## SHEET - An Introduction to Statistical Learning Chapter 2 - Statistical Learning

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## 1 Statistical Learning

## 1.1 Courses' Demonstrations

We suppose that we observe a quantitative response Y and p different predictors,  $X_1, X_2, \ldots, X_p$ . We assume that there is some relationship between Y and  $X = (X_1, X_2, \ldots, X_p)$ , which can be written in the very general form

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

Here f is some fixed but unknown function of  $X_1, \ldots, X_p$ , and  $\varepsilon$  is a random error term, which is independent of X and has mean zero. In this formulation, f represents the systematic information that X provides about Y.

Consider a given estimate  $\hat{f}$  and a set of predictors X, which yields the prediction  $\hat{Y} = \hat{f}(X)$ . Assume for a moment that both  $\hat{f}$  and X are fixed. Then, we show that

$$E(Y - \hat{Y})^2 = E[f(X) + \varepsilon - \hat{f}(X)]^2$$

$$= [f(X) - \hat{f}(X)]^2 + \operatorname{Var}(\varepsilon)$$

$$= \operatorname{Var}(\hat{f}) + \operatorname{Bias}(\hat{f})^2 + \operatorname{Var}(\varepsilon)$$
(2.3)
$$(2.7)$$

Demonstration:  $E(y - \hat{y})^2$ We have

$$\begin{split} E[\varepsilon] &= 0 \\ E[y] &= E[f + \varepsilon] = E[f] = f \\ Var[X] &= E[X^2] - E[X]^2 \Leftrightarrow E[X^2] = \mathrm{Var}[X] + E[X]^2 \\ \mathrm{Var}[y] &= E[(y - E[y])^2] = E[(y - f)^2] \end{split}$$

Then

$$\begin{aligned} \mathbf{E}[(\mathbf{y} - \hat{\mathbf{y}})^2] &= E[(y - \hat{f})^2] \\ &= E[y^2] + E[\hat{f}^2] - E[2y\hat{f}] \\ &= \mathrm{Var}[y] + E[y]^2 + \mathrm{Var}[\hat{f}] + E[\hat{f}]^2 - 2fE[\hat{f}] \\ &= \mathrm{Var}[y] + \mathrm{Var}[\hat{f}] + (f^2 - 2fE[\hat{f}] + E[\hat{f}]^2) \end{aligned}$$

We have

$$(E[f^2 - \hat{f}])^2 = (f^2 - E[\hat{f}])^2 = f^2 - 2fE[\hat{f}] + E[\hat{f}]^2$$

$$Var(y) = E[(y - E[y])^2] = E[(f + \varepsilon - f)^2] = E[\varepsilon^2] = Var(\varepsilon)$$

Then

$$\begin{split} \mathbf{E}[(\mathbf{y} - \hat{\mathbf{y}})^2] &= \mathrm{Var}[y] + \mathrm{Var}[\hat{f}] + (f - E[\hat{f}])^2 \\ &= \mathrm{Var}[y] + \mathrm{Var}[\hat{f}] + E[(f - \hat{f})]^2 \\ &= \mathrm{Var}[\varepsilon] + \mathrm{Var}[\hat{f}] + \mathrm{Bias}[\hat{f}]^2 \\ \mathbf{E}[(\mathbf{y} - \hat{\mathbf{y}})^2] &= \mathbf{Var}[\varepsilon] + \mathbf{Var}[\hat{\mathbf{f}}] + \mathbf{Bias}[\hat{\mathbf{f}}]^2 \end{split}$$