

# About our Final Exam

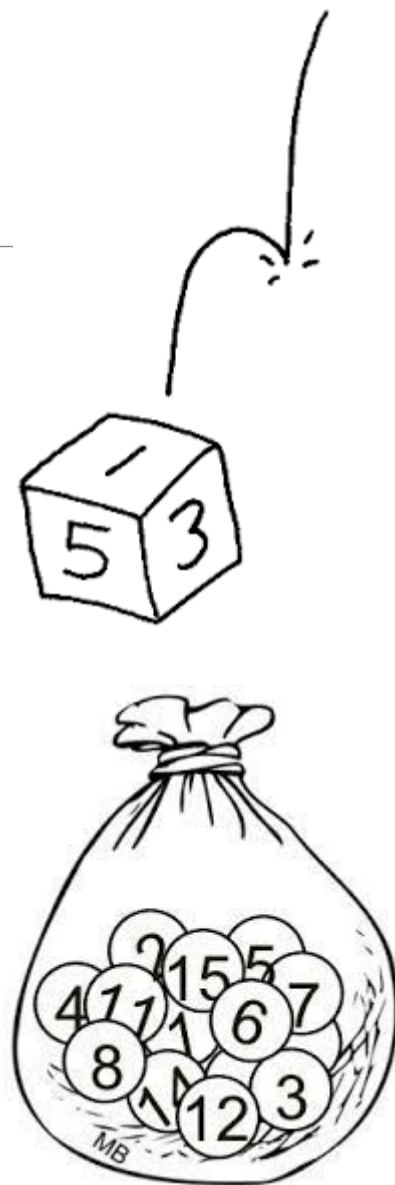
- Final exam ONLY accounts for 40% of the overall score.
- Including 7 **problem-solving** questions with sufficient **hints**.
- **Read and understand** each question carefully.
- Bring your **calculator**.



# Lecture 10

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- Joint PDF of Functions of R.V.s
- Expectation of R.V.s
- Quiz 3





What if we consider  $(Y_1, Y_2)$  instead of a single transformed variable  $Z$ ?

$$Y_1 = g_1(X_1, X_2), Y_2 = g_2(X_1, X_2)$$

# Joint PDF of functions of continuous R.V.s

$(X_1, X_2)$  are continuous R.V.s with joint PDF  $f(X_1, X_2)$ ,

Given  $Y_1 = g_1(X_1, X_2)$ ,  $Y_2 = g_2(X_1, X_2)$ .

## Conditions:

Check P224, single variable case:  $f_Y(y) = f_X[g^{-1}(y)] \left| \frac{d}{dy} g^{-1}(y) \right|$

1.  $y_1, y_2$  can be **uniquely** solved for  $x_1, x_2$ , i.e.,  $x_1 = h_1(y_1, y_2)$ ,  $x_2 = h_2(y_1, y_2)$ ;
2.  $g_1, g_2$  are **continuous** at all points  $(x_1, x_2)$ , such that

$$J(x_1, x_2) = \begin{vmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \end{vmatrix} \equiv \frac{\partial g_1}{\partial x_1} \frac{\partial g_2}{\partial x_2} - \frac{\partial g_2}{\partial x_1} \frac{\partial g_1}{\partial x_2} \neq 0$$

Joint PDF of  $(y_1, y_2)$  is given by

$$f_{Y_1, Y_2}(y_1, y_2) = f_{X_1, X_2}(x_1, x_2) |J(x_1, x_2)|^{-1},$$

$$x_1 = h_1(y_1, y_2), x_2 = h_2(y_1, y_2)$$

# Joint PDF of functions of continuous R.V.s

Single variable case (from P225 of textbook):

$$f_Y(y) = f_X[g^{-1}(y)] \left| \frac{d}{dy} g^{-1}(y) \right|$$

$\Rightarrow$

$$f_Y(y) = f_X[x] \left| \frac{dx}{dy} \right|, x = g^{-1}(y)$$

$\Rightarrow$

$$f_Y(y) = f_X[x] \left| \frac{dy}{dx} \right|^{-1}, x = g^{-1}(y)$$

Terms to terms correspondence.

