

## Examination on Statistical Signal Processing

June 2021

### PROBLEM A

Consider the scalar (real) valued hidden Markov process defined by the following equations.

$$\begin{aligned}X_n &= a_n X_{n-1} + U_n \\Y_n &= c_n X_n + \sqrt{\beta} W_n\end{aligned}$$

where for integer  $n \geq 0$ ,  $\{X_0, U_n, W_n\}$  are independent  $\mathcal{N}(0, 1)$ ,  $\beta > 0$ .

A.1 Recall Kalman equations in the context of this simplified model. Notation conventions are

$$\begin{aligned}X_n^- &= E(X_n | Y_{0:n-1}) \\ \hat{X}_n &= E(X_n | Y_{0:n}) \\ P_n^- &= \text{cov}(X_n - X_n^-) \\ P_n &= \text{cov}(X_n - \hat{X}_n)\end{aligned}$$

All these quantities are scalars. (Matlab notation is used, for example  $Y_{0:n} \equiv (Y_0, \dots, Y_n)$ ).

A.2 Let  $a_n = a$ ,  $0 < a < 1$ ,  $c_n = c$ . From the recursion relations between  $P_n$  and  $P_n^-$ ,  $P_n^-$  and  $P_{n-1}$  deduce a relation between  $P_n$  and  $P_{n-1}$ .

A.3 To calculate the asymptotic expression of  $P_n$  take  $P_n = P = \text{const.}$  in this equation and solve for  $P$ .

A.4 Describe the behavior of  $P$  with respect to the noise variance  $\beta$  and the dynamics  $a_n = a$  and comment the result.

## PROBLEM B

In this problem we view the beginning of the EM algorithm for the identification of a Markov chain.  $(X_n), n \geq 0$  is a Markov sequence with values in  $\{1, -1\}$  and  $p(X_0 = 1) = 1/2$ . For  $n \geq 1$ , the transition probabilities  $p(x_n|x_{n-1})$  are given by the matrix

$$A = \begin{bmatrix} \frac{1+\varepsilon}{2} & \frac{1-\varepsilon}{2} \\ \frac{1-\varepsilon}{2} & \frac{1+\varepsilon}{2} \end{bmatrix}$$

where  $0 < \varepsilon < 1$  is a parameter to be estimated. The observed signal is  $Y_n = X_n + \sqrt{\beta}W_n$ ,  $n = 0 : N$ , such that  $W_n \sim \mathcal{N}(0, 1)$  is an additive noise independent of  $(X_n)$  and  $\beta > 0$  is to be estimated. The vector of parameters is  $\theta = (\varepsilon, \beta)$ .

B.1. Check that  $p(x_n|x_{n-1}) = (1 + \varepsilon x_{n-1}x_n)/2$ .

B.2 Let  $f_{0:N}(x_{0:N}) \equiv f_{0,\dots,N}(x_0, \dots, x_N)$  be *any* probability density on  $\{x_{0:N}\}$ . Argue from Jensen's inequality to show that

$$\log p(y_{0:N}|\theta) \geq H(\theta) + C_0$$

where

$$H(\theta) = \sum_{x_{0:N}} f_{0:N}(x_{0:N}) \log p(x_{0:N}, y_{0:N}|\theta)$$

and  $C_0$  is a term independent of  $\theta$ .

B.3 By conditioning  $y_{0:N}$  on  $x_{0:N}$  and using properties of Markov sequences and independent sequences show that

$$\begin{aligned}\log p(x_{0:N}, y_{0:N} | \theta) &= -\frac{1}{2\beta} \sum_{n=0}^N (y_n - x_n)^2 - \frac{1}{2}\beta \\ &\quad + \sum_{n=1}^N \log(1 + \varepsilon x_{n-1} x_n) + C_1\end{aligned}$$

where  $C_1$  is a term independent of  $\theta$ .

B.4 Combine this relation with the expression of  $H(\theta)$  to show that  $H(\theta)$  is maximized by the equations

$$\beta = \sum_{n=0}^N \sum_{\{x_n\}} f_n(x_n) (y_n - x_n)^2$$

and

$$\sum_{n=0}^N \sum_{\{x_{n-1}x_n\}} f_{n-1,n}(x_{n-1}, x_n) \frac{x_{n-1}x_n}{1 + \varepsilon x_{n-1}x_n} = 0$$

B.5 Solve this last equation in  $\varepsilon$  (consider that  $x_{n-1}x_n$  takes only 2 values).

## PROBLEM C

Let  $(S_n), n \geq 0$  a random sequence with  $\pm 1$  values and probability distributions  $p_N$  such that for  $J_n > 0$

$$\begin{aligned}p_N(s_{1:N}) &= q_N(s_{1:N}) / Z_N \\ &= \frac{\exp -\frac{1}{2} \sum_{n=1}^N J_n s_{n-1} s_n}{\sum_{\{s_{1:N}\}} \exp -\frac{1}{2} \sum_{n=1}^N J_n s_{n-1} s_n}\end{aligned}$$

C.1 Compute the conditional distribution

$$p_N(s_n | \tilde{s}_n)$$

where  $\tilde{s}_n$  is the vector  $(s_i, i \neq n)$ , deduce that  $(S_n)$  is a Markov sequence and write its transitions matrix.

C2. Let  $(Y_n), n \geq 0$  be a sequence of random observations on  $S_n$  such that

$$Y_n = S_n + W_n$$

where the  $W_n$  are i.i.d  $\mathcal{N}(0, \beta)$ . Define the *Hamiltonian*

$$H(s_{1:N}) = -\frac{1}{2} \sum_{n=1}^N J_n s_{n-1} s_n + \sum_{n=1}^N y_n s_n$$

Show that maximizing (in  $s_{1:N}$ ) the joint probability

$$p(s_{1:N}, y_{1:N})$$

is equivalent to compute the limit for  $t \rightarrow \infty$  of the *finite temperature estimates* defined by

$$\hat{s}_n(t) = \frac{\sum_{s_n} s_n \exp tH(s_{1:N})}{\sum_{s_n} \exp tH(s_{1:N})}$$

C3. For fixed  $t$  calculate the expression for  $\hat{s}_n(t)$  show that it takes the following form and interpret this result:

$$\hat{s}_n(t) = \tanh \{t(y_n - \varphi_n)\}$$