

1.

$$(a) d_{VCH} = D + 1 = 57 + 1 = 58$$

$$(b) E_{out}(h_g) \leq E_{in}(h_g) + \sqrt{\frac{8}{N} \ln \frac{4[(2N)^{d_{VCH}} + 1]}{\delta}} \quad \delta = 0.1$$

$$E_{out}(h_g) \leq E_{in}(h_g) + \sqrt{\frac{8}{3000} \ln \frac{4[(2 \cdot 3000)^{58} + 1]}{0.1}}$$

$$E_{out}(h_g) \leq E_{in}(h_g) + 1.1642$$

$$(c) D = 10 \quad d_{VCH} = 11 \quad N = 10000$$

$$\varepsilon = \sqrt{\frac{8}{N} \ln \frac{4[(2N)^{d_{VCH}} + 1]}{\delta}} = \sqrt{\frac{8}{10000} \ln \frac{4[(2 \cdot 10000)^{11} + 1]}{0.1}} = 0.3002$$

$$(d) \varepsilon = \sqrt{\frac{8}{N} \ln \frac{4[(2N)^{58} + 1]}{\delta}} = 0.1$$

$$\frac{8}{N} \ln \frac{4[(2N)^{58} + 1]}{0.1} = 0.01$$

$$\ln \frac{4[(2N)^{58} + 1]}{0.1} = \frac{0.01 N}{8}$$

$$[(2N)^{58} + 1] = \frac{e^{\frac{0.01 N}{8}} \cdot 0.1}{4}$$

$$(2N)^{58} + 1 = 0.025 e^{\frac{0.01 N}{8}}$$

$$N = 622555$$

$$q \quad D=10 \quad d_{vc}(H)=11$$

$$\Sigma = \sqrt{\frac{\frac{8}{N} \ln \frac{4[(2N)^{0.1}+1]}{0.1}}{0.1}} = 0.1$$

$$\frac{8}{N} \ln \frac{4[(2N)^{0.1}+1]}{0.1} = 0.01$$

$$\ln \frac{4[(2N)^{0.1}+1]}{0.1} = \frac{0.01 \cdot N}{8}$$

$$[(2N)^{0.1}+1] = e^{\frac{0.01 \cdot N}{8}} \cdot \frac{0.1}{4}$$

$$N = 111307$$

e. The best model selected from training dataset models cardinality is 1.

$$f. \quad \Sigma = \sqrt{\frac{\frac{1}{2N} \ln \frac{2M}{8}}{\frac{1}{2 \cdot 10^4} \ln \frac{2}{0.1}}} = 0.03$$

2.4.

(a) set $x_i = \begin{bmatrix} 1 \\ a_1 \\ a_2 \\ \vdots \\ a_d \end{bmatrix}$

$$\underline{X} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & \dots \\ a_1 & b_1 & & & & \\ a_2 & b_2 & & & & \\ \vdots & \vdots & & & & \\ a_d & b_d & & & & \end{bmatrix} \quad (d+1) \times (d+1) \text{ matrix}$$

$(d+1) \times (d+1)$

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$$h(\underline{X}) = \underline{W}^T \underline{X} = \begin{bmatrix} w_{a0} & w_{b0} \\ w_{a1} & w_{b1} \\ w_{a2} & \vdots \\ \vdots & w_{bd} \\ w_{ad} & w_{bd} \end{bmatrix}^T \times \begin{bmatrix} 1 & 1 & 1 & 1 & \dots \\ a_1 & b_1 & & & \\ a_2 & b_2 & & & \\ \vdots & \vdots & & & \\ a_d & b_d & & & \end{bmatrix}$$

\underline{X} is non singular, you can find \underline{W}^T that can map

\underline{X} so that $h(\underline{X}) = \text{sgn}(\underline{W}^T \underline{X}) = \text{diag}(1)$

$\underline{W}^T = \underline{X}^{-1}$ since \underline{X} is non singular.

so there are at least $d+1$ possible dichotomies,

$d_{vc} \geq d+1$

c) \underline{X} is linearly independent. so X_{d+2} term = X_k must be a linear combination of other points.

$$X_k = X_{d+2} = \sum_{i=0}^d a_i X_i \quad \begin{matrix} (d+1) \times (d+2) \\ (d+1) \times (d+1) \end{matrix}$$

assume $h(X_k) = \text{sgn}(W_k^T X_k) = 0$ W_k^T can be any row of W^T

$$h(X_k) = \text{sgn}(W_k^T X_k) = \text{sgn}\left(W_k^T \sum_{i=0}^d a_i X_i\right) \text{ has to be } 1$$

since W_k^T is chosen from W^T and there is always some $a_i X_i$ such that $\text{sgn}(W_i^T a_i X_i) = 1$

