

Recall :- S - Sample Space , $\mathcal{F}$ - Events , $\mathbb{P}$ - Probability

Experiment :-  all outcomes from the experiment

$X: S \rightarrow \mathbb{R}$ is a random variable, S - Countable / finite
 $\Rightarrow \text{Range}(X)$ - Countable - Discrete Random variable

Distribution
of
 X

$\left\{ \begin{array}{l} \text{Range}(X) \subseteq \mathbb{R} , \quad x \in \text{Range}(X) - \mathbb{P}(X=x) := f_x(x) \\ f_x: \text{Range}(X) \rightarrow [0,1] - \text{Probability mass function of } X. \end{array} \right.$

$x \quad \text{-----} \quad x \quad \text{-----} \quad x$

Question :- [Bernoulli trials] "On average how many successes will
Example 2.1.2
be there after n trials?"

4 - Summarising Discrete Random Variables :

Experiment: Roll a die: The outcomes are $\{1, 2, \dots, 6\}$ Average value of outcome?

Conventional idea:

$$\frac{1+2+3+4+5+6}{6} = 3.5$$

|||

$$1\left(\frac{1}{6}\right) + 2\left(\frac{1}{6}\right) + 3\left(\frac{1}{6}\right) + 4\left(\frac{1}{6}\right) + 5\left(\frac{1}{6}\right) + 6\left(\frac{1}{6}\right)$$

weight each outcome
according to the
Probability of its outcome

Definition 4.1.1. Let $X: S \rightarrow T$ be a discrete random variable.
 (i.e. S - countable / finite $\Rightarrow T$ is countable / finite)

Then the expected value of X is written as
 $E[X]$ and is given by

$$E[X] := \sum_{t \in T} t \mathbb{P}(X=t) \quad \begin{matrix} \text{[Series]} \\ \text{Sum} \end{matrix}$$

provided that the sum converges absolutely. In this case, we say X has "finite Expectation". If the sum diverges to $\pm \infty$, then we say X has infinite expectation. If the sum diverges but not to $\pm \infty$, we say that the expected value of X is undefined.

Example 4.1.2 X - takes 3 values 200, 20, 0

such that $\mathbb{P}(X=200) = \frac{1}{1000}$, $\mathbb{P}(X=20) = \frac{27}{1000}$

$$\mathbb{P}(X=0) = \frac{972}{1000}$$

$$\begin{aligned} E[X] &:= \sum_{t \in T} t \mathbb{P}(X=t) = 0 \cdot \frac{972}{1000} + 20 \cdot \frac{27}{1000} + 200 \cdot \frac{1}{1000} \\ &= 0.74. \end{aligned}$$

Theorem 4.1.3 $X: S \rightarrow T$ such that $X(s) = c$ for some $c \in \mathbb{R}$ $\forall s \in S$.

Then $E[X] = c$.

Proof:-

$$P(X=c) = 1$$

$$\Rightarrow E[X] = c \cdot P(X=c) = c \cdot 1 = c$$

□

- This is written in short as: $E[c] = c$.

- $T = \text{Range}(X)$ is finite then $E[X] = \sum_{t \in T} t P(X=t) < \infty$,

and X has finite Expectation.

Example 4.1.4:- $\text{Range}(X) = \{2, 4, 8, 16, \dots\}$

$$P(X=2^k) = \frac{1}{2^k} \quad \forall k \geq 1$$

$$E[X] = \sum_{t \in T} t P(X=t) = \sum_{k=1}^{\infty} 2^k \cdot \frac{1}{2^k} = \infty$$

$$\left[S_n = \sum_{k=1}^n 2^k \cdot \frac{1}{2^k} = \sum_{k=1}^n 1 = n \right]$$

$\Rightarrow S_n \rightarrow \infty$ as $n \rightarrow \infty$

X has infinite Expectation.

Example 4.1.5

$$\text{Range}(X) = \{-2, 4, -8, 16, \dots\}$$

$$P(X = (-2)^k) = \frac{1}{2^k} \quad k \geq 1$$

$$E[X] = \sum_{t \in T} t P(X=t) = \sum_{k=1}^{\infty} (-2)^k \frac{1}{2^k}$$

$$\left[S_n = \sum_{k=1}^n (-2)^k \frac{1}{2^k} = \sum_{k=1}^n (-1)^k = \begin{cases} -1 & n \text{ odd} \\ 0 & n \text{ even} \end{cases} \Rightarrow S_n \text{ -diverges} \right]$$

[not to $\pm \infty$]

$E[X]$ is not defined.

Lemma 4.1.6 : let $X: S \rightarrow T$ be a discrete random variable.
 $E[X]$ is a real number if and only if $\underbrace{E[|X|]} < \infty$.
($Y = |X|$, $E[Y]$)

Proof to be done soon

Explanation / Significance : $X: S \rightarrow T$ is a random variable

Suppose $E[X] = \sum_{t \in T} t P(X=t) = a \quad (a \in \mathbb{R})$

What does it tell you about X ?

