Bias-Variance Trade off in Machine Learning

Introduction

Bias and variance are two fundamental sources of error in machine learning models. Understanding their trade off is crucial for building models that generalize well to unseen data.

- Bias: Error due to overly simplistic assumptions in the learning algorithm.
- Variance: Error due to sensitivity to small fluctuations in the training set.

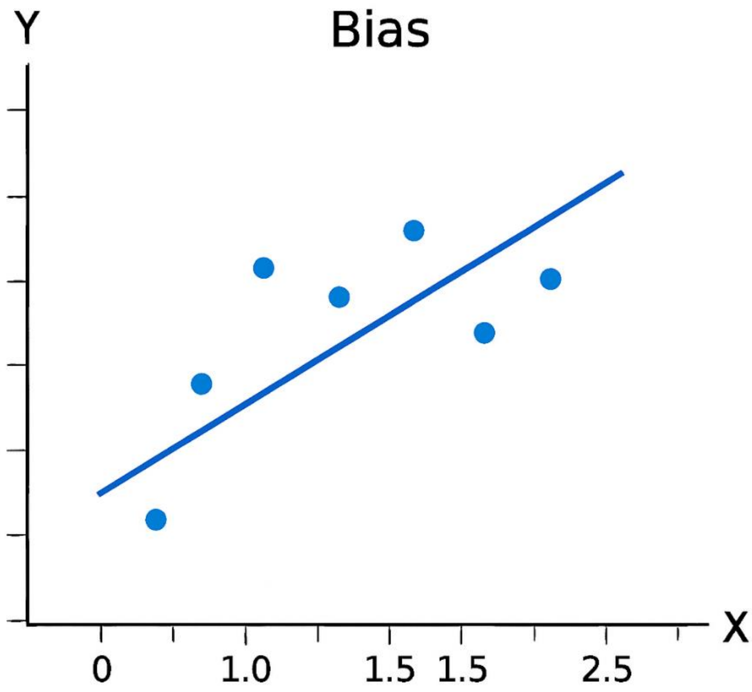
The goal is to minimize both, but they often conflict.

Bias

- High Bias: Model makes strong assumptions, leading to underfitting.

- Example: Linear regression applied to non-linear data.

- Diagram: A straight line failing to capture curved data points.



Characteristics:

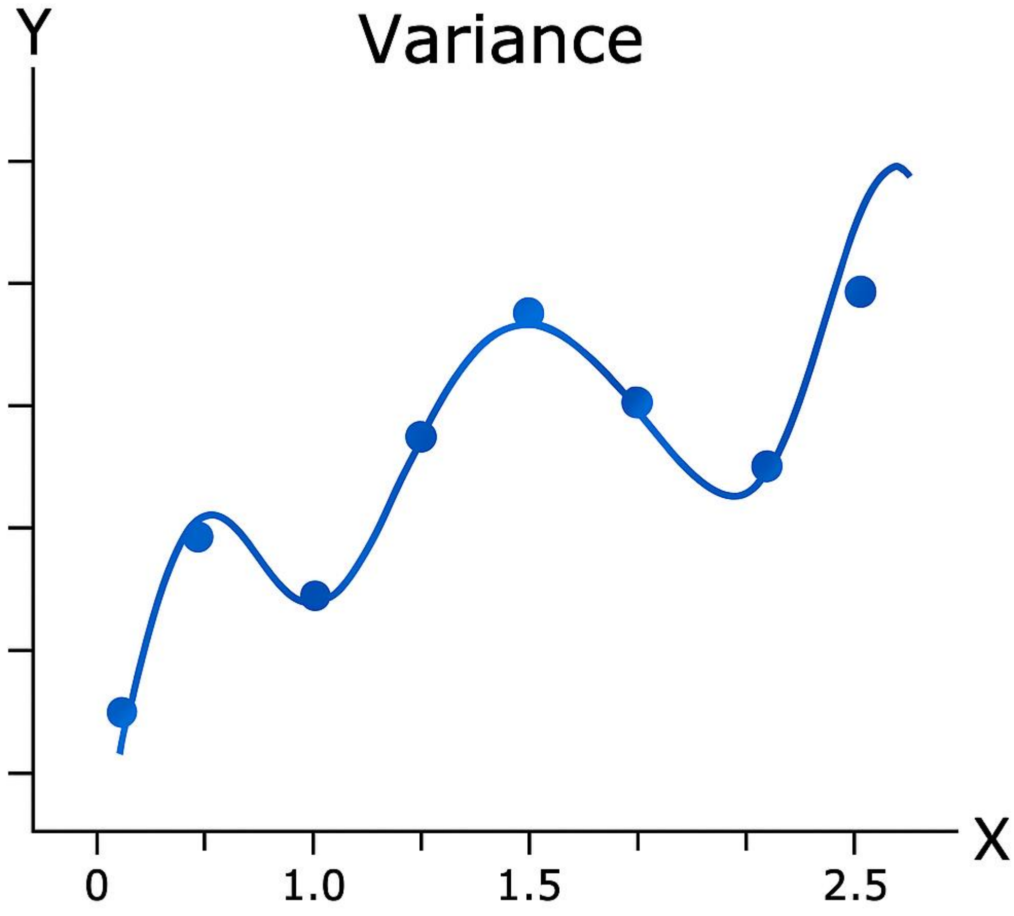
- Oversimplified model

- Poor training and test accuracy

- Underfitting

Variance

- High Variance: Model is too complex, capturing noise instead of signal.
- Example: High-degree polynomial regression.
- Diagram: A wiggly curve passing through almost every data point.



Characteristics:

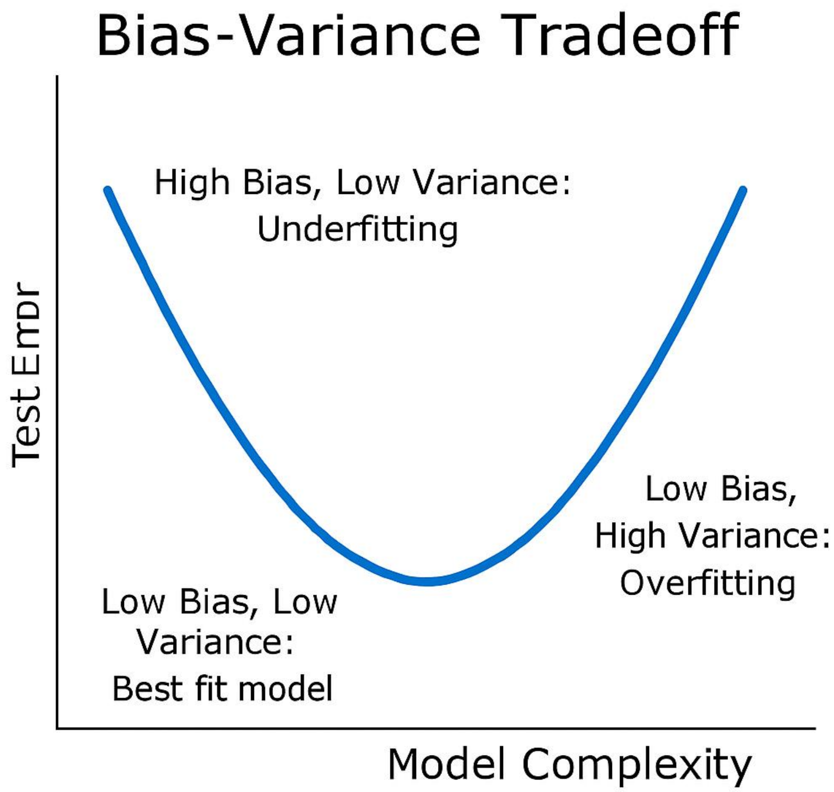
- Excellent training accuracy
- Poor test accuracy
- Overfitting

Bias-Variance Trade off

Error decomposition: [Total Error = Bias^2 + Variance + Irreducible Error]

- Low Bias, High Variance: Overfitting
- High Bias, Low Variance: Underfitting
- Low Bias, Low Variance: Best fit model

Diagram: U-shaped curve showing test error minimized at the balance point.



Best Fit Model

For the best fit model:

Low Bias: Captures underlying patterns.

Low Variance: Generalizes well to unseen data.

Strategies to achieve balance:

- Cross-validation
- Regularization (L1/L2)
- Ensemble methods (bagging, boosting)

Conclusion

The ideal model achieves low bias and low variance, avoiding both underfitting and overfitting.