## **High Dimensional Statistics**

2nd Semester, 2023-2024

Homework 3 (Deadline: Jun 23)

1. (10 pts) Given a set  $T \subset K$ . Recall the definition of the covering number:  $N(T, d, \varepsilon)$  is the smallest number of points in T which form a  $\varepsilon$ -covering of T under the metric d. Suppose we are allowed to use the points outside of T to do covering. Then the smallest number of points that are needed to form a  $\varepsilon$ -covering of T is referred to as the exterior covering number, denoted  $N^{ext}(T, d, \varepsilon)$ . Show that

$$N^{ext}(T, d, \varepsilon) \le N(T, d, \varepsilon) \le N^{ext}(T, d, \varepsilon/2).$$

2. (10pts) Define

$$T^{n}(s) = \{ x \in \mathbb{R}^{n} : \|x\|_{0} \le s, \|x\|_{2} \le 1 \},\$$

where  $||x||_0$  counts the number of non-zero entries in x. Show that the Gaussian complexity of  $T^n(s)$ , denoted  $\mathcal{G}(T^n(s)) = \mathbb{E}\left[\sup_{x \in T^n(s)} \langle g, x \rangle\right], g \sim \mathcal{N}(0, I_n)$ , satisfies

$$\mathcal{G}(T^n(s)) \lesssim \sqrt{s \log\left(\frac{en}{s}\right)}.$$

3. (20 pts) Let  $B_1^n = \{x : ||x||_1 \le 1\}$  be the  $\ell_1$ -norm unit ball. We have already seen that the Gaussian complexity of  $B_1^n$  satisfies

$$\mathcal{G}(B_1^n) = \mathbb{E}\left[\sup_{\|x\|_1 \le 1} \langle g, x \rangle\right] \lesssim \sqrt{\log n}, \quad g \sim \mathcal{N}(0, I_n)$$

based on the duality between  $\ell_1$ -norm and  $\ell_{\infty}$ -norm. In this problem, we attempt to provide a bound for  $\mathcal{G}(B_1^n)$  based on the Dudley integral.

• For  $\varepsilon > 0$  being sufficiently small, show that the covering of  $B_1^n$  under the  $\ell_2$ -norm satisfies

$$\sqrt{\log \mathcal{N}(B_1^n, \|\cdot\|_2, \varepsilon)} \lesssim \min\{\varepsilon^{-1}\sqrt{\log n}, \sqrt{n} \cdot \log(1/\varepsilon)\}.$$

Hint: Volume argument as presented in Lecture 4 may be useful in providing one bound.

- Using the above result and the Dudley integral to provide a bound for  $\mathcal{G}(B_1^n)$ .
- 4. (10 pts) Assume  $X, Y \in \mathbb{R}^n$  are finite centered Gaussian Processes. Suppose that there exist a pair of index sets  $A, B \subset \{1, \dots, n\}^2$  for which

$$\mathbb{E} [X_i X_j] \leq \mathbb{E} [Y_i Y_j] \quad \text{for all} \quad (i, j) \in A;$$
  
$$\mathbb{E} [X_i X_j] \geq \mathbb{E} [Y_i Y_j] \quad \text{for all} \quad (i, j) \in B;$$
  
$$\mathbb{E} [X_i X_j] = \mathbb{E} [Y_i Y_j] \quad \text{for all} \quad (i, j) \notin A \cup B$$

Let  $f : \mathbb{R}^n \to \mathbb{R}$  be a function whose second derivative satisfies

$$\partial_{ij} f \ge 0$$
 for all  $(i, j) \in A;$   
 $\partial_{ij} f \le 0$  for all  $(i, j) \in B.$ 

Show that

$$\mathbb{E}\left[f(X)\right] \le \mathbb{E}\left[f(Y)\right].$$

5. (10 pts) Let  $\phi_j : \mathbb{R} \to \mathbb{R}$   $(j = 1, \dots, n)$  be 1-Lipschitz (i.e.,  $|\phi_j(t) - \phi_j(s)| \le |t - s|$ ). Let  $w_j$  $(j = 1, \dots, n)$  be i.i.d  $\mathcal{N}(0, 1)$  random variables. For any  $T \subset \mathbb{R}^n$ , show that

$$\mathbb{E}\left[\sup_{t=(t_1,\cdots,t_n)\in T}\sum_{j=1}^n w_j\phi_j(t_j)\right] \leq \mathbb{E}\left[\sup_{t=(t_1,\cdots,t_n)\in T}\sum_{j=1}^n w_jt_j\right].$$

What does the above result mean in terms of the Gaussian complexity?

- 6. (10 pts) Show the convex property of KL divergence, i.e., prove that for  $0 \le \alpha \le 1$ , we have
  - (a)  $D(\alpha \mathbb{P}_1 + (1-\alpha)\mathbb{P}_2 ||\mathbb{Q}) \le \alpha D(\mathbb{P}_1 ||\mathbb{Q}) + (1-\alpha)D(\mathbb{P}_2 ||\mathbb{Q}),$
  - (b)  $D(\mathbb{P} \| \alpha \mathbb{Q}_1 + (1 \alpha) \mathbb{Q}_2) \le \alpha D(\mathbb{P} \| \mathbb{Q}_1) + (1 \alpha) D(\mathbb{P} \| \mathbb{Q}_2).$
- 7. (15 pts) Assume X obeys the uniform distribution on  $[\theta, \theta + 1]$  and the task is to estimate  $\theta$  from i.i.d observations  $X_1, \dots, X_n$ . A natural estimator is the first order statistic

$$X^{(1)} = \min_k X_k.$$

(a) Prove that

$$\mathbb{E}\left[ (X^{(1)} - \theta)^2 \right] = \frac{2}{(n+1)(n+2)}$$

(b) Use Le Cam method to show that the minimax risk to estimate  $\theta$  in the squared error is lower bounded by  $c/n^2$  where c > 0 is a numerical constant.