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Part- B

Q.1] • Bias Variance Decomposition is a way of analyzing a learning algorithm's expected generalized error with respect to 3 terms: Bias, Variance and Noise.

→ Assuming g(x) as generalization error which is taken ~~from~~ for predicting new target 't' for an input 'x'.

$$E[(t-g(x))]^2$$

Error in estimations can be written as

$$\cancel{E[(t-y(x))]^2} = E[t-(y(x))]^2 = E[t-g(x)]^2$$

$$= E[(\underbrace{t-g(x)}_{a} + \underbrace{g(x)-y(x)}_{b})^2]$$

$$= E[t-(g(x))^2] + E[[g(x)-y(x)]^2]$$
$$+ 2E[(t-g(x))g(x)-y(x)].$$

* It is of the form a^2+b^2+2ab.

$$\Rightarrow E[[(y(x)-g(x)]^2] \quad \text{— (1)}$$

Eqn (1) ~~can~~ be written as

$$E_D[(g(x)-y(x,D))^2].$$

$$= E_D[[\underbrace{y(x,D)-E_d[y(x,D)]}_{p} + \underbrace{E_D[y(x,D)]-g(x)}_{q}]^2$$

$$= E_D[p^2+q^2+2qp]$$

$$= E_D[(y(x,D)-E_d(y(x,D))]^2 + E_D[E_D[y(x,D)-g(x)]^2$$
$$+ 2E_D[(y(x,D)-E_D(y(x,D))][E_D(y_{x},D)-g(x))]$$

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=> The above eqⁿ can be written ~~as~~ in terms of Variance, bias & noise as:-

$E^{(loss)} = \text{Variance} + \text{Bias}^2 + \text{Noise}$

- Thus we can represent the help of overfitting loss with help of the above equation as the total loss will be sum of variance, noise & square of bias

→ Graphical proof:-

* let $g(x)$ be expectation
let $y(x)$ be parametric approach.