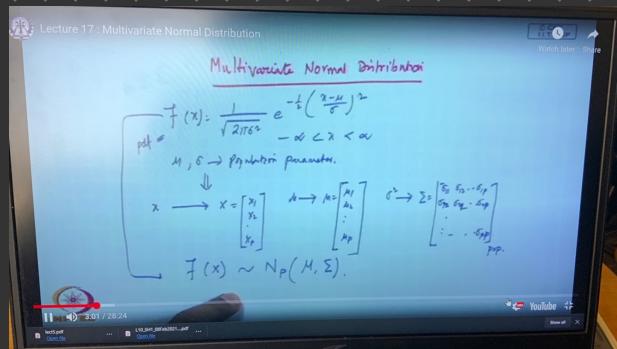


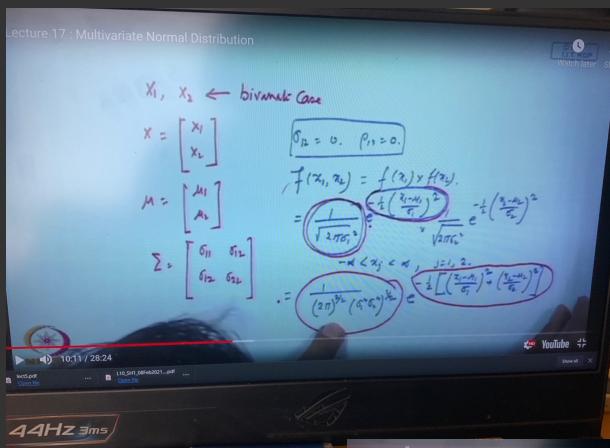


# Lecture 1



For bivariate case:

Assume they're independent



Derive density exponent from population

Lecture 17 : Multivariate Normal Distribution

$$f(x_1, x_2) = f(x_1) \times f(x_2) = \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} e^{-\frac{1}{2} \left[ \frac{(x_1 - \mu_1)^2}{\sigma_1^2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2} \right]}$$

$$= \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} e^{-\frac{1}{2} [(x - \mu)^T \Sigma^{-1} (x - \mu)]}$$

$$f(x_1, x_2, \dots, x_p) = \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} e^{-\frac{1}{2} [(x - \mu)^T \Sigma^{-1} (x - \mu)]}$$

Resembles ellipse

Multivariate Normal Distribution(Contd)

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \quad \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$|\Sigma| = \sigma_1^2 \sigma_2^2 - \sigma_{12}^2 = \sigma_1^2 \sigma_2^2 - (\rho_{12} \sigma_1 \sigma_2)^2 = \sigma_1^2 \sigma_2^2 (1 - \rho_{12}^2)$$

$$\Sigma^{-1} = \frac{1}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \begin{bmatrix} \sigma_2^2 & -\sigma_{12}^2 \\ -\sigma_{12}^2 & \sigma_1^2 \end{bmatrix}$$

$$-\frac{1}{2} [(x - \mu)^\top \Sigma^{-1} (x - \mu)] = -\frac{1}{2} \left[ x_1 - \mu_1, x_2 - \mu_2 \right] \frac{1}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \begin{bmatrix} \sigma_2^2 & -\sigma_{12}^2 \\ -\sigma_{12}^2 & \sigma_1^2 \end{bmatrix} \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix}$$

Lecture 18 : Multivariate Normal Distribution(Contd)

$$= -\frac{1}{2} \left[ x_1 - \mu_1, x_2 - \mu_2 \right] \frac{1}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \left[ \sigma_2^2 (x_1 - \mu_1) - \sigma_{12} (x_2 - \mu_2) \right]$$

$$= -\frac{1}{2} \cdot \frac{1}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \left[ \sigma_2^2 (x_1 - \mu_1) - \sigma_{12} (x_1 - \mu_1)(x_2 - \mu_2) + \sigma_{12}^2 (x_2 - \mu_2)^2 \right]$$

$$= -\frac{1}{2} \cdot \frac{1}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \left[ \sigma_2^2 (x_1 - \mu_1)^2 - 2 \sigma_{12} (x_1 - \mu_1)(x_2 - \mu_2) + \sigma_{12}^2 (x_2 - \mu_2)^2 \right]$$

$$= -\frac{1}{2} \cdot \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \left[ \frac{(x_1 - \mu_1)^2}{\sigma_1^2} - 2 \frac{\sigma_{12}}{\sigma_1 \sigma_2} \left( \frac{x_1 - \mu_1}{\sigma_1} \right) \left( \frac{x_2 - \mu_2}{\sigma_2} \right) + \left( \frac{x_2 - \mu_2}{\sigma_2} \right)^2 \right]$$

$$= -\frac{1}{2} \cdot \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \left[ \left( \frac{x_1 - \mu_1}{\sigma_1} \right)^2 - 2 \beta_{12} \left( \frac{x_1 - \mu_1}{\sigma_1} \right) \left( \frac{x_2 - \mu_2}{\sigma_2} \right) + \left( \frac{x_2 - \mu_2}{\sigma_2} \right)^2 \right]$$

