Math 170B Winter 2017

Problem Set 5

Lecturer: Steven Heilman Kyle Barron

Exercise 1

Let X be a standard Gaussian random variable. Let t > 0 and let n be a positive even integer. Show that

$$\mathbf{P}(X > t) \le \frac{(n-1)(n-3)\cdots(3)(1)}{t^n}.$$

That is, the function $t \mapsto \mathbf{P}(X > t)$ decays faster than any monomial.

Proof: Let X be a standard Gaussian random variable and let t > 0. Let n be a positive even integer. Recall that from problem set 3, question 2, we found that for n even, $E[X^n] = (n-1)(n-3)\cdots 1$. Now using the Markov Inequality we have

$$\mathbf{P}(X > t) \le \mathbf{P}(|X| > t) = \mathbf{P}(X^n > t^n) \le \frac{\mathbf{E}[X^n]}{t^n} = \frac{(n-1)(n-3)\cdots 1}{t^n},$$

where the second equality is since n is even, and the inequality is using the Markov Inequality, since X^n is nonnegative.

Exercise 2

Let X be a random variable. Let t > 0. Show that

$$\mathbf{P}(|X| > t) \le \frac{\mathbf{E}X^4}{t^4}.$$

Proof: Let X be a random variable and let t > 0.

$$\mathbf{P}(|X| > t) = \mathbf{P}(|X|^4 > t^4)$$
$$= \mathbf{P}(X^4 > t^4)$$
$$\leq \frac{\mathbf{E}[X^4]}{t^4}.$$

where the first equality is true because x^4 is an increasing function when $x \ge 0$ (and here both |X| and t are nonnegative), the second equality is true because $x^4 \ge 0$ always, and the third line uses the Markov Inequality.

Exercise 3

(The Chernoff Bound.) Let X be a random variable and let r > 0. Show that, for any t > 0,

$$\mathbf{P}(X > r) \le e^{-tr} M_X(t).$$

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Consequently, if X_1, \ldots, X_n are independent random variables with the same CDF, and if r, t > 0,

$$\mathbf{P}\left(\frac{1}{n}\sum_{i=1}^{n}X_{i}>r\right)\leq e^{-trn}(M_{X_{1}}(t))^{n}.$$

For example, if X_1, \ldots, X_n are independent Bernoulli random variables with parameter 0 , and if <math>r, t > 0,

$$\mathbf{P}\left(\frac{X_1 + \dots + X_n}{n} - p > r\right) \le e^{-trn} (e^{-tp} [pe^t + (1-p)])^n.$$

And if we choose t appropriately, then the quantity $\mathbf{P}\left(\frac{1}{n}\sum_{i=1}^{n}(X_i-p)>r\right)$ becomes exponentially small as either n or r become large. That is, $\frac{1}{n}\sum_{i=1}^{n}X_i$ becomes very close to its mean. Importantly, the Chernoff bound is much stronger than either Markov's or Cheyshev's inequality, since they only respectively imply that

$$\mathbf{P}\left(\left|\frac{X_1+\cdots+X_n}{n}-p\right|>r\right)\leq \frac{2p(1-p)}{nr},\quad \mathbf{P}\left(\left|\frac{X_1+\cdots+X_n}{n}-p\right|>r\right)\leq \frac{p(1-p)}{nr^2}.$$

Exercise 4

Let X_1, X_2, \ldots be independent random variables, each with exponential distribution with parameter $\lambda = 1$. For any $n \geq 1$, let $Y_n := \max(X_1, \ldots, X_n)$. Let 0 < a < 1 < b. Show that $\mathbf{P}(Y_n \leq a \log n) \to 0$ as $n \to \infty$, and $\mathbf{P}(Y_n \leq b \log n) \to 1$ as $n \to \infty$. Conclude that $Y_n / \log n$ converges to 1 in probability as $n \to \infty$.

Exercise 5

We say that random variables X_1, X_2, \ldots converge to a random variable X in L_2 if

$$\lim_{n \to \infty} \mathbf{E}|X_n - X|^2 = 0.$$

Show that, if X_1, X_2, \ldots converge to X in L_2 , then X_1, X_2, \ldots converges to X in probability.

Is the converse true? Prove your assertion.

