

STAT 330 - Mathematical Statistics

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Last updated: October 24, 2020

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Chapter 2

Univariate Random Variable

LECTURE 1 | 2020-09-09

Review probability model, random variable (r.v.), expectation, and moment generating function.

2.1 Probability Model and Random Variable

DEFINITION 2.1.1: Probability model

A **probability model** is used for a random experiment and consists of three components:

- (I) Sample space
- (II) Event
- (III) Probability (density) function

DEFINITION 2.1.2: Sample space

A **sample space** S is the collection of all possible outcomes of one single random experiment.

DEFINITION 2.1.3: Event

An **event** is a subset of S and is denoted by A .

EXAMPLE 2.1.4

Toss a coin twice. This is a random experiment because we do not know the outcome before we toss the coin twice.

- $S = \{(H, H), (H, T), (T, H), (T, T)\}$

Define A : First toss is an H .

Clearly, $A = \{(H, H), (H, T)\} \subseteq S$, so A is an event.

DEFINITION 2.1.5: Probability function

A **probability function** $\mathbb{P}(\cdot)$ is a function that satisfies the following axioms:

- (I) $\mathbb{P}(A) \geq 0$ for any event A
- (II) $\mathbb{P}(S) = 1$
- (III) **Additivity property:** If A_1, A_2, A_3, \dots are pairwise mutually exclusive events; that is, $A_i \cap A_j = \emptyset$ for all $i \neq j$, then

$$\mathbb{P}\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} \mathbb{P}(A_i)$$

EXAMPLE 2.1.6

Toss a coin twice, given one event A ,

$$\mathbb{P}(A) = \frac{\# \text{ of outcomes in } A}{4}$$

since $|S| = 4$. $\mathbb{P}(\cdot)$ satisfies the three properties, therefore $\mathbb{P}(\cdot)$ is a probability function.

PROPOSITION 2.1.7: Additional Properties of the Probability Set Function

Let A and B be events with sample space S and let $\mathbb{P}(\cdot)$ be a probability function, then

- (1) $\mathbb{P}(\emptyset) = 0$
- (2) If A and B are mutually exclusive events, then $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B)$
- (3) $\mathbb{P}(\bar{A}) = 1 - \mathbb{P}(A)$
- (4) If $A \subseteq B$, then $\mathbb{P}(A) \leq \mathbb{P}(B)$

Proof of: 2.1.7

Proof of (1): Let $A_1 = S$ and $A_i = \emptyset$ for $i = 2, 3, \dots$. Since $\bigcup_{i=1}^{\infty} A_i = S$, then by (III) it follows that

$$\mathbb{P}(S) = \mathbb{P}(S) + \sum_{i=2}^{\infty} \mathbb{P}(\emptyset)$$

and by (II) we have

$$1 = 1 + \sum_{i=2}^{\infty} \mathbb{P}(\emptyset)$$

By (I) the right side is a series of non-negative numbers which must converge to the left side which is 1 which is finite which results in a contradiction unless $\mathbb{P}(\emptyset) = 0$ as required.

Proof of (2): Let $A_1 = A$, $A_2 = B$, and $A_i = \emptyset$ for $i = 3, 4, \dots$. Since $\bigcup_{i=1}^{\infty} A_i = A \cup B$, then by (III)

$$\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) + \sum_{i=3}^{\infty} \mathbb{P}(\emptyset)$$

and since $\mathbb{P}(\emptyset) = 0$ by the result of (1) it follows that

$$\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B)$$

Proof of (3): Since $S = A \cup \bar{A}$ and $A \cap \bar{A} = \emptyset$ then by (II) and by (2) it follows that

$$1 = \mathbb{P}(S) = \mathbb{P}(A \cup \bar{A}) = \mathbb{P}(A) + \mathbb{P}(\bar{A})$$

as required.

Proof of (4): Since

$$B = (A \cap B) \cup (\bar{A} \cap B) = A \cup (\bar{A} \cap B)$$

and $A \cap (\bar{A} \cap B) = \emptyset$ then by (2)

$$\mathbb{P}(B) = \mathbb{P}(A) + \mathbb{P}(\bar{A} \cap B)$$

But by (1), $\mathbb{P}(\bar{A} \cap B) \geq 0$, so the result now follows.

EXERCISE 2.1.8

Let A and B be events with sample space S and let $\mathbb{P}(\cdot)$ be a probability function, then prove the following:

1. $0 \leq \mathbb{P}(A) \leq 1$
2. $\mathbb{P}(A \cap \bar{B}) = \mathbb{P}(A) - \mathbb{P}(A \cap B)$
3. $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cap B)$

1. $\mathbb{P}(A) \geq 0$ follows from (1). From (3) we have $\mathbb{P}(\bar{A}) = 1 - \mathbb{P}(A)$. But from (1) $\mathbb{P}(\bar{A}) \geq 0$ and therefore $\mathbb{P}(A) \leq 1$.

2. Since $A = (A \cap B) \cup (A \cap \bar{B})$ and $(A \cap B) \cap (A \cap \bar{B}) = \emptyset$, then by (2)

$$\mathbb{P}(A) = \mathbb{P}(A \cap B) + \mathbb{P}(A \cap \bar{B})$$

as required.

3. $\mathbb{P}(A \cup B) = \mathbb{P}(A \cap \bar{B}) + \mathbb{P}(A \cap B) + \mathbb{P}(\bar{A} \cap B)$. By the previous result,

$$\mathbb{P}(A \cap \bar{B}) = \mathbb{P}(A) - \mathbb{P}(A \cap B) \quad \text{and} \quad \mathbb{P}(\bar{A} \cap B) = \mathbb{P}(B) - \mathbb{P}(A \cap B)$$

Therefore,

$$\begin{aligned} \mathbb{P}(A \cup B) &= (\mathbb{P}(A) - \mathbb{P}(A \cap B)) + \mathbb{P}(A \cap B) + (\mathbb{P}(B) - \mathbb{P}(A \cap B)) \\ &= \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cap B) \end{aligned}$$

as required.

DEFINITION 2.1.9: Conditional probability

Suppose A and B are two events with $\mathbb{P}(B) > 0$. Then the **conditional probability** of A given that B has occurred is

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}$$

DEFINITION 2.1.10: Independent events

Suppose A and B are two events. A and B are **independent events** if and only if

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$$

Clearly, $\mathbb{P}(A | B) = \mathbb{P}(A)$ if and only if A and B are independent since

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(A)\mathbb{P}(B)}{\mathbb{P}(B)} = \mathbb{P}(A)$$

EXAMPLE 2.1.11

Toss a coin twice.

- A : First toss is H
- B : Second toss is T

$$\mathbb{P}(A) = \frac{\# \text{ of outcomes in } A}{4} = \frac{2}{4} \quad \text{and} \quad \mathbb{P}(B) = \frac{2}{4}$$

$$\mathbb{P}(A \cap B) = \frac{1}{4} = \mathbb{P}(A)\mathbb{P}(B)$$

therefore A and B are independent.

DEFINITION 2.1.12: Random variable

A **random variable** (r.v.) X is a function from a sample space S to the real numbers \mathbb{R} ; that is,

$$X : S \rightarrow \mathbb{R}$$

satisfies for any given $x \in \mathbb{R}$ $\{X \leq x\}$ is an event.

$$\{X \leq x\} = \{\omega \in S : X(\omega) \leq x\} \subseteq S$$

EXAMPLE 2.1.13

Toss a coin twice. Let X be the number of heads (H) in two tosses. Verify that X is a random variable.

Solution. Possible values of X : 0, 1, 2. Given $x \in \mathbb{R}$, $\{X \leq x\}$.

- $x < 0 \implies \{X \leq x\} = \emptyset$
- $x = 0 \implies \{X \leq x\} = \{X = 0\} = \{(T, T)\} \subseteq S$
- $x = 1 \implies \{X \leq x\} = \{X = 1\} = \{(H, T), (T, H)\} \subseteq S$
- $x = 2 \implies \{X \leq x\} = \{X = 2\} = \{(H, H)\} \subseteq S$

Thus, X is a random variable.

DEFINITION 2.1.14: Cumulative distribution function

The **cumulative distribution function** (c.d.f.) of a random variable X is defined by

$$F(x) = \mathbb{P}(X \leq x)$$

for all $x \in \mathbb{R}$. Note that the c.d.f. is defined for all \mathbb{R} .

DEFINITION 2.1.15: Properties — Cumulative Distribution Function

- (1) F is a non-decreasing function; that is, if $x_1 \leq x_2$, then $F(x_1) \leq F(x_2)$.

By looking at:

- $\{X \leq x_1\} \subseteq \{X \leq x_2\}$ if $x_1 \leq x_2$.

- (2) $\lim_{x \rightarrow \infty} F(x) = 1$ and $\lim_{x \rightarrow -\infty} F(x) = 0$.

By looking at:

- $x \rightarrow \infty: \{X \leq x\} \rightarrow S$
- $x \rightarrow -\infty: \{X \leq x\} \rightarrow \emptyset$

- (3) $F(x)$ is a right continuous function; that is, for any $a \in \mathbb{R}$,

$$\lim_{x \rightarrow a^+} F(x) = F(a)$$

- (4) For all $a < b$

$$\mathbb{P}(a < X \leq b) = \mathbb{P}(X \leq b) - \mathbb{P}(X \leq a) = F(b) - F(a)$$

- (5) For all b

$$\mathbb{P}(X = b) = \mathbb{P}(\text{jump at } b) = \lim_{t \rightarrow b^+} F(t) - \lim_{t \rightarrow b^-} F(t) = F(b) - \lim_{t \rightarrow b^-} F(t)$$

LECTURE 2 | 2020-09-09

2.2 Discrete Random Variables

DEFINITION 2.2.1: Discrete random variable

If a random variable X can only take finite or countable values, X is a **discrete random variable**.

In this case, $F(x)$ is a right-continuous step function.

REMARK 2.2.2

When we say **countable**, we mean something you can enumerate such as \mathbb{Z} or \mathbb{N}^+ .

DEFINITION 2.2.3: Probability function

If X is a discrete random variable, then the **probability function** (p.f.) of X is given by

$$f(x) = \begin{cases} \mathbb{P}(X = x) = F(x) - \lim_{\varepsilon \rightarrow 0^+} F(x - \varepsilon) & \text{if } X \text{ can take value } x \\ 0 & \text{if } X \text{ cannot take value } x \end{cases}$$

DEFINITION 2.2.4: Support set

The set $A = \{x : f(x) > 0\}$ is called the **support set** of X . These are all the possible values X can take.

