

# Solution of Sensor Fusion Homework 3

## 1 Homework 3

The key point (or trick) of this homework is to realize that even though we use symbols  $x_1, \dots, x_N$  in the problem setting, it does not imply that they would denote the unknown  $\mathbf{x}$  in the problem.

(a)

We have

$$J(a, b) = \sum_{n=1}^N (y_n - a x_n - b)^2. \quad (1)$$

The derivative w.r.t  $a$  is

$$\begin{aligned} \frac{\partial J}{\partial a} &= -2 \sum_{n=1}^N x_n (y_n - a x_n - b) \\ &= -2 \left( \sum_{n=1}^N x_n y_n - a \sum_{n=1}^N x_n^2 - b \sum_{n=1}^N x_n \right) \end{aligned} \quad (2)$$

and w.r.t  $b$  it is

$$\begin{aligned} \frac{\partial J}{\partial b} &= -2 \sum_{n=1}^N (y_n - a x_n - b) \\ &= -2 \left( \sum_{n=1}^N y_n - a \sum_{n=1}^N x_n - b \underbrace{\sum_{n=1}^N 1}_{=N} \right). \end{aligned} \quad (3)$$

Setting the derivatives to zero thus gives

$$\begin{aligned} -2 \left( \sum_{n=1}^N x_n y_n - a \sum_{n=1}^N x_n^2 - b \sum_{n=1}^N x_n \right) &= 0 \\ -2 \left( \sum_{n=1}^N y_n - a \sum_{n=1}^N x_n - b N \right) &= 0, \end{aligned} \quad (4)$$

that is,

$$\begin{aligned} a \sum_{n=1}^N x_n^2 + b \sum_{n=1}^N x_n &= \sum_{n=1}^N x_n y_n \\ a \sum_{n=1}^N x_n + b N &= \sum_{n=1}^N y_n. \end{aligned} \quad (5)$$

This can be written as matrix equation

$$\begin{bmatrix} \sum_{n=1}^N x_n^2 & \sum_{n=1}^N x_n \\ \sum_{n=1}^N x_n & N \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum_{n=1}^N x_n y_n \\ \sum_{n=1}^N y_n \end{bmatrix} \quad (6)$$

which can be solved as

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum_{n=1}^N x_n^2 & \sum_{n=1}^N x_n \\ \sum_{n=1}^N x_n & N \end{bmatrix}^{-1} \begin{bmatrix} \sum_{n=1}^N x_n y_n \\ \sum_{n=1}^N y_n \end{bmatrix}. \quad (7)$$

If we define

$$\begin{aligned} S_x^2 &= \frac{1}{N} \sum_{n=1}^N x_n^2, & \bar{x} &= \frac{1}{N} \sum_{n=1}^N x_n \\ S_{x,y} &= \frac{1}{N} \sum_{n=1}^N x_n y_n, & \bar{y} &= \frac{1}{N} \sum_{n=1}^N y_n \end{aligned} \quad (8)$$

Equation (7) can be written as

$$\begin{aligned} \begin{bmatrix} a \\ b \end{bmatrix} &= \begin{bmatrix} S_x^2 & \bar{x} \\ \bar{x} & 1 \end{bmatrix}^{-1} \begin{bmatrix} S_{x,y} \\ \bar{y} \end{bmatrix} = \frac{1}{S_x^2 - \bar{x}^2} \begin{bmatrix} 1 & -\bar{x} \\ -\bar{x} & S_x^2 \end{bmatrix} \begin{bmatrix} S_{x,y} \\ \bar{y} \end{bmatrix} \\ &= \frac{1}{S_x^2 - \bar{x}^2} \begin{bmatrix} S_{x,y} - \bar{x} \bar{y} \\ -\bar{x} S_{x,y} + S_x^2 \bar{y} \end{bmatrix} = \frac{1}{S_x^2 - \bar{x}^2} \begin{bmatrix} S_{x,y} - \bar{x} \bar{y} \\ -\bar{x} S_{x,y} + (S_x^2 - \bar{x}^2) \bar{y} + \bar{x}^2 \bar{y} \end{bmatrix} \\ &= \begin{bmatrix} \frac{S_{x,y} - \bar{x} \bar{y}}{S_x^2 - \bar{x}^2} \\ \bar{y} - \frac{S_{x,y} - \bar{x} \bar{y}}{S_x^2 - \bar{x}^2} \bar{x} \end{bmatrix} \end{aligned} \quad (9)$$

If we further define

$$\begin{aligned} s_x^2 &= S_x^2 - \bar{x}^2 \\ s_{x,y} &= S_{x,y} - \bar{x} \bar{y}, \end{aligned} \quad (10)$$

then we can write the estimates as

$$\begin{aligned} a &= \frac{s_{x,y}}{s_x^2}, \\ b &= \bar{y} - c \bar{x}, \end{aligned} \quad (11)$$

which matches the form e.g. given in [https://en.wikipedia.org/wiki/Simple\\_linear\\_regression#Fitting\\_the\\_regression\\_line](https://en.wikipedia.org/wiki/Simple_linear_regression#Fitting_the_regression_line) although we should never trust Wikipedia.

(b)

As it is said in the problem hint, the unknown vector is

$$\mathbf{x} = \begin{bmatrix} a \\ b \end{bmatrix} \quad (12)$$

We now need to figure out a matrix  $\mathbf{G}$  such that if we define

$$\begin{aligned} \mathbf{y} &= \begin{bmatrix} y_1 & \dots & y_N \end{bmatrix}^\top, \\ \mathbf{r} &= \begin{bmatrix} r_1 & \dots & r_N \end{bmatrix}^\top, \end{aligned} \quad (13)$$

the following:

$$\mathbf{y} = \mathbf{G} \mathbf{x} + \mathbf{r} \quad (14)$$

is equivalent to the following:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} a x_1 + b \\ \vdots \\ a x_N + b \end{bmatrix} + \begin{bmatrix} r_1 \\ \vdots \\ r_N \end{bmatrix}. \quad (15)$$

We now notice that

$$\begin{bmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_N & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} a x_1 + b \\ \vdots \\ a x_N + b \end{bmatrix} \quad (16)$$

and thus our  $\mathbf{G}$  should be

$$\mathbf{G} = \begin{bmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_N & 1 \end{bmatrix}. \quad (17)$$

which reduces our problem into the canonical form (14) and we can also notice that

$$J(\mathbf{x}) = (\mathbf{y} - \mathbf{G} \mathbf{x})^\top (\mathbf{y} - \mathbf{G} \mathbf{x}) = \sum_{n=1}^N (y_n - a x_n - b)^2 = J(a, b). \quad (18)$$

Using the least squares solution from course material now gives

$$\begin{aligned}
\hat{\mathbf{x}}_{\text{LS}} &= (\mathbf{G}^\top \mathbf{G})^{-1} \mathbf{G}^\top \mathbf{y} \\
&= \left( \begin{bmatrix} x_1 & \dots & x_N \\ 1 & \dots & 1 \end{bmatrix} \begin{bmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_N & 1 \end{bmatrix} \right)^{-1} \begin{bmatrix} x_1 & \dots & x_N \\ 1 & \dots & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} \\
&= \begin{bmatrix} \sum_{n=1}^N x_n^2 & \sum_{n=1}^N x_n \\ \sum_{n=1}^N x_n & N \end{bmatrix}^{-1} \begin{bmatrix} \sum_{n=1}^N x_n y_n \\ \sum_{n=1}^N y_n \end{bmatrix}
\end{aligned} \tag{19}$$

which is now the same as (7) and can be simplified in the same way.