

# Model Selection and Validation

Model Selection: Choosing best Alg & Params.

Example

Fitting a polynomial to learn function  $R \rightarrow R$



## §2 Validation

### Theorem 1

Let  $h$  be a predictor and  $V = \{(x_1, y_1), \dots, (x_n, y_n)\}$  a collection of  $n$  samples in  $\mathcal{D}$ .

Assume a loss function  $\ell \in [0, 1]$ .

Then for every  $\delta \in (0, 1)$ :

with prob at least  $1 - \delta$ , we have

$$|L(h) - L(h^*)| \leq \sqrt{\frac{\log(1/\delta)}{2n}}$$

### Theorem 2

Let  $H = \{h_1, \dots, h_M\}$ , other assumptions as above

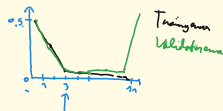
with prob at least  $1 - \delta$

$$\forall h \in H: |L(h) - L(h^*)| \leq \sqrt{\frac{\log(2M/\delta)}{2n}}$$

## § Model Selection over

Plot training & Validation error against complexity of the model

e.g. polynomials



## §3 What to do if learning fails

Get a larger set of samples

Change hypothesis class

- average it
- reduce it
- complexity thereof
- change growth constant

Change the feature representation  
change the optimization algorithm

## §1 Error decomposition

$h_s$  is learned on training set  $S$

$h^* = \arg \min_{h \in H} L(h)$

$$L_D(h_s) = \underbrace{L_D(h^*)}_{\text{optimal error}} + \underbrace{(L_D(h_s) - L_D(h^*))}_{\text{estimation error}}$$

$$L(h_s) = \underbrace{(L_D(h_s) - L_D(h_s^*))}_{\text{fitting error}} + \underbrace{(L_D(h_s^*) - L_D(h^*))}_{\text{noise for analysis}} + \underbrace{L_S(h_s^*)}_{\text{noise for validation}}$$

$$L(h_s) = \underbrace{L_S(h_s) - L_S(h^*)}_{\leq 0} + \underbrace{(L_S(h^*) - L_D(h^*))}_{h^* \text{ is optimal on } S, \text{ fitting error}} + \underbrace{L_D(h^*)}_{\text{optimal error}}$$

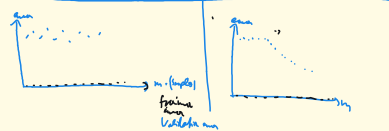
If  $L_S(h_s)$  is large  $\rightarrow$  fitting error is large  
 $\Leftrightarrow$  estimation error is large

## §2 Learning Curves

Assume  $L(h^*)$  is small ( $\approx 0$ )

$m < VC$  dim of the class  
high approximation error

$m > VC$  dim  
approximation error  $\approx 0$



## §3 Summary

