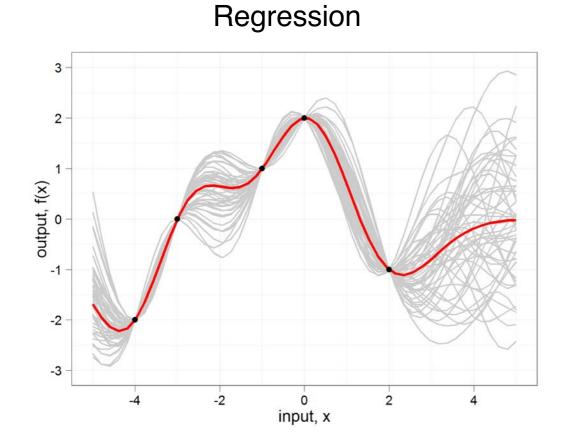
ENM 53 I: Data-driven modeling and probabilistic scientific computing

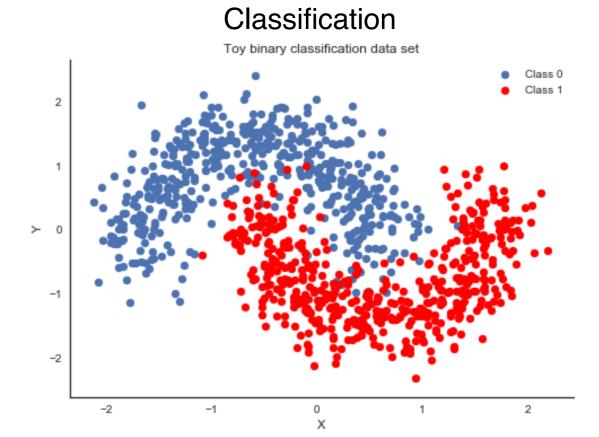
Lecture #5: Bayesian linear regression



# Supervised learning

$$f: \mathcal{X} o \mathcal{Y}$$
  $\mathcal{D} = \{ oldsymbol{x}, oldsymbol{y} \}, \ oldsymbol{x} \in \mathcal{X}, \ oldsymbol{y} \in \mathcal{Y}$   $oldsymbol{y} = f(oldsymbol{x}) + \epsilon$   $p(f(oldsymbol{x}^*) | oldsymbol{x}^*, \mathcal{D})$ 



