

① a) (ii) results in a more accurate estimator for  $N > 1$ . ~~As~~ As  $N$  becomes large the MUSE estimator weights the data portion more heavily compared to the prior and the accuracy of the estimator is then determined predominantly by  $\sigma^2$ . Since  $\sigma^2$  is smaller for (ii), this is the scenario which gives a more accurate estimator.

$$\lim_{N \rightarrow \infty} \frac{1}{1/\sigma_A^2 + N/\sigma^2} = \sigma^2/N$$

b)  $\beta \rightarrow \infty$ . This results in an uninformative prior  $p(A) = \text{constant}$  for all  $A$ . Then

$$p(A|x) = \frac{p(x|A)p(A)}{\int p(x|A)p(A)dA} = \frac{p(x|A)p(A)}{p(A) \int p(x|A)dA}$$

$\underbrace{\int p(x|A)dA}_{\text{indep of } A}$   
 since  $p(A)$  constant

Picking the max. of  $p(A|x)$ , therefore is equal to picking the max of  $p(x|A)$  which is also the MLE estimator.

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Alternative answer:  $|\bar{X}| < \alpha/2$

2a) ~~MMSE~~

$$E[\theta|x] = E(\theta) + \frac{\text{cov}(\theta, x)}{\text{var}(x)} (x - E(x))$$

$$E[\theta|x=3] = 1 + \frac{-0.5}{4} (3 - (-1))$$

$$= 1 + \frac{-0.5 \times 4}{4}$$

$$= 0.5 \text{ (MMSE)}$$

$$\hat{\theta}_{\text{MAP}} = \hat{\theta}_{\text{MMSE}} = 0.5 \text{ since } \theta, x \text{ jointly}$$

Gaussian.

$$\text{b) in this case } E[\theta|x=3] = 1 + \frac{0}{4} \times 4$$

$$= 1$$

$$\textcircled{3} \text{ a) } \hat{A}_{\text{MAP}} = \arg \max p(x|A) p(A)$$

$$p(x|A) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{\Sigma(x[n]-A)^2}{2\sigma^2}\right]$$

$$p(x|A) p(A) = \frac{0.5}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{\Sigma(x[n]-A)^2}{2\sigma^2}\right] \times$$

$$\left( \delta(A+1) + \delta(A-1) \right)$$

$$p(x|A)p(A) = \begin{cases} \frac{0.5}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{\sum(x[n]+1)^2}{2\sigma^2}\right], & A = -1 \\ \frac{0.5}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{\sum(x[n]-1)^2}{2\sigma^2}\right], & A = 1 \\ 0, & \text{otherwise} \end{cases}$$

therefore  $\hat{A}_{MAP} = \begin{cases} 1 & \text{if } r \geq \eta \\ -1 & \text{if } r < \eta \end{cases}$

equivalently  $\hat{A}_{MAP} = \begin{cases} 1 & \text{if } \sum x[n] \geq 0 \\ -1 & \text{if } \sum x[n] < 0 \end{cases}$

b)  $p(A|y) = \frac{p(y|A)p(A)}{p(y)}$  Bayes rule

$= \frac{p(y)p(A)}{p(y)}$  independence of  $y$  &  $A$

$= p(A)$

Therefore  $\hat{A}_{MMSE} = E[A|y] = E[A]$

$= \int_{-\infty}^{\infty} A(0.5\delta(A+1) + 0.5\delta(A-1))dA$

$= -1 \times 0.5 + 1 \times 0.5 = 0$

$$(4) a) \hat{\theta}[0] = \frac{\langle \theta, x[0] \rangle}{\langle x[0], x[0] \rangle} x[0]$$

$$\langle \theta, x[0] \rangle = E[\theta x[0]] = E[\theta (\theta \cdot 0 + w[0])] \\ = E[\theta w[0]] = E[\theta] E[w[0]]$$

$$= 0$$

Therefore  $\hat{\theta}[0] = 0$

Not surprising since a data point with  $n=0$  can't give us any information about the slope of a line passing through the origin.

$$b) \tilde{x}[1] = x[1] - \hat{x}[1|0]$$

$$\hat{x}[1|0] = \frac{\langle x[1], x[0] \rangle}{\langle x[0], x[0] \rangle} x[0]$$

$$= \frac{E[x[1]x[0]]}{E[x^2[0]]} x[0] = \frac{E[(\theta \cdot 1 + w[1])(\theta \cdot 0 + w[0])]}{E[(\theta \cdot 0 + w[0])^2]} x[0]$$

using independence &  $E[w] = 0, E[w] = 0 \Rightarrow 0$

$$= \frac{E[\theta w[0]] + E[w[1]w[0]]}{E[\theta^2] + E[w[0]^2]} x[0]$$

$$= 0$$

Therefore  $\tilde{x}[1] = x[1]$

$$\hat{\theta}[1] = \hat{\theta}[0] + \Delta \hat{\theta}[1|0] = \Delta \hat{\theta}[1|0]$$

$$\Delta \hat{\theta}[1|0] = \frac{\langle \theta, \tilde{x}[1] \rangle}{\langle \tilde{x}[1], \tilde{x}[1] \rangle^2} \tilde{x}[1]$$

$$= \frac{\langle \theta, x[1] \rangle}{\langle x[1], x[1] \rangle^2} x[1]$$

$$= \frac{E(\theta x[1])}{E(x[1]^2)} x[1] = \frac{E(\theta \times (\theta + w[1]))}{E[(\theta + w[1])^2]} x[1]$$

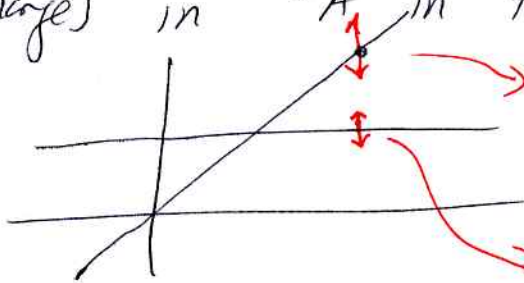
$$= \frac{E(\theta^2) + \cancel{E(\theta)E(w[1])}}{E(\theta^2) + E[w[1]^2] + \cancel{2E(\theta)E(w[1])}} x[1]$$

$$= \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma^2} x[1]$$

c)  $x[n]$  is much more sensitive to change in  $\theta$  for large  $n$  in the model

$x[n] = \theta n + w[n]$  compared to

the sensitivity of  $x[1]$  with respect to changes in  $A$  in the model  $x[1] = A + w[1]$



changing the slope by  $\Delta \theta$  changes  $x[n]$  by  $(\Delta \theta)n$

here  $x[1]$  changes by  $\Delta A$