

Buenas tardes!

Proyectos MC + DM

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Clase 19

Probabilidad conjunta:

Ec. Liouville ecuación de
movimiento de un sistema de N
partículas \Rightarrow densidad de probabilidad

jerarquía
BBGKY

$$f_n(x_1, x_2, x_3, \dots, x_n)$$

función
de dist.
de n part.

distribuciones conjuntas

Dados $x_1, x_2, x_3, \dots, x_n$ variables aleatorias cada una tomada de una dist. podemos construir un vector

$$X = (x_1, x_2, x_3, \dots, x_n)$$

proceso estocástico

$$P(\bar{X} \in \beta) = \int_{\beta} f(x_1, \dots, x_n) dx_1, \dots, dx_n$$

densidad de probabilidad
densidad reducida

densidad
marginal

reducida \rightarrow

$$f_X(x) = \int_{xy} f(x, y) dy$$

densidad de
prob de x
indep de y 1º c
hace y

regla
de Bayes

$$f_{Y|X}(y|x) = \frac{f(x,y)}{f_X(x)}$$

$$E[Y|X=x] = \int y f_{Y|X}(y|x) dx$$

si variables aleatorias son indep.

$$\Rightarrow f(x_1, \dots, x_n) = f(x_1) f(x_2) \dots f(x_n)$$

if x_1, x_2, \dots, x_n are indep

$$E[a + b_1 x_1 + b_2 x_2 + \dots + b_n x_n]$$

$$= a + b_1 \mu_1 + b_2 \mu_2 + \dots + b_n \mu_n$$

$$E[x_i] = \mu_i$$

$$E[x_1, x_2, \dots, x_n] = \mu_1 \mu_2 \mu_3 \dots \mu_n$$

Covariance

$$\text{Cov}(X, Y) = E[(X - \overset{\mu}{E[X]})(Y - \overset{\mu}{E[Y]})]$$

$$\text{Var}(X) = \text{Cov}(X, X)$$

$$\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_x \sigma_y} \quad \text{Corr. coefficient}$$

$$\sigma_x = \sqrt{\text{Var}(X)}$$

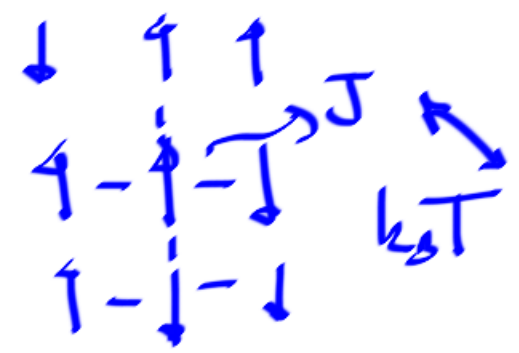
$$Cov(X, Y) = E[XY] - E[X]E[Y]$$

s: x, y are indep

$$E[0]$$

$$= 0$$

computer



Fonctions de variables aléatoires:

$X \rightarrow$ se extrae de una distribución determinada

cuál es la distribución de una función de X

$$\begin{array}{l} f_X(x) \\ f_Z(z) \end{array} \quad ? \quad z = g(x)$$

Ex

gen $z = aX + b$

can $a \neq 0$

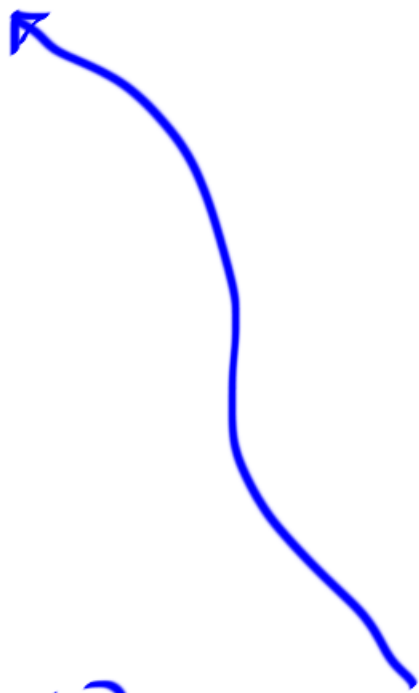
$$F_z(z) = P(z \leq z)$$

$$= P\left(x \leq \frac{z-b}{a}\right)$$

$$= F_x\left(\frac{z-b}{a}\right)$$

→ integrand

$$f_z(z) = \frac{d}{dz} P(z \leq z) = \frac{d}{dz} P\left(x \leq \frac{z-b}{a}\right) = \frac{dP(x \leq \frac{z-b}{a})}{dx} \cdot \frac{dx}{dz}$$



