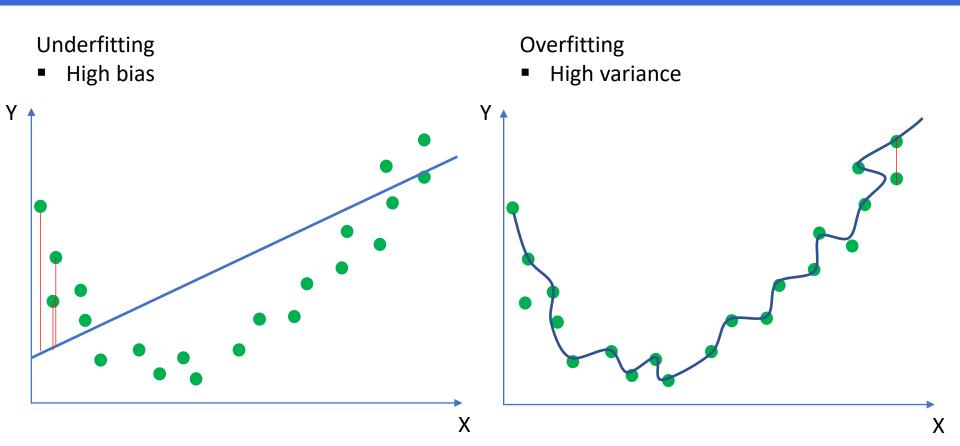
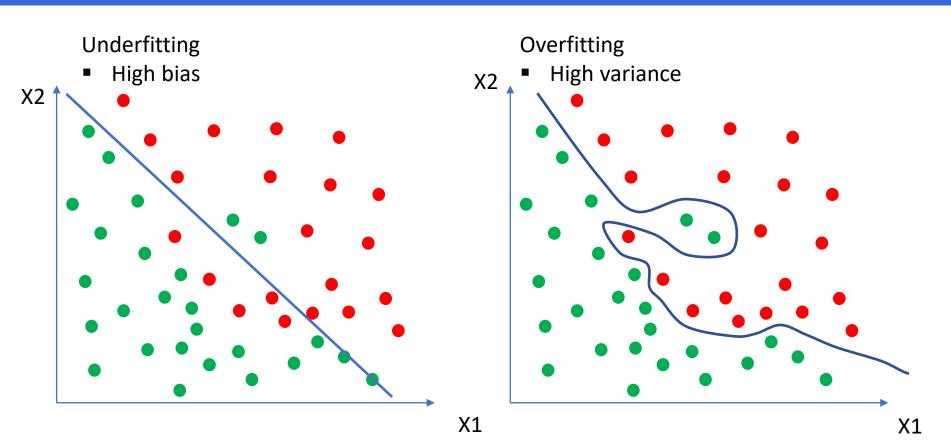
Regression Example

