# Foundations of Machine Learning Al2000 and Al5000

FoML-06 Linear Regression

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### So far in FoML

- What is ML and the learning paradigms
- Probability refresher
- MLE, MAP, and fully Bayesian treatment









Dataset D

- Input variable
- Output variable
- Simplest linear model











### Linear Basis function Models

- Fix the number of parameters M s.t.
- Choose M-1 basis functions x:
- Mapping/Approximation:

$$y(\mathbf{x}, \mathbf{w}) =$$





### Example Basis functions

Components of input

Powers of input





## Example Basis Function

Gaussian basis functions





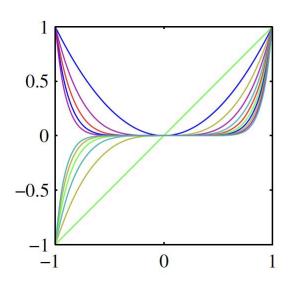
## Example Basis Function

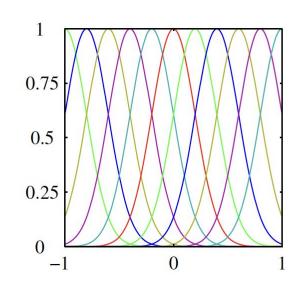
Logistic sigmoid basis functions

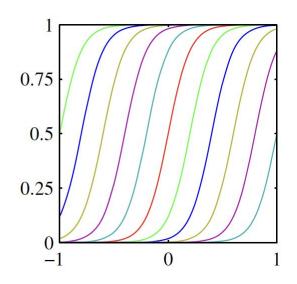




### Example Basis Function











# Linear Regression via MLE





Given data D

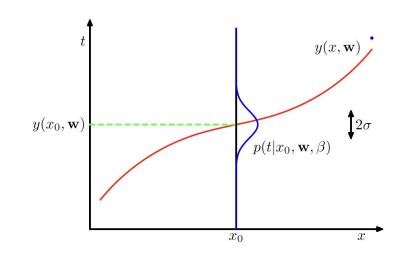
$$D = \{(x_1, t_1), (x_2, t_2), \dots (x_N, t_N)\} = \{\mathbf{x}, \mathbf{t}\}$$

Input variables

Target variables

Linear Model with basis functions

$$y(\mathbf{x}, \mathbf{w}) =$$





### Maximum Likelihood

Assume Gaussian noise around the target

$$t = y(x, \mathbf{w}) + \sigma \cdot \epsilon, \quad \epsilon \in \mathcal{N}(0, 1)$$





### Maximum Likelihood

Assume Gaussian noise around the target

$$t = y(x, \mathbf{w}) + \sigma \cdot \epsilon, \quad \epsilon \in \mathcal{N}(0, 1)$$

$$p(t|x, \mathbf{w}, \beta) =$$

Data matrix

Targets vector





# ML: sum of squares error

Likelihood

$$p(\mathbf{t}|\mathbf{X}, \mathbf{w}, \beta) = \prod_{i=1}^{N} \mathcal{N}(t_i|\mathbf{w}^T \boldsymbol{\phi}(\mathbf{x}_i), \beta^{-1})$$

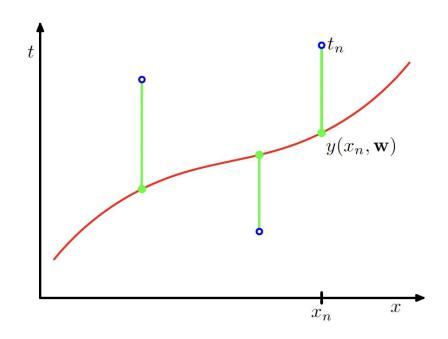
NLL =

Sum-of-squared error  $E_D$  (w) =





# ML: sum of squares error







#### ML Estimates

Minimize the NLL (or, the sum of squared errors)





### **ML** Estimates

Optimal w\* satisfies

$$\mathbb{E}[t'|\mathbf{x}',\mathbf{w_{ML}}] =$$





# Next SGD



