

# Homework Assignment 1

Due via canvas Feb 11th

SDS 384-11 Theoretical Statistics

Please **do not** add your name to the HW submission.

1. (1+3+(1+1+2) pts) We will do some examples of convergence in distribution and convergence in probability here.

- (a) Let  $X_n \sim N(0, 1/n)$ . Does  $X_n \xrightarrow{d} 0$ ?

*Solution.* Yes, first we show that  $X_n$  converges in probability to 0.

$$\begin{aligned}\lim_{n \rightarrow \infty} \Pr(|X_n - 0| > \epsilon) &= \lim_{n \rightarrow \infty} \Pr(|X_n|^2 > \epsilon^2) \\ &\leq \lim_{n \rightarrow \infty} \frac{\text{var}(X_n)}{\epsilon^2} \\ &= \lim_{n \rightarrow \infty} \frac{1}{n\epsilon^2} \\ &= 0\end{aligned}$$

Thus  $X_n \xrightarrow{p} 0$  which implies that  $X_n \xrightarrow{d} 0$ .

- (b) Let  $\{X_n\}$  be independent r.v.'s such that  $P(X_n = n^\alpha) = 1/n$  and  $P(X_n = 0) = 1 - 1/n$  for  $n \geq 1$ , where  $\alpha \in (-\infty, \infty)$  is a constant. For what values of  $\alpha$ , will you have  $X_n \xrightarrow{q.m} 0$ ? For what values will you have  $X_n \xrightarrow{p} 0$ ?

*Solution.*

Convergence in quadratic mean:

$$\begin{aligned}E[|X_n|^2] &= (n^\alpha)^2 \frac{1}{n} \\ &= \frac{n^{2\alpha}}{n}\end{aligned}$$

The above will converge to zero if  $2\alpha < 1$ , or  $\alpha < \frac{1}{2}$ .

Convergence in Probability:

For  $\epsilon \geq n^\alpha$  we have  $\Pr(|X_n| > \epsilon) = 0$ . For  $\epsilon < n^\alpha$  we have  $\Pr(|X_n| > \epsilon) = \frac{1}{n}$ . This probability converges to zero for all values of  $\alpha$ .

- (c) Consider the average of  $n$  i.i.d random variables  $X_1, \dots, X_n$  with  $E[X_1] = \mu$  and  $E[|X_1|] < \infty$ . Write true or false. Explain.

- i.  $\bar{X}_n = o_P(1)$  *Solution.* We know that  $\bar{X}_n$  converges to  $\mu$  in probability. If  $\mu \neq 0$ ,  $\bar{X}_n = o_P(1)$  is false.
- ii.  $\exp(\bar{X}_n - \mu) = o_P(1)$  *Solution.* We know that  $\bar{X}_n - \mu$  converges to 0 in probability. By continuous mapping, If  $\exp(\bar{X}_n - \mu) \xrightarrow{P} 1$ . So false.
- iii.  $(\bar{X}_n - \mu)^2 = O_P(1/n)$   
*Solution.* Fix  $\epsilon > 0$ . Now  $P((\bar{X}_n - \mu)^2 \geq \underbrace{\frac{\sigma^2}{\epsilon}}_{M_\epsilon}) \leq \epsilon$ . So, its true.

2. (8 pts) Consider random variables  $X_1, \dots, X_n$  be IID r.v's with mean  $\mu$  and variance  $\sigma^2 := \text{var}(X_i)$ . We will use the following statistic to estimate  $\theta = \mu^2$ .

$$\hat{\theta} = \frac{1}{\binom{n}{2}} \sum_{i < j} X_i X_j$$

- (a) Find constants  $C_1, C_2$  where

$$\hat{\theta} - \mu^2 = \frac{C_1}{\binom{n}{2}} \sum_{i < j} (X_i - \mu)(X_j - \mu) + \frac{C_2 \mu}{n} \sum_i (X_i - \mu)$$

*Solution.*

$$C_1 = 1, C_2 = 2.$$

- (b) Show that the first term is  $O_P(1/n)$  and the second term is  $O_P(1/\sqrt{n})$ .

*Solution.*

Calculate variance of the first part to note that

$$\frac{1}{n^4} \text{var} \left( \sum_{i \neq j} (X_i - \mu)(X_j - \mu) \right) = \sum_{i \neq j} E[(X_i - \mu)^2] E[(X_j - \mu)^2] \leq \sigma^4 / n^2$$

Similarly compute the variance of the second part to see that it is  $c/n$  for some constant  $c$ . Note that a random var  $X$  with mean zero is always  $O_P(\sqrt{\text{var}(X)})$ . To see this, note:

$$P(|X| \geq \sqrt{\text{var}(X)/\epsilon}) \leq \epsilon$$

- (c) Argue that  $\hat{\theta} \xrightarrow{P} \mu^2$ . *Solution.*

So, by this logic,  $\text{var}(\hat{\theta} - \mu^2) \leq C/n$ , which shows  $\hat{\theta} \xrightarrow{P} \mu^2$  via convergence in quadratic mean. To see this note that  $\text{var}(A + B) \leq 2 \max(\text{var}(A), \text{var}(B))$ .

3. (8 pts) If  $X_n \xrightarrow{d} X \sim \text{Poisson}(\lambda)$ , is it necessarily true that  $E[g(X_n)] \rightarrow E[g(X)]$ ?

