



**Definition**

We want to estimate a random variable  $x : \Omega \rightarrow \mathbf{R}^n$  from a random variable  $y : \Omega \rightarrow \mathbf{R}^n$  using an estimator  $\phi : \mathbf{R}^m \rightarrow \mathbf{R}^n$  which is affine.<sup>1</sup> In other words,  $\phi(\xi) = A\xi + b$  for some  $A \in \mathbf{R}^{n \times m}$  and  $b \in \mathbf{R}^n$ . We will use the mean squared error cost.

We want to find  $A$  and  $b$  to minimize

$$\mathbf{E}\|Ax + b - y\|^2.$$

*Proof.* Express  $\mathbf{E}(\|Ax + b - y\|^2)$  as  $\mathbf{E}((Ax + b - y)^\top (Ax + b - y))$

$$\begin{aligned} & + \operatorname{tr}(A\mathbf{E}(xx^\top)A^\top) + \mathbf{E}(x)^\top A^\top b - \operatorname{tr}(A^\top \mathbf{E}(yx^\top)) \\ & + b^\top A\mathbf{E}(x) + b^\top b - b^\top \mathbf{E}(y) \\ & - \operatorname{tr}(A\mathbf{E}(xy^\top)) - \mathbf{E}(y)^\top b + \mathbf{E}(yy^\top) \end{aligned}$$

The gradients with respect to  $b$  are

$$\begin{aligned} & + 0 + A\mathbf{E}(x) - 0 \\ & + A\mathbf{E}(x) + 2b - \mathbf{E}(y) \\ & - 0 - \mathbf{E}(y) + 0 \end{aligned}$$

so  $2A\mathbf{E}(x) + 2b - 2\mathbf{E}(y)$ . The gradients with respect to  $A$  are

$$\begin{aligned} & + \mathbf{E}(xx^\top)A^\top + \mathbf{E}(xx^\top)^\top A^\top + \mathbf{E}(x)b^\top - \mathbf{E}(yx^\top)^\top \\ & + \mathbf{E}(x)b^\top + 0 - 0 \\ & - \mathbf{E}(xy^\top) - 0 + 0 \end{aligned}$$

so  $2\mathbf{E}(xx^\top)A^\top + 2\mathbf{E}(x)b^\top - 2\mathbf{E}(xy^\top)$ . We want  $A$  and  $b$  solutions to

$$A\mathbf{E}(x) + b - \mathbf{E}(y) = 0$$

$$\mathbf{E}(xx^\top)A^\top + \mathbf{E}(x)b^\top - \mathbf{E}(xy^\top) = 0$$

so first get  $b = \mathbf{E}(y) - A\mathbf{E}(x)$ . Then express

$$\mathbf{E}(xx^\top)A^\top + \mathbf{E}(x)(\mathbf{E}(y) - A\mathbf{E}(x))^\top - \mathbf{E}(xy^\top) = 0.$$

$$\mathbf{E}(xx^\top)A^\top + \mathbf{E}(x)\mathbf{E}(y)^\top - \mathbf{E}(x)\mathbf{E}(x)^\top A^\top - \mathbf{E}(xy^\top) = 0.$$

$$(\mathbf{E}(xx^\top) - \mathbf{E}(x)\mathbf{E}(x)^\top)A^\top = \mathbf{E}(xy^\top) - \mathbf{E}(x)\mathbf{E}(y)^\top.$$

$$\operatorname{cov}(x, x)A^\top = \operatorname{cov}(x, y).$$

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<sup>1</sup>Actually, the development flips this. Future editions will correct.

So  $A^\top = (\text{cov}(x, x))^{-1} \text{cov}(x, y)$  means  $A = \text{cov}(y, x)(\text{cov}(x, x))^{-1}$  is a solution. Then  $b = \mathbf{E}(y) - \text{cov}(y, x) \text{cov}(x, x)^{-1} \mathbf{E}(x)$ . So to summarize, the estimator  $\phi(x) = Ax + b$  is

$$\text{cov}(y, x)(\text{cov } x, x)^{-1}x + \mathbf{E}(y) - \text{cov}(y, x)(\text{cov}(x, x))^{-1}\mathbf{E}(x)$$

or

$$\mathbf{E}(y) + \text{cov}(y, x)(\text{cov } x, x)^{-1}(x - \mathbf{E}(x))$$

□

