


Ej 1

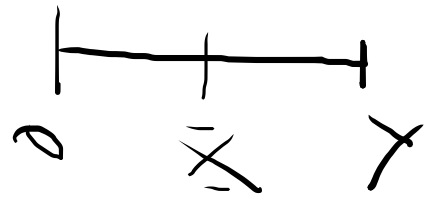
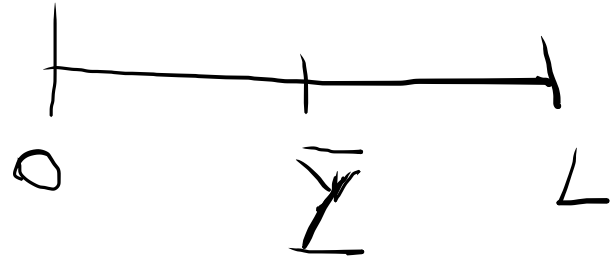
Juan	Pedro
2	1
3	1
3	2
4	1, 2, 3
5	1, 2, 3, 4
6	1, 2, 3, 4, 5

 $P(\bar{X}=c) = \frac{1}{6}$
 $\{1, 2, 3, 4, 5, 6\}$

Gano Juan.

$$\hat{P} = \frac{\text{casos favorables}}{\text{casos posibles}} = \frac{4}{15}$$

Ej 2



$$\bar{Y} \sim U[0, L] \quad E[\bar{Y}] = L/2$$

$$\bar{X} \sim U[0, \bar{Y}] \Rightarrow E[\bar{X} | \bar{Y} = y] = y/2$$

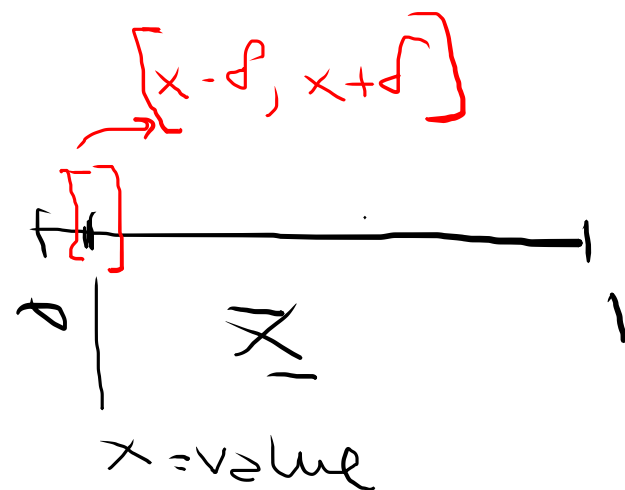
$$E[\bar{X}] = E[E[\bar{X} | \bar{Y}]] = E[\bar{Y}/2] = \frac{E[\bar{Y}]}{2} = \frac{L}{4}$$

Ej 3

$$\bar{X}, \bar{Y} \sim U[0, 1] \text{ iid}$$

$$\bar{Z} = \bar{X} + \bar{Y}$$

$$E[\bar{Z} | \bar{X}] = E[X + Y | X = x] = \underbrace{E[\bar{X} | \bar{X} = x]}_x + \underbrace{E[Y | X]}_{E[Y]} = x + \frac{1}{2}$$



