

$$\text{error} = \text{bias}^2 + \text{variance} + \text{noise}$$

Noise:

other cr\*p

Bias:

how far away you fall from actual

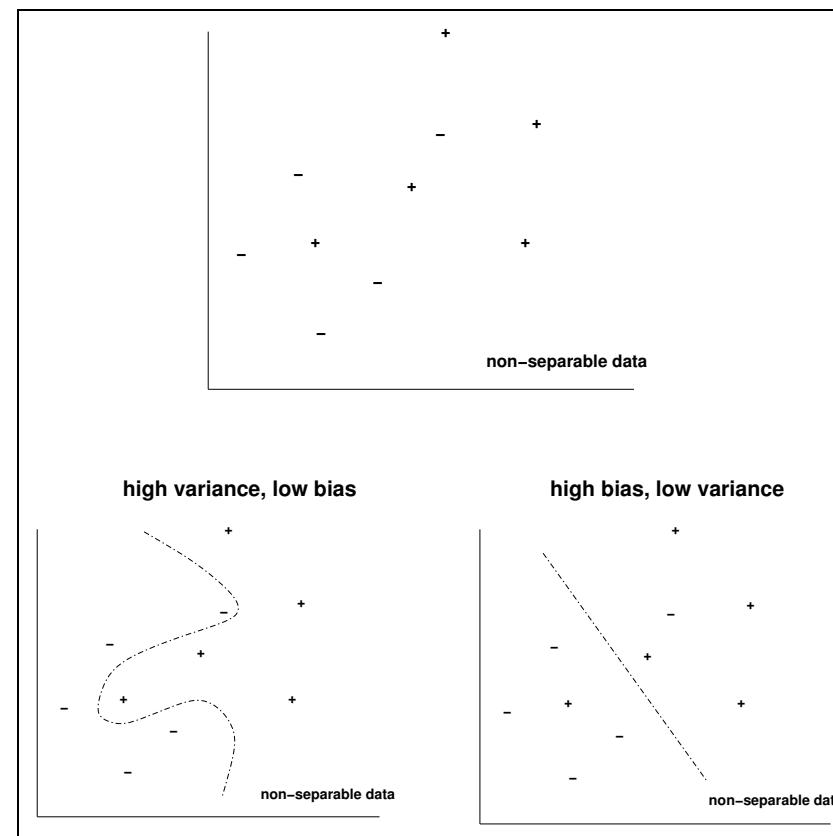
Variance:

how much you dance around

btw, standard deviation =  $\sqrt{\text{variance}}$

# Bias Variance in Classification

- There are several ways to define the concept of bias and variance for classification problems, but the key tradeoff between them remains.



