

$$\begin{aligned}
 1. \quad E_{\text{out}}(g^{(0)}) &= E_{x,y} \left[ (g^{(0)} - f(x))^2 \right] = E_{x,y} \left[ (g^{(0)} - (f(x) + \varepsilon))^2 \right] = \\
 &= E_{x,y} \left[ (g^{(0)})^2 + f(x)^2 + \varepsilon^2 + 2\varepsilon f(x) - 2g^{(0)}f(x) - 2\varepsilon g^{(0)} \right] = \\
 &\stackrel{\gamma = f(x) + \varepsilon}{=} E_{x,y} \left[ (g^{(0)} - f(x))^2 + 2\varepsilon(f(x) - g^{(0)}) + \varepsilon^2 \right] = \\
 &\stackrel{\varepsilon \sim N(0, \sigma^2)}{=} E_x \left[ E_y \left[ (g^{(0)} - f(x))^2 + 2\varepsilon(f(x) - g^{(0)}) + \varepsilon^2 \right] \right] = \\
 &= E_x \left[ (g^{(0)} - f(x))^2 + 2E_y(\varepsilon)(f(x) - g^{(0)}) + E_y(\varepsilon^2) \right] = \\
 &= E_x \left[ (g^{(0)} - f(x))^2 \right] + \sigma^2
 \end{aligned}$$


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$$E_D [E_{\text{out}}(g^{(0)})] = E_0 E_m \underbrace{[(g^{(0)} - f(x))^2]}_{\text{bias}^2} + \sigma^2 = \text{bias}^2 + \text{Var} + \sigma^2$$

$\longleftrightarrow$   
 $\downarrow$

$$2- \quad a) \quad X \sim \tilde{f} \rightarrow \tilde{w} = (X^T X)^{-1} X^T \tilde{y}$$

$$X \tilde{w} = \tilde{y} \quad \tilde{f}(z) = z^T \tilde{w} = z^T (X^T X)^{-1} X^T \tilde{y}$$

Moore-Penrose inverse

$$b) \quad E[(\hat{y} - \tilde{f}(z))^2] = \underbrace{\text{Var}[\varepsilon]}_{Xw=y} + \underbrace{(y - E(\tilde{f}(z)))^2}_{\text{bias}} + \underbrace{\text{Var}[\tilde{f}(z)]}_{\text{Var}(\tilde{w})}$$

$$c) \quad \tilde{w} = (X^T X)^{-1} \underbrace{X^T \tilde{y}}_{\tilde{y} + \varepsilon} = \underbrace{(X^T X)^{-1} X^T y}_{w} + \underbrace{(X^T X)^{-1} X^T \varepsilon}_{\text{bias}} \quad E[\tilde{w}] = w$$

bias = 0

$$d) \quad \underbrace{\text{Var}(\tilde{w})}_{\text{Var}(\tilde{f}(z))} = \text{Var}((X^T X)^{-1} X^T \varepsilon) = (X^T X)^{-1} X^T I_n X (X^T X)^{-1} = \underbrace{(X^T X)^{-1}}_{\text{Var}(\tilde{w}) = \text{Var}(\tilde{f}(z))}$$

e) ✓  
↳ positive semi definite

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$$\underbrace{z^T (X^T X)^{-1} z}_{\text{Var}(\tilde{w})} \geq 0$$

$$3- \quad 1, k_1(a, b) = (a_1 b_1 + a_2 b_2)^2 = a_1^2 b_1^2 + a_2^2 b_2^2 + 2 a_1 a_2 b_1 b_2 =$$

$$= [a_1^2 b_1^2] + [a_2^2 b_2^2] + [\sqrt{2} a_1 a_2] [\sqrt{2} b_1 b_2] = \phi(a)^T \phi(b) = [a_1^2 \quad a_2^2 \quad \sqrt{2} a_1 a_2]$$

$$\rightarrow \phi(a) = \begin{bmatrix} a_1^2 \\ a_2^2 \\ \sqrt{2} a_1 a_2 \end{bmatrix}$$