There there is at most $d+1$ points.

$$dV_c \leq d+1$$

$$\text{so } dV_c = d+1$$

2.24.

$$a.1 \quad g^D(x) = ax + b$$

$$a = \frac{f(x)}{x} \quad b = 0$$

$$g(x) = \frac{y_1}{x_1} x$$

$$\text{set } y_i = f(x_i)$$

a.2

$$\text{set } y_i = f(x_i)$$

$$y = ax + b$$

$$(x_1, y_1) \quad (x_2, y_2)$$

$$a = \frac{y_1 - y_2}{x_1 - x_2}$$

$$y_1 = \frac{y_1 - y_2}{x_1 - x_2} x_1 + b$$

$$b = y_1 - \frac{y_1 - y_2}{x_1 - x_2} x_1$$

$$b = \frac{y_1 x_1 - y_1 x_2 - y_2 x_1 + y_2 x_2}{x_1 - x_2}$$

$$g^D(x) = \frac{y_1 - y_2}{x_1 - x_2} x + \frac{y_2 x_1 - y_1 x_2}{x_1 - x_2}$$

$$\bar{g}(x) = E_D[g^D(x)] = E_D \left[\frac{y_1 - y_2}{x_1 - x_2} x + \frac{y_2 x_1 - y_1 x_2}{x_1 - x_2} \right]$$

$$= E_D \left[\frac{y_1 - y_2}{x_1 - x_2} x \right] + E_D \left[\frac{y_2 x_1 - y_1 x_2}{x_1 - x_2} \right]$$

since x is uniformly distributed between $[-1, 1]$ $p(x_i) = \frac{1}{2}$

$$= \int_{-1}^1 \int_{-1}^1 \frac{y_1 - y_2}{x_1 - x_2} \frac{1}{2} \cdot \frac{1}{2} dx_2 dx_1 + \int_{-1}^1 \int_{-1}^1 \frac{y_2 x_1 - y_1 x_2}{x_1 - x_2} \frac{1}{2} \cdot \frac{1}{2} dx_2 dx_1$$

$$= \frac{1}{4} \int_{-1}^1 \int_{-1}^1 \frac{x_1^2 - x_2^2}{x_1 - x_2} dx_2 dx_1 + \frac{1}{4} \int_{-1}^1 \int_{-1}^1 \frac{x_1 x_2 (x_2 - x_1)}{x_1 - x_2} dx_2 dx_1$$

\Downarrow
 $x_1 + x_2$
 \Downarrow
 $(-x_1, x_2)$

$$= \frac{1}{4} \int_{-1}^1 \left. x_1 x_2 + \frac{1}{2} x_2^2 \right|_{-1}^1 dx_1 + \frac{1}{4} \int_{-1}^1 \left. -\frac{1}{2} x_1 x_2^2 \right|_{-1}^1 dx_1$$

$x_1 + \frac{1}{2} - (-x_1 + \frac{1}{2})$
 \Downarrow
 $-\frac{1}{2} x_1 + \frac{1}{2} x_1 = 0$

\Downarrow
 $2x_1$

$$= \frac{1}{4} \int_{-1}^1 2x_1 dx_1 + 0$$

$$= \frac{1}{4} x_1^2 \Big|_{-1}^1 + 0 = \frac{1}{4} \cdot 0 + 0 = 0$$

(b) $\bar{g}(x)$ create n datapoints that satisfy $y = x^2$

from that dataset choose m datasets. each dataset

has two datapoints. According to these two datapoints predict a and b and take mean over all D .

$$\bar{g}(x) = \bar{a}x + \bar{b}$$

$E_d(E_{out})$ According to \bar{a} and \bar{b} , constructing $\bar{g}(x)$

evaluate $\overline{g(x)^2} \rightarrow \overline{g(x)f} + f^2$ over all n datapoints and take the mean. value.

