MATH 556 - EXERCISES 7: SOLUTIONS

1. (a) $Y_n = \max\{X_1, ..., X_n\}$ so in the limit as $n \longrightarrow \infty$ we have the limit for *fixed* y as

$$F_{Y_n}(y) = \{F_X(y)\}^n = y^n \longrightarrow \begin{cases} 0 & y < 1 \\ 1 & y \geq 1 \end{cases}$$

that is, a step function with single step of size 1 at $y = 1$. Hence the limiting random variable Y is a discrete variable with $P[Y = 1] = 1$, that is, the limiting distribution is *degenerate* at 1. For $Z_n = \min\{X_1, ..., X_n\}$ so in the limit as $n \longrightarrow \infty$ we have the limit for *fixed* z as

$$F_{Z_n}(z) = 1 - \{1 - F_X(z)\}^n = 1 - (1 - z)^n \longrightarrow \begin{cases} 0 & z \leq 0 \\ 1 & z > 0 \end{cases}$$

that is, a step function with single step of size 1 at $z = 0$. Hence the limiting random variable Z is a discrete variable with $P[Z = 0] = 1$: the limiting distribution is *degenerate* at 0. Note here that the limiting function is **not** a cdf as it is not right-continuous, but that the limiting distribution does still exist - the ordinary definition of convergence in distribution only refers to pointwise convergence **at points of continuity of the limit function**, and here is limit function is not continuous at zero.

Note that these results are intuitively reasonable as, as the sample size gets increasingly large, we will obtain a random variable arbitrarily close to each end of the range. Note also that these results describe *convergence in distribution*, but also we have for $1 > \varepsilon > 0$, as $n \longrightarrow \infty$

$$P[|Y_n - 1| < \varepsilon] = P[1 - Y_n < \varepsilon] = P[1 - \varepsilon < Y_n] = 1 - P[Y_n < 1 - \varepsilon] = 1 - \varepsilon^n \longrightarrow 1$$

$$P[|Z_n - 0| < \varepsilon] = P[Z_n < \varepsilon] = 1 - (1 - \varepsilon)^n \longrightarrow 1$$

so we also have *convergence in probability* of Y_n to 1 and of Z_n to 0.

(b) $Z_n = \min\{X_1, ..., X_n\}$ so

$$F_{Z_n}(z) = 1 - \{1 - F_X(z)\}^n = 1 - \left(1 - \left(1 - \frac{1}{z}\right)\right)^n = 1 - \frac{1}{z^n} \qquad z > 1$$

and so, in the limit as $n \longrightarrow \infty$ we have the limit for *fixed* z as

$$F_{Z_n}(z) \longrightarrow \begin{cases} 0 & z \leq 1 \\ 1 & z > 1 \end{cases}$$

that is, a step function with single step of size 1 at $z = 1$. Hence the limiting random variable Z is a discrete variable with

$$P[Z = 1] = 1$$

and the limiting distribution is *degenerate* at 1. Again, here, the limiting function is not a cdf as it not right continuous.

Now if $U_n = Z_n^n$, we have from first principles that for $u > 1$

$$F_{U_n}(u) = P[U_n \leq u] = P[Z_n^n \leq u] = P\left[Z_n \leq u^{1/n}\right] = 1 - \frac{1}{\left(u^{1/n}\right)^n} = 1 - \frac{1}{u}$$

which is a valid cdf, but which does not depend on n. Hence the limiting distribution of U_n is precisely

$$F_U(u) = 1 - \frac{1}{u} \qquad u > 1$$

(c) $Y_n = \max\{X_1, ..., X_n\}$ so

$$F_{Y_n}(y) = \{F_X(y)\}^n = \left(\frac{1}{1+e^{-y}}\right)^n \qquad y \in \mathbb{R}$$

and so, in the limit as $n \longrightarrow \infty$ we have the limit for *fixed* y as $F_{Y_n}(y) \longrightarrow 0$ for all y. Hence there is *no limiting distribution*.

However if $U_n = Y_n - \log n$, we have from first principles that for $u > -\log n$

$$F_{U_n}(u) = P[U_n \le u] = P[Y_n - \log n \le u]$$
$$= P[Y_n \le u + \log n] = F_{Y_n}(u + \log n) = \left(\frac{1}{1+e^{-u-\log n}}\right)^n$$

so that

$$F_{U_n}(u) = \left(\frac{1}{1+\dfrac{e^{-u}}{n}}\right)^n = \left(1+\frac{e^{-u}}{n}\right)^{-n} \longrightarrow \exp\left\{-e^{-u}\right\} \qquad \text{as } n \longrightarrow \infty$$

which is a valid cdf. Hence the limiting distribution is

$$F_U(u) = \exp\left\{-e^{-u}\right\} \qquad u \in \mathbb{R}$$

(d) $Y_n = \max\{X_1, ..., X_n\}$ so

$$F_{Y_n}(y) = \{F_X(y)\}^n = \left(\frac{\lambda y}{1+\lambda y}\right)^n \qquad y > 0$$

and so, in the limit as $n \longrightarrow \infty$ we have the limit for *fixed* y as

$$F_{Y_n}(y) \longrightarrow 0 \qquad \text{for all } y$$

Hence there is *no limiting distribution*.

