

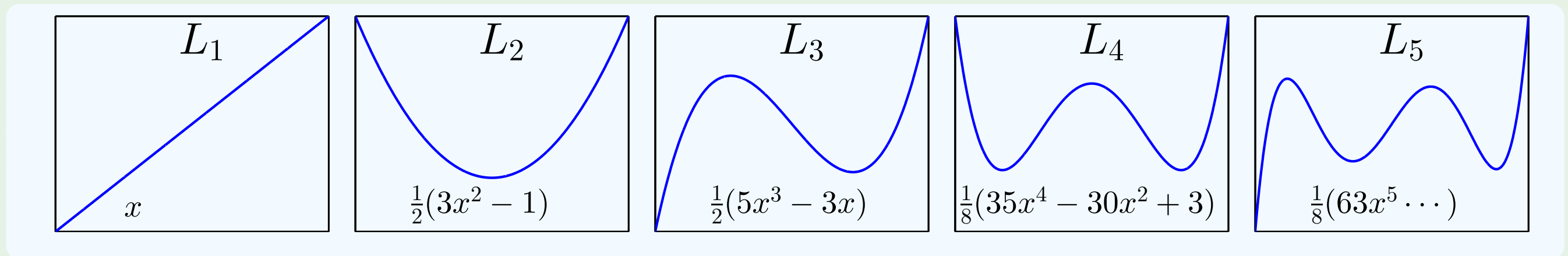
The polynomial model

\mathcal{H}_Q : polynomials of order Q

linear regression in \mathcal{Z} space

$$\mathbf{z} = \begin{bmatrix} 1 \\ L_1(x) \\ \vdots \\ L_Q(x) \end{bmatrix} \quad \mathcal{H}_Q = \left\{ \sum_{q=0}^Q w_q L_q(x) \right\}$$

Legendre polynomials:



Unconstrained solution

Given $(x_1, y_1), \dots, (x_N, y_n) \longrightarrow (\mathbf{z}_1, y_1), \dots, (\mathbf{z}_N, y_n)$

$$\text{Minimize } E_{\text{in}}(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N (\mathbf{w}^\top \mathbf{z}_n - y_n)^2$$

$$\text{Minimize } \frac{1}{N} (\mathbf{Z}\mathbf{w} - \mathbf{y})^\top (\mathbf{Z}\mathbf{w} - \mathbf{y})$$

$$\mathbf{w}_{\text{lin}} = (\mathbf{Z}^\top \mathbf{Z})^{-1} \mathbf{Z}^\top \mathbf{y}$$

Constraining the weights

Hard constraint: \mathcal{H}_2 is constrained version of \mathcal{H}_{10} with $w_q = 0$ for $q > 2$

Softer version: $\sum_{q=0}^Q w_q^2 \leq C$ “soft-order” constraint

Minimize $\frac{1}{N} (\mathbf{Z}\mathbf{w} - \mathbf{y})^\top (\mathbf{Z}\mathbf{w} - \mathbf{y})$

subject to: $\mathbf{w}^\top \mathbf{w} \leq C$

Solution: \mathbf{w}_{reg} instead of \mathbf{w}_{lin}

Solving for \mathbf{w}_{reg}

Minimize $E_{\text{in}}(\mathbf{w}) = \frac{1}{N} (\mathbf{Z}\mathbf{w} - \mathbf{y})^\top (\mathbf{Z}\mathbf{w} - \mathbf{y})$

