

**MODULE 4****UNIT 1      LIMIT THEOREMS****CONTENT**

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**1.0 INTRODUCTION**

The most important theoretical results in probability are limit theorems. In this unit we prove often useful tools in probability, the Chebychev's inequality. This inequality is then used to deduce the law of large numbers for independent and identically distributed random variables. In section 8.5 the central limit theorem which is a fundamental result in the theory and applications of probability theory is given.

**2.0 OBJECTIVES**

At the end of this unit, you should be able to:

- Prove the Chebychev's inequality
- Verify inequalities using Chebychev's inequality
- State the law of large numbers of Bernoulli Trails
- Apply approximation theorem for solution of real functions

**3.0 MAIN CONTENT****3.1 Chebychev's Inequality**

Chebychev's inequality gives an upper bound in terms of variance of a random variable  $X$  for probability that  $X$  deviates from its mean by more than  $k$  units.

**Theorem 3.1:** *Chebychev's Inequality*

Let  $X$  be a random variable (discrete or continuous) with mean  $\mu$  and variance  $\sigma^2$ . Then for any positive number  $k$  we have

$$P\{|X - \mu| > k\} \leq \frac{\sigma^2}{k^2}$$

Or equivalently

$$P\{|X - \mu| \geq k\sigma\} \leq \frac{1}{k^2}.$$

**Proof:**

Let  $X$  be a non-negative random variable such that  $E(X) = \mu < \infty$ .

Define another random variable  $Y$  as follows:

$$Y = \begin{cases} 0 & \text{if } X < k \\ k & \text{if } X \geq k \end{cases}$$

This new variable  $Y$  is a discrete variable having two values  $0, k$ . The probability density function of  $Y$  can be written thus:

$y$	$0$	$k$
$P(Y = y)$	$P(X < k)$	$P(X \geq k)$

Hence,

$$E(Y) = 0P(X < k) + kP(X \geq k)$$

That is

$$E(Y) = kP(X \geq k).$$

Since the variable  $X \geq Y$  for all possible values, we have

$$E(X) \geq E(Y) = kP(X \geq k),$$

Thus,

$$P(X \geq k) \leq \frac{E(X)}{k} \tag{2}$$

Equation (2) is called the Markov inequality and can be generalized thus: For any  $j \geq 0, k > 0$

$$P\{|W| \geq k\} \leq \frac{E|W|^j}{k^j} \tag{3}$$

The proof of Chebychev's inequality is an immediate consequence of (3) by putting  $j=2$  and  $W = X - \mu$ , we obtain

$$P\{|X - \mu| \geq k\} \leq \frac{E(X - \mu)^2}{k^2} = \frac{\sigma^2}{k^2}$$

Since  $(X - \mu)^2 \geq k^2 \iff |X - \mu| > k$ , we have

$$P\{|X - \mu| > k\} = P\{(X - \mu)^2 \geq k^2\} \leq \frac{\sigma^2}{k^2}$$

Thus

$$P\{|X - \mu| \leq k\} \leq \frac{\sigma^2}{k^2}$$

**Example 3.1**

Let  $X$  be a random variable having Poisson distribution with mean  $\lambda$  and variance  $\sigma^2$ . Use Chebychev's inequality to show that

(i)  $P\{|X - \lambda| \geq 1\} \leq \lambda$  (ii)  $P\left(X > \frac{3\lambda}{2}\right) \leq \frac{4}{\lambda}$

**Solution**

Using Chebychev's inequality with  $\mu = \lambda$ , and  $\sigma^2 = \lambda$  we have

(i)  $P\{|X - \mu| \geq k\} \leq \frac{\lambda}{k^2}$   
 Putting  $k = 1$  we obtain  $P\{|X - \mu| \geq k\} \leq \lambda$ .

(ii) Let  $\frac{\sigma^2}{k^2} = \frac{4}{\lambda} \implies \sigma^2 = \frac{4k^2}{\lambda}$   
 On substituting for  $\sigma^2$  we have  $\lambda^2 = 4k^2, k^2 = \left(\frac{\lambda}{2}\right)^2, k = \frac{\lambda}{2}$ .