$Z_n = \min\{X_1, ..., X_n\}$ so in the limit as $n \longrightarrow \infty$ we have the limit for *fixed* $z > 0$ as

$$F_{Z_n}(z) = 1 - \{1 - F_X(z)\}^n = 1 - \left(1 - \left(1 - \frac{1}{1+\lambda z}\right)\right)^n = 1 - \frac{1}{(1+\lambda z)^n} \longrightarrow \begin{cases} 0 & z \le 0 \\ 1 & z > 0 \end{cases}$$

that is, a step function with single step of size 1 at $z = 0$. Hence the limiting random variable Z is a discrete variable with $\mathrm{P}[Z = 0] = 1$ that is, the limiting distribution is *degenerate* at 0. Again, the limiting function is not a cdf as it not right continuous, but this does not affect out conclusion, as the limit function is not continuous at 0.

If $U_n = Y_n/n$, we have from first principles that for $u > 0$

$$F_{U_n}(u) = P[U_n \le u] = P[Y_n/n \le u] = P[Y_n \le nu] = F_{Y_n}(nu) = \left(\frac{\lambda n u}{1+\lambda n u}\right)^n$$

so that

$$F_{U_n}(u) = \left(\frac{\lambda n u}{1+\lambda n u}\right)^n = \left(1+\frac{1}{n\lambda u}\right)^{-n} \longrightarrow \exp\left\{-\frac{1}{\lambda u}\right\} \qquad \text{as } n \longrightarrow \infty$$

which is a valid cdf. Hence the limiting distribution is

$$F_U(u) = \exp\left\{-\frac{1}{\lambda u}\right\} \qquad u > 0$$

If $V_n = nZ_n$, we have from first principles that for $u > 0$

$$F_{V_n}(v) = P\left[V_n \le v\right] = P\left[nZ_n \le v\right] = P\left[Z_n \le v/n\right] = F_{Z_n}(v/n) = 1 - \left(\frac{1}{1 + \dfrac{\lambda v}{n}}\right)^n$$

so that

$$F_{V_n}(v) = 1 - \left(1 + \frac{\lambda v}{n}\right)^{-n} = 1 - \left(1 + \frac{\lambda v}{n}\right)^{-n} \longrightarrow 1 - \exp\left\{-\lambda v\right\} \qquad \text{as } n \longrightarrow \infty$$

which is a valid cdf. Hence the limiting distribution is

$$F_V(v) = 1 - \exp\left\{-\lambda v\right\} \qquad v > 0$$

Hence the limiting random variable $V \sim Exponential(\lambda)$.

$Y_n = \max\left\{X_1, ..., X_n\right\}$ so

$$F_{Y_n}(y) = \left\{F_X(y)\right\}^n = (1 - e^{-\lambda y})^n \qquad y > 0$$

2. Key is to find the i.i.d random variables $X_1, ..., X_n$ such that

$$X = \sum_{i=1}^{n} X_i$$

and then to use the Central Limit Theorem result for large n

$$Z_n = \frac{\sum\limits_{i=1}^{n} X_i - n\mu}{\sqrt{n\sigma^2}} \xrightarrow{d} Z \sim Normal(0,1) \qquad \therefore \qquad X = \sum_{i=1}^{n} X_i \sim \mathcal{AN}(n\mu, n\sigma^2)$$

where $\mu = \mathbb{E}_X\left[X_i\right]$ and $\sigma^2 = \text{Var}_X\left[X_i\right]$

(a) $X \sim Binomial(n, \theta) \implies X = \sum\limits_{i=1}^{n} X_i$ where $X_i \sim Bernoulli(\theta)$ so that $\mu = \mathbb{E}_X\left[X_i\right] = \theta$ and $\sigma^2 = \text{Var}_X\left[X_i\right] = \theta(1-\theta)$ and hence

$$Z_n = \frac{\sum\limits_{i=1}^{n} X_i - n\theta}{\sqrt{n\theta(1-\theta)}} \xrightarrow{d} Normal(0,1) \qquad \therefore \qquad X \sim \mathcal{AN}(n\theta, n\theta(1-\theta))$$

