

M3396: September 9<sup>th</sup>, 2024.

## Bias.

Def'n. Let  $\hat{\theta}$  be a point estimator for the parameter  $\theta$ .  
The **bias** of the estimator  $\hat{\theta}$  is defined as

$$\text{bias}(\hat{\theta}) := \mathbb{E}_{\theta}[\hat{\theta}] - \theta$$

Def'n. The **mean squared error** of  $\hat{\theta}$  is defined as

$$\text{MSE}[\hat{\theta}] := \mathbb{E}_{\theta}[(\hat{\theta} - \theta)^2]$$

## Assessing Model Accuracy.

Say, we have the "usual" model:

$$Y = f(X) + \epsilon$$

Say, we fit our model to some **training data**:

$$\text{Tr} = \{(x_i, y_i) : i = 1, \dots, N\}$$

Let  $\hat{f}$  be the fit of the model to our Tr

$$\text{MSE}_{\text{Tr}} := \text{Ave}_{i \in \{1, \dots, N\}} \frac{(y_i - \hat{f}(x_i))^2}{N} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{f}(x_i))^2$$

We propose to look @ other data

$$\text{Te} = \{(x_i, y_i) : i = 1, \dots, M\}$$

These are our testing data.

We calculate:

$$\text{MSE}_{\text{Te}} := \text{Ave}_{i \in \{1, \dots, M\}} (y_i - \hat{f}(x_i))^2 = \frac{1}{M} \sum_{i=1}^M (y_i - \hat{f}(x_i))^2$$