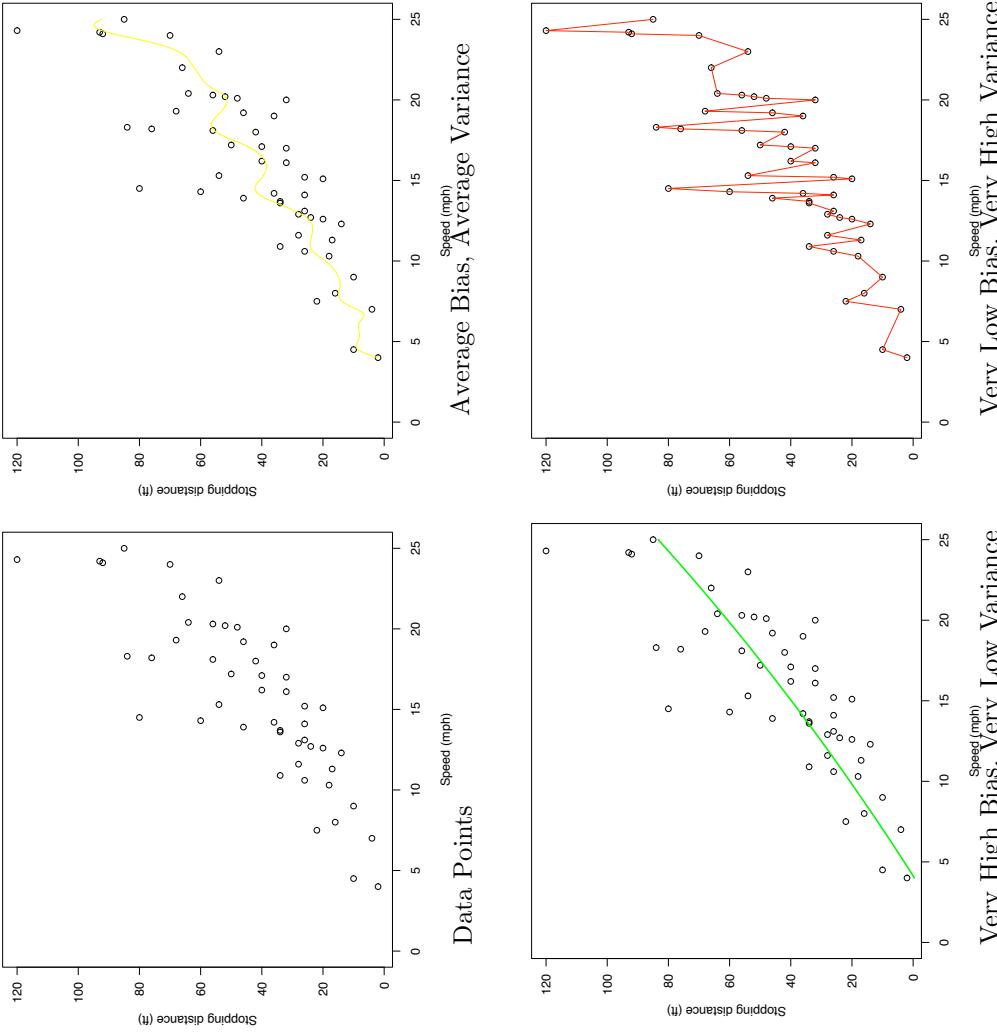


Figure 1: Examples of function estimations with different levels of bias and variance

# Dependence of Bias-Variance on Model Complexity

- $h(x) = \sin(2\pi x)$
- Regularization parameter  $\lambda$
- $L=100$  data sets
- Each with  $N=25$
- 24 Gaussian Basis functions
  - No of parameters  $M=25$
- Total Error function:

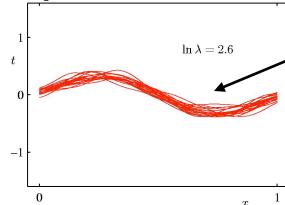
$$\frac{1}{2} \sum_{n=1}^N \left\{ t_n - \mathbf{w}^T \phi(\mathbf{x}_n) \right\}^2 + \frac{\lambda}{2} \mathbf{w}^T \mathbf{w}$$

where  $\phi$  is a vector of basis functions

Result of averaging multiple solutions with complex model gives good fit

Weighted averaging of multiple solutions is at heart of Bayesian approach: not wrt multiple data sets but wrt posterior distribution of parameters

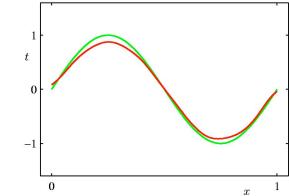
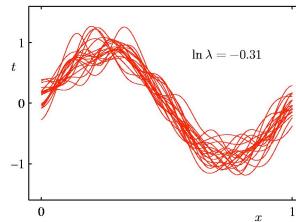
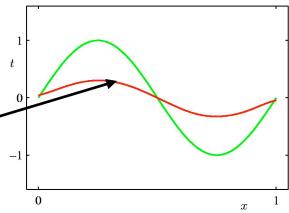
20 Fits for  
25 data  
points each