(b) $X \sim Poisson(\lambda) \implies X = \sum\limits_{i=1}^{n} X_i$ where $X_i \sim Poisson\left(\lambda/n\right)$ so that $\mu = \mathbb{E}_X\left[X_i\right] = \lambda/n$ and $\sigma^2 = \text{Var}_X\left[X_i\right] = \lambda/n$ and hence

$$Z_n = \frac{\sum\limits_{i=1}^{n} X_i - n\dfrac{\lambda}{n}}{\sqrt{n\left(\lambda/n\right)}} = \frac{\sum\limits_{i=1}^{n} X_i - \lambda}{\sqrt{\lambda}} \xrightarrow{d} Normal(0,1) \qquad \therefore \qquad X \sim \mathcal{AN}(\lambda, \lambda)$$

Note that this uses the result that the sum of independent Poisson variables also has a Poisson distribution (proved using mgfs), and also note that this is in agreement with the mgf limit result.

(c) $X \sim NegBinomial(n,\theta) \Longrightarrow X = \sum\limits_{i=1}^{n} X_i$ where $X_i \sim Geometric(\theta)$ so that $\mu = \mathbb{E}_X[X_i] = 1/\theta$ and $\sigma^2 = \text{Var}_{f_X}[X_i] = (1-\theta)/\theta^2$ and hence

$$Z_n = \frac{\sum\limits_{i=1}^{n} X_i - n\dfrac{1}{\theta}}{\sqrt{n\left((1-\theta)/\theta^2\right)}} \xrightarrow{d} Normal(0,1) \qquad \therefore \qquad X \sim \mathcal{AN}\left(\frac{n}{\theta}, \frac{n(1-\theta)}{\theta^2}\right)$$

(d) $X \sim Gamma(\alpha,\beta) \Longrightarrow X = \sum\limits_{i=1}^{n} X_i$ where $X_i \sim Gamma\left(\dfrac{\alpha}{n},\beta\right)$ so that $\mu = \mathbb{E}_X[X_i] = \dfrac{\alpha}{n\beta}$ and $\sigma^2 = \text{Var}_X[X_i] = \dfrac{\alpha}{n\beta^2}$ and hence

$$Z_n = \frac{\sum\limits_{i=1}^{n} X_i - n\dfrac{\alpha}{n\beta}}{\sqrt{n\alpha/(n\beta^2)}} = \frac{\sum\limits_{i=1}^{n} X_i - \dfrac{\alpha}{\beta}}{\sqrt{\alpha/\beta^2}} \xrightarrow{d} Normal(0,1) \qquad \therefore \qquad X \sim \mathcal{AN}\left(\frac{\alpha}{\beta}, \frac{\alpha}{\beta^2}\right)$$

3. $X_i \sim Poisson(\lambda)$ so $\sum\limits_{i=1}^{n} X_i \sim Poisson(n\lambda)$ by mgfs and hence by the CLT,

$$\sum_{i=1}^{n} X_i \sim \mathcal{AN}(n\lambda, n\lambda) \qquad \therefore \qquad \overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \sim \mathcal{AN}\left(\lambda, \frac{\lambda}{n}\right)$$

and hence, for $\varepsilon > 0$

$$P\left[\left|\overline{X} - \lambda\right| < \varepsilon\right] = P\left[\lambda - \varepsilon < \overline{X} < \lambda + \varepsilon\right] \approx \Phi\left(\frac{\varepsilon}{\sqrt{\lambda/n}}\right) - \Phi\left(\frac{-\varepsilon}{\sqrt{\lambda/n}}\right) \longrightarrow 1$$

as $n \longrightarrow \infty$. Hence, $\overline{X}$ *converges in probability* to λ

$$\overline{X} \xrightarrow{p} \lambda$$

Now, if $T_n = \exp\{-M_n\}$, then for $\varepsilon > 0$ we have

$$P\left[\left|T_n - e^{-\lambda}\right| < \varepsilon\right] = P\left[e^{-\lambda} - \varepsilon < T_n < e^{-\lambda} + \varepsilon\right] = P\left[-\log(e^{-\lambda} + \varepsilon) < M_n < -\log(e^{-\lambda} - \varepsilon)\right]$$

and hence

$$P\left[\left|T_n - e^{-\lambda}\right| < \varepsilon\right] =\approx \Phi\left(\frac{-\log(e^{-\lambda} - \varepsilon) - \lambda}{\sqrt{\lambda/n}}\right) - \Phi\left(\frac{-\log(e^{-\lambda} + \varepsilon) - \lambda}{\sqrt{\lambda/n}}\right) \longrightarrow 1$$

as $n \longrightarrow \infty$. Hence, T_n *converges in probability* to $e^{-\lambda}$.

