

Probability ReviewRandom variables : X, U

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

density function f : $\underbrace{P(X \in A)}_{\text{A}} = \int_A f(x) dx$

distribution function: F : $F(x) = P(X \leq x)$
 $= \int_{-\infty}^x f(x) dx$

Expected value : $E(X) = \int x f(x) dx$

Variance : $\text{Var}(X) = E((X - \mu)^2)$ $\mu = E(X).$
 $= E(X^2) - (E(X))^2.$

k^{th} moment of X = $E(X^k).$

Moment generating function :

$MGF_X = M_x(t) = E(e^{tX})$
 $= \int e^{tx} f(x) dx.$

$M(0) = \int f(x) dx = 1$

$M'(t) = \int x e^{tx} f(x) dx$

$M'(0) = \int x f(x) dx = E(X).$

$M^{(k)}(0) = E(X^k).$



Characteristic Function

$$\begin{aligned}\varphi_X(t) &= \mathbb{E}(e^{itX}) && \text{cost}x + i\sin tx \\ &= \int e^{itx} f(x) dx && \text{Fourier transform of } f \\ &= \hat{f}(t).\end{aligned}$$

Transformations

X has density f , let $Y = g(X)$.

What is the density function for Y ?

(assume g is monotone increasing)

$$\begin{aligned}P(Y \in A) &= P(g(X) \in A) \\ &= P(X \in g^{-1}(A)).\end{aligned}$$

$$= \int_{g^{-1}(A)} f(x) dx$$

let $x = g^{-1}(y)$

$$\Rightarrow g(x) = y$$

$y \in A$

$$= \int_A f(g^{-1}(y)) \underbrace{\frac{dg^{-1}}{dx}}_{dy} dy$$

$$\frac{dg}{dx} dx = dy$$

$$dx = \underbrace{\frac{1}{dg/dx}}_{dy} dy$$

$h(y)$, the density
of Y .

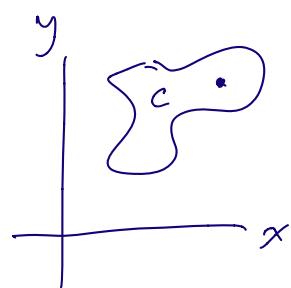
Multi-dimensional distributions.

Consider 2 random variables X, Y .

Joint probability density: $f(x,y)$

$$P(X \in A, Y \in B) = \iint_{B \cap A} f(x,y) dx dy$$

$$P(X, Y \in C) = \int_C f(x,y) dx dy$$



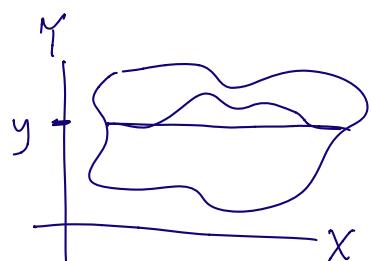
X, Y are independent if $P(X \in A, Y \in B) = P(X \in A) P(Y \in B)$.

$$\Rightarrow f(x,y) = \underbrace{f_x(x)}_{\text{marginal densities}} \underbrace{f_y(y)}_{\text{marginal densities}}.$$

$$f_x(x) = \int f(x,y) dy.$$

Conditional random variables

$$P(X \in A | Y=y) = \frac{f(x,y)}{f_y(y)} = f_{X|Y}(x|y).$$



$$\Rightarrow \int \frac{f(x,y)}{f_y(y)} dx = \frac{1}{f_y(y)} \underbrace{\int f(x,y) dx}_{= 1}.$$

Bivariate transformations

$$U = g_1(X, Y) \quad \Rightarrow \quad \text{What is the density of } U, V?$$

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Covariance and correlation

$$\text{Cov}(X, Y) = \mathbb{E}((X - \mu_X)(Y - \mu_Y)) = \text{Cov}(Y, X).$$

If X, Y are independent, then:

$$= \mathbb{E}(X - \mu_X) \mathbb{E}(Y - \mu_Y)$$

$$= 0.$$

$$\text{Correlation of } X, Y = \rho_{XY} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)} \sqrt{\text{Var}(Y)}} \in [-1, 1].$$

Standard deviation of X

Multidimensional Normal Random variables

X_1, \dots, X_n be $N(\mu_i, \sigma_{ii}^2)$ random variables.

$$\text{and } \text{Cov}(X_i, X_j) = \sigma_{ij}^2$$

The covariance matrix = $C_{ij} = \sigma_{ij}^2$

$n \times n$ matrix

$$C = \begin{pmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \sigma_{13}^2 & \dots & \sigma_{1n}^2 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \sigma_{n1}^2 & \sigma_{n2}^2 & \sigma_{n3}^2 & \dots & \sigma_{nn}^2 \end{pmatrix}$$

$$\text{joint pdf} = \frac{1}{(2\pi)^{n/2}} \underbrace{\frac{1}{|C|}}_{\text{determinant of } C} e^{(\vec{x} - \mu)^T C^{-1} (\vec{x} - \mu)/2}$$

$$\vec{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \quad [4]$$

$$\int f(x_1, \dots, x_n) dx_1 \dots dx_n = 1.$$

$$\mathbb{E}(x_j) = \int x_j f(x_1, \dots, x_n) dx_1 \dots dx_n.$$

Inequalities

Markov inequality:

If $X > 0$, and $\mathbb{E}(X) < \infty$, then

for any $t > 0$,

$$P(X > t) \leq \frac{\mathbb{E}(X)}{t}$$

$$\begin{aligned} \mathbb{E}(X) &= \int_0^\infty x f(x) dx = \int_0^t x f(x) dx + \int_t^\infty x f(x) dx \\ &\geq \int_t^\infty x f(x) dx \\ &\geq t \int_t^\infty f(x) dx = t P(X > t) \end{aligned}$$

$$\Rightarrow \mathbb{E}(X) \geq t P(X > t).$$

$$\Rightarrow P(X > t) \leq \frac{\mathbb{E}(X)}{t}.$$