

# STAT 205A - Problem Set 05

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**(5.1)** Let  $(X_n)$  be i.i.d. with  $E|X| < \infty$ . Let  $M_n = \max(X_1, \dots, X_n)$ . Prove that  $\frac{1}{n}M_n \rightarrow 0$  a.s.

**proof** Let  $S_n = \sum_{i=1}^n |X_i|$ . By the SLLN, we have  $\frac{S_n}{n} \rightarrow E|X|$  a.s. Now we have

$$\frac{|X_n|}{n} = \frac{S_n}{n} - \frac{S_{n-1}}{n} = \frac{S_n}{n} - \frac{S_{n-1}}{n-1} \frac{n-1}{n}$$

and since  $\lim_{n \rightarrow \infty} \frac{S_n}{n} = E|X|$  a.s. and  $\frac{n-1}{n} = 1$  a.s., we have with probability 1,  $\frac{|X_n|}{n}$  converges and its limit is 0. Now for all  $\omega \in \Omega$  such that  $\frac{|X_n(\omega)|}{n} \rightarrow 0$ , we have

$$|M_n(\omega)| \leq \max(|X_1(\omega)|, \dots, |X_n(\omega)|)$$

therefore taking the limsup

$$\limsup_n \frac{|M_n|}{n} \leq \limsup_n \frac{\max(|X_1(\omega)|, \dots, |X_n(\omega)|)}{n} = \limsup_n \frac{|X_n(\omega)|}{n} = 0$$

thus  $\frac{M_n(\omega)}{n}$  converges to 0. This proves that  $\frac{M_n}{n} \rightarrow 0$  a.s.

**(5.2)** Let  $0 \leq X_1 \leq X_2 \leq \dots$  be random variables such that  $E X_n \sim an^\alpha$  and  $\text{var}(X_n) \leq Bn^\beta$ , where  $B < \infty$ , and  $0 < \beta < 2\alpha < \infty$ . Prove that  $n^{-\alpha} X_n \rightarrow a$  a.s.

**proof** Since  $E X_n \sim an^\alpha$ , there exists  $N$  such that for all  $n > N$ ,  $E X_n > 0$ . Without loss of generality, we restrict the sequence to the terms  $(X_n)_{n > N}$ . Let  $Y_n = \frac{X_n}{E X_n}$ . Then  $E Y_n = 1$ ,  $\text{var} = \frac{\text{var} X_n}{(E X_n)^2}$ , and to prove the result, it suffices to show that  $Y_n \rightarrow 1$  a.s. Indeed, if  $Y_n \rightarrow 1$  a.s., then  $\frac{X_n}{n^\alpha} = a Y_n \frac{E X_n}{a n^\alpha}$ , and this converges to  $a$  whenever  $Y_n$  converges to 1.

Let  $\epsilon > 0$ . Using Chebyshev's inequality, we can bound deviations of  $Y_n$

$$P(|Y_n - 1| \geq \epsilon) \leq \frac{\text{var} Y_n}{\epsilon^2} = \frac{\text{var} X_n}{\epsilon^2 (E X_n)^2} \leq \frac{Bn^\beta}{\epsilon^2 (E X_n)^2} \sim \frac{B}{\epsilon^2 a} \frac{1}{n^{2\alpha-\beta}}$$

where  $2\alpha - \beta > 0$  by assumption.

If we consider a subsequence  $(Y_{n_j})_j$ , the deviations of the subsequence are then given by

$$P(|Y_{n_j} - 1| \geq \epsilon) \leq \sim \frac{B}{\epsilon^2 a} \frac{1}{n_j^{2\alpha-\beta}}$$

in particular, if we choose  $n_j = j^\gamma$  where  $\gamma$  is an integer and  $\gamma > \frac{1}{2\alpha-\beta}$ , then the upper bound become summable since

$$\frac{1}{n_j^{2\alpha-\beta}} = \frac{1}{j^{\gamma(2\alpha-\beta)}}$$

and  $\gamma(2\alpha - \beta) > 1$ .

Therefore by the first Borel-Cantelli Lemma,  $P(|Y_{n_j} - 1| \geq \epsilon \text{ infinitely often}) = 0$ . Therefore almost surely,  $|Y_n - 1| < \epsilon$  ultimately. And since this is true for all  $\epsilon$ , we have  $Y_{n_j} \rightarrow 1$  a.s.