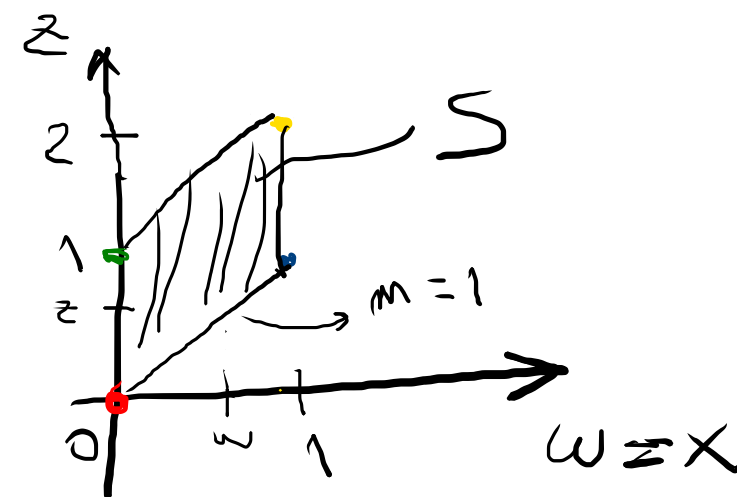
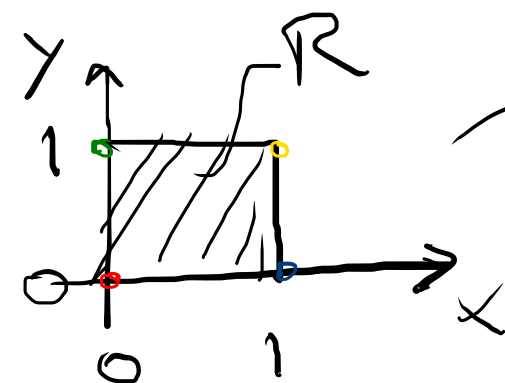
$$E[\bar{x}\bar{z} | \bar{x} = x] = x E[\bar{z} | \bar{x}] = x \left(x + \frac{1}{2}\right)$$

$$E[xz | z] = z E[x | z]$$

$$|E[\bar{x}\bar{z}]|$$

$$\begin{cases} z = x + y \\ w = x \end{cases}$$

$$x, y \sim U[0, 1] \text{ i.i.d.}$$



$$\begin{aligned} (x, y) = (0, 0) &\rightarrow (w, z) = (0, 0) \\ &= (1, 0) \rightarrow = (1, 1) \\ &= (0, 1) \rightarrow = (0, 1) \\ &= (1, 1) \rightarrow (1, 2) \end{aligned}$$

$$J = \begin{vmatrix} \frac{\partial w}{\partial x} & \frac{\partial w}{\partial y} \\ \frac{\partial z}{\partial x} & \frac{\partial z}{\partial y} \end{vmatrix} = \begin{vmatrix} 1 & 0 \\ 1 & 1 \end{vmatrix} = 1$$

$$E[\underline{w} | \bar{z} = z] \equiv E[\underline{x} | \bar{z} = z]$$

\uparrow
 Part transformation
 $(w = x)$

$$z \in [0, 1] \Rightarrow w \in [0, z] \Rightarrow x \in [0, z] \Rightarrow E[\underline{x} | \bar{z} \in [0, 1]] = \frac{z}{2}$$

$\underbrace{\hspace{1.5cm}}_{\text{unif.}}$

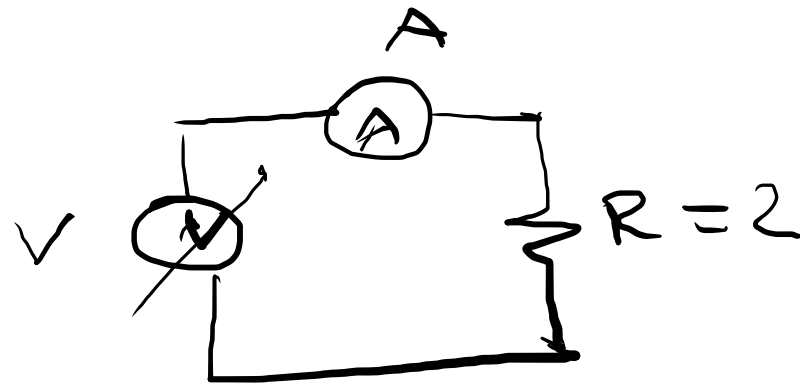
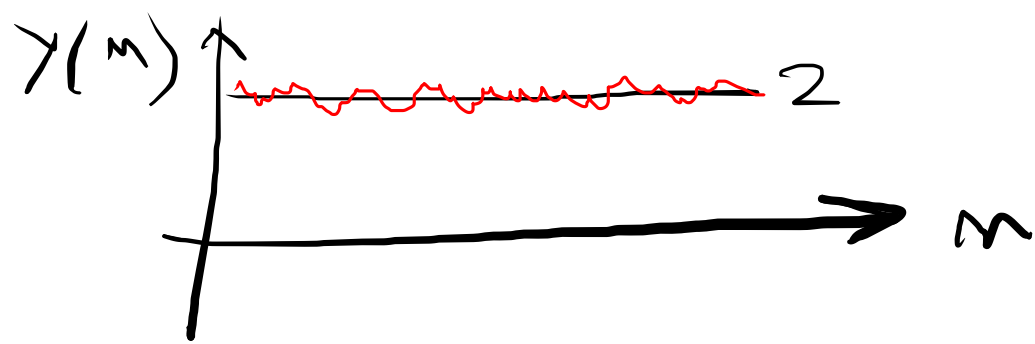
$$z \in [1, 2] \rightarrow x \in [z-1, 1] \Rightarrow E[\underline{x} | \bar{z} \in [1, 2]] = \frac{z-1+1}{2} = \frac{z}{2}$$

