
STAT 30400 : DISTRIBUTION THEORY

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HOMEWORK 5



Solutions by

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STAT 30400, Homework 5

1. (15 pts) Let W_1 , W_2 and W_3 be three mutually independent exponential random variables with parameter $\lambda > 0$, and let J be a Bernoulli random variable, independent of the W s, with parameter θ in $(0,1)$. Set

$$X = (1 - \theta)W_1 + JW_3,$$

$$Y = (1 - \theta)W_2 + JW_3.$$

- (a) Find the joint distribution function of X and Y .

Let $f_W(w) = \lambda e^{-\lambda w} \mathbb{1}_{\{w \geq 0\}}$ and $F_W(w) = [1 - e^{-\lambda w}] \mathbb{1}_{\{w \geq 0\}}$ be the density function and distribution function of W_1 , W_2 and W_3 . Let $Z = JW_3$, since J and W_3 are independent,

$$\begin{aligned} f_Z(z) &= \begin{cases} f_W(z) \mathbb{P}(J = 1) & , z = 0 \\ \mathbb{P}(J = 0) & , z > 0 \\ 0 & , z < 0 \end{cases} \\ &= \begin{cases} \theta f_W(z) & , z = 0 \\ 1 - \theta & , z > 0 \\ 0 & , z < 0 \end{cases} \end{aligned}$$

Then for $0 \leq x < y$,

$$\begin{aligned} F_{(X,Y)}(x,y) &= \mathbb{P}(X \leq x, Y \leq y) \\ &= \mathbb{P}(X \leq x, Y \leq y | J = 0) \mathbb{P}(J = 0) + \mathbb{P}(X \leq x, Y \leq y | J = 1) \mathbb{P}(J = 1) \\ &= (1 - \theta) \mathbb{P}\left(W_1 \leq \frac{x}{1 - \theta}, W_2 \leq \frac{y}{1 - \theta}\right) \\ &\quad + \int_0^\infty \theta \mathbb{P}\left(W_1 \leq \frac{x - z}{1 - \theta}, W_2 \leq \frac{y - z}{1 - \theta}, W_3 = z\right) dz \\ &= (1 - \theta) F\left(\frac{x}{1 - \theta}\right) F_W\left(\frac{y}{1 - \theta}\right) + \int_0^x \theta F\left(\frac{x - z}{1 - \theta}\right) F\left(\frac{y - z}{1 - \theta}\right) f_W(z) dz \end{aligned}$$

While

$$\begin{aligned} &(1 - \theta) F\left(\frac{x}{1 - \theta}\right) F_W\left(\frac{y}{1 - \theta}\right) \\ &= (1 - \theta) (1 - e^{-\frac{\lambda(x)}{1 - \theta}}) (1 - e^{-\frac{\lambda(y)}{1 - \theta}}) \\ &\quad + \int_0^x \theta F\left(\frac{x - z}{1 - \theta}\right) F\left(\frac{y - z}{1 - \theta}\right) f_W(z) dz \\ &= \int_0^x \theta (1 - e^{-\frac{\lambda(x - z)}{1 - \theta}}) (1 - e^{-\frac{\lambda(y - z)}{1 - \theta}}) \lambda e^{-\lambda z} dz \\ &= \theta \lambda \int_0^x e^{-\lambda z} - (e^{-\frac{\lambda}{1 - \theta} x} + e^{-\frac{\lambda}{1 - \theta} y}) e^{\frac{\theta \lambda}{1 - \theta} z} + e^{-\frac{\lambda}{1 - \theta} (x + y)} e^{\frac{1 + \theta}{1 - \theta} z} dz \\ &= \theta - \theta e^{-\lambda x} - (1 - \theta) (e^{-\lambda x} + e^{-\frac{\lambda}{1 - \theta} (y - \theta x)}) + (1 - \theta) (e^{-\frac{\lambda}{1 - \theta} x} + e^{-\frac{\lambda}{1 - \theta} y}) \\ &\quad + \frac{\theta(1 - \theta)}{1 + \theta} e^{-\frac{\lambda}{1 - \theta} (y - \theta x)} - \frac{\theta(1 - \theta)}{1 + \theta} e^{-\frac{\lambda}{1 - \theta} (y + x)} \\ &= \theta - e^{-\lambda x} + (1 - \theta) (e^{-\frac{\lambda}{1 - \theta} x} + e^{-\frac{\lambda}{1 - \theta} y}) - \frac{1 - \theta}{1 + \theta} e^{-\frac{\lambda}{1 - \theta} (y - \theta x)} - \frac{\theta(1 - \theta)}{1 + \theta} e^{-\frac{\lambda}{1 - \theta} (y + x)}. \end{aligned}$$

