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قسم الاحصاء

التوزيعات الاحتمالية
Probability Distributions

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Chapter Four

1. The Mathematical Expectation

The expected value is the average value of a random variable over many repetitions of an experiment. It is a fundamental concept used to summarize the characteristics of a probability distribution.

If X is a discrete random variable with p.m.f. $p(x)$ the expected value of X , $E(x)$ is given by:

$$E(x) = \sum_{\forall x} x p(x)$$

If X is a continuous random variable with p.d.f. $f(x)$ the expected value of X , $E(x)$ is given by:

$$E(x) = \int_{\forall x} x f(x) dx$$

2. The Moments

Moments are expected values of powers of a random variable used to describe the shape and spread of a distribution. The full collection of moments includes the expected values of all positive integral powers of X .

The $r - th$ moment of a random variable X , denoted by μ_r , is given by:

1. Moments about the origin

$$\mu_r = E(x^r)$$

$$\mu_1 = E(x^1) = E(x) \quad (\text{First Moment})$$

$$\mu_2 = E(x^2) \quad (\text{Second Moment})$$

$$\mu_3 = E(x^3) \quad (\text{Third Moment})$$

⋮
⋮

For a discrete random variable:

$$\mu_r = E(x^r) = \sum_{\forall x} x^r p(x)$$

For a continuous random variable:

$$\mu_r = E(x^r) = \int_{\forall x} x^r f(x) dx$$

2. Moments about the mean (Central Moments)

$$\mu_r = E(x - \mu)^r$$

$$\mu_1 = E(x - \mu)^1 = E(x - \mu) = 0 \quad (\text{First Central Moment})$$

$$\mu_2 = E(x - \mu)^2 = \text{variance} \quad (\text{Second Central Moment})$$

$$\mu_3 = E(x - \mu)^3 \quad (\text{Third Central Moment})$$

⋮
⋮

For a discrete random variable:

$$\mu_r = E(x - \mu)^r = \sum_{\forall x} (x - \mu)^r p(x)$$

For a continuous random variable:

$$\mu_r = E(x - \mu)^r = \int_{\forall x} (x - \mu)^r f(x) dx$$

Remark: The mean and variance can be calculated using moments. The first moment gives the mean and the second moment helps to find the variance.

$$\mu_x = E(x)$$

$$\text{var}(x) = \sigma_x^2 = E(x^2) - (E(x))^2$$

Theorems:

1. If X be a random variable, $g(x)$ be any function of X then

$$E[g(x)] = \sum_{\forall x} g(x) p(x) \quad \text{if } X \text{ is discrete r. v.}$$

$$E[g(x)] = \int_{-\infty}^{\infty} g(x) f(x) dx \quad \text{if } X \text{ is continuous r. v.}$$

2. If c is constant, then $E(c) = c$
3. $E(cx) = c E(x)$
4. $E(x_1 + x_2) = E(x_1) + E(x_2)$ x_1, x_2 are tow random variables
5. $E(ax_1 + bx_2) = aE(x_1) + bE(x_2)$
6. $var(a) = 0$
7. $var(ax + b) = a^2 var(x)$

Ex.1: If X is the value shown when rolling a fair die. Find the expected value of X .

$$p(x) = \begin{cases} \frac{1}{6} & x = 1, 2, 3, 4, 5, 6 \\ 0 & o. w. \end{cases}$$

Solution:

$$E(x) = \sum_{\forall x} x p(x) = \sum_{x=1}^6 x p(x)$$

$$= (1) * p(1) + (2) * p(2) + (3) * p(3) + (4) * p(4) + (5) * p(5) + (6) * p(6)$$

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

Ex.2: Let X be the r.v. with the following p.d.f.

$$p(x) = \begin{cases} 2x & 0 < x < 1 \\ 0 & o. w. \end{cases}$$

Find the mathematical expectation of X .