Thus

$$P\{|X - \mu| \geq \frac{\lambda}{2}\} \leq \frac{4}{\lambda}$$

Since  $|X - \lambda| \geq \frac{\lambda}{2}$  if and only if  $X - \lambda < -\frac{\lambda}{2}$  or  $X - \lambda > \frac{\lambda}{2}$ , we see that

$$P\{|X - \lambda| \geq \frac{\lambda}{2}\} = P\{X - \lambda < -\frac{\lambda}{2}\} + P\left(X - \lambda > \frac{\lambda}{2}\right)$$

$$= P\left(X < \frac{\lambda}{2}\right) + P\left(X > \frac{3\lambda}{2}\right) \leq \frac{4}{\lambda}$$

Since  $P\left(X < \frac{\lambda}{2}\right) \geq 0$ , we have

$$P\left(X > \frac{3\lambda}{2}\right) \leq \frac{4}{\lambda}$$

**3.2 The Law of Large Numbers of Bernoulli Trials**

Let  $X_1, X_2, \dots, X_n$  be independent and identically distributed Bernoulli random variables and let  $X = X_1 + X_2 + \dots + X_n$  be Binomial random variables (number of successes), with parameters  $n$  and  $p$ . The mean and variance of  $X$  are  $np$  and  $npq$  respectively.

The mean  $\mu$  grows as  $n$  increases but the standard deviation grows only as  $\sqrt{n}$ .

Using Chebychev's inequality

$$P\{|X - np| > \epsilon\} \leq \frac{npq}{\epsilon^2} \leq \frac{n}{\epsilon^2}$$

**Theorem 8.2**

Let  $X$  be the number of successes in  $n$  independent Bernoulli trials with probability of success  $p$ . For any  $\epsilon > 0$ ,

$$P \left\{ \left| \frac{X}{n} - p \right| > \epsilon \right\} \leq \frac{pq}{n\epsilon^2} \leq \frac{1}{4n\epsilon^2}$$

and

$$\lim_{n \rightarrow \infty} P \left\{ \left| \frac{X}{n} - p \right| > \epsilon \right\} = 0$$

**Proof:**

Applying Chebychev's inequality

$$E \left( \frac{X}{n} \right) = p, \text{Var} \left( \frac{X}{n} \right) = \frac{1}{n^2} \cdot npq = \frac{pq}{n}$$

$$\frac{\text{Var} \left( \frac{X}{n} \right)}{\epsilon^2} = \frac{pq}{n\epsilon^2} \rightarrow 0 \text{ as } n \rightarrow \infty$$

$$pq = (1-p)p \leq \frac{1}{4} \text{ for all } p, 0 \leq p < 1$$

Hence

$$P \left\{ \left| \frac{X}{n} - p \right| \geq \epsilon \right\} \rightarrow 0 \text{ as } n \rightarrow \infty$$

This means that for large number  $n$  we can be almost certain that  $\frac{X}{n}$  will be very close to probability of success. This shows that the relative frequency of success in  $n$  independent Bernoulli trials converges (in a probabilistic sense) to the theoretical probability of success at each trial. This important result can be stated more precisely as the law of large numbers.

### The Law of Large Numbers

### 3.3 The Weak Law of Large Numbers

Let  $X_1, X_2, \dots, X_n$  be independent and identically distributed random variables with all  $E(X_i^2) < \infty$  and let  $S_n = X_1 + X_2 + \dots + X_n$ .

We know that

$$E(X_1) = E(X_2) = \dots = E(X_n), E(S_n) = nE(X_1) \text{ and } \text{Var}(S_n) = n\text{Var}(X_1)$$

$$E \left( \frac{S_n}{n} \right) = \frac{1}{n} E(S_n) = \frac{1}{n} \cdot n E(X_1) = E(X_1)$$

$$\text{Var} \left( \frac{S_n}{n} \right) = \frac{1}{n^2} \text{Var}(S_n) = \frac{n\text{Var}(X_1)}{n^2} = \frac{1}{n} \text{Var}(X_1)$$

This shows that expectation of  $\frac{S_n}{n}$  is equal to the expectation of  $X_1$  and the standard deviation of  $\frac{S_n}{n}$  is

$$\sqrt{\left\{ \frac{\text{Var}(X_1)}{n} \right\}} = \frac{\text{Std } X_1}{\sqrt{n}}$$

Which tends to zero as  $n$  tends to infinity. Thus, the distribution of  $S_n/n$  becomes more and more concentrated near  $E(X_1)$ .

We state the more general result in the following theorem.

