

## Math 608D, Assignment 1: Due Friday, Feb 2

1. **Concentration on the cube.** Let  $B_\infty^n := \{x \in \mathbf{R}^n : \|x\|_\infty \leq 1\} := \{x \in \mathbf{R}^n : -1 \leq x_i \leq 1\}$ . Let  $y = [1, 1, \dots, 1]/\sqrt{n}$  and consider a diagonal hyperplane through the cube,  $H := \{x \in B : \langle x, y \rangle = 0\}$ . Let  $H_\epsilon$  be the  $\epsilon$  neighborhood of  $H$ , i.e.,  $H_\epsilon := \{x \in B_\infty^n : |\langle x, y \rangle| \leq \epsilon\}$ . Give a bound on

$$\frac{\text{vol}(H_\epsilon)}{\text{vol}(B_\infty^n)}.$$

Above,  $\text{vol}$  is the usual Lebesgue measure of volume, i.e.,  $\text{vol}(B_\infty^n) = 2^n$ .

Note that for  $\epsilon \geq \sqrt{n}$ ,  $H_\epsilon = B_\infty^n$ . Is the bound you give showing concentration? I.e., does it show that  $H_\epsilon$  contains most of the volume even when  $\epsilon \ll \sqrt{n}$ ?

2. Prove the following version of Bernstein inequality:

**Theorem 0.1 (Bernstein inequality for bounded random variables)** Let  $X_1, X_2, \dots, X_N$  be independent, mean-zero, random variables which are all uniformly bounded by a positive scalar  $M$ , i.e.,  $\|X_i\|_\infty \leq M$ . Then for any  $t > 0$ ,

$$P\left(\left|\sum_{i=1}^N X_i\right| \geq t\right) \leq 2 \exp\left(-C \min\left(\frac{t^2}{\sum_i \mathbf{E}[X_i^2]}, \frac{t}{M}\right)\right).$$

**Remark 0.2** This version is quite useful for bounded random variables which have standard deviation much lower than  $M$ . As seen in class for sums of sub-exponential random variables, there is a combination of sub-Gaussian behavior and sub-exponential behavior in the bound.

3. As can be seen from the above version of Bernstein inequality, being able to control a random variable in multiple ways can lead to better tail bounds. Now suppose you have a sequence of mean-zero independent random variables  $X_1, X_2, \dots, X_N$  having the following properties:

- (a)  $\|X_i\|_1 := \mathbf{E}|X_i| = \eta$ .
- (b)  $\|X_i\|_2 := \sqrt{\mathbf{E}X_i^2} = \sigma$ ,
- (c)  $\|X_i\|_\infty = M$ ,
- (d)  $\|X_i\|_{\Psi_1} = a_1$ ,
- (e)  $\|X_i\|_{\Psi_2} = a_2$ .

(a) What can you say about the ordering of  $\eta, \sigma, M, a_1, a_2$ ? (Which is largest? etc.)

(b) In the same spirit as Bernstein inequality above, can you give a tail bound using some subset of the above properties? To be interesting, this bound should be a significant improvement over bounds that can be made using a single property, at least for some values of  $t$ . *Note: This is a very open-ended problem. However, I know of at least one useful solution which Xiaowei Li and Halyun Jeong came up with last year, which is leading to a nice improvement in a random matrix theory result.*

4. We show that Gaussian concentration extends, in an important special case, to sub-Gaussian variables. Let  $X$  be a vector with independent random entries  $X_1, X_2, \dots, X_n$ . Suppose for each  $i$

$$\mathbf{E}X_i = 0, \quad \mathbf{E}X_i^2 = 1, \quad \|X_i\|_{\Psi_2} \leq 10.$$

Show that the following hold:

- (a)  $\| \|X\|_2 \|_{\Psi_2} \leq C\sqrt{n}$ . (This part is not so exciting.)
  - (b)  $\| \|X\|_2 - \sqrt{n} \|_{\Psi_2} \leq C$ . (This part matches Gaussian concentration, is tricky to prove, and was the first step in a publication that arose from this class two years ago.)
5. A few months ago Nick Harvey nicely synthesized the analysis of stochastic gradient descent to a toy problem about a certain stochastic process. Prove or disprove Conjecture 2.1 from his notes. To be clear about the conjecture, the inequality should hold for all  $\delta < 1/2$ .