

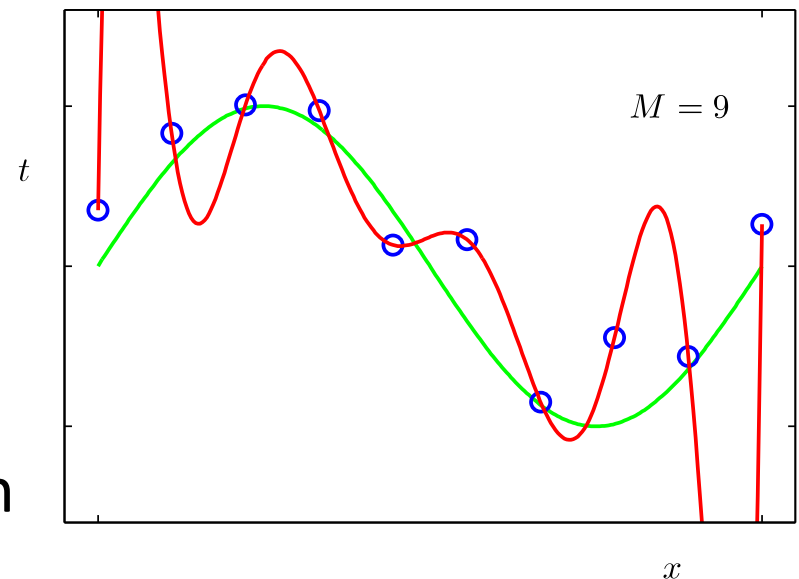
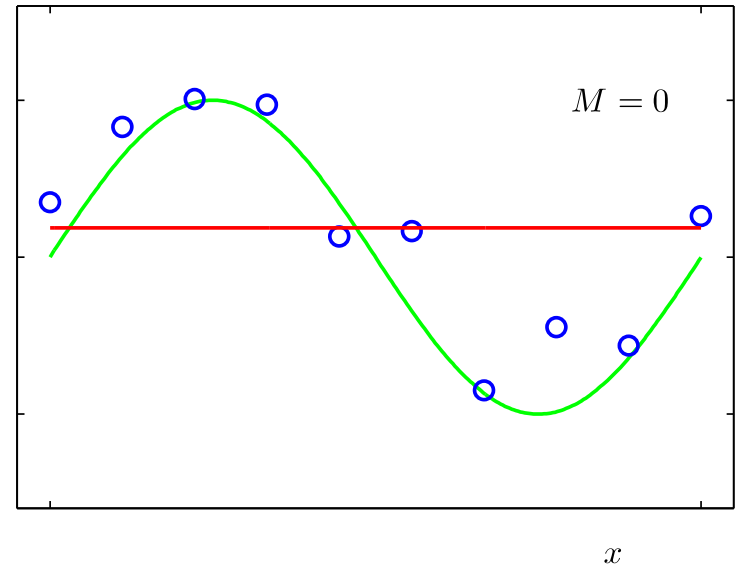
CSE 446  
Learning Theory

# Administrative

- Quiz section next week: midterm problems & answers, differentiation review
- Lecture next week
  - Will post video lectures for Wed & Fri
  - TA will go over material in detail in class and answer questions

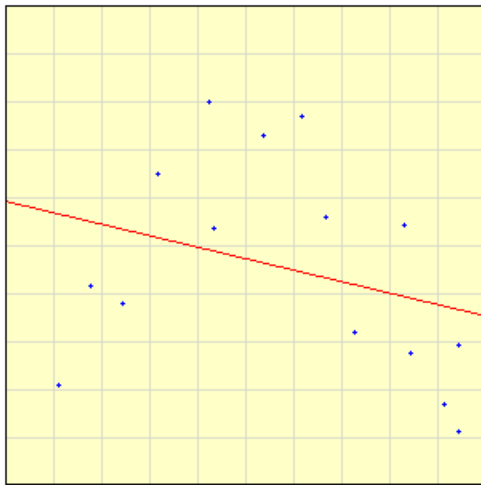
# Bias-Variance tradeoff – Intuition

- **Model too simple:** does not fit the data well
  - A *biased* solution
  - Simple = fewer features
  - Simple = more regularization
- **Model too complex:** small changes to the data, solution changes a lot
  - A *high-variance* solution
  - Complex = more features
  - Complex = less regularization



# Bias-Variance Tradeoff

- Choice of hypothesis class introduces learning bias
  - More complex class  $\rightarrow$  less bias
  - More complex class  $\rightarrow$  more variance

