

# STATS 7022 – Data Science PG Assignment 1

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## Question 2: Variance-Bias Trade-Off

We have:

- General form:  $Y = f(X) + \epsilon$
- Mean square error (MSE):  $MSE = E[(y - \hat{f}(x))^2]$
- Bias:  $b_f(\hat{f}(x)) = E[\hat{f}(x)] - f(x)$  (1)

- Variance:  $\text{var}(\hat{f}(x)) = E[(\hat{f}(x) - E[\hat{f}(x)])^2]$  (2)

From a single new observation  $(x_0, Y_0)$ , MSE becomes:

$$\begin{aligned} & E[(Y_0 - \hat{f}(x_0))^2] \\ &= E[(f(x_0) + \epsilon - \hat{f}(x_0))^2] \\ &= E[(f(x_0) - \hat{f}(x_0) + \epsilon)^2] \\ &= E[(f(x_0) - \hat{f}(x_0))^2] + 2E[(f(x_0) - \hat{f}(x_0))\epsilon] + E[\epsilon^2] \\ &= E[(f(x_0) - \hat{f}(x_0))^2] + 2E[f(x_0)\epsilon - \hat{f}(x_0)\epsilon] + E[\epsilon^2] \\ &= E[(f(x_0) - \hat{f}(x_0))^2] + 2E[f(x_0)\epsilon] - 2E[\hat{f}(x_0)\epsilon] + E[\epsilon^2] \end{aligned} \quad (3)$$

By definition,  $\epsilon$  is independent of  $\mathbf{X}$ ,  $E[\epsilon] = 0$ ,  $E[\epsilon^2] = \text{var}(\epsilon)$ , (3) becomes:

$$\begin{aligned} & E[(Y_0 - \hat{f}(x_0))^2] \\ &= E[(f(x_0) - \hat{f}(x_0))^2] + 2E[f(x_0)]E[\epsilon] - 2E[\hat{f}(x_0)]E[\epsilon] + E[\epsilon^2] \\ &= E[(f(x_0) - \hat{f}(x_0))^2] + \text{var}(\epsilon) \\ &= E[(f(x_0) - E[\hat{f}(x)] + E[\hat{f}(x)] - \hat{f}(x_0))^2] + \text{var}(\epsilon) \\ &= E[(f(x_0) - E[\hat{f}(x_0)]) - (\hat{f}(x_0) - E[\hat{f}(x_0)])]^2 + \text{var}(\epsilon) \\ &= E[(E[\hat{f}(x_0)] - f(x_0))^2] + E[(\hat{f}(x_0) - E[\hat{f}(x_0)])^2] \\ &\quad - 2E[(f(x_0) - E[\hat{f}(x_0)])E[(\hat{f}(x_0) - E[\hat{f}(x_0)])]] + \text{var}(\epsilon) \end{aligned} \quad (4)$$

Substitute (1) and (2) into (4), we have:

$$\begin{aligned}
& E \left[ \left( Y_0 - \hat{f}(x_0) \right)^2 \right] \\
&= E \left[ b_f \left( \hat{f}(x_0) \right)^2 \right] + \text{var} \left( \hat{f}(x_0) \right) + \text{var}(\epsilon) \\
&\quad - 2E \left[ (f(x_0) - E[\hat{f}(x_0)]) \right] E \left[ (\hat{f}(x_0) - E[\hat{f}(x_0)]) \right]
\end{aligned} \tag{5}$$

We have:  $E[\hat{f}(x_0)]$  and  $f(x_0)$  are constant,  $b_f \left( \hat{f}(x_0) \right)$  is also a constant. Thus:

$$E \left[ b_f \left( \hat{f}(x_0) \right)^2 \right] = b_f \left( \hat{f}(x_0) \right)^2$$

The equation (5) becomes:

$$\begin{aligned}
& E \left[ \left( Y_0 - \hat{f}(x_0) \right)^2 \right] \\
&= b_f \left( \hat{f}(x_0) \right)^2 + \text{var} \left( \hat{f}(x_0) \right) + \text{var}(\epsilon) \\
&\quad - 2E \left[ (f(x_0) - E[\hat{f}(x_0)]) \right] E \left[ (\hat{f}(x_0) - E[\hat{f}(x_0)]) \right]
\end{aligned} \tag{6}$$

Because  $E[\hat{f}(x_0)]$  is a constant:  $E \left[ E[\hat{f}(x_0)] \right] = E[\hat{f}(x_0)]$

So:

$$\begin{aligned}
& E \left[ (\hat{f}(x_0) - E[\hat{f}(x_0)]) \right] \\
&= E[\hat{f}(x_0)] - E \left[ E[\hat{f}(x_0)] \right] \\
&= E[\hat{f}(x_0)] - E[\hat{f}(x_0)] \\
&= 0
\end{aligned} \tag{7}$$

Substitute (7) into (6), we have:

$$E \left[ \left( Y_0 - \hat{f}(x_0) \right)^2 \right] = b_f \left( \hat{f}(x_0) \right)^2 + \text{var} \left( \hat{f}(x_0) \right) + \text{var}(\epsilon)$$