

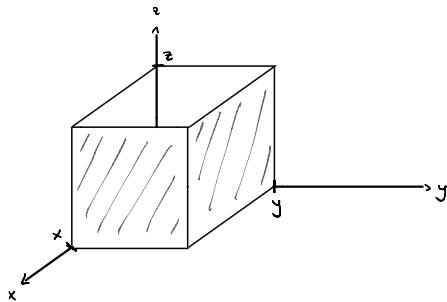
# Parcial 4 - Métodos Computacionales

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## Optimización

3. a)



b) El área superficial corresponde a la suma de las áreas laterales y de la base. Como cada cara tiene área  $xy$ ,  $xz$  o  $yz$  según

corresponda, podemos ver a partir del dibujo que el área superficial es  $A(x, y, z) = xy + yz + xz$ . Como hacemos la restricción de que  $A(x, y, z) = 12$ , entonces

$$A(x, y, z) = xy + yz + xz = 12.$$

$$\nabla A(x, y, z) = xy^2, xz^2, yz^2$$

$$\text{Restricción: } xy + yz + xz = 12, \quad x, y, z \geq 0.$$

$$\text{Sea } A(x, y, z) = xy + yz + xz - 12.$$

$$\begin{aligned} \text{Lagrange: } \nabla V &= \lambda \nabla A \\ (y^2, xz, xy) &= \lambda(y+2z, x+2z, y+2x) \end{aligned}$$

$$\begin{cases} y^2 = \lambda(y+2z) & (1) \\ xz = \lambda(x+2z) & (2) \\ xy = \lambda(y+2x) & (3) \end{cases}$$

$$\Rightarrow (1) \ y = \frac{2\lambda z}{z-\lambda}, (2) \ x = \frac{2\lambda z}{z-\lambda} \Rightarrow y = x$$

$$(3) \ x^2 = \lambda(4x) \rightarrow x = 4\lambda$$

$$(2) \ 4x^2 = 4\lambda^2 + 2z\lambda \rightarrow z = 2\lambda \Rightarrow x = 2z$$

Aplicando la restricción, vemos que  $x = y = z = 2 \Rightarrow \underline{\underline{V(2,2,1) = 4}}$ .

Distribuciones continuas de probabilidad:

2. Dada la función de probabilidad conjunta:

$$f(x,y) = \begin{cases} \frac{2}{3}(x+2y) & 0 \leq x \leq 1, 0 \leq y \leq 1 \\ 0 & \text{otro caso} \end{cases}$$

a) Verifique que sea una función de densidad conjunta válida:

• Para  $x \in \mathbb{R} \setminus [0,1]$  y  $y \in \mathbb{R} \setminus [0,1]$ ,  $f(x,y) = 0 \geq 0$ .

Para  $x \in [0,1]$  y  $y \in [0,1]$ ,  $f(x,y) = \frac{2}{3}(x+2y) \geq 0$  pues  $x+2y \geq 0$ . ( $x \geq 0$  y  $y \geq 0$ ).

$$\begin{aligned} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) dy dx &= 0 + \int_0^1 \int_0^1 \frac{2}{3}(x+2y) dx dy = \int_0^1 \left[ \frac{2}{3}x^2 + \frac{4}{3}xy \right]_0^1 dy = \int_0^1 \left[ \frac{1}{3} + \frac{4}{3}y \right] dy \\ &= \left[ \frac{1}{3}y + \frac{2}{3}y^2 \right]_0^1 = \frac{1}{3} + \frac{2}{3} = 1. \end{aligned}$$

$$\begin{aligned} b) \quad \text{Para } 0 \leq x \leq 1: \quad g(x) &= \int_{-\infty}^{\infty} f(x,y) dy = 0 + \int_0^1 f(x,y) dy = \int_0^1 \frac{2}{3}(x+2y) dy \\ &= \left[ \frac{2}{3}x + \frac{4}{3}y \right]_0^1 = \frac{2}{3}xy + \frac{2}{3}y^2 \Big|_0^1 = \frac{2}{3}x + \frac{2}{3} = \frac{2}{3}(x+1) \end{aligned}$$

$$\text{Para } x \in \mathbb{R} \setminus [0,1]: \quad g(x) = \int_{-\infty}^{\infty} f(x,y) dy = 0.$$

