

are in majority.

Bias-Variance Decomposition of Error

Let the test example $\underline{z}_1 \underline{z}_2 \underline{z}_3 \dots \underline{z}_t$ be fixed.

Variance in the error reflects the instability in classifying a given test example \underline{z}_i

Assume that the true label y_i for an example \underline{x}_i be given as Ground truth $y_i = \underbrace{f(\underline{x}_i)}_{\text{noise}} + \underbrace{\epsilon_i}_{\text{measurement}}$ noise zero mean

The true function f is unknown.

Assume that a model learned using the training set S predicts the label of a test example \underline{z}_i as

prediction $\hat{y}_i = g(\underline{z}_i, S)$

Model depends on S .

The mean square error (MSE) of the prediction over a test dataset is given as

t: test example $\frac{1}{t} \sum_{i=1}^t \left(\underbrace{\hat{y}_i}_{\text{pred}} - \underbrace{y_i}_{\text{GT}} \right)^2$

$$= \frac{1}{t} \sum_{i=1}^t \left(\underbrace{g(\underline{z}_i, S)}_{\hat{y}_i} - \underbrace{f(\underline{z}_i) + \epsilon_i}_{y_i} \right)^2$$

Expected MSE over different choices of the training set

on the same test examples.

$$\mathbb{E}_S[\text{MSE}] = \frac{1}{t} \sum_{i=1}^t \mathbb{E}_S \left[\underbrace{g(\underline{z}_i, S)}_a - \underbrace{f(\underline{z}_i)}_b - \underbrace{\epsilon_i}_b \right]^2$$

$$\mathbb{E}[a^2 + b^2 + 2ab] = \mathbb{E}[a^2] + \mathbb{E}[b^2] + \mathbb{E}[2ab]$$

$$\mathbb{E}[\text{MSE}] = \frac{1}{t} \sum_{i=1}^t \mathbb{E} \left[\underbrace{(g(z_i, s) - f(z_i))^2}_{a^2} \right] + \underbrace{\frac{1}{t} \sum_{i=1}^t \mathbb{E}[\epsilon_i^2]}_{b^2}$$

2nd term
variance
of the noise

$$\rightarrow \frac{2}{t} \sum_{i=1}^t \mathbb{E} \left[\underbrace{g(z_i, s) - f(z_i)}_{a \cdot b} \right] \mathbb{E}[\epsilon_i]$$

mean of the noise is zero

First term:

$$\frac{1}{t} \sum_{i=1}^t \mathbb{E} \left[\underbrace{(g(z_i, s) - f(z_i))^2}_{\substack{\text{prediction} \\ \text{true function}}} \right]$$

$$= \frac{1}{t} \sum_{i=1}^t \mathbb{E} \left[\left\{ \underbrace{(f(z_i) - \mathbb{E}_s[g(z_i, s)])}_a + \underbrace{(\mathbb{E}_s[g(z_i, s)] - g(z_i, s))}_b \right\}^2 \right]$$

$$= \frac{1}{t} \sum_{i=1}^t \mathbb{E}_s \left[\underbrace{(f(z_i) - \mathbb{E}_s[g(z_i, s)])^2}_{a^2} \right]$$

A(I)

$$+ \frac{1}{t} \sum_{i=1}^t \mathbb{E}_s \left[\underbrace{(\mathbb{E}_s[g(z_i, s)] - g(z_i, s))^2}_{b^2} \right]$$

A(II)

$$+ \frac{2}{t} \sum_{i=1}^t \mathbb{E}_s \left[\underbrace{(f(z_i) - \mathbb{E}_s[g(z_i, s)])}_a \right] \times \underbrace{\mathbb{E}_s \left[(\mathbb{E}_s[g(z_i, s)] - g(z_i, s)) \right]}_b$$