Proof: Let $X, X_1, X_2, ...$ be random variables such that $X_1, X_2, ...$ converge to X in L_2 . That is,

$$\lim_{n \to \infty} \mathbb{E}[|X_n - X|^2] = 0.$$

We want to show that $X_1, X_2, ...$ converges to X in probability, that is, if for all $\epsilon > 0$,

$$\lim_{n \to \infty} \mathbf{P}(|X_n - X| > \epsilon) = 0.$$

First recall that the Markov Inequality says that

$$\mathbf{P}(|Z| \ge t) \le \frac{\mathrm{E}[|Z|^2]}{t^2}, \forall t > 0.$$

Let $\epsilon > 0$, let $t = \epsilon$, and let $Z = X_n - X$. So then we have

$$\mathbf{P}(|X_n - X| > \epsilon) \le \frac{\mathrm{E}[(X_n - X)^2]}{\epsilon^2}.$$

Since we know that $X_1, X_2, ...$ converge to X in L^2 ,

$$\lim_{n \to \infty} \mathbb{E}[(X_n - X)^2] = 0 \Rightarrow \lim_{n \to \infty} \mathbf{P}(|X_n - X| > \epsilon) = 0.$$

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So $X_1, X_2, ...$ converge in probability.

Recall that

Exercise 6

Let $X_1, X_2, ...$ be independent, identically distributed random variables such that $E|X| < \infty$ and $var(X) < \infty$. For any $n \ge 1$, define

$$Y_n := \frac{1}{n} \sum_{i=1}^n X_i^2.$$

Show that Y_1, Y_2, \ldots converges in probability. Express the limit in terms of EX and var(X).

Proof: Let $X_1, X_2, ...$ be independent and identically distributed with $\mathrm{E}[|X|] < \infty$ and $\mathrm{Var}(X) < \infty$. Define

$$Y_n := \frac{1}{n} \sum_{i=1}^n X_i^2.$$

Let $\epsilon > 0$. To show that $Y_1, Y_2, ...$ converges in probability we need to show that $\lim_{n \to \infty} \mathbf{P}(|Y_n - Y| > \epsilon) = 0$. I'll show that Y, the limit of Y_n as $n \to \infty$, is equal to the second moment of X_1 (which is the same for all X since they're independent and identically distributed).

$$\mathbf{P}(|Y_n - Y| > \epsilon) = P\left(\left|\frac{x_1^2 + \dots + x_n^2}{n} - \mathbf{E}[X_1^2]\right| > \epsilon\right)$$

$$= \frac{1}{\epsilon^2} \mathbf{E}\left[\left|\frac{x_1^2 + \dots + x_n^2}{n} - \mathbf{E}[X_1^2]\right|^2\right]$$

$$= \frac{1}{\epsilon^2} \mathbf{E}\left[\left(\frac{x_1^2 + \dots + x_n^2}{n} - \frac{n\mathbf{E}[X_1^2]}{n}\right)^2\right]$$

$$= \frac{1}{\epsilon^2} \mathbf{E}\left[\left(\frac{x_1^2 + \dots + x_n^2}{n} - \frac{\mathbf{E}[X_1^2] + \dots + \mathbf{E}[X_n^2]}{n}\right)^2\right]$$

$$= \frac{1}{\epsilon^2} \mathbf{E}\left[\left(\frac{x_1^2 + \dots + x_n^2}{n} - \frac{\mathbf{E}[X_1^2 + \dots + X_n^2]}{n}\right)^2\right]$$

$$= \frac{1}{\epsilon^2 n^2} \mathbf{E}\left[\left(x_1^2 + \dots + x_n^2 - \mathbf{E}[X_1^2 + \dots + X_n^2]\right)^2\right]$$

$$= \frac{1}{\epsilon^2 n^2} \mathbf{Var}(X_1^2 + \dots + X_n^2)$$

$$= \frac{1}{\epsilon^2 n} \mathbf{Var}(X_1^2).$$

Now letting $n \to \infty$, we have that $\frac{\operatorname{Var}(X_1^2)}{\epsilon^2 n} \to 0$. Therefore, Y_1, Y_2, \dots converges in probability to $\operatorname{E}[X_1^2] = \operatorname{Var}(X_1) + \operatorname{E}[X_1]^2$.