

# Stats 3D03 — Mid-Term Test 2

**November 20, 2017**

**Instructor:** Prof. N. Balakrishnan

**Total Marks:** 15

**Duration:** 75 mins.

- (1) Suppose the joint density function of  $X$  and  $Y$  is

$$f(x, y) = C(y - x), \quad 0 < x < y < 1.$$

Then:

- (a) Find the normalizing constant  $C$  that would make the above  $f(x, y)$  to be a valid density function;
- (b) Derive the marginal density functions of  $X$  and  $Y$ ;
- (c) Derive the conditional density functions of  $X | (Y = y)$  and of  $Y | (X = x)$ ;
- (d) Prove that  $\frac{X}{Y}$  and  $Y$  are independent;
- (e) Use Part (d) to determine  $\text{Cov}(X, Y)$ .

**(5 marks)**

- (2) Suppose  $X \sim \text{Poisson}(\lambda_1)$  and  $Y \sim \text{Poisson}(\lambda_2)$  are independent random variables. Then:

- (a) Find the moment generating function of  $X$ ;
- (b) Deduce from Part (a) the mean and variance of  $X$ ;
- (c) Using Part (a), identify the distribution of  $X + Y$ .

**(3 marks)**

- (3) Suppose  $X \sim \chi^2_{\nu_1}$  and  $Y \sim \chi^2_{\nu_2}$  are independent random variables. Then:

- (a) Derive an expression for  $E(X^r)$  (the  $r^{\text{th}}$  moment of  $X$ ) and discuss when it will exist;
- (b) If  $U = \frac{X}{X+Y}$  and  $V = X + Y$ , derive the joint density function of  $U$  and  $V$ ;
- (c) Identify the distributions of  $U$  and  $V$ ;
- (d) Are  $U$  and  $V$  independent, and explain why or why not?

**(4 marks)**

- (4) Suppose  $X \sim \chi_{\nu_1}^2$  and  $Y \sim \chi_{\nu_2}^2$  are independent random variables, and  $W = \frac{X/\nu_1}{Y/\nu_2}$ . Then,  $W$  is said to have a  $F$ -distribution with degrees of freedom  $(\nu_1, \nu_2)$ .
- (a) Derive the probability density function of  $W$ ;
  - (b) Find  $E(W)$  (the mean) and comment.

**(4 marks)**

- (5) Suppose  $X_1, \dots, X_m$  and  $Y_1, \dots, Y_n$  are random samples from  $N(\mu_X, \sigma^2)$  and  $N(\mu_Y, \sigma^2)$  distributions, respectively. Our interest is in constructing  $100(1-\alpha)\%$  confidence interval for the mean difference  $\mu_X - \mu_Y$ . Then:

- (a) Explain the construction of the pivot (outline the steps of the process);
- (b) What is the distribution of the pivot?
- (c) Use Parts (a) and (b) to derive an exact  $100(1 - \alpha)\%$  confidence interval for  $\mu_X - \mu_Y$ ;
- (d) In the construction of the pivot, if you use a pooled estimate of  $\sigma^2$  (by pooling the estimates of  $\sigma^2$  from the two samples), provide a justification as to why that pooling is the best!

**(4 marks)**

**Good luck!**

# Stats 3D03

[1]

## Solutions for Mid-term Test 2

$$1. (a) \int_{x=0}^1 \int_{y=x}^1 f(x,y) = C \int_{x=0}^1 \frac{(y-x)^2}{2} dx = \frac{C}{2} \int_{x=0}^1 (1-x)^2 dx \\ = -\frac{C}{6} (1-x)^3 \Big|_0^1 = \frac{C}{6} = 1$$

$$\Rightarrow C = 6. \quad (1 \text{ mark})$$

$$(b) f_x(x) = 6 \int_{y=x}^1 (y-x) dy = 6 \frac{(y-x)^2}{2} \Big|_x^1 = 3(1-x)^2, 0 < x < 1$$

$$f_y(y) = 6 \int_0^y (y-x) dx = -6 \frac{(y-x)^2}{2} \Big|_0^y = 3y^2, 0 < y < 1. \quad (1 \text{ mark})$$

$$(c) f_{x|y}(x|y) = \frac{f(x,y)}{f_y(y)} = \frac{6(y-x)}{3y^2} = \frac{2(y-x)}{y^2}, 0 < x < y.$$

$$f_{y|x}(y|x) = \frac{f(x,y)}{f_x(x)} = \frac{6(y-x)}{3(1-x)^2} = \frac{2(y-x)}{(1-x)^2}, x < y < 1. \quad (1 \text{ mark})$$

