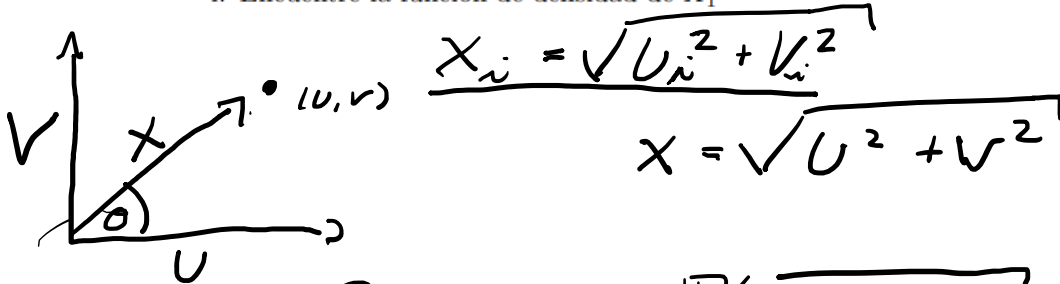


P1. Se quiere estudiar el comportamiento de un vector bidimensional que tiene sus dos componentes ortogonales, independientes y que siguen una distribución normal. Al realizar las mediciones respectivas de cada componente, se obtiene una MAS $U = (U_1, \dots, U_n)$ de n observaciones con $U_n \sim \mathcal{N}(0, \sigma^2)$ y una MAS $V = (V_1, \dots, V_n)$ de n observaciones con $V_n \sim \mathcal{N}(0, \sigma^2)$. En específico, se busca estudiar el comportamiento de los módulos de los vectores obtenidos. Se obtiene una nueva MAS $X = (X_1, \dots, X_n)$

i. Encuentre la función de densidad de X_1



$$P(X \leq x) = P(\sqrt{U^2 + V^2} \leq x)$$

$$D_x = \{(u, w) \mid \sqrt{u^2 + w^2} \leq x\}$$

Entonces

$$P(X \leq x) = F_X(x) = \iint_{D_x} f_{U,W}(u, w) du dw$$

$$= \iint_{D_x} f_U(u) f_W(w) du dw$$

$$U \sim \mathcal{N}(0, \sigma^2), W \sim \mathcal{N}(0, \sigma^2)$$

$$F_X(x) = \iint_{D_x} \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{1}{2}\frac{u^2}{\sigma^2}} \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{1}{2}\frac{w^2}{\sigma^2}} du dw$$

$$= \frac{1}{2\pi\sigma^2} \iint_{D_x} e^{-\frac{1}{2\sigma^2}(u^2 + w^2)} du dw$$

$$r^2 = u^2 + w^2, \quad \theta \in [0, 2\pi]$$

$$= \frac{1}{2\pi\sigma^2} \int_0^{2\pi} \int_0^x e^{-\frac{1}{2\sigma^2} r^2} r dr d\theta$$

$$= \frac{1}{\sigma^2} \int_0^x e^{-\frac{1}{2\sigma^2} r^2} r dr$$

$$\frac{\partial F_X(x)}{\partial x} = f_X(x)$$

$$\Rightarrow \boxed{f_X(x) = \frac{x}{\sigma^2} e^{-\frac{1}{2\sigma^2} x^2}} \quad x \sim \text{Rayleigh}(\sigma)$$

P2: Consideremos el estimador de la varianza

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (\bar{x}_n - x_i)^2 \quad || \quad \bar{x}_n$$

$$i) E(S^2) = \sigma^2.$$

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n \bar{x}_n^2 + x_i^2 - 2x_i \bar{x}_n$$

$$= \frac{1}{n-1} \left[n \bar{x}_n^2 - 2 \bar{x}_n \sum_{i=1}^n x_i + \sum_{i=1}^n x_i^2 \right]$$

$$= \frac{1}{n-1} \left[n \bar{x}_n^2 - 2n \bar{x}_n \bar{x}_n + \sum_{i=1}^n x_i^2 \right] = \frac{1}{n-1} \left[\sum_{i=1}^n x_i^2 - n \bar{x}_n^2 \right]$$

$$E(S^2) = E \left[\frac{1}{n-1} \left(\sum_{i=1}^n x_i^2 - n \bar{x}_n^2 \right) \right]$$

$$= \frac{1}{n-1} \left(\underbrace{E \left(\sum_{i=1}^n x_i^2 \right)}_{(1)} - n \underbrace{E \left(\bar{x}_n^2 \right)}_{(2)} \right) = \star \star$$

Antes de calcular 1, veamos lo siguiente

$$\text{Var}(X) = E[(X - E(X))^2]$$

$$= E[X^2 - 2E(X)X + E(X)^2]$$

$$= E(X^2) - 2E(X)E(X) + E(X)^2$$

$$= E(X^2) - E(X)^2$$

$$\underline{\text{Var}(X)} = E(X^2) - E(X)^2$$

$$(1) = E \left(\sum_{i=1}^n x_i^2 \right) = \sum_{i=1}^n E(x_i^2)$$

$$= \sum_{i=1}^n E(x_i^2) - E(x_i)^2 + E(x_i)^2$$

$$= \sum_{i=1}^n \text{Var}(x_i) + E(x_i)^2$$

$$x_i \sim N(\mu, \sigma^2)$$

$$= \sum_{i=1}^n \sigma^2 + \mu^2$$

$$= n(\sigma^2 + \mu^2) = (1)$$

$$(2) = E(\bar{x}_n^2) = E(\bar{x}_n) - E(\bar{x}_n)^2 + E(\bar{x}_n)^2$$

$$\textcircled{2} = \underline{E(\bar{X}_n^2)} = E(\bar{X}_n^2) - E(\bar{X}_n)^2 + E(\bar{X}_n)^2$$