Joint PDF of  $(y_1, y_2)$  (from P280 of textbook):

$$f_{Y_1, Y_2}(y_1, y_2) = f_{X_1, X_2}(x_1, x_2) |J(x_1, x_2)|^{-1},$$
$$x_1 = h_1(y_1, y_2), x_2 = h_2(y_1, y_2)$$

$$J(x_1, x_2) = \begin{vmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \end{vmatrix}$$

**Ex. 7a (P281)** Let  $X_1$  and  $X_2$  be jointly continuous random variables with probability density function  $f_{X_1, X_2}(X_1, X_2)$ . Let  $Y_1 = X_1 + X_2$ ,  $Y_2 = X_1 - X_2$ . Find the joint density function of  $Y_1$  and  $Y_2$  in terms of  $f_{X_1, X_2}(X_1, X_2)$ .

**Sol.** Let  $Y_1 = g_1(X_1, X_2) = X_1 + X_2$ ;  $Y_2 = g_2(X_1, X_2) = X_1 - X_2$ .

$$J(x_1, x_2) = \begin{vmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \end{vmatrix} = \begin{vmatrix} 1 & 1 \\ 1 & -1 \end{vmatrix} = -2$$

and  $x_1 = \frac{y_1 + y_2}{2}$ ,  $x_2 = \frac{y_1 - y_2}{2}$

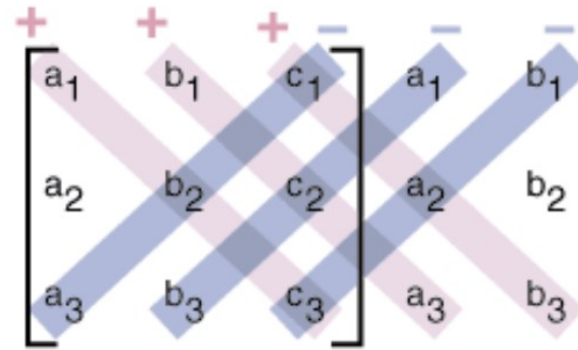
$$\begin{aligned} f_{Y_1, Y_2}(y_1, y_2) &= f_{X_1, X_2}(x_1, x_2) |J(x_1, x_2)|^{-1} \\ &= \frac{1}{2} f_{X_1, X_2} \left( \frac{y_1 + y_2}{2}, \frac{y_1 - y_2}{2} \right) \end{aligned}$$

Further readings on  $n$  random variables in Chapter 6.7.

Ex. 7d (P285) Let  $X_1, X_2$  and  $X_3$  be independent standard normal variables. If  $Y_1 = X_1 + X_2 + X_3$ ,  $Y_2 = X_1 - X_2$ , and  $Y_3 = X_1 - X_3$ , compute the joint density function of  $Y_1, Y_2, Y_3$ .

$$f_{X_1, X_2, X_3}(x_1, x_2, x_3) = \frac{1}{(2\pi)^{3/2}} e^{-\sum_{i=1}^3 x_i^2 / 2}$$

$$f_{Y_1, Y_2}(y_1, y_2) = f_{X_1, X_2}(x_1, x_2) |J(x_1, x_2)|^{-1}$$



$$\det A = (a_1 b_2 c_3 + b_1 c_2 a_3 + c_1 a_2 b_3) - (a_3 b_2 c_1 + b_3 c_2 a_1 + c_3 a_2 b_1)$$