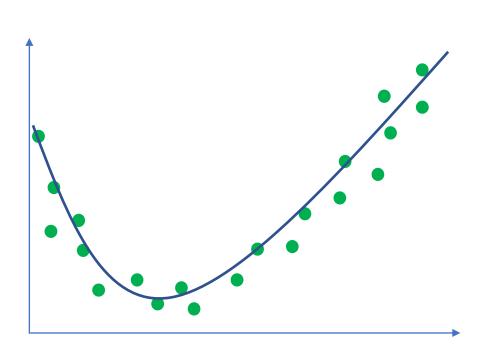


Classification Example

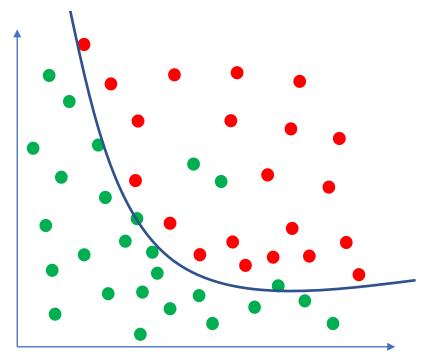


Good Fits

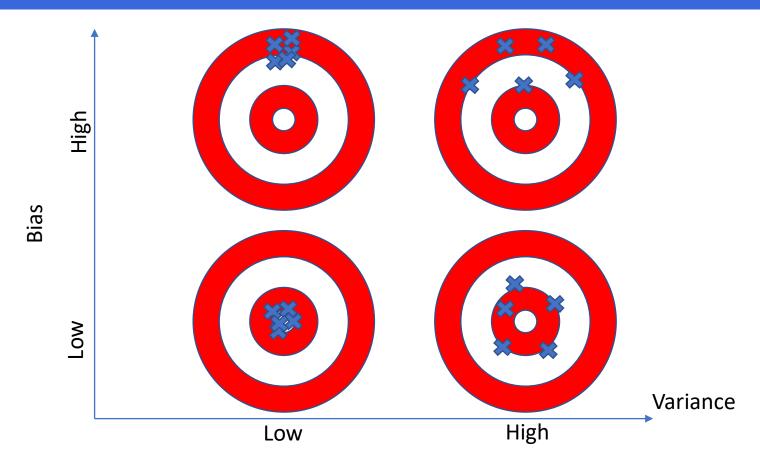
Regression Example



Classification Example



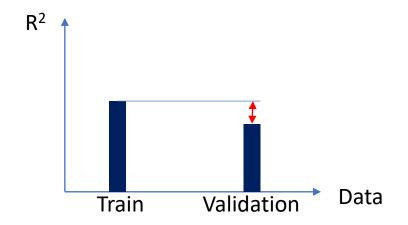
Bias and Variance



Bias and Variance

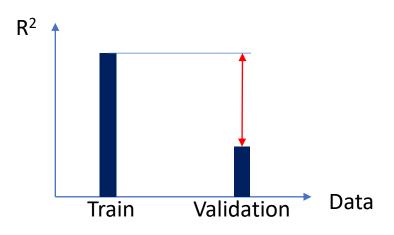
Bias

- Difference prediction / actual values of training data
- Example High Bias / Low Variance
 - R^2=0.5 for training
 - R^2=0.48 for validation



Variance

- Difference prediction of training data
 vs. prediction validation data
- Example Low Bias / High Variance
 - R^2=0.97 for training
 - R^2=0.3 for validation



Bias and Variance

Adding more parameters to a model increases model complexity

Model complexity 个

Bias ↓

Variance ↑

Using a more complex model

Model complexity ↑

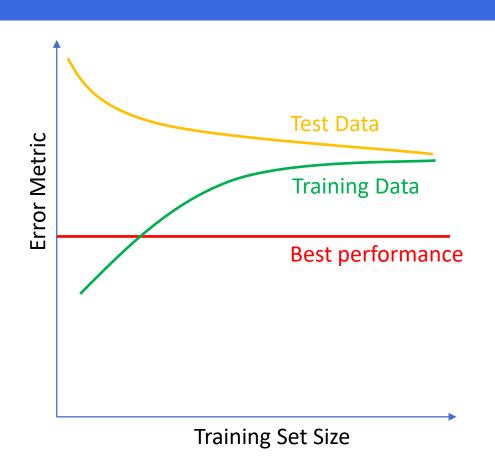
Bias ↓

Variance ↑

Bias

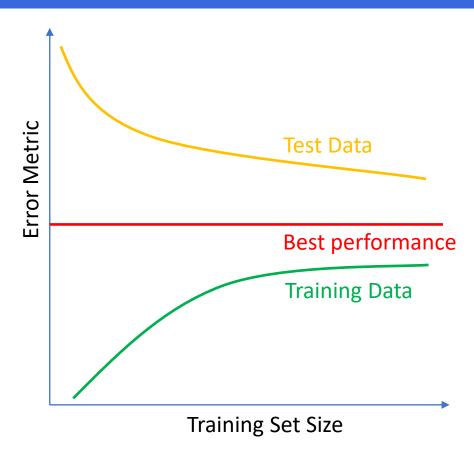
High Bias

- Learns fast
- Easy to understand (fewer parameters)
- Poor performance on complex problems
- → Underfitting



Variance

- High Variance → Large change of predictions if different training data is used
- Low variance algorithms: Linear
 Regression, LDA, Logistic Regression
- High variance algorithms: Decision Trees, kNN, SVM
- High Variance → more paramaters
- Good training performance, poor validation performance → poor generalization
- → Overfitting



Bias Variance Tradeoff

- Goal:
 - low bias / low variance
 - Good prediction performance
- Bias and variance have opposite directions
- Linear ML algorithms typically high bias, low variance
- Non-linear ML algorithms typically low bias, high variance
- Non-linear ML algorithms often have hyperparameters for tuning