4. (a) Clearly if the sequence converges, it converges to 1 or 2, and as $n \longrightarrow \infty$ it is clear that the probability $P[X_n = 1] \longrightarrow 0$, so we check whether the limit is 2.

We have

$$E\left[|X_n - 2|^2\right] = \left(|-1|^2 \times \frac{1}{n}\right) + \left(|0|^2 \times \frac{n-1}{n}\right) = \frac{1}{n} \longrightarrow 0 \qquad \text{as } n \longrightarrow \infty$$

so $X_n \xrightarrow{r=2} 2$; we can also prove directly that, for $\epsilon > 0$,

$$P[|X_n - 2| < \epsilon] = P[X_n = 2] = 1 - \frac{1}{n} \longrightarrow 1 \qquad \text{as } n \longrightarrow \infty$$

so $X_n \xrightarrow{p} 2$ (although this does follow because of the convergence in $r = 2$ mean).

(b) Here it seems that X_n may converge to 1; we have

$$E\left[|X_n - 1|^2\right] = \left(|n^2 - 1|^2 \times \frac{1}{n}\right) + \left(|0|^2 \times \frac{n-1}{n}\right) = \frac{(n^2-1)^2}{n} \not\rightarrow 0 \qquad \text{as } n \longrightarrow \infty$$

so X_n does not converge in $r = 2$ mean to 1; by similar arguments, it can be shown that X_n does not converge in this mode to any fixed constant. However, we can prove that, for $\epsilon > 0$,

$$P[|X_n - 1| < \epsilon] = P[X_n = 1] = 1 - \frac{1}{n} \longrightarrow 1 \qquad \text{as } n \longrightarrow \infty \quad \therefore X_n \xrightarrow{p} 1.$$

(c) Here it seems that X_n may converge to 0; we have

$$E\left[|X_n - 0|^2\right] = \left(|n|^2 \times \frac{1}{\log n}\right) + \left(|0|^2 \times 1 - \frac{1}{\log n}\right) = \frac{n^2}{\log n} \not\rightarrow 0 \qquad \text{as } n \longrightarrow \infty$$

so X_n does not converge in $r = 2$ mean to 0; by similar arguments, it can be shown that X_n does not converge in this mode to any fixed constant. However, for $\epsilon > 0$,

$$P[|X_n - 0| < \epsilon] = P[X_n = 0] = 1 - \frac{1}{\log n} \longrightarrow 1 \qquad \text{as } n \longrightarrow \infty \quad X_n \xrightarrow{p} 0.$$

1.* (a) Let A_n be the event $(X_n \neq 0)$. Then $P(A_n) = 1/n$, and hence

$$\sum_{n=1}^{\infty} P(A_n) = \infty.$$

The events $A_1, A_2, \ldots$ are independent, so by the BC Lemma part (II),

$$P(A_n \text{ occurs i.o}) = 1,$$

so X_n does not converge a.s. to 0. X_n only takes values in $\{0, 1\}$, and $P[X_n = 0] > 0$ for any finite n, so X_n does not converge to 1 a.s. either. Hence X_n does not converge a.s. to any real value.

(b) We have

$$E\left[|X_n|\right] = E\left[I_{[0,n^{-1})}\left(U_n\right)\right] = P\left[U_n \leq n^{-1}\right] = \frac{1}{n}$$

so

$$X_n \stackrel{r=1}{\longrightarrow} X_B$$

where $P\left[X_B = 0\right] = 1$, and we have convergence in r^{th} mean to zero for $r = 1$.

2.* $P[X_n = 0] \longrightarrow 1$ as $n \longrightarrow \infty$, so we check zero as a possible limiting variable. For a.s. convergence,

$$P\left[\lim_{n \longrightarrow \infty} |X_n| < \epsilon\right] = P\left[\lim_{n \longrightarrow \infty} X_n < \epsilon\right] = P[Z < 1] = 1$$

as the sequence of sets defined by $(0, 1 - n^{-1})$ increases to limit $(0, 1)$ as $n \longrightarrow \infty$, so we do have a.s. convergence to zero. However, for convergence in rth mean: we have

$$E[|X^r|] = n^r \times P[X = n] + 0 \times P[X = 0] = \frac{n^r}{n}$$

so $\{X_n\}$ does not converge in rth mean to zero for any $r \geq 1$.

3.* Here we use the Borel-Cantelli Lemma, part (b); as

$$\sum_{n=1}^{\infty} P[X_n = 1] = \infty$$

and the events concerned are independent, then $P[\ X_n = 1 \text{ infinitely often }] = 1$.