

# Homework Assignment 3

Due in class, Wednesday March 7th

SDS 384-11 Theoretical Statistics

- Suppose that  $X_1$  and  $X_2$  are zero-mean and sub-Gaussian with parameters  $\sigma_1$  and  $\sigma_2$  respectively. **Assume that the variance parameters are equal to the sub-gaussian parameters, i.e.  $E[X_1^2] = \sigma_1^2$  and  $E[X_2^2] = \sigma_2^2$ . This is needed for part (a) and (c) uses part (a).**
  - Show that the MGF of  $V := X_1^2 - E[X_1^2]$  can be bounded as  $E[e^{tV}] \leq e^{2\sigma_1^4 t^2}$  for  $0 \leq t \leq 1/4\sigma_1^2$ . *Hint: write the mgf in terms of  $X_1$  and an independent standard normal.*
  - If  $X_1$  and  $X_2$  are not independent, show that  $X_1 + X_2$  is sub-Gaussian with parameter at most  $\sqrt{2(\sigma_1^2 + \sigma_2^2)}$ .
  - If  $X_1$  and  $X_2$  are independent, show that  $X_1 X_2$  is sub-exponential with parameters  $(\sqrt{2}\sigma_1\sigma_2, \sqrt{2}\sigma_1\sigma_2)$ . **It seems that there is a typo in Martin's book, which is fixed. Thanks to Mohamed.**
- Let  $X_1, X_2, \dots, X_n$  be i.i.d. samples of random variable with density  $f$  on the real line. A standard estimate of  $f$  is the kernel density estimate

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - X_i}{h}\right)$$

where  $K : \mathbb{R} \rightarrow [0, \infty)$  is a kernel function satisfying  $\int_{-\infty}^{\infty} K(t)dt = 1$ , and  $h$  is a bandwidth parameter. We will measure the quality of  $\hat{f}$  using

$$\|\hat{f} - f\|_1 := \int_{-\infty}^{\infty} |\hat{f}(t) - f(t)|dt.$$

Prove that:

$$P(\|\hat{f} - f\|_1 \geq E\|\hat{f} - f\|_1 + \delta) \leq e^{-cn\delta^2},$$

where  $c$  is some constant.

- Let  $\{X_i\}_{i=1}^n$  be an i.i.d. sequence of Bernoulli variables with parameter  $\alpha \in (0, 1/2]$ , and consider the binomial random variable  $Z_n = \sum_i X_i$ . We want to prove for any  $\delta \in (0, \alpha)$ ,

$$P(Z_n \leq \delta n) \leq \exp(-nKL(\delta|\alpha)) \quad KL(\delta|\alpha) := \delta \log \frac{\delta}{\alpha} + (1 - \delta) \log \frac{1 - \delta}{1 - \alpha}$$

where  $KL(p, q)$  is the Kullback-Leibler divergence between two bernoullis with parameters  $p, q$  respectively. Show that the above is strictly better than Hoeffding's inequality.

4. Now we will prove a lower bound on the binomial tail to show that indeed what you derived in the last question is sharp upto polynomial factors. Define  $m = \lfloor n\delta \rfloor$  and  $\delta' = \frac{m}{n}$ .

- (a) Prove  $\frac{1}{n} \log P(Z_n \leq \delta n) \geq \frac{1}{n} \log \binom{n}{m} + \delta' \log \alpha + (1 - \delta') \log(1 - \alpha)$ .  
 (b) Show that

$$\frac{1}{n} \log \binom{n}{m} \geq -\delta' \log \delta' - (1 - \delta') \log(1 - \delta') - \frac{\log(n+1)}{n}$$

*Hint: Use the fact that for  $Y \sim \text{Bin}(n, m/n)$   $P(Y = k)$  is maximized at  $k = m$ .*

- (c) Now show that

$$P(Z_n \leq \delta n) \geq \frac{1}{n+1} \exp(-nKL(\delta||\alpha))$$