- (a)  $g(x) = 1(x \in (0, 10))$

*Solution.* It is not necessarily true that  $E[g(X_n)] \rightarrow E[g(X)]$  because there is a discontinuity in  $g$  at 0 and 10. Take the following counter example:

Let  $X_n = X + \frac{1}{n}$ . It is simple to show that  $X_n \xrightarrow{P} X$ , thus  $X_n \xrightarrow{d} X$ .

$$\lim_{n \rightarrow \infty} \Pr(|X_n - X| > \epsilon) = \lim_{n \rightarrow \infty} \Pr(|X + \frac{1}{n} - X| > \epsilon) = \lim_{n \rightarrow \infty} \Pr(\frac{1}{n} > \epsilon) = 0$$

Now we need to show that  $E[g(X_n)] \not\rightarrow E[g(X)]$ . We pick a convenient  $\lambda$  to show that the result doesn't hold. For simplicity let  $\lambda \rightarrow 0$ . Thus  $E[g(X)] = \Pr(X \in (0, 10)) = 0$  as  $\lambda \rightarrow 0$ , however

$$E[g(X_n)] = \Pr(X_n \in (0, 10)) = 1$$

as  $\lambda \rightarrow 0$ , thus  $E[g(X_n)] \not\rightarrow E[g(X)]$ .

(b)  $g(x) = e^{-x^2}$

*Solution.* Yes, from the Portmanteau Theorem it is true that  $E[g(X_n)] \rightarrow E[g(X)]$  because  $g(x)$  is bounded by 0 and 1 and continuous on the real line.

(c)  $g(x) = \text{sgn}(\cos(x))$  [ $\text{sgn}(x) = 1$  if  $x > 0$ ,  $-1$  if  $x < 0$  and  $0$  if  $x = 0$ .]

*Solution.* Yes it is true that  $E[g(X_n)] \rightarrow E[g(X)]$ . First the function  $g(x)$  is bounded as it only takes on the values  $(-1, 0, 1)$ . Second the discontinuities only occur when  $\cos(x) = 0$  which can be defined by the set  $A = \{\pi(\frac{1}{2} + n)\}_{n=0}^{\infty}$ . We define  $C(g) = \mathbb{R} - A$  to be the set of values on which  $g(x)$  is continuous. Since  $X$  only takes on integer values  $\Pr(X \in C(g)) = 1$ , thus by the Portmanteau theorem  $E[g(X_n)] \rightarrow E[g(X)]$ .

(d)  $g(x) = x$  *Solution.* Since  $g(x)$  is not bounded, it is not necessarily true that  $E[g(X_n)] \rightarrow E[g(X)]$ . Take the following counter example: Let

$$= \begin{cases} X & \text{w.pr. } \frac{n-1}{n} \\ n & \text{w.pr. } \frac{1}{n} \end{cases} \quad (1)$$

Clearly  $X_n \xrightarrow{d} X$ , however

$$\begin{aligned} \lim_{n \rightarrow \infty} E[g(X_n)] &= \lim_{n \rightarrow \infty} E[X_n] \\ &= \lim_{n \rightarrow \infty} \left( \frac{1}{n}n + E[X] \frac{n-1}{n} \right) \\ &= 1 + E[X] \\ &\neq E[X] \end{aligned}$$

Therefore  $E[g(X_n)] \not\rightarrow E[g(X)]$ .

4. (6 pts) Let  $X_1, \dots, X_n$  be independent r.v's with mean zero and variance  $\sigma_i^2 := E[X_i^2]$  and  $s_n^2 = \sum_i \sigma_i^2$ . If  $\exists \delta > 0$  s.t. as  $n \rightarrow \infty$ ,

$$\frac{\sum_i E|X_i|^{2+\delta}}{s_n^{2+\delta}} \rightarrow 0,$$

then  $\sum_i X_i/s_n$  converges weakly to the standard normal.

*Soln.*

*Proof.* We want to show that

$$\frac{\sum_i E|X_i|^{2+\delta}}{s_n^{2+\delta}}$$

shows up in the upper bound on the quantity in the Lindeberg condition. If the above quantity converges to 0 as  $n \rightarrow \infty$  then the Lindeberg must also be satisfied and thus  $\sum_i X_i/s_n \xrightarrow{d} N(0, 1)$ .

$$\begin{aligned} \frac{1}{s_n^2} \sum_{i=1}^n E[|X_i|^2 1(|X_i| \geq \epsilon s_n)] &= \frac{1}{s_n^2} \sum_{i=1}^n E \left[ |X_i|^2 1(|X_i|^\delta \geq \epsilon^\delta s_n^\delta) \right] \\ &\leq \frac{1}{s_n^2} \sum_{i=1}^n E \left[ |X_i|^2 \frac{|X_i|^\delta}{\epsilon^\delta s_n^\delta} \right] \\ &= \frac{1}{\epsilon^\delta} \frac{\sum_{i=1}^n E|X_i|^{2+\delta}}{s_n^{2+\delta}} \end{aligned}$$

We used the fact that for a positive number  $X$ ,

$$1(X \geq \epsilon) \leq X/\epsilon.$$

Thus, under the condition, the Lindeberg condition is also met. □