

Show all work clearly and in order. Circle or box your final answer but points will be awarded based on a correct solution. A solution should always justify the steps taken and explain the assumptions needed to reach a final answer (e.g. how do you know you are not dividing by zero in the last step?).

Multivariate Transformations

Transformations of a Random Vector

A *random vector* is a vector of random variables. It is the multivariate version of a random variable. Just like each random variable has a distribution, the random vector has a distribution characterised by a joint PMF or PDF. We can transform this random vector just like we transform a random variable using a *one-to-one* transformation. Suppose (X, Y) is a continuous random vector with joint PDF $f_{X,Y}(x, y)$ and g is some transformation where $u = g_1(x, y)$ and $v = g_2(x, y)$. If the components of g (g_1 and g_2) are one-to-one transformations of $\text{supp}(X, Y)$ to $\text{supp}(U, V)$ where $\text{supp}(U, V) = \{(u, v) : u = g_1(x, y) \text{ and } v = g_2(x, y) \text{ for some } (x, y) \in \text{supp}(X, Y)\}$, then the inverse transformations $x = h_1(u, v)$ and $y = h_2(u, v)$ exist. Furthermore, we can define the Jacobian of this transformation H by

$$J = \begin{pmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{pmatrix}.$$

The Jacobian is the matrix of first derivatives. When J consists of only one component (e.g. x) instead of two or more (e.g. x and y), then it is a vector and we call it the *gradient*. In this case, H consists of two one-to-one functions of u and v , so the Jacobian is a square matrix. Assuming J is not zero over $\text{supp}(U, V)$, the joint pdf of (U, V) is zero outside of its support and given by

$$f_{U,V}(u, v) = f_{X,Y}(h_1(u, v), h_2(u, v)) \cdot |J|$$

on its support. $|J|$ denotes the determinant of the J matrix.

Q1: Joint PMF without Jacobian

Show that if $X \sim \text{Poisson}(\theta)$ and $Y \sim \text{Poisson}(\lambda)$ and X and Y are independent, then $X + Y \sim \text{Poisson}(\theta + \lambda)$. Recall that if $U \sim \text{Poisson}(\xi)$, then

$$f_U(u) = \frac{\xi^u e^{-\xi}}{u!}$$

and if U and V are independent, then

$$f_{U,V}(u, v) = f_U(u) \cdot f_V(v).$$

Q2: Joint PDF with Jacobian

Let X and Y be independent, standard normal variables (i.e. mean zero and variance one). Consider the transformation H where $(U, V) = H(X, Y)$, $U = X + Y$ and $V = X - Y$.

- (a) What is the joint PDF of X and Y ?
- (b) Find $h_1(u, v)$ and $h_2(u, v)$.
- (c) Is the transformation H one-to-one? Why?
- (d) What is $\text{supp}(X, Y)$ and $\text{supp}(U, V)$?
- (e) Find the joint PDF of (U, V) .
- (f) Are U and V independent? How do you know?

Q3

Consider U as the random variable above and $V = Y$.

- (a) What is $\mathbb{E}[U]$? $\mathbb{E}[V]$?
- (b) What is $\text{Var}(U)$? $\text{Var}(V)$?
- (c) What is $\text{Cov}(U, V)$?

Q3

Let X and Y be independent $N(0, 1)$ random variables. Consider the transformation $U = \frac{X}{Y}$. Find $f_U(u)$. (Hint: You want to define H such that it consists of two one-to-one transformations, so you can use the Jacobian transformation to obtain a joint PDF and then the marginal for U . Try $V = |Y|$ and note that $\text{supp}(X, Y) \neq \text{supp}(U, V)$).

Q4

Prove that $\text{Var}(X \pm Y) = \text{Var}(X) + \text{Var}(Y) \pm 2 \cdot \text{Cov}(X, Y)$

Q5

Prove that $\text{Cov}(aX + b, cY + d) = a \cdot b \cdot \text{Cov}(X, Y)$ for any random variables X and Y and $a, b, c, d \in \mathbb{R}$.