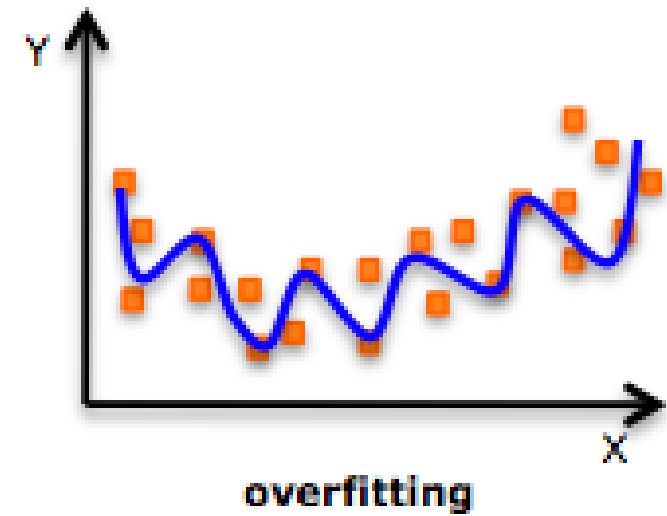
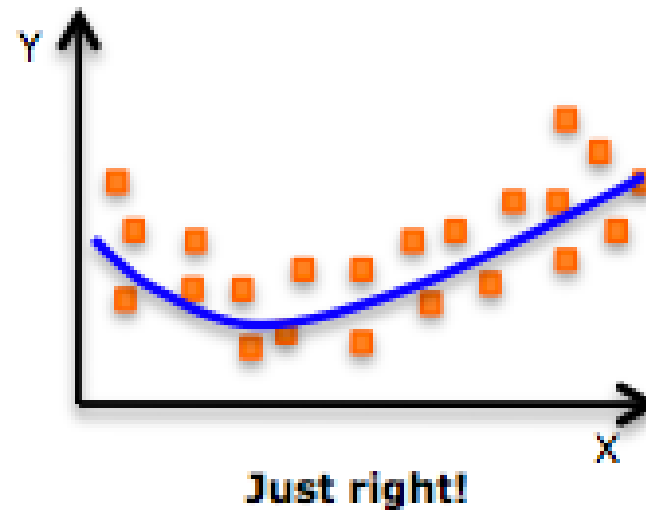
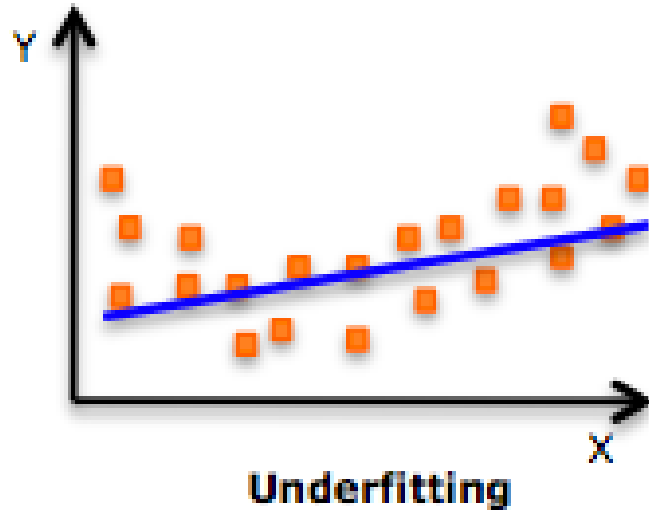


L2 Regularization Derivate

Why Regularization?

- Constraint the parameter values
- Avoid over-fitting phenomenon



L2 Regularization in Linear Regression

- Prediction

$$\hat{y} = \mathbf{x}^T \boldsymbol{\beta} = \beta_0 + \sum_i x_i \beta_i$$

- Original Objective

$$\min J(\boldsymbol{\beta}) = \min \sum_{(x,y)} (\mathbf{x}^T \boldsymbol{\beta} - y)^2$$

- L2-Regularized Objective

$$\min \sum_{(x,y)} (\mathbf{x}^T \boldsymbol{\beta} - y)^2 + \lambda \|\boldsymbol{\beta}\|^2$$

Derivative with L2 Regularization

$$\begin{aligned}\frac{\partial J(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} &= \sum_{(x,y)} 2\boldsymbol{x} \cdot (\boldsymbol{x}^T \boldsymbol{\beta} - y) + \frac{\partial \lambda \|\boldsymbol{\beta}\|^2}{\partial \boldsymbol{\beta}} \\ &= \sum_{(x,y)} 2\boldsymbol{x} \cdot (\boldsymbol{x}^T \boldsymbol{\beta} - y) + 2\lambda \boldsymbol{\beta}\end{aligned}$$

Closed-form with L2-Regularization

$$\begin{aligned}\nabla_{\boldsymbol{\beta}} J(\boldsymbol{\beta}) &= 0 \\ \nabla_{\boldsymbol{\beta}} \left(\frac{1}{2} \|\mathbf{X}\boldsymbol{\beta} - \mathbf{y}\|^2 + \frac{\lambda}{2} \|\boldsymbol{\beta}\|^2 \right) &= 0 \\ \nabla_{\boldsymbol{\beta}} \left(\frac{1}{2} (\mathbf{X}\boldsymbol{\beta} - \mathbf{y})^T (\mathbf{X}\boldsymbol{\beta} - \mathbf{y}) + \frac{\lambda}{2} \boldsymbol{\beta}^T \boldsymbol{\beta} \right) &= 0 \\ \mathbf{X}^T \mathbf{X} \boldsymbol{\beta} - \mathbf{X}^T \mathbf{y} + \lambda \boldsymbol{\beta} &= 0 \\ \mathbf{X}^T \mathbf{X} \boldsymbol{\beta} - \mathbf{X}^T \mathbf{y} + \lambda \mathbf{I} \boldsymbol{\beta} &= 0\end{aligned}$$

Closed-form with L2-Regularization (Cont'd)

$$\mathbf{X}^T \mathbf{X} \boldsymbol{\beta} - \mathbf{X}^T \mathbf{y} + \lambda \mathbf{I} \boldsymbol{\beta} = 0$$

$$\mathbf{X}^T \mathbf{y} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}) \boldsymbol{\beta}$$

$$\boldsymbol{\beta} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I})^{-1} \mathbf{X}^T \mathbf{y}$$