$$\textcircled{*} = \text{Var}(\bar{X}_n) + E(\bar{X}_n)^2$$

$$\bullet X_i \sim N(\mu, \sigma^2)$$

$$\bullet \sum X_i \sim N(n\mu, n\sigma^2)$$

$$\bullet \frac{1}{n} \sum X_i \sim \frac{1}{n} N(n\mu, n\sigma^2) = N\left(\frac{n\mu}{n}, \frac{n\sigma^2}{n^2}\right)$$

$$= N\left(\mu, \frac{\sigma^2}{n}\right) //$$

$$\bar{X}_n \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

$$\textcircled{*} = \boxed{\frac{\sigma^2}{n} + \mu^2 = \textcircled{2}}$$

$$\textcircled{**} = \frac{1}{n-1} \left(n(\sigma^2 + \mu^2) - n\left(\frac{\sigma^2}{n} + \mu^2\right) \right)$$

$$= \sigma^2 //$$

Se tiene que $E(S^2) = \sigma^2$.

Esto es que el estimador sea insesgado

ii) Calcular la varianza de S^2 .

$\bullet \bar{X}_n \perp\!\!\!\perp S^2$. (Se verá después) \rightarrow Necesario para el desarrollo "a mano" y el que veremos ahora.

$$\begin{aligned} \bullet W &= \sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma} \right)^2 \\ &= \sum_{i=1}^n \left(\frac{(X_i - \bar{X}_n) + (\bar{X}_n - \mu)}{\sigma} \right)^2 \\ &= \sum_{i=1}^n \left(\frac{X_i - \bar{X}_n}{\sigma} \right)^2 + \sum_{i=1}^n \left(\frac{\bar{X}_n - \mu}{\sigma} \right)^2 + 2 \left(\frac{\bar{X}_n - \mu}{\sigma} \right) \sum_{i=1}^n \left(\frac{X_i - \bar{X}_n}{\sigma} \right) \\ &= \frac{1}{\sigma^2} \sum_{i=1}^n (X_i - \bar{X}_n)^2 + n \left(\frac{\bar{X}_n - \mu}{\sigma} \right)^2 \end{aligned}$$

$$\begin{aligned} \sum_{i=1}^n X_i - n\bar{X}_n \\ = n\bar{X}_n - n\bar{X}_n = 0 \end{aligned}$$

$$W = \frac{(n-1) S^2}{\sigma^2} + n \left(\frac{\bar{X}_n - \mu}{\sigma} \right)^2$$

$$W = \underbrace{\frac{(n-1)s^2}{\sigma^2}}_{\chi^2_?} + \underbrace{n \left(\frac{\bar{X}_n - \mu}{\sigma} \right)^2}_{\chi^2_?}$$

z^2 distribuye como sigue:
 $\bar{X}_n - \mu \sim N(0, \frac{\sigma}{\sqrt{n}})$
 $\frac{\bar{X}_n - \mu}{\sigma} \sim N(0, \frac{1}{n})$

$$Z = \sqrt{n} \left(\frac{\bar{X}_n - \mu}{\sigma} \right) \sim N(0, 1)$$

$$Z^2 \sim \chi^2_1$$

$$\bullet \sum \underbrace{\left(\frac{X_i - \mu}{\sigma} \right)^2}_{N(0,1)}$$

$$X_i \sim N(\mu, \sigma^2)$$

$$X_i - \mu \sim N(0, \sigma^2)$$

$$\frac{X_i - \mu}{\sigma} \sim N(0, 1)$$

$$W \sim \chi^2_n$$

$$\rightarrow P_W(t) = E[e^{tW}] = E[e^{t \left(\frac{(n-1)s^2}{\sigma^2} + Z^2 \right)}]$$

$$s^2 \perp \bar{X}_n \Rightarrow E[e^{t \left(\frac{(n-1)s^2}{\sigma^2} \right)} e^{tZ^2}]$$

$$= P_{\frac{(n-1)s^2}{\sigma^2}}(t) \cdot P_{Z^2}(t)$$

$$\bullet P_W(t) = P_{\frac{(n-1)s^2}{\sigma^2}}(t) \cdot P_{Z^2}(t)$$

$$W \sim \chi^2_n, Z^2 \sim \chi^2_1$$

$$(1-2t)^{-\frac{n}{2}} = P_{\frac{(n-1)s^2}{\sigma^2}}(t) \cdot (1-2t)^{-\frac{1}{2}}$$

$$(1-2t)^{-\frac{(n-1)}{2}} = P_{\frac{(n-1)s^2}{\sigma^2}}(t)$$

se concluye que

$$\frac{(n-1)s^2}{\sigma^2} \sim \chi^2_{n-1}$$

Entonces, ahora podemos calcular $\text{Var}(S^2)$

$$\text{Var}(S^2) = \text{Var}\left(\frac{1}{n-1} \sum (x_i - \bar{x}_n)^2\right)$$

$$= \text{Var}\left(\frac{1}{n-1} \frac{\sigma^2}{\sigma^2} \sum (x_i - \bar{x}_n)^2\right)$$

$$= \left(\frac{\sigma^2}{n-1}\right)^2 \text{Var}\left(\underbrace{\frac{n-1}{\sigma^2} S^2}_{\chi^2_{n-1}}\right)$$

$$= \frac{\sigma^4}{(n-1)^2} 2(n-1)$$

$$= \boxed{\frac{2\sigma^4}{n-1} = \text{Var}(S^2)} //$$