

# MTH 383/683: Homework #3

Due Date: September 22, 2023

## 1 Problems for Everyone

1. **Sum of Exponential is Gamma.** Let  $X_1, \dots, X_n$  be  $n$  independent and identically distributed exponential random variables with parameter  $\lambda > 0$  and let  $Z = X_1 + \dots + X_n$ . Recall from the last homework that the moment generating function of each  $X_i$  is given by

$$\phi(t) = \mathbb{E}[e^{tX_i}] = \frac{\lambda}{\lambda - t}.$$

for  $t < \lambda$ .

- Find the moment generating function of  $Z$ .
- A random variable  $Y$  is said to have a gamma distribution with parameter  $\lambda > 0$  if it has the following probability density

$$f(y) = \begin{cases} \frac{\lambda^n}{(n-1)!} y^{n-1} e^{-\lambda y}, & y \geq 0 \\ 0, & y < 0 \end{cases},$$

where  $n \in \mathbb{N}$ . Find the moment generating function  $Y$  and use this result to prove that the sum of  $n$  independent and identically distributed exponential random variables is a gamma distribution.

2. **Sum of Gaussian is Gaussian** Let  $X_1, X_2$  be two independent but not necessarily identically distributed Gaussian random variables. Recall from last homework that the moment generating function of a Gaussian random variable with mean  $\mu$  and standard deviation  $\sigma$  is given by

$$\phi(t) = \mathbb{E}[e^{tX}] = e^{\mu + t^2\sigma^2/2}.$$

By computing its moment generating function, prove that  $Z = X_1 + X_2$  is also a Gaussian random variable.

3. **Calculations with Joint Density** Let  $\vec{X} = (X, Y)$  be a random vector with joint density

$$f(x, y) = \begin{cases} 6x^2y & 0 \leq x \leq y \text{ and } x + y \leq 2 \\ 0 & \text{elsewhere} \end{cases}.$$

- Find the probability density functions of  $X$  and  $Y$ .
- Are  $X$  and  $Y$  independent random variables?

4. **Example of Uncorrelated Random Variables that are not Independent** Let  $X$  be a standard Gaussian. Show that  $\text{Cov}(X, X^2) = 0$ , yet  $X$  and  $X^2$  are not independent.

5. **The Covariance Matrix of a Random Vector is Always Positive Definite.** Let  $C$  be the covariance matrix of the random vector  $X = (X_1, \dots, X_n)$ . Show that  $C$  is always positive semidefinite, i.e.,

$$\sum_{i=1}^{\infty} \sum_{j=1}^{\infty} a_i a_j C_{ij} \geq 0.$$

for any  $a_1, \dots, a_n \in \mathbb{R}^n$ . Hint: Write the left side as the variance of some random variable.

6. **A Linear Transformation of a Gaussian Vector is also Gaussian.** Let  $X = (X_1, \dots, X_n)$  be an  $n$ -dimensional Gaussian vector and  $M$  a  $m \times n$  matrix.

- Show that  $Y = MX$  is also a Gaussian vector.
- If the covariance matrix of  $X$  is  $C$ , write the covariance matrix of  $Y$  in terms of  $M$  and  $C$ .

### Homework #3

#### #1

Prove that the sum of I.I.D. exponentially distributed random variables has a  $\Gamma$ -distribution.

#### Solution:

Let  $X_1, \dots, X_n$  have exponential distributions with parameter  $\lambda > 0$ . Therefore,

$$\begin{aligned}\phi(t) &= E[e^{t(X_1 + \dots + X_n)}] \\ &= E[e^{tX_1 + \dots + tX_n}] \\ &= E[e^{tX_1} \dots e^{tX_n}] \\ &= E[e^{tX_1}] \dots E[e^{tX_n}] \\ &= \frac{\lambda}{\lambda-t} \dots \frac{\lambda}{\lambda-t} \\ &= \frac{\lambda^n}{(\lambda-t)^n}.\end{aligned}$$

Now, if we let  $\Upsilon$  be a  $\Gamma$ -distribution it follows that

$$\begin{aligned}E[e^{t\Upsilon}] &= \frac{\lambda^n}{(n-1)!} \int_0^\infty e^{ty} y^{n-1} e^{-\lambda y} dy \\ &= \frac{\lambda^n}{(n-1)!} \int_0^\infty y^{n-1} e^{-(\lambda-t)y} dy \\ &= \frac{\lambda^n}{(n-1)!} \left( -\frac{1}{\lambda-t} y^{n-1} e^{-(\lambda-t)y} \Big|_0^\infty + \int_0^\infty \frac{n-1}{\lambda-t} y^{n-2} e^{-(\lambda-t)y} dy \right) \\ &= \frac{\lambda^n}{(n-2)!} \frac{1}{(\lambda-t)} \int_0^\infty y^{n-2} e^{-(\lambda-t)y} dy\end{aligned}$$

Inductively it follows that

$$E[e^{t\Upsilon}] = \frac{\lambda^n}{(\lambda-t)^n} = \phi(t)$$

#2.