Solution:

$$E(x) = \int_{\forall x} x f(x) dx = \int_0^1 x 2x dx = \int_0^1 2x^2 dx = 2 \left[\frac{x^3}{3} \right]_0^1 = 2 \left[\frac{1}{3} - \frac{0}{3} \right] = \frac{2}{3}$$

Ex.3: Let we have the following p.m.f.

x	-1	0	1	2
$p(x)$	1/8	3/8	1/4	1/4

1. Prove that $p(x)$ is a valid probability mass function
2. Compute $E(x), E(x^2), E(2x + 1), var(3x + 2)$
3. Compute the second central moment (μ_2) of the random variable X .

Solution:

$$1. \sum_{\forall x} p(x) = 1 \Rightarrow \frac{1}{8} + \frac{3}{8} + \frac{2}{8} + \frac{2}{8} = \frac{8}{8} = 1$$

$$2. E(x) = \sum_{\forall x} x p(x) = \sum_{x=-1}^2 x p(x) = (-1) * \frac{1}{8} + (0) * \frac{3}{8} + (1) * \frac{1}{4} + (2) * \frac{1}{4} = \frac{5}{8} = 0.625$$

$$E(x^2) = \sum_{\forall x} x^2 p(x) = \sum_{x=-1}^2 x^2 p(x) = (-1)^2 * \frac{1}{8} + (0)^2 * \frac{3}{8} + (1)^2 * \frac{1}{4} + (2)^2 * \frac{1}{4} = \frac{11}{8}$$

$$E(2x + 1) = 2E(x) + E(1) = 2 * \frac{5}{8} + 1 = \frac{18}{8}$$

$$var(x) = E(x^2) - (E(x))^2 = \frac{11}{8} - \left(\frac{5}{8}\right)^2 = \frac{11}{8} - \frac{25}{64} = \frac{63}{64}$$

$$var(3x + 2) = 9 var(x) + 0 = 9 var(x) = 9 * \frac{63}{64} = \frac{567}{64}$$

$$3. \mu_2 = E(x - \mu)^2 = \sum_{x=-1}^2 (x - \mu)^2 p(x)$$

$$= (-1 - 0.625)^2 * \frac{1}{8} + (0 - 0.625)^2 * \frac{3}{8} + (1 - 0.625)^2 * \frac{1}{4} + (2 - 0.625)^2 * \frac{1}{4} = 0.9845$$

Ex.4: Let we have the following p.d.f.

$$f(x) = \begin{cases} 6x(1-x) & 0 < x < 1 \\ 0 & \text{o.w.} \end{cases}$$

1. Prove that $f(x)$ is a valid probability mass function
2. Compute $E(x), E(x^2), E(5x), var(6x)$.

Solution:

$$1. \int_{\forall x} f(x) dx = 1$$

$$6 \int_0^1 (x - x^2) dx = 6 \left[\frac{x^2}{2} - \frac{x^3}{3} \right]_0^1 = 6 \left[\frac{1}{2} - \frac{1}{3} \right] = 3 - 2 = 1$$

$$2. E(x) = \int_{\forall x} x f(x) dx = 6 \int_0^1 x (x - x^2) dx = 6 \int_0^1 (x^2 - x^3) dx$$

$$= 6 \left[\frac{x^3}{3} - \frac{x^4}{4} \right]_0^1 = 6 \left[\frac{1}{3} - \frac{1}{4} \right] = 6 \left[\frac{1}{12} \right] = \frac{1}{2}$$

$$E(x^2) = \int_0^1 x^2 f(x) dx = \int_0^1 x^2 6x(1-x) dx = 6 \int_0^1 (x^3 - x^4) dx$$

$$= 6 \left[\frac{x^4}{4} - \frac{x^5}{5} \right]_0^1 = 6 \left[\frac{1}{4} - \frac{1}{5} \right] = 6 \left[\frac{1}{20} \right] = \frac{6}{20}$$

$$E(5x) = 5E(x) = 5 * \frac{1}{2} = \frac{5}{2}$$

$$var(x) = E(x^2) - (E(x))^2 = \frac{6}{20} - \left(\frac{1}{2} \right)^2 = \frac{6}{20} - \frac{1}{4} = \frac{6}{20} - \frac{5}{20} = \frac{1}{20}$$

$$var(6x) = 36 * var(x) = 36 * \frac{1}{20} = \frac{36}{20}$$

Ex.5: Find the mean and variance of a discrete uniform distribution using its moments.

