CO#1 – Queueing Theory

Session#12:

Session Topic: Joint Distribution Functions, Independent Random

Variables

Probability, Statistics and Queueing Theory

(Course code: 21MT2103RA)







JOINT DISTRIBUTIONS

Outlines

- -Discrete/Continuous Random Bivariate Variables
- Joint Probability Distributions
- Marginal Probability Distributions
- Conditional Probability Distributions
- Independence, Covariance and Correlation
- -Random vector

(DEEMED TO BE UNIVERSITY)

Introduction Bivariate Frequency Distributions

• For example, suppose you throw two coins, X and Y, simultaneously and record the outcome as an ordered pair of values. Imagine that you threw the coin 8 times, and observed the following (1=Head, 0 = Tail)

(X,Y)	f
(1,1)	2
(1,0)	2
(0,1)	2
(0,0)	2

• To graph the bivariate distribution, you need a 3 dimensional plot, although this can be drawn in perspective in 2 dimensions

Joint distribution of bivariate random variables



In general, if X and Y are two random variables, the probability distribution that defines their simultaneous behavior is called a joint probability distribution.

For example: X: the length of one dimension of an injection-molded part, and Y: the length of another dimension. We might be interested in $P(2.95 \le X \le 3.05 \text{ and } 7.60 \le Y \le 7.80).$

Discrete case

Definition: If X and Y are discrete RV's, then (X,Y)is called a jointly discrete bivariate RV.

The joint (or bivariate) pmf is

$$f(x,y) = \Pr(X = x, Y = y).$$

Properties: (1)
$$0 \le f(x, y) \le 1$$
.

$$(2) \sum_{x} \sum_{y} f(x, y) = 1.$$

(3)
$$A \subseteq \Re^2 \Rightarrow \Pr((X,Y) \in A) = \sum \sum_{(x,y) \in A} f(x,y)$$
.



Continuous case

Definition: If X and Y are cts RV's, then (X,Y) is a **jointly cts RV** if there exists a function f(x,y) such that



- (1) $f(x,y) \geq 0, \forall x,y$.
- (2) $\iint_{\mathbb{R}^2} f(x, y) dx dy = 1.$ (3) $\Pr(A) = \Pr((X, Y) \in A) = \iint_A f(x, y) dx dy.$

In this case, f(x,y) is called the **joint pdf**.

is the volume between A and f(x,y)

Marginal Probability Distribution



Discrete case

Definition: If X and Y are jointly discrete, then the marginal pmf's of X and Y are, respectively,

$$f_X(x) = \sum_y f(x, y)$$

and

$$f_Y(y) = \sum_x f(x, y)$$

Continuous case

Definition: If X and Y are jointly continuous random variable, then the **marginal pdf's** of X and Y are, respectively;

$$f_X(x) = \int_{\mathcal{Y}} f(x, y) dy$$

and

$$f_Y(y) = \int f(x, y) \ dx$$

General Example for discrete bivariate random varial

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If X and Y are two discrete random variables, their joint distribution may be represented by a formula or a table below:

	Y1	Y2	••••	Yn	Marginal pdf of X g(X)
X1	f(x1,y1)	f(x1,y2)	••••	f(x1,yn)	g(x1)
X2	f(x2,y1)	f(x2,y2	•••	f(x2,yn)	g(x2)
••••	••••	••••	••••	••••	•••
Xm	f (xm , y 1)	f(xm,y2	••••	f(x2,yn)	g(xm)
Marginal pdf of Y h(y)	h(y1)	h(y2)	•••	h(yn)	↓ Total =1

Discrete case example



	2/7	1/7	0	9/21
Y=15	1/3	1/21	0	8/21
Y=20	1/7	0	1/21	4/21
P(X=x)	16/21	4/21	1/21	1

The marginal pmf's of X and Y respectively, are given by:

$$P(X = x) = f_X(x) = \begin{cases} \frac{16}{21}, & x = 1\\ \frac{4}{21}, & x = 3\\ \frac{1}{21}, & x = 7 \end{cases} \qquad P(Y = y) = f_Y(y) = \begin{cases} \frac{9}{21}, & y = 10\\ \frac{8}{21}, & y = 15\\ \frac{4}{21}, & y = 20 \end{cases}$$

$$P(Y = y) = f_Y(y) = \begin{cases} \frac{21}{8}, & y = 10\\ \frac{8}{21}, & y = 15\\ \frac{4}{21}, & y = 20 \end{cases}$$

where 16/21+4/21+1/21=1

Also,

9/21+8/21+4/21=1

P(X=2)=?