PROPOSITION 2.2.5: Properties of the Probability Function

- (1) $f(x) \geq 0$ for all $x \in \mathbb{R}$
- (2) $\sum_{x \in A} f(x) = 1$

Review some commonly used discrete random variables:

- **Bernoulli.** $X \sim \text{Bernoulli}(p)$ where X can only take two possible values 0 (failure) or 1 (success). Let p be the probability of a success for a single trial. So,

$$\mathbb{P}(X = 1) = p \quad \text{and} \quad \mathbb{P}(X = 0) = 1 - p$$

Therefore,

$$f(x) = \mathbb{P}(X = x) = p^x(1 - p)^{1-x}$$

Example: Toss a coin twice. Let X be the number of heads. Then $X \sim \text{Bernoulli}(p)$

- **Binomial.** $X \sim \text{Binomial}(n, p)$. Suppose we have **Bernoulli Trials**:

- We run n trials
- Each trial is independent of each other
- Each trial has two possible outcomes: 0 (failure), 1 (success)

$$\mathbb{P}(X_i = 1) = p$$

Let X be the number of success across these n trials and p be the success probability for a single trial.

$$X = \sum_{i=1}^n X_i$$

X_i is the outcome of the i th trial.

$$\mathbb{P}(X_i = 1) = p$$

where $X_i \sim \text{Bernoulli}(p)$. Therefore,

$$f(x) = \mathbb{P}(X = x) = \binom{n}{x} p^x (1 - p)^{n-x}$$

- **Geometric.** $X \sim \text{Geometric}(p)$. Let X be the number of failures before the first success. X can take values $0, 1, 2, \dots$

$$f(x) = \mathbb{P}(X = x) = (1 - p)^x p$$

Example. X = number of tails before you get the first head.

- **Negative Binomial.** $X \sim \text{Negative Binomial}(r, p)$. Let X be the number of failures before you get r success. X can take values $0, 1, 2, \dots$

$$f(x) = \mathbb{P}(X = x) = \binom{x + r - 1}{x} (1 - p)^x p^r$$

Example. X = number of tails before you get the r th head.

- **Poisson.** $X \sim \text{Poisson}(\mu)$ where $X = 0, 1, \dots$

$$f(x) = \mathbb{P}(X = x) = \frac{\mu^x}{x!} e^{-\mu}$$

where $x = 0, 1, 2, \dots$

2.3 Continuous Random Variables

DEFINITION 2.3.1: Continuous random variable

Suppose X is a random variable with c.d.f. F . If F is a continuous function for all $x \in \mathbb{R}$ and F is differentiable except possibly at countably many points, then X is called a **continuous random variable**.

Note that this is not a rigorous definition, but it will be used in this course.

DEFINITION 2.3.2: Probability density function, Support set

The **probability density function** (p.d.f.) of a continuous random variable is

$$f(x) = \begin{cases} F'(x) & \text{if } F(x) \text{ is differentiable at } x \\ 0 & \text{otherwise} \end{cases}$$

The set $A = \{x : f(x) > 0\}$ is called the **support set** of X .

Continuous case: $f(x) \neq \mathbb{P}(X = x)$

$$\mathbb{P}(x < X \leq x + \delta) \approx f(x)\delta$$

since

$$\lim_{\delta \rightarrow 0} \frac{F(x + \delta) - F(x)}{\delta} = F'(x) = f(x)$$

DEFINITION 2.3.3: Properties — Probability Density Function

- (I) $f(x) \geq 0$ for all $x \in \mathbb{R}$
- (II) $\int_{-\infty}^{\infty} f(x) dx = \lim_{x \rightarrow \infty} F(x) - \lim_{x \rightarrow -\infty} F(x) = 1$
- (III) $f(x) = F'(x) = \lim_{h \rightarrow 0} \frac{F(x+h) - F(x)}{h}$
- (IV) $F(x) = \int_{-\infty}^x f(t) dt$ since $F(-\infty) = 0$.
- (V) $\mathbb{P}(a < X \leq b) = \mathbb{P}(X \leq b) - \mathbb{P}(X \leq a) = F(b) - F(a) = \int_a^b f(x) dx$
- (VI) $\mathbb{P}(X = b) = F(b) - \lim_{a \rightarrow b^-} F(a) = F(b) - F(b) = 0 \neq f(b)$ since F is continuous.

EXAMPLE 2.3.4

Suppose the c.d.f. of X is

$$F(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & x \geq b \end{cases}$$

Find the p.d.f. of X .

Solution.

$$f(x) = \begin{cases} \frac{1}{b-a} & a < x < b \\ 0 & \text{otherwise} \end{cases}$$

We note that $X \sim \text{Uniform}[a, b]$

EXAMPLE 2.3.5

Let the p.d.f. be defined as follows.

$$f(x) = \begin{cases} \frac{\theta}{x^{\theta+1}} & x \geq 1 \\ 0 & x < 1 \end{cases}$$

- (i) For what values of θ is f a p.d.f.

- (ii) Find $F(x)$.
 (iii) Find $\mathbb{P}(-2 < X < 3)$.

Solution.

- (i) Note that $\frac{\theta}{x^{\theta+1}} \geq 0$ for all $\theta \geq 0$.

Case 1: $\theta = 0$. $f(x) \equiv 0$, then f cannot be a pdf since $\int_{-\infty}^{\infty} f(x) dx = 0 \neq 1$

Case 2: $\theta > 0$.

$$\int_{-\infty}^{\infty} f(x) dx = \int_{-\infty}^1 f(x) dx + \int_1^{\infty} f(x) dx = \int_1^{\infty} \frac{\theta}{x^{\theta+1}} dx = [-x^{-\theta}]_1^{\infty} = 1$$

Therefore, f is a p.d.f. when $\theta > 0$.

- (ii) $F(x) = \mathbb{P}(X \leq x)$.

Case 1: $x < 1$.

$$\mathbb{P}(X \leq x) = \int_{-\infty}^x f(t) dt = 0$$

Case 2: $x \geq 1$.

$$\mathbb{P}(X \leq x) = \int_{-\infty}^x f(t) dt = \int_{-\infty}^1 f(t) dt + \int_1^x f(t) dt = \int_1^x \frac{\theta}{t^{\theta+1}} dt = [-t^{-\theta}]_1^x = 1 - x^{-\theta}$$

- (iii) $\mathbb{P}(-2 < X < 3)$. Either use the c.d.f. we found or the p.d.f.

Using the c.d.f. we have

$$F(3) - F(-2) = (1 - 3^{-\theta}) - 0$$

Using the p.d.f. we have

$$\int_{-2}^3 f(x) dx = \int_{-2}^1 f(x) dx + \int_1^3 f(x) dx = \int_1^3 f(x) dx = \text{exercise}$$

LECTURE 3 | 2020-09-13

We first introduce a function that will be used.

DEFINITION 2.3.6: Gamma function

The **gamma function**, denoted $\Gamma(\alpha)$ for all $\alpha > 0$, is given by

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x} dx$$

PROPOSITION 2.3.7: Properties of the Gamma Function

- (1) $\Gamma(\alpha) = (\alpha - 1)\Gamma(\alpha - 1)$ for $\alpha > 1$
- (2) $\Gamma(n) = (n - 1)!$ when $n \geq 1$ is a positive integer
- (3) $\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}$

We don't need to know the following proof, but I checked it out for fun. Content not found in the syllabus is usually labelled with a dagger (†).

Proof of: † 2.3.7

Proof of (1). Suppose $\alpha > 1$.

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x} dx$$

Let $u = x^{\alpha-1} \Rightarrow du = (\alpha-1)x^{\alpha-2} dx$ and $dv = e^{-x} dx \Rightarrow v = -e^{-x}$. Now, recall from MATH 138:

$$\int u dv = uv - \int v du$$

So,

$$\begin{aligned} \Gamma(\alpha) &= [(\alpha-1)x^{\alpha-2}(-e^{-x})]_0^{\infty} - \int_0^{\infty} (-e^{-x})(\alpha-1)x^{\alpha-2} dx \\ &= 0 + (\alpha-1) \int_0^{\infty} e^{-x} x^{\alpha-2} dx \\ &= (\alpha-1)\Gamma(\alpha) \end{aligned}$$

Proof of (2). Using (1):

$$\begin{aligned} \Gamma(\alpha) &= (\alpha-1)\Gamma(\alpha-1) \\ &= (\alpha-1)(\alpha-2)\Gamma(\alpha-3) \\ &= (\alpha-1)(\alpha-2)\cdots(3)(2)(1)\Gamma(1) \end{aligned}$$

We know that $\Gamma(1) = 1$ by using the definition (trivial), therefore the result now follows.

Proof of (3). Sketch:

- Let $u = x^2$, so $du = 2x dx$. Let $\alpha = \frac{1}{2}$, so the integral looks like:

$$\Gamma\left(\frac{1}{2}\right) = 2 \int_0^{\infty} e^{-u^2} du$$

- Compute $[\Gamma(\frac{1}{2})]^2$. Using polar coordinates, compute the following double integral.

$$4 \int_0^{\infty} \int_0^{\infty} e^{-(u^2+v^2)} dv du$$

One will have to compute the Jacobian Matrix.

- Solve for $\Gamma\left(\frac{1}{2}\right)$ explicitly now.

Author's note: This was covered in MATH 237 when I took it (F19).

EXAMPLE 2.3.8

The p.d.f. is given by

$$f(x) = \begin{cases} \frac{x^{\alpha-1} e^{-x/\beta}}{\Gamma(\alpha)\beta^{\alpha}} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

when $\alpha > 0$ and $\beta > 0$. We say that $X \sim \text{Gamma}(\alpha, \beta)$.

We also say that α is the scale parameter and β is the shape parameter for this distribution.

Verify that $f(x)$ is a p.d.f.

Solution. Showing $f(x) \geq 0$ is trivial. Now,

$$\int_{-\infty}^{\infty} f(x) dx = \int_0^{\infty} \frac{x^{\alpha-1} e^{-x/\beta}}{\Gamma(\alpha)\beta^\alpha} dx$$

Let $y = x/\beta \Rightarrow x = y\beta$ and $dx = \beta dy$. Therefore,

$$\int_{-\infty}^{\infty} f(x) dx = \int_0^{\infty} \frac{y^{\alpha-1} \beta^{\alpha-1} e^{-y}}{\Gamma(\alpha)\beta^\alpha} (\beta) dy = \frac{1}{\Gamma(\alpha)} \int_0^{\infty} y^{\alpha-1} e^{-y} dy = 1$$

EXAMPLE 2.3.9

Suppose the p.d.f. is given by

$$f(x) = \begin{cases} \frac{\beta}{\theta^\beta} x^{\beta-1} e^{-(x/\theta)^\beta} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

with $\alpha > 0$ and $\beta > 0$. Then, $X \sim \text{Weibull}(\theta, \beta)$. Verify that $f(x)$ is a p.d.f.