Sol. Let  $Y_1 = X_1 + X_2 + X_3$ ,  $Y_2 = X_1 - X_2$ , and  $Y_3 = X_1 - X_3$ , the Jacobian matrix is given as

$$J(x_1, x_2, x_3) = \begin{vmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} & \frac{\partial g_1}{\partial x_3} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} & \frac{\partial g_2}{\partial x_3} \\ \frac{\partial g_3}{\partial x_1} & \frac{\partial g_3}{\partial x_2} & \frac{\partial g_3}{\partial x_3} \end{vmatrix} = \begin{vmatrix} 1 & 1 & 1 \\ 1 & -1 & 0 \\ 1 & 0 & -1 \end{vmatrix} = 3$$

and  $x_1 = \frac{y_1+y_2+y_3}{3}, x_2 = \frac{y_1-2y_2+y_3}{3}, x_3 = \frac{y_1+y_2-2y_3}{3}$

$$f_{Y_1, Y_2, Y_3}(y_1, y_2, y_3) = \frac{1}{3} f_{X_1, X_2, X_3} \left( \frac{y_1+y_2+y_3}{3}, \frac{y_1-2y_2+y_3}{3}, \frac{y_1+y_2-2y_3}{3} \right)$$

We see that

$$f_{Y_1, Y_2, Y_3}(y_1, y_2, y_3) = \frac{1}{3(2\pi)^{3/2}} e^{-Q(y_1, y_2, y_3)/2}$$

where

$$Q(y_1, y_2, y_3) = \left( \frac{y_1 + y_2 + y_3}{3} \right)^2 + \left( \frac{y_1 - 2y_2 + y_3}{3} \right)^2 + \left( \frac{y_1 + y_2 - 2y_3}{3} \right)^2$$



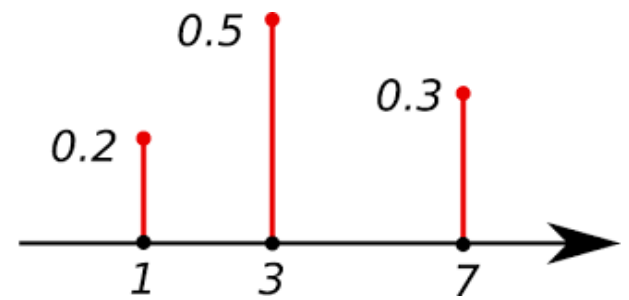
# Lecture 10

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- Joint PDF of Functions of R.V.s
- Expectation of R.V.s
- Quiz



# Discrete random variables



PMF

$$P(X = x) = p(x)$$

Experiment  
outcomes

Discrete  
Random  
Variable,  $X$

Definition

Properties

Support

Without performing the experiment:

- The support is a set of possible values our R.V. will take on.
- Next up: How do we predict the **next value**?

The “expected value”!

# Expectation of a discrete R.V.

The **expectation** of a discrete random variable  $X$  is defined as:

$$E(X) = \sum_{x:p(x)>0} x \cdot p(x)$$

- **Note:** **weighted sum** over all values of  $X = x$  that have non-zero probability.
- Other names: **mean**, expected value, weighted average, **center of mass**, first moment.

# Expectation of a die rolling



What is the expected value of a 6-sided die roll?

1. Define random variables

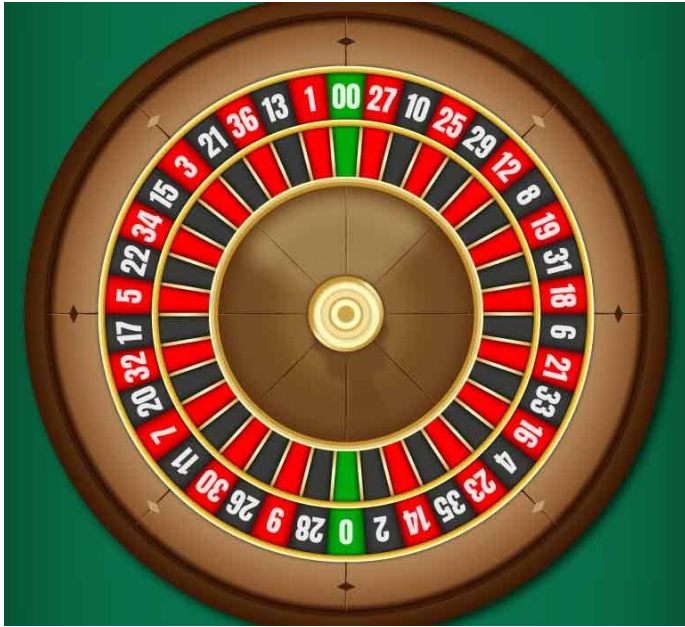
$X$  = R.V. for value of roll

2. Solve

$$P(X = x) = \begin{cases} 1/6 & x \in \{1, \dots, 6\} \\ 0 & \text{otherwise} \end{cases}$$

