ECE 543: Statistical Learning Theory

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Homework 1

Assigned February 11; due February 24, 2021

Note: natural logarithms are used throughout.

1. A concentration bound for χ^2 random variables. Let X_1, \ldots, X_n be i.i.d. Gaussian random variables with mean 0 and variance 1. The sum of their squares, $U = X_1^2 + \ldots + X_n^2$ has the χ^2 distribution with n degrees of freedom. In this problem, you will prove the following tail bound for U:

$$\mathbf{P}\left(U-n \ge 2\sqrt{nt}+2t\right) \le e^{-t}, \quad \text{for all } t > 0.$$
(1)

(a) Let Z be a real-valued random variable, such that the bound

$$\log \mathbf{E}[e^{sZ}] \le \frac{vs^2}{2(1-cs)} \tag{2}$$

holds with some v, c > 0 for all 0 < s < 1/c. Use the Chernoff bounding trick to prove that

$$\mathbf{P}\left(Z \ge \sqrt{2vt} + ct\right) \le e^{-t}$$

for all t > 0.

(b) Now use the result of part (a) to prove (1).

Hint: Show that Z = U - n satisfies (2) for suitable choices of v and c. You may also find the following inequality useful:

$$-s - \frac{1}{2}\log(1 - 2s) \le \frac{s^2}{1 - 2s}, \quad 0 < s < 1/2.$$

2. Convexity. Let I be an interval of the real line. A function $f: I \to \mathbb{R}$ is called *convex* if

$$f(\lambda x + (1 - \lambda)y) \le \lambda f(x) + (1 - \lambda)f(y)$$

for all $\lambda \in [0, 1]$ and all $x, y \in I$. Equivalently, f is convex if the straight line segment joining the points (x, f(x)) and (y, f(y)) for any two $x, y \in I$ lies above the graph of f. Here are some useful facts about convex functions:

- Second-order condition. If I is an open interval and f is twice differentiable on I, then it is convex if and only if $f''(x) \ge 0$ for all $x \in I$.
- Jensen's inequality. If $f: I \to \mathbb{R}$ is convex, then for any random variable X with values in I,

$$f(\mathbf{E}[X]) \le \mathbf{E}[f(X)].$$

In this problem, you will get to explore the world of convex functions.

(a) Given a pair $x, y \in I$, consider the function $F_{x,y}: [0,1] \to \mathbb{R}$, defined by

$$F_{x,y}(t) = f(x + t(y - x)).$$

Prove that f is convex if and only if $F_{x,y}$ is convex for all $x, y \in I$.

Note: the function f is not necessarily differentiable.

(b) Suppose that $g : [0, a] \to \mathbb{R}$ is convex and monotone increasing. Prove that the function f(x) = g(|x|) is convex on the interval [-a, a].

(c) Use convexity to prove the following inequality: for any a > 0,

$$e^{ax} \le \cosh a + x \sinh a, \qquad -1 \le x \le 1.$$

(d) Let U be a real-valued random variable. Prove that its logarithmic moment-generating function $\psi(a) = \log \mathbf{E}[e^{aX}]$ is convex on the real line. (You may assume that interchanging derivative and expectation is permissible.)

3. Improving the Hoeffding bound. Let X_1, \ldots, X_n be *n* independent Bernoulli(θ) random variables. Their sum $S = X_1 + \ldots + X_n$ is a Binomial (n, θ) random variable. The Hoeffding bound tells us that, for any $\alpha \in [\theta, 1]$,

$$\mathbf{P}\left(S \ge \alpha n\right) \le e^{-2n(\alpha - \theta)^2}.$$
(3)

In this problem, you will obtain an improvement of (3).

