

tinyurl.com/edmlpr

0111 4
①

- Tutorials:
- 1st sheet up
 - Meetings next week
(TBA soon!)
 - Answers released
end next week

Assignment pairs:

see website

Hypothesis Forum

- Share links, code snippets
- Get code review
- Ask Q's
- Post answers 

Linear Regression Reminders

Model $f(\underline{x}) = \underline{w}^T \underline{\phi}(\underline{x})$

Can minimize

$$\underbrace{\sum_n (y^{(n)} - \underline{w}^T \underline{\phi}(\underline{x}^{(n)}))^2}_{= (y - \Phi \underline{w})^T (y - \Phi \underline{w})} \text{ wrt } \underline{w}$$

$$\underline{\phi}(\underline{x}) = [\phi_1(\underline{x}) \ \phi_2(\underline{x}) \dots \phi_k(\underline{x})]^T$$

$\phi_k(\underline{x})$ any scalar function

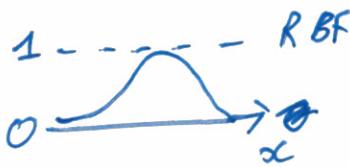
- Monomial, eg $x_2, x_3x_4^3, \dots$

- RBF

$$\overset{\text{"}}{\underline{w}^T} \underset{\text{"}}{\text{springs}} = \text{smooth wave}$$

- Sigmoid

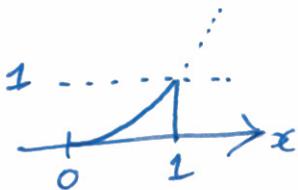




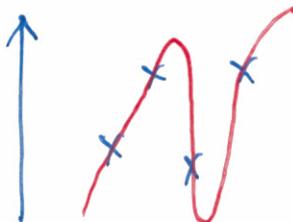
If w are bounded



then f^n bounded



(Chebfun)



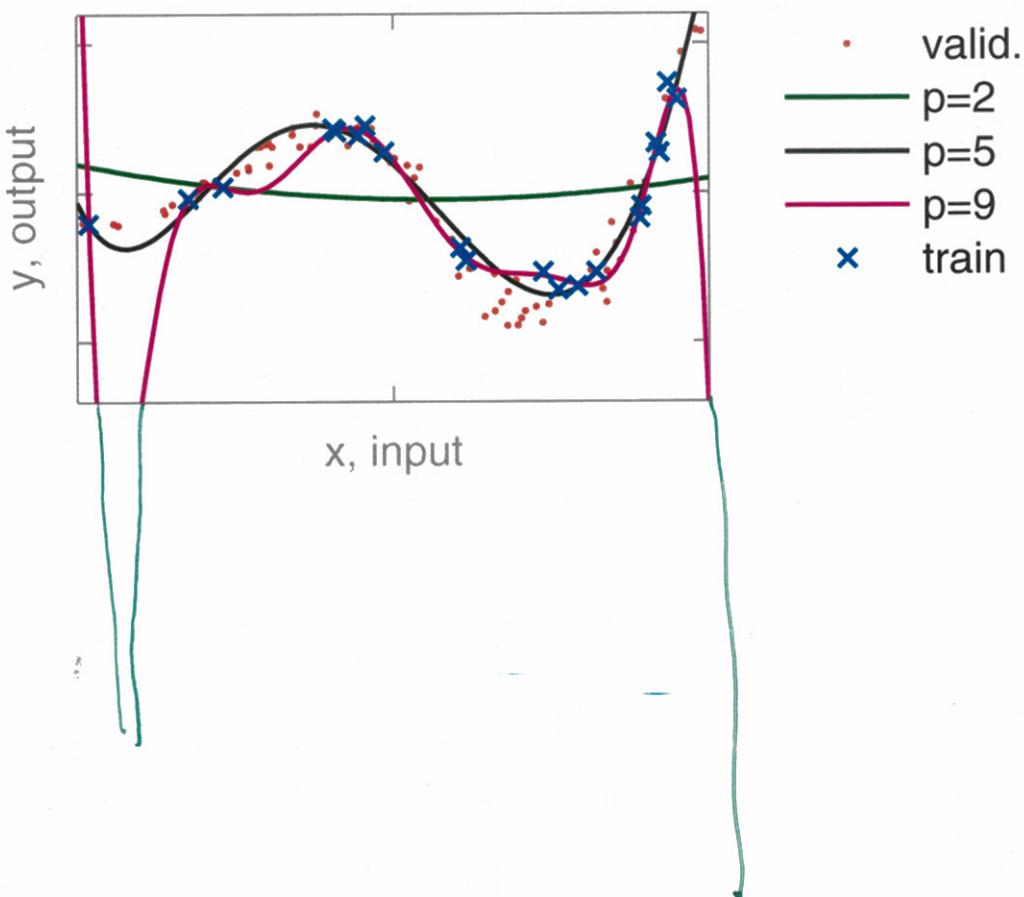
Large derivatives are bad

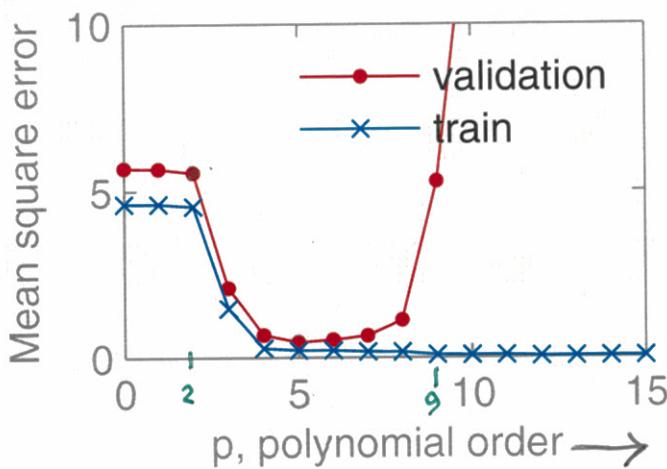
If w are bounded
 \rightarrow derivatives also bounded.

RBF always extrapolates to 0.

Sigmoids extrapolate like this







$\leftarrow \log \lambda$ regularization const

Generalization

$$E_{\text{gen}} = \mathbb{E}_{p(\underline{x}, y)} [L(y, f(\underline{x}))]$$

↑
Loss function

We assume there is some fixed distribution $p(\underline{x}, y)$ on future inputs & outputs

$$E_{\text{gen}} = \iint L(y, f(\underline{x})) p(\underline{x}, y) d\underline{x} dy$$

unbiased

Monte Carlo approximation

$$\approx \frac{1}{M} \sum_{m=1}^M L(y^{(m)}, f(\underline{x}^{(m)})) = E_{\text{test}}$$

$$y^{(m)}, \underline{x}^{(m)} \sim p(\underline{x}, y)$$

Draw examples from held out test set.

But not if model was selected so E_{test} is small.

Data Splits

Training set: fit w

(Don't fit:

Order of a polynomial

of RBFs

Regularization constants.)

Validation set:
(Development set)

To fit λ , model choices

Test set: To report estimate
of generalization error.

Reading: Kaggle blog.