P(Y=15)=?

P(X > 1, Y > 10) = ?



Discrete case example (Read)

Example: 3 sox in a box (numbered 1,2,3). Draw 2 sox at random w/o replacement. X = # of first sock, Y = # of second sock. The joint pmf f(x,y) is

	X = 1	X = 2	X = 3	Pr(Y=y)
Y = 1	0	1/6	1/6	1/3
Y = 2	1/6	0	1/6	1/3
Y = 3	1/6	1/6	0	1/3
Pr(X = x)	1/3	1/3	1/3	1

Pr(X = x) is the "marginal" distribution of X. Pr(Y = y) is the "marginal" distribution of Y.

By the law of total probability,

$$Pr(X = 1) = \sum_{y=1}^{3} Pr(X = 1, Y = y) = 1/3.$$

$$P(Y=3)=?$$



In addition,

$$Pr(X \ge 2, Y \ge 2)$$

$$= \sum_{x \ge 2} \sum_{y \ge 2} f(x, y)$$

$$= f(2, 2) + f(2, 3) + f(3, 2) + f(3, 3)$$

$$= 0 + 1/6 + 1/6 + 0 = 1/3.$$

Continuous case example: Read

Example: Suppose that

$$f(x,y) = \begin{cases} 4xy & \text{if } 0 \le x \le 1, \ 0 \le y \le 1 \\ 0 & \text{otherwise} \end{cases}$$

Find the prob (volume) of the region $0 \le y \le 1 - x^2$.

$$V = \int_0^1 \int_0^{1-x^2} 4xy \, dy \, dx$$

=
$$\int_0^1 \int_0^{\sqrt{1-y}} 4xy \, dx \, dy$$

= 1/3.



Example of joint density for continuous r.v.'s

• Let the joint density of X and Y be

$$f(x, y) = \begin{cases} 2e^{-x}e^{-2y}, & 0 < x < \infty, & 0 < y < \infty \\ 0, & \text{otherwise} \end{cases}$$

- Prove that
 - (1) $P{X>1,Y<1} = e^{-1}(1-e^{-2})$
 - (2) $P\{X < Y\} = 1/3$
 - (3) $F_X(a) = 1 e^{-a}$, a > 0, and 0 otherwise.



Note: Going from cdf's to pdf's (continuous case).

1-dimension:
$$f(x) = F'(x) = \frac{d}{dx} \int_{-\infty}^{x} f(t) dt$$
.

2-D:
$$f(x,y) = \frac{\partial^2}{\partial x \partial y} F(x,y) = \frac{\partial^2}{\partial x \partial y} \int_{-\infty}^x \int_{-\infty}^y f(s,t) dt ds$$
.



Bivariate Cumulative distribution Functions (CDF's)

Definition: The joint (bivariate) cdf of X and Y is

$$F(x,y) \equiv P(X \le x, Y \le y)$$
, for all x, y .

$$F(x,y) = \begin{cases} \sum \sum_{s \le x, t \le y} f(s,t) & \text{discrete} \\ \int_{-\infty}^{y} \int_{-\infty}^{x} f(s,t) \, ds \, dt & \text{continuous} \end{cases}$$

Prooerties

- F(x,y) is non-decreasing in both x and y.

- \bigcirc F(x,y) is cts from the right in both x and y.



A company that services air conditioner units in residences and office blocks is interested in how to schedule its technicians in the most efficient manner

- The random variable X, taking the values 1,2,3 and 4, is the service time in hours
- The random variable Y, taking the values 1,2 and 3, is the number of air conditioner units

Y =	X=service time					
number of units	1 2 3		3	4		
1	0.12	0.08	0.07	0.05		
2	0.08	0.15	0.21	0.13		
3	0.01	0.01	0.02	0.07		

probability

Joint p.m.f and the total

$$\sum_{i} \sum_{j} P_{ij} = 0.12 + 0.08 + \dots + 0.07 = 1$$

 Joint cumulative distribution function

$$F(2,2) = p_{11} + p_{12} + p_{21} + p_{22}$$
$$= 0.12 + 0.18 + 0.08 + 0.15$$
$$= 0.43$$

Conditional Probability Distribution





- Conditional probability distributions
 - The probability of the random variable X under the knowledge provided by the value of Y is given by
 - Discrete case

$$p_{i|j} = P(X = i | Y = j) = \frac{P(X = i, Y = j)}{P(Y = j)} = \frac{p_{ij}}{p_{+j}}$$

Continuous case

$$f_{X|Y=y}(x) = \frac{f(x, y)}{f_Y(y)}$$

The conditional probability distribution is a **probability distribution**.

