

## Statistics 522, Problem Set 1 Solutions

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1. Complete the proof of (7) in Inequality 3.4 on page 212, Pfs. i.e. show how the two one-sided arguments combine to yield the inequality with absolute value signs.

**Solution:** Let  $\tau \equiv \inf\{k \leq n : |S_k| \geq \lambda\}$ . Thus  $[\tau = k] = [|S_1| < \lambda, \dots, |S_{k-1}| < \lambda, |S_k| \geq \lambda]$ ,  $k = 1, \dots, n$ , and  $\sum_{k=1}^n [\tau = k] = [\max_{1 \leq k \leq n} |S_k| \geq \lambda]$ . Thus, with

$$a \equiv \min_{1 \leq k \leq n} P(|S_n - S_k| < (1 - c)\lambda),$$

$$\begin{aligned} aP(\max_{1 \leq k \leq n} |S_k| \geq \lambda) &\leq \sum_{k=1}^n P(|S_n - S_k| < (1 - c)\lambda)P(\tau = k) \\ &= \sum_{k=1}^n P([\tau = k] \cap [|S_n - S_k| < (1 - c)\lambda]) \quad \text{by independence} \\ &= \sum_{k=1}^n P([\tau = k] \cap [|S_k| \geq \lambda] \cap [|S_n - S_k| < (1 - c)\lambda]) \\ &\leq \sum_{k=1}^n P([\tau = k] \cap [|S_n| \geq c\lambda]) \\ &= P(|S_n| \geq c\lambda). \end{aligned}$$

2. Exercise 10.3.3, page 213, Pfs: Suppose that  $\epsilon_1, \dots, \epsilon_n$  are i.i.d. Rademacher random variables. Let  $a_1, \dots, a_n$  be real constants. For  $p \geq 1$  it holds that

$$A_p \left( \sum_1^n a_k^2 \right)^{1/2} \leq \left( E \left| \sum_1^n a_k \epsilon_k \right|^p \right)^{1/p}.$$

for some constants  $A_p$  and  $B_p$ . Establish this for  $p = 1$  with  $A_1 = 1/\sqrt{3}$  and  $B_1 = 1$ . [Hint: use Littlewood's inequality with  $r, s, t$  equal to 4, 2, 1.]

**Solution:** For  $p = 1$  it follows from Liapunov's inequality that  $E|Y| \leq (E|Y|^2)^{1/2}$ , so with  $Y = \sum_1^n a_k \epsilon_k$

$$E(Y^2) = \sum_1^n a_k^2,$$

and this gives the upper bound with  $B_1 = 1$ . For the lower bound we use Littlewood's inequality with  $r, s, t$  equal to  $r, 2, 1$  as suggested by the hint. Thus  $m_4 m_1^2 \geq m_2^3$ , or

$$E|Y|^2 \leq \{E|X|^4\}^{1/3} \{E|X|\}^{2/3},$$

or

$$\frac{\{E|Y|^2\}^{3/2}}{\{E|Y|^4\}^{1/2}} \leq E|Y|.$$

With  $Y = \sum_{i=1}^n a_i \epsilon_i$  we find that  $E(Y^2) = \sum_{i=1}^n a_i^2$  and

$$\begin{aligned} E|X|^4 &= E\left\{ \sum_{j,j',k,k'=1}^n a_j a_{j'} a_k a_{k'} \epsilon_j \epsilon_{j'} \epsilon_k \epsilon_{k'} \right\} \\ &= \sum_{i=1}^n a_i^4 + \binom{4}{2} \sum_{j < j'} a_j^2 a_{j'}^2 \\ &= \sum_{i=1}^n a_i^4 + 6 \sum_{j < j'} a_j^2 a_{j'}^2 \\ &\leq 3 \left( \sum_{i=1}^n a_i^2 \right)^2. \end{aligned}$$

Hence it follows that

$$E|Y| \geq \frac{\{E|Y|^2\}^{3/2}}{\{E|Y|^4\}^{1/2}} \geq \frac{(\sum a_i^2)^{3/2}}{\sqrt{3} \sum a_i^2} = \frac{1}{\sqrt{3}} \left( \sum_{i=1}^n a_i^2 \right)^{1/2}.$$

We conclude that Khintchine's inequality holds for  $p = 1$  with  $A_1 = 1/\sqrt{3}$  and  $B_1 = 1$ . The best possible constants  $A_p$  and  $B_p$  are known for all  $p$ ; for  $p = 1$  the best possible value of  $A_p$  is  $1/\sqrt{2}$ , and this is due to Szarek (1976), *Studia Math.* **63**, 197-208.

3. Exercise 10.3.4, page 213, Pfs. Hint: Use Jensen's inequality. Let  $X_1, \dots, X_n$  be independent with 0 means, and independent of the i.i.d. Rademacher rv's  $\epsilon_1, \dots, \epsilon_n$ ; thus  $P(\epsilon_k = \pm 1) = 1/2$ . Let  $\Phi$  be convex and  $\nearrow$  on  $R$ . Then

$$E\Phi\left(\left|\sum_1^n \epsilon_k X_k\right|/2\right) \leq E\Phi\left(\left|\sum_1^n X_k\right|\right) \leq E\Phi\left(2\left|\sum_1^n \epsilon_k X_k\right|\right).$$