bias evaluate $(\bar{g}(x) - f)^2$ over all n datapoints

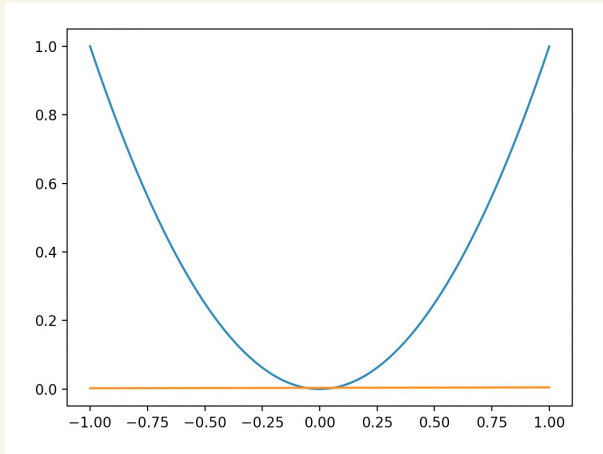
variance evaluate $g^p(x) - \bar{g}(x)$ over all m D

then evaluate over all x . take the mean value

✓C7

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mean of g(x): 0.0012758160000001643 * x + 0.003622166864800001  
Ed(Eout): 0.5313779652362515  
bias: 0.2024364889312275  
variance: 0.33462168972675377  
  
Process finished with exit code 0
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$$E_d[E_{out}] = \text{bias} + \text{variance}$$



$$d. \quad E_{out} = E_x [(g(x) - f(x))^2] = E_x [(ax+b) - f(x)]^2$$

$$= E_x [(ax+b - x^2)^2]$$

$$= E_x [-2ax^3 + a^2x^2 + 2abx + b^2 - 2bx^2 + x^4]$$

$$= -2a E_x(x^3) + a^2 E_x(x^2) + 2ab E_x(x) + b^2 - 2b E(x^2) + E(x^4)$$

$$= -2a \cdot \frac{1}{2} \int_{-1}^1 x^3 dx + a^2 \frac{1}{2} \int_{-1}^1 x^2 dx + 2ab \frac{1}{2} \int_{-1}^1 x dx + b^2 - 2b \frac{1}{2} \int_{-1}^1 x^2 dx + \frac{1}{2} \int_{-1}^1 x^4 dx$$

$$= -2a \cdot \frac{1}{2} \left(\frac{1}{4} x^4 \Big|_{-1}^1 \right) + \frac{a^2}{2} \left(\frac{1}{3} x^3 \Big|_{-1}^1 \right) + ab \left(\frac{1}{2} x^2 \Big|_{-1}^1 \right) + b^2 - b \left(\frac{1}{3} x^3 \Big|_{-1}^1 \right) + \frac{1}{2} \left(\frac{1}{5} x^5 \Big|_{-1}^1 \right)$$

$$= -a \times 0 + \frac{a^2}{2} \left(\frac{2}{3} \right) + ab(0) + b^2 - b \frac{2}{3} + \frac{1}{2} \cdot \frac{2}{5}$$

$$= \frac{a^2}{3} + b^2 - \frac{2b}{3} + \frac{1}{5}$$

$$= \frac{a^2 - 2b}{3} + b^2 + \frac{1}{5}$$

$$a = x_1 + x_2 \quad b = -x_1 x_2$$

$$E_0(E_{out}) = E_0 \left[\frac{a^2 + b^2}{3} + \frac{1}{5} \right]$$

$$= E_0 \left[\frac{(X_1 + X_2)^2 + 2X_1X_2}{3} \right] + E_0[X_1^2X_2^2] + \frac{1}{5}$$

$$= \frac{1}{4} \int_{-1}^1 \int_{-1}^1 \frac{X_1^2 + X_2^2 + 2X_1X_2}{3} dX_1 dX_2 + \frac{1}{4} \int_{-1}^1 \int_{-1}^1 X_1^2 X_2^2 dX_1 dX_2 + \frac{1}{5}$$

$$= \frac{1}{4} \int_{-1}^1 \left. \frac{\frac{1}{3}X_1^3 + X_1X_2^2 + 2X_1^2X_2}{3} \right|_{-1}^1 dX_2 + \frac{1}{4} \int_{-1}^1 \left. \frac{1}{3} X_1^3 X_2^2 \right|_{-1}^1 dX_2 + \frac{1}{5}$$

$$= \frac{1}{4} \int_{-1}^1 \frac{\frac{2}{3} + 2X_2^2}{3} dX_2 + \frac{1}{4} \int_{-1}^1 \frac{2}{3} X_2^2 dX_2 + \frac{1}{5}$$

$$= \frac{1}{4} \cdot \frac{1}{3} \left[\frac{2}{3}X_2 + \frac{2}{3}X_2^3 \right]_{-1}^1 + \frac{1}{4} \left[\frac{2}{9} X_2^3 \right]_{-1}^1 + \frac{1}{5}$$

$$= \frac{1}{12} \left[\frac{2}{3} + \frac{2}{3} - \left(-\frac{2}{3} - \frac{2}{3} \right) \right] + \frac{1}{4} \left[\frac{2}{9} + \frac{2}{9} \right] + \frac{1}{5}$$

