

Regularization - 1

(Interview imp)

→ Bias Variance tradeoff -

$$\rightarrow \underbrace{cgo}_x \mid \underbrace{ig, lg}_y$$

we want a fn st: $y = f(x)$

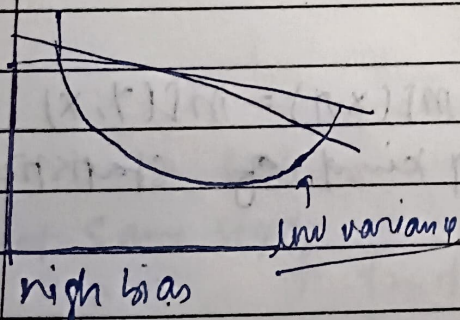
$$\&, \quad y = f(x) + \underbrace{\text{error}}_{\text{irreducible}}$$

we want $f(x)$ for populatⁿ but we only have sample so we get $f'(x)$
 $\hat{y} = f'(x)$

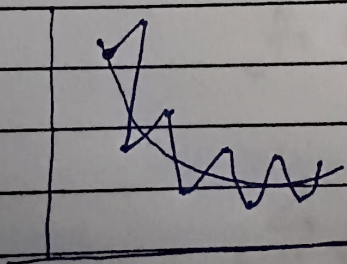
$$y - \hat{y} = f(x) - f'(x) \quad [\text{reducible error}]$$

• Bias → inability of ML model to fit in training data

high bias → very less fit (low variance)
 low bias



'Variance - how much ML predict' changes when training data is changed

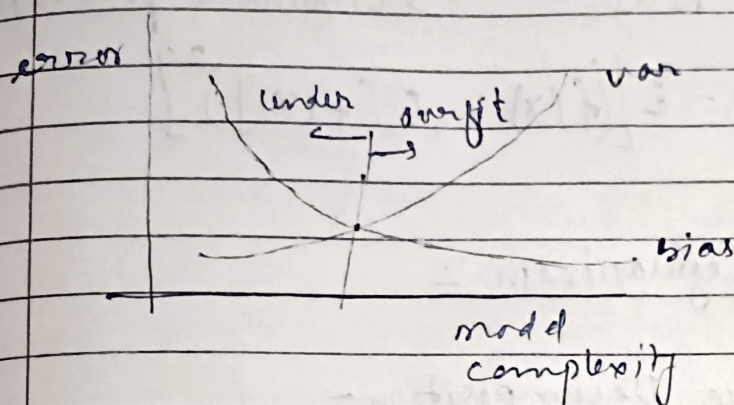


→ low bias but high variance

- high bias then underfitting
- low bias then overfitting

we want low bias & low variance

But if we minimize bias then var. increases



- Expected values -

↳ avg outcome of a R.V over a large no. of trials or experiments

Discrete R.V $\Rightarrow E(X) = x_1 \cdot P(x_1) + x_2 \cdot P(x_2) + \dots + x_n \cdot P(x_n)$

\Rightarrow Expected value $\xrightarrow{\text{means}}$ Population mean
 $\text{Var}[X] \rightarrow$ var of population

$$\text{Var}[X] = E[X^2] - (E[X])^2$$

$$E[(X - E[X])^2]$$

Bias -

↳ a systematic error that a model introduces because it cannot capture true relⁿ in data

↳ It is diff b/w Expected predictⁿ of our model & correct value which we are trying to predict.

→ true $f^h f(x)$ we know $f'(x)$
So

$$\text{Bias} = E[f'(x)] - f(x)$$

$$\text{If } E[f'(x)] = f(x)$$

$\Rightarrow \text{Bias} = 0 \Rightarrow \text{Unbiased predictor}$

$$\cdot \text{var}(f'(x)) = E[(f'(x) - E[f'(x)])^2]$$