$$x = \frac{z-b}{a} \quad \frac{dx}{dz} = \frac{1}{a}$$

$$f_z(z) = f_x\left(\frac{z-b}{a}\right) \cdot \frac{1}{a} \quad \text{para } a > 0$$

s. $a < 0$ $z = \frac{1}{|a|}x + b$ ←

$$f_z(z) = f_x\left(\frac{z-b}{a}\right) \frac{1}{|a|}$$

$\frac{E_d z}{\text{produto}}$

Er from General

$$z = g(X) \Rightarrow X = \overset{\text{invertible}}{g^{-1}}(z)$$

$$\begin{aligned}\overline{F}_z(z) &= P(z \leq z) = P(X \leq g^{-1}(z)) \\ &= \overline{F}_X(g^{-1}(z))\end{aligned}$$

$$f_z(z) = \frac{dP(z \leq z)}{dz} = \frac{d}{dx} P(X \leq g^{-1}(z)) \cdot \frac{dx}{dz}$$

$$f_z(z) = f_x(g^{-1}(z)) \frac{dg^{-1}(z)}{dz} //$$

E_x

$$z = x^2 \rightarrow g^{-1}(z)$$

$$x = \pm \sqrt{z}$$

E_y

$$f_z(z) = f_x(\sqrt{z}) \frac{1}{\sqrt{z}}$$

Ex.

$f_x =$ Gaussian

$$\sigma'^2 = \sigma^2 a^2$$

$$\langle X \rangle = 0$$

$$\langle Z \rangle = b$$

$$Z = aX + b$$

$$\downarrow$$

$$\langle Z \rangle = \langle aX + b \rangle = a \langle X \rangle + b = b$$

$$f_Z(z) = \frac{1}{|a|} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(z-b)^2}{2\sigma^2}}$$

Form
canonica

$$= \frac{1}{\sqrt{2\pi\sigma'^2}} e^{-\frac{(z - \langle Z \rangle)^2}{2\sigma'^2}}$$

$$f_x = \text{Gaussian} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-x^2/2\sigma^2}$$

$$z = a e^x$$

$$x = \ln \frac{z}{a} = f^{-1}(z)$$

$$f_z(z) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2} \left(\ln \frac{z}{a} \right)^2} \cdot \frac{a}{z}$$

log normal

E_i

Procesos estocásticos (multivariables)

Transformaciones lineales

$$\text{Sea } \vec{x} = (x_1, \dots, x_n)^T = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

y sea A una matriz $m \times n$

la transformación de $\vec{x} \rightarrow \vec{z}$

$$\vec{z} = A \vec{x}$$

Como se comporta $\vec{\mu}_z$, $\overleftrightarrow{\Sigma}_z$

$$1) \vec{\mu}_z = A \vec{\mu}_x$$

$$2) \overleftrightarrow{\Sigma}_z = A \Sigma_x A^T$$

$$1) \vec{\mu}_z = E[\vec{z}] = E[A\vec{x}] = A E[\vec{x}]$$

$\vec{\mu}_z = A \vec{\mu}_x //$

$$\begin{aligned}
\vec{\Sigma}_z &= E [(\bar{z} - \bar{\mu}_z) (z - \mu_z)^T] \\
&= E [A(\bar{x} - \bar{\mu}_x) (A(\bar{x} - \bar{\mu}_x))^T] \\
&= E [A(\bar{x} - \bar{\mu}_x) (\bar{x} - \bar{\mu}_x)^T A^T] \\
&= A \underbrace{E [(\bar{x} - \bar{\mu}_x) (\bar{x} - \bar{\mu}_x)^T]}_{\vec{\Sigma}_x} A^T \\
\vec{\Sigma}_z &= A \vec{\Sigma}_x A^T
\end{aligned}$$

$$f_{\vec{z}}(\vec{z}) = \frac{f_{\vec{x}}(A^{-1}\vec{z})}{|A|} \quad |E_d$$

$|A| \rightarrow$ determinante de A.

