

1. Consider two discrete random variables  $X, Y$  with joint probabilities given by the contingency table:

$P(X, Y)$	$Y = -1$	$Y = 0$	$Y = +1$
$X = -1$	.05	.10	.15
$X = 0$	.15	.15	.10
$X = +1$	.15	.00	.15

(a) [2 marks] Find the *Minimum Mean Square Error* (MMSE) predictor of  $Y$  given  $X$ , i.e. the conditional expectation  $g(X) = \mathbb{E}[Y|X]$ , and the MSE it achieves, i.e.  $\mathbb{E}[(Y - g(X))^2]$ .

$$f_{Y|X=-1} = \begin{cases} 1/6, & Y = -1 \\ 1/3, & Y = 0 \\ 1/2, & Y = +1 \end{cases}$$

$$\begin{aligned} \mathbb{E}[Y|X=-1] &= \sum_{y=-1}^1 y f(y|X=-1) \\ &= -1 \cdot 1/6 + 0 \cdot 1/3 + 1 \cdot 1/2 \\ &= -1/6 + 1/2 = 1/3 \end{aligned}$$

$$f_{Y|X=0} = \begin{cases} 15/40 = 3/8, & Y = -1 \\ 15/40 = 3/8, & Y = 0 \\ 1/4 = 2/8, & Y = 1 \end{cases}$$

$$\mathbb{E}[Y|X=0] = -3/8 + 2/8 = -1/8$$

$$f_{Y|X=1} = \begin{cases} 1/2, & Y = -1 \\ 0, & Y = 0 \\ 1/2, & Y = 1 \end{cases}$$

$$\mathbb{E}[Y|X=1] = 0$$

$$\frac{1}{9} - \frac{1}{24}$$

$$g(x) \begin{cases} g(x=-1) = 1/3 \\ g(x=0) = -1/8 \\ g(x=1) = 0. \end{cases}$$

$$E[(Y-g(x))^2] = E[Y^2 - 2Yg(x) + (g(x))^2]$$

$$E[Y] = \sum_x \sum_y y P(x,y)$$

$$= (-1)(0.05) + (-1)(0.15) + (-1)(0.15) \\ + 0.15 + 0.1 + 0.15 = 0.05$$

$$E[Y^2] = 0.05 + 0.15 + 0.15 + 0.15 + 0.1 + 0.15 \\ = 0.65.$$

$$E[Y^2] - 2 E[Y g(x)] + E[(g(x))^2]$$

$$X=-1, \\ = 0.65 - 2 \cdot \frac{1}{3} \cdot 0.05 + \frac{1}{9}$$

$$= \frac{131}{180} \approx 0.73$$

$$X=0, \\ = 0.65 - 2 \cdot (-\frac{1}{8}) \cdot 0.05 + \frac{1}{64} = \frac{217}{320} \approx 0.68$$

$$\begin{aligned}
 X &= 1, \\
 &= 0.65 \\
 \text{MSE} &= \begin{cases} \frac{131}{180}, & X = -1 \\ \frac{217}{320}, & X = 0 \\ \frac{13}{20}, & X = 1 \end{cases}
 \end{aligned}$$

- (b) [2 marks] Find the *Best Linear Predictor* (BLP) of  $Y$  given  $X$ , i.e.  $\hat{Y} = \hat{a} + bX$ , for the BLP coefficients  $a, b$ , and the MSE it achieves.  
(Note: This is an example where the MMSE predictor and the BLP are different.)

The coefficients of the BLP are found by

$$\text{solving } E[(Y - \hat{Y})Y_n] = 0, \quad n=1,2,3.$$

$$Y_1 = -1, Y_2 = 0, Y_3 = 0.$$

$$\Rightarrow E[(Y - (a + bX))Y_n],$$

$$E[Y \cdot Y_n] - aE[Y_n] - bE[X \cdot Y_n] = 0.$$

$$Y_n [E[Y] - a - bE[X]] = 0.$$

$$E[Y] = a.$$

$$a = 0.05.$$

MSE

$$\mathbb{E}[(Y - 0.05)^2]$$

$$= \mathbb{E}[Y^2] - 0.1\mathbb{E}[Y] + 0.025$$

$$= 0.65 - 0.005 + 0.025$$

$$= 0.6475.$$

2. Consider the AR(1) model  $X_t = \phi X_{t-1} + W_t$ ,  $W_t \sim \text{WN}(0, \sigma_w^2)$ .

(a) [3 marks] Find the covariance between the 1- & 2-step-ahead BLP errors, i.e. find

$$\text{Cov}[(X_{n+1} - X_{n+1}^n)(X_{n+2} - X_{n+2}^n)]$$

as a function of  $(\phi, \sigma_w^2)$ .

(Note: this should be *non-zero*; generally the different-step-ahead forecasts will be correlated.)

$$X_{n+1} = \alpha_1 X_n + W_n$$

$$E[X_{n+1}X_n] = \alpha_1 E[X_n^2]$$

$$\gamma(1) = \alpha_1 \gamma(0)$$

$$\alpha_1 = \frac{\gamma(1)}{\gamma(0)} = \phi$$

$$\hat{X}_{n+1} = \phi X_n$$

$$\hat{X}_{n+2}^n = \phi^2 X_n$$

$$\text{Cov}[(X_{n+1} - \phi X_n)(X_{n+2} - \phi^2 X_n)]$$

$$= \text{Cov}(X_{n+1}, X_{n+2}) - \phi^2 \text{Cov}(X_{n+1}, X_n)$$

$$- \phi \text{Cov}(X_n, X_{n+2}) + \phi^3 \text{Cov}(X_n, X_n)$$

$$= \gamma(1) - \phi^2 \gamma(1) - \phi \gamma(2) + \phi^3 \gamma(0)$$

$$= \phi \cdot \frac{\sigma_w^2}{1-\phi^2} - \phi^2 \cdot \frac{\phi \sigma_w^2}{1-\phi^2} - \phi \cdot \frac{\phi^2 \cdot \cancel{\sigma_w^2}}{1-\phi^2} + \phi^3 \cdot \frac{\cancel{\sigma_w^2}}{1-\phi^2}$$

$$= \frac{\phi \sigma_w^2}{1-\phi^2} (1-\phi^2) = \phi \cdot \sigma_w^2$$

- (b) [3 marks] Find the covariance between the subsequent 1-step-ahead BLP errors, i.e. find  $\text{Cov}[(X_n - X_n^{n-1})(X_{n+1} - X_{n+1}^n)]$  as a function of  $(\phi, \sigma_w^2)$ .  
(Note: These are similar to the model residuals *given perfect knowledge of the parameters*.)