

We now present a very important application of (e).

Thm: Suppose (X_1, X_2, \dots, X_k) is a (discrete or cont) random vector such that each X_i has finite mean. Then for all $\alpha_1, \alpha_2, \dots, \alpha_k \in \mathbb{R}$, the linear combination $\alpha_1 X_1 + \alpha_2 X_2 + \dots + \alpha_k X_k$ has finite mean and

$$E(\alpha_1 X_1 + \alpha_2 X_2 + \dots + \alpha_k X_k) = \alpha_1 E(X_1) + \alpha_2 E(X_2) + \dots + \alpha_k E(X_k).$$

Remarks: ① Note that the space V of all (real valued) random variables ^(defined on the same sample space) forms a vector space ^(in its generality) over \mathbb{R} . The above result [^] says that

$$S = \{X \in V : X \text{ has finite mean}\}$$

is a linear subspace of V , and the expectation map $E: S \rightarrow \mathbb{R}$ defined by

$$E: X \mapsto E(X)$$

is a linear map (i.e., a linear functional).

② The linearity of expectation is very useful - we shall see a few examples.

Proof of Thm (stated in Pg (151)): Take any $\alpha_1 \in \mathbb{R}$.

We shall first show that $\alpha_1 X_1$ has finite mean and $E(\alpha_1 X_1) = \alpha_1 E(X_1)$. We give the proof when X_1 is discrete ^{with pmf p_{X_1}} (The cont case is left as an exercise.) Note that

taking $h: \mathbb{R} \rightarrow \mathbb{R}$ as $h(x) = \alpha_1 x$ and

$$\text{observing } \sum_{x \in \text{Range}(X_1)} |h(x)| p_{X_1}(x)$$

$$= \sum_{x \in \text{Range}(X_1)} |\alpha_1 x| p_{X_1}(x)$$

$$= |\alpha_1| \sum_{x \in \text{Range}(X_1)} |x| p_{X_1}(x) < \infty, \quad [\because X_1 \text{ has finite mean}]$$

we get that $h(X_1) = \alpha_1 X_1$ has

finite mean. Therefore using (e) with the above choice of h , we obtain that

$$E(\alpha_1 X_1) = E(h(X_1))$$

$$= \sum_{x \in \text{Range}(X_1)} h(x) p_{X_1}(x) = \sum_{x \in \text{Range}(X_1)} \alpha_1 x p_{X_1}(x)$$

$$= \alpha_1 \sum_{x \in \text{Range}(X_1)} x p_{X_1}(x) = \alpha_1 E(X_1)$$

completing the proof of this step.

We now show the following: if X_1, X_2 have finite mean, then so does each linear combination $\alpha_1 X_1 + \alpha_2 X_2$ (here $\alpha_1, \alpha_2 \in \mathbb{R}$) and $E(\alpha_1 X_1 + \alpha_2 X_2) = \alpha_1 E(X_1) + \alpha_2 E(X_2)$.

Because of the previous ~~st~~ step, it is enough to show this step for $\alpha_1 = \alpha_2 = 1$.

Therefore, we need to show the following: if X_1, X_2 have finite mean, then so does $X_1 + X_2$ and $E(X_1 + X_2) = E(X_1) + E(X_2)$.

We shall show this when $\underline{X} = (X_1, X_2)$ is a cont random vector. (The discrete case is left as an exercise.) with a joint pdf f_{X_1, X_2} .

Define $h: \mathbb{R}^2 \rightarrow \mathbb{R}$ by $h(x_1, x_2) = x_1 + x_2$.