**Theorem 8.3:** A (WLLN) Weak Law of Large Numbers for Independent Random Variables. Let  $X_1, X_2, \dots, X_n$  be independent and identically distributed random variables with finite mean  $\mu$  and  $\sigma^2$ . Let  $S_n = X_1 + X_2 + \dots + X_n$ , then for  $\delta > 0$ .

$$\lim_{n \rightarrow \infty} P\left(\left|\frac{S_n}{n} - \mu\right| > \delta\right) = 0 \tag{4}$$

**Proof:**

Applying Chebychev's inequality to  $\frac{S_n}{n}$ , we have

$$\begin{aligned} \mu &= E\left(\frac{S_n}{n}\right), \text{Var}\left(\frac{S_n}{n}\right) = \frac{1}{n^2} \text{Var}(S_n) \\ P\left\{\left|\frac{1}{n}S_n - E(X)\right| > \delta\right\} &\leq \frac{2\sigma^2 X}{\sigma^2 n} \end{aligned}$$

For at least one  $k$  satisfying  $n \leq k \leq m$ .

**Corollary 1:**

Let  $f(x)$  be a continuous real function on  $[0, 1]$ . Then as  $n \rightarrow \infty$  uniformly with respect to

$$E\left\{f\left(\frac{S_n}{n}\right)\right\} \rightarrow f(p).$$

**Corollary II: Weierstrass Approximation Theorem.**

Let  $f(x)$  be a continuous real function on  $[0, 1]$  defined on the real interval  $0 \leq p \leq 1$  and let

$$P_n(p) = \sum_{k=0}^n f\left(\frac{k}{n}\right) C_k p^k (1-p)^{n-k}.$$

Then  $P_n(p) \rightarrow f(p)$  as  $n \rightarrow \infty$  and the convergence is uniform in  $p$ .  $P_n(x)$  is called the Bernstein Polynomials.

**Theorem 8.5**

A WLLN for independent but not necessarily identical random variables.

Let  $X_1, X_2, \dots, X_n$  be independent random variables with all

$E(X_i^2) < \infty$  and let  $S_n = X_1 + X_2 + \dots + X_n$  and  $\mu = E\left(\frac{S_n}{n}\right)$ , then

$$P\left\{\left|\frac{S_n}{n} - \mu_n\right| \geq \epsilon\right\} \leq \frac{1}{\epsilon^2 n^2} \{Var(X_1) + Var(X_2) + \dots + Var(X_n)\}, \epsilon > 0.$$

When  $Var X_i \leq M$  for all  $i$ , that is when the variances are all bounded by a constant which does not depend on  $n$ , then we have

$$P\left\{\left|\frac{S_n}{n} - \mu_n\right| \geq \epsilon\right\} \leq \frac{M}{\epsilon^2 n} \rightarrow 0 \text{ as } n \rightarrow \infty.$$

### 3.4 The Central Limit Theorem

The central limit theorem is a fundamental result in the theory and application of probability. The law of large numbers asserts that  $\frac{S_n}{n}$  in a series of  $n$  independent trials with constant probability of success in one trial tends (in a certain probabilistic sense) to  $p$  as  $n$  increases. But this assertion does not tell us anything about the distribution of  $\frac{S_n}{n}$ .

as  $n$  becomes large. The answer to this question is given by the so-called central limit theorem. The theorem asserts that under quite general conditions the sum of independent variables has the Normal distribution in the limit.

**Theorem 8.6: Central limit theorem**

Let  $X_1, X_2, \dots, X_n$

be a sequence of independent random variables with  $E(X_i) = \mu$  and  $\text{Var}(X_i) = \sigma_i^2$ ,  $i = 1, 2, \dots$ . Let  $S_n = X_1 + X_2 + \dots + X_n$ . Then under general conditions,

$$Z_n = \frac{S_n - E(S_n)}{\sqrt{\text{Var } S_n}} = \frac{S_n - \sum_{i=1}^n \mu_i}{\sqrt{\sum_{i=1}^n \sigma_i^2}}$$

Has approximately the standard Normal distribution.

**The Identically Distribution Case**

**Theorem 8.7**

Let  $X_1, X_2, \dots, X_n$  be independent identically distributed random variables. Then

$$(i) \quad Z_n = \frac{S_n - n\mu}{\sqrt{n\sigma^2}} \quad (ii) \quad Z_n = \frac{\frac{S_n}{n} - \mu}{\sqrt{\sigma^2/n}}$$

tend to the standard normal distribution as  $n \rightarrow \infty$ .