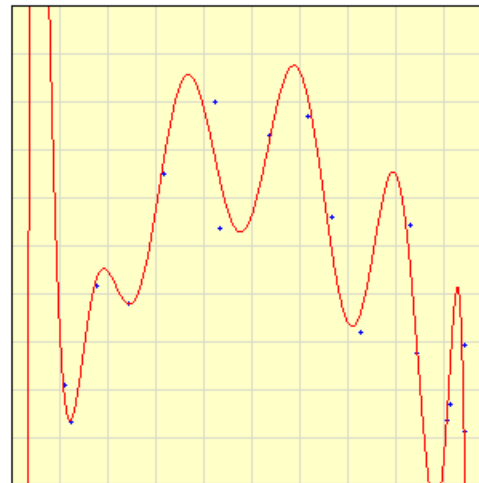


Select points by clicking on the graph or press

Example

Degree of polynomial:   Fit Y to X  
 Fit X to Y

Calculate View Polynomial Reset

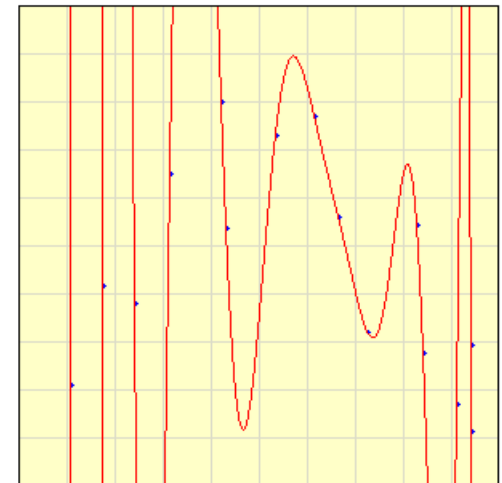


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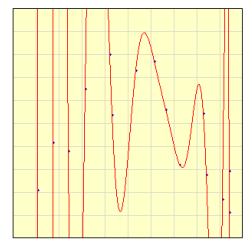
Select points by clicking on the graph or press

Example

Degree of polynomial:   Fit Y to X  
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Calculate View Polynomial Reset

# Error as a function of number of training examples for a fixed model complexity

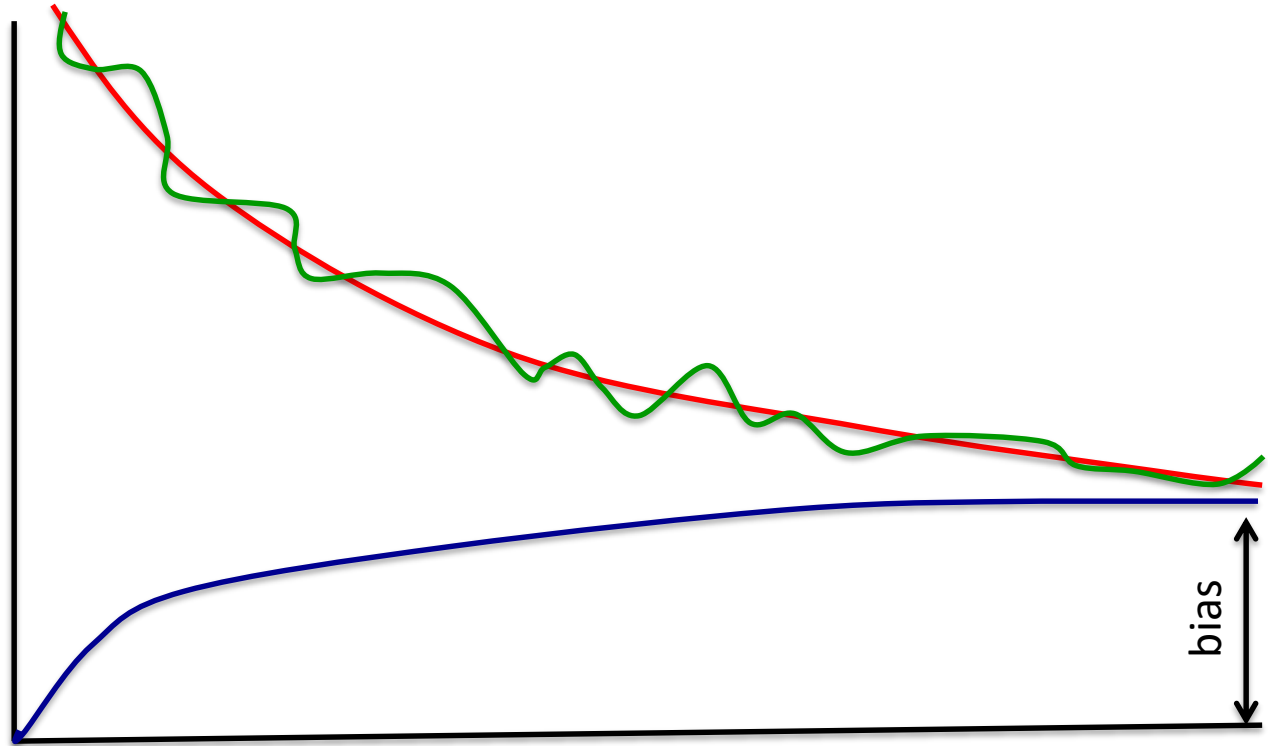


Select points by clicking on the graph or press [Example](#)  
Degree of polynomial:   Fit Y to X  
 Fit X to Y

