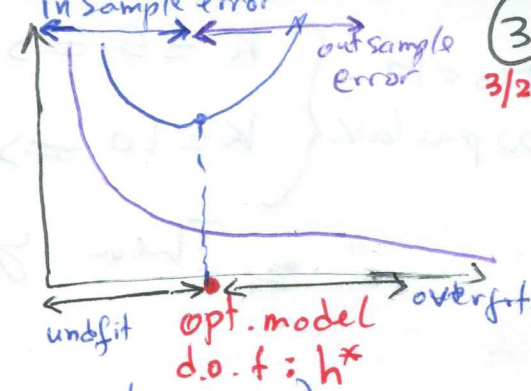
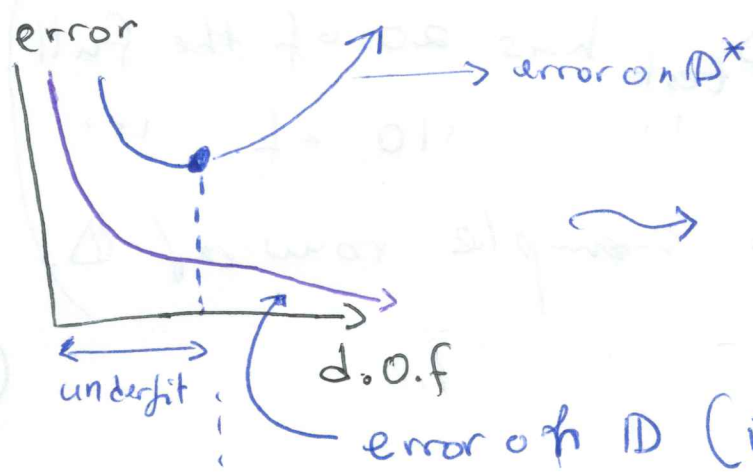


degree of freedom
d.o.f



error on D^*
new data
out of sample on error

See page 51 Learning Data.

$$Y = f(x) + \epsilon$$

To have a new data, get new D^* different from D
get a new historical data and run new model from the

➤ In-sample
How do we validate?

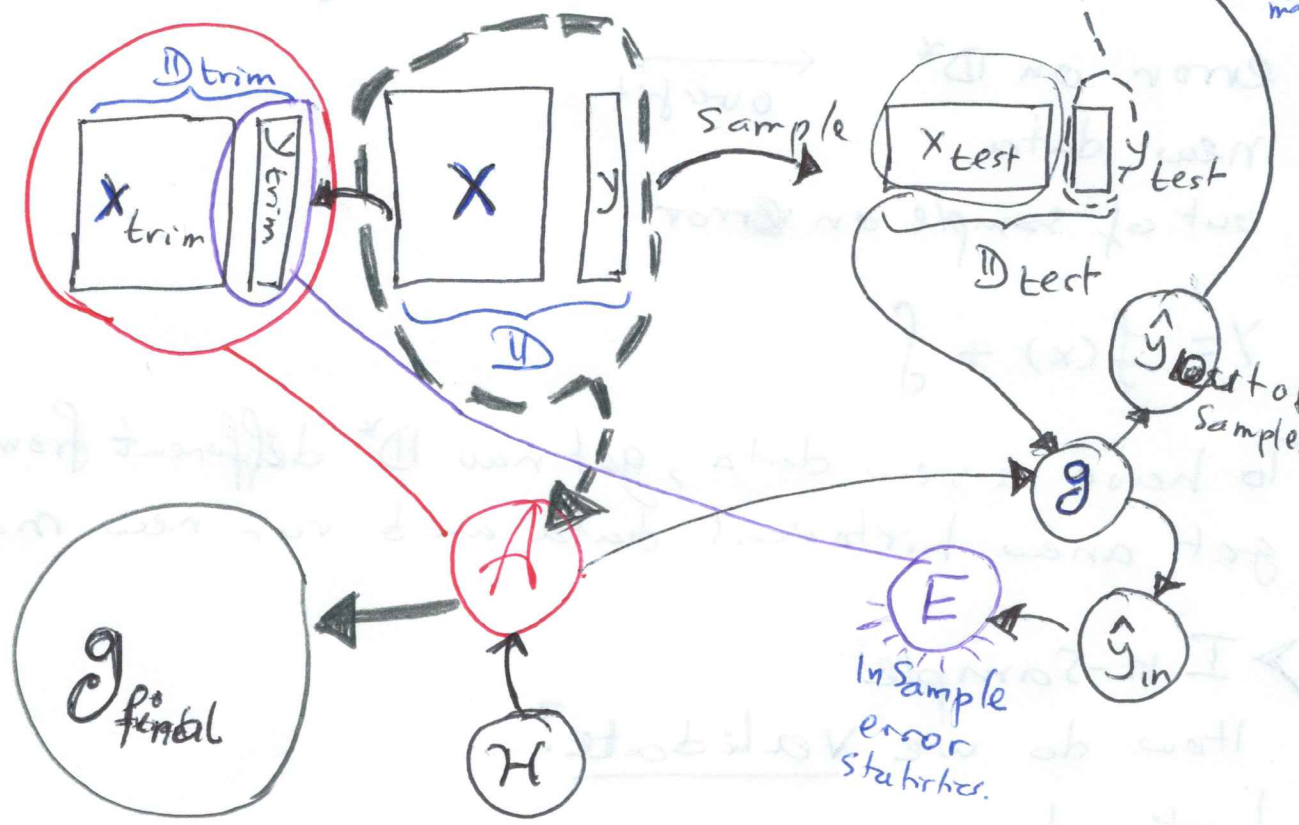
Look at:
Need new data $\notin D$, i.e., never seen by A_i
never incorporate in g . and compare y 's to \hat{y} 's from g .