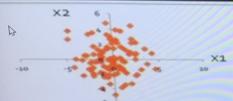
$$= -\frac{1}{2} \cdot \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} (1 - \beta_{12}^2)$$

If  $\rho_{12} = 0$ ,

$$\text{Exponent} = -\frac{1}{2} \left[ \left( \frac{x_1 - \mu_1}{\sigma_1} \right)^2 + \left( \frac{x_2 - \mu_2}{\sigma_2} \right)^2 \right]$$

Lecture 18 : Multivariate Normal Distribution(Contd)

## Bivariate normal density function



Let  $x_1$  and  $x_2$  are independent with pdf  $N(\mu_1, \sigma_1^2)$  and  $N(\mu_2, \sigma_2^2)$ , respectively. That means  $\sigma_{12} = 0$ .

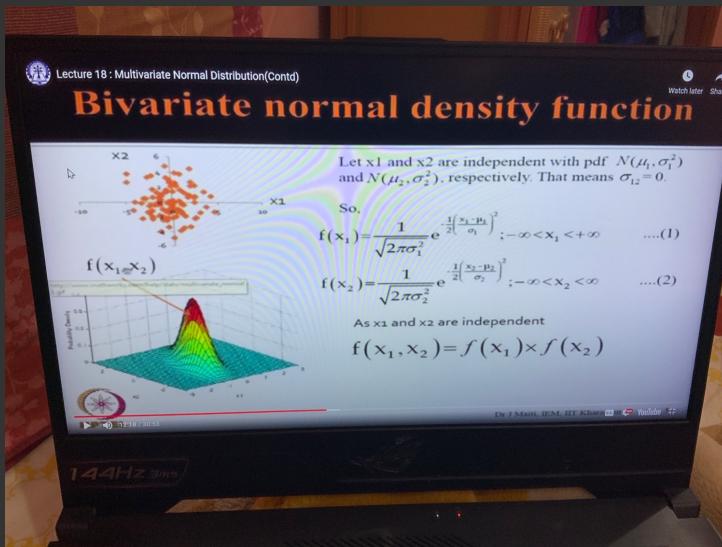
So,

$$f(x_1) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{1}{2}\left(\frac{x_1 - \mu_1}{\sigma_1}\right)^2}; -\infty < x_1 < +\infty \quad \dots(1)$$

$$f(x_2) = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{1}{2}\left(\frac{x_2 - \mu_2}{\sigma_2}\right)^2}; -\infty < x_2 < +\infty \quad \dots(2)$$

As  $x_1$  and  $x_2$  are independent

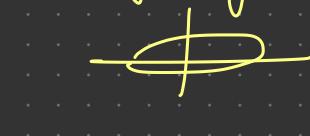
$$f(x_1, x_2) = f(x_1) \times f(x_2)$$



Represent ellipse:



If variability along  $x_1$  is more



$$\text{If } \sigma_1^2 = \sigma_2^2$$



Lecture 18 : Multivariate Normal Distribution(Contd)

### Properties of MND

- (i) If  $X_{psl} \sim N_p(\mu, \Sigma)$ , then  $X_j \sim N(\mu_j, \sigma_j^2)$  for all  $X_j$ ,  $j = 1, 2, \dots, p$ .
- (ii) If  $X_{psl} \sim N_p(\mu, \Sigma)$ , then the subset of  $X_{psl}$ , i.e.,  $X_{qsl} \sim N_q(\mu, \Sigma)$ .
- (iii) If  $X_{psl} \sim N_p(\mu, \Sigma)$ , then the linear combination of  $X_j$ ,  $j = 1, 2, \dots, p$ , is univariate normal.
- (iv) If  $X_{psl} \sim N_p(\mu, \Sigma)$ , then the q linear combination of  $X_j$ ,  $j = 1, 2, \dots, p$ , is multivariate (q-dimension) normal.

