

ELE 535: Machine Learning and Pattern  
Recognition  
Homework 4

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Monday 15<sup>th</sup> October, 2018

**Exercise 1:** Determine general sufficient conditions (if any exist) under which the indicated function  $f$  is convex.

- a)  $f : \mathbb{R} \rightarrow \mathbb{R}$  with  $f(x) = |x|$ .
- b)  $f : (0, \infty) \rightarrow \mathbb{R}$  with  $f(x) = x \ln(x)$ .
- c)  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  with  $f(x) = (x^T Q x)^3$ . Here  $Q \in \mathbb{R}^{n \times n}$  is symmetric PSD.
- d)  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  with  $f(x) = 1 + e^{\sum_{i=1}^n |x_i|^3}$ .
- e) For  $x \in \mathcal{C} = \{x \in \mathbb{R}^n : x_i > 0, i = 1, \dots, n\}$  let  $\ln(x) = [\ln(x_i)] \in \mathbb{R}^n$  and define  $f(x) = x^T \ln(x)$

**Answer:**

- a) Simply applying the triangle inequality we get

$$\begin{aligned} f(\lambda x + (1 - \lambda)y) &= |\lambda x + (1 - \lambda)y| \\ &\leq \lambda|x| + (1 - \lambda)|y| = \lambda f(x) + (1 - \lambda)f(y) \end{aligned}$$

Thus, it is convex.

- b) Here, we take the second derivative since it is continuous on the domain,

$$f''(x) = \frac{1}{x} > 0 \quad \forall x \in (0, \infty)$$

As this is always positive, then we have that  $f$  is strongly convex.

- c) Here, we use theorem 7.3.2e) that states that  $h(x) = g(f(x))$  is convex if  $g$  is convex and non decreasing on the range of  $f$ . Here we have  $f(x) = x^T Q x$  whose range is  $[0, \infty)$  as  $Q$  is PSD and  $g(x) = x^3$ . Thus, on  $[0, \infty)$ , we have that  $g'(x) = 3x^2 \geq 0$  and  $g''(x) = 6x \geq 0$  which means that  $g$  is non decreasing and convex respectively. Thus, we have shown that the original function is convex.
- d) Again, we use the same theorem as in the previous part. First  $g(x) = 1 + e^x$  and  $f(x) = (\sum_{i=1}^n |x_i|^3)$ . The range of  $f(x)$  is  $[0, \infty)$ . We also have  $g'(x) = e^x$  and  $g''(x) = e^x$  which are both always positive and so non decreasing and convex. This shows that the original function is convex.

e) We have that  $f(x) = x^T \ln(x)$  which is just a short form for

$$[f(x)]_i = x_i \ln(x_i)$$

Thus, we have

$$\begin{aligned} [\nabla f(x)]_i &= 1 + \ln(x_i) \\ [Hf(x)]_{ii} &= \frac{1}{x_i} \text{ and } [Hf(x)]_{ij} = 0 \text{ for } i \neq j \end{aligned}$$

**Exercise 2:** You want to learn an unknown function  $f : [0, 1] \rightarrow \mathbb{R}$  using a set of noisy measurements  $(x_j, y_j)$ , with  $y_j = f(x_j) + \epsilon_j$ ,  $j = 1, \dots, m$ . Your plan is to approximate  $f(\cdot)$  by a Fourier series on  $[0, 1]$  with  $q \in \mathbb{N}$  terms:

$$f_q(x) = \frac{a_0}{2} + \sum_{k=1}^q a_k \cos(2\pi kx) + b_k \sin(2\pi kx).$$

To control the smoothness of  $f_q(\cdot)$ , you also decide to penalize the size of the coefficients  $a_k, b_k$  more heavily as  $k$  increases.

- a) Formulate the above problem as a regularized regression problem.
- b) For  $q = 2$ , display the regression matrix, the label vector  $y$ , and the regularization term.
- c) Comment briefly on how to select  $q$ .

**Answer:**

**Exercise 3:** Let  $D \in \mathbb{R}^{n \times n}$  be diagonal with nonnegative diagonal entries and consider the problem:

$$\min_{x \in \mathbb{R}^n} \|x - y\|_2^2 + \lambda \|Dx\|_2^2$$

This problem seeks to best approximate  $y \in \mathbb{R}^n$  with a nonuniform penalty for large entries in  $x$ .

- a) Solve this problem using the solution of ridge regression.
- b) Show that the objective function is separable into a sum of decoupled terms. Show that this decomposes the problem into  $n$  independent scalar problems.
- c) Find the solution of each scalar problem.
- d) By putting these scalar solutions together, find and interpret the solution to the original problem.

**Answer:**

**Exercise 4:** Let  $X \in \mathbb{R}^{n \times m}$  and  $y \in \mathbb{R}^m$  be given, and  $\lambda > 0$ . Consider the problem

$$w^* = \arg \min_{w \in \mathbb{R}^n} \|y - X^T w\|_2^2 + \lambda \|w\|_2^2$$

From the notes we know that there exists a unique solution  $w^*$  and that  $w^* \in \mathcal{R}(X)$ . Using the above and these two results, show that  $w^* = X(X^T X + \lambda I_m)^{-1} y$ .

**Answer:**

**Exercise 5:** One form of regularized least squares can be posed as:

$$w^* = \arg \min_{w \in \mathbb{R}^n} \|Fw - y\|_2^2 + \lambda \|Gw - g\|_2^2$$

where  $F \in \mathbb{R}^{m \times n}$ ,  $y \in \mathbb{R}^m$ ,  $G \in \mathbb{R}^{k \times n}$ ,  $g \in \mathbb{R}^k$ , and  $\lambda > 0$ .

- a) Show that a sufficient condition for the above to have a unique solution is that  $\text{rank}(G) = n$ .
- b) Show that a necessary and sufficient condition is that  $\mathcal{N}(F) \cap \mathcal{N}(G) = \mathbf{0}$ .

**Answer:**