

1. Key result: Given x is observed, if c is used to predict Y , MSE is

$$E[(Y - c)^2|x] = \text{var}[Y|x] + \{E[Y|x] - c\}^2$$

In particular, the best predictor is $E[Y|x]$, and its MSE is $\text{var}[Y|x]$.

Predictor	MSE
(a) $E[X_2 1] = \Pr(X_2 = 1 X_1 = 1) = 0$	$\text{var}[X_2 1] = 0$
(b) $E[X_2 0] = \Pr(X_2 = 1 X_1 = 0) = 1/3$	$\text{var}[X_2 0] = 1/3 \times (1 - 1/3) = 2/9$
(c) 0	$\text{var}[X_2 0] + (1/3 - 0)^2 = 2/9 + 1/9 = 1/3$
(d) $E(X_1) = 1/4$	$\text{var}[X_2 1] + (0 - 1/4)^2 = 1/16$
(e) $1/4$	$\text{var}[X_2 0] + (1/3 - 1/4)^2 = 2/9 + 1/144 \approx 0.23$

Notes:

(a) Given $X_1 = 0$, $X_2 = 0$, a constant.

(c) Yes, the outcome is 0 or 1, but the prediction is $1/3$. More directly, MSE is $E[(X_2 - 0)^2|0] = 1/3$.

2. (a) Since $E(X_1) = K/N$,

$$E(E[X_2|X_1]) = \frac{K - K/N}{N - 1} = \frac{K}{N}$$

(b) The numerator is

$$K(N - K) - K(1 - X_1) - (N - K)X_1 + X_1(1 - X_1)$$

Since X_1 is either 0 or 1, $X_1(1 - X_1) = 0$, so the formula is obtained.

$$\text{var}[X_2|X_1] = \frac{K(N - K) - K(1 - X_1) - (N - K)X_1}{(N - 1)^2}$$

(c) Combining $\text{var}(E[X_2|X_1]) = \text{var}(X_1)/(N - 1)^2$ and $\text{var}(X_1) = K(N - K)/N^2$ gives the first formula.

The second formula follows from computing the expectation of (b), and $E(1 - X_1) = (N - K)/N$.

(d) The sum is

$$\frac{K(N - K)}{(N - 1)^2} \frac{1 + N^2 - 2N}{N^2} = \frac{K(N - K)}{N^2}$$

which is $\text{var}(X_2)$, as expected.

3. (a) Integration by parts gives

$$\Gamma(\alpha + 1) = \int_0^\infty x^\alpha e^{-x} dx = [-x^\alpha e^{-x}]_0^\infty + \alpha \int_0^\infty x^{\alpha-1} e^{-x} dx$$

Since $\alpha > 0$, $0^\alpha = 0$. Also $x^\alpha e^{-x} \rightarrow 0$ as $x \rightarrow \infty$. Hence the formula.

(b)

$$E(X) = \frac{\lambda^\alpha}{\Gamma(\alpha)} \int_0^\infty x x^{\alpha-1} e^{-\lambda x} dx = \frac{\Gamma(\alpha + 1)}{\lambda \Gamma(\alpha)} \times \frac{\lambda^{\alpha+1}}{\Gamma(\alpha + 1)} \int_0^\infty x^{(\alpha+1)-1} e^{-\lambda x} dx = \frac{\alpha}{\lambda}$$

Similarly

$$E(X^2) = \frac{\Gamma(\alpha + 2)}{\lambda^2 \Gamma(\alpha)} \times \frac{\lambda^{\alpha+2}}{\Gamma(\alpha + 2)} \int_0^\infty x^{(\alpha+2)-1} e^{-\lambda x} dx = \frac{(\alpha + 1)\alpha}{\lambda^2}$$

$$\text{var}(X) = \frac{(\alpha + 1)\alpha}{\lambda^2} - \frac{\alpha^2}{\lambda^2} = \frac{\alpha}{\lambda^2}$$

4. $Y_n \stackrel{d}{=} Z_1^2 + \dots + Z_n^2$, where Z_i 's are IID standard normal RVs. $a = E(Y_n) = nE(Z_1^2) = n$.
 $\text{var}(Y_n) = n\text{var}(Z_1^2) = n(E(Z_1^4) - 1^2) = 2n$. $b = \text{SD}(Y_n) = \sqrt{2n}$.

5. (a) Predictor:

$$E[Y|x] = \mu_Y + \frac{\rho\sigma_Y}{\sigma_X}(x - \mu_X)$$

MSE is $\text{var}[Y|x] = (1 - \rho^2)\sigma_Y^2$.

(b)

$$E[Y|X] = \mu_Y + \frac{\rho\sigma_Y}{\sigma_X}(X - \mu_X)$$

Since X is normal, $E[Y|X]$ is also normal, with expectation

$$E(E[Y|X]) = \mu_Y + \frac{\rho\sigma_Y}{\sigma_X}(E(X) - \mu_X) = \mu_Y$$

and variance

$$\text{var}(E[Y|X]) = \frac{\rho^2\sigma_Y^2}{\sigma_X^2} \times \sigma_X^2 = \rho^2\sigma_Y^2$$

$\text{var}[Y|X]$ is the constant $(1 - \rho^2)\sigma_Y^2$, which is also $E(\text{var}[Y|X])$. Hence, as expected,

$$\sigma_Y^2 = \text{var}(E[Y|X]) + E(\text{var}[Y|X])$$

[This is an instance of “analysis of variance”: $\text{var}(Y) = \text{“variance explained by } X\text{”} + \text{“residual variance”}$.]

(c) Mean MSE: $E(\text{var}[Y|X]) = (1 - \rho^2)\sigma_Y^2$.

(d) From the variance matrix, $\text{cov}(X, Y) = \rho\sigma_X\sigma_Y$. Hence the correlation is ρ .

(e) Rearrange terms in formula of $E[Y|x]$.

[The formula expresses “regression to the mean”. For example, in the Pearson data set, $\rho \approx 0.5$. Look at fathers who are 2 SDs above average, i.e., $(x - \mu_X)/\sigma_X = 2$. The mean height of their sons is only $(E[Y|x] - \mu_Y)/\sigma_Y = 1$ SD above average.]