What is remarkable about this theorem is that all we need to know about  $X$  is its mean and variance and there is no need to specify the nature of its distribution. Also  $X$  can be discrete, continuous or both. The outline of the proof is given below,

**Proof:**

Let  $M_X(t) = E(e^{tX})$ ,  $S_n(t) = [E(e^{tX})]^n$

Let  $Z_n = \frac{sn - n\mu}{\sqrt{n\sigma^2}} = \frac{sn}{\sqrt{n\sigma^2}} - \sqrt{n} \frac{\mu}{\sigma}$ .

The m.g.f of  $Z_n$  is

$$M_{Z_n}(t) = e^{(\sqrt{n\mu/\sigma})t} \left[ M_X \left( \frac{t}{\sigma\sqrt{n}} \right) \right]^n$$

Taking log we have

$$\ln M_{Z_n}(t) = -\sqrt{n} \frac{\mu}{\sigma} t - n \ln M_X \left( \frac{t}{\sigma\sqrt{n}} \right).$$

Using Maclaurin series

$$M(t) = 1 + M'(0)t + M'' \frac{(0)t^2}{2!} + \dots$$

From above we have

$$\ln M_{Z_n}(t) = -\sqrt{n} \frac{\mu t}{\sigma} + n \ln \left[ 1 + \frac{\mu t}{\sigma\sqrt{n}} + \frac{(\mu^2 - \sigma^2)t^2}{2n\sigma^2} + A \right] \quad (7)$$

where A is the remainder term from Maclaurin series. Similarly, when the Maclaurin series

$$\ln(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} + \dots$$

is used to expand  $\ln \left( 1 + \frac{\mu t}{\sigma\sqrt{n}} + \frac{(\mu^2 + \sigma^2)}{n\sigma^2} t + A \right)$ . setting  $x = \frac{\mu t}{\sigma\sqrt{n}} + \frac{(\mu^2 + \sigma^2)t^2}{2n\sigma^2} + A$ ,

we find that

$$\begin{aligned} & \ln \left( 1 + \frac{\mu t}{\sigma\sqrt{n}} + \frac{(\mu^2 + \sigma^2)}{n\sigma^2} t + A \right) \\ &= \frac{\mu t}{\sigma\sqrt{n}} + \frac{(\mu^2 + \sigma^2)}{n\sigma^2} t + A - \frac{1}{2} \left[ \frac{\mu t}{\sigma\sqrt{n}} + \frac{(\mu^2 + \sigma^2)}{n\sigma^2} t + A \right]^2 + \dots \end{aligned}$$

It is left as an exercise to show that for large n.

$$\left| \frac{\mu t}{\sigma\sqrt{n}} + \frac{(\mu^2 + \sigma^2)}{2n\sigma^2} + A \right| < 1.$$

On substituting in (7) we obtain

$$\begin{aligned} \ln M_{Z_n}(t) &= -\sqrt{n} \frac{\mu t}{\sigma} \\ &+ n \left\{ \frac{\mu t}{\sigma\sqrt{n}} + \frac{(\mu^2 - \mu^2)}{2n\sigma^2} + A - \frac{1}{2} \left[ \frac{\mu t}{\sigma\sqrt{n}} + \frac{(\mu^2 + \sigma^2)t^2}{2n\sigma^2} + A \right]^2 + \dots \right\} \end{aligned}$$

It can easily be shown that as  $n \rightarrow \infty$

$$\ln M_{Z_n}(t) = \frac{t^2}{2}.$$

Hence,

$$\lim_{n \rightarrow \infty} M_{Z_n}(t) = e^{t^2/2},$$

the moment generating function of a random variable having the standard normal distribution.

**Theorem**

Let  $X_n, n > 1$ , and  $X$  be random variables such that  $\lim_{n \rightarrow \infty} M_{X_n}(t) = M_X(t)$ ,  $-\infty < t < \infty$ .

Then  $\lim_{n \rightarrow \infty} F_{X_n}(x) = F_X(x)$  at all points where  $F_X(x)$  is continuous.

**Example 8.2**

A boy throws a fair die 100 times. What is the probability that his mean score will exceed 3.

