

# EECS 126: Probability and Random Processes

## Solutions to Problem Set 10 (mid-term 2)

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### Problem 1

a) False.

A counterexample: let  $X$  and  $B$  be independent random variables,  $X \sim N(0, 1)$ ,  $B$  is a Bernoulli random variable where  $P(B = -1) = P(B = 1) = 0.5$ . Let  $Y = BX$ , obviously  $X$  and  $Y$  are not independent,  $X \sim N(0, 1)$  and  $E(XY) = E(X^2B) = E(X^2)E(B) = 0$ .

b) False.

Proof by contradiction: suppose there exists a function  $g$ , s.t.  $Y = g(X)$  is uniformly distributed in  $[0, 1]$ . Then let  $a = g(1)$ ,

$$Pr(Y = a) = Pr(g(X) = a) = Pr(g(X) = g(1)) \geq Pr(X = 1) > 0$$

It's impossible because  $Y$  is a uniform random variable.

c) True.

*proof :*

The MMSE estimation of  $X$  is  $\hat{X} = E(X|Y)$ , so

$$E(\tilde{X}) = E(X - \hat{X}) = E(X) - E(\hat{X}) = E(X) - E(E(X|Y)) = E(X) - E(X) = 0$$

$$\begin{aligned} Cov(\tilde{X}, Y) &= E(\tilde{X}Y) - E(\tilde{X})E(Y) \\ &= E(\tilde{X}Y) \\ &= E((X - E(X|Y))Y) \\ &= E(XY) - E(YE(X|Y)) \\ &= E(XY) - E(E(XY|Y)) \\ &= E(XY) - E(XY) \\ &= 0 \end{aligned}$$

### Problem 2

a) We will show that  $X_i \sim N(0, 1)$  using proof by induction.

*proof :*  $X_0 \sim N(0, 1)$ , suppose  $X_k \sim N(0, 1)$ . Then  $X_k$  and  $N_{k+1}$  have the same pdf

$$f_{X_k}(x) = f_{N_{k+1}}(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

Then  $\forall x \in \mathcal{R}$

$$\begin{aligned}
f_{X_{k+1}}(x) &= f_{X_k}(x)P(B_{k+1} = 0) + f_{N_{k+1}}(x)P(B_{k+1} = 1) \\
&= p \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} + (1-p) \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \\
&= \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}
\end{aligned} \tag{1}$$

We just proved by induction that  $X_i \sim N(0, 1)$ .

b) No.

Proof by contradiction, assume that  $X, Y$  are jointly continuous. Then  $\exists$  pdf  $f_{X_1 X_2}(x_1, x_2)$ , s.t. for every subset  $D$  of the two dimensional-plane:

$$P((X_1, X_2) \in D) = \int \int_{(x_1, x_2) \in D} f_{X_1 X_2}(x_1, x_2) dx_1 dx_2$$

Let  $D = \{(x_1, x_2) \in \mathcal{R}^2 : x_1 = x_2\}$ , then  $P((X_1, X_2) \in D) = P(X_1 = X_2) = 0.5$

But if  $D$  is a set of area zero in  $\mathcal{R}^2$ , thus  $\int \int_{(x_1, x_2) \in D} f_{X_1 X_2}(x_1, x_2) dx_1 dx_2 = 0$ . Now we have a contradiction. Thus the origin assumption that  $X, Y$  are jointly continuous is false.

c) From part a), we know that  $E(X_i) = 0$ .

$$\begin{aligned}
Cov(X_1, X_2) &= E(X_1 X_2) - E(X_1)E(X_2) \\
&= E(E(X_1 X_2 | B_2)) \\
&= E(X_1 X_2 | B_2 = 0)P(B_2 = 0) + E(X_1 X_2 | B_2 = 1)P(B_2 = 1) \\
&= E(X_1^2)(1-p) + E(X_1 N_2)p \\
&= (1-p)
\end{aligned}$$

d) If  $B_{i+1} = B_{i+2} = \dots = B_j = 0$ , then  $X_j = X_i$ ,  $E(X_i X_j) = 1$ .

Otherwise  $\exists l, i+1 \leq l \leq j : B_l = 0$ , let  $k, i+1 \leq k \leq j$  be the maximum index, s.t.  $B_k = 1$ , then  $X_j = N_k$  and  $N_k$  and  $X_i$  are independent,  $E(X_i X_j) = 0$ . So:

$$\begin{aligned}
Cov(X_i, X_j) &= E(X_i X_j) - E(X_i)E(X_j) \\
&= E(E(X_i X_j | B_{i+1}, B_{i+2}, \dots, B_j)) \\
&= E(X_i X_j | B_{i+1} = B_{i+2} = \dots = B_j = 0)P(B_{i+1} = B_{i+2} = \dots = B_j = 0) \\
&\quad + E(X_i X_j | \exists l, i+1 \leq l \leq j : B_l = 0)Pr(\exists l, i+1 \leq l \leq j : B_l = 0) \\
&= E(X_i^2)(1-p)^{j-i} + 0 \\
&= (1-p)^{j-i}
\end{aligned}$$

### Problem 3

a) Condition on  $X = x$ ,  $Y$  is uniformly distributed in  $[x^2, x^2 + 1]$ . Thus the conditional expectation of  $Y$  given  $X = x$  is  $x^2 + 0.5$ . So the MMSE estimator is  $\hat{X} = E(Y|X) = X^2 + 0.5$

b) Some of the statistics of  $X$  and  $Y$  are  $E(X) = 0$ ,

$$E(X^2) = \int_{-0.5}^{0.5} x^2 dx = \frac{1}{12}$$

$$E(Y) = E(E(Y|X)) = E(X^2 + 0.5) = \frac{7}{12}$$

$$E(Y^2) = E(E(Y^2|X)) = \int_{-0.5}^{0.5} \int_{x^2}^{x^2+1} y^2 dy dx = \frac{7}{12}$$

The LLSE estimator is  $\hat{Y} = aX + b$ . Then

$$E((Y - \hat{Y})^2) = E((Y - aX - b)^2) = E(Y^2) + a^2 E(X^2) \quad (2)$$

c) The MMSE estimator  $\hat{Y} = X^2 + 0.5$  has a quadratic form. So the best quadratic estimator (in mean square sense) is just the MMSE estimator  $X^2 + 0.5$

d)  $X, Y$  are jointly Gaussian, so the MMSE estimator for  $Y$  given  $X$  is  $aX + b$ , thus the best quadratic estimator (in mean square sense) is just the MMSE estimator  $aX + b$ , so  $a_3 = 0$ .