Solution. $f(x) \geq 0$ for every $x \in \mathbb{R}$. Now,

$$\int_{-\infty}^{\infty} f(x) dx = \int_0^{\infty} \frac{\beta}{\theta^\beta} x^{\beta-1} e^{-(x/\theta)^\beta} dx$$

Let $y = (x/\theta)^\beta \Rightarrow x = \theta y^{1/\beta}$ and $dx = (\theta/\beta) y^{(1/\beta)-1} dy$. Therefore,

$$\int_{-\infty}^{\infty} f(x) dx = \int_0^{\infty} \frac{\beta}{\theta^\beta} \theta^{\beta-1} y^{(\beta-1)/\beta} e^{-y} \frac{\theta}{\beta} y^{(1/\beta)-1} dy = \int_0^{\infty} e^{-y} dy = \Gamma(1) = 1$$

EXAMPLE 2.3.10: Normal

The p.d.f. is given by

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{(x-\mu)^2}{2\sigma^2} \right\}$$

for $x \in \mathbb{R}$, $\mu \in \mathbb{R}$, $\sigma^2 > 0$. Verify that $f(x)$ is a p.d.f.

Solution.

$f(x) \geq 0$ obviously.

Case 1: $\mu = 0$ and $\sigma^2 = 1$, then we say X follows a **standard normal** distribution. We want to show that

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{x^2}{2} \right\} dx = 1$$

Since the function is symmetrical around 0, we have the following equivalent integral.

$$2 \int_0^{\infty} \frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{x^2}{2} \right\} dx$$

Let $y = x^2/2 \Rightarrow x = \sqrt{2y}$ and $dx = \frac{\sqrt{2}}{2} y^{-1/2} dy$. Therefore,

$$= \frac{2}{\sqrt{2\pi}} \int_0^{\infty} e^{-y} \frac{\sqrt{2}}{2} y^{-1/2} dy = \frac{1}{\sqrt{\pi}} \int_0^{\infty} y^{1/2-1} e^{-y} dy = \left(\frac{1}{\sqrt{\pi}} \right) \Gamma \left(\frac{1}{2} \right) = 1$$

Case 2: For general μ and σ^2 ,

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{(x-\mu)^2}{2\sigma^2} \right\} dx$$

Let $z = \frac{x - \mu}{\sigma} \Rightarrow x = \mu + \sigma z$ and $dx = \sigma dz$. Therefore,

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{z^2}{2}\right\} \sigma dz = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{z^2}{2}\right\} dz = 1$$

using Case 1.

2.4 Expectation

DEFINITION 2.4.1: Expectation of discrete random variable

Suppose X is a discrete random variable with support A and p.f. $f(x)$. Then,

$$\mathbb{E}[X] = \sum_{x \in A} x f(x)$$

if $\sum_{x \in A} |x| f(x) < \infty$ (finite). If $\sum_{x \in A} |x| f(x) = \infty$ (infinite), then $\mathbb{E}[X]$ does not exist.

DEFINITION 2.4.2: Expectation of continuous random variable

Suppose X is a continuous random variable with support A and p.d.f. $f(x)$. Then,

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} x f(x) dx$$

if $\int_{-\infty}^{\infty} |x| f(x) dx < \infty$ (finite). Similarly, if $\int_{-\infty}^{\infty} |x| f(x) dx = \infty$ (infinite), then $\mathbb{E}[X]$ does not exist.

EXAMPLE 2.4.3: Discrete

Suppose

$$f(x) = \frac{1}{x(x+1)} = \frac{1}{x} - \frac{1}{x+1}$$

for $x = 1, 2, \dots$. The support set is $A = \{1, 2, \dots\}$. We note that $f(x)$ is a p.f. since $f(x) \geq 0$ and

$$\sum_{x \in A} f(x) = \sum_{x=1}^{\infty} \left(\frac{1}{x} - \frac{1}{x+1} \right) = 1 - \frac{1}{2} + \frac{1}{2} - \frac{1}{3} + \dots = 1$$

Find $\mathbb{E}[X]$.

Solution.

$$\sum_{x \in A} |x| f(x) = \sum_{x=1}^{\infty} x \left(\frac{1}{x} - \frac{1}{x+1} \right) = \sum_{x=1}^{\infty} \frac{1}{x+1} = \infty$$

Therefore, $\mathbb{E}[X]$ does not exist!

EXAMPLE 2.4.4: Continuous

Let the p.d.f. be defined as $f(x) = \frac{1}{x^2 + 1}$ for $x \in \mathbb{R}$. This is known as the Cauchy distribution (or Student's T-distribution with 1 degree of freedom). Find $\mathbb{E}[X]$.

Solution.

$$\int_{-\infty}^{\infty} |x|f(x) dx = \int_{-\infty}^{\infty} |x| \frac{1}{x^2 + 1} dx = 2 \int_0^{\infty} \frac{x}{x^2 + 1} dx = [\ln|x^2 + 1|]_0^{\infty} = \infty$$

$\mathbb{E}[X]$ does not exist! The following is **wrong**:

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} xf(x) dx = \int_{-\infty}^{\infty} \frac{x}{1 + x^2} dx = 0$$

since the integral above with $|x|$ is infinite. You must always remember to check that the $\mathbb{E}[X]$ is finite (using $|X|$) for both the discrete and continuous case.

EXAMPLE 2.4.5: Bernoulli and Binomial Random Variable

Suppose $X \sim \text{Bernoulli}(p)$.

$$\mathbb{P}(X = 1) = p \quad \text{and} \quad \mathbb{P}(X = 0) = 1 - p$$

We know $\mathbb{E}[X] = (1)\mathbb{P}(X = 1) + (0)\mathbb{P}(X = 0) = p$

Now suppose $X \sim \text{Binomial}(n, p)$. Find $\mathbb{E}[X]$.

Solution.

$$\mathbb{E}[X] = \sum_{x \in A} xf(x) = \sum_{x=0}^n x \binom{n}{x} p^x (1-p)^{n-x}$$

This is hard to do. But, we know we can use the relationship between the Binomial and Bernoulli random variable so,

$$X = \sum_{i=1}^n X_i$$

Therefore,

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathbb{E}[X_i] = np$$

EXAMPLE 2.4.6

Suppose for a random variable X the p.d.f. is given by $f(x) = \frac{\theta}{x^{\theta+1}}$ for $x \geq 1$ and 0 when $x < 1$. Assume $\theta > 0$. Find $\mathbb{E}[X]$ and for what values of θ , does $\mathbb{E}[X]$ exist.

Solution.

$$\int_{-\infty}^{\infty} |x|f(x) dx = \int_1^{\infty} (x) \frac{\theta}{x^{\theta+1}} dx = \theta \int_1^{\infty} \frac{1}{x^{\theta}} dx < \infty \iff \theta > 1$$

from MATH 138. So, if $\theta > 1$ then $\mathbb{E}[X]$ exists. Also,

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} xf(x) dx = \int_1^{\infty} \frac{\theta x}{x^{\theta+1}} dx = \theta \int_1^{\infty} \frac{1}{x^{\theta}} dx = \frac{\theta}{\theta - 1}$$

DEFINITION 2.4.7: Expectation (Discrete)

If X is a discrete random variable with probability function $f(x)$ and support set A , then the **expectation** of the random variable $g(X)$ is defined by

$$\mathbb{E}[g(X)] = \sum_{x \in A} g(x)f(x)$$

provided the sum converges absolutely; that is, provided

$$\sum_{x \in A} |g(x)|f(x) < \infty$$

DEFINITION 2.4.8: Expectation (Continuous)

If X is a continuous random variable with p.d.f. $f(x)$ and support set A , then the **expectation** of the random variable $g(X)$ is defined by

$$\mathbb{E}[g(X)] = \int_{-\infty}^{\infty} g(x)f(x) dx$$

provided the integral converges absolutely; that is, provided

$$\int_{-\infty}^{\infty} |g(x)|f(x) dx < \infty$$

THEOREM 2.4.9: Expectation is a Linear Operator

Suppose X is a random variable with probability (density) function $f(x)$, and a and b are real constants, and $g(x)$ and $h(x)$ are real-valued functions. Then,

$$\mathbb{E}[aX + b] = a\mathbb{E}[X] + b$$

$$\mathbb{E}[ag(X) + bh(X)] = a\mathbb{E}[g(X)] + b\mathbb{E}[h(X)]$$

Proof of: 2.4.9

Omitted from the lecture and hence these notes. See Course Notes for most of the proof.

DEFINITION 2.4.10: Variance

The variance of a random variable is defined as

$$\sigma^2 = \mathbb{V}(X) = \mathbb{E}[(X - \mu)^2]$$

where $\mu = \mathbb{E}[X]$.

DEFINITION 2.4.11: Special Expectations

(I) The k th moment (about the origin) of a random variable

$$\mathbb{E}[X^k]$$

(II) The k th moment about the mean of a random variable

$$\mathbb{E}[(X - \mu)^k]$$

THEOREM 2.4.12: Properties of Variance

If X is a random variable, then

$$\mathbb{V}(X) = \mathbb{E}[X^2] - \mu^2$$

where $\mu = \mathbb{E}[X]$. Note that the variance of X exists if $\mathbb{E}[X^2] < \infty$.

Proof of: 2.4.12

Omitted from the lecture and hence these notes. See Course Notes for most of the proof.

EXAMPLE 2.4.13

Suppose $X \sim \text{Poisson}(\theta)$, the p.f. is defined as $f(x) = \frac{\theta^x}{x!} e^{-\theta}$ for $x = 0, 1, 2, \dots$. Find $\mathbb{E}[X]$ and $\mathbb{V}(X)$.