$$g(x) = \begin{cases} \frac{2}{3}(x+1) & 0 \leq x \leq 1 \\ 0 & \text{otro caso.} \end{cases}$$

$$\begin{aligned} \text{Para } 0 \leq y \leq 1: \quad h(y) &= \int_{-\infty}^{\infty} f(x,y) dx = 0 + \int_0^1 \frac{2}{3}(x+2y) dx = \int_0^1 \left[ \frac{2}{3}x + \frac{4}{3}y \right] dx \\ &= \left[ \frac{1}{3}x^2 + \frac{4}{3}xy \right]_0^1 = \frac{1}{3} + \frac{4}{3}y = \frac{1}{3}(1+4y). \end{aligned}$$

$$\text{Para } y \in \mathbb{R} \setminus [0,1]: \quad h(y) = \int_{-\infty}^{\infty} f(x,y) dx = 0.$$

$$h(y) = \begin{cases} \frac{1}{3}(1+4y) & 0 \leq y \leq 1 \\ 0 & \text{otro caso} \end{cases}$$

$$\begin{aligned} c) \quad E(x) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f(x,y) dx = 0 + \int_0^1 \int_0^1 x \cdot \frac{2}{3}(x+2y) dy dx = \int_0^1 \int_0^1 \left[ \frac{2}{3}x^2 + \frac{4}{3}xy \right] dy dx \\ &= \int_0^1 \left[ \frac{2}{3}x^2y + \frac{2}{3}x^2y^2 \right]_0^1 dx = \int_0^1 \left[ \frac{2}{3}x^3 + \frac{1}{3}x^2 \right] dx = \left[ \frac{2}{9}x^4 + \frac{1}{3}x^3 \right]_0^1 = \frac{2}{9} + \frac{1}{3} = \frac{5}{9} \end{aligned}$$

$$d) E(y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f(x,y) dy dx = 0 + \int_0^1 \int_0^1 y \cdot \frac{2}{3} (x+2y) dy dx = \int_0^1 \int_0^1 \frac{2}{3} xy + \frac{4}{3} y^2 dy dx$$

$$= \int_0^1 \left[ \frac{1}{3} xy^2 + \frac{4}{9} y^3 \right]_0^1 dx = \int_0^1 \frac{1}{3} x + \frac{4}{9} dx = \left[ \frac{1}{6} x^2 + \frac{4}{9} x \right]_0^1 = \frac{1}{6} + \frac{4}{9} = \frac{11}{18}$$

e)  $\text{Cov}(x,y) = E(xy) - E(x)E(y)$ . Solo falta calcular  $E(xy)$ :

$$E(xy) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f(x,y) dy dx = \int_0^1 \int_0^1 xy \cdot \frac{2}{3} (x+2y) dy dx = \int_0^1 \int_0^1 \frac{2}{3} x^2 y + \frac{4}{3} x y^2 dy dx$$

$$= \int_0^1 \left[ \frac{1}{3} x^2 y^2 + \frac{4}{9} x y^3 \right]_0^1 dx = \int_0^1 \frac{1}{3} x^2 + \frac{4}{9} x dx = \left[ \frac{1}{9} x^3 + \frac{2}{9} x^2 \right]_0^1 = \frac{1}{9} + \frac{2}{9} = \frac{1}{3}$$

$$\text{Cov}(x,y) = \frac{1}{3} - \frac{11}{18} \cdot \frac{5}{9} = -\frac{1}{162} \approx -0.00617.$$

$$f) \text{Cov}(x,y) = E((x - \bar{x})(y - \bar{y})) = E((x - E(x))(y - E(y))) = E((x - \frac{5}{9})(y - \frac{11}{18}))$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \frac{5}{9})(y - \frac{11}{18}) f(x,y) dy dx = \int_0^1 \int_0^1 \left( xy - \frac{5}{9}y - \frac{11}{18}x + \frac{55}{162} \right) \cdot \frac{2}{3} (x+2y) dy dx$$