$$E[\underline{x} | \bar{z}] = \frac{z}{2} \quad w, z \in S.$$

$$\Rightarrow E[xz | z] = z E[x | z] = \frac{z^2}{2}$$

Ej 4

$$y(n) = 2 + w(n), \quad w(n) \sim N(0, 1)$$



$$\hat{x} = \frac{V}{R} + w(n)$$

Medio muestral

$$\hat{y} = \bar{y} = \frac{1}{N} \sum_{n=0}^{N-1} y(n) \rightarrow E[w(n)] = 0$$

$$E[\hat{y}] = \frac{1}{N} \sum_{n=0}^{N-1} \underbrace{E[y]}_2 = \frac{1}{N} \cdot N \cdot 2 = 2 \quad \leftarrow \text{estimador insesgado de la media}$$

$$\text{var}[y] = 1$$

\hat{X} estimador de un parámetro de Ξ (por ej. la media)

$$\hat{X} = g(\bar{X}) = g(x_i) \quad x_i \text{ surgen de } \bar{X}$$

\hat{X} es una v.a. $\rightarrow E[\hat{X}]$

$$\text{var}[\hat{X}]$$

\vdots

parámetro a estimar

bias (sesgo) $\rightarrow b = E[\hat{X}] - \mu = 0 \leftarrow \text{insesgado}$
 $\neq 0 \leftarrow \text{sesgado.}$

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

$$\text{MSE}[\hat{X}] = \text{var}[\hat{X}] + (b[\hat{X}])^2$$

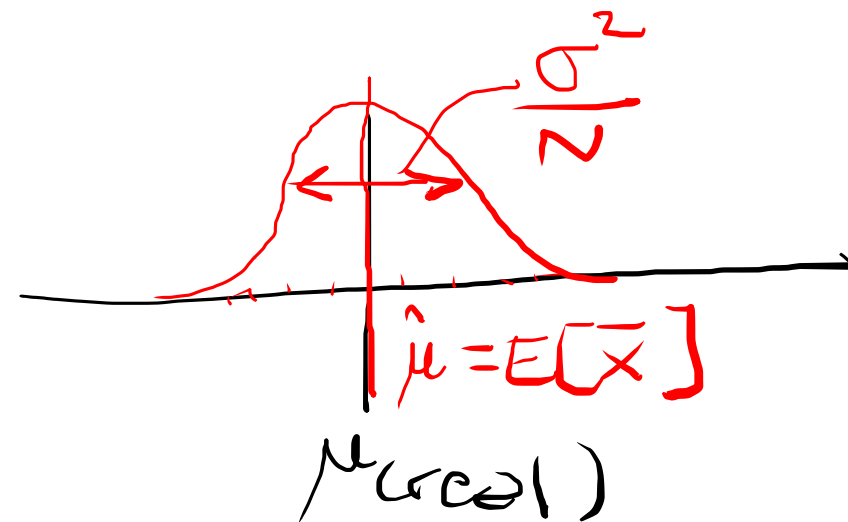
Estimador media muestral:

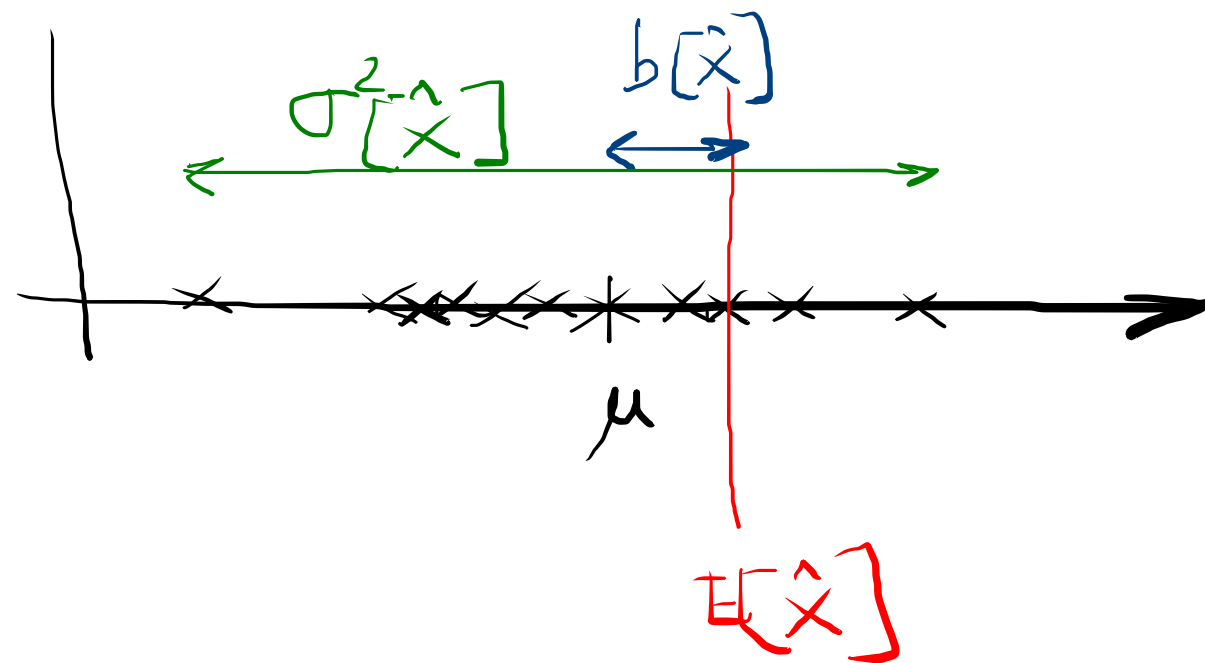
$$\bar{x} = \frac{1}{N} \sum_{i=0}^{N-1} x_i$$

$$\left[\begin{array}{l} x_i \sim \mu, \sigma^2 \\ x_i \text{ iid.} \end{array} \right]$$

$$E[\bar{x}] = \frac{1}{N} \sum_{i=0}^{N-1} \underbrace{E[x_i]}_{\mu} = \frac{1}{N} \underbrace{\sum_{i=0}^{N-1} \mu}_{N\mu} = \mu \leftarrow \text{insesgado.}$$

$$\text{var}[\bar{x}] = \frac{1}{N^2} \underbrace{\sum_{i=0}^{N-1} \sigma^2}_{N\sigma^2} = \frac{\sigma^2}{N}$$





$\bar{X} \rightarrow x_i$ (muestras)

$\hat{X} \rightarrow \hat{x}_i = g(x_i)$

Quiero estimar μ

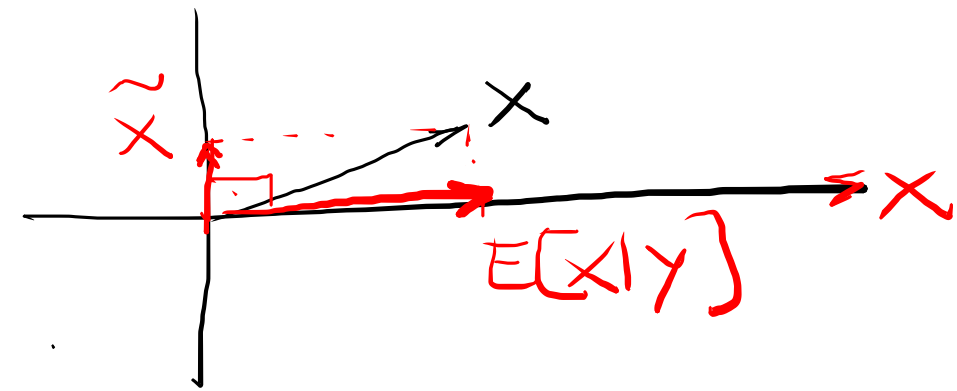
con \hat{X}

$$MSE = var + b^2$$

$$\tilde{x}^2 = x - \hat{x} \quad \hat{x} = E[x|y] \Rightarrow E[\tilde{x}] = E[E[x|y]] = E[x]$$