Solution. The support is non-negative, so $|x| = x$. Therefore,

$$\mathbb{E}[X] = \sum_{x=0}^{\infty} x \frac{\theta^x}{x!} e^{-\theta} = \sum_{x=1}^{\infty} \frac{x}{x!} \theta^x e^{-\theta} = \theta \sum_{x=1}^{\infty} \frac{\theta^{x-1}}{(x-1)!} e^{-\theta}$$

Let $y = x - 1$, then

$$\mathbb{E}[X] = \theta \sum_{y=0}^{\infty} \frac{\theta^y}{y!} e^{-\theta}$$

We know $e^{\theta} = \sum_{y=0}^{\infty} \frac{\theta^y}{y!}$, so $\mathbb{E}[X] = \theta$.

$$\mathbb{V}(X) = \mathbb{E}[X^2] - \mu^2$$

Let's find $\mathbb{E}[X^2]$:

$$\begin{aligned} \mathbb{E}[X^2] &= \sum_{x=0}^{\infty} x^2 \frac{\theta^x}{x!} e^{-\theta} \\ &= \sum_{x=1}^{\infty} \frac{x}{(x-1)!} \theta^x e^{-\theta} \\ &= \sum_{x=1}^{\infty} \frac{(x-1) + 1}{(x-1)!} \theta^x e^{-\theta} \\ &= \sum_{x=1}^{\infty} \frac{x-1}{(x-1)!} \theta^x e^{-\theta} + \sum_{x=1}^{\infty} \frac{1}{(x-1)!} \theta^x e^{-\theta} \end{aligned}$$

Looking at the first sum (since the second sum was computed before):

$$\sum_{x=2}^{\infty} \frac{\theta^2}{(x-2)!} \theta^{x-2} e^{-\theta} + \theta$$

Let $y = x - 2$:

$$\mathbb{E}[X^2] = \sum_{y=0}^{\infty} \frac{\theta^2 \theta^y}{y!} e^{-\theta} + \theta = \theta^2 + \theta$$

Therefore,

$$\mathbb{V}(X) = \mathbb{E}[X^2] - \mu^2 = (\theta^2 + \theta) - \theta^2 = \theta$$

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EXAMPLE 2.4.14

If $X \sim \text{Gamma}(\alpha, \beta)$, prove that

$$\mathbb{E}[X^p] = \frac{\beta^p \Gamma(\alpha + p)}{\Gamma(\alpha)}$$

for $p > -\alpha$.

Solution. Recall that

$$f(x) = \begin{cases} \frac{x^{\alpha-1} e^{-x/\beta}}{\Gamma(\alpha) \beta^\alpha} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

So,

$$\mathbb{E}[X^p] = \int_{-\infty}^{\infty} x^p f(x) dx = \int_0^{\infty} x^p \frac{x^{\alpha-1} e^{-x/\beta}}{\Gamma(\alpha) \beta^\alpha} dx$$

There are two methods to solve this integral:

Method 1: Rewrite the function as the p.d.f. of a gamma distribution.

$$= \int_0^{\infty} \frac{x^{p+\alpha-1} e^{-x/\beta}}{\Gamma(\alpha) \beta^\alpha} dx$$

which is close to the p.d.f. of $\text{Gamma}(p + \alpha, \beta)$.

$$= \int_0^{\infty} \frac{x^{p+\alpha-1} e^{-x/\beta}}{\Gamma(\alpha + p) \beta^{\alpha+p}} \times \underbrace{\frac{\Gamma(\alpha + p) \beta^{\alpha+p}}{\Gamma(\alpha) \beta^\alpha}}_{\text{constant}} dx = \frac{\Gamma(\alpha + p) \beta^p}{\Gamma(\alpha)} \times 1$$

Method 2: Rewrite the function as a gamma function.

$$\mathbb{E}[X^p] = \int_0^{\infty} \frac{x^{(p+\alpha)-1} e^{-x/\beta}}{\Gamma(\alpha) \beta^\alpha} dx$$

Let $y = x/\beta \Rightarrow x = \beta y$ and $dx = \beta dy$. Therefore,

$$= \int_0^{\infty} \frac{\beta^{p+\alpha-1} y^{(p+\alpha)-1} e^{-y}}{\Gamma(\alpha) \beta^\alpha} (\beta) dy = \frac{\beta^p}{\Gamma(\alpha)} \int_0^{\infty} y^{(p+\alpha)-1} e^{-y} dy = \frac{\Gamma(p + \alpha)}{\Gamma(\alpha)} \beta^p$$

Additionally,

- $\mathbb{E}[X] = \frac{\beta \Gamma(\alpha + 1)}{\Gamma(\alpha)} = \alpha \beta$
- $\mathbb{E}[X^2] = \frac{\beta^2 \Gamma(\alpha + 2)}{\Gamma(\alpha)} = \frac{\beta^2 (\alpha + 1) \Gamma(\alpha + 1)}{\Gamma(\alpha)} = \alpha(\alpha + 1) \beta^2$
- $\mathbb{V}(X) = \mathbb{E}[X^2] - \mu^2 = \alpha(\alpha + 1) \beta^2 - \alpha^2 \beta^2 = \alpha \beta^2$

2.5 Moment Generating Functions

DEFINITION 2.5.1: Moment generating function

Suppose X is a random variable, then

$$M(t) = \mathbb{E}[e^{tX}]$$

is called the **moment generating function** (m.g.f.) of X if $M(t)$ exists for $t \in (-h, h)$ with some $h > 0$.

REMARK 2.5.2

If we are able to find some $h > 0$ such that for any $t \in (-h, h)$, $\mathbb{E}[e^{tX}] < \infty$, then we say $M(t)$ is the m.g.f. of X .

EXAMPLE 2.5.3

Suppose $X \sim \text{Gamma}(\alpha, \beta)$. Find $M(t)$. Recall the p.d.f. is

$$f(x) = \begin{cases} \frac{x^{\alpha-1} e^{-x/\beta}}{\Gamma(\alpha)\beta^\alpha} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

Solution.

$$\begin{aligned} M(t) &= \mathbb{E}[e^{tX}] \\ &= \int_{-\infty}^{\infty} e^{tx} f(x) dx \\ &= \int_0^{\infty} e^{tx} \frac{x^{\alpha-1} e^{-x/\beta}}{\Gamma(\alpha)\beta^\alpha} dx \\ &= \int_0^{\infty} \frac{x^{\alpha-1} e^{-x(\frac{1}{\beta} - t)}}{\Gamma(\alpha)\beta^\alpha} dx \\ &= \int_0^{\infty} \frac{x^{\alpha-1} e^{-x/\tilde{\beta}}}{\Gamma(\alpha)\beta^\alpha} dx \end{aligned}$$

where

$$\tilde{\beta} = \frac{1}{\left(\frac{1}{\beta} - t\right)}$$

Continuing,

$$\begin{aligned} &= \int_0^{\infty} \frac{x^{\alpha-1} e^{-x/\tilde{\beta}}}{\Gamma(\alpha)\tilde{\beta}^\alpha} \left(\frac{\tilde{\beta}^\alpha}{\beta^\alpha}\right) dx \\ &= \frac{\tilde{\beta}^\alpha}{\beta^\alpha} (1) \\ &= (1 - \beta t)^{-\alpha} \end{aligned}$$

The moment generating function must be non-negative since $1 - \beta t > 0$ and therefore, $t < 1/\beta$. Take $h = 1/\beta$.

EXAMPLE 2.5.4

If $X \sim \text{Poisson}(\theta)$, the p.f. is given by $f(x) = \frac{\theta^x e^{-\theta}}{x!}$ for $x = 0, 1, 2, \dots$. Find $M(t)$.

Solution.

$$\begin{aligned}
 M(t) &= \mathbb{E}[e^{tX}] \\
 &= \sum_{x=0}^{\infty} e^{tx} \frac{\theta^x e^{-\theta}}{x!} \\
 &= \sum_{x=0}^{\infty} \frac{(e^t \theta)^x e^{-\theta}}{x!} \\
 &= e^{-\theta} \sum_{x=0}^{\infty} \frac{(e^t \theta)^x}{x!} \\
 &= e^{-\theta} \exp \{e^t \theta\} \\
 &= \exp \{\theta (e^t - 1)\}
 \end{aligned}$$

for all $t \in \mathbb{R}$.

Three important properties of $M(t)$.

THEOREM 2.5.5: Moment Generating Function of a Linear Function

Suppose the random variable X has moment generating function $M_X(t)$ defined for $t \in (-h, h)$ for some $h > 0$. Let $Y = aX + b$ where $a, b \in \mathbb{R}$ and $a \neq 0$. Then, the moment generating function of Y is

$$M_Y(t) = e^{bt} M_X(at)$$

for $|t| < \frac{h}{|a|}$.

Proof of: 2.5.5

$$\begin{aligned}
 M_Y(t) &= \mathbb{E}[e^{tY}] \\
 &= \mathbb{E}[e^{t(aX+b)}] \\
 &= e^{bt} \mathbb{E}[e^{atX}] && \text{exists for } |at| < h \\
 &= e^{bt} M_X(at) && \text{for } |t| < \frac{h}{|a|}
 \end{aligned}$$

as required.

EXAMPLE 2.5.6

- (i) If $Z \sim N(0, 1)$, find $M_Z(t)$.
- (ii) If $X \sim N(\mu, \sigma^2)$, find $M_X(t)$.

Solution.

(i)

$$\begin{aligned}
M_Z(t) &= \mathbb{E}[e^{tZ}] \\
&= \int_{-\infty}^{\infty} e^{tx} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{x^2}{2}\right\} dx \\
&= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{x^2 - 2tx}{2}\right\} dx \\
&= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{(x-t)^2 - t^2}{2}\right\} dx && \text{complete the square} \\
&= \exp\left\{\frac{t^2}{2}\right\} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{(x-t)^2}{2}\right\} dx
\end{aligned}$$

where the integral is the p.d.f. of $N(\mu = t, \sigma^2 = 1)$. Therefore,

$$\mathbb{E}[e^{tZ}] = \exp\left\{\frac{t^2}{2}\right\}$$

(ii) $X = \sigma Z + \mu$ where $Z \sim N(0, 1)$.

$$\begin{aligned}
M_X(t) &= e^{\mu t} M_Z(\sigma t) \\
&= e^{\mu t} \exp\left\{\frac{(\sigma t)^2}{2}\right\} \\
&= \exp\left\{\frac{(\sigma t)^2}{2} + \mu t\right\}
\end{aligned}$$

THEOREM 2.5.7: Moments from Moment Generating Function

Suppose the random variable X has moment generating function $M(t)$ defined for $t \in (-h, h)$ for some $h > 0$. Then, $M(0) = 1$ and

$$M^{(k)}(0) = \mathbb{E}[X^k]$$

for $k = 1, 2, \dots$ where

$$M^{(k)}(t) = \frac{d^k}{dt^k} [M(t)]$$

is the k th derivative of $M(t)$.

Proof of: 2.5.7

Omitted from the lecture and hence these notes. See Course Notes for most of the proof.

EXAMPLE 2.5.8

Gamma(α, β) has m.g.f. $M(t) = (1 - \beta t)^{-\alpha}$ for $t < 1/\beta$. What is $\mathbb{E}[X]$ and $\mathbb{V}(X)$?