Because a conditional probability mass function $f_{Y|x}(y)$ is a probability mass function for all y in R_x , the following properties are satisfied:

$$(1) \quad f_{Y|x}(y) \ge 0$$

$$(2) \quad \sum_{R_x} f_{Y|x}(y) = 1$$

(3)
$$P(Y = y | X = x) = f_{Y|x}(y)$$

(5-5)



Conditional Mean and Variance

Definition

Let R_x denote the set of all points in the range of (X, Y) for which X = x. The **conditional mean** of Y given X = x, denoted as E(Y|x) or $\mu_{Y|x}$, is

$$E(Y|x) = \sum_{R_{\tau}} y f_{Y|x}(y)$$
 (5-6)

and the **conditional variance** of Y given X = x, denoted as V(Y|x) or $\sigma_{Y|x}^2$, is

$$V(Y|x) = \sum_{R_x} (y - \mu_{Y|x})^2 f_{Y|x}(y) = \sum_{R_x} y^2 f_{Y|x}(y) - \mu_{Y|x}^2$$

Example (Exercise: Air Conditioner)

Marginal probability distribution of Y

$$P(Y = 3) = p_{+3} = 0.01 + 0.01 + 0.02 + 0.07 = 0.11$$

Conditional distribution of X

$$p_{1|Y=3} = P(X=1|Y=3) = \frac{p_{13}}{p_{+3}} = \frac{0.01}{0.11} = 0.091$$

Conditional Probability Distribution Conditional Probability Distribution



Example: The marginal probability distribution for X and Y.

y=number of times	x=number of bars of signal strength				
city name is stated	1	2	3	Marginal probability distribution of Y	
4	0.15	0.1	0.05	0.3	
3	0.02	0.1	0.05	0.17	
2	0.02	0.03	0.2	0.25	
1	0.01	0.02	0.25	0.28	
	0.2	0.25	0.55		

Marginal probability distribution of X

$$P(Y=1 | X=3) = P(X=3, Y=1) / P(X=3)$$

= $f_{x,y}(3,1) / f_x(3) = 0.25 / 0.55 = 0.454$

$$E(Y|1) = \sum_{y} y f_{Y|1}(y)$$

$$= 1(0.05) + 2(0.1) + 3(0.1) + 4(0.75) = 3.55$$

$$V(Y|1) = \sum_{y} (y - \mu_{Y|x})^2 f_{Y|1}(y)$$

$$= (1 - 3.55)^2 0.05 + (2 - 3.55)^2 0.1 + (3 - 3.55)^2 0.1 + (4 - 3.55)^2 0.75$$

=0.748

Expected Values for Jointly Distributed Continuous R.V.s

• Let X and Y be continuous random variables with joint probability density function f(x, y). We define E(X) and E(Y) as

$$E(X) = \int_{-\infty}^{\infty} x f_X(x) dx$$
 and $E(Y) = \int_{-\infty}^{\infty} y f_Y(y) dy$.

• Example. For the random variables X and Y from the previous slide, $f_X(x) = e^{-x}$, x > 0 and $f_Y(y) = 2e^{-2y}$, y > 0.

That is, X and Y are exponential random variables. It follows that

$$E(X) = 1$$
 and $E(Y) = \frac{1}{2}$.

Independence, Covariance and Correlation (1/13) Independence

Discrete case

Two random variables X and Y are said to be independent if and only if

$$P[X=x,Y=y] = P[X=x] P[Y=y]$$
 for all real numbers x and y.