Solution (cont.)

so, for $0 \leq x < y$,

$$F_{(X,Y)}(x, y) = 1 - e^{-\lambda x} - \frac{1-\theta}{1+\theta} e^{-\frac{\lambda}{1-\theta}(y-\theta x)} + \frac{1-\theta}{1+\theta} e^{-\frac{\lambda}{1-\theta}(y+x)}.$$

Since X and Y are symmetry in the sense that $F(x, y) = F(y, x)$, we have

$$F_{(X,Y)}(x, y) = \begin{cases} 1 - e^{-\lambda x} - \frac{1-\theta}{1+\theta} e^{-\frac{\lambda}{1-\theta}(y-\theta x)} + \frac{1-\theta}{1+\theta} e^{-\frac{\lambda}{1-\theta}(y+x)} & , 0 \leq x < y \\ 1 - e^{-\lambda y} - \frac{1-\theta}{1+\theta} e^{-\frac{\lambda}{1-\theta}(x-\theta y)} + \frac{1-\theta}{1+\theta} e^{-\frac{\lambda}{1-\theta}(y+x)} & , x \geq y \geq 0 \\ 0 & , x < 0 \text{ or } y < 0 \end{cases}$$

$$= \begin{cases} 1 - e^{-\lambda \min\{x,y\}} - \frac{1-\theta}{1+\theta} e^{-\frac{\lambda}{1-\theta}(x+y-(1-\theta) \min\{x,y\})} + \frac{1-\theta}{1+\theta} e^{-\frac{\lambda}{1-\theta}(y+x)} & , x \geq 0, y \geq 0 \\ 0 & , x < 0 \text{ or } y < 0 \end{cases}$$

(b) Find the marginal densities of X and Y .

For $x \geq 0$,

$$F_X(x) = \lim_{y \rightarrow \infty} F_{(X,Y)}(x, y)$$

$$= \begin{cases} 1 - e^{-\lambda x} & , x \geq 0 \\ 0 & , x < 0 \end{cases}$$

Analogously, $F_Y(y) = (1 - e^{-\lambda y}) \mathbb{1}_{y \geq 0}$.

(c) Find the copula, C_θ , associated with (X, Y) . Show that C_θ is absolutely continuous in θ , and find C_0 and C_1 .

Since for $u, v \in (0, 1)$,

$$F_Y^{-1}(u) = F_X^{-1}(u) = -\frac{1}{\lambda} \log(1 - u)$$

and $F_X^{-1}(u) \leq F_Y^{-1}(v)$ for $u \leq v$, we have for $u < v$

$$C_\theta(u, v) = F_{(X,Y)}(F_X^{-1}(u), F_Y^{-1}(v))$$

$$= u - \frac{1-\theta}{1+\theta} (1-u)^{\frac{\theta}{1-\theta}} (1-v)^{\frac{1}{1-\theta}} + \frac{1-\theta}{1+\theta} (1-u)^{\frac{1}{1-\theta}} (1-v)^{\frac{1}{1-\theta}}.$$

Therefore,

$$C_\theta(u, v) = \min\{u, v\} - \frac{1-\theta}{1+\theta} (1-u)^{\frac{1}{1-\theta}} (1-v)^{\frac{1}{1-\theta}} (1 - \min\{u, v\})^{-1} + \frac{1-\theta}{1+\theta} (1-u)^{\frac{1}{1-\theta}} (1-v)^{\frac{1}{1-\theta}}$$

$$= \min\{u, v\} - \frac{1-\theta}{1+\theta} (1-u)^{\frac{1}{1-\theta}} (1-v)^{\frac{1}{1-\theta}} \frac{\min\{u, v\}}{1 - \min\{u, v\}},$$

$$\frac{dC_\theta}{d\theta} = \frac{2}{(1+\theta^2)} (1-u)^{\frac{1}{1-\theta}} (1-v)^{\frac{1}{1-\theta}} \frac{\min\{u, v\}}{1 - \min\{u, v\}}$$

$$- \frac{1}{(1+\theta)(1-\theta)} (1-u)^{\frac{1}{1-\theta}} (1-v)^{\frac{1}{1-\theta}} \ln[(1-u)(1-v)] \frac{\min\{u, v\}}{1 - \min\{u, v\}},$$

Solution (cont.)

