| CS 5565, HW6(Moving | g Beyond | Linearity) | 85pts | (65 pts | Undergra | d) |
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1. (15 points total) Suppose that a curve \hat{g} is computed to smoothly fit a set of n points using the following formula:

$$\hat{g} = \arg\min_{g} \left(\sum_{i=1}^{n} (y_i - g(x_i))^2 + \lambda \int [g^{(m)}(x)]^2 dx \right)$$

where $g^{(m)}$ represents the *m*th derivative of g (and $g^{(0)} = g$). Provide example sketches of \hat{g} in each of the following scenarios.

- (a) (3 points) $\lambda = \infty$, m = 0
- (b) (3 points) $\lambda = \infty$, m = 1
- (c) (3 points) $\lambda = \infty$, m = 2
- (d) (3 points) $\lambda = \infty$, m = 3
- (e) (3 points) $\lambda = 0$, m = 3
- 2. (10 points total) Suppose we fit a curve with basis functions $b_1(X) = X$, $b_2(X) = (X-1)^2 I(X \ge 1)$. (Note that $I(X \ge 1)$ equals 1 for $X \ge 1$ and 0 otherwise.) We fit the linear regression model

$$Y = \beta_0 + \beta_1 b_1(X) + \beta_2 b_2(X) + \epsilon,$$

and obtain coefficient estimates $\hat{\beta}_0 = 1$, $\hat{\beta}_1 = 1$, $\hat{\beta}_2 = -2$.

Sketch the estimated curve between X=-2 and X=2. Note the intercepts, slopes, and other relevant information.

3. (10 points total) Suppose we fit a curve with basis functions $b_1(X) = I(0 \le X \le 2) - (X - 1)I(1 \le X \le 2)$, $b_2(X) = (X - 3)I(3 \le X \le 4) + I(4 < X \le 5)$. We fit the linear regression model

$$Y = \beta_0 + \beta_1 b_1(X) + \beta_2 b_2(X) + \epsilon,$$

and obtain coefficient estimates $\hat{\beta}_0 = 1$, $\hat{\beta}_1 = 1$, $\hat{\beta}_2 = 3$.

Sketch the estimated curve between X=-2 and X=2. Note the intercepts, slopes, and other relevant information.

4. (15 points total) Consider two curves, \hat{g}_1 and \hat{g}_2 defined by

$$\hat{g}_{1} = \arg\min_{g} \left(\sum_{i=1}^{n} (y_{i} - g(x_{i}))^{2} + \lambda \int \left[g^{(3)}(x) \right]^{2} dx \right),$$

$$\hat{g}_{2} = \arg\min_{g} \left(\sum_{i=1}^{n} (y_{i} - g(x_{i}))^{2} + \lambda \int \left[g^{(4)}(x) \right]^{2} dx \right).$$

$$\hat{g}_2 = \arg\min_{g} \left(\sum_{i=1}^{n} (y_i - g(x_i))^2 + \lambda \int [g^{(4)}(x)]^2 dx \right),$$

where $g^{(m)}$ represents the mth derivative of g.

- (a) (5 points) As $\lambda \longrightarrow \infty$, will \hat{g}_1 or \hat{g}_2 have the smaller training RSS?
- (b) (5 points) As $\lambda \longrightarrow \infty$, will \hat{g}_1 or \hat{g}_2 have the smaller test RSS?
- (c) (5 points) For $\lambda = 0$, will \hat{g}_1 or \hat{g}_2 have the smaller training and test RSS?
- 5. (20 points total (extra credit undergraduate)) It was mentioned in the chapter that a cubic regression spline with one knot at ξ can be obtained using a basis of the form x, x^2 , x^3 , $(x \xi)^3_+$, where $(x \xi)^3_+ = (x \xi)^3$ if $x > \xi$ and equals 0 otherwise. We will now show that a function of the form

$$f(x) = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \beta_4 (x - \xi)_+^3$$

is indeed a cubic regression spline, regardless of the values of $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$.

(a) (5 points) Find a cubic polynomial

$$f_1(x) = a_1 + b_1 x + c_1 x^2 + d_1 x^3$$

such that $f(x) = f_1(x)$ for all $x \leq \xi$. Express a_1, b_1, c_1, d_1 in terms of $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$.

(b) (5 points) Find a cubic polynomial

$$f_2(x) = a_2 + b_2 x + c_2 x^2 + d_2 x^3$$

such that $f(x) = f_2(x)$ for all $x > \xi$. Express a_2, b_2, c_2, d_2 in terms of $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$.

- (c) (5 points) Show that $f_1(\xi) = f_2(\xi)$. That is, f(x) is continuous at ξ .
- (d) (5 points) Show that $f'_1(\xi) = f'_2(\xi)$. That is, f'(x) is continuous at ξ .
- (e) (5 points) Show that $f_1''(\xi) = f_2''(\xi)$ i.e. f(x) is indeed a cubic spline.
- 6. (15 points) Construct a natural cubic spline that passes through the points (1,2),(2,4), and (3,3).