Dr J Mano, IITM, BT Kharagpur

144Hz Ems

Multivariate Normal Distribution(Contd)

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix} \quad X_1, X_2, \dots, X_p \sim N_1(\mu_1, \sigma_1^2)$$

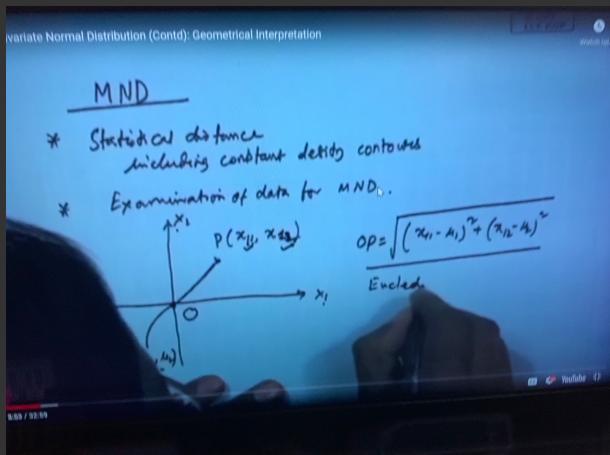
$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_p \end{bmatrix} \quad \mu_1, \mu_2, \dots, \mu_p$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1p} \\ \sigma_{21} & \sigma_2^2 & \dots & \sigma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{p1} & \sigma_{p2} & \dots & \sigma_{pp} \end{bmatrix}$$

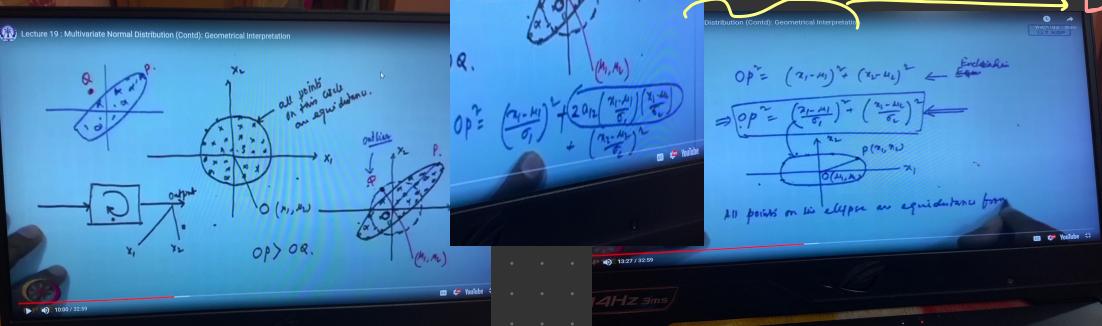
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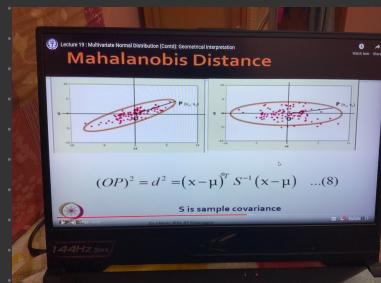
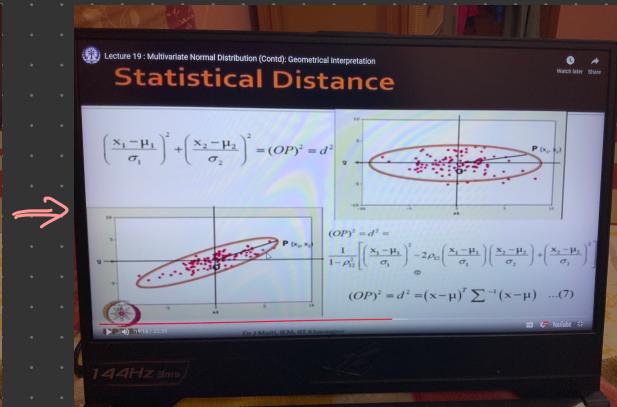
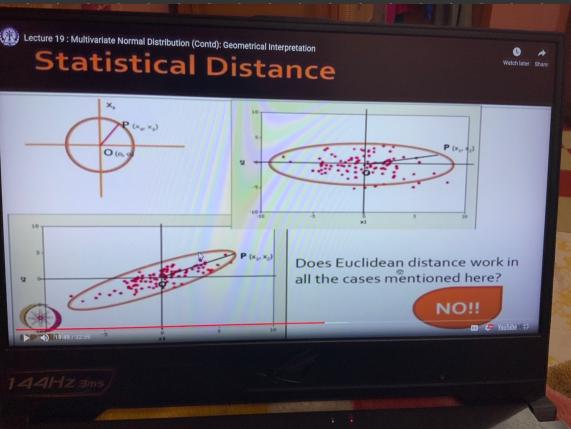
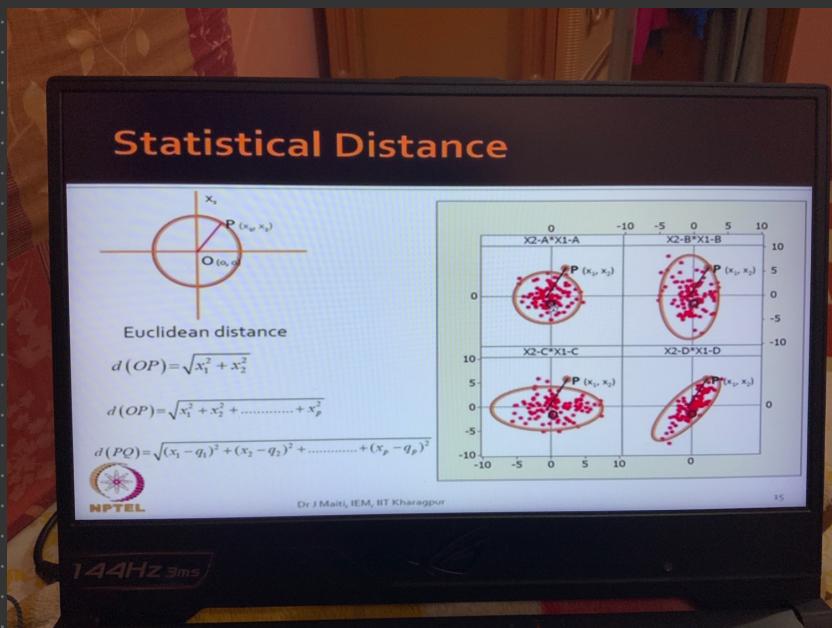
Lecture 19 geometric representation  
Statistical distance including constant density contour  
Examination of data for MND