Solution. For $\mathbb{E}[X]$ we find $M'(t)$.

$$M'(t) = (-\alpha)(1 - \beta t)^{-\alpha-1}(-\beta) = (\alpha\beta)(1 - \beta t)^{-\alpha-1}$$

We know,

$$\mathbb{E}[X] = M'(0) = \alpha\beta$$

For $\mathbb{V}(X)$ we find $M''(t)$.

$$M''(t) = (\alpha\beta)(-\alpha-1)(-\beta)(1 - \beta t)^{-\alpha-2}$$

Now, $M''(0) = \alpha\beta^2(\alpha + 1) = \mathbb{E}[X^2]$. Therefore,

$$\mathbb{V}(X) = \mathbb{E}[X^2] - \mu^2 = \alpha\beta^2(\alpha + 1) - (\alpha\beta)^2 = \alpha\beta^2$$

EXAMPLE 2.5.9

The m.g.f. of $\text{Poisson}(\theta)$ is $M(t) = \exp\{\theta(e^t - 1)\}$. Find $\mathbb{E}[X]$ and $\mathbb{V}(X)$.

Solution.

$$M'(t) = \exp\{\theta(e^t - 1)\} \theta e^t$$

Therefore,

$$\mathbb{E}[X] = M'(0) = \theta$$

Now,

$$M''(t) = \exp\{\theta(e^t - 1)\} \theta^2 e^{2t} + \theta e^t \exp\{\theta(e^t - 1)\}$$

Therefore,

$$M''(0) = \mathbb{E}[X^2] = \theta^2 + \theta$$

So,

$$\mathbb{V}(X) = \mathbb{E}[X^2] - \mu^2 = \theta^2 + \theta - (\theta)^2 = \theta$$

THEOREM 2.5.10: Uniqueness Theorem for Moment Generating Functions

Suppose the random variable X has moment generating function $M_X(t)$ and the random variable Y has moment generating function $M_Y(t)$. $M_X(t) = M_Y(t)$ for all $t \in (-h, h)$ for some $h > 0$ if and only if X and Y have the same distribution; that is,

$$\mathbb{P}(X \leq s) = F_X(s) = F_Y(s) = \mathbb{P}(Y \leq s)$$

for all $s \in \mathbb{R}$.

EXAMPLE 2.5.11

Suppose X has m.g.f. $M_X(t) = \exp\left\{\frac{t^2}{2}\right\}$.

- (i) Find m.g.f. of $Y = 2X - 1$
- (ii) Find $\mathbb{E}[Y]$ and $\mathbb{V}(Y)$
- (iii) What is the distribution of Y .

Solution.

$$(i) \quad M_Y(t) = e^{-t} \exp\left\{\frac{(2t)^2}{2}\right\} = \exp\{2t^2 - t\}.$$

(ii)

$$M'_Y(t) = \exp\{2t^2 - t\} (4t - 1)$$

Therefore,

$$\mathbb{E}[Y] = M'_Y(0) = -1$$

Also,

$$M''_Y(t) = \exp\{2t^2 - t\} (4t - 1)^2 + 4 \exp\{2t^2 - t\}$$

and

$$\mathbb{E}[Y^2] = M''_Y(0) = 1 + 4 = 5$$

Therefore,

$$\mathbb{V}(Y) = \mathbb{E}[Y^2] - \mu^2 = 5 - 1 = 4$$

(iii) $M_Y(t) = \exp\{2t^2 - t\}$ is the m.g.f. of $N(-1, 4)$ since if $X \sim N(\mu, \sigma^2)$, then (by previous example)

$$M_X(t) = e^{\mu t} \exp\left\{\frac{\sigma^2 t^2}{2}\right\}$$

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EXAMPLE 2.5.12: Uniqueness Theorem

Suppose $M_X(t) = (1 - 2t)^{-1}$. What is the distribution of X ?

Solution. $X \sim \text{Gamma}(\alpha = 1, \beta = 2)$.

Chapter 3

Multivariate Random Variables

3.1 Joint and Marginal Cumulative Distribution Functions

Purpose: to characterize a joint distribution of two random variables.

DEFINITION 3.1.1: Joint cumulative distribution function

Suppose X and Y are random variables defined on a sample space S . The **joint cumulative distribution function** of X and Y is given by

$$F(x, y) = \mathbb{P}(X \leq x, Y \leq y)$$

for $(x, y) \in \mathbb{R}^2$.

$\mathbb{P}(X \leq x, Y \leq y)$: “What is the probability these two events occur simultaneously”

REMARK 3.1.2

Since $\{X \leq x\}$ and $\{Y \leq y\}$ are both events, $F(x, y)$ is well-defined as we consider $\{X \leq x\} \cap \{Y \leq y\}$.

REMARK 3.1.3

If we have more than two random variables, say X_1, X_2, \dots, X_n . We can similarly define the cumulative distribution function as

$$F(x_1, \dots, x_n) = \mathbb{P}(X_1 \leq x_1, \dots, X_n \leq x_n)$$

However, in this course we will only focus on two events X and Y .

DEFINITION 3.1.4: Joint cumulative distribution function

- (I) F is non-decreasing in x for fixed y
- (II) F is non-decreasing in y for fixed x
- (III) $\lim_{x \rightarrow -\infty} F(x, y) = 0$ and $\lim_{y \rightarrow -\infty} F(x, y) = 0$

By looking at

$$\{X \leq x\} \cap \{Y \leq y\}$$

$\xrightarrow{\text{as } x \rightarrow -\infty} 0 \quad \quad \quad \xrightarrow{\text{as } y \rightarrow -\infty} 0$

(IV)

$$\lim_{(x, y) \rightarrow (-\infty, -\infty)} F(x, y) = 0 \quad \text{and} \quad \lim_{(x, y) \rightarrow (\infty, \infty)} F(x, y) = 1$$

DEFINITION 3.1.5: Marginal distribution function

The **marginal distribution function** of X is given by

$$F_1(x) = \lim_{y \rightarrow \infty} F(x, y) = \mathbb{P}(X \leq x)$$

for $x \in \mathbb{R}$.

The **marginal distribution function** of Y is given by

$$F_2(y) = \lim_{x \rightarrow \infty} F(x, y) = \mathbb{P}(Y \leq y)$$

for $y \in \mathbb{R}$.

REMARK 3.1.6

The definition of marginal distribution function tells us that we can know all information about marginal c.d.f. from the joint c.d.f. but the marginal c.d.f. cannot give full information about joint c.d.f.

3.2 Bivariate Discrete Distributions

DEFINITION 3.2.1: Joint discrete random variables

Suppose X and Y are both discrete random variables, then X and Y are **joint discrete random variables** X and Y .

DEFINITION 3.2.2: Joint probability function, Support set

Suppose X and Y are discrete random variables. The **joint probability function** of X and Y is given by

$$f(x, y) = \mathbb{P}(X = x, Y = y)$$

for $(x, y) \in \mathbb{R}^2$.

The set $A = \{(x, y) : f(x, y) > 0\}$ is called the **support set** of (X, Y) .

DEFINITION 3.2.3: Properties — Joint Probability Function

(I) $f(x, y) \geq 0$ for $(x, y) \in \mathbb{R}^2$

(II) $\sum_{(x, y) \in A} f(x, y) = 1$

(III) For any set $R \subseteq \mathbb{R}^2$

$$P[(X, Y) \in R] = \sum_{(x, y) \in R} f(x, y)$$

EXAMPLE 3.2.4

Suppose we want to find $\mathbb{P}(X \leq Y)$. What is the corresponding set R ?

Solution. $R = \{(x, y) : x \leq y\}$

Suppose we want to find $\mathbb{P}(X + Y \leq 1)$. What is the corresponding set R ?

Solution. $R = \{(x, y) : x + y \leq 1\}$

DEFINITION 3.2.5: Marginal probability function

Suppose X and Y are discrete random variables with joint probability function $f(x, y)$. The **marginal probability function** of X is given by

$$f_1(x) = \mathbb{P}(X = x) = \mathbb{P}(X = x, Y < \infty) = \sum_y f(x, y)$$

for $x \in \mathbb{R}$.

The **marginal probability function** of Y is given by

$$f_2(y) = \mathbb{P}(Y = y) = \mathbb{P}(X < \infty, Y = y) = \sum_x f(x, y)$$

for $y \in \mathbb{R}$.

EXAMPLE 3.2.6

Suppose that X and Y are discrete random variables with joint p.f. $f(x, y) = kq^2p^{x+y}$ where

- $x = 0, 1, 2, \dots$
- $y = 0, 1, 2, \dots$
- $0 < p < 1$
- $q = 1 - p$

(i) Determine k .

(ii) Find marginal p.f. of X and find marginal p.f. of Y .

(iii) Find $\mathbb{P}(X \leq Y)$.

Solution.

(i) $k > 0$ since if $k = 0$ then the summation of the joint p.f. will be 0 (but needs to be 1).

$$\sum_{x=0}^{\infty} \sum_{y=0}^{\infty} f(x, y) = 1$$

Therefore,

$$k \left(\sum_{x=0}^{\infty} \sum_{y=0}^{\infty} p^{x+y} q^2 \right) = kq^2 \left(\sum_{x=0}^{\infty} p^x \right) \left(\sum_{y=0}^{\infty} p^y \right) = kq^2 \left(\frac{1}{1-p} \right) \left(\frac{1}{1-p} \right) = k$$

Thus, $k = 1$.

(ii) Marginal p.f. of X :

$$f_1(x) = \mathbb{P}(X = x) = \sum_{y=0}^{\infty} q^2 p^{x+y} = q^2 p^x \left(\sum_{y=0}^{\infty} p^y \right) = q^2 p^x \left(\frac{1}{1-p} \right) = p^x (1-p)$$

Support of X : $x = 0, 1, 2, \dots$

By symmetry,

$$f_2(y) = \mathbb{P}(Y = y) = qp^y$$

Support of Y : $y = 0, 1, 2, \dots$

(iii) Find $\mathbb{P}(X \leq Y)$.

$$\begin{aligned}
\mathbb{P}(X \leq Y) &= \sum_{x=0}^{\infty} \sum_{y=x}^{\infty} (q^2 p^{x+y}) \\
&= \sum_{x=0}^{\infty} q^2 p^x \sum_{y=x}^{\infty} p^y \\
&= \sum_{x=0}^{\infty} q^2 p^x \left(\frac{p^x}{1-p} \right) \\
&= q \sum_{x=0}^{\infty} p^{2x} \\
&= q \left(\frac{1}{1-p^2} \right) \\
&= \frac{1}{1+p}
\end{aligned}$$

REMARK 3.2.7: Interesting Fact

If X and Y are *continuous* random variables and have the same distribution and **independent**,

$$\mathbb{P}(X \leq Y) = \frac{1}{2}$$

3.3 Bivariate Continuous Distributions

DEFINITION 3.3.1: Joint probability density function, Support set

Suppose that $F(x, y)$ is a continuous function and that

$$f(x, y) = \frac{\partial^2}{\partial x \partial y} [F(x, y)]$$

exists and is a continuous function except possibly along a finite number of curves. Suppose also that

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy = 1$$

Then X and Y are said to be continuous random variables with **joint probability density function** f . The set $A = \{(x, y) : f(x, y) > 0\}$ is called the support set of (X, Y) .