Let  $X_1, X_2$  be two independent Gaussian random variables.  
Prove that  $Z = X_1 + X_2$  is a Gaussian random variable.

Solution:

Computing, we have that

$$\begin{aligned} \phi(t) &= \mathbb{E}[e^{tZ}] \\ &= \mathbb{E}[e^{t(X_1+X_2)}] \\ &= \mathbb{E}[e^{tX_1} e^{tX_2}] \\ &= \mathbb{E}[e^{tX_1}] \mathbb{E}[e^{tX_2}] \\ &= e^{t\mu_1 + t^2\sigma_1^2} e^{t\mu_2 + t^2\sigma_2^2/2} \\ &= e^{t(\mu_1 + \mu_2) + (t^2\sigma_1^2 + \sigma_2^2)t^2/2} \end{aligned}$$

Therefore,  $Z$  is a Gaussian random variable with mean  $\mu = \mu_1 + \mu_2$  and variance  $\sigma_1^2 + \sigma_2^2$ .

#3.

Let  $\vec{X} = (X, Y)$  be a random vector with joint density

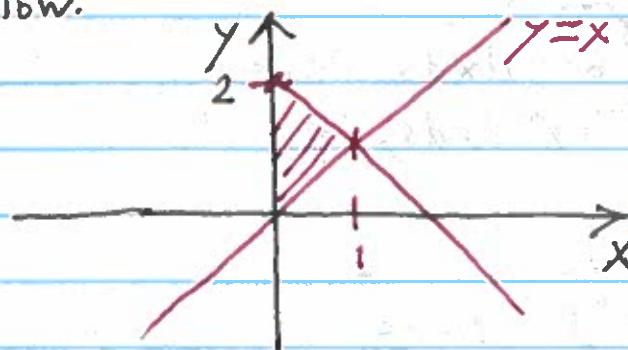
$$f(x, y) = \begin{cases} 6xy, & 0 \leq x \leq y \text{ and } xy \leq 2, \\ 0, & \text{e.w.} \end{cases}$$

(a) Find the probability density functions of  $X$  and  $Y$ .

(b) Are  $X$  and  $Y$  independent random variables?

Solution:

(a) The regions in which  $f(x,y) \geq 0$  are plotted below:



Therefore,

$$P(X \leq x) = \begin{cases} 0 & \text{if } x < 0 \\ \int_0^x \int_s^2 6s^2 dy ds & \text{if } 0 \leq x < 1 \\ 1 & \text{if } x \geq 1 \end{cases}$$

$$= \begin{cases} 0 & \text{if } x < 0 \\ \int_0^x 3s^2 y^2 \Big|_s^2 ds & \text{if } 0 < x < 1 \\ 1 & \text{if } x \geq 1 \end{cases}$$

$$= \begin{cases} 0 & \text{if } x < 0 \\ \int_0^x [3(2-s)^2 s^2 - 3s^4] ds & \text{if } 0 < x < 1 \\ 1 & \text{if } x \geq 1 \end{cases}$$

$$\Rightarrow f(x) = dP(X \leq x) = \frac{d}{dx} \left[ 3s^2 [4 - 4s + s^2 - s^4] \right]$$

$$\Rightarrow f(x) = 12s^3[1-s].$$

We also have that

$$P(Y \leq y) = \begin{cases} 0 & \text{if } y < 0 \\ \int_0^y \int_0^s 6x^2 s dx ds & \text{if } 0 \leq y < 1 \\ \int_0^1 \int_0^s 6x^2 s dx ds + \int_1^y \int_0^2 6x^2 s dx ds & \text{if } 1 \leq y < 2 \\ 1 & \text{if } y \geq 2 \end{cases}$$

$$\Rightarrow g(y) = \frac{d}{dy} P(T \leq y)$$

$$= \begin{cases} 0, & y < 0 \text{ or } y > 2 \\ \frac{d}{dy} \int_0^y \int_0^s 6x^2 s dx ds, & 0 < y < 1 \\ \frac{d}{dy} \int_1^y \int_s^2 6x^2 s dx ds, & 1 < y < 2 \end{cases}$$

$$= \begin{cases} 0, & y < 0 \text{ or } y > 2 \\ \frac{d}{dy} \int_0^y 2s^4 ds, & 0 < y < 1 \\ \frac{d}{dy} \int_1^y 2(2-s)^3 ds, & 1 < y < 2 \end{cases}$$

$$\Rightarrow g(y) = \begin{cases} 0, & y < 0 \text{ or } y > 2 \\ 2y^4, & 0 < y < 1 \\ 2(2-y)^3, & 1 < y < 2 \end{cases}$$