Now consider  $\omega$  such that  $Y_{n_j} \rightarrow 1$  a.s. We have for all  $n_j \leq n \leq n_{j+1}$ ,

$$\frac{X_{n_j}(\omega)}{\mathbb{E} X_{n_{j+1}}} \leq \frac{X_n(\omega)}{\mathbb{E} X_n} \leq \frac{X_{n_{j+1}}(\omega)}{\mathbb{E} X_{n_j}}$$

which can be rewritten as

$$\frac{\mathbb{E} X_{n_j}}{\mathbb{E} X_{n_{j+1}}} Y_{n_j}(\omega) \leq Y_n(\omega) \leq \frac{\mathbb{E} X_{n_{j+1}}}{\mathbb{E} X_{n_j}} Y_{n_{j+1}}(\omega)$$

both bounds converge to 1, as  $j \rightarrow \infty$  (by assumption on the expectation,  $\frac{\mathbb{E} X_{n_j}}{\mathbb{E} X_{n_{j+1}}} \sim 1$ , and by choice of  $\omega$ ,  $Y_{n_j}(\omega) \rightarrow 1$ ). This shows that for all such  $\omega$ ,  $Y_n(\omega) \rightarrow 1$ . This proves that whenever  $Y_{n_j} \rightarrow 1$ , then  $Y_n \rightarrow 1$ , which concludes the proof.

**(5.3)** Prove that the following are equivalent

- (i)  $X_n \rightarrow X$  in probability
- (ii) There exists a sequence  $\epsilon_n \downarrow 0$  such that  $P(|X_n - X| > \epsilon_n) \leq \epsilon_n$  for all  $n$ .
- (iii)  $\mathbb{E} \min(X_n - X, 1) \rightarrow 0$

**proof**

- (i)  $\Rightarrow$  (ii): we have for all  $\epsilon > 0$ ,  $P(|X_n - X| > \epsilon) \rightarrow 0$  as  $n \rightarrow \infty$ . In particular, taking  $\epsilon = 1/k$ ,  $k \geq 1$ , there exists  $N_k$  such that for all  $n > N_k$ ,  $P(|X_n - X| > 1/k) \leq 1/k$ . Without loss of generality, we can assume the sequence  $N_k$  non-decreasing. Now define the sequence  $\epsilon_n$  as follows
  - for all  $n \leq N_1$ ,  $\epsilon_n = 1$ . Then for all  $n \leq N_1$ , we do have  $P(|X_n - X| > \epsilon_n) \leq 1 = \epsilon_n$ .
  - for all  $k \geq 1$ , for all  $n \in (N_k, N_{k+1}]$ ,  $\epsilon_n = \frac{1}{k}$ . Then we have by definition of  $N_k$  for all  $n \in (N_k, N_{k+1})$ ,  $P(|X_n - X| > \epsilon_n) \leq \frac{1}{k} = \epsilon_n$ .
- (ii)  $\Rightarrow$  (i): Let  $\epsilon > 0$ . Since  $\epsilon_n \downarrow 0$ , there exists  $N$  such that for all  $n > N$ ,  $\epsilon_n < \epsilon$ . For all  $n > N$ , we have  $|X_n - X| > \epsilon \Rightarrow |X_n - X| > \epsilon_n$ , therefore  $P(|X_n - X| > \epsilon) \leq P(|X_n - X| > \epsilon_n) \leq \epsilon_n$ , which converges to 0 as  $n \rightarrow \infty$ . This shows  $X_n \rightarrow X$  in probability.
- (i)  $\Rightarrow$  (iii): let  $\epsilon > 0$ . Writing the expectation as an integral, we can partition  $\Omega = A \cup A^c$ , where  $A = \{\omega : \min(|X_n - X|, 1) > \epsilon/2\}$ . Then

$$\begin{aligned} \mathbb{E} \min(|X_n - X|, 1) &= \int_{\Omega} \min(|X_n - X|, 1) d\mu \\ &= \int_A \min(|X_n - X|, 1) d\mu + \int_{A^c} \min(|X_n - X|, 1) d\mu \end{aligned}$$

for all  $\omega \in A^c$ , we have  $\min(X_n(\omega) - X(\omega), 1) \leq \epsilon/2$ , therefore  $\int_{A^c} \min(|X_n - X|, 1) d\mu \leq \epsilon/2$ .

To bound the second term in the sum, we use convergence in probability: for all  $\omega \in A$ , we have  $\min(X_n(\omega) - X(\omega), 1) \leq 1$ , thus  $\int_A \min(|X_n - X|, 1) d\mu \leq \mu(A) = P(|X_n - X| > \epsilon/2)$  which converges to 0 by assumption. Therefore there exists  $N$  such that for all  $n > N$ ,  $\int_A \min(|X_n - X|, 1) d\mu \leq \epsilon/2$ . Combining the two bounds, we have for all  $n > N$ ,  $\mathbb{E} \min(|X_n - X|, 1) \leq \epsilon$ . Since this is true for all  $\epsilon > 0$ , we have the desired result.

- (iii)  $\Rightarrow$  (i): Let  $0 < \epsilon < 1$ . Consider the function  $\phi(x) = \min(x, 1)$ , defined on  $\mathbb{R}_+$ . We have by Markov's inequality

$$P(\phi(|X_n - X|) > \epsilon) \leq \frac{E \min(|X_n - X|, 1)}{\phi(\epsilon)} = \frac{E \min(|X_n - X|, 1)}{\epsilon}$$

which converges to 0 by assumption. This concludes the proof.

**(5.4. Investment problem)** Assume that at the beginning of each year, you can buy bonds for \$1 that are worth \$ $a$  at the end of the year, or stocks that are worth a random amount  $V_n \geq 0$ . If you always invest a fixed proportion  $p$  of your wealth in bonds, then your wealth at the end of year  $n + 1$  is

$$W_{n+1} = W_n(ap + (1 - p)V_n)$$

where  $a \geq 1$ . Suppose  $V_1, V_2, \dots$  are i.i.d. with  $E V_n^2 < \infty$  and  $E \frac{1}{V_n^2} < \infty$

- (i) Show that  $\frac{\log W_n}{n} \rightarrow c(p)$  a.s., where  $c(p)$  is a function of  $p$

**proof** We first observe that

- by convexity of  $x \mapsto x^2$ ,  $(E V)^2 < E V^2 < \infty$  thus  $E V < (E V^2)^{\frac{1}{2}} < \infty$
- by convexity of  $x \mapsto x^{-2}$ ,  $\frac{1}{(E V)^2} < E \frac{1}{V^2} < \infty$  thus  $E V > \frac{1}{(E \frac{1}{V^2})^{\frac{1}{2}}} > 0$

Let  $w_1$  be the initial wealth. Then we have for all  $n$ ,

$$\frac{\log W_n}{n} = \frac{w_1 + \sum_{i=1}^n \log(ap + (1 - p)V_i)}{n}$$

where the first term  $\frac{w_1}{n}$  is deterministic and converges to 0. The random variables  $\log(ap + (1 - p)V_n)$  are i.i.d. To show that they have finite expectation, we first have the following upper bound by concavity of the log:

$$E \log(ap + (1 - p)V) \leq \log E(1 + ap + (1 - p)V) = \log(1 + ap + (1 - p)E V) < \infty$$

and to obtain a lower bound, we distinguish two cases: if  $p > 0$ , then  $\log(ap + (1 - p)V) \geq \log(p)$  and taking the expectation we have  $E \log(ap + (1 - p)V) > \log(p) > -\infty$ . If  $p = 0$ , then we need to check  $E \log V > -\infty$ . This is obtained by writing

$$\begin{aligned} E \log V &\geq E 1_{V < 1} \log V \\ &\geq E 1_{V < 1} \left( \frac{1}{2} - \frac{1}{2V^2} \right) && \text{since for all } v < 1, \frac{1}{2} - \frac{1}{2v^2} \leq \log v \\ &> -\infty && \text{since } E \frac{1}{V^2} < \infty \end{aligned}$$

Therefore by the SLLN

$$\frac{\sum_{i=1}^n \log(ap + (1 - p)V_i)}{n} \rightarrow E \log(ap + (1 - p)V) \text{ a.s.}$$

which shows that

$$\frac{\log W_n}{n} \rightarrow E \log(ap + (1 - p)V) \text{ a.s.}$$

- (ii) Show that  $c(p)$  is concave

**proof** Let  $c(p) = E \log(ap + (1-p)V)$ , and let  $l(\omega)(p) = ap + (1-p)V(\omega)$ , a linear function in  $p$ . We have for all  $p, p' \in [0, 1]$ , and for all  $\lambda \in [0, 1]$ , and all  $\omega$ ,

$$\begin{aligned} \log l(\omega)(\lambda p + (1-\lambda)p') &= \log \lambda l(\omega)(p) + (1-\lambda) \log l(\omega)(p') && \text{by linearity of } e(\omega)(\cdot) \\ &\geq \lambda \log l(\omega)(p) + (1-\lambda) \log l(\omega)(p') && \text{by Jensen's inequality} \end{aligned}$$

then taking the expectation, we have

$$c(\lambda p + (1-\lambda)p') \geq \lambda c(p) + (1-\lambda)c(p')$$

i.e.  $c(\cdot)$  is concave.

- (iii) By investigating  $c'(0)$  and  $c'(1)$ , give sufficient conditions on  $V$  that guarantee that the optimal choice of  $p$  is in  $(0, 1)$

**proof** Assuming the conditions of the derivation under the expectation theorem hold, we have

$$c'(p) = E \frac{a - V}{ap + (1-p)V}$$

thus

$$\begin{aligned} c'(0) &= E \frac{a - V}{V} \\ c'(1) &= E \frac{a - V}{a} \end{aligned}$$

and we have  $c'(p)$  is non-increasing since  $c$  is concave, thus  $c'(0) \geq c'(1)$ . To have the expectation minimal in the open interval  $p \in (0, 1)$ , it suffices that the derivative vanishes inside  $(0, 1)$ , i.e.  $c'(0) < 0 < c'(1)$ , i.e.

$$E \frac{a - V}{V} < 0 < \frac{a - V}{a}$$

which we can rewrite as

$$\begin{aligned} E \frac{1}{V} &> \frac{1}{a} \\ EV &> a \end{aligned}$$

- (iv) Suppose  $P(V = 1) = P(V = 4) = \frac{1}{2}$ . Find the optimal  $p$  as a function of  $a$ .

**answer** Under this assumption, we have

$$\begin{aligned} EV &= \frac{1}{2}(1 + 4) = \frac{5}{2} \\ E \frac{1}{V} &= \frac{1}{2}\left(1 + \frac{1}{4}\right) = \frac{5}{8} \end{aligned}$$

and we have by (iii) the following cases:

- (a) if  $a \geq EV = \frac{5}{2}$ , then  $c'(1) \geq 0$ , and  $p = 1$  is optimal (buy all bonds).  
(b) if  $a \leq \frac{1}{E \frac{1}{V}} = \frac{8}{5}$ , then  $c'(0) \leq 0$ , and  $p = 0$  is optimal (buy all stock).

(c) if  $a \in (\frac{8}{5}, \frac{5}{2})$ , then  $c'(0) < 0 < c'(1)$  and the optimal  $p$  is strictly in  $(0, 1)$ . In this case we can compute the derivative of  $c$ :

$$c'(p) = \frac{1}{2} \left( \frac{a-1}{ap+(1-p)} + \frac{a-4}{ap+4(1-p)} \right)$$

and  $c'(p) = 0$  if and only if

$$\frac{a-1}{ap+(1-p)} + \frac{a-4}{ap+4(1-p)} = 0$$

i.e.

$$(a-1)(ap+4(1-p)) + (a-4)(ap+(1-p)) = 0$$

i.e.

$$2p(a-4)(a-1) + 5a - 8 = 0$$

i.e.

$$p(a) = \frac{8-5a}{2(a-4)(a-1)}$$

note that this expression is increasing in  $a$ , as one expects (if the value of bond increases),  $p(a) \in (0, 1)$  whenever  $a \in (\frac{5}{8}, \frac{5}{2})$ .

**(5.5)** Prove the deterministic lemma we used in the proof of the Glivenko-Cantelli Theorem

**Lemma 1** If  $F_1, F_2, \dots$  and  $F$  are distribution functions and

(i)  $F_n(x) \rightarrow F(x)$  for all  $x \in \mathbb{Q}$

(ii)  $F_n(x) \rightarrow F(x)$  and  $F_n(x-) \rightarrow F(x-)$  for each atom  $x$  of  $F$

then  $F_n$  converges uniformly to  $F$ .