$$\mathbb{E}_s \mathbb{E}_s [g(z_i, s)] = \mathbb{E}_s [g(z_i, s)]$$

$$- \mathbb{E}_s [g(z_i, s)] = 0$$

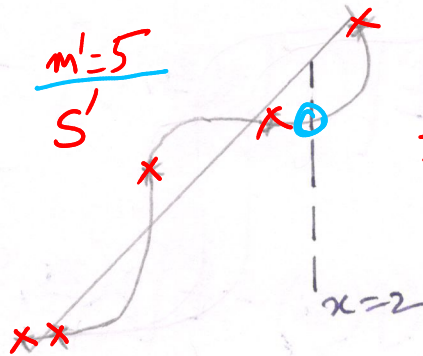
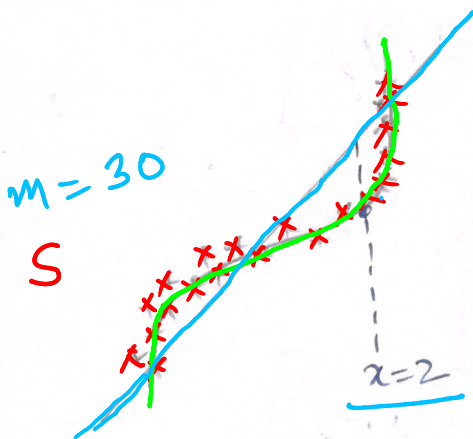
$$\mathbb{E}_S[\text{MSE}] = \frac{1}{t} \sum_{i=1}^t \mathbb{E}[(g(z_i, S) - f(z_i))^2] + \frac{1}{t} \sum_{i=1}^t \mathbb{E}[\epsilon_i^2]$$

$$= \frac{1}{t} \sum_{i=1}^t \mathbb{E}[(f(z_i) - \mathbb{E}_S[g(z_i, S)])^2]$$

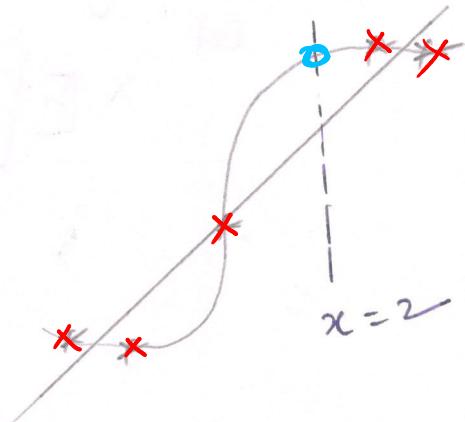
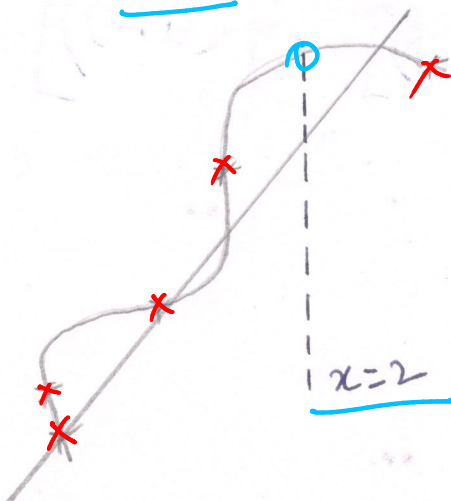
$$+ \frac{1}{t} \sum_{i=1}^t \mathbb{E}[(\mathbb{E}_S[g(z_i, S)] - g(z_i, S))^2] + \frac{1}{t} \sum_{i=1}^t \mathbb{E}[\epsilon_i^2]$$

