

# STAT 330: Lecture 3

2024 Spring

May 16, 2024

## Review of the Last Lecture

1. Discrete Random Variables
  - Definition
  - Pmf
  - Support
  - Properties
  - Commonly used discrete random variables.
2. Continuous Random Variables
  - Definition
  - Pdf
  - Support
  - Properties

## Overview of This Lecture

1. Gamma Function
2. Some common continuous random variables
3. Expectation, Variance, Moment

## 1 Gamma Function

- Notation:  $\Gamma(\alpha)$ ,  $\alpha > 0$

- Definition:

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy$$

- Properties:

$$\textcircled{1} \quad \Gamma(1) = \int_0^\infty y^0 e^{-y} dy = \int_0^\infty e^{-y} dy = -\{e^{-y}\Big|_0^{+\infty}\} = -(0-1) = 1$$

$$\textcircled{2} \quad \underline{\Gamma(\alpha) = (\alpha-1) \cdot \Gamma(\alpha-1)} \quad [\text{Integration by part}]$$

$$\Gamma(\alpha-1) = \int_0^\infty y^{\alpha-2} e^{-y} dy = \frac{1}{\alpha-1} \{ y^{\alpha-1} e^{-y} \Big|_0^{+\infty} + \int_0^{+\infty} y^{\alpha-1} e^{-y} dy \} = \frac{1}{\alpha-1} \cdot \Gamma(\alpha)$$

$$\textcircled{3} \quad n \in \mathbb{Z}^+, \quad \Gamma(n) = (n-1)! \quad [\text{using } \textcircled{1} \& \textcircled{2}]$$

$$\textcircled{4} \quad \Gamma(\frac{1}{2}) = \sqrt{\pi}$$

## 2 Some Continuous Random Variables

### 2.1 Gamma Distribution

Notation  $X \sim \text{Gam}(\alpha, \beta)$  and  $\alpha > 0, \beta > 0$ .

Support  $(0, +\infty)$

pdf  $f(x) = \frac{x^{\alpha-1} e^{-x/\beta}}{T(\alpha) \beta^\alpha}, x > 0.$

$\int_{-\infty}^{+\infty} f(x) dx = \int_0^{+\infty} \frac{x^{\alpha-1} e^{-x/\beta}}{T(\alpha) \beta^\alpha} dx.$  change variable.

$y = \frac{x}{\beta} \Rightarrow x = \beta y$   
 $\Rightarrow dx = \beta dy$

 $= \left\{ \int_0^{+\infty} y^{\alpha-1} e^{-y} dy \right\} / T(\alpha) = 1$

## 2.2 Weibull Distribution

Notation  $X \sim \text{Wei}(\theta, \beta)$ ,  $\theta, \beta > 0$

Support  $(0, +\infty)$

$$\text{pdf } f(x) = \frac{\beta}{\theta^\beta} x^{\beta-1} e^{-\left(\frac{x}{\theta}\right)^\beta}, x > 0$$

$$\int_{-\infty}^{+\infty} f(x) dx = \int_0^{+\infty} \frac{\beta}{\theta^\beta} x^{\beta-1} e^{-\left(\frac{x}{\theta}\right)^\beta} dx$$

$$= \int_0^{+\infty} e^{-y} dy = T(1) = 1$$

change variable.  
 $y = \left(\frac{x}{\theta}\right)^\beta$   
 $x = \theta y^{\frac{1}{\beta}}$   
 $dx = \theta y^{\frac{1}{\beta}-1} \cdot \frac{1}{\beta} dy$

## 2.3 Normal Distribution

Notation  $X \sim \text{Norm}(\mu, \sigma^2)$ ,  $\mu \in \mathbb{R}$ ,  $\sigma^2 > 0$

Support  $A = \mathbb{R}$ .

$$\text{pdf } f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\}, -\infty < x < \infty$$

① Special case.  $\mu=0, \sigma^2=1$ . Standard normal distribution.

