

$$\begin{aligned}
R(f) &= \mathbb{E} (Y - f(X))^2 = \mathbb{E} (Y - \eta(X) + \eta(X) - f(X))^2 \\
&= \mathbb{E} (Y - \eta(X))^2 + \mathbb{E} (\eta(X) - f(X))^2 + \\
&\quad \underbrace{2 \mathbb{E} (Y - \eta(X))(\eta(X) - f(X))}_{R^*} \\
&= \mathbb{E} \left[\mathbb{E} [(Y - \eta(X))(\eta(X) - f(X)) | X] \right] \\
&= \mathbb{E} \left[\mathbb{E} [Y - \eta(X) | X] (\eta(X) - f(X)) \right] \\
&= \mathbb{E} \left[\underbrace{\mathbb{E} [Y - \mathbb{E}[Y|X] | X]}_0 (\eta(X) - f(X)) \right] = 0
\end{aligned}$$

Suppose that f is random (\hat{f}) because it comes from training data.

$$\begin{aligned}
\mathbb{E} (\hat{f}(X) - \eta(X))^2 &= \mathbb{E} (\hat{f}(X) - \mathbb{E}[\hat{f}(X)|X])^2 + \mathbb{E} (\mathbb{E}[\hat{f}(X)|X] - \eta(X))^2 \\
&\quad + (\text{cross-term that vanishes} = 0) \\
&= \mathbb{E} [\text{Var}(\hat{f}(X)|X)] + \mathbb{E} [\text{Bias}^2(\hat{f}(X)|X)]
\end{aligned}$$

$$\text{w/ } \text{Bias}(\hat{f}(X)|X) = \mathbb{E}[\hat{f}(X)|X] - \eta(X)$$

$$\text{prop } R(\hat{f}) = R^* + \mathbb{E} [\text{Bias}^2(\hat{f}(X)|X) + \text{Var}(\hat{f}(X)|X)]$$