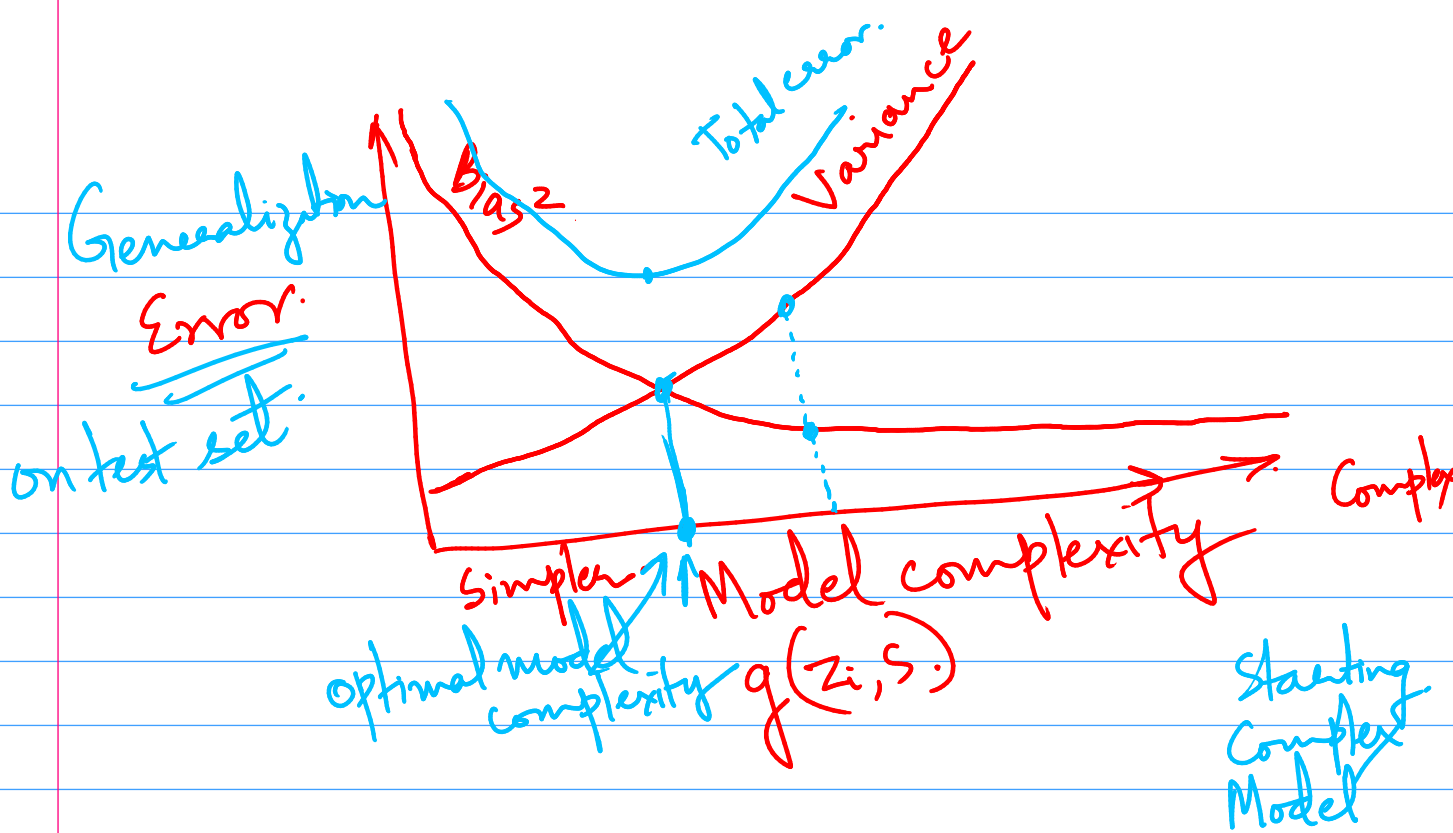
$$\mathbb{E}[\text{MSE}] = \frac{1}{t} \sum_{i=1}^t \left[\underbrace{(f(z_i) - \mathbb{E}_S[g(z_i, S)])^2}_{\text{true function target}} + \underbrace{(\mathbb{E}_S[g(z_i, S)] - g(z_i, S))^2}_{\text{Variance of the model prediction}} + \mathbb{E}[\epsilon_i^2] \right]$$

