

MULTIVARIATE CONDITIONAL & MARGINAL NORMAL DISTRIBUTION: A PROBABILITY APPROACH

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ABSTRACT: *Suppose that vector random variable $X = (X_1, X_2, X_3, \dots, X_p)^T$ has a multivariate normal distribution then the probability distribution function (Pdf) is given by*

$$f(X) = \frac{e^{-\frac{1}{2}[X-\mu]\Sigma^{-1}[X-\mu]}}{(2\pi)^{p/2} |\Sigma|^{\frac{1}{2}}}$$

where variance-covariance matrix $=\Sigma$ and is of order $p \times p$ and the expected value $=\mu$ is of order $P \times 1$ vector. Now by considering the partitioning X into two components X_1 and X_2 of orders q and $p - q$ respectively where $q \leq p$, that is

$$X = \begin{bmatrix} X^{(1)} \\ X^{(2)} \end{bmatrix}$$

Then we can deduce that

(a) The marginal distribution of X_1 , and

(b) The conditional distribution of X_2 given that $X_1 = x_1$

.Both (a) and (b) are also separately multivariate's normal distributions

Proof: Since we know that $X \sim N_p(\mu, \Sigma)$, then Pdf of X is $f(X) = \frac{e^{-\frac{1}{2}[X-\mu]\Sigma^{-1}[X-\mu]}}{(2\pi)^{p/2} |\Sigma|^{\frac{1}{2}}}$ and if X is partitioned so that $X =$

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_q \\ \dots \\ X_{q+1} \\ \vdots \\ X_p \end{bmatrix} = \begin{bmatrix} X^{(1)} \\ X^{(2)} \end{bmatrix} = X \text{ and } \mu = \begin{bmatrix} \mu^{(1)} \\ \mu^{(2)} \end{bmatrix} \text{ and } \Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)} X^{(2)}-\mu^{(2)}] \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}^{-1} [X^{(1)}-\mu^{(1)} X^{(2)}-\mu^{(2)}]}}{(2\pi)^{p/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}}$$

$$\Sigma^{-1} = \begin{pmatrix} \Sigma_{22} & -\Sigma_{12} \\ -\Sigma_{21} & \Sigma_{11} \end{pmatrix} / \begin{matrix} \Sigma_{22}\Sigma_{11} - \Sigma_{12}\Sigma_{21} \\ \Sigma_{22}\Sigma_{11} - \Sigma_{12}\Sigma_{21} = \Sigma_{22}\Sigma_{11} \end{matrix} (1-\rho^2)^{\frac{1}{2}} \text{ and } f(X^{(1)}) = \int f(X^{(1)}, X^{(2)}) dX^{(2)} = \frac{e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)}] \Sigma_{11}^{-1} [X^{(1)}-\mu^{(1)}]}}{(2\pi)^{q/2} |\Sigma_{11}|^{\frac{1}{2}}}$$

$$f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2\Sigma_{11}\Sigma_{11}(1-\rho^2)} [X^{(1)}-\mu^{(1)}] \Sigma_{22} [X^{(1)}-\mu^{(1)}] - 2[X^{(1)}-\mu^{(1)}] \Sigma_{12} [X^{(2)}-\mu^{(2)}] + [X^{(2)}-\mu^{(2)}] \Sigma_{11} [X^{(2)}-\mu^{(2)}]}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}} \text{ and}$$

$$f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2(1-\rho^2)} [X^{(1)}-\mu^{(1)}] \Sigma_{11}^{-1} [X^{(1)}-\mu^{(1)}] - 2[X^{(1)}-\mu^{(1)}] \Sigma_{12} / \Sigma_{11} \Sigma_{22} [X^{(2)}-\mu^{(2)}] + [X^{(2)}-\mu^{(2)}] \Sigma_{22}^{-1} [X^{(2)}-\mu^{(2)}]}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}}$$

