

Suppose we develop

\hat{f} from a training

dataset

$$S = \left\{ \begin{array}{l} (\vec{X}_1, Y_1), \\ \vdots \\ (\vec{X}_n, Y_n) \end{array} \right\}$$

$Y =$ course grade (%)

$X_{Q1} =$ Quiz 1 grade

$$Y = 0.5 X_m + 0.15 X_{Q1} + 0.15 X_{HW} + 0.2 X_{F}$$

$$\hat{Y} = \hat{f}(X_{Q1})$$

$$Y = f(X_{Q1}) + \epsilon$$

random variable

$$Y = f(X) + \varepsilon$$

assume $E_{\varepsilon}[\varepsilon] = 0$

then $\text{Var}(\varepsilon) = E_{\varepsilon}\varepsilon^2 - \left(E(\varepsilon)\right)^2 \rightarrow 0$

$$Y - \hat{Y} \quad \text{all random variables}$$
$$Y - \hat{f}(X) \quad = Y, X, \varepsilon, S$$
$$f(X) + \varepsilon - \hat{f}(X)$$

How good is \hat{f} ?

Test it with (X, Y)

$$\hat{f}(X) = \hat{Y}$$

Is Y close to \hat{Y} ? $\hat{Y} - Y$

$$E_{X,S,\epsilon,Y} (Y - \hat{Y})^2$$

expected test squared
prediction error

Bias - Variance decomposition

S is independent of X, Y
"training" " " " test
X is independent of ϵ

$$\begin{aligned}
& E_{X,S,\varepsilon,Y} [Y - \hat{Y}]^2 \\
&= E_{X,S,\varepsilon,Y} [f(X) + \varepsilon - \hat{f}_S(X)]^2 \\
&\stackrel{(1)}{=} E_{X,S,\varepsilon} [f(X) + \varepsilon - \hat{f}_S(X)]^2 \\
&\stackrel{(2)}{=} E_X E_S E_\varepsilon [f(X) + \varepsilon - \hat{f}_S(X)]^2 \\
&= E_X E_S E_S \left(\underbrace{(f(X) - \hat{f}_S(X))}_{\text{FOIL}} + (\varepsilon) \right)^2 \\
&= E_X E_S E_\varepsilon \left[(f(X) - \hat{f}_S(X))^2 + 2\varepsilon (f(X) - \hat{f}_S(X)) + \varepsilon^2 \right] \rightarrow 0 \\
&= E_X E_S (f(X) - \hat{f}_S(X))^2 + \underbrace{E_X E_S E_\varepsilon (2\varepsilon (f(X) - \hat{f}_S(X)))}_{\rightarrow 0} + E_X E_S E_\varepsilon [\varepsilon^2] \text{Var}(\varepsilon) \\
&= E_X \left[(f(X) - E_S \hat{f}_S(X))^2 \right] + \text{Var}_S \hat{f}_S(X) + \text{Var}_\varepsilon(\varepsilon) \\
&= E_{Y,X,S,\varepsilon} [Y - \hat{Y}]^2
\end{aligned}$$

$$\begin{aligned}
& E_S [f(x) - \hat{f}_S(x)]^2 \\
&= E_S [f^2(x) - 2f(x)\hat{f}_S(x) \\
&\quad + \hat{f}_S^2(x)] \\
&= E_S f^2(x) - 2f(x) E_S \hat{f}_S(x) + E_S [\hat{f}_S^2(x)] \\
&= \left(f^2(x) - 2f(x) E_S [\hat{f}_S(x)] \right) + E_S [\hat{f}_S^2(x)] \\
&\quad + [E_S \hat{f}_S(x)]^2 - [E_S \hat{f}_S(x)]^2 \\
&= [f(x) - E_S \hat{f}_S(x)]^2 + \text{Var}_S(\hat{f}_S(x))
\end{aligned}$$

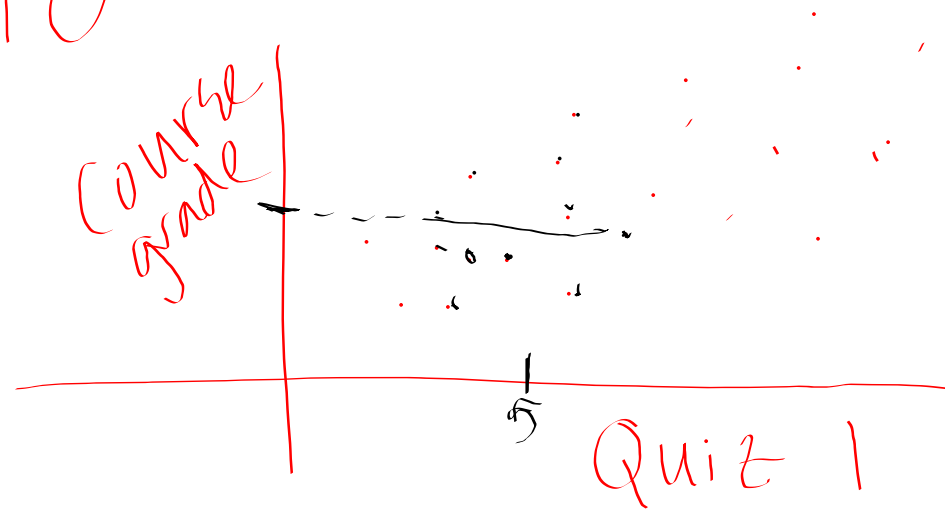
$\text{Var}_\epsilon(\epsilon) = \text{irreducible error}$

$E_x \text{Var}_s \hat{f}_s(x) = \text{spread of estimated } f \text{ over different training sets } S, \text{ averaged over test points } x$

$E_x [\text{bias}]^2, \text{ bias} = f(x) - E_s \hat{f}_s(x)$

KNN for regression

$K=10$



kNN

$$\hat{Y} = \sum_{i \in N_0} \frac{Y_i}{K}$$

where N_0 is the set of K nearest points to x_0

kNN for regression