$$= \frac{1}{12} \cdot \frac{8}{3} + \frac{1}{4} \cdot \frac{4}{9} + \frac{1}{5}$$

$$= \frac{2}{9} + \frac{1}{9} + \frac{1}{5} = \frac{8}{15}$$

$$\text{bias} = E_x [(g(x) - f(x))^2]$$

$$= E_x [(0 - x^2)^2]$$

$$= E_x [x^4] = \frac{1}{2} \int_{-1}^1 x^4 dx = \frac{1}{2} \left[\frac{1}{5} x^5 \right]_{-1}^1$$

$$= \frac{1}{2} \left(\frac{1}{5} - \frac{1}{5} \right) = \frac{1}{5} = 0.2$$

$$\text{variance} = E_x [E_y [(g(x) - f(x))^2]]$$

$$= E_x [E_y [(ax+b - 0)^2]] = E_x [E_y [a^2 x^2 + 2abx + b^2]]$$

$$= E_x [E_y [(x_1 + x_2)^2 x^2 - 2(x_1 + x_2) x_1 x_2 x + x_1^2 x_2^2]]$$

$$= E_x \left[\frac{1}{4} \int_{-1}^1 \int_{-1}^1 x^2 (x_1^2 + 2x_1 x_2 + x_2^2) - 2(x_1^2 x_2 + x_2^2 x_1) x + x_1^2 x_2^2 dx_1 dx_2 \right]$$

$$= E_x \left[\frac{1}{4} \int_{-1}^1 x^2 \left(\frac{1}{3} x_1^3 + x_1^2 x_2 + x_2^2 x_1 \right) - 2 \left(\frac{1}{3} x_1^3 x_2 + \frac{1}{2} x_1^2 x_2^2 \right) x + \frac{1}{3} x_1^3 x_2^2 \right]_{-1}^1 dx_2$$

$$x^2 \left(\frac{1}{3} + x_2 + x_2^2 \right) - 2 \left(\frac{1}{3} x_2 + \frac{1}{2} x_2^2 \right) x + \frac{1}{3} x_2^2$$

$$- \left(x^2 \left(-\frac{1}{3} + x_2 - x_2^2 \right) - 2 \left(-\frac{1}{3} x_2 + \frac{1}{2} x_2^2 \right) x - \frac{1}{3} x_2^2 \right)$$

$$\underline{x^2 \left(\frac{2}{3} + 2x_2^2 \right) - 2 \left(\frac{2}{3} x_2 \right) x + \frac{2}{3} x_2^2}$$

$$= E_x \frac{1}{4} \left(X^2 \left(\frac{2}{3} X_2 + \frac{2}{3} X_1^3 \right) - \frac{4}{3} \frac{1}{2} X_2^2 X + \frac{2}{3} \cdot \frac{1}{3} X_2^3 \right) \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$

$$X^2 \left(\frac{2}{3} + \frac{2}{3} \right) - \frac{2}{3} X + \frac{2}{9} - \left[X^2 \left(-\frac{2}{3} - \frac{2}{3} \right) - \frac{2}{3} X - \frac{2}{9} \right]$$

$$= \frac{4}{3} X^2 - \frac{2}{3} X + \frac{2}{9} - \left[-\frac{4}{3} X^2 - \frac{2}{3} X - \frac{2}{9} \right]$$

$$= \left(\frac{8}{3} X^2 + \frac{4}{9} \right) \frac{1}{4}$$

$$= E_x \left(\frac{2}{3} X^2 + \frac{1}{9} \right)$$

$$= \frac{1}{2} \int_{-1}^1 \left(\frac{2}{3} X^2 + \frac{1}{9} \right) dx$$

$$= \frac{1}{2} \left(\frac{2}{9} X^3 + \frac{1}{9} X \right) \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$

$$= \frac{1}{2} \left(\frac{2}{9} + \frac{1}{9} + \frac{2}{9} + \frac{1}{9} \right) = \frac{6}{9} \cdot \frac{1}{2} = \frac{1}{3}$$

4.3

(a) deterministic noise will decrease.

(b) deterministic noise will increase.

4.5

$$(a) W^T \Gamma^T \Gamma W = \sum_{q=0}^Q w_q^2$$

$$\Gamma^T \Gamma = I \quad \Gamma = I$$

$$(b) W^T \Gamma^T \Gamma^T W = \left(\sum_{q=0}^Q w_q \right)^2$$

$$W^T \Gamma^T = \sum_{q=0}^Q w_q$$

$$\Gamma^T = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$$