

## WEIGHTED OVERDETERMINED LINEAR SYSTEMS

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### ABSTRACT

*The purpose of this paper is to introduce the weighted overdetermined linear systems and to solve them in the sense of the least squares method*

**Keywords:** overdetermined linear system, weighted overdetermined linear system, least squares method

### 1 Introduction

Let us consider the real matrix  $A = (a_{ij})_{\substack{i=\overline{1,m} \\ j=\overline{1,n}}}$ , and the real, transposed arrays  $x = (x_1, x_2, \dots, x_n)^T \in \mathbb{R}^n$  and  $b = (b_1, b_2, \dots, b_m)^T \in \mathbb{R}^m$ , respectively. The linear system  $A \cdot x = b$  is called overdetermined linear system, if  $m > n$ . Generally, the overdetermined linear system is incompatible, i.e. doesn't exist an array  $x^* = (x_1^*, x_2^*, \dots, x_n^*)^T \in \mathbb{R}^n$  such that  $A \cdot x^* = b$ . It is well known to obtain the solution of the overdetermined linear system using the least squares method, see for example [1] and [2].

### 2 Main part

Let us consider the weight array  $p = (p_1, p_2, \dots, p_m)^T \in \mathbb{R}^m$ , where  $p_i > 0$  for every  $i = \overline{1, m}$ . We denote by  $\sqrt{p} = (\sqrt{p_1}, \sqrt{p_2}, \dots, \sqrt{p_m}) \in \mathbb{R}^m$  and for the vectors  $x = (x_1, x_2, \dots, x_m)^T \in \mathbb{R}^m$  and  $y = (y_1, y_2, \dots, y_m)^T \in \mathbb{R}^m$  we introduce the following product  $x \otimes y = (x_1 \cdot y_1, x_2 \cdot y_2, \dots, x_m \cdot y_m) \in \mathbb{R}^m$ . Let us take the weighted matrix  $A_p = (\sqrt{p_i} \cdot a_{ij})_{\substack{i=\overline{1,m} \\ j=\overline{1,n}}}$ , and the weighted vector  $b_p = \sqrt{p} \otimes b \in \mathbb{R}^m$ . So to the overdetermined linear system  $A \cdot x = b$  we can attach the weighted overdetermined linear system  $A_p \cdot x = b_p$ . It is immediately that these two linear systems are equivalent. This means that, generally, the weighted overdetermined linear system is incompatible, i.e. doesn't exist an array  $x^* = (x_1^*, x_2^*, \dots, x_n^*)^T \in \mathbb{R}^n$  such

that  $A_p \cdot x^* = b_p$ . For this reason, instead of the classical solution  $x^*$ , we consider such array  $\bar{x} = (\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n) \in \mathbb{R}^n$  for which the function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $f(x) = \|A_p \cdot x - b_p\|_m^2$  takes the minimal value, where  $\|\cdot\|_m$  means the Euclidean norm on the space  $\mathbb{R}^m$ . The array  $\bar{x} \in \mathbb{R}^n$ , which minimizes the function  $f$ , it is accepted like the solution of the overdetermined linear system  $A_p \cdot x = b_p$  in the sense of the least squares method. We can observe that  $f(x) \geq 0$  for all  $x \in \mathbb{R}^n$  and the minimal point  $\bar{x} \in \mathbb{R}^n$  verifies the following system of equations with partial derivatives  $\frac{\partial f}{\partial x_k}(\bar{x}) = 0$  for every  $k = \overline{1, n}$ . We calculate the partial derivatives:

$$\frac{\partial f}{\partial x_k}(x) = \sum_{i=1}^n 2 \cdot \left( \sum_{j=1}^m \sqrt{p_i} \cdot a_{ij} x_j - \sqrt{p_i} \cdot b_i \right) \cdot \sqrt{p_i} \cdot a_{ik} = 0,$$

and we obtain

$$\sum_{i=1}^n \sqrt{p_i} \cdot a_{ik} \cdot \left( \sum_{j=1}^m \sqrt{p_i} \cdot a_{ij} x_j - \sqrt{p_i} \cdot b_i \right) = 0$$

for every  $k = \overline{1, n}$ . This linear system has the matrix form  $A_p^T \cdot (A_p \cdot x - b_p) = \theta_{\mathbb{R}^m}$ . This is a Cramer's type linear system with  $n$  equations and  $n$  unknowns, so  $\bar{x} \in \mathbb{R}^n$  will be the classical solution of this Cramer's linear system. Consequently the classical solution  $\bar{x} \in \mathbb{R}^n$  of the linear system  $(A_p^T \cdot A_p) \cdot x = A_p^T \cdot b_p$  it is accepted like solution of the weighted overdetermined linear system  $A_p \cdot x = b_p$  in the sense of the least squares approach.

