

EE 641 Final Exam
Fall 2010

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Instructions

- This exam contains 4 problems worth a total of 154 points.
- You may not use any notes, textbooks, or calculators.
- Answer questions precisely and completely. Credit will be subtracted for vague answers.

Good luck.

Problem 1. (36pt)

Consider the p dimensional random vector, X , with distribution

$$p(x) = \frac{1}{z} \exp \left\{ -\frac{1}{2} x^t B x \right\}$$

- Give an expression for the normalizing constant z .
- Assuming that X is a Markov random field with neighborhood system ∂s for $s \in \{1, \dots, p\}$, then specify which values of B must be zero.
- Compute an expression for the conditional density $p(x_s | x_r \text{ for } r \neq s)$.
- Compute an expression for the marginal density $p(x_s)$.

$$a) \quad z = (2\pi)^{p/2} |B|^{-1/2}$$

$$b) \quad \forall s, r \text{ s.t. } r \notin \partial s \Rightarrow B_{r,s} = B_{s,r} = 0$$

$$c) \quad p(x_s | x_r \neq s) = p(x_s | x_{\partial s})$$

$$= \frac{1}{z} \exp \left\{ -\frac{1}{2\sigma^2} (x_s - \mu)^2 \right\}$$

$$\frac{\partial}{\partial x_s} \log p(x_s | x_{\partial s}) = \frac{\partial}{\partial x_s} \log p(x)$$

$$- \frac{(x_s - \mu)}{\sigma^2} = - \sum_n x_n B_{ns} = - \sum_{n \in \partial s \cup \{s\}} B_{sn} x_n$$

$$= - \left(B_{ss} x_s + \sum_{n \in \partial s} B_{sn} x_n \right)$$

$$= - B_{ss} \left(x_s + \sum_{n \in \partial s} \frac{B_{sn}}{B_{ss}} x_n \right)$$

$$\sigma^2 = \frac{1}{B_{ss}} \quad \mu = - \sum_{n \in \partial s} \frac{B_{sn}}{B_{ss}} x_n$$

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$$d) \quad E[xx^T] = R = B^{-1}$$

$$E[x_s^2] = R_{ss} = (B^{-1})_{ss}$$

$$p(x_s) = \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{1}{2(B^{-1})_{ss}} x_s^2 \right\}$$

Problem 2.(72pt)

Let X_n for $n = 0$ to $N - 1$ be a discrete-valued Markov chain with homogeneous transition probability matrix P and initial probability density given by

$$\pi_i^{(0)} = P\{X_0 = i\} .$$

Furthermore, assume all the entries of P and $\pi^{(0)}$ are strictly positive and that the number of states of the Markov chain are finite.

- a) Write the expression for the probability of the sequence $\{X_n\}_{n=0}^{N-1}$.
- b) Write an algorithmic recursion for the probability

$$\pi_i^{(n)} = P\{X_n = i\} .$$

(Hint: The recursion should start at $n = 1$ and increment until $n = N - 1$.)

- c) Show that the discrete density, $p(x) = P\{X = x\}$, is a Gibbs distribution with neighborhood system given by

$$\partial n = \{n - 1, n + 1\} \cap \{0, \dots, N - 1\} .$$

- d) Use the Hammersley-Clifford Theorem to Prove that X is a Markov random field with neighborhood system ∂n .
- e) Does a stationary distribution exist for this Markov chain? If it does exist, specify a set of equations (or a matrix equation) which can be used to determine the stationary distribution? What is the name of this set of equations?

For the following parts, let π be the stationary distribution for the Markov chain, and assume that $\pi^{(0)} = \pi$.

- f) Derive an explicit and closed form expression for the transition probabilities of the time-reversed Markov chain.

$$Q_{j,i} = P\{X_n = i | X_{n+1} = j\} .$$

- g) Is the time reversed Markov chain homogeneous? Why or why not?
- h) Derive conditions for the Markov chain to be reversible in terms of π and P .

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$$a) \quad p(x) = \pi_{x_0}^{(0)} \prod_{n=1}^{N-1} P_{x_{n-1} x_n}$$

$$b) \quad \pi_i^{(n)} = \sum_{j=1}^M \pi_j^{(n-1)} P_{ji}$$

For $n=1$ to $N-1$

$$c) \quad \log p(x) = \underbrace{\log \pi_{x_0}^{(0)}}_{-V_0(x_0)} + \sum_{n=1}^{N-1} \underbrace{\log (P_{x_{n-1} x_n})}_{-V_n(x_n, x_{n-1})}$$

$$p(x) = 1 \exp \left\{ - \left(V_0(x_0) + \sum_{n=1}^{N-1} V_n(x_n, x_{n-1}) \right) \right\}$$