Let $a = (1-u)(1-v) \in (0, 1)$, $x = \frac{1}{1-\theta} \in (1, \infty)$, $f(x) = xa^x$ for $x \in (1, \infty)$. $f'(x) = a^x(1+x \ln a)$. If $\ln a \geq -1$, then $f'(x) \leq 0$ and $f(x) \leq a$; If $\ln a < -1$, then $f'(x) < 0$ for $x < -\frac{1}{\ln a}$ and $f'(x) < 0$ for $x > -\frac{1}{\ln a}$, so $f(x) \leq -\frac{1}{\ln a} a^{-\frac{1}{\ln a}}$. Therefore,

$$\begin{aligned} \left| \frac{dC_\theta}{d\theta} \right| &\leq 2(1-u)(1-v) \frac{\min\{u, v\}}{1 - \min\{u, v\}} + \frac{1}{1-\theta} [(1-u)(1-v)]^{\frac{1}{1-\theta}} \frac{\min\{u, v\}}{1 - \min\{u, v\}} \\ &= \begin{cases} 2a \frac{\min\{u, v\}}{1 - \min\{u, v\}} + a \frac{\min\{u, v\}}{1 - \min\{u, v\}} & , \text{ if } \ln a \geq -1 \\ 2a \frac{\min\{u, v\}}{1 - \min\{u, v\}} - \frac{1}{\ln a} a^{-\frac{1}{\ln a}} \frac{\min\{u, v\}}{1 - \min\{u, v\}} & , \text{ if } \ln a < -1 \end{cases} \end{aligned}$$

i.e., C_θ is Lipschitz continuous with respect to θ . Therefore, C_θ is absolutely continuous in θ .

$$C_0(u, v) = \lim_{\theta \rightarrow 0^+} C_\theta(u, v) = \min\{u, v\} - (1-u)(1-v)(1 - \min\{u, v\})^{-1} + (1-u)(1-v)$$

$$C_1(u, v) = \lim_{\theta \rightarrow 1^-} C_\theta(u, v) = \min\{u, v\}$$

2. (10 pts) Let X have a $N(\mu, 1)$ distribution and let $Y = X^2$.

(a) Find the density $f_Y(y)$ of Y . (This is known as *noncentral chi-square*)

Let $f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x-\mu)^2}$ be the density function of X . Let $\mathcal{X}_1 = (-\infty, 0)$, $\mathcal{X}_2 = [0, \infty)$ and $\mathcal{X} = \mathcal{X}_1 \cup \mathcal{X}_2$, then in \mathcal{X}_i , X and Y have one-to-one relationship g_i .

$$\begin{aligned} f_Y(y) &= \sum_{\substack{x \in \mathcal{X}_i \\ x = g_i^{-1}(y)}} f_X(g_i^{-1}(x)) \left| \frac{dg_i^{-1}(y)}{dy} \right| \mathbb{1}_{y>0} \\ &= [f_X(\sqrt{y}) + f_X(-\sqrt{y})] \left| \frac{1}{\sqrt{|y|}} \right| \mathbb{1}_{y>0} \\ &= \left[\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\sqrt{y}-\mu)^2} + \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(-\sqrt{y}-\mu)^2} \right] \frac{1}{\sqrt{y}} \mathbb{1}_{y>0} \\ &= \frac{1}{\sqrt{2\pi}} y^{-\frac{1}{2}} e^{-\frac{1}{2}(y+\mu^2)} (e^{\mu\sqrt{y}} + e^{-\mu\sqrt{y}}) \mathbb{1}_{y>0} \end{aligned}$$

(b) Show that we can write:

$$f_Y(y) = \sum_{k=0}^{\infty} \mathbb{P}(R = k) f_{2k+1}(y),$$

where R is distributed Poisson($\mu^2/2$) and f_m is the χ_m^2 density. Give an interpretation of this formula.

