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Find $f(X)$ that minimizes $E[(Y - f(X))^2|X]$

Asked 3 years ago Active 3 years ago Viewed 2k times



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Let X and Y random variables with $E(Y) = \mu$ and $E(Y^2) < \infty$. Deduce that the random variable $f(X)$ that minimizes $E[(Y - f(X))^2|X]$ is $f(X) = E[Y|X]$.



I just find the minimum with derivatives



1

$$\frac{d}{df(X)} E[(Y - f(X))^2|X] = -2E[Y - f(X)|X]$$

$$= -2E[Y|X] + 2E[f(X)|X] = 0$$

$$\Leftrightarrow E[Y|X] = E[f(X)|X]$$

$$\Leftrightarrow f(X) = E[Y|X]$$

Is this right?

I founded this solution

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$$\begin{aligned}\mathbb{E}[(Y - c)^2] &= \mathbb{E}[Y^2 - 2Yc + c^2] = \mathbb{E}[Y^2] - 2c\mathbb{E}[Y] + c^2 \\ &= \mathbb{E}[Y^2] - 2c\mu + c^2.\end{aligned}$$

Find the extreme point by differentiating,

$$\frac{d}{dc}(\mathbb{E}[Y^2] - 2c\mu + c^2) = -2\mu + 2c = 0 \quad \Rightarrow c = \mu.$$

Since, $\frac{d^2}{dc^2}(\mathbb{E}[Y^2] - 2c\mu + c^2) = 2 > 0$ this is a min-point.

b) We have

$$\begin{aligned}\mathbb{E}[(Y - f(X))^2 | X] &= \mathbb{E}[Y^2 - 2Yf(X) + f^2(X) | X] \\ &= \mathbb{E}[Y^2 | X] - 2f(X)\mathbb{E}[Y | X] + f^2(X),\end{aligned}$$

which is minimized by $f(X) = \mathbb{E}[Y | X]$ (take $c = f(X)$ and $\mu = \mathbb{E}[Y | X]$ in a).

c) We have

$$\mathbb{E}[(Y - f(X))^2] = \mathbb{E}[\mathbb{E}[(Y - f(X))^2 | X]],$$

so the result follows from b).

Is this wrong too?

probability

statistics

derivatives

expectation

edited Sep 5 '16 at 14:35

asked Sep 5 '16 at 13:23



Roland

1,380

1

12

34

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13:29

▲ @Did I wouldn't call it so wrong, nor innovative. It makes sense if one minimizes the square for a given (fixed) value of X - in that case it's the direct generalization of showing that the value of a that minimizes $E[(X-a)^2]$ is $a = E(X)$. – [leonbloy](#) Sep 5 '16 at 13:37

▲ @leonbloy What is $\frac{\partial}{\partial f(X)}$ already? You see. It seems that, despite your good heart, I will stick to "very far from being right"... – [Did](#) Sep 5 '16 at 13:39

▲ See eg ocw.mit.edu/courses/electrical-engineering-and-computer-science/... – [leonbloy](#) Sep 5 '16 at 13:39

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2 Answers



2



Let us try to make your argument more rigorously legitimate. First, let's agree that the goal is to find some (measurable) function $f : \mathbb{R} \rightarrow \mathbb{R}$ such that for any (measurable) function $g : \mathbb{R} \rightarrow \mathbb{R}$ the inequality

$$\mathbb{E}[(Y - f(X))^2 | X] \leq \mathbb{E}[(Y - g(X))^2 | X] \quad (1)$$

holds almost surely. Now, let Ω be the sample space on which X is defined and let $h(X) : \Omega \rightarrow \mathbb{R}$ be a representative of $\mathbb{E}[Y | X]$ and $k(X)$ be a representative of $\mathbb{E}[Y^2 | X]$, each defined for every $\omega \in \Omega$. Then,

$$\mathbb{E}[(Y - f(X))^2 | X] = k(X) - 2f(X)h(X) + f(X)^2$$

(where equality means the RHS is in the equivalence class of the LHS). Now, for a fixed $\omega \in \Omega$, if we minimize

$$k(X)(\omega) - 2\lambda h(X)(\omega) + \lambda^2$$

in the variable λ , using differentiation as you have above, you will find that $\lambda = h(X)(\omega)$. Thus, for each $\omega \in \Omega$, defining $\lambda(\omega) = h(X)(\omega)$ minimizes the previous expression pointwise in Ω . Thus with $f(X) = h(X)$, Eq. (1) is minimized almost surely.

[edited Sep 5 '16 at 14:11](#)

[answered Sep 5 '16 at 14:03](#)

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Hint: the typical trick is the minus-and-add trick: with $Z = E(Y|X)$,

1

$$\begin{aligned} E[(Y - f(X))^2|X] &= E[(Y - Z + Z - f(X))^2|X] \\ &= E[(Y - Z)^2|X] + 2E[(Y - Z)(Z - f(X))|X] + E[(Z - f(X))^2|X]. \end{aligned}$$

Now note that

$$E[(Y - Z)(Z - f(X))|X] = (Z - f(X)) \underbrace{E[Y - Z|X]}_0 = 0.$$

What now can you infer about $E[(Y - f(X))^2|X]$ and $E[(Y - Z)^2|X]$?

edited Sep 5 '16 at 15:46

answered Sep 5 '16 at 13:29



yurnero

7,827

1

9

26