$$E[X] = 1 \left(\frac{1}{6}\right) + 2 \left(\frac{1}{6}\right) + 3 \left(\frac{1}{6}\right) + 4 \left(\frac{1}{6}\right) + 5 \left(\frac{1}{6}\right) + 6 \left(\frac{1}{6}\right) = 3.5$$

# Expectation of a roulette spinning



Game of Roulette: Bet 1 dollar

Win: get 35 dollars;

Lose: lose 1 dollar.

$$E(X) = 35 \cdot \frac{1}{38} - 1 \cdot \frac{37}{38} \approx -0.0526$$

What is the meaning of expected value?

It is a value that closest to the value of next occurrence.

# Expectation of a continuous R.V.

Discrete

$$E(X) = \sum_x x p(x)$$

$$f(x)\Delta_x \approx P\{x \leq X \leq x + \Delta_x\}$$



$$\Sigma \Rightarrow \int$$

Continuous

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

**Quick check**

Find  $E[X]$  when the density function of  $X$  is

$$f(x) = \begin{cases} 2x & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Sol.

$$E[X] = \int x f(x) dx = \int_0^1 2x^2 dx = \frac{2}{3}$$

Ex. Assume R.V.  $X \sim \pi(\lambda)$ , find  $E(X)$ .

Ex. Assume R.V.  $X \sim U(a, b)$ , find  $E(X)$ .

Ex. Assume R.V.  $X \sim \exp(\theta)$ , find  $E(X)$ .

Hint:  $\int e^{ax} dx = \frac{1}{a} e^{ax}$

Ex. Assume R.V.  $X \sim \pi(\lambda)$ , find  $E(X)$ .

Sol.

$$P\{X = k\} = \frac{\lambda^k e^{-\lambda}}{k!}, \quad k = 0, 1, 2, \dots$$

$$E(X) = \sum_{k=0}^{+\infty} k \cdot \frac{\lambda^k e^{-\lambda}}{k!} = \lambda e^{-\lambda} \sum_{k=1}^{+\infty} \frac{\lambda^{k-1}}{(k-1)!} = \lambda e^{-\lambda} \cdot e^{\lambda} = \lambda$$

Power series expansion

Ex. Assume R.V.  $X \sim U(a, b)$ , find  $E(X)$ .

Sol.

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

$$E(X) = \int_{-\infty}^{\infty} x f(x) dx = \int_a^b \frac{x}{b-a} dx = \frac{a+b}{2}$$



**Ex.** R.V.  $X$  follows exponential distribution

$$f(x) = \begin{cases} \frac{1}{\theta} e^{-\frac{x}{\theta}}, & x > 0 \\ 0, & x \leq 0 \end{cases} \quad (\theta > 0)$$

Find  $E(X)$ .

**Hint:**  $\int e^{ax} dx = \frac{1}{a} e^{ax}$

Sol. 
$$E(X) = \int_0^{\infty} x \cdot \frac{1}{\theta} e^{-\frac{x}{\theta}} dx$$

**Integration by part:** 
$$\int_a^b u(x)v'(x)dx = [u(x)v(x)]_a^b - \int_a^b u'(x)v(x)dx$$

$$\begin{aligned} &= \left[ -x \cdot e^{-\frac{x}{\theta}} \right]_0^{\infty} + \int_0^{\infty} e^{-\frac{x}{\theta}} dx \\ &= [0 - 0] + \left[ -\theta e^{-\frac{x}{\theta}} \right]_0^{\infty} \\ &= 0 + (0 + \theta) = \theta \end{aligned}$$