(a) Use the Chernoff bounding trick to show that, for any $\alpha \in [\theta, 1]$,

$$\mathbf{P}\left(S \ge \alpha n\right) \le e^{-nd(\alpha \|\theta)},\tag{4}$$

where

$$d(\alpha \| \theta) := \alpha \log \frac{\alpha}{\theta} + (1 - \alpha) \log \frac{1 - \alpha}{1 - \theta}$$

is the Kullback–Leibler divergence (or relative entropy) between Bernoulli(α) and Bernoulli(θ) random variables.

(b) Prove that the bound in (4) is, indeed, tighter than the Hoeffding bound (3).

4. Generalizing Hoeffding's inequality. In class, we have proved Hoeffding's inequality that gives an exponential bound on the deviation probability $\mathbf{P}[|X_1 + \ldots + X_n| \ge t]$ for a sum of independent random variables that are bounded and have zero mean. In this problem, you will develop a generalization of Hoeffding's inequality to sums of dependent random variables that satisfy a certain weak orthogonality condition.

(a) In preparation for the rest of the problem, derive the inequality

$$\cosh x \le e^{x^2/2}, \qquad x \in \mathbb{R}$$

as a consequence of Hoeffding's lemma.

Hint: Find a suitable bounded random variable U, such that $\cosh x = \mathbf{E}[e^{xU}]$.

(b) We say that a collection X_1, \ldots, X_n of random variables is a *multiplicative system* if, for any $1 \le k \le n$ and any set of k indices $1 \le i_1 < i_2 < \ldots < i_k \le n$,

$$\mathbf{E}[X_{i_1}X_{i_2}\ldots X_{i_k}]=0.$$

Prove that if X_1, \ldots, X_n are a multiplicative system, then

$$\mathbf{E}\left[\prod_{i=1}^{n}(a_{i}X_{i}+b_{i})\right]=\prod_{i=1}^{n}b_{i}$$

for any choice of real constants a_1, \ldots, a_n and b_1, \ldots, b_n .

(c) Let U_1, \ldots, U_n be *n* possibly dependent random variables, and let *Z* be any real-valued random variable jointly distributed with them. For each *i*, define the martingale difference $X_i = \mathbf{E}[Z|U^i] - \mathbf{E}[Z|U^{i-1}]$ (where $\mathbf{E}[Z|U^0] \equiv \mathbf{E}Z$). Prove that X_1, \ldots, X_n are a multiplicative system.

(d) Consider a multiplicative system X_1, \ldots, X_n , such that $-c_i \leq X_i \leq c_i$ for each *i*, where $c_i > 0$ are some finite constants. Prove that, for any t > 0,

$$\mathbf{E}\left[\exp\left(t\sum_{i=1}^{n}X_{i}\right)\right] \leq \prod_{i=1}^{n}\cosh(tc_{i}).$$

(e) Now for the final step: prove that if X_1, \ldots, X_n are a multiplicative system of random variables satisfying the boundedness condition of part (c), then

$$\mathbf{P}\left(\left|\sum_{i=1}^{n} X_{i}\right| \ge t\right) \le 2\exp\left(-\frac{t^{2}}{2\sum_{i=1}^{n} c_{i}^{2}}\right).$$

5. Bin packing. This is a classical application of McDiarmid's inequality. Let X_1, \ldots, X_n be i.i.d. random variables taking values in [0, 1]. Each X_i is the size of a package to be shipped. The packages are shipped in bin of size 1, so each bin can hold any set of packages whose

sizes sum to at most 1. Let $B_n = f(X_1, \ldots, X_n)$ be the minimal number of bins needed to ship the packages with sizes X_1, \ldots, X_n . Computing B_n is a hard combinatorial optimization problem; however, we can say something about its mean and tail behavior.

- (a) Let μ be the common mean of the X_i 's. Prove that $\mathbf{E}B_n \ge n\mu$.
- (b) Prove that, for any $\varepsilon > 0$,

$$\mathbf{P}\left(\frac{B_n}{n} \le \mu - \varepsilon\right) \le \exp\left(-2n\varepsilon^2\right).$$