Homework Assignment 3

Due March 6th by midnight.

SDS 384-11 Theoretical Statistics

1. In this question we consider the Jackknife estimate of variance of a symmetrical measurable function of $n-1$ variables S. Let $X_1, \ldots, X_n - 1$ be i.i.d. Consider $S = S(X_1, \ldots, X_{n-1})$. Now let

$$S_i = S(X_1, \ldots, X_{i-1}, X_{i+1}, \ldots, X_n)$$

So $S = S_n$. If S has finite variance, then the Jackknife estimate of its variance is given by:

$$\text{var}_{JACK}(S) = \sum_i \left(S_i - \frac{\sum_j S_j}{n} \right)^2$$

In Efron and Stein's Annals of Statistics paper in 1981 the following remarkable result was proven.

$$\text{var}(S) \leq E\left(\text{var}_{JACK}(S)\right) \tag{1}$$

This is what we will prove here today. First define $V_i = E[S|X_1, \ldots, X_i] - E[S|X_1, \ldots, X_{i-1}]$.

(a) Prove that $\text{var}(S) = \sum_{i=1}^{n-1} EV_i^2$

(b) Prove that $E\text{var}_{JACK}(S) = (n-1)E[(S_1 - S_2)^2]/2$

(c) Now prove Eq 1.

2. In this question we will look at the Gaussian Lipschitz theorem. Consider $X_1, \ldots, X_n \overset{iid}{\sim} N(0, 1)$.

(a) Prove that the order statistics are 1-Lipschitz.

(b) Now show that, for large enough n,

$$c\sqrt{\log n} \leq E[\max_i X_i] \leq \sqrt{2 \log n}$$

where c is some universal constant.

i. For the upper bound, let $Y = \max_i X_i$. First show that $\exp(tE[Y]) \leq \sum_i E \exp(tX_i)$. Now pick a t to get the right form.

ii. For the lower bound, do the following steps.

A. Show that $E[Y] \geq \delta P(Y \geq \delta) + E[\min(Y, 0)]$

B. Now show that $E[\min(Y, 0)] \geq E[\min(X_1, 0)]$

C. Finally, relate $P(Y \geq \delta)$ to $P(X_1 \geq \delta)$ by using independence.

D. Now show that $P(X_1 \geq \delta) \geq \exp(-\delta^2/\sigma^2)/c$, for some universal constant c.

E. Choose the parameter δ carefully to have $P(X_1 \geq \delta) \geq 1/n$, for large enough n.

3. In class we proved McDiarmid's inequality for bounded random variables. But now we will look at extensions for unbounded R.V's. Take a look at "Concentration in unbounded metric spaces and algorithmic stability" by Aryeh Kontorovich, `https://arxiv.org/pdf/1309.1007.pdf`. Reproduce the proof of theorem 1. The steps of this proof is very similar to the martingale based inequalities we looked at in class.

4. Let $\mathcal{P}$ be the set of all distributions on the real line with finite first moment. Show that there does not exist a function $f(x)$ such that $Ef(X) = \mu^2$ for all $P \in \mathcal{P}$ where μ is the mean of P, and X is a random variable with distribution P.

5. Let g_1 and g_2 be estimable parameters within $\mathcal{P}$ with respective degrees m_1 and m_2.

   (a) Show $g_1 + g_2$ is an estimable parameter with degree $\leq \max(m_1, m_2)$.

   (b) Show $g_1 g_2$ is an estimable parameter with degree at most $m_1 + m_2$.