## MATH 697 FALL 2017

## PROBLEM SET 2: DUE THURSDAY WEEK 6

- (1) Let  $J: \mathbb{R}^p \to \mathbb{R}$  be a convex (not necessarily differentiable) function. In class, we defined the **subdifferential** of J at a point  $x \in \mathbb{R}^p$ , denoted  $\partial J(x)$ .
  - (a) Show that  $\partial J(x)$  is a closed and convex set.
  - (b) Let  $x_k$  and  $p_k$  be sequences such that  $p_k \in \partial J(x_k)$  for every k. Show that if  $x_k \to x$  and  $p_k \to p$ , then  $p \in \partial J(p)$ .
- (2) Consider the (constrained) minimization problem

$$|\mathbf{X}\beta - \mathbf{y}|_2^2$$
 with constraint  $|\beta|_2 \le t$ ,

where  $\mathbf{X}^t\mathbf{X}$  is assumed to be invertible. Show that if  $|\hat{\beta}|_2 > t$ , with  $\hat{\beta}$  being the least squares solution, then the constrained solution, denoted  $\hat{\beta}_0$ , must be such that

$$|\hat{\beta}_0|_2 = t \text{ and } \mathbf{X}^t (\mathbf{X}\hat{\beta}_0 - \mathbf{y}) \perp \hat{\beta}_0.$$

(3) This exercise is intended to generate more interesting simulated data using a (non-linear) additive model. Fix coefficients  $\beta = (\beta_0, \beta_1, \beta_2, \beta_3)$  of your choice, and then generate a set of n = 100 data points  $(x_i, y_i)$  of the form

$$y_i = f_{\beta}(x_i) + \varepsilon_i$$

the  $x_i$  are always given by i.i.d. standard normals, the  $\varepsilon_i$  are i.i.d. normals with mean zero and variance 0.5, and  $f_{\beta}(x) = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3$ .

Then, save the generated data of pairs  $(x_i, y_i)$  in a file (in csv format, for instance) and produce a plot of this data (when you submit the plot, indicate the  $\beta$  you used).

- (4) To the data generated in the previous problem, apply the standard least squares method and indicate the  $\hat{\beta}$  you obtained. Produce a plot containing the  $\hat{y}$  and training data.
- (5) Do the same as before but instead of least squares, applying ridge regression with  $\lambda = 10, 20$ , and 50. Produce a plot as in the previous case for each of the values of  $\lambda$ .