Let  $X$  represent the outcome of each toss. Possible values of  $X$  are 1, 2, 3, 4, 5, 6.  $E(X) = 3.5$ .  $\text{Var}(X) = 2.92$ .

That is  $\mu = 3.5$ ,  $\sigma^2 = 2.92$

Let  $\bar{X}$  be the mean score. By the central limit theorem  $\bar{X}$  is normally distributed with mean 3.5 and  $\text{Var} \sigma^2/n$ .

$$\frac{\sigma^2}{n} = \frac{2.92}{100}$$

Hence,

$$Z = \frac{\bar{X} - 3.5}{\sqrt{0.0292}}$$

has a standard normal distribution.

$$P(\bar{X} > 3) = P\left(Z > \frac{-0.5}{0.170}\right) = P(Z > -2.94) = 0.9984.$$

**Example 8.3**

Marks in an I.Q examination are normally distributed with mean 55 and standard deviation 10. What is the probability that

- (i) the mean mark of a group of 10 students will be above 50
- (ii) the mean mark of a group of 20 students will be between 40 and 50.
- (iii) the sum of the marks of the 10 students will be less than 500.

**Solution**

Let  $X_1, X_2, \dots, X_{10}$  be the marks scored by each student respectively.

$$E(X_1) = E(X_2) = \dots = E(X_{10}) = 55$$



$$\sigma_{X_1} = \sigma_{X_2} = \sigma_{X_n} = 10.$$

- (i)  $\bar{X}$  = mean, be the central limit theory (assuming  $n = 10$  is large enough for this distribution)  $\frac{\bar{X} - 55}{\sigma/\sqrt{n}}$  has a standard Normal distribution.

$$\frac{\bar{X} - 55}{10/\sqrt{10}} = \frac{\bar{X} - 55}{\sqrt{10}}$$

$$P(\bar{X} > 50) = P\left(\frac{\bar{X} - 55}{\sqrt{10}} > \frac{50 - 55}{\sqrt{10}}\right) = 0.9306.$$

- (ii) The mean mark of a group of 20 students between will be between 40 and 50. In this case,  $n = 20$ .

$$P(40 < \bar{X} < 50) = P(\bar{X} < 50) - P(\bar{X} \leq 40)$$

$$P(\bar{X} \leq 40) = P\left(z \leq \frac{40 - 55}{\sqrt{5}}\right) = P(Z \leq -3\sqrt{5}) = 0.00$$

$$P(\bar{X} < 50) = P\left(z < \frac{50 - 55}{\sqrt{5}}\right) = P(Z < -\sqrt{5}) = 0.01$$

Hence

$$P(40 < \bar{X} < 50) = 0.01 - 0.00 = 0.01$$

- (iii)  $S_{10} = X_1 + X_2 + \dots + X_{10}$

$\frac{S_{10} - n\mu}{\sqrt{n}\sigma}$  has a standard Normal

$$\frac{S_{10} - 550}{\sqrt{1000}} = \frac{500 - 550}{10\sqrt{10}} = \frac{-50}{10\sqrt{10}} = -1.53$$

Hence,

$$P(S_n < 500) = 0.057.$$

### 3.5 Normal Approximately to the Binomial Distribution

Let  $X_1, X_2, \dots, X_n$  be independent identically distributed Bernoulli trials where

$$X_i = \begin{cases} 1 & \text{with probability } P \\ 0 & \text{with probability } 1 - P \end{cases}$$

$E(X_i) = p$  and  $\text{Var}(X_i) = p(1 - p)$ . From theorem 2, the distribution

$$\frac{S_n - E(S_n)}{\sqrt{np(1-p)}} \rightarrow \text{standard Normal.}$$

where  $S_n = X_1 + X_2 + \dots + X_n$

$$E(S_n) = np$$

$$\text{Var}(S_n) = np(1-p), \sigma^2 = np(1-p).$$

Note that  $S_n$  has binomial distribution with mean  $np$  and variance  $np(1-p)$ .

$$P(S_n \leq y) = \sum_{k=0}^y \binom{n}{k} p^k (1-p)^{n-k}$$

For large  $n$

$$P(S_n \leq y) = P\left\{Z_n \leq \frac{y - np}{\sqrt{np(1-p)}}\right\}$$

$$\varphi = \left(\frac{y - np}{\sqrt{np(1-p)}}\right)$$

where  $Z_n$  is standard Normal random variable. Thus, from above we have

$$F_{S_n}(y) = P(S_n \leq y) = \sum_{k=0}^y \binom{n}{k} p^k (1-p)^{n-k} = \varphi\left(\frac{y - np}{\sqrt{np(1-p)}}\right)$$

### Example 8.3

It is claimed that 60% of the voters in a given ward are going to vote for party A. Assuming that all voters will vote, and that there are 100 voters. What is the probability that Party A receives at least 50 votes.