Solution:

$$p(x, n) = \begin{cases} 1/n & x = 1, 2, 3, \dots, n \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} 1. \mu_x = E(x) &= \sum_{\forall x} x p(x) = \sum_{x=1}^n x \frac{1}{n} = \frac{1}{n} \sum_{x=1}^n x \\ &= \frac{1}{n} (1 + 2 + \dots + n) \end{aligned}$$

Recall that $\sum_{i=1}^n i = \frac{n(n+1)}{2}$

$$\mu_x = \frac{1}{n} (1 + 2 + \dots + n) = \frac{1}{n} * \frac{n(n+1)}{2} = \frac{(n+1)}{2}$$

$$2. \text{var}(x) = \sigma_x^2 = E(x^2) - (E(x))^2$$

$$\begin{aligned} E(x^2) &= \sum_{\forall x} x^2 p(x) = \sum_{x=1}^n x^2 \frac{1}{n} = \frac{1}{n} \sum_{x=1}^n x^2 \\ &= \frac{1}{n} (1^2 + 2^2 + \dots + n^2) \end{aligned}$$

Recall that $\sum_{i=1}^n i^2 = \frac{n(n+1)(2n+1)}{6}$

$$\begin{aligned} E(x^2) &= \frac{1}{n} (1^2 + 2^2 + \dots + n^2) = \frac{1}{n} * \frac{n(n+1)(2n+1)}{6} \\ &= \frac{(n+1)(2n+1)}{6} \end{aligned}$$

$$\text{var}(x) = \sigma_x^2 = E(x^2) - (E(x))^2$$

$$\begin{aligned} \text{var}(x) &= \frac{(n+1)(2n+1)}{6} - \left(\frac{n+1}{2}\right)^2 = \frac{(n+1)(2n+1)}{6} - \frac{(n+1)^2}{4} \\ &= \frac{2(n+1)(2n+1) - 3(n+1)^2}{12} \\ &= \frac{2[2n^2 + n + 2n + 1] - 3[n^2 + 2n + 1]}{12} \end{aligned}$$

$$\text{var}(x) = \sigma_x^2 = \frac{4n^2 + 6n + 2 - 3n^2 - 6n - 3}{12} = \frac{n^2 - 1}{12}$$

Ex.6: Find the mean and variance of a Bernoulli distribution using its moments.

Solution:

$$p(x, p) = \begin{cases} p^x (1-p)^{1-x} & x = 0, 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} 1. \mu_x = E(x) &= \sum_{\forall x} x p(x) = \sum_{x=0}^1 x p^x (1-p)^{1-x} \\ &= (0)p^0(1-p)^{1-0} + (1)p^1(1-p)^{1-1} = p \end{aligned}$$

$$2. \text{var}(x) = \sigma_x^2 = E(x^2) - (E(x))^2$$

$$\begin{aligned} E(x^2) &= \sum_{\forall x} x^2 p(x) = \sum_{x=0}^1 x^2 p^x (1-p)^{1-x} \\ &= (0)^2 p^0 (1-p)^{1-0} + (1)^2 p^1 (1-p)^{1-1} = p \end{aligned}$$

$$\begin{aligned} \text{var}(x) = \sigma_x^2 &= E(x^2) - (E(x))^2 \\ &= p - p^2 = p(1-p) = pq \end{aligned}$$

Ex.7: Find the mean and variance of a continuous uniform distribution using its moments.

