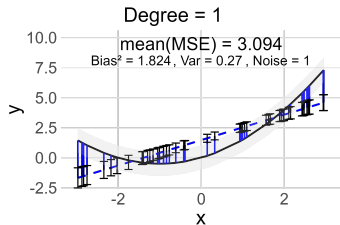


Introduction to Machine Learning

Advanced Risk Minimization

Bias-Variance Decomposition (Deep-Dive)

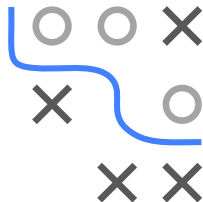


Learning goals

- Decompose generalization error of a learner specifically for L2 loss into
 - Bias of the learner
 - Variance
 - Inherent noise in the data

BIAS-VARIANCE DECOMPOSITION

Generalization error of learner \mathcal{I} : Expected error of model $\hat{f}_{\mathcal{D}_n}$, on training sets of size n , evaluated on a fresh, random test sample



$$GE_n(\mathcal{I}) = \mathbb{E}_{\mathcal{D}_n \sim \mathbb{P}_{xy}^n, (\mathbf{x}, y) \sim \mathbb{P}_{xy}} (L(y, \hat{f}_{\mathcal{D}_n}(\mathbf{x}))) = \mathbb{E}_{\mathcal{D}_n, xy} (L(y, \hat{f}_{\mathcal{D}_n}(\mathbf{x})))$$

Expectation is taken over all training sets **and** independent test sample

We assume that the data is generated by

$$y = f_{\text{true}}(\mathbf{x}) + \epsilon$$

with zero-mean homoskedastic error $\epsilon \sim (0, \sigma^2)$ independent of \mathbf{x} .

BIAS-VARIANCE DECOMPOSITION

$$(*) = \mathbb{E}_{\mathcal{D}_n}((y - \hat{f}_{\mathcal{D}_n}(\mathbf{x}))^2) = y^2 + \underbrace{\mathbb{E}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})^2)}_{(1)} - 2 \underbrace{\mathbb{E}_{\mathcal{D}_n}(y \hat{f}_{\mathcal{D}_n}(\mathbf{x}))}_{(2)} =$$

Using that $\mathbb{E}(z^2) = \text{Var}(z) + \mathbb{E}^2(z)$, we see that

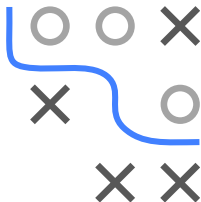
$$= y^2 + \text{Var}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})) + \mathbb{E}_{\mathcal{D}_n}^2(\hat{f}_{\mathcal{D}_n}(\mathbf{x})) - 2y\mathbb{E}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x}))$$

Plug in the definition of y

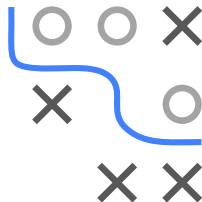
$$= f_{\text{true}}(\mathbf{x})^2 + 2\epsilon f_{\text{true}}(\mathbf{x}) + \epsilon^2 + \text{Var}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})) + \mathbb{E}_{\mathcal{D}_n}^2(\hat{f}_{\mathcal{D}_n}(\mathbf{x})) - 2(f_{\text{true}}(\mathbf{x}) + \epsilon)\mathbb{E}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x}))$$

Reorder terms and use the binomial formula

$$= \epsilon^2 + \text{Var}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})) + (f_{\text{true}}(\mathbf{x}) - \mathbb{E}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})))^2 + 2\epsilon(f_{\text{true}}(\mathbf{x}) - \mathbb{E}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})))$$



BIAS-VARIANCE DECOMPOSITION



$$(*) = \epsilon^2 + \text{Var}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})) + (f_{\text{true}}(\mathbf{x}) - \mathbb{E}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})))^2 + 2\epsilon(f_{\text{true}}(\mathbf{x}) - \mathbb{E}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})))$$

Let us come back to the generalization error by taking the expectation over all fresh test observations $(\mathbf{x}, y) \sim \mathbb{P}_{xy}$:

$$\begin{aligned} GE_n(\mathcal{I}) = & \underbrace{\sigma^2}_{\text{Variance of the data}} + \underbrace{\mathbb{E}_{xy} \left[\text{Var}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x}) \mid \mathbf{x}, y) \right]}_{\text{Variance of learner at } (\mathbf{x}, y)} \\ & + \underbrace{\mathbb{E}_{xy} \left[((f_{\text{true}}(\mathbf{x}) - \mathbb{E}_{\mathcal{D}_n}(\hat{f}_{\mathcal{D}_n}(\mathbf{x})))^2 \mid \mathbf{x}, y) \right]}_{\text{Squared bias of learner at } (\mathbf{x}, y)} + \underbrace{0}_{\text{As } \epsilon \text{ is zero-mean and independent}} \end{aligned}$$