que ocurre si: $\vec{z} = \gamma(\vec{x})$

$$f_{\vec{z}}(\vec{z}) = f_{\vec{x}}(\gamma^{-1}(\vec{z})) \cdot |J_{\vec{z}}(\gamma^{-1})| \det$$

$$\leadsto J_{\vec{x}}(\gamma) = \begin{vmatrix} \partial \gamma_1 / \partial x_1 & \dots & \partial \gamma_1 / \partial x_n \\ \partial \gamma_n / \partial x_1 & \dots & \partial \gamma_n / \partial x_n \end{vmatrix}^{\text{det}}$$

Gaussian multidimensional

une variable $f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$

variable standard \rightarrow $\frac{\sigma}{\sqrt{E}}$
norme

Si, heu, le transforme

$$z = \mu + \sigma X \quad \Rightarrow \quad X = \frac{z - \mu}{\sigma}$$
$$f_z(z) = \frac{1}{\sqrt{2\pi} |\sigma|} e^{-\frac{1}{2} \left(\frac{z - \mu}{\sigma}\right)^2}$$

n dimensions

$$\vec{x} = (x_1, \dots, x_n)$$

$$f_{\vec{x}}(\vec{x}) = \frac{1}{(2\pi)^{n/2}}$$

x_i independent

$$e^{-\frac{1}{2} (x_1, \dots, x_n) \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}}$$

$$e^{-\frac{1}{2} (x_1, \dots, x_n) (x_1, \dots, x_n)^T}$$

$$= \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \vec{x} \cdot \vec{x}^T}$$

$$\vec{z} = \vec{\mu} + B \vec{x}$$

$$\Sigma_x = B B^T$$
$$E[\vec{z}] = \vec{\mu}$$

$$\vec{y} = \vec{z} - \vec{\mu} = B \vec{x}$$

$$f_{\vec{y}}(\vec{y}) = \frac{f_{\vec{x}}(B^{-1}\vec{y})}{|B|} \quad \begin{matrix} (x_1, \dots, x_n) \\ \uparrow \\ \uparrow \end{matrix} \left(\begin{matrix} \\ \\ \end{matrix} \right)$$

$$= \frac{1}{|B|(2\pi)^{n/2}} e^{-\frac{1}{2} ((B^{-1}\vec{y})^T (B^{-1}\vec{y}))}$$

$$= \frac{1}{|B|(2\pi)^{n/2}} e^{-\frac{1}{2} \vec{y}^T (B^{-1})^T B^{-1} \vec{y}}$$

$$\begin{aligned} (B^{-1})^T B^{-1} &= (B^T)^{-1} B^{-1} = (B^T B)^{-1} \\ &= \Sigma_x^{-1} \end{aligned}$$

$$B^T B = \Sigma$$

$$|B^T B| = |\Sigma|$$

$$|B^T B| = |B|^2 = |\Sigma|$$

$$|B| = \sqrt{|\Sigma|}$$

$$f_{\bar{y}}(y) = \frac{1}{\sqrt{|\Sigma|} (2\pi)^{n/2}} e^{-\frac{1}{2} y^T (\Sigma^{-1}) y}$$

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

Theorem limite proxima close

$$(B^T)^{-1} = (B^{-1})^T \quad \boxed{E_1}$$

$$- \quad h(x) = \int_{t_3 x}^{x^2} f(t) dt$$

$$- \quad \frac{dh(x)}{dx} = - f(t_3 x) \sec^2 x + 2 f(x^2) x$$

Leibniz's rule

Proxima close

Venus 14 hours

Close 20