$$(d) \text{ Let } U = \frac{X}{Y} \text{ and } V = Y$$

$$\Rightarrow X = UV = UV \text{ and } Y = V$$

$$|J| = \begin{vmatrix} V & U \\ 0 & 1 \end{vmatrix} = V$$

$$\therefore f_{U,V}(u,v) = 6(v-u)v = 6v^2(1-u), 0 < u < 1, 0 < v < 1 \\ \Rightarrow U \text{ and } V \text{ are independent by Factorization Thm.}$$

$$(e) E(X) = \int_0^1 3x(1-x)^2 dx = 3B(2,3) = 3 \cdot \frac{1 \cdot 2}{4!} = \frac{1}{4} \quad (1 \text{ mark})$$

$$E(Y) = \int_0^1 3y^3 dy = \frac{3}{4}. \quad (1 \text{ mark})$$

$$E(U) = 2 \int_0^1 u(1-u) du = 2B(2,2) = 2 \cdot \frac{1 \cdot 1}{3!} = \frac{1}{3}$$

$$E(V^2) = 3 \int_0^1 v^4 dv = \frac{3}{5}. \Rightarrow E(XY) = E(UV^2) = \frac{1}{3} \times \frac{3}{5} = \frac{1}{5} = \frac{1}{50} = \frac{16-15}{20}$$

[2]

2.  $X \sim \text{Poisson}(\lambda_1)$ ,  $Y \sim \text{Poisson}(\lambda_2)$ .

(a)  $f_X(x) = e^{-\lambda_1} \frac{\lambda_1^x}{x!}, x=0,1,\dots$

$$M_X(t) = E(e^{tX}) = e^{-\lambda_1} \sum_{x=0}^{\infty} (\lambda_1 e^t)^x / x! = e^{-\lambda_1 + \lambda_1 e^t}$$

(1 mark)

(b)  $\frac{d}{dt} M_X(t) = e^{-\lambda_1} \cdot e^{\lambda_1 e^t} \lambda_1 e^t \Rightarrow \text{Mean} = \frac{d}{dt} M_X(t) \Big|_{t=0} = \lambda_1$

$$\frac{d^2}{dt^2} M_X(t) = e^{-\lambda_1} e^{\lambda_1 e^t} (\lambda_1 e^t)^2 + e^{-\lambda_1} e^{\lambda_1 e^t} \lambda_1 e^t$$

$$\Rightarrow E(X^2) = \frac{d^2}{dt^2} M_X(t) \Big|_{t=0} = \lambda_1^2 + \lambda_1$$

$$\Rightarrow \text{Var}(X) = E(X^2) - (EX)^2 = \lambda_1^2 + \lambda_1 - \lambda_1^2 = \lambda_1.$$

(1 mark)

(c) Let  $Z = X+Y$ .

MGF of  $Z$  is

$$\begin{aligned} M_Z(t) &= E(e^{tZ}) = E(e^{tX} \cdot e^{tY}) = E(e^{tX}) E(e^{tY}) \\ &= e^{-\lambda_1 + \lambda_1 e^t} \cdot e^{-\lambda_2 + \lambda_2 e^t} \\ &= e^{-(\lambda_1 + \lambda_2) + (\lambda_1 + \lambda_2) e^t} \end{aligned}$$

$$\Rightarrow Z = X+Y \sim \text{Poisson}(\lambda_1 + \lambda_2).$$

(1 mark)

3.  $X \sim \chi^2_{v_1}$ ,  $Y \sim \chi^2_{v_2}$ , and are independent.

(3)

$$(a) E(X^n) = \frac{1}{2^{v_1/2} \Gamma(v_1/2)} \int_0^\infty e^{-\frac{x}{2}} x^{\frac{v_1}{2} + n - 1} dx$$

$$= \frac{1}{2^{v_1/2} \Gamma(\frac{v_1}{2})} 2^{\frac{v_1}{2} + n} \Gamma\left(\frac{v_1 + n}{2}\right)$$

$$= 2^n \Gamma\left(\frac{v_1 + n}{2}\right) / \Gamma\left(\frac{v_1}{2}\right).$$

