Department of Electrical \& Computer Engineering
University of California, Santa Barbara

ECE 240A
Winter 2010
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H.O. \#21

## EXAMPLE FINAL EXAM

## INSTRUCTIONS

This exam is open book and open notes. It consists of 4 problems and is worth a total of 160 points. The problems are not of equal difficulty, so use discretion in allocating your time. Attempt to answer all questions in any order.

## 1. SUFFICIENT STATISTICS AND ML ESTIMATION (40 points)

Suppose that $\left\{X_{1}, X_{2}, \ldots, X_{N}\right\}$ is a random sample drawn according to the following probability mass function (pmf):

$$
\begin{equation*}
p_{X}(x)=\binom{2}{x} \theta^{x}(1-\theta)^{2-x} I_{\{0,1,2\}}(x), \tag{1}
\end{equation*}
$$

where $I(x)$ is the indicator function and $\theta>0$ is an unknown (nonrandom) parameter.
(a) Find a one-dimensional sufficient statistic.
(b) This statistic is obviously minimal sufficient. Determine if it is also complete. (Hint: Note that the pmf of the sufficient statistic is similar to that in (1), except that it has parameters $\{\theta, 2 N\}$.)
(c) Find the maximum-likelihood estimators for $P\left[X_{i}=0\right]=\theta$ and $P\left[X_{i}=2\right]=\theta^{2}$.
(d) Determine if these estimators are unbiased.

## 2. KALMAN PREDICTOR (40 points)

When the measurement noise $v(k)$ and the unmeasurable disturbance $w(k)$ are correlated (with cross-correlation matrix $S$ ), the one-step Kalman predictor is given by

$$
\begin{gather*}
\hat{x}(k+1 \mid k)=\Phi \hat{x}(k \mid k-1)+\Psi u(k)+L(k) \tilde{z}(k \mid k-1)  \tag{2}\\
L(k)=\left[\Phi P(k \mid k-1) H^{T}+\Gamma S\right] \times\left[H P(k \mid k-1) H^{T}+R\right]^{-1}  \tag{3}\\
\begin{aligned}
P(k+1 \mid k)= & {[\Phi-L(k) H] P(k \mid k-1)[\Phi-L(k) H]^{T} } \\
& +\Gamma Q \Gamma^{T}-\Gamma S L^{T}(k)-L(k) S \Gamma^{T}+L(k) R L^{T}(k)
\end{aligned}
\end{gather*}
$$

where $L(k)$ is the Kalman predictor gain, $\tilde{z}(k \mid k-1)$ is the usual prediction error, and we have assumed that the state-variable parameters are time invariant. Note that if $S=0$, these equations reduce to the standard Kalman predictor covered in class.

Consider the following scalar measurable process:

$$
\begin{equation*}
z(k)=v(k)+w(k-1) \tag{5}
\end{equation*}
$$

where $v(k)=w(k)$ is a stationary white-noise sequence with zero mean and unit variance.
(a) For this process, determine the parameters of the first-order (scalar) state-variable model, i.e., specify $\Phi, \Psi, \Gamma, H$, and the variances $Q$ and $R$.
(b) For the system in (5) and from your answer in part (a), show that the one-step Kalman predictor of $z(k+1)$ is

$$
\hat{z}(k+1 \mid k)=L(k)[z(k)-\hat{z}(k \mid k-1)] .
$$

(c) For $S=1$, show that (3) and (4) reduce to

$$
\begin{equation*}
L(k)=[P(k \mid k-1)+1]^{-1} \quad \text { and } \quad P(k+1 \mid k)=1-L(k) . \tag{6}
\end{equation*}
$$

(d) Let $B(k)=P^{-1}(k \mid k-1)$ and show that, with the initial condition $B(0)=1, L(k)$ in (6) is

$$
L(k)=\frac{k+1}{k+2} .
$$

## 3. UNBIASED ESTIMATION AND MAP ESTIMATION (40 points)

Suppose that $\hat{\theta}_{1}$ and $\hat{\theta}_{2}$ are two independent unbiased estimators of $\theta$ with variances $\sigma_{1}^{2}$ and $\sigma_{2}^{2}$, respectively. Consider the new estimator

$$
\hat{\theta}=\alpha \hat{\theta}_{1}+\beta \hat{\theta}_{2}
$$

where $\alpha$ and $\beta$ are nonrandom constants.
(a) Find $\alpha$ and $\beta$ such that the variance of $\hat{\theta}$ is minimum and $\hat{\theta}$ is unbiased.
(b) What is the corresponding minimum value of the variance?
(c) What are the optimal values of $\alpha$ and $\beta$ as $\sigma_{2}^{2} \rightarrow \infty$ ? What is the corresponding minimum value of the variance?

Consider now the random variable $Z$ which has a Poisson distribution with mean $\theta$ :

$$
f(z)=\frac{\theta^{z}}{z!} e^{-\theta} I_{\{0,1, \ldots\}}(z)
$$

where $\theta$ is also a random variable with the following exponential distribution:

$$
f(\theta)=\lambda e^{-\lambda \theta} I_{[0, \infty)}(\theta)
$$

where the constant parameter $\lambda>0$ is known. (Note that parts (d) and (e) below are independent of parts (a)-(c) above.)
(d) Find the maximum a posteriori (MAP) estimator of $\theta$ from the single measurement $Z$.
(e) How does you answer compare to the maximum likelihood (ML) estimator of $\theta$ ?

## 4. MS ESTIMATION (40 points)

Suppose that $X$ and $Y$ are correlated random variables with the following density functions:

$$
\begin{gathered}
f_{X \mid Y}(x \mid y)=\frac{1}{\sqrt{2 \pi}} e^{-\frac{1}{2}\left(x-y-\frac{y^{2}}{2}\right)^{2}} \\
f_{Y}(y)=e^{-y} I_{[0, \infty)} .
\end{gathered}
$$

Note that since $Y$ is exponential with parameter $\lambda=1$, the moments are $E\left(Y^{k}\right)=k!$.
(a) Find the nonlinear minimum mean-square (MS) estimator $\hat{X}$ of $X$ given that we observe $Y$.
(b) From your answer in part (a), determine the corresponding minimum value of the MS error.
(c) Find the linear minimum MS estimator of $X$ given that we observe $Y$. Your answer should be of the form $\hat{X}=a Y+b$ where $a$ and $b$ are constants to be determined.
(d) From your answer in part (c), determine the corresponding minimum value of the MS error. (Hint: Suppose we know $E(U \mid V)$. Then $E(U)=E_{V}[E(U \mid V)]$ where the outer expectation is over $V$.