This definition of independence for discrete random variables translates into the statement that X and Y are independent if and only if a cell value is the product of the row total times the column total. i.e

$$p_{ij} = p_{i+}p_{+j}$$
 for all values i of X and j of Y

Continuous case

For continuous random variables, the condition for independence of X and Y becomes X and Y are independent if and only if

$$f(x, y) = f_X(x) f_Y(y)$$
 for all x and y

The marginal density functions can be multiplied together to produce the joint density function. Thus the random variables X and Y are independent.

Independence, Covariance and Correlation (2/13)

Example: (Discrete case)

Are the random variables X and Y described above with the following joint probability density table independent?

Y Values						
		0	1	2	3	
	0	1/8	0	0	0	1/8
X Values	1	0	1/8	1/8	1/8	3/8
	2	0	1/4	1/8	0	3/8
	3	0	1/8	0	0	1/8
		1/8	1/2	1/4	1/8	

The random variables are not independent because, for example P[X=0,Y=1] = 0 but P[X=0] = 1/8 and P[Y=1] = 4/8.

Example: (continuous case)

For the joint density function f(x,y) = 1 for x on [0,1] and y on [0,1] and 0 otherwise, the marginal density function of X, $f_X(x) = 1$ for x on [0,1] and the marginal density function of Y, $f_Y(y) = 1$ for y on [0,1]. The marginal density functions can be multiplied together to produce the joint density function. Thus the random variables X and Y are independent

Independence, Covariance and Correlation (3/13)

Functions of Independent Random Variables

- **Theorem**. Let X and Y be independent random variables and let g and h be real valued functions of a single real variable. Then
- (i) g(X) and h(Y) are also independent random variables
- (ii) E[g(X)h(Y)] = E[g(X)]E[h(Y)].

• Example. If X and Y are independent, then $E[(\sin X)e^{Y}] = E[\sin X]E[e^{Y}].$

Independence, Covariance and Correlation (4/13) Covariance

$$Cov(X,Y) = E((X - E(X))(Y - E(Y)))$$

$$= E(XY) - E(X)E(Y)$$

$$Cov(X,Y) = E((X - E(X))(Y - E(Y)))$$

$$= E(XY - XE(Y) - E(X)Y + E(X)E(Y))$$

$$= E(XY) - E(X)E(Y) - E(X)E(Y) + E(X)E(Y)$$

$$= E(XY) - E(X)E(Y)$$

- May take any positive or negative numbers.
- Independent random variables have a covariance of zero
- What if the covariance is zero?

$$E(XY)=E(X)E(Y)$$

Independence, Covariance and Correlation (5/13)

General Properties of (Cov(X, Y))

$$4 - Cov(\sum_{i=1}^{n} X_{i}, \sum_{j=1}^{m} Y_{j}) = \sum_{i=1}^{n} \sum_{j=1}^{m} Cov(X_{i}, Y_{j})$$

$$5 - Var(\sum_{i=1}^{n} X_{i}) = Cov(\sum_{i=1}^{n} X_{i}, \sum_{j=1}^{n} X_{i})$$

$$= \sum_{i=1}^{n} Var(X_{i}) + \sum_{i \neq j} \sum Cov(X_{i}, X_{j})$$

$$= \sum_{i=1}^{n} Var(X_{i}) + 2\sum_{i < j} \sum Cov(X_{i}, X_{j})$$

Independence, Covariance and Correlation (6/13)

• Properties of $Cov(X_1, X_2)$

$$Cov(X_1, X_2) = E[X_1 X_2] - E[X_1]E[X_2]$$

, Cov(ax, bY) = ab Cov(X,Y)

$$\Rightarrow Cov(X_{1}, X_{2}) = Cov(X_{2}, X_{1})$$

$$Cov(X_{1}, X_{1}) = Var(X_{1}) \quad Cov(X_{2}, X_{2}) = Var(X_{2})$$

$$Cov(X_{1} + X_{2}, X_{1}) = Cov(X_{1}, X_{1}) + Cov(X_{2}, X_{1})$$

$$Cov(X_{1} + X_{2}, X_{1} + X_{2}) = Cov(X_{1}, X_{1}) + Cov(X_{1}, X_{2}) + Cov(X_{2}, X_{1}) + Cov(X_{2}, X_{2})$$

$$\Rightarrow Var(X_1 + X_2) = Var(X_1) + Var(X_2) + 2Cov(X_1, X_2)$$

Independence, Covariance and Correlation (7/13)