$$\mathcal{E}_{\text{train}}(w) = \frac{1}{N_{\text{train}}} \sum_{i=1}^{N_{\text{train}}} (x_i \cdot w - y_i)^2$$

$$\mathcal{E}_{\text{true}}(w) = E_{p(x)} (x_i \cdot w - y_i)^2$$

$$\mathcal{E}_{\text{test}}(w) = \frac{1}{N_{\text{test}}} \sum_{i=1}^{N_{\text{test}}} (x_i \cdot w - y_i)^2$$



little data

infinite data

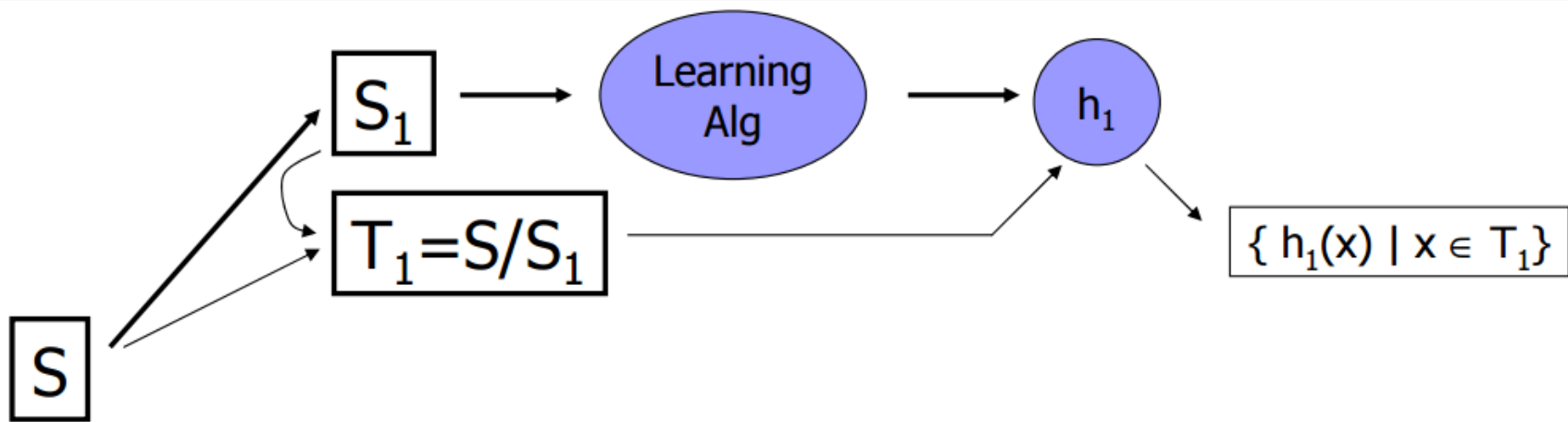
# Measuring Bias and Variance

- In practice (unlike in theory), only *ONE training set D*
- Simulate multiple training sets by bootstrap replicates
  - $D' = \{x \mid x \text{ is drawn at random with replacement from } D \}$
  - $|D'| = |D|$