Proof.

$$\begin{aligned} \mathbb{P}(R = k) &= \frac{\mu^{2k}}{2^k k!} e^{-\frac{\mu^2}{2}} \\ f_m(x) &= \frac{1}{2^{\frac{m}{2}} \Gamma(\frac{m}{2})} x^{\frac{m}{2}-1} e^{-\frac{x}{2}} \mathbb{1}_{x>0} \end{aligned}$$

we have

$$\sum_{k=0}^{\infty} \mathbb{P}(R = k) f_{2k+1}(y) = y^{-\frac{1}{2}} e^{-\frac{1}{2}(y+\mu^2)} \sum_{k=0}^{\infty} \frac{\mu^{2k} y^k}{2^{\frac{2k+1}{2}} k! \Gamma(\frac{2k+1}{2})}$$

Since

$$\Gamma\left(\frac{2k+1}{2}\right) = \frac{2k-1}{2} \cdot \frac{2k-3}{2} \cdots \frac{1}{2} \Gamma\left(\frac{1}{2}\right) = \frac{(2k-1)!!}{2^k} \sqrt{\pi},$$

and

$$(2k)! = (2k)!! \cdot (2k-1)!! = 2^k \cdot k! \cdot (2k-1)!,$$

we have

$$\begin{aligned} y^{-\frac{1}{2}} e^{-\frac{1}{2}(y+\mu^2)} \sum_{k=0}^{\infty} \frac{\mu^{2k} y^k}{2^{\frac{2k+1}{2}} k! \Gamma(\frac{2k+1}{2})} &= y^{-\frac{1}{2}} e^{-\frac{1}{2}(y+\mu^2)} \sum_{k=0}^{\infty} \frac{\mu^{2k} y^k}{\sqrt{2\pi} (2k)!} \\ &= \frac{1}{\sqrt{2\pi}} y^{-\frac{1}{2}} e^{-\frac{1}{2}(y+\mu^2)} \sum_{k=0}^{\infty} \frac{\mu^{2k} y^k}{(2k)!} \\ &= \frac{1}{\sqrt{2\pi}} y^{-\frac{1}{2}} e^{-\frac{1}{2}(y+\mu^2)} \left[\sum_{k=0}^{\infty} \frac{(\mu\sqrt{y})^k}{k!} + \sum_{k=0}^{\infty} \frac{(-\mu\sqrt{y})^k}{k!} \right] \\ &= \frac{1}{\sqrt{2\pi}} y^{-\frac{1}{2}} e^{-\frac{1}{2}(y+\mu^2)} (e^{\mu\sqrt{y}} + e^{-\mu\sqrt{y}}) \\ &= f_Y(y) \end{aligned}$$

□

3. (10 pts) Let X and Y be independent random variable with distribution function F and representing function R . Let $\Delta = \mathbb{E}(|X - Y|)$ be the *Gini's mean difference*. Show that,

$$\Delta = 2 \int_{-\infty}^{\infty} F(x)[1 - F(x)]dx = 2 \int_0^1 (2u - 1)R(u)du.$$

[Hint: for the first equality show that,

$$\Delta = 2\mathbb{E} \left(\int_{-\infty}^{\infty} \mathbb{1}_{X \leq t < Y} dt \right),$$

and reverse the order of integration; justify the reversal. For the second equality, give separate arguments depending on whether X is integrable or not. When X is integrable argue that

$$\Delta = 2 \iint_{(u,v): u < v} [R(u) - R(v)]dudv.$$

Proof. Let $X, Y \stackrel{iid}{\sim} F$. For all $x, y \in \mathbb{R}$, if $x < y$, then $y - x = \int_{\mathbb{R}} \mathbb{1}_{x \leq t < y} dt$; if $x \geq y$, then $x - y = \int_{\mathbb{R}} \mathbb{1}_{y \leq t < x} dt$. So

$$\begin{aligned} \Delta &= \mathbb{E}|X - Y| \\ &= \mathbb{E} \left(\int_{\mathbb{R}} \mathbb{1}_{X \leq t < Y} dt + \int_{\mathbb{R}} \mathbb{1}_{Y \leq t < X} dt \right) \\ &= 2\mathbb{E} \left(\int_{-\infty}^{\infty} \mathbb{1}_{X \leq t < Y} dt \right). \end{aligned}$$