$$f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2(1-\rho^2)} [X^{(1)}-\mu^{(1)}] \Sigma_{11}^{-1} [X^{(1)}-\mu^{(1)}] - 2[X^{(1)}-\mu^{(1)}] \Sigma_{12} / \Sigma_{11} \Sigma_{22} [X^{(2)}-\mu^{(2)}] + [X^{(2)}-\mu^{(2)}] \Sigma_{22}^{-1} [X^{(2)}-\mu^{(2)}] + (X_1 - \mu_1) \rho^2 \Sigma_{11}^{-1} ((X_1 - \mu_1) - (X_1 - \mu_1) \rho^2 \Sigma_{11}^{-1} ((X_1 - \mu_1)))}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}}$$

$$f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2(1-\rho^2)\Sigma_{22}} [X^{(2)}-\mu^{(2)} - \rho \Sigma^{-1/2} \Sigma_{22}^{-1/2} \Sigma_{11}^{-1} (X^{(1)}-\mu^{(1)})] \Sigma_{22} [X^{(2)}-\mu^{(2)} - \rho \Sigma^{-1/2} \Sigma_{22}^{-1/2} \Sigma_{11}^{-1} (X^{(1)}-\mu^{(1)})] \Sigma_{11}^{-1} [X^{(1)}-\mu^{(1)}]}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}} e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)}] \Sigma_{11}^{-1} [X^{(1)}-\mu^{(1)}]}$$

$$(X_1 - \mu_1) \rho^2 \Sigma_{11}^{-1} ((X_1 - \mu_1)) \frac{e^{-\frac{1}{2(1-\rho^2)\Sigma_{22}} [X^{(2)}-\mu^{(2)} - \rho \Sigma^{-1/2} \Sigma_{22}^{-1/2} \Sigma_{11}^{-1} (X^{(1)}-\mu^{(1)})] \Sigma_{22} [X^{(2)}-\mu^{(2)} - \rho \Sigma^{-1/2} \Sigma_{22}^{-1/2} \Sigma_{11}^{-1} (X^{(1)}-\mu^{(1)})] \Sigma_{11}^{-1} [X^{(1)}-\mu^{(1)}]}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}} e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)}] \Sigma_{11}^{-1} [X^{(1)}-\mu^{(1)}]}$$

$$\frac{f(X^{(1)}, X^{(2)})}{f(X^{(1)})} = \frac{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}}{e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)}] \Sigma_{11}^{-1} [X^{(1)}-\mu^{(1)}]}} \frac{1}{(2\pi)^{q/2} |\Sigma_{11}|^{\frac{1}{2}}}$$

$$f(X^{(2)} / X^{(1)}) = \frac{e^{-\frac{1}{2(1-\rho^2)\Sigma_{22}} [X^{(2)}-\mu^{(2)} - \rho \Sigma^{-1/2} \Sigma_{22}^{-1/2} \Sigma_{11}^{-1} (X^{(1)}-\mu^{(1)})] \Sigma_{22} [X^{(2)}-\mu^{(2)} - \rho \Sigma^{-1/2} \Sigma_{22}^{-1/2} \Sigma_{11}^{-1} (X^{(1)}-\mu^{(1)})] \Sigma_{11}^{-1} [X^{(1)}-\mu^{(1)}]}}{(2\pi)^{p-q/2} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}}$$

The marginal distributions of X_1 and X_2 are also normal with mean vector μ_i and covariance matrix $(\Sigma_{ii}, i=1, 2)$, respectively.