**Solution:** Let  $X'_1, \dots, X'_n$  be an independent copy of  $X_1, \dots, X_n$ . Then since  $E(X'_k) = 0$ , it follows that

$$E\Phi\left(\left|\sum_1^n X_k\right|\right) = E\Phi\left(\left|\sum_1^n (X_k - EX'_k)\right|\right)$$

$$\begin{aligned}
&\leq E_X \Phi(E_{X'} | \sum_1^n (X_k - X'_k)|) \\
&\quad \text{by Jensens' inequality since } |\cdot| \text{ is convex} \\
&\leq E_X E_{X'} \Phi(| \sum_1^n (X_k - X'_k)|) \quad \text{since } \Phi \text{ is convex} \\
&= E_{X, X', \epsilon} \Phi(| \sum_1^n \epsilon_k (X_k - X'_k)|) \\
&\leq E_{X, X', \epsilon} \Phi(2\{ | \sum_1^n \epsilon_k X_k | + | \sum_1^n \epsilon_k X'_k | \}/2) \\
&\quad \text{since } \Phi \text{ is } \nearrow \\
&\leq \frac{1}{2} \left\{ E\Phi(2\{ | \sum_1^n \epsilon_k X_k | \}) + E\Phi(2\{ | \sum_1^n \epsilon_k X'_k | \}) \right\} \\
&\quad \text{since } \Phi \text{ is convex} \\
&= E\Phi(2\{ | \sum_1^n \epsilon_k X_k | \}) \\
&\quad \text{since the two terms have the same expectation.}
\end{aligned}$$

Thus the second inequality holds (the one on the right). Similarly, to prove the first inequality (the one on the left),

$$\begin{aligned}
E\Phi(| \sum_1^n \epsilon_k X_k | / 2) &= E\Phi(| \sum_1^n \epsilon_k (X_k - EX'_k) | / 2) \\
&\leq E_{X, \epsilon} \Phi(E_{X'} | \sum_1^n \epsilon_k (X_k - X'_k) | / 2) \\
&\quad \text{by Jensens' inequality since } |\cdot| \text{ is convex} \\
&\leq E_{X, \epsilon} E_{X'} \Phi(| \sum_1^n \epsilon_k (X_k - X'_k) | / 2) \quad \text{since } \Phi \text{ is convex} \\
&= E_{X, X'} \Phi(| \sum_1^n (X_k - X'_k) | / 2) \\
&\leq E_{X, X'} \Phi(\{ | \sum_1^n X_k | + | \sum_1^n X'_k | \} / 2) \\
&\quad \text{since } \Phi \text{ is } \nearrow \\
&\leq \frac{1}{2} \left\{ E\Phi(\{ | \sum_1^n X_k | \}) + E\Phi(\{ | \sum_1^n X'_k | \}) \right\} \\
&\quad \text{since } \Phi \text{ is convex}
\end{aligned}$$

$$= E\Phi\left(\left|\sum_1^n \epsilon_k X_k\right|\right)$$

since the two terms have the same expectation.

4. (A weak law of large numbers under the assumption of uncorrelated summands.) Suppose that  $X_1, X_2, \dots$  are uncorrelated and  $E(X_j^2) \leq M < \infty$  for all  $j \geq 1$ . Show that  $\bar{X} - E(\bar{X}_n) = (S_n - ES_n)/n \rightarrow_p 0$  and  $\bar{X}_n - E(\bar{X}_n) \rightarrow_2 0$  as  $n \rightarrow \infty$ .

**Solution:** Since the  $X_n$ 's are uncorrelated,

$$\text{Var}(S_n) = \sum_{j=1}^n \text{Var}(X_j) + \sum_{i \neq j} \text{Cov}(X_i, X_j) = \sum_{j=1}^n \text{Var}(X_j) \leq \sum_{j=1}^n E(X_j^2) \leq nM$$

and hence  $\text{Var}(\bar{X}_n) = n^{-2}\text{Var}(S_n) \leq M/n$ . Therefore, by Chebychev's inequality

$$P(|\bar{X}_n - E(\bar{X}_n)| \geq \epsilon) \leq \epsilon^{-2}\text{Var}(\bar{X}_n) \leq \epsilon^{-2}\frac{M}{n} \rightarrow 0$$

for every  $\epsilon > 0$ ; i.e.  $\bar{X}_n - E(\bar{X}_n) \rightarrow_p 0$ . Since  $E[\bar{X}_n - E(\bar{X}_n)]^2 = \text{Var}(\bar{X}_n) \leq M/n \rightarrow 0$ , we also have  $\bar{X}_n - E(\bar{X}_n) \rightarrow_2 0$ .

5. ( $L_1$ -convergence in the SLLN.) Suppose that  $X_1, \dots, X_n, \dots$  are i.i.d with  $E|X_1| < \infty$ . Show that  $\bar{X}_n \rightarrow_1 \mu \equiv E(X_1)$ ; i.e.  $E|\bar{X}_n - \mu| \rightarrow 0$  as  $n \rightarrow \infty$ . [Hint: show that  $|\bar{X}_n| \leq Y_n$  where  $Y_n$  is uniformly integrable, and that this implies the uniform integrability of  $\bar{X}_n$ .

**Solution:** Note that

$$|\bar{X}_n| \leq n^{-1} \sum_{i=1}^n |X_i| \equiv Y_n$$

where  $Y_n$  is uniformly integrable by Vitali's theorem:  $E(Y_n) = E|X_1|$  for every  $n$  and  $Y_n \rightarrow_{a.s.} E|X_1| \equiv Y_0$  by the strong law of large numbers and  $E(Y_n) \rightarrow E(Y_0) = E|X_1|$ . It follows that  $\{\bar{X}_n\}$  is uniformly integrable, and by Vitali's theorem again  $E|\bar{X}_n - \mu| \rightarrow 0$  as  $n \rightarrow \infty$ ; i.e.  $\bar{X}_n \rightarrow_1 \mu \equiv E(X_1)$ .