*High  $\lambda$*

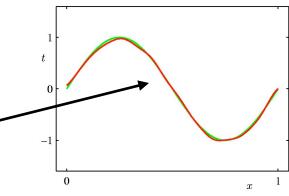
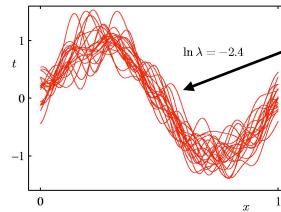
{ Low  
Variance  
High bias

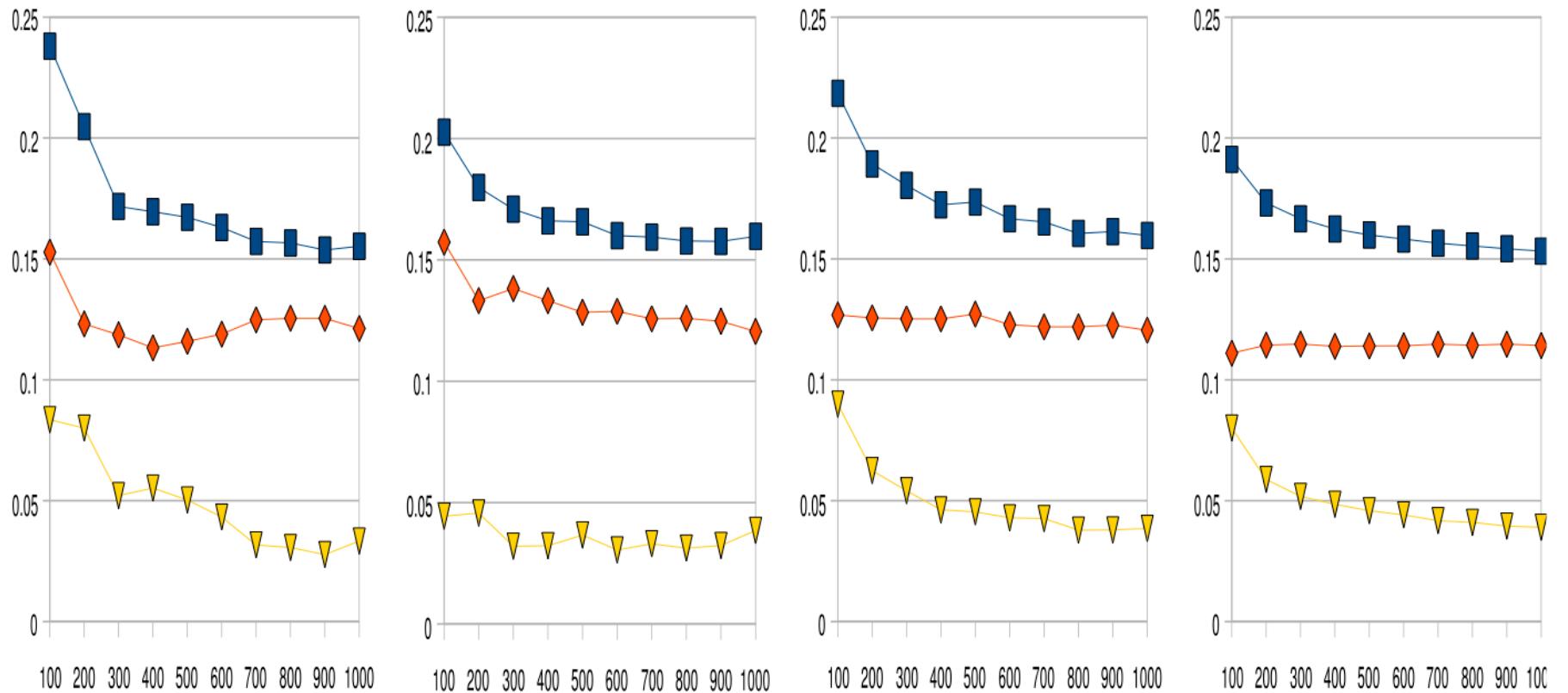
Red: Average of Fits  
Green: Sinusoid from which  
data was generated