Pretend: $D = D_{\text{train}} \cup D_{\text{test}}$

This is one possible strategy.
use this to build g
use this to validate g

We select K
where $\frac{1}{K} := \text{prop of } D \text{ is } D_{\text{test}}$.

Most popular. $\begin{cases} k=5 \Rightarrow D_{\text{test}} \text{ has } 20\% \text{ of the full} \\ k=10 \Rightarrow \text{ } \end{cases}$
 Then you sample row of D .



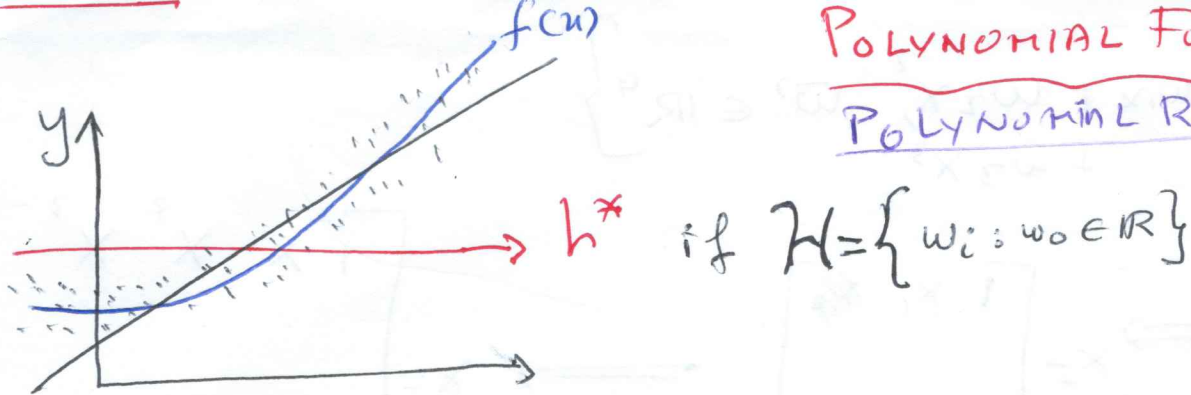
Would you agree g_{final} is better than g ?
 Sample error will be less than other error.

