

# HW13 — Book

## Leon Chapter #6 6.71

$$\therefore N_1 \sim \text{Binomial}(100, p)$$

$$N' \sim \text{Binomial}(100, p)$$

$$N_2 = N_1 + N'$$

$N_1$  and  $N'$  are independent

$$\therefore E[N_1] = E[N'] = 100p$$

$$E[N_2] = E[N_1 + N'] = E[N_1] + E[N'] = 200p$$

$$V[N_1] = V[N'] = 100p(1-p)$$

$$V[N_2] = V[N_1 + N'] \stackrel{\text{id}}{=} V[N_1] + V[N'] = 200p(1-p)$$

$$\text{Cov}(N_1, N_2) = \text{Cov}(N_1, N_1 + N') \stackrel{\text{id}}{=} V[N_1] = 100p(1-p)$$

$$(a) \hat{N}_2^{\text{LMSE}} = E[N_2] + \frac{\text{Cov}(N_1, N_2)}{V[N_1]} (N_1 - E[N_1])$$

$$= 200p + \frac{100p(1-p)}{100p(1-p)} (N_1 - 100p)$$

$$= N_1 + 100p$$

$$\text{MSE} = V[N_2 | N_1] = V[N_1 + N' | N_1] = V[N'] = 100p(1-p)$$

$$(b) \hat{N}_2^{\text{MMSE}} = E[N_2 | N_1] = E[N_1 + N' | N_1] \stackrel{\text{id}}{=} N_1 + E[N'] = N_1 + 100p$$

$$\text{MSE} = V[N'] = 100p(1-p)$$

$$(c) \hat{N}_2^{\text{MAP}} = \underset{n_2}{\text{argmax}} P(N_2 = n_2 | N_1 = n_1)$$

$$\therefore P(N_2 = n_2) = \binom{200}{n_2} p^{n_2} (1-p)^{200-n_2}$$

$$P(N_1 = n_1 | N_2 = n_2) = \binom{100}{n_1} \left(\frac{n_2}{200}\right)^{n_1} \left(1 - \frac{n_2}{200}\right)^{100-n_1}$$

$$\therefore P(N_2 = n_2 | N_1 = n_1) \propto \binom{100}{n_1} \left(\frac{n_2}{200}\right)^{n_1} \left(1 - \frac{n_2}{200}\right)^{100-n_1} \cdot \binom{200}{n_2} p^{n_2} (1-p)^{200-n_2}$$

6.71. Let  $N_1$  be the number of Web page requests arriving at a server in the period  $(0, 100)$  ms and let  $N_2$  be the *total* combined number of Web page requests arriving at a server in the period  $(0, 200)$  ms. Assume page requests occur every 1-ms interval according to independent Bernoulli trials with probability of success  $p$ .

- Find the minimum linear mean square estimator for  $N_2$  given  $N_1$  and the associated mean square error.
- Find the minimum mean square error estimator for  $N_2$  given  $N_1$  and the associated mean square error.
- Find the maximum a posteriori estimator for  $N_2$  given  $N_1$ .
- Repeat parts a, b, and c for the estimation of  $N_1$  given  $N_2$ .

$$\therefore \hat{N}_2^{\text{MAP}} = \arg \max_{n_2} \left[ \left( \frac{n_2}{200} \right)^{n_1} \left( 1 - \frac{n_2}{200} \right)^{100-n_1} \cdot \binom{200}{n_2} p^{n_2} (1-p)^{200-n_2} \right]$$

$$\text{if } p \ll 1, \hat{N}_2^{\text{MAP}} \approx n_1 + 100p = E[N_2 | N_1 = n_1]$$

$$(d) \text{ Similarly: } \hat{N}_1^{\text{LMSE}} = \hat{N}_1^{\text{MMSE}} = N_2 - 100p$$

$$\text{MSE}_{\text{LMSE}} = \text{MSE}_{\text{MMSE}} = 100p(1-p)$$

6.72. Let  $Y = X + N$  where  $X$  and  $N$  are independent Gaussian random variables with different variances and  $N$  is zero mean.

- (a) Plot the correlation coefficient between the "observed signal"  $Y$  and the "desired signal"  $X$  as a function of the signal-to-noise ratio  $\sigma_X/\sigma_N$ .
- (b) Find the minimum mean square error estimator for  $X$  given  $Y$ .
- (c) Find the MAP and ML estimators for  $X$  given  $Y$ .
- (d) Compare the mean square error of the estimators in parts a, b and c.

## Leon Chapter #6 6.72

(a)  $X \sim N(0, \sigma_X^2)$   $N \sim N(0, \sigma_N^2)$  they are independent

$$\therefore \text{Var}(Y) = \text{Var}(X + N) = \text{Var}(X) + \text{Var}(N) = \sigma_X^2 + \sigma_N^2$$

$$\text{Cov}(X, Y) = \text{Cov}(X, X) + \text{Cov}(X, N) = \text{Var}(X) = \sigma_X^2$$

$$\therefore \rho_{XY} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} = \frac{\sigma_X^2}{\sqrt{\sigma_X^2(\sigma_X^2 + \sigma_N^2)}} = \sqrt{\frac{\sigma_X^2}{\sigma_X^2 + \sigma_N^2}}$$

$$\text{Suppose } \text{SNR} = \sigma_X^2 / \sigma_N^2$$

$$\therefore \rho_{XY} = \sqrt{\frac{\text{SNR}}{1 + \text{SNR}}}$$

$$(b) \hat{X}^{\text{MMSE}} = E[X|Y] = \frac{\sigma_X^2}{\sigma_X^2 + \sigma_N^2} Y$$

$$(c) \therefore P(Y|X) \sim N(X, \sigma_N^2)$$

$$\therefore P(X|Y) \propto P(Y|X)P(X) \sim N\left(\frac{\sigma_X^2}{\sigma_X^2 + \sigma_N^2} Y, \frac{\sigma_X^2 \sigma_N^2}{\sigma_X^2 + \sigma_N^2}\right)$$

$$\hat{X}^{\text{MAP}} = \frac{\sigma_X^2}{\sigma_X^2 + \sigma_N^2} Y$$

$$\therefore P(Y|X) \sim N(X, \sigma_N^2)$$

$$\therefore \hat{X}^{\text{ML}} = \arg\max_x P(Y|X) = Y$$

$$(d) \text{MSE}_{\text{MMSE}} = \text{MSE}_{\text{MAP}} = E\left[\left(X - \frac{\sigma_X^2}{\sigma_X^2 + \sigma_N^2} Y\right)^2\right] = \frac{\sigma_X^2 \sigma_N^2}{\sigma_X^2 + \sigma_N^2}$$

$$\text{MSE}_{\text{ML}} = E[(X - Y)^2] = \sigma_X^2 + \sigma_N^2$$

$\therefore$  MMSE and MAP are better than ML