Solution:

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

$$\begin{aligned} 1. \mu_x = E(x) &= \int_{\forall x} x f(x) dx = \int_a^b x \frac{1}{b-a} dx = \frac{1}{b-a} \int_a^b x dx \\ &= \frac{1}{b-a} \left[\frac{x^2}{2} \right]_a^b = \frac{1}{b-a} * \frac{b^2 - a^2}{2} = \frac{1}{b-a} * \frac{(b-a)(b+a)}{2} = \frac{a+b}{2} \end{aligned}$$

$$2. \text{var}(x) = \sigma_x^2 = E(x^2) - (E(x))^2$$

$$\begin{aligned} E(x^2) &= \int_{\forall x} x^2 f(x) dx = \int_a^b x^2 \frac{1}{b-a} dx = \frac{1}{b-a} \int_a^b x^2 dx \\ &= \frac{1}{b-a} \left[\frac{x^3}{3} \right]_a^b = \frac{1}{b-a} * \frac{b^3 - a^3}{3} = \frac{1}{b-a} * \frac{(b-a)(b^2 + ab + a^2)}{3} \\ &= \frac{a^2 + ab + b^2}{3} \end{aligned}$$

$$\text{var}(x) = \sigma_x^2 = E(x^2) - (E(x))^2$$

$$= \frac{a^2 + ab + b^2}{3} - \left(\frac{a+b}{2} \right)^2$$

$$= \frac{a^2 + ab + b^2}{3} - \frac{a^2 + 2ab + b^2}{4}$$

$$= \frac{4(a^2 + ab + b^2) - 3(a^2 + 2ab + b^2)}{12}$$

$$= \frac{4a^2 + 4ab + 4b^2 - 3a^2 - 6ab - 3b^2}{12} = \frac{a^2 - 2ab + b^2}{12} = \frac{(b-a)^2}{12}$$

Ex.8: Find the mean and variance of a exponential distribution using its moments.

Solution:

$$f(x, \theta) = \begin{cases} \theta e^{-\theta x} & x > 0 \\ 0 & \text{o.w.} \end{cases}$$

$$1. \mu_x = E(x) = \int_{\forall x} x f(x) dx = \int_0^{\infty} x \theta e^{-\theta x} dx = \theta \int_0^{\infty} x e^{-\theta x} dx$$

$$\text{But } \int_0^{\infty} x^{\alpha-1} e^{-\beta x} dx = \frac{\Gamma \alpha}{\beta^\alpha}, \alpha = 2 \quad \beta = \theta$$

$$\mu_x = E(x) = \theta * \frac{\Gamma 2}{\theta^2} = \frac{1}{\theta}$$

$$2. \text{var}(x) = \sigma_x^2 = E(x^2) - (E(x))^2$$

$$E(x^2) = \int_{\forall x} x^2 f(x) dx = \int_0^{\infty} x^2 \theta e^{-\theta x} dx = \theta \int_0^{\infty} x^2 e^{-\theta x} dx$$

$$\text{But } \int_0^{\infty} x^{\alpha-1} e^{-\beta x} dx = \frac{\Gamma \alpha}{\beta^\alpha}, \quad \alpha = 3 \quad \beta = \theta$$

$$E(x^2) = \theta * \frac{\Gamma 3}{\theta^3} = \frac{2}{\theta^2}$$

$$\text{var}(x) = \sigma_x^2 = E(x^2) - (E(x))^2 = \frac{2}{\theta^2} - \left(\frac{1}{\theta}\right)^2 = \frac{2}{\theta^2} - \frac{1}{\theta^2} = \frac{1}{\theta^2}$$

Ex.9: Let $X \sim \text{exp}(2)$. Find

$$1. \mu_x \quad 2. \sigma_x^2 \quad 3. E(3x) \quad 4. \text{var}(2x + 1)$$

Solution:

$$f(x, 2) = \begin{cases} 2 e^{-2x} & x > 0 \\ 0 & \text{o.w.} \end{cases}$$

$$1. \mu_x = E(x) = \frac{1}{\theta} = \frac{1}{2}, \quad 2. \text{var}(x) = \sigma_x^2 = \frac{1}{\theta^2} = \frac{1}{4}$$

$$3. E(3x) = 3E(x) = 3 * \frac{1}{2} = \frac{3}{2}$$

$$4. \text{var}(2x + 1) = 4 \text{var}(x) + 0 = 4 * \frac{1}{4} = 1$$

Ex.10: Let $X \sim \text{Po}(3)$. Find

$$1. \mu_x \quad 2. \sigma_x^2 \quad 3. E(2x + 1) \quad 4. \text{var}(3x + 9)$$

Solution:

$$p(x, \lambda) = \begin{cases} \frac{e^{-3} 3^x}{x!} & x = 0, 1, \dots \\ 0 & \text{otherwise} \end{cases}$$

$$1. \mu_x = E(x) = \lambda = 3 \quad 2. \text{var}(x) = \sigma_x^2 = \lambda = 3$$

$$3. E(2x + 1) = 2E(x) + 1 = 2 * 3 + 1 = 7$$

$$4. \text{var}(3x + 9) = 9 \text{var}(x) + 0 = 9 * 3 = 27$$

3. The Moment Generating Function

The moment generating function denoted by $M_x(t)$ for a random variable X is defined to be the expectation of the exponential function e^{tx} . Where t all real numbers.

$$M_x(t) = E(e^{tx}) = \sum_{\forall x} e^{tx} p(x) \quad \text{if } X \text{ is discrete random variable}$$

$$M_x(t) = E(e^{tx}) = \int_{\forall x} e^{tx} f(x) dx \quad \text{if } X \text{ is continuous random variable}$$

We call $M_x(t)$ the moment generating function because all of the moments of X can be obtained by differentiating $M_x(t)$ and then evaluating the result at $t=0$.

$$M'_x(0) = E(x) = m_1 \quad \text{1st moment}$$

$$\dot{M}_x(0) = E(x^2) = m_2 \quad \text{2nd moment}$$

$$\ddot{M}_x(0) = E(x^3) = m_3 \quad \text{3rd moment}$$

⋮

$$M_x^{(r)}(0) = E(x^r) = m_r \quad \text{rth moment}$$

Ex.11: A fair coin is flipped twice, let X be the number of heads that occur.

1. Find the MGF.
2. Find the mean and variance of X using the MGF.

Solution:

$$p(x) = \begin{cases} 1/4 & x = 0 \\ 1/2 & x = 1 \\ 1/4 & x = 2 \\ 0 & o.w. \end{cases}$$

$$\begin{aligned} 1. M_x(t) &= E(e^{tx}) = \sum_{\forall x} e^{tx} p(x) = \sum_{x=0}^2 e^{tx} p(x) \\ &= e^{t(0)} p(0) + e^{t(1)} p(1) + e^{t(2)} p(2) \end{aligned}$$

$$= e^0 * \frac{1}{4} + e^t * \frac{1}{2} + e^{2t} * \frac{1}{4}$$

$$M_x(t) = \frac{1}{4} + \frac{1}{2}e^t + \frac{1}{4}e^{2t}$$

$$2. \dot{M}_x(0) = E(x) = \mu_x$$

$$\dot{M}_x(t) = 0 + \frac{1}{2}e^t + \frac{1}{4}e^{2t}(2) = \frac{1}{2}e^t + \frac{1}{2}e^{2t}$$

$$E(x) = \mu_x = \dot{M}_x(0) = \frac{1}{2}e^0 + \frac{1}{2}e^0 = \frac{1}{2} + \frac{1}{2} = 1$$

$$var(x) = \sigma_x^2 = E(x^2) - (E(x))^2$$

$$\dot{M}_x(t) = \frac{1}{2}e^t + \frac{1}{2}e^{2t}(2) = \frac{1}{2}e^t + e^{2t}$$

$$E(x^2) = \dot{M}_x(0) = \frac{1}{2}e^0 + e^0 = \frac{1}{2} + 1 = \frac{3}{2}$$

$$var(x) = E(x^2) - (E(x))^2 = \frac{3}{2} - (1)^2 = \frac{1}{2}$$

Ex.12: Let X be a random variable with the following p.d.f.