General Properties of (Cov(X, Y))

$$4 - Cov(\sum_{i=1}^{n} X_{i}, \sum_{j=1}^{m} Y_{j}) = \sum_{i=1}^{n} \sum_{j=1}^{m} Cov(X_{i}, Y_{j})$$

$$5 - Var(\sum_{i=1}^{n} X_{i}) = Cov(\sum_{i=1}^{n} X_{i}, \sum_{j=1}^{n} X_{i})$$

$$= \sum_{i=1}^{n} Var(X_{i}) + \sum_{i \neq j} \sum Cov(X_{i}, X_{j})$$

$$= \sum_{i=1}^{n} Var(X_{i}) + 2\sum_{i < j} \sum Cov(X_{i}, X_{j})$$

Independence, Covariance and Correlation (8/13)

• Example (Air conditioner maintenance)

$$E(X) = 2.59, E(Y) = 1.79$$

$$E(XY) = \sum_{i=1}^{4} \sum_{j=1}^{3} ijp_{ij}$$

$$= (1 \times 1 \times 0.12) + (1 \times 2 \times 0.08)$$

$$+ \cdots + (4 \times 3 \times 0.07) = 4.86$$

$$Cov(X,Y) = E(XY) - E(X)E(Y)$$

$$= 4.86 - (2.59 \times 1.79) = 0.224$$

$$3 0.01 0.01 0.02 0.07$$

Exercise: Find Var(X), Var (Y)

Independence, Covariance and Correlation (9/13)

Correlation

• The correlation is a measure of the <u>linear</u> relationship between X and Y. It is obtained by dividing the covariance by the product of the two standard deviations, i.e.,

$$Corr(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}}$$

- The correlation assumes values between -1 and 1.
- A value close to 1 implies a strong **positive** relationship.
- A value close to -1 implies a strong **negative** relationship.
- A value close to zero implies little or no relationship.
- The independent random variables have a correlation of zero.

Independence, Covariance and Correlation (10/13)

An important implication of independence

Suppose that the components X and Y of the discrete bivariate random variable (X,Y) are independent. Then its covariance is zero

Always $E(X-\mu)=0$

$$\begin{split} &\sigma_{XY} = \text{cov}(X,Y) \\ &= \sum_{\mathbf{x} \in X(\Omega)} \sum_{\mathbf{y} \in Y(\Omega)} (\mathbf{x} - \boldsymbol{\mu}_{\mathbf{X}})(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{Y}}) P(\mathbf{X} = \mathbf{x} \wedge \mathbf{Y} = \mathbf{y}) \\ &= \sum_{\mathbf{x} \in X(\Omega)} \sum_{\mathbf{y} \in Y(\Omega)} (\mathbf{x} - \boldsymbol{\mu}_{\mathbf{X}})(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{Y}}) P(\mathbf{X} = \mathbf{x})^T \mathbf{Y} = \mathbf{y}) \\ &= \sum_{\mathbf{x} \in X(\Omega)} (\mathbf{x} - \boldsymbol{\mu}_{\mathbf{X}}) P(\mathbf{X} = \mathbf{x}) \left[\sum_{\mathbf{y} \in Y(\Omega)} -\boldsymbol{\mu}_{\mathbf{Y}}) P(\mathbf{Y} = \mathbf{y}) \right] \\ &= E(\mathbf{X} - \boldsymbol{\mu}_{\mathbf{X}}) E(\mathbf{Y} - \boldsymbol{\mu}_{\mathbf{Y}}) \\ &= 0 \end{split}$$

Independence, Covariance and Correlation (11/13)

The continuous case

$$\begin{split} \sigma_{XY} &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X)(y - \mu_Y) f_{XY}(x, y) dy dx \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X)(y - \mu_Y) f(x) f(y) dy dx \\ &= \int_{-\infty}^{\infty} (x - \mu_X) f(x) \int_{-\infty}^{\infty} (y - \mu_Y) f(y) dy dx \\ &= \int_{-\infty}^{\infty} (x - \mu_X) f(x) \left[\int_{-\infty}^{\infty} (y - \mu_Y) f(y) dy \right] dx \\ &= \left[\int_{-\infty}^{\infty} (y - \mu_Y) f(y) dy \right] \int_{-\infty}^{\infty} (x - \mu_X) f(x) dx \\ &= E(Y - \mu_Y) E(X - \mu_X) \\ &= 0. \end{split}$$

