1. A Brief Summary of Expectation

For a random variable X,

$$H[X] \stackrel{\text{def}}{=} \left\{ \begin{array}{l} \sum_{k \in S_k} k P(X=k) \\ \sum_{k \in S_k} x f(x) dx \end{array} \right. \times : \text{ discrete}$$

$$P.D.F$$

E[X]: the expected value X.

Move generally, let  $g: \mathbb{R} \to \mathbb{R}$ , then g(X) is also a R.V.

with 
$$\mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(x) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(x) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}(X=k) \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g(k) \, \mathbb{P}[g(X)] \right\} \times \mathbb{E}[g(X)] \stackrel{\text{def}}{=} \left\{ \sum_{k \in S_X} g$$

Moreover, 
$$Var(X) \stackrel{\text{def}}{=} \mathbb{E}[(X - \mathbb{E}[X])^2]$$

$$= \mathbb{E}[X^2] - (\mathbb{E}[X])^2$$
easier way to calculate

## 2. Tutorial on Multivariate Calculus

**Problem 2.** Let (X,Y) be a random vector with joint probability density function given by

$$f_{X,Y}(x,y) = \begin{cases} ce^{-2(x+y)}, & 0 < x < y \\ 0, & \text{otherwise} \end{cases}$$

Find the value of c that makes  $f_{X,Y}$  a valid joint probability density function.

$$\mathit{Hint:}\ \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}f_{X,Y}(x,y)dxdy=1.$$

$$1 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{x,y}(x,y) dy dx$$

$$= C \int_{0}^{\infty} \int_{x}^{\infty} e^{-2x} \cdot e^{-2y} dy dx$$

$$= C \int_{0}^{\infty} e^{-2x} \cdot (-\frac{1}{2}) e^{-3y} \Big|_{y=x}^{y=\infty} dx$$

$$= \frac{c}{2} \int_{0}^{\infty} e^{-4x} dx$$

$$= \frac{c}{2} \cdot (-\frac{1}{4}) e^{-4x} \Big|_{x=y}^{x=0}$$

$$= \frac{c}{2} \cdot \frac{1}{4}$$

**Problem 3.** Let (X, Y, Z) be a random vector with joint probability density function given by

$$f_{X,Y,Z}(x,y,z) = \begin{cases} c, & 0 < x < y < z < 2 \\ 0, & \text{otherwise} \end{cases}$$

Find the value of c that makes  $f_{X,Y,Z}$  a valid joint probability density function.

Hint: 
$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y,Z}(x,y,z) dx dy dz = 1.$$

$$1 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{x,Y,2}(x,y,z) dxdydz$$

$$= \int_{0}^{2} \int_{0}^{2} \int_{0}^{y} c dxdydz$$

To see (\*):

- Take the integration of x, which satisfies 0 < x < y, so the bound for x is 0 and y.
- $\bigcirc$  take the integration of y, which satisfies 0< y<2(since never already taken the integration of x, so the bound of y is independent of x)
- 3) take the integration of  $\frac{1}{2}$ , which satisfies  $0 < \frac{1}{2} < 2$

So 
$$(*)$$

$$= \int_{0}^{2} \int_{0}^{2} cy \, dy \, dz$$

$$= \frac{c}{2} \int_{0}^{2} z^{2} \, dz$$

$$= \frac{c}{2} \cdot \frac{8}{3} = \frac{4c}{3}$$
So  $c = \frac{3}{4}$ 

## 3. Gramma Function

Gamma Function 
$$\Gamma(x) \stackrel{\text{def}}{=} \int_{0}^{\infty} x^{d-1} e^{-x} dx \quad \alpha > 0$$

Facts: 
$$D \Gamma(1) = \int_{0}^{\infty} e^{-x} dx = 1$$
 (Useful)

$$(4) \quad \alpha, \beta > 0 : \int_{0}^{\infty} \chi^{\alpha +} e^{-\beta \chi} dx = \frac{\mathcal{I}(\alpha)}{\beta^{\alpha}}$$

HW5 P4 (b): Let  $X \sim exp(1)$ ,  $Y = X^{\beta}$ , then calculate the n-th moment of Y, which is  $H[Y^{n}]$ , when  $\beta=3$ ? Soln:  $X \sim exp(1) \Rightarrow PDF f_{X}(X) = \begin{cases} e^{-X} & X>0 \\ o & o.\omega. \end{cases}$ 

$$\mathbb{E}[Y^n] = \mathbb{E}[X^{\beta n}]$$

$$= \int_0^\infty x^{\beta n} e^{-x} dx$$

$$= \int_0^\infty x^{(\beta n+1)-1} e^{-x} dx$$

$$= \Gamma(\beta n+1)$$

when  $\beta=3$ ,  $3nt1 \in \mathbb{N}$ , so by Facts  $0: \mathbb{E}[Y^n]=(3n)!$ 

## 4. Exponential Distribution

From Table of Distribution, we can see for  $X \sim \exp(\chi)$ 

$$PDF \quad f_{X}(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & o \leq \infty. \end{cases}$$

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

$$= \begin{cases} 1 - e^{-\lambda x} & x > 0 \\ 0 & x \le 0 \end{cases}$$

Mean E[X]= 1

Variance  $Var(X) = \frac{1}{\lambda^2}$ 

 $\frac{\Omega}{\Omega}$ : How to apply what you learnt from prob. class to verify  $\int_0^\infty \chi e^{-d\chi} dx = \frac{1}{d^2}$  and  $\int_0^\infty \chi^2 e^{-d\chi} dx = \frac{2}{d^3}$  without using integration by parts, for d>0?

$$A: \int_0^\infty x e^{-\alpha x} dx$$

= 
$$\frac{1}{\alpha} \int_{0}^{\infty} x \, de^{-dx} dx$$
 (\*)

Now, Define a Random variable  $Y \sim \exp(d)$ , then its density

Distribution table

and mean 
$$\mathbb{E}[Y] = \int_0^\infty y \, de^{-dy} \, dy = \frac{1}{\alpha}$$

So (x)  

$$= \frac{1}{\alpha} \int_{0}^{\infty} \chi de^{-d\chi} dx = \frac{1}{\alpha^{2}} \cdot \frac{1}{\alpha} = \frac{1}{\alpha^{2}}$$

$$\int_{0}^{\infty} x^{2} e^{-\alpha x} dx$$

$$= \frac{1}{d} \int_{0}^{\infty} x^{2} \alpha e^{-\alpha x} dx$$

$$=\frac{1}{d}\left(\frac{1}{d^2}+\frac{1}{d^2}\right)=\frac{2}{d^3}$$

We will see a lot of integration like this later in the future.