$$f(x) = \begin{cases} 2e^{-2x} & x > 0 \\ 0 & o.w. \end{cases}$$

1. Find the m.g.f. of X .
2. Use the m.g.f. to find the mean and variance.
3. Use the m.g.f. to find 3rd moment of X .

Solution:

$$1. M_x(t) = E(e^{tx}) = \int_{\forall x} e^{tx} f(x) dx$$

$$\begin{aligned} M_x(t) &= \int_0^{\infty} e^{tx} 2e^{-2x} dx = 2 \int_0^{\infty} e^{tx} e^{-2x} dx = 2 \int_0^{\infty} e^{-2x+tx} dx \\ &= 2 \int_0^{\infty} e^{-(2-t)x} dx = \frac{-2}{(2-t)} \int_0^{\infty} -(2-t)e^{-(2-t)x} dx \end{aligned}$$

$$M_x(t) = \frac{-2}{(2-t)} [e^{-(2-t)x}]_0^\infty = \frac{-2}{(2-t)} [e^{-\infty} - e^0] = \frac{2}{(2-t)} = 2(2-t)^{-1}$$

$$2. \dot{M}_x(0) = E(x) = \mu_x$$

$$\dot{M}_x(t) = 2(-1)(2-t)^{-2}(-1) = 2(2-t)^{-2}$$

$$\dot{M}_x(0) = 2(2-0)^{-2} = \frac{2}{4} = \frac{1}{2}$$

$$\ddot{M}_x(t) = 2(-2)(2-t)^{-3}(-1) = 4(2-t)^{-3}$$

$$E(x^2) = \ddot{M}_x(0) = 4(2-0)^{-3} = \frac{4}{8} = \frac{1}{2}$$

$$\text{var}(x) = E(x^2) - (E(x))^2 = \frac{1}{2} - \left(\frac{1}{2}\right)^2 = \frac{1}{4}$$

$$3. \overset{\cdot}{\ddot{M}}_x(t) = 4(-3)(2-t)^{-4}(-1) = 12(2-t)^{-4}$$

$$\overset{\cdot}{\ddot{M}}_x(0) = E(x^3) = 12(2-0)^{-4} = \frac{12}{16} = \frac{3}{4}$$

Ex.13: Let X be a Bernoulli random variable with parameter p

1. Find the m.g.f. of X .
2. Use the m.g.f. to find the mean and variance.

Solution:

$$p(x, p) = \begin{cases} p^x (1-p)^{1-x} & x = 0, 1 \\ 0 & \text{otherwise} \end{cases}$$

$$1. M_x(t) = E(e^{tx}) = \sum_{\forall x} e^{tx} p(x) = \sum_{x=0}^1 e^{tx} p^x (1-p)^{1-x} \\ = e^{t(0)} p^{(0)} (1-p)^{1-0} + e^{t(1)} p^{(1)} (1-p)^{1-1} = q + pe^t$$

$$2. \dot{M}_x(0) = E(x) = \mu_x$$

$$\dot{M}_x(t) = 0 + pe^t = pe^t$$

$$E(x) = \mu_x = \dot{M}_x(0) = pe^0 = p$$

$$\ddot{M}_x(t) = pe^t$$

$$E(x^2) = \ddot{M}_x(0) = pe^0 = p$$

$$\text{var}(x) = E(x^2) - (E(x))^2 = p - (p)^2 = p(1 - p) = pq$$

Ex.14: Let X be a continuous uniform distribution with parameters (a, b) . Find the m.g.f. of X .

Solution:

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

$$\begin{aligned} M_x(t) &= E(e^{tx}) = \int_{\forall x} e^{tx} f(x) dx = \int_a^b e^{tx} \frac{1}{b-a} dx \\ &= \frac{1}{b-a} \int_a^b e^{tx} dx = \frac{1}{b-a} * \frac{1}{t} \int_a^b t e^{tx} dx = \frac{1}{b-a} * \frac{1}{t} [e^{tx}]_a^b \end{aligned}$$

$$M_x(t) = \frac{e^{tb} - e^{ta}}{(b-a)t}$$

Ex.15: Let X be a negative binomial distribution with parameters (r, p) . Find the m.g.f. of X .

