Tutorial 1

# **Bias and Variance**

ISLR 1-2, ESL 1-2







#### Common Paradigms

- Supervised vs. Unsupervised Learning
- Regression vs. Classification
- Prediction vs. Inference
- Accuracy vs. Interpretability

Bias-Variance Tradeoff

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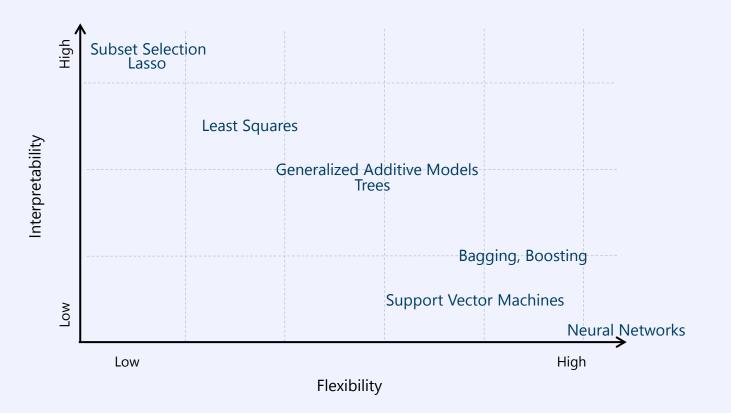
Bias-Variance Tradeoff

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#### Accuracy vs. Interpretability



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### Assessing model accuracy

In regression, we assess the quality of fit by mean squared error (MSE)

• over training data, it is defined as

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left( y_i - \hat{f}(x_i) \right)^2$$

which we typically refer to as the training error

• we are generally more interested in the error over **unseen** data

$$avg(\hat{f}(x_0) - y_0)^2$$

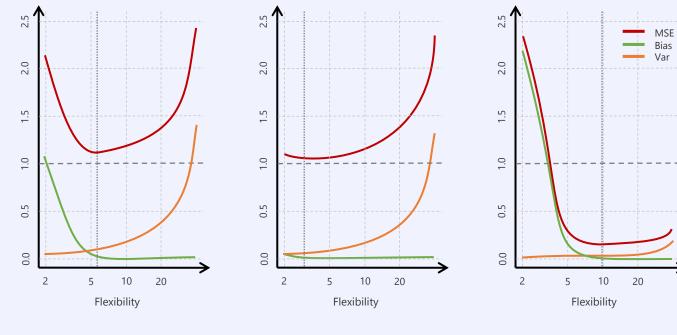
which we typically call the test error or generalization error

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#### Bias-Variance Decomposition



Synthetic data example 1 Moderately nonlinear function Synthetic data example 2 Almost linear function Synthetic data example 3 Highly nonlinear function

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## Nearest Neighbors

#### *k*-nearest neighbors (*k*NN)

Classifies each point to the majority class among its k nearest neighbors, i.e.

$$\arg \max_{j=1,\dots,k} \ \frac{1}{k} \sum_{i \in \mathcal{N}_0} I(y_i = j)$$

where  $\mathcal{N}_0$  are the k data points nearest to  $x_0$ 