H

END

POLYNOMIAL FUNCTIONS

POLYNOMIAL REGRESSIONS



$$h^* \text{ if } \mathcal{H} = \{w_0 + w_1 x : w_0, w_1 \in \mathbb{R}\}$$

I "see" misspecification error.
I need to make \mathcal{H} "i.e. more d.o.f"

Weierstrass Approximation Theorem

For every continuous $f \in C[a, b]$ where its domain is $x \in [a, b]$, \exists a polynomial function P such that

$$\forall \epsilon > 0, \forall x \in [a, b] |f(x) - p(x)| < \epsilon$$

First Polynomial be degree 2

$$\text{Let } \mathcal{H} = \{w_0 + w_1 x + w_2 x^2, \vec{w} \in \mathbb{R}^3\}$$

$$X = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}_{p=1} \xRightarrow{\text{use Linear Model}} X = \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix}_{p+1} \Rightarrow X = \begin{bmatrix} 1 & x_1 & x_1^2 \\ \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 \end{bmatrix}_{p+1+1=2p+1}$$

How to get the best from this model?

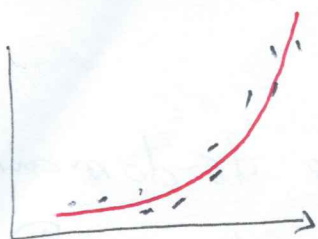
Ans.: it is a linear model: $\vec{b} = (X^T X)^{-1} X^T \vec{y}$

$$H = \{ w_0 + w_1 x + w_2 x^2 + w_3 x^3, \bar{w} \in \mathbb{R}^4 \}$$

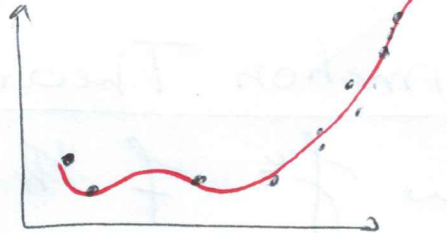
$$x = \begin{bmatrix} x_1 \\ x \end{bmatrix} \Rightarrow x = \begin{bmatrix} 1 & x_1 & x_1^2 & x_1^3 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 & x_n^3 \end{bmatrix} \Rightarrow X = \begin{bmatrix} 1 & x_1 & x_1^2 & x_1^3 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 & x_n^3 \end{bmatrix}$$

Linear model \Rightarrow estimate error is very small

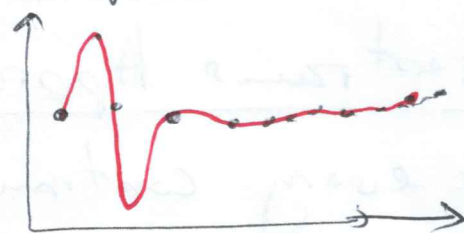
Degree 3



Degree 8



Degree 13



Let $n=5$ and $d=4$

$$x = \begin{bmatrix} \vdots \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \Rightarrow \begin{bmatrix} 1 & x_2 & x_2^2 & x_2^3 & x_2^4 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 & x_n^3 & x_n^4 \end{bmatrix} \Rightarrow \underbrace{\begin{bmatrix} 1 & x_1 & x_1^2 & x_1^3 & x_1^4 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_5 & x_5^2 & x_5^3 & x_5^4 \end{bmatrix}}_X$$

determinant $= \prod_{i=1}^n \prod_{j=i+1}^n (x_j - x_i) \neq 0$

if x_1, \dots, x_n are unique.

I could have this:

$$x = \begin{bmatrix} \vdots \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \Rightarrow x = \begin{bmatrix} \vdots \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \Rightarrow x = \begin{bmatrix} 1 & x_1 & \log(x_1) \\ \vdots & \vdots & \vdots \\ 1 & x_n & \log(x_n) \end{bmatrix}$$

\rightarrow other functions / transformation of the predictors.