Independence, Covariance and Correlation (12/13)

Example : (Air conditioner maintenance)

$$Var(X) = 1.162, \quad Var(Y) = 0.384$$

$$Corr(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}}$$

$$= \frac{0.224}{\sqrt{1.162 \times 0.384}} = 0.34$$

Independence, Covariance and Correlation (13/13)

Moments of bivariate random variables

Joint moments of (X,Y):

```
EX, EY

EX<sup>2</sup>, EXY, EY<sup>2</sup>

EX<sup>3</sup>, EX<sup>2</sup>Y, EXY<sup>2</sup>, EY<sup>3</sup>
```

Joint central moments of (X,Y):

```
E(X-EX), E(Y-EY)

E(X-EX)^2, E(X-EX)(Y-EY), E(Y-EY)^2

E(X-EX)^3, E(X-EX)^2(Y-EY), E(X-EX)(Y-EY)^2, E(Y-EY)^3
```

- I read from my textbook that cov(X,Y)=0 does not guarantee X andY are independent. But if they are independent, their covariance must be 0. I could not think of any proper example yet; could someone provide one?
- Easy example: Let X be a random variable that is -1 or +1 with probability 0.5. Then let Y be a random variable such that Y=0 if X=-1, and Y is randomly -1 or +1 with probability 0.5 if X=1.
- Clearly X and Y are highly dependent (since knowing Y allows me to perfectly know X), but their covariance is zero: They both have zero mean, and

$$\mathbb{E}[XY] = (-1) \cdot 0 \qquad \cdot P(X = -1)$$

$$+ 1 \qquad \cdot 1 \qquad \cdot P(X = 1, Y = 1)$$

$$+ 1 \qquad \cdot (-1) \cdot P(X = 1, Y = -1)$$

$$= 0.$$

• Or more generally, take any distribution P(X) and any P(Y|X) such that P(Y=a|X)=P(Y=-a|X) for all X (i.e., a joint distribution that is symmetric around the x axis), and you will always have zero covariance. But you will have non-independence whenever $P(Y|X)\neq P(Y)$; i.e., the conditionals are not all equal to the marginal. Or ditto for symmetry around the y axis.

Exercices

(1) Let the joint distribution of X and Y is given by : $f(x,y) = 2xy \cdot y = 1 \cdot 2 \cdot 3 \cdot y = 1 \cdot 2 \cdot 3$

$$f(x,y) = cxy, x=1,2,3; y=1,2,3.$$

Find

- (i) the constant c,
- (ii) (ii) p(x=2,y=3),
- (iii) $P(1 \le X \le 2, Y \le 2) P(Y < 2), p(X=1) p(Y=3)$

Find the marginal probability mass functions of X and Y above and determine whether x and Y are independent

(2) Let X, Y have joint density functions

$$f(x,y) = \begin{cases} c(x^2 + y^2) & 0 \le x \le 1, 0 \le y \le 1\\ 0 & \text{, otherwise} \end{cases}$$

Determine

- (a) the constant c
- (b) $P(X < \frac{1}{2}, Y > \frac{1}{2})$, $P(\frac{1}{4} < X < \frac{3}{4})$
- (d) $P(Y < \frac{1}{4})$
- (e) Find the marginal distribution functions of X and Y.
- 3(f) Are X, Y independent



(3) The joint distributions are given in each question. Find the conditional distribution of

- (a) X given Y
- (b) Y given X

2.58)
$$f(x,y) = (\frac{xy}{36}),$$

 $x = 1, 2, 3 \text{ and } y = 1, 2, 3$

(2.59)
$$f(x, y) = \begin{cases} \frac{3}{2}(x^2 + y^2), & 0 \le x \le 1, \ 0 \le y \le 1 \\ o, & \text{otherwise} \end{cases}$$

(2.60)
$$f(x, y) = \begin{cases} (x+y), & 0 \le x \le 1, \ 0 \le y \le 1 \\ o, \text{ otherwise} \end{cases}$$

(2.61)
$$f(x, y) = \begin{cases} e^{-(x+y)}, & x \ge 0, y \ge 0 \\ o, & \text{otherwise} \end{cases}$$