

On the stability problem for conditional expectation

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Abstract: The behavior of the conditional expectation $E\{X|Y\}$ under a small perturbation Z of the conditioning random variable Y is analyzed. We show that if Y and Z are independent then $E\{X|Y+\varepsilon Z\}$ converges to $E\{X|Y\}$ in mean as $\varepsilon \rightarrow 0$ for all integrable X , provided the distribution of Y is absolutely continuous. We also show that the limit is $E\{X|Y, Z\}$ rather than $E\{X|Y\}$, i.e., there is no stability, when Y is a discrete (i.e., countably valued) random variable. Finally, we show that in general $E\{X|Y+\varepsilon Z\}$ might have no limit in distribution as $\varepsilon \rightarrow 0$.

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1. Introduction

In this note we investigate the stability of the conditional expectation $E\{X|Y\}$ under a small additive perturbation by a random variable Z , i.e., we study the behavior of $E\{X|Y+\varepsilon Z\}$ as $\varepsilon \rightarrow 0$. In the case when Y and Z are independent real valued and the convergence is understood in probability it is possible to answer the stability problem completely. Namely, we show that $E\{X|Y+\varepsilon Z\}$ converges to $E\{X|Y\}$ as $\varepsilon \rightarrow 0$, if Y is absolutely continuous, $E\{X|Y+\varepsilon Z\}$ converges to $E\{X|Y, Z\}$ as $\varepsilon \rightarrow 0$, if Y is discrete, and there is no limit in general. The same question can be asked also when Y and Z are \mathbb{R}^d -valued random variables or when Y and Z are replaced by stochastic processes $\{Y_t\}$; however, the information that we have in those cases is far less complete and is left out of this note.

The following result gives a sufficient condition for the stability of the conditional expectation under independent perturbations.

Theorem 1.1. *If Y, Z are independent, the distribution of Y is absolutely continuous with respect to the Lebesgue measure on \mathbb{R} and $E\{|X|\} < \infty$, then*

$$E\{X|Y+\varepsilon Z\} \rightarrow E\{X|Y\} \quad \text{in } L_1\{dP\} \quad \text{as } \varepsilon \rightarrow 0. \quad (1.1)$$

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Remark 1. Suitable modifications in the proof of Theorem 1 show that the conclusion holds also for dependent random variables Y, Z , provided they have joint density.

Remark 2. In general, to show that (1.1) holds for all integrable X , it is enough to consider all X of the form $X = \phi(Z)$, where $\phi: \mathbb{R} \rightarrow \mathbb{R}$ is bounded and uniformly continuous. Indeed, by the standard approximation argument, the finite sums $\sum \phi_i(Z)\Psi_i(Y)$, where ϕ_i, Ψ_i are bounded and uniformly continuous, are dense in $L_1(\sigma(Y, Z), dP)$. For a single term of the sum we have

$$E\{\phi(Z)\Psi(Y) | Y + \varepsilon Z\} = \Psi(Y + \varepsilon Z)E\{\phi(Z) | Y + \varepsilon Z\} + \theta_\varepsilon,$$

where

$$\theta_\varepsilon = E\{\phi(Z)(\Psi(Y) - \Psi(Y + \varepsilon Z)) | Y + \varepsilon Z\} \rightarrow 0 \text{ in } L_1(dP) \text{ as } \varepsilon \rightarrow 0.$$

Therefore $E\{\phi(Z)\Psi(Y) | Y + \varepsilon Z\} \rightarrow \Psi(Y)E\{\phi(Z) | Y\}$, provided (1.1) is established for $X = \phi(Z)$.

Remark 3. The argument given above also shows that (1.1) holds for all $\sigma(Y)$ -measurable integrable X . As a consequence, one easily gets that if Y has a density, $E\{|Z|^p\} < \infty$ for some $p \geq 1$ and $E\{Z\} = 0$, then $E\{Y | Y + \varepsilon Z\} = Y + \varepsilon Z + o(\varepsilon)$, where $\|o(\varepsilon)\|_p / |\varepsilon| \rightarrow 0$ as $\varepsilon \rightarrow 0$. Indeed,

$$E\{Y | Y + \varepsilon Z\} = Y + \varepsilon Z - \varepsilon E\{Z | Y + \varepsilon Z\} \text{ and } E\{Z | Y + \varepsilon Z\} \rightarrow E\{Z\}$$

by Theorem 1.1. Szablowski (1986, Corollary 1.2) shows that if one conditions Z rather than Y , then the representation

$$E\{Z | Y + \varepsilon Z\} = E\{Z\} + \varepsilon\beta(Y + \varepsilon Z) + o(\varepsilon)$$

permits one to determine the distribution of Y , which then has to be absolutely continuous.