REMARK 3.3.2

We will arbitrarily define $f(x, y)$ to be equal to 0 when $\frac{\partial^2}{\partial x \partial y} [F(x, y)]$ does not exist, although we can define it to be any real number.

DEFINITION 3.3.3: Properties — Joint Probability Density Function

- (I) $f(x, y) \geq 0$ for all $(x, y) \in \mathbb{R}^2$
 (II) For any set $R \subseteq \mathbb{R}^2$:

$$P[(X, Y) \in R] = \iint_{(x, y) \in R} f(x, y) dx dy$$

EXAMPLE 3.3.4

To find $\mathbb{P}(X \leq Y)$, the region is $R = \{(x, y) : x \leq y\}$. Therefore,

$$\mathbb{P}(X \leq Y) = \iint_{x \leq y} f(x, y) dx dy$$

DEFINITION 3.3.5: Marginal probability density function

Suppose X and Y are continuous random variables with p.d.f. $f(x, y)$. The **marginal probability density function** of X is given by

$$f_1(x) = \int_{-\infty}^{\infty} f(x, y) dy$$

for $x \in \mathbb{R}$ and the **marginal probability density function** of Y is given by

$$f_2(y) = \int_{-\infty}^{\infty} f(x, y) dx$$

for $y \in \mathbb{R}$.

$$P[(X, Y) \in \mathbb{R}] = \iint_{\mathbb{R}} f(x, y) dx dy = \int_x \int_y f(x, y) dx dy$$

Helpful theorem from MATH 237 that some of you may have forgot:

THEOREM 3.3.6: †*y* first, then *x*Let $R \subset \mathbb{R}^2$ be defined by

$$y_\ell(x) \leq y \leq y_u(x) \quad \text{and} \quad x_\ell \leq x \leq x_u$$

where $y_\ell(x)$ and $y_u(x)$ are continuous for $x_\ell \leq x \leq x_u$. If $f(x, y)$ is continuous on R , then

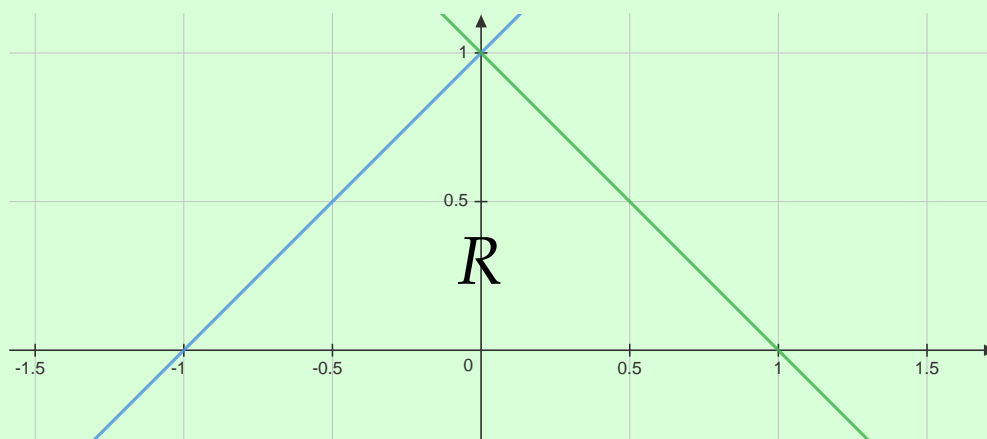
$$\iint_R f(x, y) dA = \int_{x_\ell}^{x_u} \int_{y_\ell(x)}^{y_u(x)} f(x, y) dy dx$$

x first, then *y*Let $R \subset \mathbb{R}^2$ be defined by

$$x_\ell(y) \leq x \leq x_u(y) \quad \text{and} \quad y_\ell \leq y \leq y_u$$

where $x_\ell(y)$ and $x_u(y)$ are continuous for $y_\ell \leq y \leq y_u$. If $f(x, y)$ is continuous on R , then

$$\iint_R f(x, y) dA = \int_{y_\ell}^{y_u} \int_{x_\ell(y)}^{x_u(y)} f(x, y) dx dy$$

We use ℓ for “lower” and u for “upper.”**EXAMPLE 3.3.7**Describe the region R above the x -axis.**Solution.** R can be described by the set of two inequalities (you can actually verify this in Desmos if you *really* forgot how this works):

$$0 \leq y \leq 1$$

$$y - 1 \leq x \leq 1 - y$$

Using the theorem above,

$$\int_0^1 \int_{y-1}^{1-y} f(x, y) dx dy$$

encouraged to draw the diagrams when following the examples.

EXAMPLE 3.3.8

Let X and Y be continuous random variables with joint p.d.f.

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

- (i) Show $f(x, y)$ is a joint p.d.f.
- (ii) Find
 - (a) $\mathbb{P}(X \leq 1/3, Y \leq 1/2)$
 - (b) $\mathbb{P}(X \leq Y)$
 - (c) $\mathbb{P}(X + Y \leq 1/2)$
 - (d) $\mathbb{P}(XY \leq 1/2)$
- (iii) Find marginal p.d.f. of X and Y .

Solution.

- (i) Note that $f(x, y) \geq 0$. We need to show

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dy dx = 1$$

$$\begin{aligned} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dy dx &= \int_0^1 \int_0^1 (x + y) dy dx \\ &= \int_0^1 \left[x + \frac{y^2}{2} \right]_0^1 dx \\ &= \int_0^1 \left(x + \frac{1}{2} \right) dx \\ &= \left[\frac{x^2}{2} + \frac{x}{2} \right]_0^1 \\ &= 1 \end{aligned}$$

- (ii) (a) Take $R = \{(x, y) : 0 \leq x \leq 1/3, 0 \leq y \leq 1/2\}$.

$$\begin{aligned} \int_0^{1/3} \int_0^{1/2} (x + y) dy dx &= \int_0^{1/3} \left[xy + \frac{y^2}{2} \right]_0^{1/2} dx \\ &= \int_0^{1/3} \left(\frac{x}{2} + \frac{1}{8} \right) dx \\ &= \left[\frac{x^2}{4} + \frac{x}{8} \right]_0^{1/3} \\ &= \frac{1}{36} + \frac{1}{24} \\ &= \frac{5}{72} \end{aligned}$$

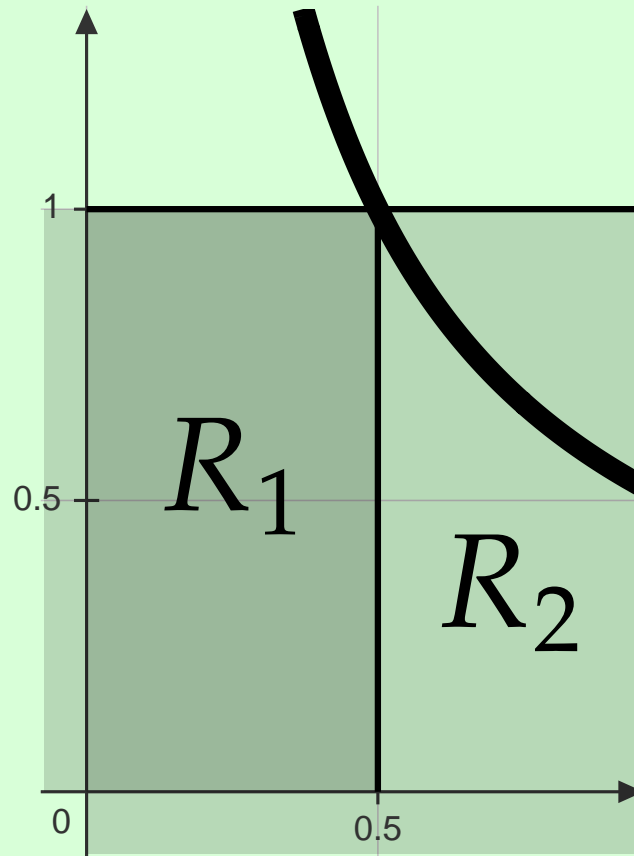
(b) $R = \{(x, y) : 0 \leq x \leq 1, x \leq y \leq 1\}$.

$$\begin{aligned} \int_0^1 \int_x^1 (x+y) dy dx &= \int_0^1 \left[xy + \frac{y^2}{2} \right]_x^1 dx \\ &= \int_0^1 x + \frac{1}{2} - x^2 - \frac{x^2}{2} dx \\ &= \left[\frac{x^2}{2} + \frac{x}{2} - \frac{x^3}{3} - \frac{x^3}{2} \left(\frac{1}{3} \right) \right]_0^1 \\ &= \frac{1}{2} \end{aligned}$$

(c) $R = \{(x, y) : 0 \leq x \leq 1/2, 0 \leq y \leq (1/2) - x\}$

$$\begin{aligned} \int_0^{1/2} \int_0^{(1/2)-x} (x+y) dy dx &= \int_0^{1/2} \left[xy + \frac{y^2}{2} \right]_0^{(1/2)-x} dx \\ &= \int_0^{1/2} \left(\frac{x}{2} - x^2 + \frac{1}{8} - \frac{x}{2} + \frac{x^2}{2} \right) dx \\ &= \int_0^{1/2} \frac{1}{8} - \frac{x^2}{2} dx \\ &= \left[\frac{x}{8} - \frac{x^3}{2} \left(\frac{1}{3} \right) \right]_0^{1/2} \\ &= \frac{1}{24} \end{aligned}$$

(d) This example is a bit complicated, so I included a figure.