*Low  $\lambda$*

{ High  
Variance  
Low bias

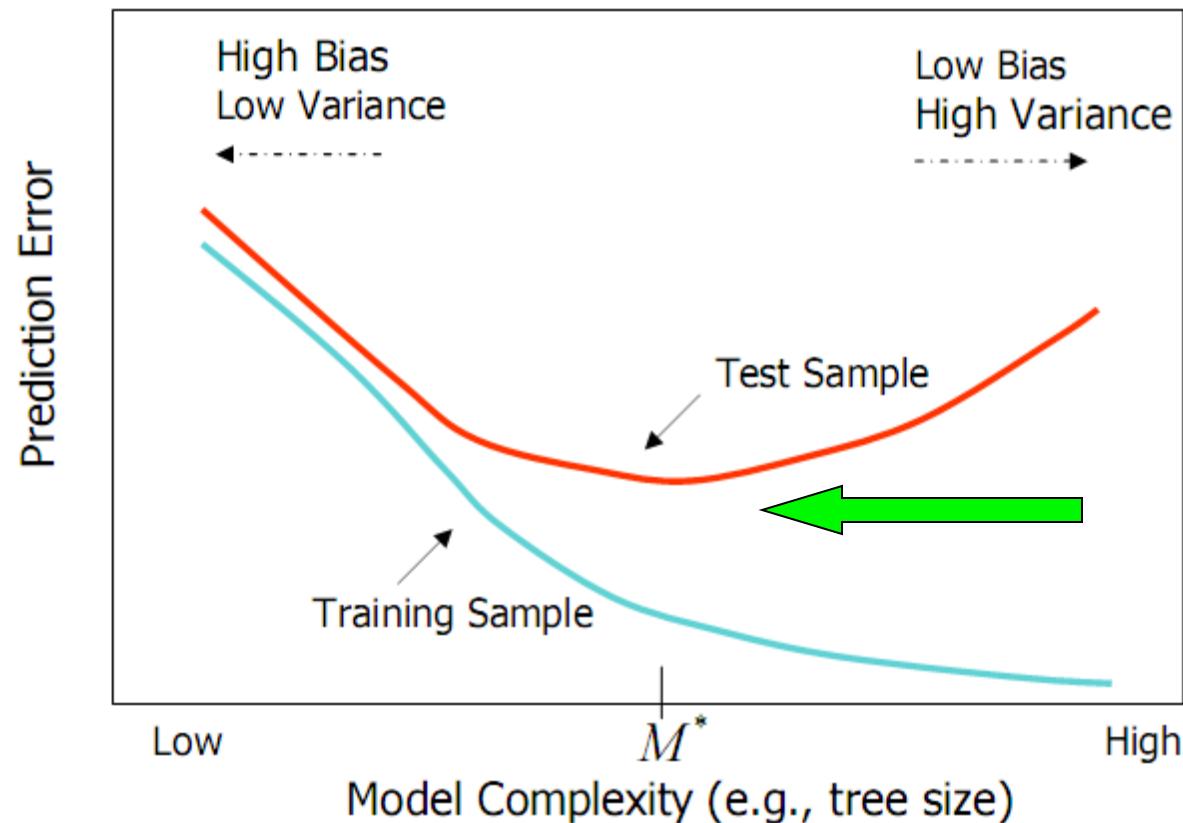




**Fig. 1.** Various bias variance decompositions on the same problem (see text for description). Training set size on x-axis, error (top line) bias (middle line) and variance (bottom line) on y-axis.

# Bias and Variance

- Ensemble methods
  - Combine learners to reduce variance



from Elder, John. From Trees to Forests and Rule Sets - A Unified Overview of Ensemble Methods. 2007.