DEPARTMENT OF MATHEMATICS COLLEGE OF EDUCATION FOR PURE SCIENCE UNIVERISTY OF ANBAR

ASSIST. PRF. DR. MUSTAFA I. NAIF

8.2° A

BY

PROBABILITY AND STATISTICS 2







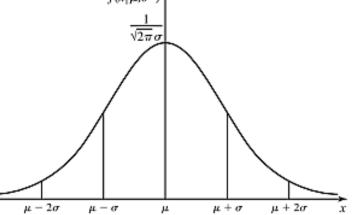
Dutline :- LECTURE 11#

- Continuous distributions
 3- Normal distribution
- Definition
- **Expected value Variance**
- Moment generating function
- Characteristic function
- Standard Normal distribution

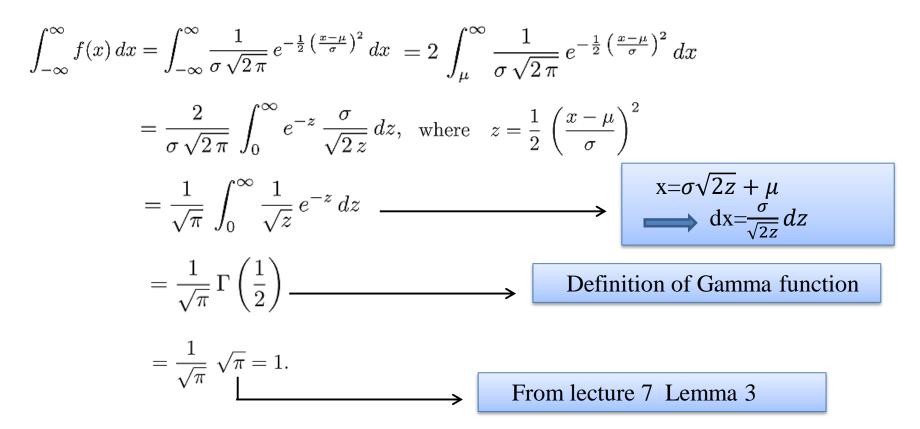
Definition: A random variable X is said to have a normal distribution if its probability density function is given by:

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2}, \qquad -\infty < x < \infty,$$

where $-\infty < \mu < \infty$ and $0 < \sigma^2 < \infty$ are arbitrary parameters. If X has a normal distribution with parameters μ and σ^2 , then we write X ~N(μ , σ^2). **Proof:** we must check that f is nonnegative $f(x \mid \mu, \sigma^2)$ and it integrates to 1. The nonnegative part function is always positive. Hence using property of the gamma function, we show that f integrates to 1 on IR.



Proof:



Theorem: If X ~N(μ , σ^2), then $E(X) = \mu$, $Var(X) = \sigma^2$ and $M(t) = e^{\mu t + \frac{1}{2}\sigma^2 t^2}$. **Proof:** We prove this theorem by first computing the moment generating function and finding out the mean and variance of X from it.

$$M(t) = E(e^{tX}) = \int_{-\infty}^{\infty} e^{tx} f(x) dx = \int_{-\infty}^{\infty} e^{tx} \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2} dx$$
$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{t(\sigma z+\mu)} e^{-\frac{1}{2}z^2} dz, \qquad z = \frac{x-\mu}{\sigma}$$
$$= \frac{e^{t\mu}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(z^2 - 2t\sigma z - t^2\sigma^2 + t^2\sigma^2)} dz,$$
$$= e^{t\mu + \frac{1}{2}t^2\sigma^2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(z^2 - t\sigma)^2} dz \qquad Z^{\sim}N(t\sigma, 1)$$
So, M(t)=1

Proof: The first two derivatives of the m.g.f. of X is:

 $M'(t) = \left(\mu + \sigma^{2}t\right) \exp\left(\mu t + \frac{1}{2}\sigma^{2}t^{2}\right), M''(t) = \left(\left[\mu + \sigma^{2}t\right]^{2} + \sigma^{2}\right) \exp\left(\mu t + \frac{1}{2}\sigma^{2}t^{2}\right)$ Plugging t = 0 into each of these derivatives yields: $E(X) = M'(0) = \mu \qquad \text{and} \qquad Var(X) = M''(0) - (M'(0))^{2} = \sigma^{2}$

Characteristic function: If X~ N(μ , σ^2), then

$$\varphi_X(t) = \exp\left(i\mu t - \frac{1}{2}\sigma^2 t^2\right)$$

Proof: Same as the proof of m.g.f

Example: If X is any random variable with mean μ and variance $\sigma^2 > 0$, then what are the mean and variance of the random variable $Y = \frac{X-\mu}{\sigma}$? Answer: The mean of the random variable Y is :

$$E(Y) = E\left(\frac{X-\mu}{\sigma}\right) = \frac{1}{\sigma}E\left(X-\mu\right) = \frac{1}{\sigma}\left(E(X)-\mu\right) = \frac{1}{\sigma}\left(\mu-\mu\right) = 0.$$

The variance of Y is given by:

$$Var(Y) = Var\left(\frac{X-\mu}{\sigma}\right) = \frac{1}{\sigma^2} Var\left(X-\mu\right) = \frac{1}{\sigma} Var(X) = \frac{1}{\sigma^2} \sigma^2 = 1.$$

Hence, if we define a new random variable by taking a random variable and subtracting its mean from it and then dividing the resulting by its standard deviation, then this new random variable will have zero mean and unit variance.

Definition: A normal random variable is said to be standard normal, if its mean is zero and variance is one. We denote a standard normal random variable X by $X \sim N(0,1)$.

The probability density function of standard normal distribution is the following:

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, \qquad -\infty < x < \infty.$$

SEE YOU IN THE NEXT LECTURE