We have to verify that $h(X_1, X_2)$ has finite

mean and compute the mean. To this end, observe that

$$\int_{\mathbb{R}^2} |h(\underline{x})| f_{\underline{X}}(\underline{x}) d\underline{x}$$

$$= \int_{\mathbb{R}} \int_{\mathbb{R}} |h(x_1, x_2)| f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

$$= \int_{\mathbb{R}} \int_{\mathbb{R}} |x_1 + x_2| f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

$$\leq \int_{\mathbb{R}} \int_{\mathbb{R}} |x_1| f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

$$+ \int_{\mathbb{R}} \int_{\mathbb{R}} |x_2| f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

[Using triangle inequality]

$$\stackrel{\text{Fubini} \textcircled{1}}{\text{pg } \textcircled{88}} \int_{\mathbb{R}} \int_{\mathbb{R}} |x_1| f_{X_1, X_2}(x_1, x_2) dx_2 dx_1$$

$$+ \int_{\mathbb{R}} \int_{\mathbb{R}} |x_2| f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

$$= \int_{\mathbb{R}} |x_1| \int_{\mathbb{R}} f_{X_1, X_2}(x_1, x_2) dx_2 dx_1 \\ + \int_{\mathbb{R}} |x_2| \int_{\mathbb{R}} f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

$$= \int_{\mathbb{R}} |x_1| f_{X_1}(x_1) dx_1 + \int_{\mathbb{R}} |x_2| f_{X_2}(x_2) dx_2$$

$$< \infty,$$

$[\because X_1, X_2 \text{ have finite mean}]$

which shows $h(\underline{x}) = h(X_1, X_2) = X_1 + X_2$ has finite mean. Using (e), we get

$$E(X_1 + X_2) = E[h(X_1, X_2)]$$

$$= \int_{\mathbb{R}^2} h(\underline{x}) f_{\underline{X}}(\underline{x}) d\underline{x}$$

$$= \int_{\mathbb{R}} \int_{\mathbb{R}} h(x_1, x_2) f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

$$= \int_{\mathbb{R}} \int_{\mathbb{R}} (x_1 + x_2) f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

$$= \int_{\mathbb{R}} \int_{\mathbb{R}} x_1 f_{X_1, X_2}(x_1, x_2) dx_1 dx_2 + \int_{\mathbb{R}} \int_{\mathbb{R}} x_2 f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

\uparrow
 (absolutely integrable
 by the previous
 calculation)

Fubini ②
Pg 88

$$\int_{\mathbb{R}} \int_{\mathbb{R}} x_1 f_{X_1, X_2}(x_1, x_2) dx_2 dx_1 +$$

$$\int_{\mathbb{R}} \int_{\mathbb{R}} x_2 f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

$$= \int_{\mathbb{R}} x_1 \int_{\mathbb{R}} f_{X_1, X_2}(x_1, x_2) dx_2 dx_1 +$$

$$\int_{\mathbb{R}} x_2 \int_{\mathbb{R}} f_{X_1, X_2}(x_1, x_2) dx_1 dx_2$$

$$= \int_{\mathbb{R}} x_1 f_{X_1}(x_1) dx_1 + \int_{\mathbb{R}} x_2 f_{X_2}(x_2) dx_2 = E(X_1) + E(X_2)$$

which finishes the proof of this step.

Exc: Using induction on k , show that under the hypothesis of the thm stated in Pg (151), $\alpha_1 X_1 + \alpha_2 X_2 + \dots + \alpha_k X_k$ has finite mean and

$$E\left(\sum_{i=1}^k \alpha_i X_i\right) = \sum_{i=1}^k \alpha_i E(X_i).$$

[Thanks to the first step, it is enough to solve the above exercise for $\alpha_1 = \alpha_2 = \dots = \alpha_k = 1$.]

The discrete case of the second step (which is left as an exercise) needs the following discrete version of Fubini's Thm.

Fubini's Thm: Suppose $h: \mathbb{N}^2 \rightarrow \mathbb{R}$ is a double sequence. Then the following properties hold.

① If $h \geq 0$, then

$$(\text{int}) \dots \sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} h(i, j) = \sum_{j \in \mathbb{N}} \sum_{i \in \mathbb{N}} h(i, j).$$

(Both LHS and RHS can be $+\infty$.)

② If either $\sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} |h(i, j)| < \infty$ or

$\sum_{j \in \mathbb{N}} \sum_{i \in \mathbb{N}} |h(i, j)| < \infty$, then also (int) holds.