Since  $f(x,y) \neq f(x)g(y)$  it follows that  $X, T$  are not independent.

#4

Let  $X$  be a standard Gaussian. Show that  $\text{Cov}(X, X^2) = 0$  yet  $X$  and  $X^2$  are not independent.

Solution:

Computing, we have that  $\text{Cov}(X, X^2) = E[X^3] - E[X]E[X^2] = 0$   
since

$$E[X^3] = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} x^3 e^{-x^2/2} dx = 0$$

$$E[X^2] = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} x^2 e^{-x^2/2} dx = 1$$

However,

$$P(0 < X < 1, 0 < X^2 < 1) = P(0 < X < 1),$$

$$P(0 < X < 1)P(0 < X^2 < 1) = P(0 < X < 1)P(-1 < X < 1).$$

Therefore, if these random variables are independent we have that

$$P(-1 < X < 1) = 1$$

which is a contradiction.  $\blacksquare$

#5.

Let  $C$  be the covariance matrix of  $(X_1, \dots, X_n)$ . Show that  $C$  is always positive semidefinite.  $\blacksquare$

Solution:

For any  $a_1, a_2, \dots, a_n \in \mathbb{R}$  we have that

$$\text{Var}[a_1 X_1 + \dots + a_n X_n] \geq 0$$

$$\Rightarrow \text{Cov}(a_1 X_1 + \dots + a_n X_n, a_1 X_1 + \dots + a_n X_n) = \sum_{i=1}^n \sum_{j=1}^n a_i a_j C_{ij} \geq 0.$$

#6.

Let  $\mathbf{X} = (X_1, \dots, X_n)$  be a Gaussian vector and  $M$  a  $m \times n$  matrix.

(a) Show that  $\mathbf{Y} = M\mathbf{X}$  is also Gaussian

(b) If the covariance matrix of  $\mathbf{X}$  is  $C$ , write the covariance matrix of  $\mathbf{Y}$  in terms of  $M$  and  $C$ .

### Solution:

(a) If we consider a linear combination of  $(\mathbf{Y}_1, \dots, \mathbf{Y}_m)$  we have that

$$\begin{aligned} a_1 \mathbf{Y}_1 + \dots + a_m \mathbf{Y}_m &= a_1 \sum_{i=1}^n M_{1,i} \mathbf{X}_i + \dots + a_m \sum_{i=1}^n M_{m,i} \mathbf{X}_i \\ &= \sum_{j=1}^m \sum_{i=1}^n a_j M_{j,i} \mathbf{X}_i \\ &= \sum_{j=1}^m \left( \sum_{i=1}^n a_j M_{j,i} \right) \mathbf{X}_i \\ &= \left( \sum_{j=1}^m a_j M_{j,1} \right) \mathbf{X}_1 + \dots + \left( \sum_{j=1}^m a_j M_{j,n} \right) \mathbf{X}_n \end{aligned}$$

and thus  $a_1 \mathbf{Y}_1 + \dots + a_m \mathbf{Y}_m$  is a Gaussian random variable.

(b) Computing, we have that

$$\begin{aligned} \text{Cov}(\mathbf{Y}_i, \mathbf{Y}_j) &= \text{Cov}\left(\sum_{k=1}^n M_{ik} \mathbf{X}_k, \sum_{l=1}^n M_{jl} \mathbf{X}_l\right) \\ &= \sum_{k=1}^n \sum_{l=1}^n M_{ik} M_{jl} \text{Cov}(\mathbf{X}_k, \mathbf{X}_l) \\ &= \sum_{k=1}^n \sum_{l=1}^n M_{ik} M_{jl} C_{k,l} \end{aligned}$$

Therefore, if let  $C'$  denote the covariance matrix of  $\mathbf{Y}$  it follows that

$$C' = M C M^T$$

$n \times n \quad n \times n \quad n \times n$