

- Recall:  $X$  is a Discrete Random variable
- $[T \subseteq \mathbb{R}] \quad X: S \rightarrow T \quad S$ -Countable
- $f_X(t) = P(X=t), \forall t \in T$
- $E[X] = \sum_{t \in T} t P(X=t) = \sum_{t \in T} t f_X(t)$
- $|T| < \infty \quad |T| = \infty$   $\downarrow$  absolutely convergence required for  $E[X] \in \mathbb{R}$
- $E[aX+bY] = \underbrace{aE[X]}_{<\infty} + bE[Y] \quad a, b \in \mathbb{R}$
  - $X \geq 0 \Rightarrow E[X] \geq 0$

Example 4.1.13:  $X \sim \text{Bernoulli}(p) \quad 0 < p < 1$

$P(X=1) = p \quad & P(X=0) = 1-p \quad T = \{0, 1\}$

$$\begin{aligned} E[X] &= 0 \cdot P(X=0) + 1 \cdot P(X=1) \\ &= 0 \cdot (1-p) + 1 \cdot p = p \end{aligned}$$

[ $X$  - need not assume the value  $E[X]$  with positive Probabilities]

Example 4.1.14:  $X \sim \text{Binomial}(n, p)$

$T = \{k : 0 \leq k \leq n\}$

$E[X] = \sum_{k=0}^n k P(X=k) = \sum_{k=0}^n k \binom{n}{k} p^k (1-p)^{n-k}$

$\stackrel{\text{Ex}}{=} np \quad [\text{induction}]$

$[X_1 \sim \text{Bernoulli}(p), X_2 \sim \text{Bernoulli}(p) \text{ independent}$

$\Rightarrow X = X_1 + X_2 \sim \text{Binomial}(2, p)$

$E[X] = E[X_1] + E[X_2] = p + p = 2p$

$X \sim \text{Binomial}(n, p) \text{ Then } X = X_1 + \dots + X_n \quad X_i \sim \text{Bernoulli}(p)$

$E[X] = \sum_{i=1}^n E[X_i] = np$

Example 4.1.15  $X \sim \text{Geometric}(p)$   $0 < p < 1$

$$T = \mathbb{N} \quad P(X=k) = (1-p)^{k-1} p \quad k \in \mathbb{T}$$

$$E[X] = \sum_{k=1}^{\infty} k P(X=k) \quad [T_n \geq 0]$$

$$T_n = \sum_{k=1}^n k P(X=k) = \sum_{k=1}^n k \frac{p(1-p)^{k-1}}{(1-(1-p))} = \frac{1-(1-p)^n - n(1-p)^n}{p}$$

[Analysis I :-  $\lim_{n \rightarrow \infty} b^n = 0$  ]  $\Rightarrow$   $\lim_{n \rightarrow \infty} n b^n = 0$  ]

$$\therefore T_n \rightarrow \frac{1}{p} \quad \text{as } n \rightarrow \infty.$$

$$\therefore E[X] = \frac{1}{p} \quad \square$$

4.14  $Y = f(x)$ ,  $E[X] < \infty$  What is  $E[Y] = ?$

Example 4.1.18 :-  $X \sim \text{Uniform}(\{-2, -1, 0, 1, 2\})$

$$P(X=k) = \frac{1}{5} \quad k \in \{-2, -1, 0, 1, 2\}$$

$$f: \mathbb{R} \rightarrow \mathbb{R}$$
  
$$f(x) = x^2$$

$$Y = f[X]$$

Method I :-

$$\begin{aligned} & \bullet Y = X^2 \quad \bullet P(Y=2) = \frac{1}{5} \quad \in P(Y=4) = \frac{2}{5} \\ & \bullet P(Y=1) = \frac{2}{5} \\ & \bullet E[X] = -2 \cdot \frac{-2 + -1 + 0 + 1 + 2}{5} = 0 \quad [\text{not necessary}] \\ & \bullet E[Y] = 0 \cdot \frac{1}{5} + 1 \cdot \frac{2}{5} + 4 \cdot \frac{2}{5} = 2 \end{aligned}$$

Distribution of  $Y$   
 $\downarrow$   
 $E[Y]$

$$Y = f(X) \quad X \sim \text{Uniform} \{-2, -1, 0, 1, 2\} \quad f(x) = x^2$$

Method 2

$$(f(x)=4) = (x=2 \cup x=-2)$$

$$\begin{aligned} \bullet 4 \cdot P(f(x)=4) &= 4[P(x=2) + P(x=-2)] \\ &= 2^2 P(x=2) + (-2)^2 P(x=-2) \\ &= f(2) P(x=2) + f(-2) P(x=-2) \\ \bullet 0 \cdot P(f(x)=0) &= 0 \cdot P(x=0) = f(0) P(x=0) \\ \bullet 1 \cdot P(f(x)=1) &= f(-1) P(x=-1) + f(1) P(x=1) \\ E[Y] = E[f(X)] &= 4 \cdot P(f(x)=4) + 0 \cdot P(f(x)=0) + 1 \cdot P(f(x)=1) \\ &= \sum_{k=-2}^{2} f(k) P(x=k) \end{aligned}$$