# Estimating Bias / Variance

Original Data    Bootstrap Replicate    Hypothesis     $h_1$ 's predictions

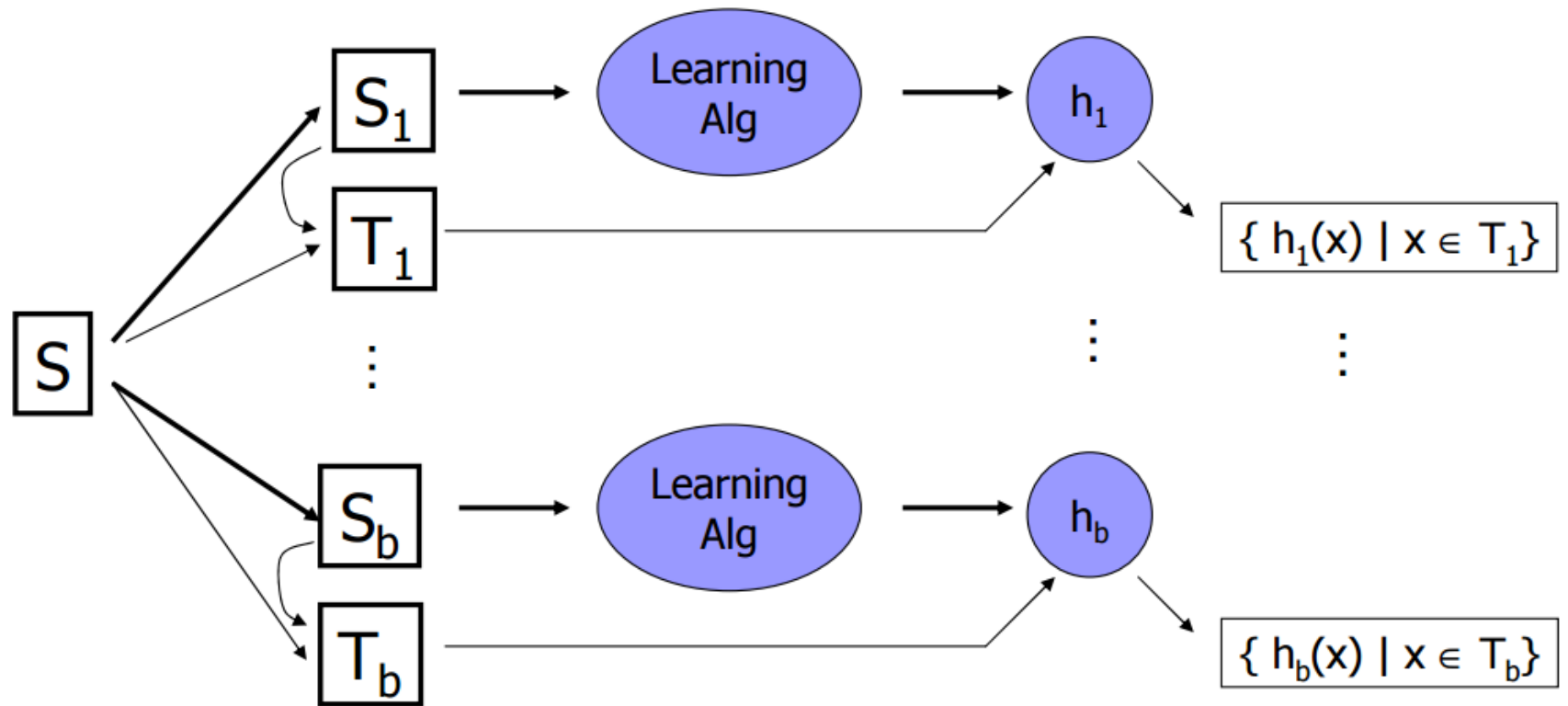
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# Estimating Bias / Variance

Original Data    Bootstrap Replicate    Hypothesis     $h$ 's predictions

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- Each  $S_i$  is bootstrap replicate
- $T_i = S / S_i$
- $h_i$  = hypothesis, based on  $S_i$



# Average Response for each $x_i$

	$x_1$	...	$x_r$
$\epsilon \in T_1$	$h_1(x_1)$	...	
$\epsilon \in T_2$	--	...	$h_2(x_r)$
$\vdots$			
$\epsilon \in T_b$	$h_b(x_1)$	...	$h_b(x_r)$

$$\underline{h(x_1)} = 1/k_1 \sum h_i(x_1) \quad \dots \quad \underline{h(x_r)} = 1/k_r \sum h_i(x_r)$$

$$\underline{h(x_j)} = \sum_{\{i: x \in T_i\}} h_i(x_j) / ||\{i: x \in T_i\}||$$

# Procedure for Measuring Bias and Variance

- Construct  $B$  bootstrap replicates of  $S$   
 $S_1, \dots, S_B$
- Apply learning alg to each replicate  $S_b$  to obtain hypothesis  $h_b$
- Let  $T_b = S \setminus S_b =$  data points not in  $S_b$   
(*out of bag* points)
- Compute predicted value  
 $h_b(x)$   
for each  $x \in T_b$

# Estimating Bias and Variance

- For each  $x \in S$ ,
  - observed response  $y$
  - predictions  $y_1, \dots, y_k$
- Compute average prediction  $\underline{h(x)} = \text{ave}_i \{y_i\}$
- Estimate bias:  $\underline{h(x)} - y$
- Estimate variance:
$$\sum_{\{i: x \in T_i\}} (h_i(x) - \underline{h(x)})^2 / (k-1)$$
- Assume noise is 0