$$\begin{bmatrix} b_1^2 \\ b_2^2 \\ \sqrt{2} b_1 b_2 \end{bmatrix}$$

$$2) \quad k_2(a, b) = (1 + a^T b)^2 = (1 + a_1 b_1 + a_2 b_2)^2 = 1 + \underbrace{a_1^2 b_1^2}_{\text{bias}} + \underbrace{a_2^2 b_2^2}_{\text{bias}} + 2 \underbrace{a_1 b_1}_{\text{cross}} + 2 \underbrace{a_2 b_2}_{\text{cross}} + 2 \underbrace{a_1 a_2 b_1 b_2}_{\text{cross}} = \phi(a)^T \phi(b)$$

$$\rightarrow \phi(a) = \begin{bmatrix} 1 \\ a_1^2 \\ a_2^2 \\ \sqrt{2} a_1 a_2 \\ \sqrt{2} a_1 a_2 \end{bmatrix}$$

$$4- \quad h_0 = b \quad D = \begin{cases} (-1, 0), (0, 1), (1, 0) \\ 1 \quad 2 \quad 3 \end{cases}$$

$$h_0 : \quad \hat{b} = \underset{b}{\operatorname{argmin}} \sum_i (y_i - b)^2 = \frac{\sum_i y_i}{n} \quad \text{LOOCV: } \begin{cases} 1: \quad \hat{b} = 1/2 \rightarrow e_1 = (\frac{1}{2})^2 \\ 2: \quad \hat{b} = 0 \rightarrow e_2 = 1 \\ 3: \quad \hat{b} = 1/2 \rightarrow e_3 = (\frac{1}{2})^2 \end{cases}$$

$$\left| \begin{array}{l} 2: b = 0 \rightarrow -2 \\ 3: b = \frac{1}{2} \rightarrow e_3 = (\frac{1}{2})^2 \\ \rightarrow CV = \frac{1}{3} \left[ 1 + \frac{1}{4} + \frac{1}{4} \right] = \frac{1}{2} \end{array} \right.$$

$$h_1: \hat{a}, \hat{b} = \underset{a, b}{\operatorname{argmin}} \sum_i (y_i - b - ax_i)^2$$

$$\rightarrow \begin{bmatrix} n & \sum a_i \\ \sum a_i & \sum a_i^2 \end{bmatrix} \begin{bmatrix} \hat{b} \\ \hat{a} \end{bmatrix} = \begin{bmatrix} \sum y_i \\ \sum y_i a_i \end{bmatrix}$$

$$\text{Loocv} \left\{ \begin{array}{l} 2: \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} \hat{b} \\ \hat{a} \end{bmatrix} = \vec{0} \rightarrow \hat{b}, \hat{a} = 0 \rightarrow e_2 = \hat{d}_2^2 = 1 \\ 3, 1: \text{challenge yourself! (use RREF)} \end{array} \right. \quad CV_2 = \frac{1}{3} [e_1 + e_2 + e_3]$$

$$CV_1 = CV_2 \rightarrow \Theta \checkmark$$

$$5- \text{ if } x^{(t)} \text{ misclassified. } w_{t+1} = w_t + \eta x^{(t)} y^{(t)}$$

induction:

$$\cdot \text{ base: } w^{(0)} = 0 = \sum_i \alpha_i x_i^{(0)}$$

$$\cdot \text{ step: } w^{(t)} = \sum_i \alpha_i x_i^{(t)} \rightarrow w^{t+1} = \sum_i \alpha'_i x_i^{(t)} \quad \alpha'_i = \begin{cases} \alpha_i & \text{if } t \\ \alpha_i + \eta y^{(t)} & \text{if } t \end{cases}$$

$$\xrightarrow{\text{on convergence}} w = \sum_i \underbrace{\eta y^{(i)} n_i}_{\text{why?}} x_i^{(i)}$$