$$E[\tilde{x}] = E[x] - \underbrace{E[\hat{x}]}_{E[x]} = 0 \rightarrow \text{esperanza del error}$$

$$E[\hat{x} \tilde{x}] = 0 \rightarrow \text{ortogonales} \\ \Rightarrow \text{descorrelacionadas}$$



$$\hat{x} = \alpha y + b \quad E[(x - \hat{x})^2] \min \rightarrow E[(x - \alpha y - b)^2]$$

fijo $\alpha \Rightarrow$ nueva v.a. $x - \alpha y \Rightarrow b \quad b = E[x - \alpha y]$

$$b = E[x] - \alpha E[y]$$

$$\frac{\partial E[\cdot]}{\partial \alpha} = 0 \Rightarrow \alpha$$

$$Y = X + W$$

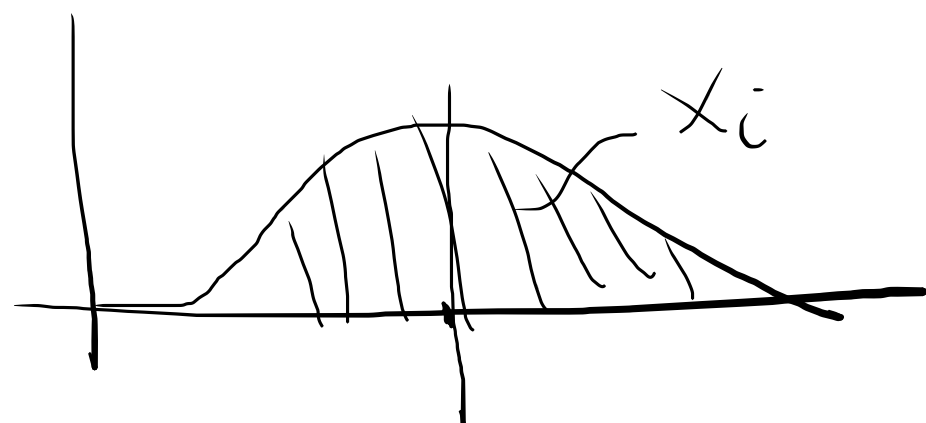
$$\begin{array}{c} \uparrow \\ E[y] \end{array} \quad \begin{array}{c} \uparrow \\ E[x] \end{array}, \text{cov}[x, y], \text{var}[y]$$

$$y^{(n)} = \theta x^{(n)} + b + \cancel{\varepsilon}$$

$$\left[\begin{array}{l} y^{(1)} = \theta x^{(1)} + b + \varepsilon^{(1)} \\ y^{(2)} = \theta x^{(2)} + b + \varepsilon^{(2)} \\ \vdots \\ y^{(n)} = \theta x^{(n)} + b + \varepsilon^{(n)} \end{array} \right. \quad y = \begin{bmatrix} y^{(1)} \\ \vdots \\ y^{(n)} \end{bmatrix} \quad \beta = \begin{bmatrix} \theta \\ b \end{bmatrix}$$

$$A = \begin{bmatrix} \tilde{x}^{(1)} & 1 \\ \vdots & \vdots \\ x^{(n)} & 1 \end{bmatrix}$$

$$\min \|y - X\|^2 \rightarrow \beta \quad y = A\beta \Rightarrow \beta = \underbrace{(A^T A)^{-1} A^T}_{\text{PinV}(A)} y.$$



$\mu = ?$

$\mu = 1$ (por ej.)

