

$$Z \sim N(0, 1)$$

$$\text{p.d.f.} : \phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \quad \forall z \in \mathbb{R}.$$

$$\text{c.d.f.} : \Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-\frac{z^2}{2}} dz$$

$$X = \mu + \sigma Z \sim N(\mu, \sigma^2)$$

$$\text{c.d.f.} : \Phi(x) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^x e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

$$\text{p.d.f.} : \phi(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Theorem: X, Y indep.

$$X \sim N(\mu_1, \sigma_1^2), \quad Y \sim N(\mu_2, \sigma_2^2).$$

$$X + Y \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

$$\text{Proof: } \varphi_X(t) = E e^{tx} = \int_{-\infty}^{+\infty} e^{tx} \cdot \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} dx.$$

$$\varphi_{X+Y}(t) = E e^{t(X+Y)} = e^{t\mu_1 + \frac{1}{2}t^2\sigma_1^2}$$

$$= E e^{tx} \cdot E e^{tY} = e^{t(\mu_1 + \mu_2) + \frac{1}{2}t^2(\sigma_1^2 + \sigma_2^2)}$$

$$= \varphi_Z(t), \quad Z \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2).$$

Multivariate Normal (MVN)

$X = (x_1, \dots, x_k)$ is said to have a MVN if every linear combination of the X have a Normal Distribution.

$\forall b_i \in \mathbb{R} \quad b_1 x_1 + b_2 x_2 + \dots + b_k x_k$ has Normal Distribution.

Theorem: $X = (x_1, \dots, x_n) \sim \text{MVN}$

$Y = (y_1, \dots, y_m) \sim \text{MVN}$

X, Y indep $\Rightarrow W = (x_1, \dots, x_n, y_1, \dots, y_m) \sim \text{MVN}$.

Theorem

MVN distribution is completely specified by knowing mean, variance of each comp, and covariance of each pair of components.

$$\left. \begin{array}{l} E(x_1), E(x_2), \dots, E(x_n) \\ \text{Var}(x_1), \dots, \text{Var}(x_n) \\ \text{Cov}(x_1, x_2) \dots \text{Cov}(x_{n-1}, x_n) \end{array} \right\} \Rightarrow \text{Specify a MVN.}$$

Proof:

MAF: $M_X(t) = E e^{t^T X} = e^{\mu^T t + \frac{1}{2} \sigma^2 t^2}$ $X \sim N(\mu, \sigma^2)$

$$M_X(t_1, t_2, \dots, t_k) = E e^{t_1 X_1 + \dots + t_k X_k}$$

$X \sim \text{MVN} \Rightarrow W = t_1 X_1 + \dots + t_k X_k$ is normal distribution.

$$\begin{aligned} M_X(t_1, t_2, \dots, t_k) &= E e^W = e^{E(W) + \frac{1}{2} \text{Var}(W)} \\ &= \exp \left\{ \sum_{i=1}^k t_i E(X_i) + \frac{1}{2} \text{Var}(t_1 X_1 + \dots + t_k X_k) \right\} \end{aligned}$$

Hence we can specify any MVN.

BVN

$$X \sim N(0,1), Y \sim N(0,1), \text{Cov}(X,Y) = \rho.$$

$$f_{X,Y}(x,y) = \frac{1}{2\pi\sqrt{1-\rho^2}} e^{-\frac{1}{2} \frac{(x^2+y^2-2\rho xy)}{(1-\rho^2)}} = \rho \cdot \phi_1 \phi_2 = \rho$$

= Correlation

= 二元正态 p.d.f.:

$$f(x,y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp \left\{ -\frac{1}{2(1-\rho^2)} \left(\frac{(x-\mu_1)^2}{\sigma_1^2} - \frac{2\rho(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2} + \frac{(y-\mu_2)^2}{\sigma_2^2} \right) \right\}$$

Generally, Independence is a stronger condition than 0 correlation.

Theorem: If $X \sim \text{MVN}$ and $X = (X_1, X_2)$

and every comp in X_1 is uncorrelated with every component of X_2 .