Since the integrated function is non-negative, by Fubini Theorem we have

$$\begin{aligned} \Delta &= 2 \int_{\mathbb{R}} \mathbb{E} \mathbb{1}_{X \leq t < Y} dt \\ &= 2 \int_{\mathbb{R}} \mathbb{P}(X \leq t < Y) dt \\ &= 2 \int_{\mathbb{R}} \mathbb{P}(X \leq t) \mathbb{P}(Y > t) dt \\ &= 2 \int_{\mathbb{R}} F(t)[1 - F(t)] dt. \end{aligned}$$

Let $U, V \stackrel{iid}{\sim} \text{Uniform}(0, 1)$, such that $X = R(U), Y = R(V)$.

(1) If X is not integrable, then $\mathbb{E}|Y| = \mathbb{E}|X| = \mathbb{E}|R(U)| = \int_0^1 |R(u)|du = \infty$

$$\begin{aligned} \Delta &= \mathbb{E}|X - Y| \\ &= \int_0^{\infty} \mathbb{P}(|X - Y| \geq t) dt \\ &\geq \int_0^{\infty} \mathbb{P}(|X| \geq t + k, |Y| \leq k) dt \\ &= \int_0^{\infty} \mathbb{P}(|X| \geq t + k) \mathbb{P}(|Y| \leq k) dt \\ &= \mathbb{P}(|Y| \leq k) \int_0^{\infty} \mathbb{P}(|X| \geq t + k) dt \\ &= \mathbb{P}(|Y| \leq k) \cdot \infty \\ &= \infty \end{aligned}$$

for sufficiently large k such that $\mathbb{P}(|Y| \leq k) > 0$. Decompose $(0, 1)$ as $(0, 1) = \{u : R(u) \geq 0, u \geq$

Solution (cont.)

$\frac{1}{2}\} \cup \{u : R(u) < 0, u < \frac{1}{2}\} \cup \{u : R(u) > 0, u < \frac{1}{2}\} \cup \{u : R(u) < 0, u > \frac{1}{2}\}$, we have

$$\begin{aligned} 0 &\geq \int_{\{u: R(u) > 0, u < \frac{1}{2}\}} (2u - 1)R(u)du \geq \int_{\{u: R(u) > 0, u < \frac{1}{2}\}} (2u - 1)R(\frac{1}{2})du > -\infty \\ 0 &\geq \int_{\{u: R(u) < 0, u > \frac{1}{2}\}} (2u - 1)R(u)du \geq \int_{\{u: R(u) < 0, u > \frac{1}{2}\}} (2u - 1)R(\frac{1}{2})du > -\infty \end{aligned}$$

Since X is not integrable, neither $R(u)$ is integrable and therefore $\int_0^1 R^+(u)du = \int_0^1 R^-(u)du = \infty$. Since $R^+(u)$ is non-negative and non-decreasing, there exists $u_0 < \infty$ such that $u_0 = \inf\{R(u) \geq 0, u \geq \frac{1}{2}\}$,

$$\begin{aligned} \int_{\{u: R(u) \geq 0, u \geq \frac{1}{2}\}} (2u - 1)R(u)du &= \int_{u_0}^1 (2u - 1)R(u)du \\ &\geq (2u_0 - 1) \int_{u_0}^1 R(u)du \\ &= (2u_0 - 1) \left[\int_0^1 R^+(u)du - \int_{u_0}^1 R^+(u)du \right] \\ &\geq (2u_0 - 1) \int_0^1 R^+(u)du - (2u_0 - 1)R^+(u_0) \\ &= \infty. \end{aligned}$$

Analogously, we also have $\int_{\{u: R(u) < 0, u < \frac{1}{2}\}} (2u - 1)R(u)du \geq \infty$. So $\int_0^1 (2u - 1)R(u)du = \infty = \Delta$.

(2) If X is integrable, $\mathbb{E}|X| = \mathbb{E}|Y| = \int_0^1 |R(u)|du < \infty$, and $\iint_{(0,1) \times (0,1)} |R(u) - R(v)|dudv \leq \iint_{(0,1) \times (0,1)} [|R(u)| + |R(v)|]dudv \stackrel{\text{Fubini}}{=} \int_0^1 \left(\int_0^1 [|R(u)| + |R(v)|]du \right) dv = \left(\int_0^1 |R(u)|du \right) + \left(\int_0^1 |R(v)|dv \right) < \infty$.