Solution:

$$p(x, r, p) = \begin{cases} C_x^{x+r-1} p^r q^x & x = 0, 1, 2, \dots \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} M_x(t) &= E(e^{tx}) = \sum_{\forall x} e^{tx} p(x) = \sum_{x=0}^{\infty} e^{tx} C_x^{x+r-1} p^r q^x \\ &= p^r \sum_{x=0}^{\infty} e^{tx} C_x^{x+r-1} q^x = p^r \sum_{x=0}^{\infty} C_x^{x+r-1} (e^t q)^x \end{aligned}$$

Recall that $\sum_{j=0}^{\infty} C_j^{j+r-1} x^j = (1-x)^{-r}$

$$M_x(t) = p^r (1 - e^t q)^{-r} = \left(\frac{p}{1 - qe^t} \right)^r$$

4. Law of Large Number

This theorem deals with the fact that under some conditions the average of a sequence of random variables converges to the expected average.

Let X_1, X_2, \dots, X_n are a random sample of size n drawn from a population with a finite mean μ . Let \bar{X}_n denote the sample mean. Then, for any $\epsilon > 0$

$$P\{|\bar{X}_n - \mu| > \epsilon\} \rightarrow 0 \text{ as } n \rightarrow \infty$$

5. Central Limit Theorem

Suppose X_1, X_2, \dots, X_n are a random sample of size n drawn from a population with a finite mean μ and a finite variance σ^2 . Let \bar{X}_n denote the sample mean. Consider the normalized random variable:

$$Z_n = \frac{\bar{X}_n - E(\bar{X}_n)}{\sqrt{\text{var}(\bar{X}_n)}}$$

Then as $n \rightarrow \infty$, the distribution of Z converges to the standard normal distribution $Z \sim SN(0,1)$.

Ex.16: Let X be the number of successes in 7000 Bernoulli trials with probability of success of 0.7 on a given trial use the central limit theorem to estimate:

1. $P(x < 4950)$
2. $P(4750 < x < 5000)$

Solution:

$$X \sim \text{Bin}(7000, 0.7)$$

$$\mu = n * p = 7000 * 0.7 = 4900$$

$$\sigma^2 = n * p * q = 7000 * 0.7 * 0.3 = 1470$$

$$\sigma = \sqrt{1470} = 38.34$$

$$X \sim N(4900, 1470)$$

$$1. P(x < 4950) = P\left(\frac{x-\mu}{\sigma} < \frac{4950-4900}{38.34}\right) = P(Z < 1.30) \\ = \phi(1.30) = 0.9032$$

$$2. P(4750 < x < 5000) = P\left(\frac{4750-4900}{38.34} < \frac{x-\mu}{\sigma} < \frac{5000-4900}{38.34}\right) \\ = P(-3.91 < Z < 2.61) = \phi(2.61) - \phi(-3.91) \\ = \phi(2.61) - [1 - \phi(3.91)] = 0.99547 - [1 - 0.99995] = 0.995$$

Ex.17: Let \bar{X}_{15} denote the mean of a random sample of size 15 drawn from a distribution whose p.d.f. is:

$$f(x) = \begin{cases} \frac{3}{2}x^2 & -1 < x < 1 \\ 0 & o.w. \end{cases}, \text{ and } \mu = 0, \sigma^2 = \frac{3}{5}$$

Use the central limit theorem to compute $P(0.03 \leq \bar{X} \leq 0.15)$.

Solution:

$$\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

$$E(\bar{X}_n) = E(\bar{X}_{15}) = \mu = 0$$

$$var(\bar{X}_n) = var(\bar{X}_{15}) = \frac{\sigma^2}{n} = \frac{3/2}{15} = \frac{3}{75}$$

$$P(0.03 \leq \bar{X} \leq 0.15) = P\left(\frac{0.03 - 0}{\sqrt{3/75}} \leq Z \leq \frac{0.15 - 0}{\sqrt{3/75}}\right) \\ = P(0.15 < Z < 0.75) = \phi(0.75) - \phi(0.15) \\ = 0.77337 - 0.55982 = 0.2135$$

Ex.18: If 10 fair dice are rolled, find the approximate probability that the sum obtained is between 30 and 40. Use the central limit theorem. Assume that for each die, $\mu_x = 3.5, \sigma_x^2 = \frac{35}{12}$.

