

Homework 1

David Wang

1) Expectations

$$\text{Model} \rightarrow Y = f(x) + \epsilon$$

$$(a) \text{Err}(x) = E[(Y - \hat{f}(x))^2 | X=x]$$

$$\Rightarrow Y - f(x) \text{ and } f(x) - \hat{f}(x) \text{ are independent} \\ \Rightarrow E[(Y - f(x) + (f(x) - \hat{f}(x)))^2 | X] \\ = E[(Y - f(x))^2 | X] + E[(f(x) - \hat{f}(x))^2 | X]$$

$$\Rightarrow \text{Distribute square} = E[(Y - f(x))^2 | X] + 2E[(Y - f(x)) \times (f(x) - \hat{f}(x)) | X] + E[(f(x) - \hat{f}(x))^2 | X]$$

$$\text{Notice: } E[Y - f(x) | X] = E[Y | X] - E[f(x) | X] = 0$$

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

$$\Rightarrow \text{variance} = \sigma_\epsilon^2 + E[(f(x) - \hat{f}(x))^2 | X]$$

$$E[(Y - f(x))^2] = E[(f(x) + \epsilon - f(x))^2] = E[\epsilon^2] = \sigma_\epsilon^2 \\ \Rightarrow \sigma_\epsilon^2 + E[(f(x) - E[\hat{f}(x)] + E[\hat{f}(x)] - \hat{f}(x))^2] \\ \Rightarrow f(x) - E[\hat{f}(x)] \text{ and } E[\hat{f}(x)] - \hat{f}(x) \text{ are independent}$$

$$\Rightarrow \text{distribute square} = \sigma_\epsilon^2 + (f(x) - E[\hat{f}(x)])^2 + (E[\hat{f}(x)] - \hat{f}(x))^2 + 2E[(\hat{f}(x) - E[\hat{f}(x)]) \times (E[f(x)] - \hat{f}(x))]$$

↓ Not really sure how this step works.

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

- (b) σ_ϵ^2 is the standard error of ϵ
 $E[\hat{f}(x)]^2$ is bias squared
 $E(f(x) - E[\hat{f}(x)])^2$ is variance

2) Covariance

a) Diagonalization $\Sigma = V \Lambda V^T$

$$N(0, I) \rightarrow N(\mu, \Sigma)$$

$$\rightarrow N(\mu, V \Lambda V^T)$$

• if $V \Lambda V^T = I$ then $\Lambda = V^{-1} I V = V^{-1} V = I \dots$

then $\Sigma = I$

• since distribution is normal (gaussian),

$$\mu = 0$$