Since R is a non-decreasing function, we have

$$\begin{aligned} \Delta &= \mathbb{E}|R(U) - R(V)| \\ &= \iint_{(0,1) \times (0,1)} |R(u) - R(v)|dudv \\ &= \iint_{0 < u < v < 1} [R(v) - R(u)]dudv + \iint_{0 < v \leq u < 1} [R(u) - R(v)]dudv \\ &= 2 \iint_{0 < u < v < 1} [R(v) - R(u)]dudv \\ &\stackrel{\text{Fubini}}{=} 2 \int_0^1 \left(\int_u^1 [R(v) - R(u)]dv \right) du \\ &= 2 \int_0^1 \left[\left(\int_u^1 R(v)dv \right) - (1 - u)R(u) \right] du \\ &= 2 \int_0^1 \left(\int_u^1 R(v)dv \right) du - 2 \int_0^1 (1 - u)R(u)du \\ &\stackrel{\text{Fubini}}{=} 2 \int_0^1 \left(\int_0^v R(v)du \right) dv - 2 \int_0^1 (1 - u)R(u)du \\ &= 2 \int_0^1 vR(v)dv + 2 \int_0^1 (u - 1)R(u)du \\ &= 2 \int_0^1 (2u - 1)R(u)du \end{aligned}$$

Solution (cont.)

A double integral can be done as an iterated integral (in either order) provided the integrand is non-negative, or the double integral is absolutely convergent. \square

4. (15 pts) Let X be an integrable random variable with standard deviation σ , mean deviation δ and mean difference Δ . Show that:

- (a) $\Delta \leq 2\delta$.

Proof. Suppose that X' and X are independent identical distributed with mean μ .

$$\begin{aligned}\Delta &= \mathbb{E}|X - X'| \\ &\leq \mathbb{E}|X - \mu| + \mathbb{E}|\mu - X'| \\ &= 2\delta\end{aligned}$$

□

- (b) $\delta \leq \Delta$.

Proof. Suppose that X' and X are independent identical distributed. Since

$$\begin{aligned}\Delta &= \mathbb{E}|X - X'| \\ &= \mathbb{E}[\mathbb{E}(|X - X'| \mid X)] \\ &\geq \mathbb{E}[|\mathbb{E}(X - X')| \mid X] \\ &= \mathbb{E}|X - \mathbb{E}X'| \\ &= \delta\end{aligned}$$

□

- (c) $\Delta \leq 2\sigma/\sqrt{3}$. If $\sigma < \infty$, equality holds if and only if X has a uniform distribution. [Hint: Use Exercise 3 and Exercise 4 from Homework 3.]

Proof. Choose quantile function $Q(u)$ as the representing function $R(u)$. Let $\mu = \mathbb{E}X = \int_0^1 Q(u)du$, then

$$\int_0^1 (2u - 1)\mu du = \frac{\mu}{2}(2u - 1)^2 \Big|_0^1 = 0.$$

So

$$\begin{aligned}\Delta &= 2 \int_0^1 (2u - 1)Q(u)du \\ &= 2 \int_0^1 (2u - 1)(Q(u) - \mu)du \\ &\leq 2 \left(\int_0^1 (2u - 1)^2 du \right)^{\frac{1}{2}} \left(\int_0^1 (Q(u) - \mu)^2 du \right)^{\frac{1}{2}} \\ &= 2 \sqrt{\frac{4}{3}u^3 - 2u^2 + u} \Big|_0^1 \cdot \sqrt{\mathbb{E}(X - \mu)^2} \\ &= \frac{2}{\sqrt{3}}\sigma,\end{aligned}$$

the inequality holds if and only if $(2u - 1)^2 = (Q(u) - \mu)^2$ almost everywhere for u in $[0, 1]$, i.e., $Q(u) = \mu + (2u - 1)$ a.s. ($Q(u)$ is nondecreasing), which means $F(x) = \frac{x - \mu + 1}{2} \mathbf{1}_{(\mu - 1, \mu + 1)}$, i.e. X has a uniform distribution. □