σ^2 es conocida

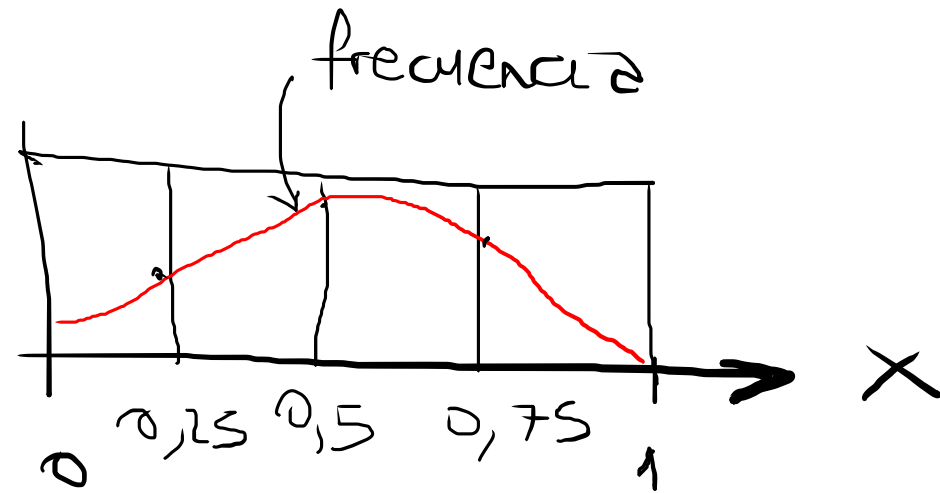
$\theta \sim$ máxima $p(x|\theta)$.

$x_1, \dots, x_n \sim \text{iid}$

$$P_{x_1 x_2 \dots x_n | \theta} = \prod P_{x_i | \theta}$$

$$\prod_{i=1}^n p(x_i | \mu) = \frac{1}{(2\pi)^{n/2}} \frac{1}{\sigma^n} \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right]$$

Histograma



$$M = 4$$

$$n = 100$$

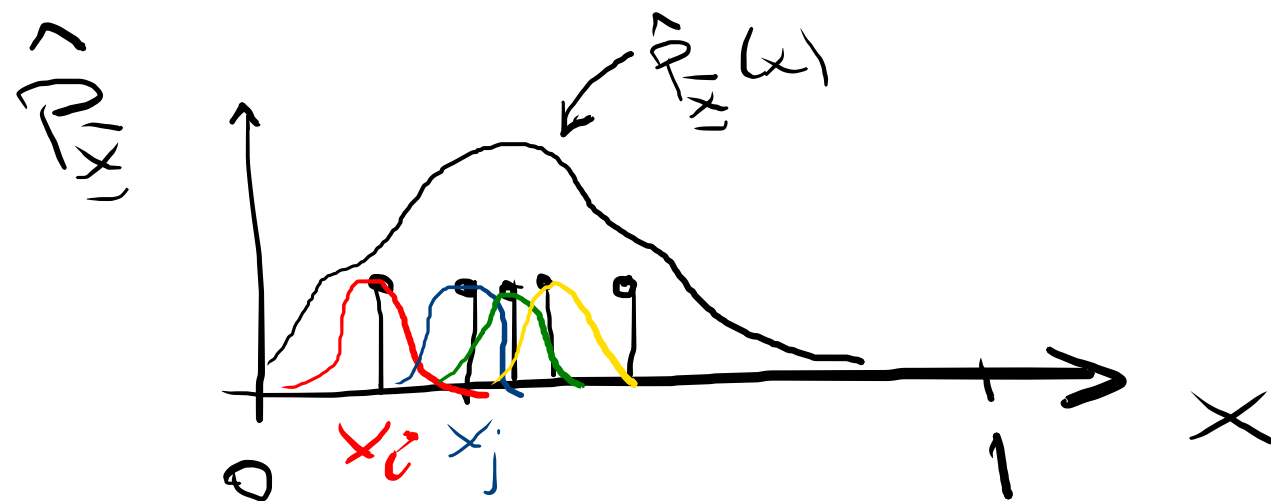
$$B_1 = \left[0, \frac{1}{M}\right]$$

$$B_2 = \left[\frac{1}{M}, \frac{2}{M}\right]$$

⋮

$$B_M = \left[\frac{M-1}{M}, 1\right]$$

Estimación de densidad de Kernel



n muestras

Σ distribuciones

$$\hat{p}_{\underline{x}}(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{\overset{\text{muestra } x_i}{x_i - x}}{\underset{\text{parámetro}}{h}}\right)$$

$$\int \hat{p}_{\underline{x}}(x) dx = 1$$