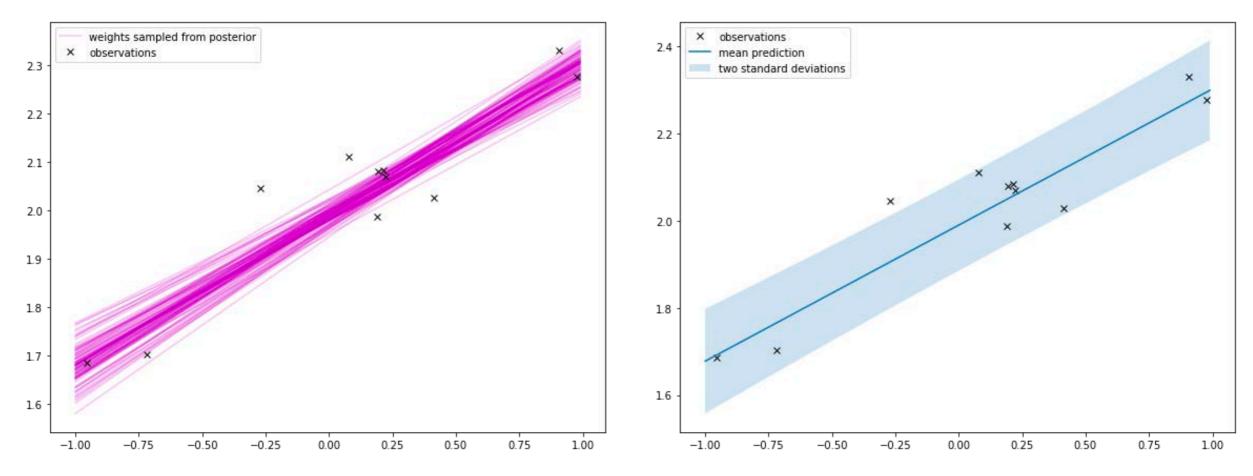


## Linear regression

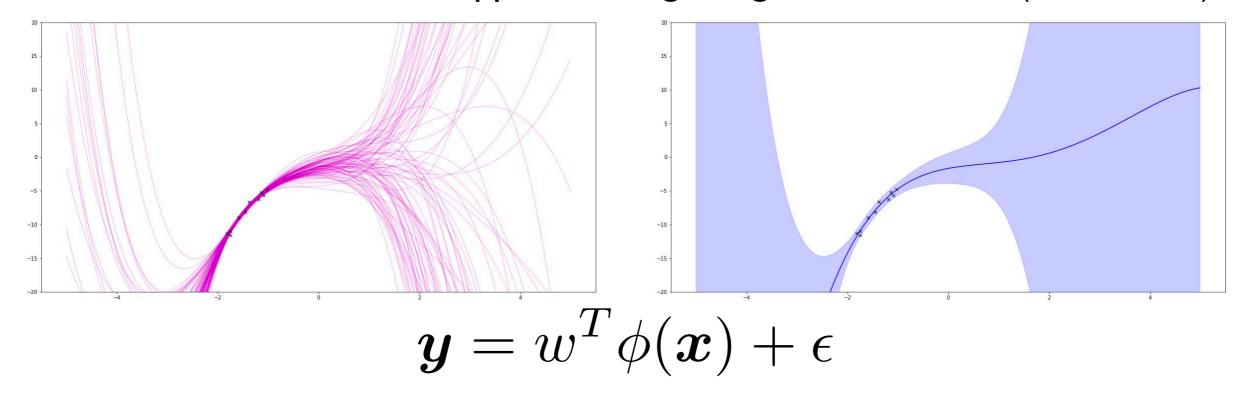
$$f: \mathcal{X} o \mathcal{Y}$$
  $\mathcal{D} = \{oldsymbol{x}, oldsymbol{y} \in \mathcal{X}, oldsymbol{y} \in \mathcal{Y}$   $oldsymbol{y} = f(oldsymbol{x}) + \epsilon$   $f(oldsymbol{x}) = w^T oldsymbol{x}$ 

"It's not just about lines and planes!"

## Bayesian linear regression with basis functions



#### Nonlinear functions can be approximating using basis functions (or features)



# Linear regression with basis functions

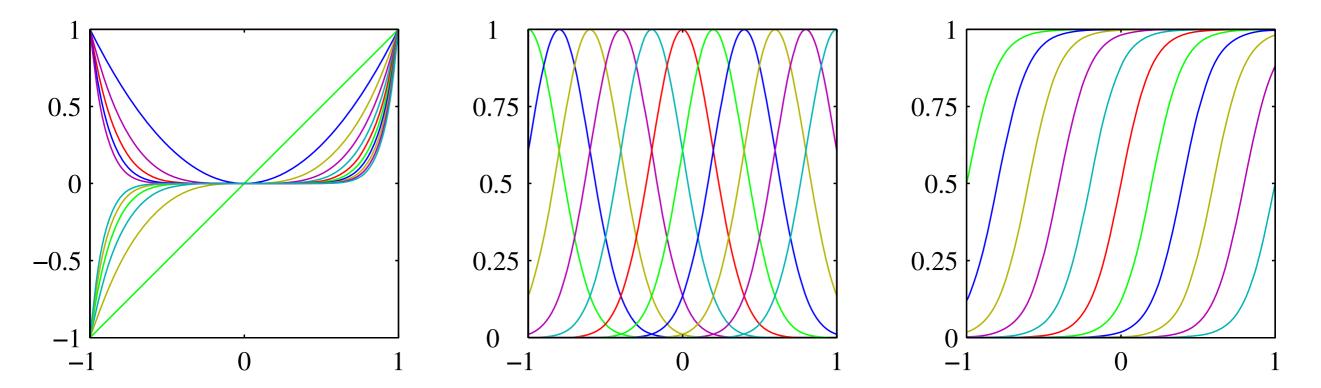
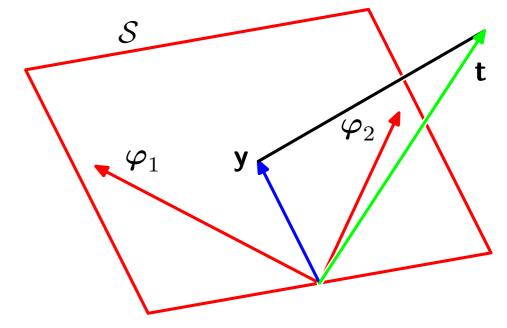