This leads to a result -

Theorem 4.1.19 Let  $X: S \rightarrow T$  be a discrete random variable.  
 $f: T \rightarrow U$  Then the expected value of  $Y = f(X)$

may be computed as

$$E[f(x)] = \sum_{t \in T} f(t) P(x=t) - \textcircled{x}$$

[ we say  $Y$  has finite expectation if  $\textcircled{x}$  converges  
 absolutely &  $\exists$  infinite & not defined as above ]

Generalisation :-  $X, Y$  are two random variables with joint  
Discrete p.m.f  $p(x, y)$

$$g: \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$$

$$E[g(X, Y)] = \sum_{\substack{x \in \text{Range}(X) \\ y \in \text{Range}(Y)}} g(x, y) p(x, y)$$

Recall:  
 $Z = X + Y$   
 $E[Z] = E[X] + E[Y]$

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## Chapter 6 Expectation of Continuous random variables

6.1:  $X: S \rightarrow \mathbb{R}$  is a continuous random variable

$$A \in \mathcal{F} \quad P(X \in A) = \int_A f_X(x) dx$$

where  $f_X(\cdot)$  ~ p.d.f of  $X$

$$[f_X: \mathbb{R} \rightarrow (0, \infty), \text{ p.c. } \in \int_{-\infty}^{\infty} f_X(x) dx = 1]$$

Definition 6.1.1: Let  $X$  be a continuous random variable with piecewise continuous p.d.f  $f_X(\cdot)$ , then expected value of  $X$  is given by:

$$E[X] = \int_{-\infty}^{\infty} x f_X(x) dx$$

- provided the integral converges absolutely, i.e. such a

$$(i.e. \lim_{m, n \rightarrow \infty} \int_{-n}^m |x| f_X(x) dx < \infty)$$

can we say that  $X$  has finite expectation and if integral diverges to  $\pm \infty$  then we say  $X$  has infinite expectation. If the integral diverges to a number which is not  $\pm \infty$  then expectation does not exist.

### Example 6.1.2

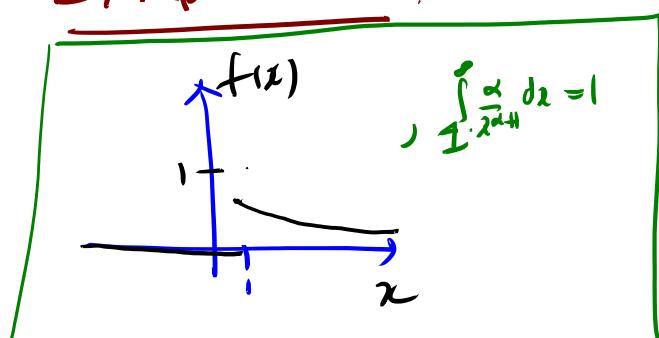
$X \sim \text{Uniform}(a, b)$ ,  $-\infty < a < b < \infty$ .

$$f_X(x) = \begin{cases} \frac{1}{b-a} & x \in (a, b) \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} E[X] &= \int_{-\infty}^{\infty} x f_X(x) dx = \int_a^b x f_X(x) dx \\ &= \int_a^b x \frac{1}{b-a} dx \\ &= \frac{1}{b-a} \left[ \frac{x^2}{2} \right]_a^b = \frac{b^2 - a^2}{2(b-a)} \\ &= \frac{a+b}{2} \end{aligned}$$

### Example 6.1.3

$0 < \alpha < 1$



$X \sim \text{Pareto}(\alpha)$

$$f_X(x) = \begin{cases} \frac{\alpha}{x^{\alpha+1}} & 1 < x < \infty \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} E[X] &= \int_{-\infty}^{\infty} x f_X(x) dx = \int_1^{\infty} x \cdot \frac{\alpha}{x^{\alpha+1}} dx \\ &= \lim_{m \rightarrow \infty} \int_1^m x \cdot \frac{\alpha}{x^{\alpha+1}} dx \end{aligned}$$

$$M > 1 \quad \int_1^M x^{-\alpha} dx = \alpha \frac{\bar{x}^{-\alpha+1}}{-\alpha+1} \Big|_1^M = \frac{\alpha}{1-\alpha} M^{1-\alpha} - \frac{\alpha}{1-\alpha}$$

$$0 < \alpha < 1 \Rightarrow \underline{1-\alpha} > 0 \therefore \left[ \text{Analogous } m \rightarrow \infty \Rightarrow M^{1-\alpha} \rightarrow \infty \right]$$

$$\therefore \int_{-\infty}^{\infty} x f_X(x) dx = \infty$$

$\therefore X$  has infinite expectation.  $\square$

### Theorem 6.1.5

$X$  be a continuous random variable with p.d.f  $f_X: \mathbb{R} \rightarrow (0, \infty)$

let  $g: \mathbb{R} \rightarrow \mathbb{R}$  piecewise continuous;  $y = g(x)$  Then expected

value of  $y$  is given by

$$E[y] = \int_{-\infty}^{\infty} g(x) f_X(x) dx.$$

as before  $E[y] \Leftarrow$  if the integral converges absolutely.

