

Jensen's Inequality for Conditional Expectations

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Let  $f$  be a real-valued Borel function,  $X$  and  $f(X)$  be integrable random variables defined on a probability space  $(\Omega, \mathcal{F}, P)$  and  $\mathcal{G}$  be a sub  $\sigma$ -field of  $\mathcal{F}$ . Jensen's inequality states that, if  $f$  is convex on an interval  $I$  containing the range of  $X$ , then

$$(1) \quad E f(X) \geq f(E X)$$

(where  $E$  denotes expectation); its generalization is

$$(2) \quad E[f(X) | \mathcal{G}] \geq f[E(X | \mathcal{G})]$$

with probability one.

One application of the generalized Jensen's inequality is in martingale theory where it is used to show that "convex functions of martingales" and "convex non-decreasing functions of submartingales" are submartingales.

The usual proof of (1), e.g. Loève [6; p. 159], uses the fact that under the hypothesis there must exist a non-decreasing function,  $m(\cdot)$ , satisfying, for all  $x$  and  $y$  in  $I$ :

$$(3) \quad f(x) - f(y) \geq m(y) (x - y)$$

(e.g. take  $m$  to be either the right or left hand derivative of  $f$ ). Then, since  $EX$  must lie in  $I$ , we have

$$(4) \quad f(X) - f(EX) \geq m(EX) (X - EX).$$

Take the expectations of both sides, giving

$$(5) \quad E f(X) - f(E X) \geq m(E X) (E X - E X) = 0$$

which proves (1).

Inequality (4) can be generalized to

$$(6) \quad f(X) - f[E(X|\mathcal{G})] \geq m[E(X|\mathcal{G})] [X - E(X|\mathcal{G})]$$

and taking the conditional expectations of both sides with respect to  $\mathcal{G}$ , would yield the analogue of (5), thereby proving (2) -- provided that the conditional expectations exist. If  $f$  can be bounded above or below then so can  $m[E(X|\mathcal{G})]$  and there is no difficulty. But in general, the hypothesis is not sufficient to guarantee the existence of the mean of the right side of (6).

For example, take  $f(x) = \exp|x|$ , let  $Y$  be any symmetric random variable with  $E \exp^2|Y| < \infty$ , but  $E Y \exp|Y|$  failing to exist. Let  $Z$  be independent of  $Y$  with values 0 and 2 each with probability 1/2. Take  $X = YZ$  and  $\mathcal{G}$  the  $\sigma$ -field generated by  $Y$ . Then the right side of (6) becomes

$$(7) \quad |Y| (Z-1) \exp|Y|$$

which has the same distribution as

$$(8) \quad Y \exp|Y|,$$

hence no mean. So while we are strongly tempted to say that the conditional expectation of (7) with respect to  $\mathcal{G}$  is

$$(9) \quad (|Y| \exp|Y|) E(Z-1) = 0,$$

we may not do so.

Loève does not give a proof of (2), but merely asserts (p. 348) that it follows from (1) and the fact that  $P\{X \geq Y\} = 1$  implies  $P\{E(X|\mathcal{H}) \geq E(Y|\mathcal{H})\} = 1$  for any  $\mathcal{H} \subset \mathcal{G}$ . We leave this as an exercise for the reader: one which we have not been able to solve.

Feller [4; p. 214] mentions (2) without proof. Neveu [7; p. 122] mentions only the case  $X \geq 0$ , without proof as an easy generalization of (1), which it is since the interval  $I$  can be bounded below. Chung [2; p. 281] has a proof of (2) which is not based on (3) and which is not quite complete.

Doob [3; p. 33] shows that once the existence of regular conditional distributions is established, (2) can be obtained from (1) in an elementary way. Indeed Breiman [1; p. 80] assigns the proof of (2) as an exercise with the above as a hint.

I prefer to build a proof around (6) as follows:

Choose  $a > 0$  and let

$$(10) \quad A = A(a) = \{|E(X|\mathcal{G})| \leq a\}.$$

Then (6) is true with  $X$  replaced by  $XI_A$  -- unless 0 is not in  $I$ , in which case  $X$  should be replaced by  $XI_A + bI_A^c$  for some  $b$  in  $I$ , and  $f(0)$  should be replaced by  $f(b)$  below. Now  $m[E(XI_A|\mathcal{G})]$  is bounded, so we are justified in concluding that

$$(11) \quad E[f(XI_A)|\mathcal{G}] \geq f[E(XI_A|\mathcal{G})].$$

Because  $A \in \mathcal{G}$ , the left side of (11) is

$$(12) \quad \begin{aligned} E[f(X)I_A + f(0)I_A^c|\mathcal{G}] \\ = E[f(X)|\mathcal{G}]I_A + f(0)I_A^c, \end{aligned}$$

while the right side is

$$(13) \quad f[E(X|\mathcal{G})I_A] = f[E(X|\mathcal{G})]I_A + f(0)I_A^c.$$

Comparing (12) and (13) we see that, in effect, on  $A$ , the  $I_A$ 's can be deleted from (11). Since  $P(A) \rightarrow 1$  as  $a \rightarrow \infty$ , this completes the proof.

Recently, I noticed (6) in Hunt [5; p. 48] with the remark that (2) then follows immediately if  $X$  is bounded and "in general by a passage to the limit". So the preceding proof fills in the details omitted by Hunt. But note that the proof will not go through if (10) is replaced by  $A = \{|X| \leq a\}$  since this set is not in  $\mathcal{G}$ .

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