Let  $p=0.6$ . prob. Of voting for A.  $n=100$ . Assuming independent voting

$$P(S_n > 50) = \sum_{k=50}^{100} \binom{100}{k} p^k (1-p)^{100-k} = \sum_{k=50}^{100} \binom{100}{k} (0.6)^k (0.4)^{100-k}$$

Using normal approximation (6) above, we have

$$P(S_n > 50) = P\left(Z \geq \frac{50 - 100 \times 0.6}{\sqrt{100(0.6)(0.4)}}\right) = P\left(Z \geq \frac{50 - 60}{\sqrt{24}}\right) = 0.9793$$

### 3.6 The Normal Approximation to the Poisson Distribution

If a random variable  $X$  has a Poisson distribution whose mean is  $\lambda$ , then for large  $\lambda$  the standardized random variable.

$$Z = \frac{X - \lambda}{\sqrt{\lambda}}$$

has a standard Normal Distribution. you will recall that  $E(X)=\lambda, \text{Var}(X)=\lambda$ , Continuity correction may be introduced.

It has been shown that the approximation is good for  $\lambda > 5$ .

**Example 8.4**

A system suffers random breakdown at a constant rate of 10 per month. Find the probability that there will be at least 8 breakdowns in any month.

Let  $X$  be the number of times the system breaks down in any month. Then  $X$  has a Poisson distribution with  $\lambda = 10$ . Thus

$$P(X > 8) = \sum_{k=8}^{\infty} \frac{e^{-10}(10)^k}{k!}$$

Using Normal approximation, we have

$$\frac{X - 10}{\sqrt{10}} \text{ has } N(0,1)$$

$$P(X \geq 8) = P\left(Z > \frac{8 - 10}{\sqrt{10}}\right) = P\left(Z > \frac{-2}{\sqrt{10}}\right) = 0.7357$$

**SELF-ASSESSMENT EXERCISE 8**

- i. It is claimed that 30% of the voters in a given local government area are going to vote for party A in a local government election. Assuming that all voters will vote, there are 4000 voters and the claim is based on a proper (unbiased) sampling method. What is the probability that Party A will receive more than 1,500 votes.
- ii. (a) Suppose that a system consists of components each of which has a probability of 0.05 of failing during a specific time. The system functions properly when at least 150 components function. Assuming these components function independently of one another, what is the probability that the system functions properly during a specific time.
  - (b) Suppose that the above system is made of  $n$  components each having a probability of 0.90 of not failing during a given time. The system will function if at least 80 percent of the components function properly. Determine  $n$  so that the probability that the system functions properly during a specific time is 0.96.

**6.0 TUTOR-MARKED ASSIGNMENT**

- 1. Let  $X$  be a non-negative interger-valued random variable whose probability generating function  $P_X(s) = E(s^X)$  is finite all  $s$ . Use Chebychev's inequality to verify the following inequalities:
  - (a)  $P(X \leq k) \leq \frac{P_X(s)}{s^k}, 0 \leq s \leq 1, k$  any positive inequalities:
  - (b)  $P(X > k) \leq \frac{P_X(s)}{s^k}, s > 1$
- 2. Prove the Chebychev's inequality.

Let  $X$  be a random variable (discrete or continuous) with  $E(X) = \mu$  and  $\text{Var}(X) = \sigma^2$ . Then for any positive constant number  $k$  we have

$$P\{|X - \mu| \geq k\sigma\} \leq \frac{1}{k^2}.$$

3. Prove that (i)  $1-x \leq e^{-x}$  for real  $x$ , (ii)  $\log x \leq x-1$  for  $x > 0$ , and

$$(iii) \prod_{i=1}^N X_i \leq e^{-\sum_{i=1}^N X_i} \text{ if } X_i \leq 1, N = 1, 2, \dots$$

## 7.0 REFERENCE/FURTHER READING

Harry Frank & Steven C. Althoen (1995). Statistics: Concepts and Applications. Cambridge University Press.