## Kadian distance



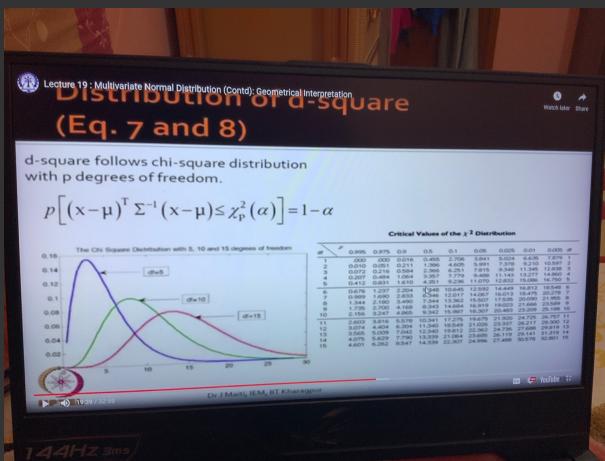
Euclidean Distance  $\rightarrow$  Bad as it doesn't capture variability between  $x_1, x_2$  Statistical Distance





Statistical distance

Exponent follows chi-square



# Lecture 20 - 20

Lecture 20 - Multivariate Normal Distribution (Contd): Examining data for multivariate normal

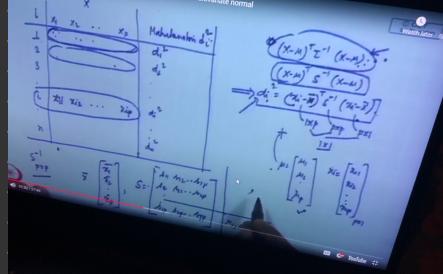
## Examining data for MND

- Testing multivariate normality is crucial
- Techniques
  - Probability plots
  - O-O plot
- Steps for Chi-square O-O plot
  - Step-1: Compute  $d_i^2 = (x_i - \bar{x})^T S^{-1} (x_i - \bar{x}), i = 1, 2, \dots, n$
  - Step-2: Order  $d_i^2$  as  $d_{(1)}^2 \leq d_{(2)}^2 \leq \dots \leq d_{(n)}^2$
  - Step-3: Graph the pairs  $(\chi^2_2((n-i+1)/2), d_{(i)}^2)$

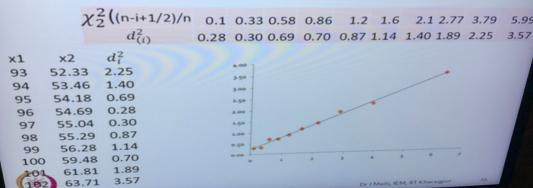


Dr. J. Subrahmanyam

Multivariate Normal Distribution (Contd): Examining data for multivariate normal



## Example-3



Lecture 20 - Multivariate Normal Distribution (Contd): Examining data for multivariate normal