Then
of order $qx1, (p-q)x1$ i.e. with a similar partition of μ and Σ

$$\mu = \begin{bmatrix} \mu^{(1)} \\ \mu^{(2)} \end{bmatrix} \text{ and } \Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \text{ of order } p \times p \text{ where}$$

The Joint Probability Distribution of $f(X)$ is

$$f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)} X^{(2)}-\mu^{(2)}] \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}^{-1} [X^{(1)}-\mu^{(1)} X^{(2)}-\mu^{(2)}]}}{(2\pi)^{p/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}}$$

Where $\Sigma^{-1} = \begin{pmatrix} \Sigma_{22} & -\Sigma_{12} \\ -\Sigma_{21} & \Sigma_{11} \end{pmatrix} / \Sigma_{22}\Sigma_{11} - \Sigma_{12}\Sigma_{21} = \Sigma_{22}\Sigma_{11} - \Sigma_{12}\Sigma_{21} = \Sigma_{22}\Sigma_{11}((1-\rho^2))^{\frac{1}{2}}$ and marginal probability of $X^{(1)}$ is

$$f(X^{(1)}) = \int f(X^{(1)}, X^{(2)})dX^{(2)} = \frac{e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)}]_{\Sigma^{-1}}[X^{(1)}-\mu^{(1)}]}}{(2\pi)^{q/2} |\Sigma_{11}|^{\frac{1}{2}}} \quad \text{where}$$

$$f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2\Sigma_{11}\Sigma_{11}(1-\rho^2)}[[X^{(1)}-\mu^{(1)}]_{\Sigma_{22}}[X^{(1)}-\mu^{(1)}] - 2[X^{(1)}-\mu^{(1)}]_{\Sigma_{12}}[X^{(2)}-\mu^{(2)}] + [X^{(2)}-\mu^{(2)}]_{\Sigma_{11}}[X^{(2)}-\mu^{(2)}]}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}} \quad \text{by simplifying}$$

we get

$$f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2(1-\rho^2)}[[X^{(1)}-\mu^{(1)}]_{\Sigma^{-1}}[X^{(1)}-\mu^{(1)}] - 2[X^{(1)}-\mu^{(1)}]_{\Sigma_{12}}/\Sigma_{11}\Sigma_{22}[X^{(2)}-\mu^{(2)}] + [X^{(2)}-\mu^{(2)}]_{\Sigma^{-1}}[X^{(2)}-\mu^{(2)}]}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}}$$

for completing square we add and subtract $(X_1 - \mu_1) \rho^2 \Sigma^{-1}_{11} (X_1 - \mu_1)$

$$f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2(1-\rho^2)}[[X^{(1)}-\mu^{(1)}]_{\Sigma^{-1}}[X^{(1)}-\mu^{(1)}] - 2[X^{(1)}-\mu^{(1)}]_{\Sigma_{12}}/\Sigma_{11}\Sigma_{22}[X^{(2)}-\mu^{(2)}] + [X^{(2)}-\mu^{(2)}]_{\Sigma^{-1}}[X^{(2)}-\mu^{(2)}] + [(X_1 - \mu_1) \rho^2 \Sigma^{-1}_{11} (X_1 - \mu_1) - (X_1 - \mu_1) \rho^2 \Sigma^{-1}_{11} (X_1 - \mu_1)]}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}}$$

By simplifying, we get

$$f(X^{(1)}, X^{(2)}) = \frac{e^{-\frac{1}{2(1-\rho^2)\Sigma_{22}}[[X^{(2)}-\mu^{(2)}-\rho\Sigma^{-1/2}_{22}\Sigma^{-1/2}_{11}(X^{(1)}-\mu^{(1)})][[X^{(2)}-\mu^{(2)}-\rho\Sigma^{-1/2}_{22}\Sigma^{-1/2}_{11}(X^{(1)}-\mu^{(1)})]]_{\Sigma^{-1}}[X^{(1)}-\mu^{(1)}]}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}} e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)}]_{\Sigma_{11}^{-1}}[X^{(1)}-\mu^{(1)}]}$$