$$\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{x^2}{2}\right\} dx = \int_0^{+\infty} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{x^2}{2}\right\} dx$$

symmetric around 0

$$\text{change variable. } t = \frac{x}{\sqrt{2}} \Rightarrow x = \sqrt{2}t, dx = \sqrt{2} dt$$

$$= \frac{1}{\sqrt{\pi}} \int_0^{+\infty} t^{-\frac{1}{2}} e^{-t} dt = 1$$

$$= T\left(\frac{1}{2}\right) = \sqrt{\pi}$$

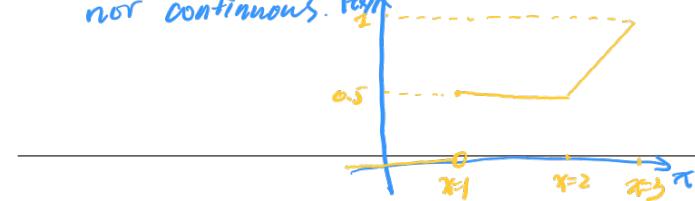
② general case.  $\mu, \sigma^2$ .

$$\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} dx$$

$$= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{t^2}{2}\right\} dt = 1$$

Change variable  
 $t = \frac{x-\mu}{\sigma}$   
 $\begin{cases} x = \mu + \sigma t \\ dx = \sigma dt \end{cases}$

\* discrete vs. continuous is NOT a dichotomy. There are r.v.s neither discrete nor continuous.



Chapter 1

### 3 Expectation (Mean)

Definition

Discrete: Suppose  $X$  is a discrete r.v. with support  $A$   
pmf:  $f(x)$ . Then.

The Expectation is defined as.

$$E(X) = \sum_{x \in A} x f(x), \text{ if } \sum_{x \in A} |x| f(x) < \infty$$

Continuous: Suppose  $X$  is a continuous r.v.  
pdf:  $f(x)$ . Then.

$$E(X) = \int_{-\infty}^{\infty} x f(x) dx, \text{ if } \int_{-\infty}^{\infty} |x| f(x) dx < \infty$$

If  $\sum_{x \in A} |x| f(x) = \infty$  or  $\int_{-\infty}^{\infty} |x| f(x) dx = \infty$

Then expectation does not exist.

Examples

Discrete. pmf.  $f(x) = \frac{1}{x(x+1)}$ ,  $A = \{1, 2, \dots\}$ .

$$\sum_{x \in A} f(x) = \sum_{x=1}^{\infty} \left( \frac{1}{x} - \frac{1}{x+1} \right) = 1 - \frac{1}{2} + \frac{1}{2} - \frac{1}{3} + \frac{1}{3} - \frac{1}{4} + \dots$$

$$\sum_{x \in A} |x| f(x) = \sum_{x=1}^{\infty} \frac{x}{x(x+1)} = \sum_{i=1}^{\infty} \frac{1}{i+1} = \infty$$

Expectation does NOT exist.

Continuous. Cauchy distribution.

pdf:  $f(x) = \frac{1}{\pi} \cdot \frac{1}{1+x^2}$ ,  $x \in \mathbb{R}$ .

$$E(X) = \int_{-\infty}^{\infty} \frac{1}{\pi} \cdot \frac{x}{1+x^2} dx = 0$$

$$\int_{-\infty}^{\infty} |x| \frac{1}{\pi} \cdot \frac{1}{1+x^2} dx = 2 \int_0^{\infty} \frac{x}{\pi} \cdot \frac{1}{1+x^2} dx = \frac{2}{\pi} \cdot \log(1+x^2) \Big|_0^{+\infty} = \infty$$

Even though we can compute "E(X)"

$E(X)$  does NOT exist.