The following result shows that there is no stability in the discrete case. No assumption of independence is needed.

Theorem 1.2. *If Y is discrete and $E\{|X|\} < \infty$ then*

$$E\{X | Y + \varepsilon Z\} \rightarrow E\{X | Y, Z\} \text{ in } L_1(dP) \text{ as } \varepsilon \rightarrow 0 \text{ for all } Z. \tag{1.2}$$

Remark 4. If in addition either

- (i) Z is discrete, or
 - (ii) Z is bounded and Y takes a finite number of values,
- then the convergence in (1.2) is also in the most sure sense.

The following observation complements Theorems 1.1 and 1.2.

Proposition 1.3. *Suppose Y, Z are independent and identically distributed. If (1.1) holds for all integrable X , then either Y is continuous (i.e., atomless), or Y is deterministic.*

Proposition 1.3 gives a necessary condition for (1.1). The following example shows that there are i.i.d. continuous (but not absolutely continuous) Y, Z such that $E\{X | Y + \varepsilon Z\}$ has no limit in distribution as $\varepsilon \rightarrow 0$.

Example. Let ξ_k, η_k be independent $\{0, 1\}$ -valued random variables. Suppose

$$P(\xi_{2k} = 1) = P(\eta_{2k} = 1) = p_1 \text{ and } P(\xi_{2k+1} = 1) = P(\eta_{2k+1} = 1) = p_2 \text{ for all } k,$$

where $0 < p_1 < p_2 < 1$ are fixed. Let

$$X = \xi_1, \quad Y = \sum_{k=1}^{\infty} \eta_k/3^k, \quad Z = \sum_{k=1}^{\infty} \xi_k/3^k.$$

Clearly, Y and Z are independent and identically distributed. Moreover, from the uniqueness of the ternary expansion in this case we see that

$$\sigma\left\{Y + \frac{1}{3^n}Z\right\} = \sigma\{\eta_1, \eta_2, \dots, \eta_n, \eta_{n+1} + \xi_1, \eta_{n+2} + \xi_2, \dots\}.$$

Therefore

$$E\left\{X \mid Y + \frac{1}{3^n}Z\right\} = E\{\xi_1 \mid \eta_{n+1} + \xi_1\} = \begin{cases} 0 & \text{if } \eta_{n+1} + \xi_1 = 0, \\ \frac{p_1(1-q)}{p_1 + q - 2p_1q} & \text{if } \eta_{n+1} + \xi_1 = 1, \\ 1 & \text{if } \eta_{n+1} + \xi_1 = 2, \end{cases}$$

where $q = p_1$ if n is even and $q = p_2$ if n is odd. In particular, $E\{X \mid Y + (1/3^n)Z\}$ has no limit in distribution as $n \rightarrow \infty$.

2. Proofs

Proof of Theorem 1.1. As it was pointed out in Remark 2, it is enough to establish (1.1) for $X = f(Z)$, where $f(\cdot)$ is a bounded continuous function. Furthermore, since the family of conditional expectations of a fixed random variable X with respect to different σ -fields is uniformly integrable, we need only to show convergence in probability.

Let $g(y)$ be the density of Y . By F_X, F_Y, F_Z we denote the cumulative distribution functions of X, Y, Z ; $\lambda(\cdot)$ denotes the Lebesgue measure and $\mu \otimes F$ is the product of measures μ and dF . Clearly,

$$E\{X \mid Y\} = \int f(z)F_Z(dz)$$

and

$$E\{X \mid Y + \varepsilon Z\} = \frac{\int f(z)g(Y + \varepsilon Z - \varepsilon z)F_Z(dz)}{\int g(Y + \varepsilon Z - \varepsilon z)F_Z(dz)}.$$

Since f is bounded, we have

$$\begin{aligned} & \left| \int f(z)g(Y + \varepsilon Z - \varepsilon z)F_Z(dz) - \int f(z)g(Y)F_Z(dz) \right| \\ & \leq \|f\|_{\infty} \int |g(Y + \varepsilon Z - \varepsilon z) - g(Y)|F_Z(dz). \end{aligned}$$

Therefore, to show that $E\{X \mid Y + \varepsilon Z\} \rightarrow E\{X \mid Y\}$ in probability, it is enough to show that

$$\int |g(Y + \varepsilon Z - \varepsilon z) - g(Y)|F_Z(dz) \rightarrow 0 \quad \text{in probability.} \tag{2.1}$$