So the cliques are $\{n, n-1\}$ and $\{0\}$

$$\Rightarrow \partial n = \{n-1, n\} \cap \{0, \dots, N-1\}$$

d) By HC Theorem

Gibbs Distribution $\Rightarrow \left\{ \begin{array}{l} \text{MRF} \\ \text{with } \partial n \\ \text{neighbourhood} \end{array} \right\}$

e) Since $\forall i, j \quad P_{ij} > 0 \Rightarrow$ irreducible
aperiodic

irreducible
aperiodic
finite $\} \Rightarrow$ ergodic

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stationary distribution given by

$$\pi = \pi P$$

Full balance equations

f)

$$P\{X_{n-1}=i, X_n=j'\} = \pi_i P_{ij'}$$

$$P\{X_{n-1}=i | X_n=j'\} = \frac{\pi_i P_{ij'}}{\sum_k \pi_k P_{kj'}} = Q_{j'i}$$

$$Q_{ji} = \frac{\pi_i P_{ij'}}{\pi_{j'}}$$

g) Yes because π and P are
not functions of time,

$\Rightarrow Q_{ji}$ is not a function of time.

h)

$$\text{reversible} \Leftrightarrow P_{ij'} = Q_{ij'}$$

$$P_{ij'} = \frac{\pi_{j'} P_{j'i}}{\pi_i}$$

$$\pi_i P_{ij} = \pi_{j'} P_{j'i} \Leftarrow \text{detailed balance equations}$$

Problem 3.(36pt)

Let X , N , and Y be Gaussian random vectors such that $X \sim N(0, R_x)$ and $W \sim N(0, R_w)$, and let θ be a deterministic vector.

a) First assume that $Y = \theta + W$, and calculate the ML estimate of θ given Y .

For the next parts, assume that $Y = X + W$.

b) Calculate an expression for $p_{x|y}(x|y)$, the conditional density of X given Y .

c) Calculate the MMSE estimate of X when $Y = X + W$.

d) Calculate an expression for the conditional variance of X given Y .

$$a) \text{ MLE } \hat{\theta}_{ML} = Y$$

$$b) \quad p(y|x) = \frac{1}{2} \exp \left\{ -\frac{1}{2} (y-x)^T R_w^{-1} (y-x) \right\}$$

$$p(x) = \frac{1}{2} \exp \left\{ -\frac{1}{2} x^T R_x^{-1} x \right\}$$

$$p(x|y) = \frac{1}{2(y)} \exp \left\{ -\frac{1}{2} \left((x-y)^T R_w^{-1} (x-y) + x^T R_x^{-1} x \right) \right\}$$

$$= \frac{1}{2} \exp \left\{ (x-\mu)^T R_{x|y}^{-1} (x-\mu) \right\}$$

$$R_{x|y}^{-1} = R_w^{-1} + R_x^{-1}$$

$$R_{x|y} = (R_w^{-1} + R_x^{-1})^{-1}$$

$$(x-y)^T R_w^{-1} + x^T R_x^{-1} = (x-\mu)^T (R_w^{-1} + R_x^{-1})$$

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

$$\begin{aligned}\mu &= (R_w^{-1} + R_x^{-1})^{-1} R_w^{-1} y \\ &= (I + R_w R_x^{-1})^{-1} y\end{aligned}$$

$$\begin{aligned}c) \quad \hat{\mu} &= (R_w^{-1} + R_x^{-1})^{-1} R_w^{-1} y \\ &= (I + R_w R_x^{-1})^{-1} y = R_x (R_w + R_x)^{-1} y\end{aligned}$$

$$d) \quad R_{x|y} = (R_w^{-1} + R_x^{-1})^{-1} = R_w (R_w + R_x)^{-1} R_x$$

Problem 4.(10pt)

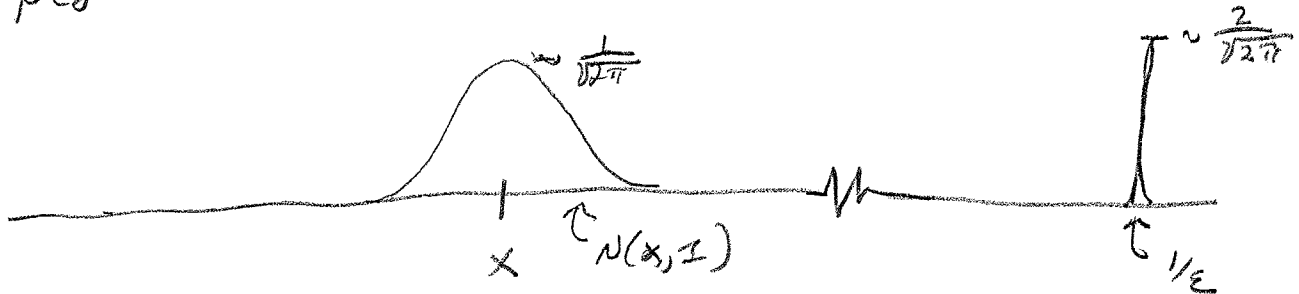
Let Y and X be random variables, and let Y_{MAP} and Y_{MMSE} be the MAP and MMSE estimates respectively of Y given X . Pick distributions for Y and X so that the MAP estimator is very "poor", but the MMSE estimator is "good".

$$Y = X + W$$

$$p(w) = (1-2\varepsilon) \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2}w^2\right\} + 2\varepsilon \frac{1}{\sqrt{2\pi} \varepsilon} \exp\left\{-\frac{1}{2\varepsilon^2}(w - 1/\varepsilon)^2\right\}$$

let $\varepsilon \rightarrow 0$

$p(y|x)$



$$\hat{Y}_{MAP} = 1/\varepsilon$$

$$\hat{Y}_{MMSE} \approx x$$