# Expectations of common distributions

Distribution	Notation	Expected Value $E(X)$
Bernoulli	$X \sim \text{Ber}(p)$	$p$
Binomial	$X \sim b(n, p)$	$np$
Poisson	$X \sim \pi(\lambda)$	$\lambda$
Uniform	$X \sim U(a, b)$	$\frac{a + b}{2}$
Exponential	$X \sim \exp(\theta)$	$\theta$
Normal	$X \sim \mathcal{N}(\mu, \sigma^2)$	$\mu$
Standard Normal	$X \sim \mathcal{N}(0, 1)$	0

Verify these results by yourselves

**Ex.** If the system  $L$  consists of 5 independent sub-systems with lifetime following PDFs

$$f(x) = \begin{cases} \frac{1}{\theta} e^{-\frac{x}{\theta}}, & x > 0 \\ 0, & x \leq 0 \end{cases} \quad (\theta > 0)$$

Find the expected system lifetime under the following connections. (1) series. (2) parallel.

$$F_{\max}(x) = [F(x)]^5$$

$$F_{\min}(x) = 1 - [1 - F(x)]^5$$

**Sol.** The CDF of  $X$  is  $F(x) = \begin{cases} 1 - e^{-\frac{x}{\theta}}, & x > 0 \\ 0, & x \leq 0 \end{cases}$

(1) Under series connection, the system lifetime  $N$  is related to  $X_1, \dots, X_5$  by  $N = \min(X_1, X_2, \dots, X_5)$ , the CDF of system lifetime is

$$F_{\min}(x) = 1 - [1 - F(x)]^5 = \begin{cases} 1 - e^{-\frac{5x}{\theta}}, & x > 0, \\ 0, & x \leq 0. \end{cases}$$

$$f_{\min}(x) = \begin{cases} \frac{5}{\theta} e^{-\frac{5x}{\theta}}, & x > 0, \\ 0, & x \leq 0. \end{cases} \quad \text{Exponential distribution}$$

$$E(N) = \int_{-\infty}^{+\infty} x f_{\min}(x) dx = \int_0^{+\infty} x \frac{5}{\theta} e^{-\frac{5x}{\theta}} dx = \frac{\theta}{5}$$

Or, identify that  $N \sim \exp\left(\frac{\theta}{5}\right) \Rightarrow E(N) = \frac{\theta}{5}$

(2) Under parallel connection, the system lifetime  $M$  is related to  $X_1, \dots, X_5$  by  $M = \max(X_1, X_2, \dots, X_5)$ , the CDF of system lifetime is

$$F_{\max}(x) = [F(x)]^5 = \begin{cases} (1 - e^{-\frac{x}{\theta}})^5, & x > 0 \\ 0, & x \leq 0 \end{cases}$$

Therefore, the PDF is

$$f_{\max}(x) = \begin{cases} \frac{5}{\theta} (1 - e^{-\frac{x}{\theta}})^4 e^{-\frac{x}{\theta}}, & x > 0 \\ 0, & x \leq 0 \end{cases}$$

$$E(M) = \int_{-\infty}^{+\infty} x f_{\max}(x) dx = \int_0^{+\infty} x \frac{5}{\theta} e^{-\frac{x}{\theta}} (1 - e^{-\frac{x}{\theta}})^4 dx = \frac{137}{60} \theta$$

# Expectations of $g(X)$

From the PMF of discrete R.V.  $X$

$Y = g(X)$	$g(x_1)$	$g(x_2)$	...	$g(x_k)$	...
$p_k$	$p_1$	$p_2$	...	$p_k$	...

$$E(Y) = E[g(X)] = \sum_{k=1}^{\infty} g(x_k) p_k$$

**Note:** We do not need  $f(y)$  to compute  $E(Y)$  !

# Expectations of $g(X)$

**Discrete** R.V.  $X$  with values  $x_i$  and PMF  $p(x_i)$ , then for any real function  $Y = g(X)$ ,

$$E[g(X)] = \sum_i g(x_i) \cdot p(x_i)$$

**Continuous** R.V.  $X$  with PDF  $f(x)$ , then for any real function  $Y = g(X)$ ,

$$E[g(X)] = \int_{-\infty}^{+\infty} g(x) \cdot f(x) dx$$

## Note:

- We do not need  $f(y)$  to compute  $E(Y)$ .
- By exploiting the **relationship** between  $X$  and  $Y$ , only  $f(x)$  is needed.

