

Minimum mean square error (MMSE) estimator

Consider two random variables X and Y with a joint pdf $f_{X,Y}(x,y)$.

Let's say we want an estimator for Y given $X = x_0$ that minimizes the mean squared error:

$$\min E[(Y - \hat{y})^2 | X = x_0]$$

This is satisfied by choosing \hat{y} to be the conditional expectation of Y .

$$\hat{y} = E[Y | X = x_0]$$

When X is a random variable, the estimator is also a random variable \hat{Y} :

$$\hat{Y} = E[Y | X]$$

Linear MMSE

We can pick a line $\hat{y}_l(x) = ax + b$ that minimizes the mean squared error. That is:

$$\min_{a, b} E[(Y - \hat{y}_l(X))^2]$$

We want this to be an unbiased estimator, so we can set b :

$$b = \mu_Y - a\mu_X$$

When we plug in this b back into the above expression, we get:

$$E[(Y - aX - \mu_Y + a\mu_X)^2] = E[((Y - \mu_Y) - (aX - \mu_X))^2]$$

After defining $\tilde{Y} = Y - \mu_Y$, $\tilde{X} = X - \mu_X$, we can rewrite the above expression as:

$$E[(\tilde{Y} - a\tilde{X})^2] = \sigma_Y^2 - 2a\sigma_{YX} + a^2\sigma_X^2$$

The value of a that minimizes this expression is:

$$a = \frac{\sigma_{YX}}{\sigma_X^2} = \rho_{YX} \frac{\sigma_Y}{\sigma_X}$$

Resulting MSE

The resulting MSE from a linear MMSE estimator is:

$$E[(\tilde{Y} - a\tilde{X})^2] = \sigma_Y^2 (1 - \rho^2) = \sigma_Y^2 \left[1 - \left(\frac{\sigma_{YX}}{\sigma_X \sigma_Y} \right)^2 \right]$$

$$\frac{\sigma_{XY}}{\sigma_X \sigma_Y \text{right}^2 \text{right}} \quad \text{\$ \$}$$

Orthogonalities

The following orthogonalities hold for the linear MSE estimator:

$$\text{\$ \$ } (Y - \tilde{Y}_1) \perp 1 \text{\$ \$}$$

(This means that that value has zero expected value.)

$$\text{\$ \$ } (Y - a\tilde{X}) \perp \tilde{X} \text{\$ \$}$$

$$\text{\$ \$ } (Y - \tilde{Y}_1) \perp \tilde{X} \text{\$ \$}$$

$$\text{\$ \$ } (Y - \tilde{Y}_1) \perp X \text{\$ \$}$$

Multivariate LMMSE estimator

$$\text{\$ \$ } \hat{Y}_1 = a_0 + a_1 X_1 + \dots + a_L X_L \text{\$ \$}$$

We set a_0 to make \hat{Y}_1 unbiased:

$$\text{\$ \$ } a_0 = \mu_Y - \sum_{j=1}^L a_j \mu_{X_j} \text{\$ \$}$$

The rest of the coefficients can be found using the following equation, also known as the normal equations:

$$\text{\$ \$ } \mathbf{C}_{XX} \mathbf{a} = \mathbf{c}_{XY} \text{\$ \$}$$

where

$$\text{\$ \$ } \mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_L \end{bmatrix} \text{\$ \$}$$

$$\text{\$ \$ } \mathbf{C}_{\mathbf{XX}} = \begin{bmatrix} \sigma_{X_1}^2 & \sigma_{X_1 X_2} & \dots & \sigma_{X_1 X_L} \\ \sigma_{X_1 X_2} & \sigma_{X_2}^2 & \dots & \sigma_{X_2 X_L} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{X_L X_1} & \sigma_{X_L X_2} & \dots & \sigma_{X_L}^2 \end{bmatrix} \text{\$ \$}$$

$$\text{\$ \$ } \mathbf{c}_{\mathbf{XY}} = \begin{bmatrix} \sigma_{X_1 Y} \\ \sigma_{X_2 Y} \\ \vdots \\ \sigma_{X_L Y} \end{bmatrix} \text{\$ \$}$$

Mean square error of multivariate LMMSE estimator

$$\text{\$ \$ } \sigma_Y^2 - \mathbf{c}_{Y\mathbf{X}} \mathbf{a} \text{\$ \$}$$

where $\mathbf{c}_{Y\mathbf{X}} = \mathbf{c}_{\mathbf{X}Y}^T$

From:

<https://www.jaeyoung.wiki/> - **Jaeyoung Wiki**

Permanent link:

https://www.jaeyoung.wiki/kb:mmse_estimator

Last update: **2024-04-30 04:03**