subject to: $\mathbf{w}^\top \mathbf{w} \leq C$

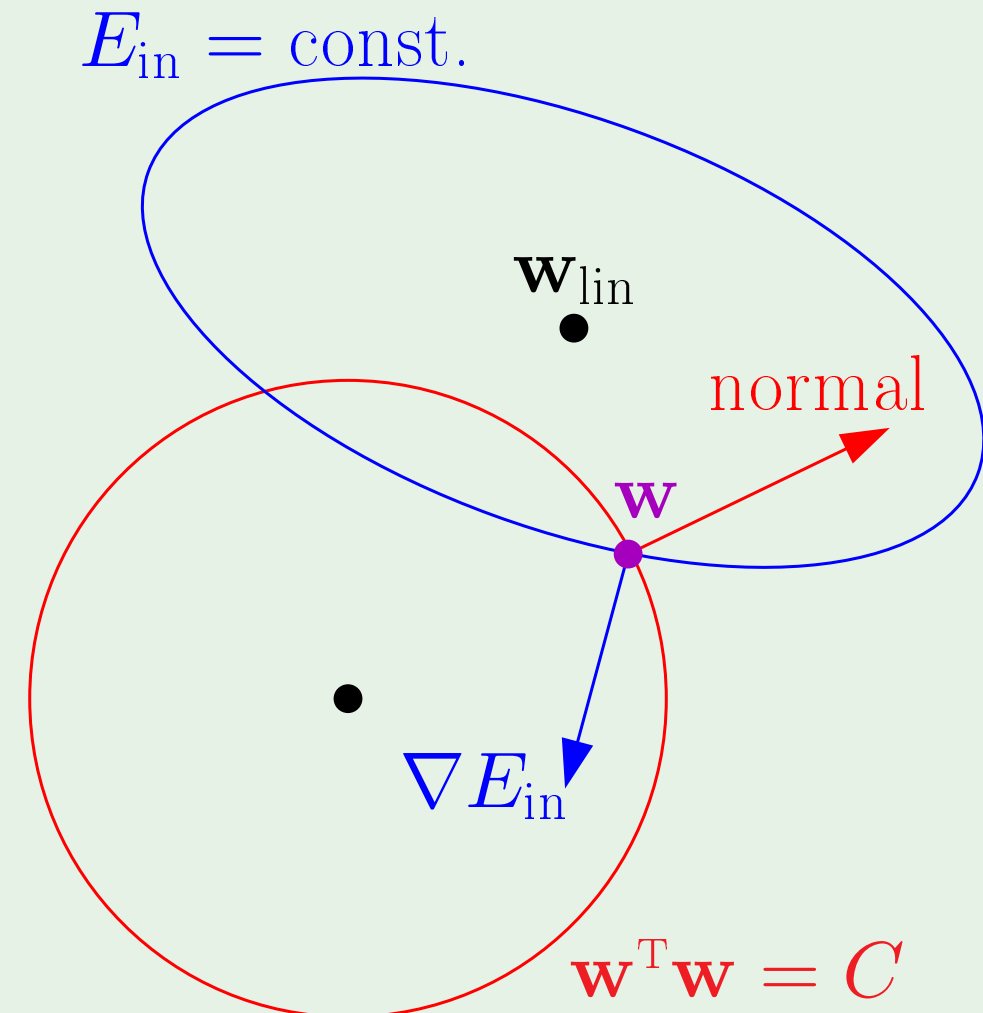
$$\nabla E_{\text{in}}(\mathbf{w}_{\text{reg}}) \propto -\mathbf{w}_{\text{reg}}$$

$$= -2\frac{\lambda}{N}\mathbf{w}_{\text{reg}}$$

$$\nabla E_{\text{in}}(\mathbf{w}_{\text{reg}}) + 2\frac{\lambda}{N}\mathbf{w}_{\text{reg}} = \mathbf{0}$$

Minimize $E_{\text{in}}(\mathbf{w}) + \frac{\lambda}{N}\mathbf{w}^\top \mathbf{w}$

$C \uparrow \quad \lambda \downarrow$



Augmented error

Minimizing $E_{\text{aug}}(\mathbf{w}) = E_{\text{in}}(\mathbf{w}) + \frac{\lambda}{N} \mathbf{w}^T \mathbf{w}$

$$= \frac{1}{N} (\mathbf{Z}\mathbf{w} - \mathbf{y})^T (\mathbf{Z}\mathbf{w} - \mathbf{y}) + \frac{\lambda}{N} \mathbf{w}^T \mathbf{w} \quad \text{unconditionally}$$

– solves –

Minimizing $E_{\text{in}}(\mathbf{w}) = \frac{1}{N} (\mathbf{Z}\mathbf{w} - \mathbf{y})^T (\mathbf{Z}\mathbf{w} - \mathbf{y})$

subject to: $\mathbf{w}^T \mathbf{w} \leq C$ ← VC formulation

The solution

Minimize $E_{\text{aug}}(\mathbf{w}) = E_{\text{in}}(\mathbf{w}) + \frac{\lambda}{N} \mathbf{w}^T \mathbf{w}$

$$= \frac{1}{N} \left((\mathbf{Z}\mathbf{w} - \mathbf{y})^T (\mathbf{Z}\mathbf{w} - \mathbf{y}) + \lambda \mathbf{w}^T \mathbf{w} \right)$$

$$\nabla E_{\text{aug}}(\mathbf{w}) = \mathbf{0} \quad \implies \quad \mathbf{Z}^T (\mathbf{Z}\mathbf{w} - \mathbf{y}) + \lambda \mathbf{w} = \mathbf{0}$$

$$\mathbf{w}_{\text{reg}} = (\mathbf{Z}^T \mathbf{Z} + \lambda \mathbf{I})^{-1} \mathbf{Z}^T \mathbf{y} \quad \text{(with regularization)}$$

as opposed to $\mathbf{w}_{\text{lin}} = (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{y}$ (without regularization)

The result

Minimizing $E_{\text{in}}(\mathbf{w}) + \frac{\lambda}{N} \mathbf{w}^T \mathbf{w}$ for different λ 's:

