

## Homework 5 solutions: convergence of random variables

EE 325: Probability and Random Processes, Autumn 2019

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1. Let  $f(t)$  be a bandlimited Fourier series defined with fundamental period  $T = 1$ . That is,

$$f(t) = \sum_{k=-b}^b a[k] \exp(j2\pi kt), \quad t \in [0, 1]$$

where  $a[k]$  are the Fourier series coefficients of  $f(t)$ . From an experiment,  $f(U_1), \dots, f(U_n)$  are obtained where  $U_1, \dots, U_n$  are given i.i.d. realizations of a Uniform $[0, 1]$  random variable. Knowing the values of  $U_1, \dots, U_n$  develop an approximation for the Fourier series coefficients  $a[k]$ . Evaluate the mean-squared error of your approximation for  $a[k]$ ? It would be desirable if the mean-squared error decreases to zero as  $n \rightarrow \infty$ .

**Solution:** In this problem, we will use a technique named as Monte-Carlo integration. Let  $g_k(U) = f(U) \exp(-j2\pi kU)$  be a function of a Uniform $[0, 1]$  random variable  $U$ . The expected value of  $g_k(U)$  is given by

$$\mathbb{E}[g_k(U)] = \int_0^1 f(u) \exp(-j2\pi ku) du. \quad (1)$$

The Fourier series coefficients of  $f(t)$  are given by

$$a[k] = \int_0^1 f(t) \exp(-j2\pi kt) dt = \mathbb{E}[g_k(U)]. \quad (2)$$

That is, an estimate of  $\mathbb{E}(g_k(U))$  will lead us to an estimate of the Fourier series coefficient  $a[k]$ . By the weak law of large numbers,

$$\hat{A}[k] := \frac{1}{n} \sum_{i=1}^n g_k(U_i) \xrightarrow{\mathbb{P}} a[k] \quad (3)$$

as  $n \rightarrow \infty$ . Since  $g_k(U_i), i = 1, \dots, n$  are i.i.d., therefore,

$$\mathbb{E} \left[ \left| \hat{A}[k] - a[k] \right|^2 \right] = \frac{\text{var}(|g_k(U)|)}{n}.$$

The careful reader would notice that  $g_k(U_i)$  is a complex variable, so the mean-squared error involves  $|g_k(U)|$  and not  $g_k(U)$ . As long as  $\text{var}(g_k(U))$  is bounded, the mean-squared error between  $\hat{A}[k]$  and  $a[k]$  decreases to zero with  $n$ .

Finally,  $\text{var}(g_k(U))$  is bounded since

$$\text{var}(|g_k(U)|) \leq \mathbb{E}[|g_k(U)|^2] = \mathbb{E}[|f(U)|^2] = \int_0^1 |f(u)|^2 du$$

the energy of  $f(t)$  in one period is bounded.

2. Let  $\{X_1, X_2, X_3, \dots\}$  be a sequence of *zero-mean* dependent random variables such that,

$$\text{cov}(X_i, X_j) = \frac{1}{n^{|i-j|}}. \quad (4)$$

Notice that as  $|i - j|$  increases, the covariance between  $X_i$  and  $X_j$  decreases. Is it true that  $(S_n/n) \xrightarrow{\mathbb{P}} c$ , where  $S_n = X_1 + X_2 + \dots + X_n$  and  $c$  is some constant? If yes, find the value of  $c$ .

**Solution:** First it will be shown that  $\text{var}(S_n/n) \rightarrow 0$ . Then, by Chebychev inequality, the convergence in probability will be established. Note that

$$\text{var}\left(\frac{S_n}{n}\right) = \frac{1}{n^2} \text{var}(S_n).$$

Unless  $\text{var}(S_n)$  grows quadratically with  $n$ , we can expect  $\text{var}(S_n/n)$  to decrease to zero. And  $\text{var}(S_n)$  will grow quadratically if  $X_1, X_2, \dots, X_n$  are heavily correlated with each other. The given covariance condition hints otherwise. That is why there is hope for  $\text{var}(S_n/n)$  to converge to zero. Formally,  $\text{var}(S_n)$  will be computed next.

$$\begin{aligned} \text{var}(S_n) &= \text{var}\left(\sum_{i=1}^n X_i\right) \\ &= \mathbb{E}\left[\left(\sum_{i=1}^n (X_i - \mu_i)\right)^2\right] \\ &= \sum_{i=1}^n \sum_{j=1}^n \mathbb{E}\left[(X_i - \mu_i)(X_j - \mu_j)\right] \\ &= \sum_{i=1}^n \sum_{j=1}^n \text{cov}(X_i, X_j) \\ &= n + \frac{2(n-1)}{n} + \frac{2(n-2)}{n^2} + \dots + \frac{2}{n^{n-1}} \end{aligned} \quad (5)$$

Using (5),

$$\begin{aligned} \text{var}\left(\frac{S_n}{n}\right) &= \frac{1}{n} + \frac{2}{n^2} - \frac{2}{n^3} + \frac{2(n-2)}{n^4} + \dots + \frac{2}{n^{n+1}}. \\ \text{Hence, } \lim_{n \rightarrow \infty} \text{var}\left(\frac{S_n}{n}\right) &= 0. \end{aligned} \quad (6)$$

Since  $\{X_n\}_{n \in \mathbb{N}}$  are zero-mean, therefore  $\mathbb{E}(S_n) = 0$ . By Chebyshev's inequality,

$$0 \leq \mathbb{P}\left(\left|\frac{S_n}{n} - 0\right| > \epsilon\right) \leq \frac{1}{\epsilon^2} \text{var}\left(\frac{S_n}{n}\right).$$

Using (6), as  $n \rightarrow \infty$ ,  $\mathbb{P}\left(\left|\frac{S_n}{n} - 0\right| > \epsilon\right) \rightarrow 0$ . Hence,  $S_n \xrightarrow{\mathbb{P}} 0$ .

3. Let  $\{X_1, X_2, X_3, \dots\}$  be an iid sequence of  $\text{Unif}[0, 1]$  random variables. Let  $Y_n = n(1 - X_{(n)})$ . Find if  $Y_n \xrightarrow{d} Y$ . If yes, find the cdf of the limit  $Y$ .

**Solution:** Recall that  $X_{(n)} = X_{n:n} = \max\{X_1, X_2, \dots, X_n\}$ . Its cdf is given by,

$$F_{X_{(n)}}(x) = \mathbb{P}(X_{(n)} \leq x) = [F_{X_1}(x)]^n, \text{ since all } \{X_n\}_{n \in \mathbb{N}} \text{ are i.i.d. random variables.} \quad (7)$$

Since  $X_n$  are i.i.d. Uniform random variables, therefore,

$$\begin{aligned} F_{X_{(n)}}(x) &= 0 \quad \text{for } x \leq 0 \\ &= x^n \quad \text{for } 0 < x \leq 1 \\ &= 1 \quad \text{for } x > 1 \end{aligned} \quad (8)$$

It is given that  $Y_n = n(1 - X_{(n)})$ , then  $F_{Y_n}(y)$  can be worked out as:

$$F_{Y_n}(y) = \mathbb{P}(Y_n \leq y) = \mathbb{P}(1 - X_{(n)} \leq y/n) = 1 - F_{X_{(n)}}(1 - y/n).$$

Using (8),

$$\begin{aligned} F_{Y_n}(y) &= 0 \quad \text{for } y < 0 \\ &= 1 - (1 - y/n)^n \quad \text{for } 0 \leq y \leq n \\ &= 1 \quad \text{for } y > n \end{aligned}$$

As  $n \rightarrow \infty$ , the interval  $y > n$  reduces to  $\infty$ . Thus,  $F_{Y_n}(y)$  can be simplified as

$$\begin{aligned} F_Y(y) &= \lim_{n \rightarrow \infty} F_{Y_n}(y) = 0 & \text{for } y < 0 \\ &= 1 - e^{-y} & \text{for } y \geq 0. \end{aligned}$$

Hence,  $Y_n \xrightarrow{d} Y$ , where  $Y$  is an Exponential(1) random variable.

4. Assume that  $\{Y_n\}_{n \in \mathbb{N}}, \{Z_n\}_{n \in \mathbb{N}}$  are sequences of random variables such that  $Y_n \xrightarrow{\mathbb{P}} Y$  and  $Z_n \xrightarrow{\mathbb{P}} Z$ . Show that  $Y_n + Z_n \xrightarrow{\mathbb{P}} Y + Z$ . (Hint: You may find the triangle inequality  $|x + y| \leq |x| + |y|$  useful.)

**Solution:**  $Y_n$  converges in probability to  $Y$ , i.e.,  $Y_n \xrightarrow{\mathbb{P}} Y$ . This is equivalent to,

$$\lim_{n \rightarrow \infty} \mathbb{P}(|Y_n - Y| > \epsilon/2) = 0, \text{ for any } \epsilon > 0.$$

Define a set  $D_Y$  as follows:

$$D_Y(n) = \{|Y_n - Y| \leq \epsilon/2\} = \{\omega : |Y_n(\omega) - Y(\omega)| \leq \epsilon/2\}.$$

Similarly, let

$$D_Z(n) = \{|Z_n - Z| \leq \epsilon/2\}.$$

Using the triangle inequality it is known that,

$$|(Y_n + Z_n) - (Y + Z)| \leq |Y_n - Y| + |Z_n - Z| \quad (9)$$

Now consider an event  $D_{YZ}$  as follows:

$$D_{YZ}(n) = \{|Y_n + Z_n - (Y + Z)| \leq \epsilon\}$$

Using the triangle inequality, observe that  $D_Y(n) \cap D_Z(n) \subseteq D_{YZ}(n)$  for all  $n \in \mathbb{N}$ .

Since  $Y_n \xrightarrow{\mathbb{P}} Y$ , it is noted that  $\mathbb{P}(D_Y(n)) \rightarrow 1$  as  $n \rightarrow \infty$ . Similarly, since  $Z_n \xrightarrow{\mathbb{P}} Z$ , it is noted that  $\mathbb{P}(D_Z(n)) \rightarrow 1$  as  $n \rightarrow \infty$ . It is further noted that  $\mathbb{P}(D_Z(n) \cap D_Y(n)) \rightarrow 1$  as  $n \rightarrow \infty$ . (Use  $\mathbb{P}(A \cap B) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cup B)$  to derive the last part.)

Therefore  $1 \geq \mathbb{P}(D_{YZ}(n)) \geq \mathbb{P}(D_Y(n) \cap D_Z(n))$ . As RHS tends to 1,  $\mathbb{P}(D_{YZ}(n))$  will converge to 1. Thus,  $(Y_n + Z_n) \xrightarrow{\mathbb{P}} (Y + Z)$ .

5. Let  $\{X_n\}_{n \in \mathbb{N}}$  be a sequence of random variable. Assume that  $X_n \sim \text{Poisson}(1/n)$ . Show that  $X_n \xrightarrow{\mathbb{P}} 0$  and  $nX_n \xrightarrow{\mathbb{P}} 0$ .

**Solution:** Since  $X_n \sim \text{Poisson}(1/n)$  therefore  $\mathbb{E}(X_n) = 1/n$ . Using the Markov inequality,

$$\mathbb{P}(|X_n| \geq \epsilon) \leq \frac{\mathbb{E}(X_n)}{\epsilon} = \frac{1}{n\epsilon} \rightarrow 0 \text{ as } n \rightarrow \infty.$$

Thus,

$$\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - 0| \geq \epsilon) = 0 \text{ or } X_n \xrightarrow{\mathbb{P}} 0.$$

For showing  $nX_n \xrightarrow{\mathbb{P}} 0$ , the Markov inequality is not useful since  $\mathbb{E}(nX_n) = 1$ . Directly probability computation will be used. For any  $\epsilon > 0$ ,

$$\mathbb{P}(nX_n > \epsilon) = \mathbb{P}(X_n > \epsilon/n) = 1 - \mathbb{P}(nX_n = 0) = 1 - \mathbb{P}(X_n = 0) = 1 - e^{-1/n}.$$

Applying limits,

$$\lim_{n \rightarrow \infty} \mathbb{P}(|nX_n - 0| \geq \epsilon) = 0 \text{ for all } \epsilon > 0$$

which proves the desired result.

6. Assuming that  $Z_n \xrightarrow{\mathbb{P}} Z$ , show that  $Z_n \xrightarrow{d} Z$ . (Hint: You need to show that  $\mathbb{P}(Z_n \leq x) \rightarrow \mathbb{P}(Z \leq x)$  for all  $x$  where  $F_Z(x)$  is continuous. If  $F_Z(x)$  is continuous at  $x$ , then there is an interval  $(x - \delta, x + \delta)$  in which  $F_Z(x)$  is continuous. Further,  $|Z_n - Z| \leq \epsilon$  with high probability. Connect these pieces with suitable inequalities to get the result.)

**Solution:** To show that  $F_{Z_n}(x) \rightarrow F_Z(x)$ , we need to show that  $\lim_{n \rightarrow \infty} \mathbb{P}(Z_n \leq x) \rightarrow \mathbb{P}(Z \leq x)$  when  $F_Z(x)$  is continuous. Using the law of total probability, first note that

$$\mathbb{P}(Z_n \leq x) - \mathbb{P}(Z \leq x) = \{\mathbb{P}(Z_n \leq x, Z > x + \delta) + \mathbb{P}(Z_n \leq x, Z \leq x + \delta)\} - \mathbb{P}(Z \leq x).$$

Similarly,  $F_Z(x)$  can be rewritten as,

$$\mathbb{P}(Z \leq x) = \mathbb{P}(Z_n \leq x + \delta, Z \leq x) + \mathbb{P}(Z_n > x + \delta, Z \leq x).$$

Using the above results we can write

$$\begin{aligned} \mathbb{P}(Z_n \leq x) - \mathbb{P}(Z \leq x) &= \mathbb{P}(Z_n \leq x, Z > x + \delta) + \mathbb{P}(Z_n \leq x, Z \leq x + \delta) - \mathbb{P}(Z_n \leq x + \delta, Z \leq x) \\ &\quad - \mathbb{P}(Z_n > x + \delta, Z \leq x). \end{aligned}$$

The first and the fourth term imply that  $|Z_n - Z| > \delta$ . Since  $Z_n \xrightarrow{\mathbb{P}} Z$ , therefore  $\mathbb{P}(|Z_n - Z| > \delta) \leq \epsilon$  for large enough  $n$ . Thus,

$$\begin{aligned} 0 \leq \mathbb{P}(Z_n \leq x) - \mathbb{P}(Z \leq x) &\leq \epsilon + \mathbb{P}(Z_n \leq x, Z \leq x + \delta) - \mathbb{P}(Z_n \leq x + \delta, Z \leq x) \\ &\leq \epsilon + \mathbb{P}(Z_n \leq x + \delta, Z \leq x + \delta) - \mathbb{P}(Z_n \leq x + \delta, Z \leq x), \end{aligned}$$

In the last step we use the fact that  $\{Z_n \leq x\} \subseteq \{Z_n \leq (x + \delta)\}$ . Finally,

$$\begin{aligned} 0 \leq \mathbb{P}(Z_n \leq x) - \mathbb{P}(Z \leq x) &\leq \epsilon + \mathbb{P}(Z_n \leq x + \delta, x \leq Z \leq x + \delta) \\ &\leq \epsilon + \mathbb{P}(x < Z \leq x + \delta) \text{ since } \mathbb{P}(A \cap B) \leq \mathbb{P}(A). \end{aligned}$$

Since  $F_Z(x)$  is continuous at  $x$ ,  $\mathbb{P}(x < Z \leq x + \delta) = F_Z(x + \delta) - F_Z(x) \rightarrow 0$  as  $\delta \rightarrow 0$ . As  $n \rightarrow \infty$ ,  $\delta$  (and  $\epsilon$ ) can be made arbitrarily small. Thus, we have  $0 \leq \mathbb{P}(Z_n \leq x) - \mathbb{P}(Z \leq x) \leq \epsilon + \epsilon_1$ , where both  $\epsilon, \epsilon_1 \rightarrow 0$  as  $n \rightarrow \infty$ . This proves the result.

Observe that the continuity of  $F_Z$  at  $x$  is critical for arguing that  $\epsilon_1 \rightarrow 0$ .

7. Let  $\{X_n\}_{n \in \mathbb{Z}}$  be a sequence of random variables. Assume  $b$  to be a real number. Show that  $X_n \xrightarrow{\mathcal{L}^2} b$  if and only if,

$$\lim_{n \rightarrow \infty} \mathbb{E}(X_n) = b \quad \text{and} \quad \lim_{n \rightarrow \infty} \text{var}(X_n) = 0.$$

**Solution:** First note that for any r.v.  $X$ ,  $\mathbb{E}((X - b)^2) = \text{var}(X) + (b - \mathbb{E}(X))^2$ . Thus,

$$\mathbb{E}(|X_n - b|^2) = \text{var}(X_n) + (b - \mathbb{E}(X_n))^2.$$

Observe that both the terms on the RHS of (7) are positive. Thus,  $\lim_{n \rightarrow \infty} \mathbb{E}(|X_n - b|^2) = 0$  if and only if  $\lim_{n \rightarrow \infty} \mathbb{E}(X_n) = b$  **and**  $\lim_{n \rightarrow \infty} \text{var}(X_n) = 0$ .

8. (*Typical sets*) Let  $X_1, X_2, \dots, X_n$  be i.i.d. Bernoulli( $p$ ) random variables. Let  $p(x), x = 0, 1$  be the pmf of  $X$ . Consider the typical set,

$$A_n(\epsilon) := \left\{ x_1^n : \left| -\frac{1}{n} \log_2(p(x_1^n)) - H_2(p) \right| \leq \epsilon \right\}.$$

(a) Show that for any fixed  $\epsilon > 0$  and large enough  $n$ ,  $\mathbb{P}((X_1, X_2, \dots, X_n) \in A_n(\epsilon)) \geq (1 - \epsilon)$ .

(b) Let  $h_2(p) = -p \log_2 p - (1 - p) \log_2 (1 - p)$ . Show that for any  $(x_1, \dots, x_n) \in A_n(\epsilon)$ ,

$$2^{-nh_2(p) - n\epsilon} \leq \mathbb{P}((X_1, \dots, X_n) = (x_1, \dots, x_n)) \leq 2^{-nh_2(p) + n\epsilon}.$$

Thus, all typical set sequences have approximately the same probability of  $\approx 2^{-nh_2(p)}$ .

(c) Show that the number of typical sequences  $|A_n(\epsilon)|$  satisfies the following inequality,

$$(1 - \epsilon)2^{nh_2(p) - n\epsilon} \leq |A_n(\epsilon)| \leq 2^{nh_2(p) + n\epsilon}.$$

Thus about  $2^{nh_2(p)}$  typical sequences are there and they require  $nh_2(p)$  bits for representation. (Hint: use the Union bound.)

**Solution:**

(a) By WLLN and using  $p(X_1^n) = \prod_{i=1}^n p(X_i)$ ,

$$-\frac{1}{n} \log_2(p(X_1^n)) \xrightarrow{\mathbb{P}} H_2(p)$$

Thus,

$$\lim_{n \rightarrow \infty} \mathbb{P} \left\{ x_1^n : \left| -\frac{1}{n} \log_2(p(x_1^n)) - H_2(p) \right| \leq \epsilon \right\} = 1$$

i.e.,  $\lim_{n \rightarrow \infty} \mathbb{P}(A_n(\epsilon)) \rightarrow 1$ . Hence for any  $\epsilon > 0$ , there exists an  $n_0$ , such that  $\mathbb{P}(A_n(\epsilon)) \geq (1 - \epsilon)$  for all  $n \geq n_0$ .

(b) On the set  $A_n(\epsilon)$ , we have,

$$\left\{ \left| -\frac{1}{n} \log_2(p(x_1^n)) - H_2(p) \right| \right\} \leq \epsilon$$

which can be rewritten as shown below:

$$\begin{aligned} -\epsilon &\leq -\frac{1}{n} \log_2(p(x_1^n)) - H_2(p) \leq \epsilon \\ -n\epsilon &\leq -\log_2(p(x_1^n)) - nH_2(p) \leq n\epsilon \\ -n\epsilon - nH_2(p) &\leq \log_2(p(x_1^n)) \leq n\epsilon - nH_2(p) \\ 2^{(-n\epsilon - nH_2(p))} &\leq p(x_1^n) \leq 2^{(n\epsilon - nH_2(p))} \end{aligned}$$

This proves the desired result.

(c) We know that  $\sum_{x_1^n \in A_n(\epsilon)} p(x_1^n) = \mathbb{P}(A_n(\epsilon)) \leq 1$ . From part(b),  $p(x_1^n) \geq 2^{(-n\epsilon - nH_2(p))}$ ,  $x_1^n \in A_n(\epsilon)$ . Using these results, the following can be derived:

$$\begin{aligned} \sum_{x_1^n \in A_n(\epsilon)} 2^{(-n\epsilon - nH_2(p))} &\leq \sum_{x_1^n \in A_n(\epsilon)} p(x_1^n) \leq 1, \text{ or} \\ 2^{(-n\epsilon - nH_2(p))} \sum_{x_1^n \in A_n(\epsilon)} 1 &\leq 1, \text{ or} \\ 2^{(-n\epsilon - nH_2(p))} |A_n(\epsilon)| &\leq 1. \end{aligned}$$

Thus  $|A_n(\epsilon)| \leq 2^{(n\epsilon + nH_2(p))}$ .

For deriving the lower bound on  $|A_n(\epsilon)|$ , consider  $\mathbb{P}(A_n(\epsilon)) \geq 1 - \epsilon$  and  $p(x_1^n) \leq 2^{(n\epsilon - nH_2(p))}$ .

$$\begin{aligned} \sum_{x_1^n \in A_n(\epsilon)} p(x_1^n) &\geq 1 - \epsilon \text{ which leads to} \\ \sum_{x_1^n \in A_n(\epsilon)} 2^{(-n\epsilon + nH_2(p))} &\geq 1 - \epsilon. \end{aligned}$$

By rearranging the terms, we get  $|A_n(\epsilon)| \geq (1 - \epsilon)2^{(n\epsilon - nH_2(p))}$ .