Proof of lemma 4.1.6 :

$$\text{Range}(X) = T$$

$$\text{Range}(|X|) = \{|t| : t \in T\} = U$$

$$E[|X|] = \sum_{u \in U} u \mathbb{P}(|X| = u)$$

} By definition

$$E[X] = \sum_{t \in T} t \mathbb{P}(X = t)$$

[as $u \in U$ came from some $t \in T$
 $\Rightarrow \hat{T}$ contains T]

$$\bullet \hat{T} = \{t \in \mathbb{R} \mid |t| \in U\}$$

$$t \in \hat{T} \text{ and } t \notin T \Rightarrow t \equiv \text{is not in Range}(X) \\ \Rightarrow \mathbb{P}(X = t) = 0.$$

$$E[X] = \sum_{t \in \hat{T}} t \mathbb{P}(X = t) \quad - \textcircled{x}$$

$$\bullet \underline{u \in U} \quad (|X| = u) = (X = u) \cup (X = -u) \quad \begin{array}{l} \text{observe:} \\ [u \in \hat{T} \text{ and } -u \in \hat{T}] \end{array}$$

$$u \cdot \mathbb{P}(|X| = u) = u [\mathbb{P}(X = u) + \mathbb{P}(X = -u)]$$

$$= u \mathbb{P}(X = u) + u \mathbb{P}(X = -u) \quad - \textcircled{xx}$$

[True even if]
 $u = 0$

$$= |u| \mathbb{P}(X = u) + (-u) \mathbb{P}(X = -u)$$

$$\sum_{u \in U} u \cdot \mathbb{P}(|X|=u) \stackrel{\textcircled{xx}}{=} \sum_{u \in U} |u| \mathbb{P}(X=u) + | -u | \mathbb{P}(X=-u)$$

$$= \sum_{t \in T} |t| \mathbb{P}(X=t)$$

$$\stackrel{\textcircled{x}}{=} \sum_{t \in T} |t| \mathbb{P}(X=t)$$

xxx

$$E[X] < \infty \Leftrightarrow \sum_{t \in T} t \mathbb{P}(X=t) \text{ converges absolutely}$$

$$\Leftrightarrow \sum_{t \in T} |t| \mathbb{P}(X=t) < \infty$$

$$\stackrel{\textcircled{xxx}}{\Leftrightarrow} \sum_{u \in U} u \mathbb{P}(|X|=u) < \infty$$

$$\Leftrightarrow E|X| < \infty$$

□

Theorem 4.1.7 : Suppose X and Y are discrete random variables, both with finite expected value and defined on sample space S . let $a, b \in \mathbb{R}$.

$$\textcircled{1} \quad E[ax] \stackrel{(*)}{=} a E[X]$$

$$\textcircled{3} \quad X \geq 0 \text{ then } E[X] \geq 0$$

$$\textcircled{2} \quad E[X+Y] \stackrel{(*)}{=} E[X] + E[Y]$$

(*) both sides are well defined

Proof:- (1) To show $E[ax] = a E[x]$

$E[x] < \infty$ by assumption.

$\cdot \underline{a=0} \Rightarrow ax = 0$

$$\Rightarrow E[0] = 0$$

$$\Rightarrow E[ax] = 0 = 0 \cdot E[x] = a E[x]$$

$\cdot \underline{a \neq 0}$

$$X: S \rightarrow U$$

$$U = \text{Range}(X)$$

$$Y = aX \quad Y: S \rightarrow T$$

$$T = \{au \mid u \in \text{Range}(X)\}$$

$$E[ax] := E[Y] := \sum_{t \in T} t P(Y=t) = \sum_{u \in U} au P(Y=au)$$

$$= \sum_{u \in U} au P(aX=au)$$

$$= a \sum_{u \in U} u P(X=u) = a E[X]$$

(2) To show $E[X+Y] = E[X] + E[Y]$

$$\left[Z = X+Y, \quad E[X+Y] = E[Z] = \sum_{z \in \text{Range}(Z)} z P(Z=z) \right]$$

$$\text{let } Z = X+Y \quad \text{Range}(Z) = \{u+v \mid u \in \text{Range}(X), v \in \text{Range}(Y)\}$$

$$\therefore E[X+Y] = E[Z] = \sum_{z \in \text{Range}(Z)} z P(Z=z)$$

$$= \sum_{\substack{u \in \text{Range}(X) \\ v \in \text{Range}(Y)}} (u+v) \mathbb{P}(X=u, Y=v)$$

Rearrangement
is okay
as
series converges
absolutely

$$= \sum_{u \in \text{Range}(X)} \sum_{v \in \text{Range}(Y)} (u+v) \mathbb{P}(X=u, Y=v)$$

$$= \sum_{u \in \text{Range}(X)} u \sum_{v \in \text{Range}(Y)} \mathbb{P}(X=u, Y=v) \\ + \sum_{v \in \text{Range}(Y)} v \sum_{u \in \text{Range}(X)} \mathbb{P}(X=u, Y=v)$$

$$\Rightarrow = \sum_{u \in \text{Range}(X)} u \mathbb{P}(X=u) + \sum_{v \in \text{Range}(Y)} v \mathbb{P}(Y=v)$$

$$\left[\Rightarrow (X=u) = \bigcup_{v \in \text{Range}(Y)} (X=u, Y=v) \text{ and } (Y=v) = \bigcup_{u \in \text{Range}(X)} (X=u, Y=v) \right]$$

$$= \mathbb{E}[X] + \mathbb{E}[Y] \quad \text{Q.E.D.}$$