(1/2 marks)

$$(b) \text{ It exists whenever } \frac{v_1}{2} + n > 0. f_{X,Y}(x,y) = \frac{1}{2^{v_1/2} 2^{v_2/2} \Gamma(v_1/2) \Gamma(v_2/2)} e^{-\frac{x}{2}} e^{-\frac{y}{2}} x^{\frac{v_1}{2}-1} y^{\frac{v_2}{2}-1}, \quad 0 < x, y < \infty.$$

$$U = \frac{X}{X+Y}, \quad V = X+Y$$

$$\Rightarrow X = UV, \quad Y = V - X = V - UV = V(1-U)$$

$$|J| = \begin{vmatrix} V & U \\ -V & 1-U \\ 1 & 1 \end{vmatrix} = V - UV + UV = V.$$

$$f_{U,V}(u,v) = \frac{2^{\frac{v_1+v_2}{2}}}{2^{\frac{v_1+v_2}{2}} \Gamma(\frac{v_1}{2}) \Gamma(\frac{v_2}{2})} e^{-\frac{v}{2}} u^{\frac{v_1}{2}-1} v^{\frac{v_2}{2}-1} \frac{v^{\frac{v_2}{2}-1}}{(1-u)^{\frac{v_2}{2}}} \sqrt{v}$$

$$= \frac{1}{B(\frac{v_1}{2}, \frac{v_2}{2})} u^{\frac{v_1}{2}-1} (1-u)^{\frac{v_2}{2}-1} \cdot \frac{1}{2^{\frac{v_1+v_2}{2}} \Gamma(\frac{v_1+v_2}{2})} e^{\frac{v}{2}} v^{\frac{v_1+v_2}{2}-1},$$

(1 mark)

$$(c) U \sim \text{Beta}\left(\frac{v_1}{2}, \frac{v_2}{2}\right) \text{ and } V \sim \chi^2_{v_1+v_2}. \quad (1/2 \text{ mark})$$

(d) By factorization theory,  $U$  and  $V$  are independent random variables. (1 mark)

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4.  $X \sim \chi_{2l_1}^2$ ,  $Y \sim \chi_{2l_2}^2$  and are independent. (1A)

$$(a) f_{X,Y}(x,y) = \frac{1}{2^{l_1/2} 2^{l_2/2}} \frac{x^{l_1/2-1} e^{-\frac{x}{2}}}{\Gamma(\frac{l_1}{2}) \Gamma(\frac{l_2}{2})} e^{-\frac{y}{2}} y^{l_2/2-1}, \text{ or } x, y > 0$$

Let  $W = \frac{l_2}{l_1} \cdot \frac{X}{Y}$  and  $V = Y$ .

$\Rightarrow X = \frac{l_1}{l_2} \cdot W V$  and  $Y = V$ .

$$|J| = \begin{vmatrix} \frac{l_1}{l_2} V & \frac{l_1}{l_2} W \\ 0 & 1 \end{vmatrix} = \frac{l_1}{l_2} V.$$

$$\Rightarrow f_{W,V}(w,v) = \frac{1}{2^{\frac{l_1+l_2}{2}} \Gamma(\frac{l_1}{2}) \Gamma(\frac{l_2}{2})} e^{-\frac{1}{2} \frac{l_1}{l_2} wv - \frac{1}{2} v} \cdot \frac{(l_1 wv)^{\frac{l_1}{2}-1}}{(l_2)^{\frac{l_1}{2}}} v^{\frac{l_2}{2}-1} \cdot \frac{l_1}{l_2} v$$

$$= \frac{1}{2^{\frac{l_1+l_2}{2}} \Gamma(\frac{l_1}{2}) \Gamma(\frac{l_2}{2})} e^{-\frac{1}{2} \left(1 + \frac{l_1}{l_2} w\right) v} \left(\frac{l_1}{l_2}\right)^{\frac{l_1}{2}} w^{\frac{l_1}{2}-1} v^{\frac{l_2}{2}-1}, \text{ or } w, v > 0.$$

$$\Rightarrow f_w(w) = \frac{\left(\frac{l_1}{l_2}\right)^{l_1/2} w^{\frac{l_1}{2}-1}}{2^{\frac{l_1+l_2}{2}} \Gamma(\frac{l_1}{2}) \Gamma(\frac{l_2}{2})} \int_0^\infty e^{-\frac{1}{2} \left(1 + \frac{l_1}{l_2} w\right) v} v^{\frac{l_1+l_2}{2}-1} dv$$

$$= \frac{\left(\frac{l_1}{l_2}\right)^{\frac{l_1}{2}} w^{\frac{l_1}{2}-1}}{2^{\frac{l_1+l_2}{2}} \Gamma(\frac{l_1}{2}) \Gamma(\frac{l_2}{2})} \frac{\Gamma(\frac{l_1+l_2}{2})}{\left(\frac{1}{2} \left(1 + \frac{l_1}{l_2} w\right)\right)^{\frac{l_1+l_2}{2}}}$$