Note the curve drawn is $xy = 1/2$. R_1 can be described with:

$$0 \leq x \leq \frac{1}{2}$$

$$0 \leq y \leq 1$$

R_2 (region below the curve) can be described with:

$$\frac{1}{2} \leq x \leq 1$$

$$0 \leq y \leq \left(\frac{1}{2}\right)/x$$

Therefore, we need to evaluate two double integrals.

$$\int_0^{1/2} \int_0^1 (x+y) dy dx + \int_{1/2}^1 \int_0^{(1/2)/x} (x+y) dy dx = \frac{3}{4}$$

(iii) The support of X is $[0, 1]$.

$$f_1(x) = 0 \iff x < 0 \text{ or } x > 1$$

Therefore, we focus on $0 \leq x \leq 1$.

$$f_1(x) = \int_{-\infty}^{\infty} f(x, y) dy = \int_0^1 (x + y) dy = \left[x + \frac{y^2}{2} \right]_0^1 = x + \frac{1}{2}$$

Thus,

$$f_1(x) = \begin{cases} x + \frac{1}{2} & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$f_2(y)$ is similar by symmetry.

EXAMPLE 3.3.9

Suppose

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

is the joint p.d.f. of (X, Y) .

- (i) Find k .
- (ii) Find
 - (a) $\mathbb{P}(X \leq 1/3, Y \leq 1/2)$
 - (b) $\mathbb{P}(X \leq Y)$
 - (c) $\mathbb{P}(X + Y \geq 1)$
- (iii) Marginal p.d.f. of X and Y .
- (iv) Suppose $T = X + Y$, find the p.d.f. of T .

Solution.

- (i) We know $f(x, y) \geq 0 \iff k \geq 0$. Actually, $k > 0$ since if $k = 0$, then $f(x, y) \equiv 0$. We solve k by solving the following:

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy = 1$$

Therefore,

$$\begin{aligned} &= \int_0^{\infty} \int_x^{\infty} ke^{-x-y} dy dx \\ &= k \int_0^{\infty} e^{-x} [-e^{-y}]_x^{\infty} dx \\ &= k \int_0^{\infty} e^{-x} e^{-x} dx \\ &= k \int_0^{\infty} e^{-2x} dx \\ &= k \left[-\frac{1}{2} e^{-2x} \right]_0^{\infty} \\ &= \frac{k}{2} \end{aligned}$$

Thus, $k/2 = 1 \implies k = 2$.

- (ii) (a) $\mathbb{P}(X \leq 1/3, Y \leq 1/2)$.

$$R = \{(x, y) : 0 \leq x \leq 1/3, x \leq y \leq 1/2\}$$

Therefore,

$$\begin{aligned}
 \mathbb{P}(X \leq 1/3, Y \leq 1/2) &= \int_0^{1/3} \int_x^{1/2} 2e^{-x-y} dy dx \\
 &= 2 \int_0^{1/3} e^{-x} [-e^{-y}]_x^{1/2} dx \\
 &= 2 \int_0^{1/3} e^{-x} (-e^{-1/2} + e^{-x}) dx \\
 &= 2 \int_0^{1/3} -e^{-1/2}e^{-x} + e^{-2x} dx \\
 &= 2 \left(-e^{-1/2} [-e^{-x}]_0^{1/3} + \left[-\frac{1}{2}e^{-2x} \right]_0^{1/3} \right) \\
 &= 2 \left(-e^{-1/2} (-e^{-1/3} + 1) + \left(-\frac{1}{2} \right) (e^{-2/3} - 1) \right) \\
 &= 2 \left(1/2 + e^{-5/6} - e^{-1/2} - \frac{1}{2}e^{-2/3} \right) \\
 &= 1 - e^{-2/3} + 2(e^{-5/6} - e^{-1/2}) \\
 &\approx 0.1427
 \end{aligned}$$

(b) $\mathbb{P}(X \leq Y)$. Note that the region is the same as the support. Therefore,

$$\mathbb{P}(X \leq Y) = \iint_{x \leq y} f(x, y) dx dy = 1$$

(c) $\mathbb{P}(X + Y \geq 1)$. Note that this region is a bit complicated, so we will consider $1 - \mathbb{P}(X + Y < 1) = 1 - \mathbb{P}(X + Y \leq 1)$. The equal sign does not account for any area (it's continuous, but not required to know in this course).

$$R = \{(x, y) : 0 \leq x \leq 1/2, x \leq y \leq 1 - x\}$$

$$\begin{aligned}
 \mathbb{P}(X + Y \leq 1) &= \int_0^{1/2} \int_x^{1-x} 2e^{-x}e^{-y} dy dx \\
 &= 2 \int_0^{1/2} e^{-x} [e^{-y}]_x^{1-x} dx \\
 &= 2 \int_0^{1/2} e^{-x} (-e^{x-1} + e^{-x}) dx \\
 &= 2 \int_0^{1/2} -e^{-1} + e^{-2x} dx \\
 &= 2 \left[-xe^{-1} - \frac{1}{2}e^{-2x} \right]_0^{1/2} \\
 &= 2 \left(\left(-\frac{1}{2}e^{-1} - \frac{1}{2}e^{-2(1/2)} \right) - \left(0 - \frac{1}{2} \right) \right) \\
 &= 2 \left(-\frac{1}{2}e^{-1} - \frac{1}{2}e^{-1} + \frac{1}{2} \right) \\
 &= 2 \left(-e^{-1} + \frac{1}{2} \right) \\
 &= 1 - 2e^{-1}
 \end{aligned}$$

Thus, $\mathbb{P}(X + Y \geq 1) = 1 - \mathbb{P}(X + Y \leq 1) = 1 - (1 - 2e^{-1}) = 2e^{-1}$.

(iii) Marginal p.d.f. of X . The support of X is $(0, \infty)$. We know $x > 0$, so

$$f_1(x) = \int_{-\infty}^{\infty} f(x, y) dy = \int_x^{\infty} 2e^{-x-y} dy = 2e^{-x} [-e^{-y}]_x^{\infty} = 2e^{-2x}$$

The marginal p.d.f. of Y . The support of Y is $(0, \infty)$. We know $y > 0$, so

$$f_2(y) = \int_0^y 2e^{-x-y} dx = 2e^{-y} [-e^{-x}]_0^y = 2e^{-y} (1 - e^{-y}) = 2e^{-y} - 2e^{-2y}$$

(iv) Suppose $T = X + Y$, find the p.d.f. of T . We first find the c.d.f. of T , then we take the derivative of T .

Support of T is $(0, \infty)$.

When $t \leq 0$, $F_T(t) = \mathbb{P}(T \leq t) = 0$, so we only focus on $t > 0$, so $F_T(t) = \mathbb{P}(T \leq t)$.

$$R = \{(x, y) : 0 \leq x \leq t/2, x \leq y \leq t - x\}$$

Therefore,

$$\begin{aligned} F_T(t) &= \int_0^{t/2} \int_x^{t-x} 2e^{-x-y} dy dx \\ &= 2 \int_0^{t/2} e^{-x} [-e^{-y}]_x^{t-x} dx \\ &= 2 \int_0^{t/2} e^{-x} (-e^{x-t} + e^{-x}) dx \\ &= 2 \int_0^{t/2} -e^{-t} + e^{-2x} dx \\ &= 2 \left[-xe^{-t} - \frac{1}{2}e^{-2x} \right]_0^{t/2} \\ &= 2 \left(\left(-\frac{t}{2}e^{-t} - \frac{1}{2}e^{-t} \right) - \left(0 - \frac{1}{2} \right) \right) \\ &= 2 \left(-\frac{t}{2}e^{-t} - \frac{1}{2}e^{-t} + \frac{1}{2} \right) \\ &= 1 - e^{-t} - te^{-t} \end{aligned}$$

So,

$$F_T(t) = \begin{cases} 1 - e^{-t} - te^{-t} & t > 0 \\ 0 & t \leq 0 \end{cases}$$

Therefore, by computing $\frac{d}{dt}[F_T(t)]$, the p.d.f. of T is

$$f_T(t) = \begin{cases} te^{-t} & t > 0 \\ 0 & t \leq 0 \end{cases}$$

3.4 Independence

DEFINITION 3.4.1: Independent

For any two random variables, we say X and Y are **independent** if and only if

$$\mathbb{P}(X \in A, Y \in B) = \mathbb{P}(X \in A)\mathbb{P}(Y \in B)$$

for any two sets A and B of real numbers.

THEOREM 3.4.2: Independent Random Variables

- (1) Suppose X and Y are random variables with cumulative distribution function $F(x, y)$. Suppose also that $F_1(x)$ is the marginal cumulative distribution function of X and $F_2(y)$ is the marginal cumulative distribution function of Y . Then X and Y are independent random variables if and only if

$$F(x, y) = F_1(x)F_2(y) \quad \forall (x, y) \in \mathbb{R}^2$$

- (2) Suppose X and Y are random variables with joint probability (density) function $f(x, y)$. Suppose also that $f_1(x)$ is the marginal probability (density) function of X with support set $A_1 = \{x : f_1(x) > 0\}$ and $f_2(y)$ is the marginal probability (density) function of Y with support set $A_2 = \{y : f_2(y) > 0\}$. Then X and Y are independent random variables if and only if

$$f(x, y) = f_1(x)f_2(y) \quad \forall (x, y) \in A_1 \times A_2$$

where $A_1 \times A_2 = \{(x, y) : x \in A_1, y \in A_2\}$.

THEOREM 3.4.3

If X and Y are independent, then $g(X)$ and $h(Y)$ are independent. Where g and h are two real-valued functions.

EXAMPLE 3.4.4

If X and Y are independent, then X^2 and Y^2 are independent. However, if X^2 and Y^2 are independent, then X and Y may not be independent. Can you find an example here? Choose X where

$$\mathbb{P}(X = 1) = \mathbb{P}(X = -1) = \frac{1}{2}$$

EXAMPLE 3.4.5

Consider the joint discrete random variable $f(x, y) = q^2 p^{x+y}$, where $x = 0, 1, \dots$ and $y = 0, 1, 2, \dots$. Then $f_1(x) = qp^x$ and $f_2(y) = qp^y$. Therefore,

$$f(x, y) = f_1(x)f_2(y)$$

shows that X and Y are independent.

Consider $f(x, y) = \begin{cases} x + y & 0 \leq x \leq 1 \\ 0 & 0 \leq y \leq y \end{cases}$ We've shown that

$$f_1(x) = \begin{cases} x + \frac{1}{2} & 0 \leq x \leq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$f_2(y) = \begin{cases} y + \frac{1}{2} & 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Here we see that $f(x, y) \neq f_1(x)f_2(y)$ Therefore, X and Y are not independent.

THEOREM 3.4.6: Factorization Theorem for Independence

Suppose X and Y are random variables with joint probability (density) function $f(x, y)$. Suppose also that A is the support set of (X, Y) , A_1 is the support set of X , and A_2 is the support set of Y . Then X and Y are independent random variables if and only if there exist non-negative functions $g(x)$ and $h(y)$ such that

$$f(x, y) = g(x)h(y) \quad \forall (x, y) \in A_1 \times A_2$$

where $A_1 \times A_2 = \{(x, y) : x \in A_1, y \in A_2\}$.