As we know that $f(x_2/x_1) = \frac{f(X^{(1)}, X^{(2)})}{f(X^{(1)})} =$

$$\frac{e^{-\frac{1}{2(1-\rho^2)\Sigma_{22}}[[X^{(2)}-\mu^{(2)}-\rho\Sigma^{-1/2}_{22}\Sigma^{-1/2}_{11}(X^{(1)}-\mu^{(1)})][[X^{(2)}-\mu^{(2)}-\rho\Sigma^{-1/2}_{22}\Sigma^{-1/2}_{11}(X^{(1)}-\mu^{(1)})]]_{\Sigma^{-1}}[X^{(1)}-\mu^{(1)}]}}{(2\pi)^{q/2} (2\pi)^{p-q/2} |\Sigma_{11}|^{\frac{1}{2}} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}} e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)}]_{\Sigma_{11}^{-1}}[X^{(1)}-\mu^{(1)}]}$$

$$\frac{e^{-\frac{1}{2}[X^{(1)}-\mu^{(1)}]_{\Sigma^{-1}}[X^{(1)}-\mu^{(1)}]}}{(2\pi)^{q/2} |\Sigma_{11}|^{\frac{1}{2}}}$$

$$f(X^{(2)}/X^{(1)}) = \frac{e^{-\frac{1}{2(1-\rho^2)\Sigma_{22}}[[X^{(2)}-\mu^{(2)}-\rho\Sigma^{-1/2}_{22}\Sigma^{-1/2}_{11}(X^{(1)}-\mu^{(1)})][[X^{(2)}-\mu^{(2)}-\rho\Sigma^{-1/2}_{22}\Sigma^{-1/2}_{11}(X^{(1)}-\mu^{(1)})]]^{-1}}}{(2\pi)^{p-q/2} |\Sigma_{22}|^{\frac{1}{2}} (1-\rho^2)^{\frac{1}{2}}}$$

$$\frac{X_2}{X_1} \sim N_{p-q} \left(\mu_2 + \rho \Sigma_{22}^{-\frac{1}{2}} \Sigma_{11}^{-\frac{1}{2}} (X_1 - \mu_1), (1-\rho^2) \Sigma_{22} \right)$$

$$\frac{X_2}{X_1} \sim N_{p-q} \left(\mu_2 + \frac{\Sigma_{12} \Sigma_{22}^{-\frac{1}{2}} \Sigma_{11}^{-\frac{1}{2}}}{\Sigma_{11}^{\frac{1}{2}} \Sigma_{22}^{\frac{1}{2}}} (X_1 - \mu_1), \left(1 - \frac{\Sigma_{12} \Sigma_{21}}{\Sigma_{11} \Sigma_{22}}\right) \Sigma_{22} \right)$$

$$\frac{X_2}{X_1} \sim N_{p-q} \left[\left(\mu_2 + \Sigma_{12} \Sigma_{11}^{-1} (X_1 - \mu_1) \right), \left(\Sigma_{22} - \Sigma_{12} \Sigma_{11}^{-1} \Sigma_{21} \right) \right]$$

Which fulfill the requirement of multivariate normal distribution.

These result can be verified for if X_1 and X_2 are independent i.e. $\rho=0$ ($\Sigma_{12}=0$) and X_2 / X_1 are independent.

$$X_2/X_1=x_1 \sim N_1(\mu_2, \Sigma_{22})$$

This result also verify if X is bidimensional random variable then the resulting distribution is bivariate conditional normal distribution i.e. if $q=1$ and $p=2$ then $\Sigma_{11}=\sigma_1^2$, $\Sigma_{12}=\sigma_{12}$ and $\Sigma_{22}=\sigma_2^2$.

$X_2/X_1=x_1 \sim N_1[(\mu_2 + \sigma_{12}(X_1 - \mu_1)/\sigma_1^2, \sigma_2^2 - (\sigma_{12}\sigma_{21})/\sigma_1^2]$ and again if X_2 is independent of X_1 , then $\sigma_{12}=\sigma_{21} = 0$ and the result fulfill univariate normal distribution

$$X_2/X_1=x_1 \sim N_1[\mu_2, \sigma_2^2]$$

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