bias^2 $\text{average prediction}^2$ Variance of noise



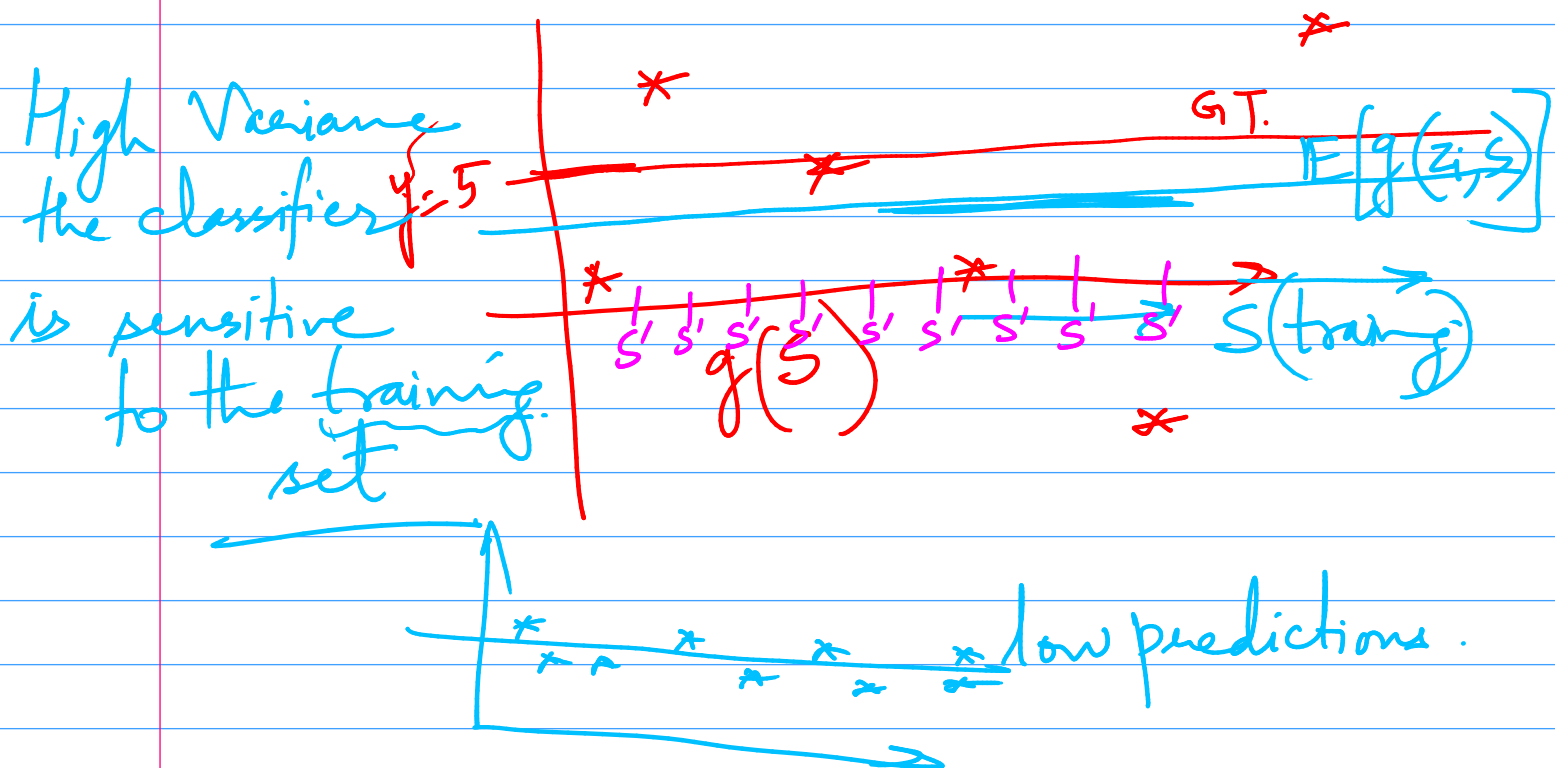
$$\text{Error} = \text{Bias}^2 + \text{Variance} + \text{Noise}$$





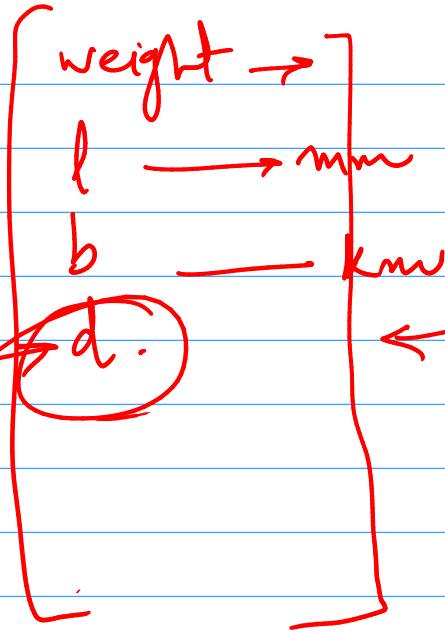
Decision trees / Pruning
early stopping
SVMs λ / C .

Regularization
Final model
of the right complexity.

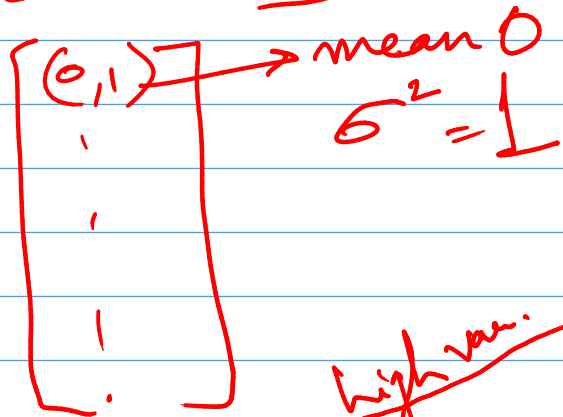


x

large range



large dynamic
range
dominate



centered.
feature