$$= \frac{\left(\frac{l_1}{l_2}\right)^{\frac{l_1}{2}} w^{\frac{l_1}{2}-1}}{B\left(\frac{l_1}{2}, \frac{l_2}{2}\right) \left(1 + \frac{l_1}{l_2} w\right)^{\frac{l_1+l_2}{2}}}, \text{ or } w < 0. \quad (3 \text{ marks})$$

$$(b) E(W) = \frac{l_2}{l_1} E\left(\frac{X}{Y}\right) = \frac{l_2}{l_1} E(X) E\left(\frac{1}{Y}\right) \text{ due to independence}$$

$$= \frac{l_2}{l_1} \frac{2 \Gamma(\frac{l_1+1}{2})}{\Gamma(\frac{l_1}{2})} \frac{2^{-\frac{l_1+1}{2}} \Gamma(\frac{l_2-1}{2})}{\Gamma(\frac{l_2}{2})} = \frac{l_2}{l_1} \cdot 2 \frac{l_1}{2} \cdot \frac{1}{2} \frac{1}{\left(\frac{l_2}{2}-1\right)}$$

$$= \frac{l_2}{l_2-2} \text{ which exists when } l_2 > 2.$$

Note it is not 1, but tends to 1 when  $l_2 \rightarrow \infty$ . (1 mark)

$$5. X_1, \dots, X_m \rightarrow N(\mu_X, \sigma^2)$$

$$(a) Y_1, \dots, Y_n \rightarrow N(\mu_Y, \sigma^2).$$

$$\text{So, } \bar{X} \rightarrow N(\mu_X, \frac{\sigma^2}{m}), \frac{(m-1)S_x^2}{\sigma^2} \sim \chi^2_{m-1}$$

$$\bar{Y} \rightarrow N(\mu_Y, \frac{\sigma^2}{n}), \frac{(n-1)S_y^2}{\sigma^2} \sim \chi^2_{n-1}$$

All are independent.

$$\Rightarrow \bar{X} - \bar{Y} \rightarrow N(\mu_X - \mu_Y, \sigma^2(\frac{1}{m} + \frac{1}{n}))$$

$$\Rightarrow \frac{(\bar{X} - \bar{Y}) - (\mu_X - \mu_Y)}{\sqrt{\sigma^2(\frac{1}{m} + \frac{1}{n})}} \rightarrow N(0, 1).$$

$$(b) \text{ Pooled variance } S_p^2 = \frac{(m-1)S_x^2 + (n-1)S_y^2}{(m+n-2)}$$

$$S_p^2(m+n-2) \xrightarrow{\frac{S_p^2}{\sigma^2}} \chi^2_{m+n-2}.$$

(1 mark)

$$\Rightarrow \frac{(\bar{X} - \bar{Y}) - (\mu_X - \mu_Y)}{\sqrt{\sigma^2(\frac{1}{m} + \frac{1}{n})}} / \sqrt{\frac{(m+n-2)S_p^2}{\sigma^2(m+n-2)}} \rightarrow t_{m+n-2}$$

$$\Rightarrow \frac{(\bar{X} - \bar{Y}) - (\mu_X - \mu_Y)}{\sqrt{S_p^2(\frac{1}{m} + \frac{1}{n})}} \rightarrow t_{m+n-2}. \quad (1 \text{ mark})$$

(c) An exact  $100(1-\alpha)\%$  CI for  $\mu_X - \mu_Y$  is

$$(\bar{X} - \bar{Y} - t_{m+n-2, \frac{\alpha}{2}} \sqrt{\frac{S_p^2(\frac{1}{m} + \frac{1}{n})}{2}}, \bar{X} - \bar{Y} + t_{m+n-2, \frac{\alpha}{2}} \sqrt{\frac{S_p^2(\frac{1}{m} + \frac{1}{n})}{2}})$$

(1 mark)

(d) Let pooled variance be  $wS_x^2 + (1-w)S_y^2$ .

$$\text{Then, } E(wS_x^2 + (1-w)S_y^2) = w\sigma^2 + (1-w)\sigma^2 = \sigma^2.$$

$$\text{Next, } \text{Var}(wS_x^2 + (1-w)S_y^2) = w^2 \frac{20^4}{m-1} + (1-w)^2 \frac{20^4}{n-1}.$$

$$\text{Differentiating wrt } w, \text{ we get } 20^4 \left( \frac{2w}{m-1} - \frac{2(1-w)}{n-1} \right) = 0$$

$$\Rightarrow w = \frac{m-1}{m+n-2}. \text{ Hence, } S_p^2.$$

(1 mark)