Figure 3.1 Examples of basis functions, showing polynomials on the left, Gaussians of the form (3.4) in the centre, and sigmoidal of the form (3.5) on the right.

## Geometrical interpretation

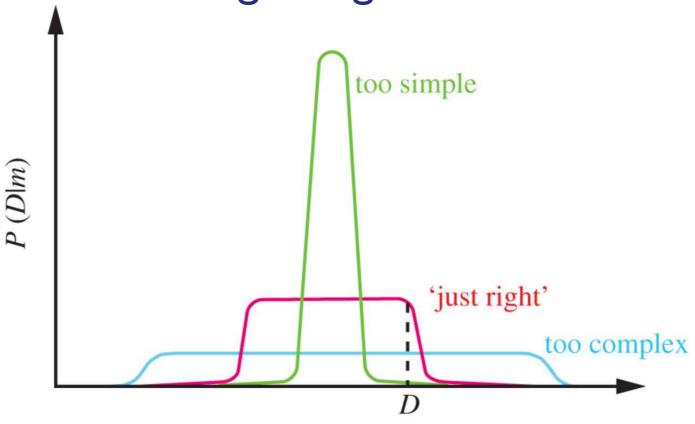
Figure 3.2 Geometrical interpretation of the least-squares solution, in an N-dimensional space whose axes are the values of  $t_1, \ldots, t_N$ . The least-squares regression function is obtained by finding the orthogonal projection of the data vector  $\mathbf{t}$  onto the subspace spanned by the basis functions  $\phi_j(\mathbf{x})$  in which each basis function is viewed as a vector  $\boldsymbol{\varphi}_j$  of length N with elements  $\phi_j(\mathbf{x}_n)$ .



## Occam's razor - Overfitting - Regularization

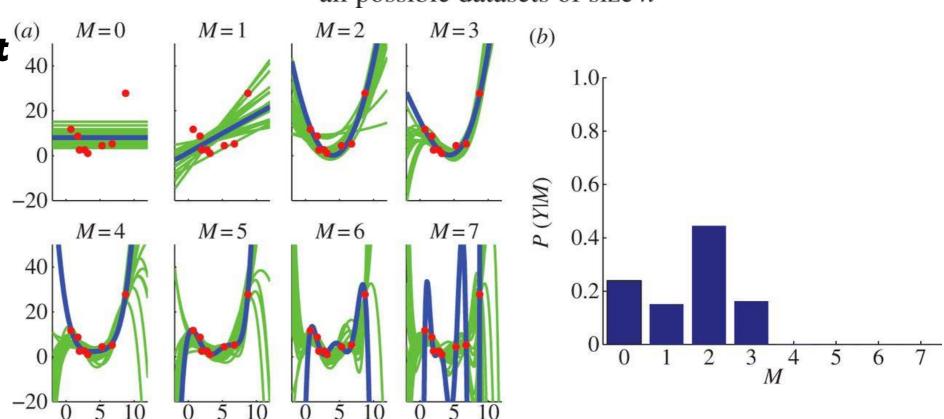
William of Ockham (~1285-1347 A.D)





all possible datasets of size *n* 

"plurality should not be posited without necessity."



Ghahramani, Z. (2013). Bayesian non-parametrics and the probabilistic approach to modelling. Phil. Trans. R. Soc. A, 371(1984), 20110553.