Next we show that the stationary point  $\bar{x} \in \mathbb{R}^n$ , which verifies the relation  $(A_p^T \cdot A_p) \cdot x = A_p^T \cdot b_p$  will be the minimal point of the function  $f$ .

**Theorem 1.** *If  $A_p$  is a matrix of type  $n \times m$ ,  $b_p$  is a column matrix of type  $m \times 1$ , and  $\bar{x} \in \mathbb{R}^n$  is the classical solution of the linear system  $A_p^T \cdot (A_p \cdot x - b_p) = \theta_{\mathbb{R}^m}$ , then for every  $y \in \mathbb{R}^m$  we obtain  $\|b_p - A_p \cdot \bar{x}\|_2 \leq \|b_p - A_p \cdot y\|_2$ .*

*Proof.* We denote the residual vectors with  $r_{\bar{x}} = b_p - A_p \cdot \bar{x}$  and  $r_y = b_p - A_p \cdot y$ . Then we have  $r_y = b_p - A_p \cdot y = b_p - A_p \cdot \bar{x} + A_p \cdot \bar{x} - A_p \cdot y = r_{\bar{x}} + A_p \cdot (\bar{x} - y)$ . Now we use the well known formulas for the transposed matrices and we get:  $r_y^T = (r_{\bar{x}} + A_p(\bar{x} - y))^T = r_{\bar{x}}^T + (\bar{x} - y)^T A_p^T$ . Consequently taking the scalar product on the space  $\mathbb{R}^n$  we obtain:

$$\begin{aligned} r_y^T \cdot r_y &= (r_{\bar{x}}^T + (\bar{x} - y)^T A_p^T) \cdot (r_{\bar{x}} + A_p(\bar{x} - y)) = \\ &= r_{\bar{x}}^T \cdot r_{\bar{x}} + (\bar{x} - y)^T \cdot A_p^T \cdot r_{\bar{x}} + \\ &+ r_{\bar{x}}^T \cdot A_p(\bar{x} - y) + (\bar{x} - y)^T A_p^T \cdot A_p(\bar{x} - y). \end{aligned}$$

But  $A_p^T \cdot r_{\bar{x}} = \theta_{\mathbb{R}^m}$  and  $r_{\bar{x}}^T A_p = (A_p^T r_{\bar{x}})^T = \theta_{\mathbb{R}^m}$ . So we can deduce that  $r_y^T \cdot r_y = r_{\bar{x}}^T \cdot r_{\bar{x}} + (\bar{x} - y)^T A_p^T \cdot A_p(\bar{x} - y)$ . Using the definition of the Euclidean norm it is easy to deduce that  $\|r_y\|_2^2 = r_y^T \cdot r_y$ . Consequently  $\|r_y\|_2^2 = \|r_{\bar{x}}\|_2^2 + \|A_p(\bar{x} - y)\|_2^2 \geq \|r_{\bar{x}}\|_2^2$ , what we must it to prove.  $\square$

The linear system  $(A_p^T \cdot A_p) \cdot x = A_p^T \cdot b_p$  can be solved by Cramer's rule from theory of determinants for  $n \in \mathbb{N}^*$  small natural numbers, but in other cases, for  $n \in \mathbb{N}^*$  great natural numbers we can use numerical methods of linear algebra.

**Consequence 1.** *If we choose the weights  $p_1 = p_2 = \dots = p_m = 1$ , then from our theorem we reobtain the well known result for overdetermined linear systems.*

**Example 1.** *Let us consider the following overdetermined linear system:*

$$\begin{cases} x + y = 2 \\ x + 2y = 3 \\ 2x + y = 4 \end{cases}$$

If we solve the linear system  $\begin{cases} x + y = 2 \\ x + 2y = 3 \end{cases}$  then we receive the solution  $x = y = 1$ , which doesn't verify the last equation:  $2x + y = 3 \neq 4$ . We obtain the same conclusion if we calculate the characteristic determinant:  $\begin{vmatrix} 1 & 1 & 2 \\ 1 & 2 & 3 \\ 2 & 1 & 4 \end{vmatrix} = 1 \neq 0$ . So our overdetermined linear system is incompatible and does not have classical solution. We attache to this overdetermined linear system the following weighted overdetermined

linear system:  $\begin{cases} \sqrt{p_1} \cdot x + \sqrt{p_1} \cdot y = 2 \cdot \sqrt{p_1} \\ \sqrt{p_2} \cdot x + 2\sqrt{p_2} \cdot y = 3 \cdot \sqrt{p_2} \\ 2\sqrt{p_3} \cdot x + \sqrt{p_3} \cdot y = 4 \cdot \sqrt{p_3} \end{cases}$