Proof: [omit from syllabus]  $\square$

Example 6.1-b: ①  $T \sim \text{Exponential}(1/5)$   $f_T(t) = \begin{cases} \frac{1}{5} e^{-\frac{1}{5}t} & t \geq 0 \\ 0 & \text{otherwise} \end{cases}$

$$E[T] = \int_0^\infty t f_T(t) dt$$

$$= \int_0^\infty t \frac{1}{5} e^{-\frac{1}{5}t} dt = \lim_{N \rightarrow \infty} \int_0^N t \frac{1}{5} e^{-\frac{1}{5}t} dt$$

$$\begin{aligned} \int_0^N t \frac{1}{5} e^{-\frac{1}{5}t} dt &= \int_0^N t d(-e^{-\frac{1}{5}t}) = t(-e^{-\frac{1}{5}t}) \Big|_0^N + \int_0^N (-e^{-\frac{1}{5}t}) dt \\ &= -N e^{-\frac{1}{5}N} + \left( -\frac{1}{5} e^{-\frac{1}{5}t} \right) \Big|_0^N \end{aligned}$$

$$\begin{aligned} &= -N e^{-\frac{1}{5}N} + 5 - 5 e^{-\frac{1}{5}N} \\ &\xrightarrow[N \rightarrow \infty]{} 0 + -(-0) \end{aligned}$$

Analysis

$\therefore T \sim \text{Exp}(1/5) \therefore E[T] = 5$ .

②  $g: \mathbb{R} \rightarrow \mathbb{R}$   $g(t) = \max\{0, 1000 - 200t\}$

$$Y = g(T)$$

$$E[Y] = \int_0^\infty g(t) f_T(t) dt$$

$$= \int_0^\infty \max\{0, 1000 - 200t\} \frac{1}{5} e^{-\frac{1}{5}t} dt$$

$$\boxed{1000 - 200t \geq 0 \quad (\Rightarrow t \leq 5)} \quad = \int_0^5 (1000 - 200t) \frac{1}{5} e^{-\frac{1}{5}t} dt$$

$$\begin{aligned}
 &= 200 \int_0^5 e^{-1/5t} dt - 200 \int_0^5 t e^{-1/5t} dt \\
 &= 200 \left( (-5) e^{-1/5t} \Big|_0^5 \right) - 200 \left[ t(-e^{-1/5t}) \Big|_0^5 + \int_0^5 e^{-1/5t} dt \right] \\
 &= 1000 - 1000 \bar{e}^1 - 200 \left[ -5\bar{e}^1 + (-5) \bar{e}^{-1/5t} \Big|_0^5 \right] \\
 &= \cancel{1000} - \cancel{1000\bar{e}^1} + \cancel{1000\bar{e}^1} + 1000 \left[ \bar{e}^1 - 1 \right] \\
 &= 1000 \bar{e}^1. \quad \square
 \end{aligned}$$

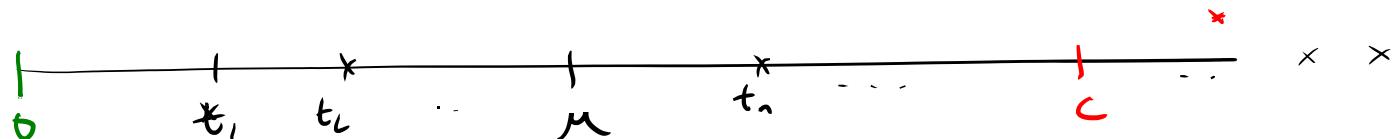
- Model for an insurance.  $\$ = \text{payment}$

Markov's Inequality:

$X$  is a <sup>non-negative</sup>  $\wedge$  discrete random variable

$$X: S \rightarrow T \quad f_X(t) = \Phi(x=t) \quad t \in T$$

$$E[X] = \mu$$



$P(X \geq c) = ?$  give bound on the probability

$$\mu = \sum_{t \in T} t \Phi(x=t)$$

$$Ex = \sum_{\substack{t \in T \\ t < c}} t \cdot P(x=t) + \sum_{\substack{t \in T \\ t \geq c}} t \cdot P(x=t)$$

$t \in T : t < c$   
 $t \cdot P(x=t) \geq 0$

$$\mu \geq 0 + \sum_{\substack{t \in T \\ t \geq c}} t \cdot P(x=t)$$

$c \geq \sum_{\substack{t \in T \\ t \geq c}} t \cdot P(x=t)$

$$ie \quad \mu \geq c \quad P(x \geq c)$$

$x \geq 0$ , discrete r.v. then  $c > 0$

 $P(x \geq c) \leq \frac{\mu}{c}$

Work with integrals:  $x$  is continuous random variable w.t.p.d.f  
 $f_x: \mathbb{R} \rightarrow \mathbb{R}$  s.t.  $f_x(x) \geq 0 \forall x \geq 0$

then

$$\text{if } \mu = E(x) \Rightarrow P(x \geq c) \leq \frac{\mu}{c}$$