$$= \int_0^1 \int_0^1 xy \cdot \frac{2}{3} (x+2y) dy dx - \frac{5}{9} \int_0^1 \int_0^1 y \cdot \frac{2}{3} (x+2y) dy dx - \frac{11}{18} \int_0^1 \int_0^1 x \cdot \frac{2}{3} (x+2y) dy dx$$

$$+ \frac{55}{162} \int_0^1 \int_0^1 \frac{2}{3} (x+2y) dy dx = E(xy) - \frac{5}{9} E(y) - \frac{11}{18} E(x) + \frac{55}{162} \cdot 1$$

$$= \frac{1}{3} - \frac{5}{9} \cdot \frac{11}{18} - \frac{11}{18} \cancel{\frac{5}{9}} + \cancel{\frac{55}{162}} = -\frac{1}{162} \approx -0.00617.$$

g) Como  $\text{cov}(x,y) \neq 0$ , las variables  $x$  y  $y$  no son independientes.

## Estimación de parámetros.

1. Sea  $A(x_1, \dots, x_n)$  donde  $A \sim N(\mu, \sigma^2)$  con parámetros  $\mu$  y  $\sigma^2$ . Muestre que los estimadores máximo verosímiles son:

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

Para  $N(\mu, \sigma^2)$  se tiene la función:

$$f(x | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Así, para varias variables independientes que se distribuyen normalmente, se define la función de verosimilitud así:

$$\begin{aligned} L(\mu, \sigma^2) &= f(x_1, \dots, x_n | \mu, \sigma^2) = f(x_1 | \mu, \sigma^2) \cdot \dots \cdot f(x_n | \mu, \sigma^2) = \prod_{i=1}^n f(x_i | \mu, \sigma^2) \\ &= \left( \frac{1}{\sqrt{2\pi\sigma^2}} \right)^n e^{-\sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2}} = \left( \frac{1}{2\pi\sigma^2} \right)^{n/2} e^{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}} \end{aligned}$$

$$\begin{aligned} \text{Para mayor comodidad, consideraremos } \tilde{L}(\mu, \sigma^2) &= \ln(L(\mu, \sigma^2)) \\ \tilde{L}(\mu, \sigma^2) &= \ln \left( \left( \frac{1}{2\pi\sigma^2} \right)^{n/2} e^{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}} \right) = \ln \left[ \left( \frac{1}{2\pi\sigma^2} \right)^{n/2} \right] + \ln \left( e^{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}} \right) \\ &= -\frac{n}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 \end{aligned}$$

Maximizaremos  $\tilde{L}$  (equivalente a maximizar  $L$  por la monotonía creciente de  $\ln$ ).

$$\begin{aligned} \frac{\partial \tilde{L}}{\partial \mu} &= -\frac{1}{2\sigma^2} \sum_{i=1}^n \frac{\partial}{\partial \mu} (x_i - \mu)^2 = -\frac{1}{2\sigma^2} \sum_{i=1}^n \frac{\partial}{\partial \mu} (x_i^2 - 2x_i\mu + \mu^2) = -\frac{1}{2\sigma^2} \sum_{i=1}^n (-2x_i + 2\mu) \\ &= -\frac{1}{2\sigma^2} \left( 2n\mu - 2 \sum_{i=1}^n x_i \right) = -\frac{n\mu}{\sigma^2} + \frac{1}{\sigma^2} \sum_{i=1}^n x_i \end{aligned}$$

$$\frac{\partial \tilde{L}}{\partial \sigma} = -\frac{n}{2} \cdot \frac{4\pi\sigma}{2\pi\sigma^2} + \frac{1}{2\sigma^3} \sum_{i=1}^n (x_i - \mu)^2 = -\frac{n}{\sigma} + \frac{1}{\sigma^3} \sum_{i=1}^n (x_i - \mu)^2$$

$$\text{Queremos } \frac{\partial \tilde{L}}{\partial \mu} = \frac{\partial \tilde{L}}{\partial \sigma} = 0 :$$

$$0 = -\frac{n\mu}{\sigma^2} + \frac{1}{\sigma^2} \sum_{i=1}^n x_i \Rightarrow \hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i = \bar{x}$$

$$0 = -\frac{n}{\sigma} + \frac{1}{\sigma^3} \sum_{i=1}^n (x_i - \mu)^2 \Rightarrow \hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu})^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

Como buscábamos.