We consider the function  $f : \mathbb{R}^2 \rightarrow \mathbb{R}$ ,  $f(x, y) =$

$$p_1 \cdot (x + y - 2)^2 + p_2 \cdot (x + 2y - 3)^2 + p_3 \cdot (2x + y - 4)^2$$

and for the linear system  $\begin{cases} \frac{\partial f}{\partial x}(x, y) = 0 \\ \frac{\partial f}{\partial y}(x, y) = 0 \end{cases}$  we obtain:

$$\begin{cases} (p_1 + p_2 + 4p_3) \cdot x + (p_1 + 2p_2 + 2p_3) \cdot y = 2p_1 + 3p_2 + 8p_3 \\ (p_1 + 2p_2 + 2p_3) \cdot x + (p_1 + 4p_2 + p_3) \cdot y = 2p_1 + 6p_2 + 4p_3. \end{cases}$$

In another way we get  $m = 3$ ,  $n = 2$ ,

$$A_p = \begin{pmatrix} \sqrt{p_1} & \sqrt{p_1} \\ \sqrt{p_2} & 2 \cdot \sqrt{p_2} \\ 2 \cdot \sqrt{p_3} & \sqrt{p_3} \end{pmatrix}, \quad b_p = \begin{pmatrix} 2 \cdot \sqrt{p_1} \\ 3 \cdot \sqrt{p_2} \\ 4 \cdot \sqrt{p_3} \end{pmatrix},$$

$$\text{so } A_p^T \cdot A_p = \begin{pmatrix} p_1 + p_2 + 4p_3 & p_1 + 2p_2 + 2p_3 \\ p_1 + 2p_2 + 2p_3 & p_1 + 4p_2 + p_3 \end{pmatrix}$$

$$\text{and } A_p^T \cdot b_p = \begin{pmatrix} 2p_1 + 3p_2 + 8p_3 \\ 2p_1 + 6p_2 + 4p_3 \end{pmatrix}. \text{ Hence our}$$

$$\text{system } A_p^T \cdot A_p \cdot x = A_p^T \cdot b_p \text{ is the same:}$$

$$\begin{pmatrix} p_1 + p_2 + 4p_3 & p_1 + 2p_2 + 2p_3 \\ p_1 + 2p_2 + 2p_3 & p_1 + 4p_2 + p_3 \end{pmatrix} \cdot \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 2p_1 + 3p_2 + 8p_3 \\ 2p_1 + 6p_2 + 4p_3 \end{pmatrix}. \text{ We denote}$$

$$\Delta = \begin{vmatrix} p_1 + p_2 + 4p_3 & p_1 + 2p_2 + 2p_3 \\ p_1 + 2p_2 + 2p_3 & p_1 + 4p_2 + p_3 \end{vmatrix},$$

$$\Delta_x = \begin{vmatrix} 2p_1 + 3p_2 + 8p_3 & p_1 + 2p_2 + 2p_3 \\ 2p_1 + 6p_2 + 4p_3 & p_1 + 4p_2 + p_3 \end{vmatrix},$$

$$\Delta_y = \begin{vmatrix} p_1 + p_2 + 4p_3 & 2p_1 + 3p_2 + 8p_3 \\ p_1 + 2p_2 + 2p_3 & 2p_1 + 6p_2 + 4p_3 \end{vmatrix},$$

We have the classical solution  $x = \frac{\Delta_x}{\Delta}$  and  $y = \frac{\Delta_y}{\Delta}$ . So our weighted overdetermined linear system admits the solution  $x = \frac{\Delta_x}{\Delta}$  and  $y = \frac{\Delta_y}{\Delta}$  in the sense of the least squares approach. For the particular case  $p_1 = p_2 = p_3 = 1$  we obtain  $x = \frac{18}{11}$  and  $y = \frac{7}{11}$ , which is the solution of the initial overdetermined linear system in the sense of the least squares method.

### 3 Conclusions

In this paper we extended the least squares method from overdetermined linear systems to weighted overdetermined linear systems.

### References

- [1] B. Finta, Analiză numerică, Editura Universității "Petru Maior", Tg. Mureș, 2004.
- [2] S. S. Rao, Applied Numerical Methods for Engineers and Scientists, Prentice Hall, Upper Saddle River, New Jersey, 2002.