

1)

$$p(x|\theta) = \theta^K (1-\theta)^{N-K} \quad K = \# \text{ of } x_i = 1$$

$$\hat{\theta} = \operatorname{argmax}_{\theta} \log p(x|\theta)$$

$$= \operatorname{argmax}_{\theta} K \log \theta + (N-K) \log (1-\theta)$$

$$\frac{d}{d\theta} \log p(x|\theta) = 0 \Rightarrow \theta = \frac{K}{N}$$

2)

a)  $\hat{\theta} = y$

b)  $\log p(x|y) = \log p(y|x) + \log p(x) + c$

$$= -(y-x)^T R_n^{-1} (y-x) - x^T R_x^{-1} x + c$$

$$= -(x-\mu)^T R^{-1} (x-\mu) + c''$$

where  $R^{-1} = (R_n^{-1} + R_x^{-1})$

$$\mu = (R_n^{-1} + R_x^{-1})^{-1} R_n^{-1} y$$

$$\hat{x}_{MMSE} = (R_n^{-1} + R_x^{-1})^{-1} R_n^{-1} y$$

$$= (R_n (R_n^{-1} + R_x^{-1}))^{-1} y$$

$$= ((R_x + R_n) R_x^{-1})^{-1} y$$

$$= R_x (R_x + R_n)^{-1} y$$

from class

$$p(y) = \prod_{n=1}^N \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{1}{2\sigma^2} \left(y_n - \sum_{i=n-N}^{n-1} h_{n-i} y_i\right)^2\right\}$$

Define

$$z_n = \begin{bmatrix} y_{n-1} \\ \vdots \\ y_{n-p} \end{bmatrix} \quad h = \begin{bmatrix} h_1 \\ \vdots \\ h_p \end{bmatrix}$$

$$\log p(y) = -\frac{1}{2\sigma^2} \sum_{n=1}^N (y_n - h^T z_n)^2 - \frac{N}{2} \log(2\pi\sigma^2)$$

$$= \frac{-N}{2\sigma^2} (\hat{\sigma}_y^2 - 2h^T b + h^T R h) - \frac{N}{2} \log(2\pi\sigma^2)$$

$$\text{where } \hat{\sigma}_y^2 = \frac{1}{N} \sum_{n=1}^N y_n^2$$

$$b = \frac{1}{N} \sum_{n=1}^N y_n z_n$$

$$R = \frac{1}{N} \sum_{n=1}^N z_n z_n^T$$

$$(\hat{\sigma}_{ML}^2, \hat{h}_{ML}) = \underset{(\sigma^2, h)}{\operatorname{argmax}} \log p(y | \sigma^2, h)$$

$$= \underset{(\sigma^2, h)}{\operatorname{argmax}} \left\{ -\frac{N}{2\sigma^2} (\hat{\sigma}_y - 2h^*b + h^*Rh) - \frac{N}{2} \log(2\pi\sigma^2) \right\}$$

• Maximize with respect to  $h$  first.

$$\begin{aligned} \nabla_h \log p(y) &= -\frac{1}{N} \nabla_h (h^*Rh - 2b^*h) \\ &= -\frac{1}{N} (2h^*R - 2b^*) = 0 \end{aligned}$$

$$\hat{h}_{ML} = R^{-1}b$$

• Compute ML estimate of  $\sigma^2$

$$\log p(y | \hat{h}_{ML}) = -\frac{1}{2\sigma^2} \sum_{n=2}^N (y_n - \hat{h}_{ML}^* z_n)^2 - \frac{N}{2} \log(2\pi\sigma^2)$$

$$= -\frac{N}{2\sigma^2} \hat{\sigma}_x^2 - \frac{N}{2} \log(2\pi\sigma^2)$$

$$\text{where } \hat{\sigma}_x^2 \triangleq \frac{1}{N} \sum_{n=2}^N \underbrace{(y_n - \hat{h}^* z_n)^2}_{x_n^2}$$

$$a) \quad 1-H(\omega) = 1-\rho e^{j\omega}$$

$$S_x(\omega) = \frac{\sigma_c^2}{|1-H(\omega)|^2}$$

$$= \frac{\sigma_c^2}{1+\rho^2} \frac{1}{1-2\frac{\rho}{1+\rho^2} \cos(\omega)}$$

$$R_x(n) = Z^{-1} \left\{ \frac{\sigma_c^2}{(1-\rho z^{-1})(1-\rho z)} \right\}$$

on unit circle  $|\rho| < 1$

$$= \frac{\sigma_c^2}{1-\rho^2} \left\{ \rho^n u(n) + \rho^{-n} u(-1-n) \right\}$$

$$p(y) = (2\pi)^{-N/2} |A|^{1/2} \exp\left\{-\frac{1}{2} y^T A y\right\}$$

find  $A$  so that

$$p(y_n | y_i, i \neq n) \sim N\left(\sum_{i=1}^N y_i g_{n-i}, \sigma_{nc}^2\right)$$

$$\frac{d}{dy_n} \log p(y_n | y_i, i \neq n) = \frac{d}{dy_n} \log p(y)$$

$$= -\sum_{i=1}^N y_i A_{in} = -A_{nn} \left( y_n + \sum_{i \neq n} y_i \frac{A_{in}}{A_{nn}} \right)$$

$$\Leftrightarrow \log p(y_n | y_i, i \neq n) = -\frac{A_{nn}}{2} \left( y_n + \sum_{i \neq n} y_i \frac{A_{in}}{A_{nn}} \right)^2 + C$$

$$\Leftrightarrow p(y_n | y_i, i \neq n) = \frac{1}{\sqrt{2\pi}} \sqrt{A_{nn}} \exp\left\{-\frac{A_{nn}}{2} \left( y_n + \sum_{i \neq n} y_i \frac{A_{in}}{A_{nn}} \right)^2\right\}$$

$$\Leftrightarrow \forall y_i \quad A_{nn} = \frac{1}{\sigma_{nc}^2} \sum_{i \neq n} y_i \frac{A_{in}}{A_{nn}} = \sum_{i=1}^N y_i g_{n-i}$$

$$\Leftrightarrow A = \frac{1}{\sigma_{nc}^2} B$$