

Problem 3 - Generalized Additive Models

1. When $j = 1$:

$$\hat{\beta}_1 = \underset{\beta}{\operatorname{argmin}} \sum_i (y_i - \alpha - \hat{f}_2(x_{2i}) - \beta x_{1i})^2 + \lambda \beta^2$$

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We find the derivative with respect to β and set it to 0:

$$-2 \sum_i x_{1i} (y_i - \alpha - \hat{\beta}_2 x_{2i} - \beta x_{1i}) + 2\lambda \beta = 0$$

$$- \sum_i x_{1i} y_i + \sum_i x_{1i} N \alpha + \sum_i x_{1i} \hat{\beta}_2 x_{2i} + \sum_i x_{1i} \beta x_{1i} + \lambda \beta = 0$$

$$\hat{\beta}_1 = \beta = \frac{\sum_i x_{1i} y_i - \sum_i x_{1i} N \alpha - \sum_i x_{1i} \hat{\beta}_2 x_{2i}}{\sum_i x_{1i} x_{1i} + \lambda}$$

When $j = 2$:

$$\hat{\beta}_2 = \underset{\beta}{\operatorname{argmin}} \sum_i (y_i - \alpha - \hat{f}_1(x_{1i}) - \beta x_{2i})^2 + \lambda \beta^2$$

$$\hat{\beta}_2 = \underset{\beta}{\operatorname{argmin}} \sum_i (y_i - \alpha - \hat{\beta}_1 x_{1i} - \beta x_{2i})^2 + \lambda \beta^2$$

Similarly we find:

$$\hat{\beta}_2 = \frac{\sum_i x_{2i} y_i - \sum_i x_{2i} N \alpha - \sum_i x_{2i} \hat{\beta}_1 x_{1i}}{\sum_i x_{2i} x_{2i} + \lambda}$$

2. Yes, it is possible for it to produce the same result as cubic Smoothing Splines. The reason for that is the objective of cubic Smoothing Splines which is to find function $g(x)$ that minimizes:

$$\sum_{i=1}^n (y_i - g(x_i))^2 + \lambda \int g''(t)^2 dt$$

Somehow we're trying to minimize a similar form, so after convergence we may end up with betas that more or less give the same result as Smoothing Splines.

3. Since $E(f_j(X_j)) = 0$, if we divide the formula for the optimal – say $\hat{\beta}_1$ – in some iteration by N it becomes independent from $\hat{\beta}_2$. Should this condition be altered then that term remains and thus we have update order dependency.
4. The smoothing operator based on cubic smoothing splines:

$$\hat{g}_\lambda = S_\lambda y = \underset{\beta}{\operatorname{argmin}} \sum_i (y_i - g(x_i))^2 + \lambda \int g''(t)^2 dt$$

$$S_\lambda = \underset{\lambda}{\operatorname{argmin}} \frac{1}{n} \sum_i (y_i - g(x_i))^2 + \lambda \int g''(t)^2 dt$$