

Recap:

↳ classification: H complexity $\equiv d_{VC}(H)$

Regression : " " " \Rightarrow Bias variance trade off

↳ $\mathcal{D} = \{(x_1, y_1), \dots, (x_n, y_n)\}$

Output hypo: $g^D : \hat{y} = g^D(x)$

Avg hypo: $\bar{g}(x) = \mathbb{E}_D [g^D(x)]$

bias $(x) = (\bar{g}(x) - f(x))^2$

var $(x) = \mathbb{E} [(g^D(x) - \bar{g}(x))^2]$

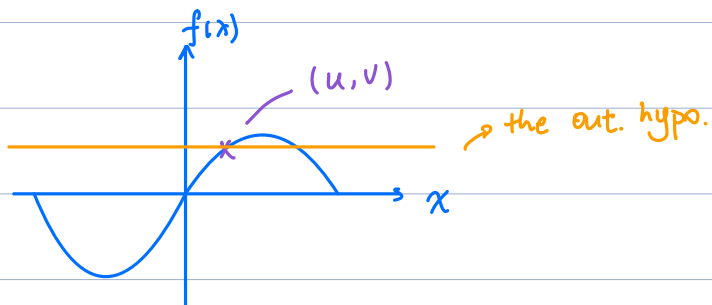
e.g. $d=1$, $x \in [-1, 1]$

$y = f(x) = \sin(\pi x)$

H : constant func

$\mathcal{D} = \{(u, v)\}$ // only one data, $N=1$

and $u \sim U(-1, 1)$ // u is randomly chose accord to $U(-1, 1)$



$g^D(x) = v, \forall x$

$\bar{g}(x) = \mathbb{E}_u [g^D(x)] = \mathbb{E}_u [v] = \mathbb{E}_u [\sin(\pi, u)] = \int_{-1}^1 \frac{1}{2} \sin(\pi u) du = 0$

$\therefore \text{bias}(x) = (0 - \sin(\pi x))^2 = \sin^2(\pi x)$

$\text{var}(x) = \mathbb{E}_u [(v - 0)^2] = \int_{-1}^1 \frac{1}{2} \sin^2(\pi u) du = \frac{1}{2}$

↳ Avg test error for sample x : $\Delta(x)$

$$\Delta(x) \triangleq \mathbb{E}_D [(g^D(x) - f(x))^2]$$

↑ ↑
output truth grd truth

e.g. In the prev example:

$$\begin{aligned}\Delta(x) &= \mathbb{E}_u [(v - \sin(\pi x))^2] \\ &= \mathbb{E}_u [v^2 + \sin^2(\pi x) - 2v \sin(\pi x)] \\ &= \mathbb{E}[v^2] + \sin^2(\pi x) - 2\mathbb{E}[v] \sin(\pi x) \\ &= \frac{1}{2} + \sin^2(\pi x) - 0 \\ &= \text{bias}(x) + \text{var}(x)\end{aligned}$$

∴ In general. $\Delta(x) = \text{bias}(x) + \text{var}(x)$

prf: $\Delta(x) \triangleq \mathbb{E}_D [(g^D(x) - f(x))^2]$

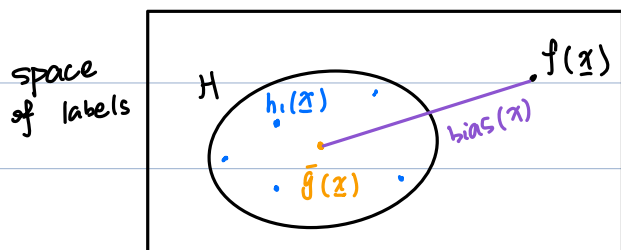
$$\begin{aligned}&= \mathbb{E}_D [((g^D(x) - \bar{g}(x)) + (\bar{g}(x) - f(x)))^2] \\ &= \mathbb{E}_D [(\bar{g}(x) - f(x))^2 + \cancel{g^D(x) - \bar{g}(x)}^2 + 2(\bar{g}(x) - f(x))(\cancel{g^D(x) - \bar{g}(x)})] \\ &= \text{bias}(x) + \text{var}(x)\end{aligned}$$

2. Bias-variance trade off for some given x :

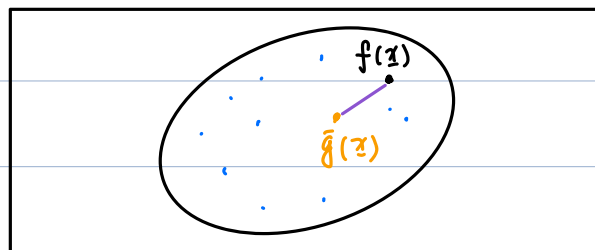
↳ Bias: How well can H approx. the target function $f(x)$

Variance: How much does the output hypo. $g^D(x)$ change with D .

For some x



small $H \Rightarrow$ { bias larger



large $H \Rightarrow$ { bias smaller

var smaller

var larger

↳ Averaging over \mathcal{X} :

$$\cdot \mathbb{E}_{\text{out}}(g^D) = \mathbb{E}_{\mathcal{X}}[(g^D(\mathcal{X}) - f(\mathcal{X}))^2], \quad \mathcal{X} \sim p(\mathcal{X})$$

Note: $\mathbb{E}_{\text{out}}(g^D)$ is random (depends on \mathcal{D})

$$\begin{aligned} \cdot \overline{\mathbb{E}_{\text{out}}} &\triangleq \mathbb{E}_{\mathcal{D}}[\mathbb{E}_{\text{out}}(g^D)] \\ &= \mathbb{E}_{\mathcal{D}}[\mathbb{E}_{\mathcal{X}}[(g^D(\mathcal{X}) - f(\mathcal{X}))^2]] \end{aligned}$$

where \mathcal{X} and \mathcal{D} are independent.

$$= \mathbb{E}_{\mathcal{X}}[\mathbb{E}_{\mathcal{D}}[(g^D(\mathcal{X}) - f(\mathcal{X}))^2]]$$

$$= \mathbb{E}_{\mathcal{X}}[\Delta(\mathcal{X})]$$

$$= \mathbb{E}_{\mathcal{X}}[\text{bias}(\mathcal{X}) + \text{var}(\mathcal{X})]$$

$$\triangleq \overline{\text{bias}} + \overline{\text{var}}$$

$$\overline{\mathbb{E}_{\text{out}}} = \overline{\text{bias}} + \overline{\text{var}}$$

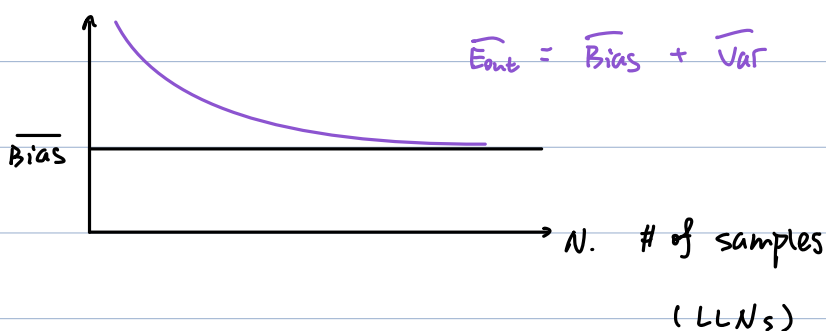
e.g. In prev example:

$$\overline{\text{bias}} = \mathbb{E}_{\mathcal{X}}[\sin^2(\pi\mathcal{X})] = \frac{1}{2}, \quad \overline{\text{var}} = \mathbb{E}_{\mathcal{X}}[\frac{1}{2}] = \frac{1}{2}$$

\uparrow
bias(\mathcal{X})

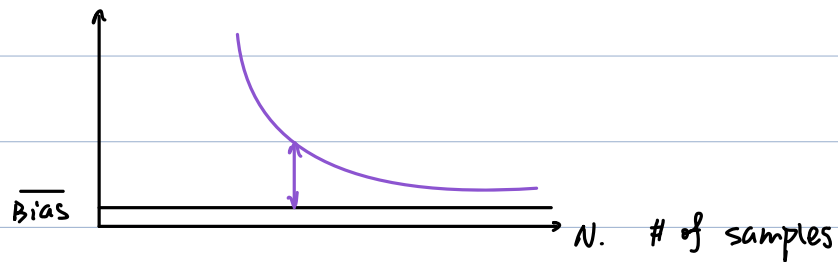
$$\therefore \overline{\mathbb{E}_{\text{out}}} = \frac{1}{2} + \frac{1}{2} = 1$$

• In general:



$$g^D(\mathcal{X}) \rightarrow \mathbb{E}_{\mathcal{D}}[g^D(\mathcal{X})]$$

• More complex H :



* If has more datapoints, can have more complex model

e.g. (prev) but now $N = 2$.