**proof** We first show that  $F_n(x) \rightarrow F(x)$  and  $F_n(x-) \rightarrow F(x-)$  for all  $x \in \mathbb{R}$ . This is true for jump points by assumption. Consider  $x \in \mathbb{R}$  such that  $F$  is continuous at  $x$ . Let  $p, q \in \mathbb{Q}$  such that  $p < x < q$ . Then for all  $n$ ,  $F_n(p) \leq F_n(x) \leq F_n(q)$ , and taking limits,

$$F(p) \leq \liminf_n F_n(x) \leq \limsup_n F_n(x) \leq F(q)$$

since  $\lim_{p \uparrow x} F(p) = \lim_{p \downarrow x} F(q) = F(x)$ , it follows that  $\liminf F_n(x) = \limsup F_n(x) = F(x)$ , which proves  $F_n(x) \rightarrow F(x)$ .

To prove the result for  $x-$ , we have for all  $n$ ,

$$F_n(x-) \leq F_n(x)$$

thus

$$\begin{aligned} \limsup_n F_n(x-) &\leq \limsup_n F_n(x) &&= F(x) \text{ by the previous part} \\ &= F(x-) &&\text{by continuity} \end{aligned}$$

now let  $q \in \mathbb{Q}$  with  $q < x$ . We have  $F_n(q) \leq F_n(x-)$  thus taking the limit

$$F(q) \leq \liminf F_n(x-)$$

and letting  $q \uparrow x-$

$$F(x-) \leq \liminf F_n(x-)$$

which proves the result.

Now we have  $F_n(x) \rightarrow F(x)$  and  $F_n(x-) \rightarrow F(x-)$  for all  $x \in \mathbb{R}$ . We next show uniform convergence. Let  $\epsilon > 0$ . There exists a finite family of points in  $\mathbb{R}$ ,  $x_1 < \dots < x_k$  such that

$$\begin{aligned} F(x_{i+1}^-) - F(x_i) &\leq \epsilon \text{ for all } i \\ F(x_1) - 0 &\leq \epsilon \\ 1 - F(x_k) &\leq \epsilon \end{aligned}$$

one can construct the sequence by induction, simply by

- $x_1 = \sup\{x : F(x) \leq \epsilon\}$
- $x_{i+1} = \sup\{x : F(x) \leq \epsilon + F(x_i)\}$

Then for each  $i$ ,  $F(x_{i+1}-) - F(x_i) \leq \epsilon$  as required. The process will terminate after finitely many iterations since we observe that for each  $i$   $F(x_{i+1}) - F(x_i) \geq \epsilon$  (otherwise  $F(x_{i+1}) < F(x_i) + \epsilon$ , and by right continuity there exists  $x > x_{i+1}$  such that  $F(x) < F(x_i) + \epsilon$ , which contradict the definition of  $x_{i+1}$ ).

Now for all  $x \in \mathbb{R}$ , there exists  $i$  such that  $x_i \leq x \leq x_{i+1}$ , thus

$$\begin{aligned} F_n(x_i) &\leq F_n(x) \leq F_n(x_{i+1}-) \\ F(x_i) &\leq F(x) \leq F(x_{i+1}-) \end{aligned}$$

thus

$$\begin{aligned} F_n(x) - F(x) &\geq F_n(x_i) - F(x_{i+1}-) \\ &= F_n(x_i) - F(x_i) + F(x_i) - F(x_{i+1}-) \\ &\geq F_n(x_i) - F(x_i) - \epsilon \end{aligned}$$

and

$$\begin{aligned} F_n(x) - F(x) &\leq F_n(x_{i+1}-) - F(x_i) \\ &= F_n(x_{i+1}-) - F(x_{i+1}-) + F(x_{i+1}-) - F(x_i) \\ &\leq F_n(x_{i+1}-) - F(x_{i+1}-) + \epsilon \end{aligned}$$

and since we proved convergence of  $F_n(x) \rightarrow F(x)$  and  $F_n(x-) \rightarrow F(x-)$  for all  $x \in \mathbb{R}$ , for  $n$  large enough we have

$$\begin{aligned} F_n(x_i) - F(x_i) &\geq -\epsilon \\ F_n(x_{i+1}-) - F(x_{i+1}-) &\leq \epsilon \end{aligned}$$

for all  $x_i$  (there are finitely many such conditions). Therefore for  $n$  large enough

$$\begin{aligned} F_n(x) - F(x) &\geq -2\epsilon \\ F_n(x) - F(x) &\leq 2\epsilon \end{aligned}$$

which concludes the proof.