

Given the system $\mathbf{A}\mathbf{x} = \mathbf{b}$, where $\mathbf{A} \in \mathbb{R}^m \times \mathbb{R}^n$, $\mathbf{x} \in \mathbb{R}^n$, and $\mathbf{b} \in \mathbb{R}^m$, find the array \mathbf{x} which verifies the first c equations and best-fits the following $m - c$ (i.e., in the sense of least-square).

The following partitioning for the matrices/arrays can be defined

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \end{bmatrix} \quad \text{with} \quad \mathbf{A}_1 \in \mathbb{R}^c \times \mathbb{R}^n \quad \text{and} \quad \mathbf{A}_2 \in \mathbb{R}^{m-c} \times \mathbb{R}^n,$$

$$\mathbf{b} = \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \end{bmatrix} \quad \text{with} \quad \mathbf{b}_1 \in \mathbb{R}^c \quad \text{and} \quad \mathbf{b}_2 \in \mathbb{R}^{m-c}.$$

(The array \mathbf{x} need not be partitioned as well.)

Defined the residual as $\mathbf{r} = \mathbf{A}\mathbf{x} - \mathbf{b}$, the task consists in minimizing the quantity $\frac{1}{2}\mathbf{r}^T\mathbf{r}$, provided $\mathbf{A}_1\mathbf{x} = \mathbf{b}_1$ holds. In other words, a *constrained optimization problem* must be solved, where the constrain is the quation

$$\mathbf{A}_1\mathbf{x} - \mathbf{b}_1 = 0, \tag{1}$$

and the quantity to be minimizezed is $\frac{1}{2}\mathbf{r}^T\mathbf{r}$.

The Lagrange function is

$$\begin{aligned} \mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}) &= \frac{1}{2}(\mathbf{A}\mathbf{x} - \mathbf{b})^T(\mathbf{A}\mathbf{x} - \mathbf{b}) + \boldsymbol{\lambda}^T(\mathbf{A}_1\mathbf{x} - \mathbf{b}_1) \\ &= \frac{1}{2}\mathbf{x}^T\mathbf{A}^T\mathbf{A}\mathbf{x} - \mathbf{x}^T\mathbf{A}^T\mathbf{b} + \frac{1}{2}\mathbf{b}^T\mathbf{b} + \mathbf{x}^T\mathbf{A}_1^T\boldsymbol{\lambda} - \mathbf{b}_1^T\boldsymbol{\lambda}, \end{aligned}$$

and its partial derivatives with respect to \mathbf{x} and $\boldsymbol{\lambda}$ are

$$\begin{aligned} \frac{\partial \Phi(\mathbf{x}, \boldsymbol{\lambda})}{\partial \mathbf{x}^T} &= \mathbf{A}^T\mathbf{A}\mathbf{x} - \mathbf{A}^T\mathbf{b} - \mathbf{A}_1^T\boldsymbol{\lambda} \\ \frac{\partial \Phi(\mathbf{x}, \boldsymbol{\lambda})}{\partial \boldsymbol{\lambda}^T} &= \mathbf{A}_1\mathbf{x} - \mathbf{b}_1 \end{aligned} \tag{2}$$

Setting eq. (2) to zero, and solving with respect to \mathbf{x} , yields

$$\mathbf{x} = (\mathbf{A}^T\mathbf{A})^{-1}(\mathbf{A}^T\mathbf{b} + \mathbf{A}_1^T\boldsymbol{\lambda}). \tag{3}$$

Inserting eq. (3) into eq. (1), and rearranging the result, leads to

$$\mathbf{A}_1(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}_1^T\boldsymbol{\lambda} = \mathbf{b}_1 - \mathbf{A}_1(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b},$$

which can be solved for $\boldsymbol{\lambda}$, whose value can be substituted back into eq. (3), eventually obtaining the solution,

$$\mathbf{x} = (\mathbf{A}^T\mathbf{A})^{-1}(\mathbf{A}^T\mathbf{b} + \underbrace{\mathbf{A}_1^T(\mathbf{A}_1(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}_1^T)^{-1}(\mathbf{b}_1 - \mathbf{A}_1(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b})}_{\boldsymbol{\lambda}}).$$