## Examples

 $X \sim \text{Beta}(n, p)$ 

$$E(X) = 1 \cdot p + 0 \cdot (1-p) = p$$

 $X \sim \text{Bin}(n, p)$ 

$$E(X) = \sum_{i=0}^n \binom{n}{i} \cdot p^i \cdot (1-p)^{n-i} \cdot i \quad (\text{too complicated})$$

$$X = \sum_{i=1}^n X_i, \quad E(X) = E\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n E(X_i) = np$$

X: pdf  $f(x) = \frac{\theta}{x^{\theta+1}}, \quad x > 1 \quad \& \quad \theta > 0.$ 

$$\int_{-\infty}^{+\infty} |x| f(x) dx = \theta \int_1^{+\infty} \frac{1}{x^\theta} dx$$

- ①  $\theta = 1, \infty$
- ②  $\theta < 1, \infty$
- ③  $\theta > 1, -\infty$

Expectation exists only when  $\theta > 1$

$$E(X) = \int_{-\infty}^{\infty} x f(x) dx$$

$$= \theta \int_1^{+\infty} \frac{1}{x^{\theta+1}} dx$$

$$= \frac{\theta}{\theta+1}$$

## Expectation of a Function of Random Variable

 $X$  is pmf  $f(x)$  r.v. what is  $E[g(x)]$ Discrete:  $E[g(x)] = \sum_{x \in A} g(x)f(x) \quad \text{if} \quad \sum_{x \in A} |g(x)|f(x) < \infty$ Continuous:  $E[g(x)] = \int_{-\infty}^{\infty} g(x)f(x)dx \quad \text{if} \quad \int_{-\infty}^{\infty} |g(x)|f(x)dx < \infty$ 

Linearity You can exchange the order of Expectation &amp; Summation.

$$\begin{aligned} E[a g(x) + b h(x)] &= E[a g(x)] + E[b h(x)] \\ &= a E[g(x)] + b E[h(x)] \end{aligned}$$

Variance Def:  $\text{Var}(X) = E[(X - \mu)^2]$ , where  $\mu = E(X)$

$$\begin{aligned} &= E[X^2 - 2\mu X + \mu^2] \\ &= E(X^2) - E(2\mu X) + \mu^2 \\ &= E(X^2) - 2\mu E(X) + \mu^2 \\ &= E(X^2) - \mu^2 \end{aligned}$$

When  $X$  has  $\mu=0$ ,  $\text{Var}(X) = E(X^2)$

Moments  $K \in \{1, 2, \dots\}$

① Default:  $\approx$   $k$ th moment of  $X$   $E(X^k)$

② Central moment:  $k$ th central moment of  $X$ .  $E\{(X-\mu)^k\}$   
variance is 2nd central moment.

③  $k$ th factorial moment.  $\underline{\mu = E(X)}$    
First moment.

$$E\{X\}_k = E\{X(X-1) \dots (X-k+1)\}$$

useful for finding the mean & variance of

Examples

$$X \sim \text{Poi}(\theta), f(x) = \frac{\theta^x}{x!} e^{-\theta}, x \in \{0, 1, \dots\}$$

$$E\{X\}_k = \sum_{x=0}^{\infty} x(x-1) \dots (x-k+1) \frac{\theta^x}{x!} e^{-\theta}$$

$$= \sum_{x=k}^{\infty} x(x-1) \dots (x-k+1) \frac{\theta^x}{x!} e^{-\theta}$$

$$= \sum_{x=k}^{\infty} \frac{x(x+1) \dots (x+k-1)}{x(x+1) \dots (x+k-1)(x-k)!} \cdot \theta^x e^{-\theta}$$

$$= \sum_{x=k}^{\infty} \frac{1}{(x-k)!} \cdot \theta^x e^{-\theta} \quad n=x-k \Rightarrow x=n+k$$

$$= \sum_{n=0}^{\infty} \frac{1}{n!} \cdot \theta^{n+k} e^{-\theta}$$

$$= \theta^k \sum_{n=0}^{\infty} \frac{1}{n!} \theta^n e^{-\theta} = \theta^k$$

$$\left. \begin{array}{l} k=1, E\{X\}_1 \end{array} \right\} = E(X) = \theta^1 = \theta$$

$$\left. \begin{array}{l} k=2, E\{X\}_2 \end{array} \right\} = E\{X(X-1)\} \\ = E(X^2) - E(X) = \theta^2$$

$$\hookrightarrow E(X^2) = \theta^2 + \theta$$

$$\text{Var}(X) = E(X^2) - [E(X)]^2 = \theta^2 + \theta - \theta^2 = \theta$$

For Poisson.  $\text{Var}(X) = E(X) = \theta$