

$$\hat{x} = \frac{E[xy] - E[x]E[y]}{E[y^2] - E[y]^2} (y - E[y])$$

$\Rightarrow$  MATLAB

$$\Rightarrow \hat{x} = \frac{ym^2 - m + 1}{1^2 + m^2} \quad \text{does not match} \rightarrow \text{this is the LLSE for part (Q4)}$$

what went wrong?? How to get  $e^{-1/x}$  and  $e^{-1/y}$  into  $\hat{x}$ ??

↑  
Comment:  
similar form.  
 $\hat{x} = -$

$$\hat{x} = m_x + R_{xy} R_y^{-1} (y - m_y)$$

$$m_x = \frac{1}{1}$$

$$m_y = E[y] = E[x+v] = \frac{1}{2} + \frac{1}{m}$$

$$\begin{aligned} R_{xy} &= E[xy] - E[x]E[y] = E[x(x+v)] - E[x]E[x+v] \\ &= E[x^2] + E[xv] - E[x]E[x] - E[x]E[v] \\ &= \frac{1}{1^2} + \frac{1}{1} \left( \frac{1}{m} \right) - \frac{1}{1^2} - \frac{1}{1} \frac{1}{m} = 0 \end{aligned}$$

Non-linear, optimal estimate:

$$\text{let } h^* = \underset{h}{\operatorname{argmin}} E[(x - h(y))(x - h(y))^T]$$

since  $E[(x - h(y))(x - h(y))^T] \geq 0$  by definition,

then if we can find  $h(y)$  s.t.  $E_{x|h} = 0$ ,  $h(y) = h^*$  since

$E_{x|h}$  cannot be any lower value.

Calculation  $\rightarrow$



$$\mathbb{E} \text{ let } h(y) = \hat{x} = \frac{1}{\lambda - \mu} - \left( \frac{e^{-\lambda y}}{e^{-\mu y} - e^{-\lambda y}} \right) y = \frac{1}{\lambda - \mu} - \left( \frac{e^{-\lambda(x+v)}}{e^{-\mu(x+v)} - e^{-\lambda(x+v)}} \right) (x+v)$$

$$\Rightarrow \mathbb{E}[(x - \hat{x})(x - \hat{x})^T] = \mathbb{E}[(x - \hat{x})^2] = \mathbb{E}[x^2] - \mathbb{E}[x\hat{x}] - \mathbb{E}[\hat{x}x] + \mathbb{E}[\hat{x}^2]$$

$$\mathbb{E}[x^2] = \frac{1}{\lambda^2}$$

$$\mathbb{E}[x\hat{x}] = \mathbb{E}\left[\frac{x}{\lambda - \mu} - \left(\frac{e^{-\lambda y}}{e^{-\mu y} - e^{-\lambda y}}\right)xy\right] \Rightarrow \text{MATLAB}$$

$$= \frac{1}{\lambda(\lambda - \mu)}$$

$$\mathbb{E}[\hat{x}x] = \mathbb{E}[x\hat{x}] \text{ (scalar)} = \mathbb{E}\left[\frac{x}{\lambda - \mu} - x(x+v) \left( \frac{e^{-\lambda x} e^{-\lambda v}}{e^{-\mu x} e^{-\mu v} - e^{-\lambda x} e^{-\lambda v}} \right)\right]$$

$$\mathbb{E}[\hat{x}^2] = \left[ \frac{1}{\lambda^2} \left( \frac{1}{\lambda - \mu} \right) - \mathbb{E}\left[(x^2 + xv) \left( \frac{e^{-\lambda x} e^{-\lambda v}}{e^{-\mu x} e^{-\mu v} - e^{-\lambda x} e^{-\lambda v}} \right)\right] \right]$$

too long...



# #8] Optimized Nonlinear estimator for binary signals

#8-Q1] obs.  $y_i = x + v_i$ ,  $x$  &  $v_i$  independent real-valued random variables

$\{v_i\}_{i=0}^{\infty}$  is a white noise Gaussian process.

$$E[v] = 0, E[v^2] = R_v = 1$$

$x = \pm 1$  w/ equal probability...

$$\hat{x} = h(y) = \tanh\left(\sum_{i=0}^{n-1} y_i\right)$$

$$P(h) = E[(x - h(y))(x - h(y))^T]$$

~~$\hat{x} = h(y)$~~  ... ?

$$= E[(x - \hat{x}_n)(x - \hat{x}_n)^T]$$

$x, \hat{x}$  scalar...

$$= E[x^2] - 2E[x\hat{x}_n] + E[\hat{x}_n^2]$$

$$\hat{x} = \tanh\left(\sum_{i=0}^{n-1} y_i\right)$$

$$E[(x - \hat{x}_n)^2] = E[E[(x - \hat{x}_n)^2 | x]]$$

$$P(x=1) = \frac{1}{2}, E[x=-1] = \frac{1}{2}$$

$$= E[(1 - \hat{x}_n)^2](0.5) + E[(-1 - \hat{x}_n)^2](0.5)$$

$$E[(1 - \hat{x}_n)^2] = E[(1 - \tanh(\sum_{i=0}^{n-1} y_i))^2]$$

$$1 - 2\hat{x}_n + \hat{x}_n^2$$

$$= 1 - 2E[\hat{x}_n] + E[\hat{x}_n^2]$$

$$1 - 2E\left[\tanh\left(\sum_{i=0}^{n-1} (x + v_i)\right)\right] + E\left[\tanh\left(\sum_{i=0}^{n-1} (1 + v_i)\right)^2\right]$$

$$\sum_{i=0}^{n-1} (1 + v_i) = n \quad \text{b/c } \{v_i\}_{i=0}^{\infty} \text{ is 0-mean, Gaussian}$$

$$= 1 - 2E[\tanh(n)] + E[\tanh(n)^2]$$

$n \gg 1$

$$\tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

$$E[(1 - \hat{x}_n)^2] = 1 - 2 + 1 = 0$$

$$E[(-1 - \hat{x}_n)^2] = E[1 + 2\hat{x}_n + \hat{x}_n^2] = 1 + 2 + 1 = 4$$

$$E[\hat{x}_n] = E\left[\tanh\left(\sum_{i=0}^{n-1} (-1 + v_i)\right)\right]$$

$$= E[\tanh(-n)] = -1$$

$$E[\hat{x}_n^2] = E[\tanh(n)^2] = 1$$

$$\Rightarrow E[(-1 - \hat{x}_n)^2] = 1 - 2 + 1 = 0$$

$$\Rightarrow E[(x - \hat{x}_n)^2] = 0 + 0 = 0$$

$$= 0 + 0 = \boxed{0} \checkmark$$