To this end, for each $\delta > 0$ let $h(\cdot) = h_\delta(\cdot)$ be a uniformly continuous probability density function such that

$$\int |g(y) - h(y)| \, dy < \delta^2.$$

For real ε let

$$A_\varepsilon = \left\{ (y, z) : \int |g(y + \varepsilon z - \varepsilon u) - h_\delta(y + \varepsilon z - \varepsilon u)| F_Z(du) > \delta \right\}.$$

By Chebyshev's inequality,

$$(\lambda \otimes F_Z)(A_\varepsilon) \leq \frac{1}{\delta} \iiint |g(y + \varepsilon z - \varepsilon u) - h(y + \varepsilon z - \varepsilon u)| \, dy F_Z(du) F_Z(dz) < \delta.$$

Let $\rho > 0$ be arbitrary. Since $F_Y \otimes F_Z$ is absolutely continuous with respect to $\lambda \otimes F_Z$, therefore

$$P((Y, Z) \in A_\varepsilon) < \rho \tag{2.2}$$

for all ε and for all δ small enough, say for all $\delta < \delta_0(\rho)$. Let

$$B = B(\varepsilon, \delta) = \left\{ (y, z) : \int |g(y + \varepsilon z - \varepsilon u) - g(y)| F_Z(du) > 4\delta \right\},$$

$$C = C(\varepsilon, \delta) = \left\{ (y, z) : \int |h(y + \varepsilon z - \varepsilon u) - h(y)| F_Z(du) > 2\delta \right\}.$$

To prove (2.1) it is enough to show that $P((Y, Z) \in B) < 3\rho$ as $\varepsilon \rightarrow 0$. Clearly

$$P((Y, Z) \in B) \leq P((Y, Z) \in A_0) + P((Y, Z) \in A_\varepsilon) + F_Y \otimes F_Z(C).$$

To end the proof it is enough to show that for every fixed $\delta > 0$,

$$F_Y \otimes F_Z(C) \rightarrow 0 \quad \text{as } \varepsilon \rightarrow 0. \tag{2.3}$$

Notice that since $h(\cdot)$ is uniformly continuous, there is an $\eta = \eta(\delta)$ such that $|h(y + \varepsilon z - \varepsilon u) - h(y)| < \delta$ except when either $|z| > \eta/|\varepsilon|$ or $|u| > \eta/|\varepsilon|$. In particular, if $(y, z) \in C$ then either $|z| > \eta/|\varepsilon|$ or

$$(y, z) \in D = \left\{ (y, z) : \int_{|u| > \eta/|\varepsilon|} |h(y + \varepsilon z - \varepsilon u) - h(y)| F_Z(du) > \delta \right\}.$$

Therefore,

$$F_Y \otimes F_Z(C) \leq P(|Z| > \eta/|\varepsilon|) + F_Y \otimes F_Z(D).$$

Clearly, $P(|Z| > \eta/|\varepsilon|) \rightarrow 0$ as $\varepsilon \rightarrow 0$. The second term tends to zero, too. Indeed, $F_Y \otimes F_Z$ is absolutely continuous with respect to $\lambda \otimes F_Z$ and by Chebyshev's inequality,

$$\begin{aligned} \lambda \otimes F_Z(D) &\leq \frac{1}{\delta} \int_{\mathbb{R}} \int_{\mathbb{R}} \int_{|u| > \eta/|\varepsilon|} [h(y + \varepsilon z - \varepsilon u) + h(y)] F_Z(du) \lambda(dy) F_Z(dz) \\ &= \frac{2}{\delta} P(|Z| > \eta/|\varepsilon|) \rightarrow 0 \quad \text{as } \varepsilon \rightarrow 0. \end{aligned}$$

This establishes (2.3) and ends the proof of Theorem 1.1. \square

Lemma 2.1. Suppose $\mathcal{F}_\varepsilon \subset \mathcal{F}$ are σ -fields. Assume for every $\delta > 0$ there is an $\varepsilon_0(\delta) > 0$ and an $A \in \mathcal{F}$ with $P(A) > 1 - \delta$ such that for all $0 < |\varepsilon| < \varepsilon_0(\delta)$,

$$\{S: S = B \cap A, B \in \mathcal{F}_\varepsilon\} \supset \{S: S = C \cap A, C \in \mathcal{F}\}. \tag{2.4}$$

Then $E\{X | \mathcal{F}_\varepsilon\} \rightarrow X$ in L_1 as $\varepsilon \rightarrow 0$ for each integrable X .

Remark. Obviously, (2.4) implies the equality of sets.

