# Summary

- The probability distribution of sample mean drawn from a population can be derived either using Normal theorem or Central Limit Theorem
- The sampling distribution of the sample mean, $\bar{x}$ , is approximated by a normal distribution when the sample is a simple random sample and the sample size, *n*, is large
- Suppose {Xk] is the sequence of Bernoulli random variables taking values 1 with probability p, and 0 with probability 1-p=q, then E(Xk) = p and V(Xk) =pq

  If Sn= ∑Xk, E (Sn) = np and V (Sn) = npq so that $\frac{Sn - np}{\sqrt{npq}}$ is a Standard Normal variate with mean 0 and variance unity

- The sample size varies according to the shape of the population

- Regardless of its shape the sampling distribution of x bar always has a mean identical to the mean of the sampled population and a standard deviation equal to the population S.D $\sigma/\sqrt{n}$

- The CLT plays an important role in Statistical Theory
  The significance of the central limit theorem lies in the fact that it permits us to use sample estimators to make inference about the population parameters without knowing anything about the shape of the frequency distribution of that population other than what we can get from the sample

- Central Limit Theorem States that Suppose X1 ,X2,...Xn, be n independent random variables having the same probability density function each with E(Xi)=μ and V(Xi) = $\sigma^2$, for i=1,2 ,...,n then
  Sn = X1+X2+....+Xn is approximately Normal with mean nμ and variance $n\sigma^2$

  Also $Z = \frac{\bar{X} - n\mu}{\sqrt{n}\sigma}$ is asymptotically N (0, 1)