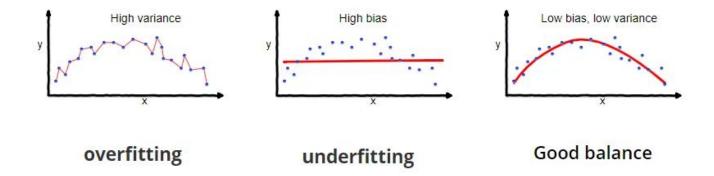
Model Complexity and Regularization

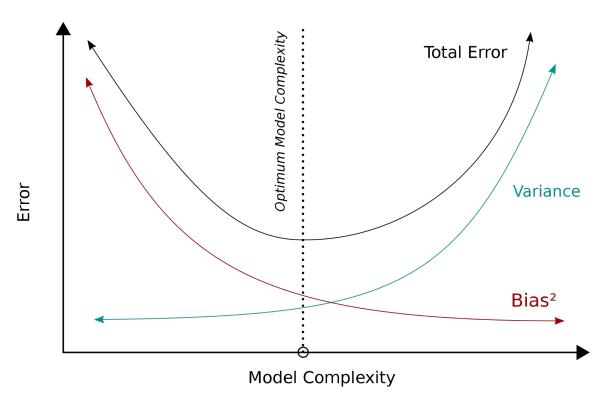
Bias vs Variance Tradeoff



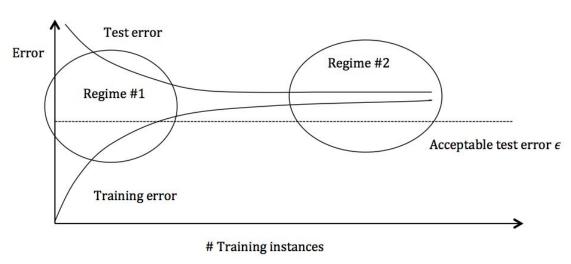
Bias: What is the inherent error that you obtain from your classifier even with infinite training data? This is due to your classifier being "biased" to a particular kind of solution (e.g. linear classifier). In other words, bias is inherent to your model.

Variance: Captures how much your classifier changes if you train on a different training set. How "over-specialized" is your classifier to a particular training set (overfitting)? If we have the best possible model for our training data, how far off are we from the average classifier?

Bias vs Variance Tradeoff



Bias vs Variance Tradeoff



Regime 1 (High Variance)

Symptoms:

- 1. Training error is much lower than test error
- 2. Training error is lower than ϵ
- Test error is above ε

Remedies:

- Add more training data
- Reduce model complexity (e.g. regularization) -- complex models are prone to high variance
- Bagging

Regime 2 (High Bias)

Symptoms:

1. Training error is higher than ϵ

Remedies:

- Use more complex model (e.g. kernelize, use non-linear models)
- Add features
- Boosting

Multivariate Linear Regression

Linear Model:

$$\hat{y} = w[0] \times x[0] + w[1] \times x[1] + ... + w[n] \times x[n]$$

Cost Function:

$$\sum_{i=1}^{M} (y_i - \hat{y_i})^2 = \sum_{i=1}^{M} \left(y_i - \sum_{j=0}^{p} w_j \times x_{ij} \right)^2$$

Multivariate Linear Regression + Regularization

Ridge Regression (L2):

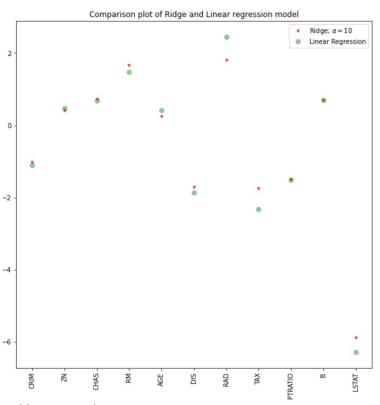
$$\sum_{i=1}^{M} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{M} \left(y_i - \sum_{j=0}^{p} w_j \times x_{ij} \right)^2 + \lambda \sum_{j=0}^{p} w_j^2$$

Lasso Regression (L1):

$$\sum_{i=1}^{M} (y_i - \hat{y_i})^2 = \sum_{i=1}^{M} \left(y_i - \sum_{j=0}^{p} w_j \times x_{ij} \right)^2 + \lambda \sum_{j=0}^{p} |w_j|$$

Goal: Minimize coefficient weights (lower model complexity) to reduce overfitting and increase generalizability

Multivariate Linear Regression + Regularization



Multivariate Linear Regression + Regularization

Dimension Reduction of Feature Space with LASSO

Linear Regression Cost function Ridge Regression Lasso Regression β_1 $|\beta_1| + |\beta_2| \le t$ $\beta_1^2 + \beta_2^2 \le c$