Proof of Lemma 2.1. By the standard approximation argument it is enough to consider $X = I_C$, the indicator function of an event $C \in \mathcal{F}$. Clearly,

$$E\{|E(I_C | \mathcal{F}_\varepsilon) - I_C|\} \leq E\{|E\{I_{C \cap A} | \mathcal{F}_\varepsilon\} - I_{C \cap A}|\} + 2P(A^c).$$

By (2.4) we have $E\{I_{C \cap A} | \mathcal{F}_\varepsilon\} - I_{C \cap A} = I_B\{E(I_A | \mathcal{F}_\varepsilon) - I_A\}$, for some $B \in \mathcal{F}_\varepsilon$. Therefore

$$E\{|E\{I_{C \cap A} | \mathcal{F}_\varepsilon\} - I_{C \cap A}|\} \leq 2E\{|I_A - P(A)|\} = 4P(A)P(A^c) < 4\delta.$$

This shows that $\|E\{I_C | \mathcal{F}_\varepsilon\} - I_C\|_1 \leq 6\delta$ for all $|\varepsilon| < \varepsilon_0(\delta)$. \square

Proof of Theorem 1.2. Given $\delta > 0$ pick a measurable set $A \subset \Omega$ with $P(A) > 1 - \delta$ and such that the following two conditions are satisfied:

- (i) YI_A has finitely many values;
- (ii) ZI_A is bounded.

Put $\mathcal{F}_\varepsilon = \sigma(Y + \varepsilon Z)$. Clearly, for all $\varepsilon \neq 0$ such that $|\varepsilon|$ is small enough we have

$$\sigma(YI_A + \varepsilon ZI_A) = \sigma(YI_A, ZI_A). \tag{2.5}$$

This shows that condition (2.4) holds with \mathcal{F}_ε given above and $\mathcal{F} = \sigma(Y, Z)$. Indeed, let $C \in \mathcal{F}$, i.e., $C = \{\omega: (Y, Z) \in \mathcal{V}\}$ for some Borel set $\mathcal{V} \subset \mathbb{R}^2$. Then

$$C \cap A = \{\omega: (YI_A, ZI_A) \in \mathcal{V}\} \cap A. \tag{2.6}$$

However, $\{\omega: (YI_A, ZI_A) \in \mathcal{V}\} = \{\omega: YI_A + \varepsilon ZI_A \in \mathcal{U}_\varepsilon\}$ for some Borel set $\mathcal{U}_\varepsilon \subset \mathbb{R}$, provided $\varepsilon \neq 0$ and $|\varepsilon|$ is small enough so that (2.5) holds. Therefore by (2.6),

$$C \cap A = A \cap \{\omega: YI_A + \varepsilon ZI_A \in \mathcal{U}_\varepsilon\} = A \cap \{\omega: Y + \varepsilon Z \in \mathcal{U}_\varepsilon\} = A \cap B$$

for some $B \in \mathcal{F}_\varepsilon$. By Lemma 2.1 the proof is complete. \square

Proof of Proposition 1.3. Suppose $a \in \mathbb{R}$ is such that $P(Y = a) > 0$. Let $C = \{\omega: Y = a, Z = a\}$, $A_\varepsilon = \{\omega: Y + \varepsilon Z = (1 + \varepsilon)a\}$. Clearly, $P(C) > 0$ and $A_\varepsilon = C$ almost surely except for at most a countable number of ε 's. In particular, $P(A_\varepsilon) = P(C) > 0$.

Let $X = \phi(Z)$ for some ϕ . By assumption $E\{\phi(Z) | Y + \varepsilon Z\} \rightarrow E\{\phi(Z)\}$ in probability. On A_ε we have

$$E\{\phi(Z) | Y + \varepsilon Z\} = \frac{1}{P(A_\varepsilon)} \int_{A_\varepsilon} \phi(Z) dP = \frac{1}{P(C)} \int_C \phi(Z) dP = \phi(a).$$

Therefore $E\{\phi(Z) | Y + \varepsilon Z\} = \phi(a)$ on a set of probability $P(C) > 0$. Since for each $\delta > 0$ we have

$$P\{|E\{\phi(Z) | Y + \varepsilon Z\} - E\{\phi(Z)\}| > \delta\} < P(C)$$

for all $\varepsilon \neq 0$ with $|\varepsilon|$ small enough, therefore $\phi(a) = E\{\phi(Z)\}$. The last equality, however, cannot be true for all functions ϕ unless $Z = a$ with probability one. This shows that if Y is not continuous, then it is deterministic and ends the proof. \square

References

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