Solution:

$$P(30 \leq \sum_{i=1}^{10} x_i \leq 40) \quad \text{Let } S = \sum_{i=1}^{10} x_i$$

$$\mu_s = E(s) = E \sum_{i=1}^{10} x_i = \sum_{i=1}^{10} E(x_i) = \sum_{i=1}^{10} 3.5 = 10 * 3.5 = 35$$

$$\sigma_s^2 = var(s) = var \sum_{i=1}^{10} x_i = \sum_{i=1}^{10} var(x_i) = \sum_{i=1}^{10} \frac{35}{12} = 10 * \frac{35}{12} = \frac{350}{12}$$

$$P(30 \leq S \leq 40) = P\left(\frac{30 - 35}{\sqrt{350/12}} \leq \frac{s - \mu_s}{\sqrt{\sigma_s^2}} \leq \frac{40 - 35}{\sqrt{350/12}}\right)$$

$$= P(-0.93 \leq Z \leq 0.93) = \phi(0.93) - \phi(-0.93)$$

$$= \phi(0.93) - [1 - \phi(0.93)] = 0.8238 - [1 - 0.8238] = 0.65$$

Ex.19: Let X random variable has the following p.d.f.

$$f(x) = \begin{cases} \frac{x^3}{4} & 0 < x < 2 \\ 0 & o.w. \end{cases}$$

Let \bar{X}_{25} denote the mean of a random sample of size 25. Use the central limit theorem to compute $P(1.5 \leq \bar{X} \leq 1.65)$.

Solution:

$$P(1.5 \leq \bar{X} \leq 1.65) = P\left(\frac{1.5 - E(\bar{X}_n)}{\sqrt{var(\bar{X}_n)}} \leq \frac{\bar{X}_n - E(\bar{X}_n)}{\sqrt{var(\bar{X}_n)}} \leq \frac{1.65 - E(\bar{X}_n)}{\sqrt{var(\bar{X}_n)}}\right)$$

$$E(x) = \int_{\forall x} x f(x) dx = \int_0^2 x \frac{x^3}{4} dx = \int_0^2 \frac{x^4}{4} dx = \frac{1}{4} \left[\frac{x^5}{5} \right]_0^2 = \frac{8}{5} = 1.6$$

$$E(\bar{X}_n) = E(\bar{X}_{25}) = \mu = 1.6$$

$$\text{var}(x) = \sigma_x^2 = E(x^2) - (E(x))^2$$

$$E(x^2) = \int_{\forall x} x^2 f(x) dx = \int_0^2 x^2 \frac{x^3}{4} dx = \int_0^2 \frac{x^5}{4} dx = \frac{1}{4} \left[\frac{x^6}{6} \right]_0^2 = \frac{8}{3}$$

$$\text{var}(x) = \sigma_x^2 = \frac{8}{3} - (1.6)^2 = \frac{8}{75} = 0.106$$

$$\text{var}(\bar{X}_n) = \text{var}(\bar{X}_{25}) = \frac{\sigma_x^2}{n} = \frac{0.106}{25} = 0.004$$

$$\bar{X} \sim N(1.6, 0.004)$$

$$P(1.5 \leq \bar{X} \leq 1.65) = P\left(\frac{1.5 - 1.6}{\sqrt{0.004}} \leq \frac{\bar{X}_n - E(\bar{X}_n)}{\sqrt{\text{var}(\bar{X}_n)}} \leq \frac{1.65 - 1.6}{\sqrt{0.004}}\right)$$

$$\begin{aligned} P(1.5 \leq \bar{X} \leq 1.65) &= P(-1.53 \leq Z_n \leq 0.77) = \phi(0.77) - \phi(-1.53) \\ &= \phi(0.77) - [1 - \phi(1.53)] = 0.7793 - [1 - 0.9369] \\ &= 0.7162 \end{aligned}$$