$\text{Cov}(X_1, X_2) = 0.$

$\Rightarrow X_1, X_2$ are independent.

Proof: $X \sim N(\mu_1, \sigma_1^2)$, $Y \sim N(\mu_2, \sigma_2^2)$

$$\begin{aligned} M_{X,Y}(t_1, t_2) &= E e^{X t_1 + Y t_2} = e^{\mu_1 t_1 + \mu_2 t_2 + \frac{1}{2}(t_1^2 \sigma_1^2 + t_2^2 \sigma_2^2 + \underbrace{2 t_1 t_2 \rho \sigma_1 \sigma_2}_{=0})} \\ &= e^{\mu_1 t_1 + \mu_2 t_2 + \frac{1}{2}(t_1^2 \sigma_1^2 + t_2^2 \sigma_2^2)} = E e^{X t_1} \cdot E e^{Y t_2} \end{aligned}$$

$\Rightarrow X, Y$ are indep.

Example: $X \sim N(\mu, \sigma^2)$

Prove: \bar{X} is indep of S^2

Solution: $\bar{X} = \frac{1}{n} (X_1 + \dots + X_n) \sim N(\mu, \frac{\sigma^2}{n})$

$$S^2 = \frac{1}{n-1} ((X_1 - \bar{X})^2 + \dots + (X_n - \bar{X})^2)$$

$$\begin{aligned} E S^2 &= \frac{1}{n-1} (X_1^2 + X_2^2 + \dots + X_n^2 - n \bar{X}^2) \\ &= \frac{1}{n-1} (n \cdot (\sigma^2 + \mu^2) - n (\frac{\sigma^2}{n} + \mu^2)) \\ &= \sigma^2 \end{aligned}$$

$$X_i - \bar{X} = \frac{n-1}{n} X_i - \frac{1}{n} \sum_{j=1, j \neq i}^n X_j \sim N(0, \frac{n-1}{n} \sigma^2)$$

$$W = (X_1 - \bar{X}, X_2 - \bar{X}, \dots, X_n - \bar{X}) \sim MVN$$

$$\text{Cov}(\bar{X}, X_i - \bar{X}) = E(\bar{X}(X_i - \bar{X})) - E(\bar{X})E(X_i - \bar{X})$$

$$= E(\bar{X}(X_i - \bar{X})) = \frac{E(X_i^2) - E[(X_i - \bar{X})^2] - E[(\bar{X})^2]}{2}$$

$$(X_i - \bar{X} + \bar{X})^2 = (X_i - \bar{X})^2 + (\bar{X})^2 + 2\bar{X}(X_i - \bar{X})$$

$$= \frac{\sigma^2 + \mu^2 - \frac{n-1}{n} \sigma^2 - (\frac{\sigma^2}{n} + \mu^2)}{2} = 0.$$

$\Rightarrow \bar{X}, W$ are independent.

$\Rightarrow \bar{X}$ is independent of any function of $(X_1 - \bar{X}, X_2 - \bar{X}, \dots, X_n - \bar{X})$.

So is S^2 .

Example: (Bivariable Normal Simulation.)

Suppose i.i.d. r.v. $X, Y \sim N(0, 1)$

Generate a BVN (Z, W) with $\begin{cases} \text{Cov}(Z, W) = \rho \\ Z \sim N(0, 1) \\ W \sim N(0, 1) \end{cases}$ by X, Y

$$Z = ax + by \quad W = cx + dy.$$

$$\Rightarrow (Z, W) \sim \text{BVN}$$

$$E Z = E W = 0.$$

$$\text{Var } Z = a^2 + b^2 = 1, \text{Var } W = c^2 + d^2 = 1.$$

$$\begin{aligned} \text{Cov}(Z, W) &= ac \text{Cov}(x, x) + bd \text{Cov}(y, y) \\ &= ac + bd = \rho. \end{aligned}$$

$$\begin{cases} a^2 + b^2 = 1 & a = 1 \quad b = 0 \\ c^2 + d^2 = 1 & c = \rho \quad d = \sqrt{1 - \rho^2} \\ ac + bd = \rho \end{cases}$$