## Proof

$$f_X(x) \Rightarrow f_Y(y) \Rightarrow E(Y)$$

The PDF of  $Y = g(X)$  is

$$f_Y(y) = \begin{cases} f_X[h(y)]|h'(y)|, & \alpha < y < \beta, \\ 0, & \text{otherwise.} \end{cases}$$

$$E(Y) = \int_{-\infty}^{+\infty} y f_Y(y) dy = \int_{\alpha}^{\beta} y f_X[h(y)] |h'(y)| dy$$

$h'(y) > 0$ :

$$\begin{aligned} E(Y) &= \int_{\alpha}^{\beta} y f_X[h(y)] h'(y) dy & h'(y) &= dx/dy \\ &\xrightarrow{y=g(x)} \int_{h(\alpha)}^{h(\beta)} g(x) f_X[h(g(x))] \frac{dx}{dy} dy = \int_{-\infty}^{+\infty} g(x) f_X(x) dx \end{aligned}$$

$h'(y) < 0$ :

$$\begin{aligned} E(Y) &= - \int_{\alpha}^{\beta} y f_X[h(y)] h'(y) dy \\ &= - \int_{+\infty}^{-\infty} g(x) f_X(x) dx = \int_{-\infty}^{+\infty} g(x) f_X(x) dx \end{aligned}$$



**Ex.** The annual demand of rare earth in the international market is denoted by a random variable  $X$  (ton).  $X$  follows a uniform distribution  $X \sim U(a, b)$ . Each ton of rare earth earns  $s$  thousands yuan. However, if it is not sold and is stored in the warehouse, it costs  $l$  thousands yuan per ton. How many tons of rare earth should be prepared to maximize the expected value of the revenue?

Let  $t$  denote the amount of rare earth prepared, and  $X$  denotes the amount of rare earth sold, the revenue is:

$$Y = g(X) = \begin{cases} sX - (t - X)l, & a < X \leq t \\ st, & t < X \leq b \end{cases}$$

Sol. Let  $t$  and  $X$  denote the amount of rare earth prepared and sold, respectively, and  $t \in [a, b]$ . The revenue can be written as

$$Y = g(X) = \begin{cases} sX - (t - X)l, & a < X \leq t \\ st, & t < X \leq b \end{cases}$$

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

$$\begin{aligned} E(Y) &= E[g(X)] = \int_a^b g(x)f(x)dx \\ &= \int_a^t [sx - (t - x)l] \frac{1}{b-a} dx + \int_t^b st \frac{1}{b-a} dx \\ &= \frac{1}{2(b-a)} [-(l+s)t^2 + 2(la + sb)t - (l+s)a^2] \end{aligned}$$

Let  $\frac{d}{dt}E(Y) = 0$ , which yields

$$-(l+s)t + (la + sb) = 0, \text{ that is } t = \frac{la+sb}{l+s}$$

## Expectation of discrete RVs

$$E(X) = \sum_{k=1}^{\infty} x_k p_k$$

$$E[g(X)] = \sum_{k=1}^{\infty} g(x_k) p_k$$

$$E[g(X, Y)] = \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} g(x_i, y_j) p_{ij}$$

$$E(X) = \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} x_i p_{ij}$$

$$E(Y) = \sum_{i=1}^{\infty} \sum_{j=1}^{\infty} y_j p_{ij}$$

## Expectation of continuous RVs

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

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

$$E[g(X, Y)] = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} g(x, y) f(x, y) dx dy$$

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

$$E(Y) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} y f(x, y) dx dy$$