very simple example:

$$\begin{aligned} x_1 + x_2 - x_3 &= 1 \\ -2x_1 + 3x_2 + x_3 &= 2. \end{aligned} \quad (4)$$

We may guess the following solutions to the  $(S_y)$ 's:  $x_{(-1,-1)} = (0, 1, 0)^T$ ,  $x_{(1,-1)} = (0, 0, 3)^T$ ,  $x_{(-1,1)} = (2, 0, 0)^T$ ,  $x_{(1,1)} = (0, 0, 0)^T$ . The performance of the algorithm may