REMARK 3.4.7

Equivalently, we can check that

- The support of A is a rectangle.
- The range of X does not depend on the values of y and the range of Y does not depend on the values of x .

EXAMPLE 3.4.8

$f(x, y) = \frac{\theta^{x+y} e^{-2\theta}}{x!y!}$ where $x, y \in \mathbb{Z}_{\geq 0}$. Are X and Y independent or not? Find the marginal p.f. of X and Y .

Solution.

$$f(x, y) = \frac{\theta^x e^{-\theta}}{x!} \frac{\theta^y e^{-\theta}}{y!} = \underbrace{\frac{\theta^x e^{-\theta}}{x!}}_{g(x)} \underbrace{\frac{\theta^y e^{-\theta}}{y!}}_{h(y)}$$

The range of X does not depend on the value of y . Therefore, X and Y are independent.

$$f_1(x) = \sum_{y=0}^{\infty} f(x, y) = \frac{\theta^x e^{-\theta}}{x!} \quad x \in \mathbb{Z}_{\geq 0}$$

$$f_2(y) = \sum_{x=0}^{\infty} f(x, y) = \frac{\theta^y e^{-\theta}}{y!} \quad y \in \mathbb{Z}_{\geq 0}$$

If we've shown that X and Y are independent, then we can verify

$$f(x, y) = g(x)h(y)$$

With $f_1(x) = C_1 g(x)$ and $f_2(y) = C_2 h(y)$ where $C_1, C_2 \in \mathbb{R}$ is a constant. We know that $C_1 C_2 = 1$.

EXAMPLE 3.4.9

If X and Y have joint p.d.f. $f(x, y) = \frac{3}{2}y(1-x^2)$ where $-1 \leq x \leq 1$ and $0 \leq y \leq 1$. Are X and Y independent? Find $f_1(x)$ and $f_2(y)$.

Solution. $f(x, y) = \underbrace{(1-x^2)}_{h(x)} \underbrace{\frac{3}{2}y}_{g(y)}$ and $A = \{(x, y) : -1 \leq x \leq 1, 0 \leq y \leq 1\}$ is a rectangle. Therefore X

and Y are independent. So,

$$f_1(x) = C_1 h(x) = C_1(1 - x^2) \quad \text{for } -1 \leq x \leq 1$$

So, let's consider the integral:

$$\int_{-1}^1 f_1(x) dx = C_1 \int_{-1}^1 (1 - x^2) dx = 1 \implies C_1 = \frac{3}{4}$$

Using our previous result, we know that

$$f_2(y) = \frac{1}{C_1} h(y) = \frac{4}{3} \cdot \frac{3}{2} y = 2y \quad 0 \leq y \leq 1$$

EXAMPLE 3.4.10: Uniform Distribution on a Semicircle

$f(x, y) = \frac{2}{\pi}$ where $0 \leq x \leq \sqrt{1 - y^2}$ and $-1 \leq y \leq 1$. The area of the semicircle is given by $\pi/2$. Are X and Y independent and find $f_1(x)$ and $f_2(y)$.

Solution. $f(x, y) = 2/\pi$. Take $g(x) = 1$ and $h(y) = 2/\pi$. Also, this is not a rectangle, so X and Y are not independent. Similarly, for a particular value of x we can easily see that y depends on x . The support of X is $[0, 1]$.

$$f_1(x) = \int_{-\sqrt{1-x^2}}^{\sqrt{1-x^2}} \frac{2}{\pi} dy = \frac{4}{\pi} \sqrt{1-x^2}$$

The support of Y is $[-1, 1]$.

$$f_2(y) = \int_0^{\sqrt{1-y^2}} \frac{2}{\pi} dx = \frac{2}{\pi} \sqrt{1-y^2}$$

Neither of these marginal distributions are uniform.

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Independence:

- (1) Definition
- (2) Check independence: $f(x, y) = f_1(x)f_2(y)$
- (3) If X and Y are independent, then $g(X)$ and $h(Y)$ are independent. The converse is not true.
- (4) Factorization Theorem
 - (i) $f(x, y) = g(x)h(y)$
 - (ii) A is a rectangle, or equivalent statements.

X and Y are independent if and only if (i) and (ii) are satisfied.

3.5 Joint Expectation

This section: extend the definition of expectation from univariate to bivariate cases.

DEFINITION 3.5.1: Joint expectation

Suppose $h(x, y)$ is a real-valued function.

If X and Y are discrete random variables with joint probability function $f(x, y)$ and support set A then

$$\mathbb{E}[h(X, Y)] = \sum_{(x, y) \in A} h(x, y) f(x, y)$$

provided the joint sum converges absolutely.

If X and Y are continuous random variables with joint probability density function $f(x, y)$ then

$$\mathbb{E}[h(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x, y) f(x, y) dx dy$$

provided the joint integral converges absolutely.

EXAMPLE 3.5.2

$$\mathbb{E}[XY] = \begin{cases} \sum_x \sum_y xy f(x, y) & X, Y \text{ are joint discrete} \\ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f(x, y) dx dy & X, Y \text{ are joint continuous} \end{cases}$$

$$\mathbb{E}[X] = \begin{cases} \sum_x \sum_y x f(x, y) & X, Y \text{ are joint discrete} \\ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f(x, y) dx dy & X, Y \text{ are joint continuous} \end{cases}$$

Alternatively,

$$\mathbb{E}[X] = \sum_x x f_1(x) = \sum_x x \left[\sum_y f(x, y) \right]$$

PROPOSITION 3.5.3: Linearity Property

Suppose X and Y are random variables with joint probability (density) function $f(x, y)$, a and b are constants, and $g(x, y)$ and $h(x, y)$ are real-valued functions. Then

$$\mathbb{E}[ag(X, Y) + bh(X, Y)] = a\mathbb{E}[g(X, Y)] + b\mathbb{E}[h(X, Y)]$$

COROLLARY 3.5.4

If X_1, \dots, X_n are random variables and a_1, \dots, a_n are real constants then

$$\mathbb{E} \left[\sum_{i=1}^n a_i X_i \right] = \sum_{i=1}^n a_i \mathbb{E}[X_i]$$

THEOREM 3.5.5: Expectation and Independence

(1) If X and Y are independent random variables and $g(x)$ and $h(y)$ are real-valued functions then

$$\mathbb{E}[g(X)h(Y)] = \mathbb{E}[g(X)]\mathbb{E}[h(Y)]$$

(2) More generally, if X_1, \dots, X_n are independent random variables and h is a real-valued function then

$$\mathbb{E}\left[\prod_{i=1}^n h(X_i)\right] = \prod_{i=1}^n \mathbb{E}[h(X_i)]$$

DEFINITION 3.5.6: Covariance

The **covariance** of random variables X and Y is defined by

$$\text{Cov}(X, Y) = \mathbb{E}[(X - \mu_X)(Y - \mu_Y)]$$

where $\mu_X = \mathbb{E}[X]$ and $\mu_Y = \mathbb{E}[Y]$.

THEOREM 3.5.7: Covariance and Independence

If X and Y are random variables then

$$\text{Cov}(X, Y) = \mathbb{E}[XY] - \mu_X\mu_Y$$

If X and Y are independent then $\text{Cov}(X, Y) = 0$.

Proof of: 3.5.7

$$\begin{aligned} \text{Cov}(X, Y) &= \mathbb{E}[(X - \mu_X)(Y - \mu_Y)] \\ &= \mathbb{E}[XY - \mu_X Y - \mu_Y X + \mu_X \mu_Y] \\ &= \mathbb{E}[XY] - \mu_X \mathbb{E}[Y] - \mu_Y \mathbb{E}[X] + \mu_X \mu_Y \\ &= \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] - \mathbb{E}[Y]\mathbb{E}[X] + \mathbb{E}[X]\mathbb{E}[Y] \\ &= \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] \end{aligned}$$

Now, if X and Y are independent, then by 3.5.5, $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y] = 0$. Thus, $\text{Cov}(X, Y) = 0$.

THEOREM 3.5.8: Results for Covariance

(1) $\text{Cov}(X, X) = \mathbb{E}[(X - \mu_X)(X - \mu_X)] = \mathbb{E}[(X - \mu_X)^2] = \mathbb{V}(X)$

(2) $\text{Cov}(X + Y, Z) = \text{Cov}(X, Z) + \text{Cov}(Y, Z)$

THEOREM 3.5.9: Variance of a Linear Combination

(1) Suppose X and Y are random variables and a and b are real constants then

$$\mathbb{V}(aX + bY) = a^2\mathbb{V}(X) + b^2\mathbb{V}(Y) + 2ab\text{Cov}(X, Y)$$

(2) Suppose X_1, \dots, X_n are random variables and a_1, \dots, a_n are real constants then

$$\mathbb{V}\left(\sum_{i=1}^n a_i X_i\right) = \sum_{i=1}^n a_i^2 \mathbb{V}(X_i) + \underbrace{\sum_{i \neq j} a_i a_j \text{Cov}(X_i, X_j)}_{\binom{n}{2} \text{ terms}} = \sum_{i=1}^n a_i^2 \mathbb{V}(X_i) + 2 \underbrace{\sum_{i < j} a_i a_j \text{Cov}(X_i, X_j)}_{\binom{n}{2} \text{ terms}}$$

(3) If X_1, \dots, X_n are random variables and a_1, \dots, a_n are real constants then

$$\mathbb{V}\left(\sum_{i=1}^n a_i X_i\right) = \sum_{i=1}^n a_i^2 \mathbb{V}(X_i)$$

EXAMPLE 3.5.10

Suppose the joint p.f. of X and Y is $f(x, y) = \frac{\theta^{x+y} e^{-2\theta}}{x!y!}$, where $x \in \mathbb{Z}_{\geq 0}$ and $y \in \mathbb{Z}_{\geq 0}$.

Find $\mathbb{V}(2X + 3Y)$.

Solution.

$$f(x, y) = \underbrace{\left(\frac{\theta^x e^{-\theta}}{x!}\right)}_{g(x)} \underbrace{\left(\frac{\theta^y e^{-\theta}}{y!}\right)}_{h(y)}$$

Thus, the range of X does not depend on Y . Therefore, X and Y are independent. In other words, we can write

$$f_1(x) = C \frac{\theta^x e^{-\theta}}{x!} \quad x \in \mathbb{Z}_{\geq 0}$$

Since $\sum_{x=0}^{\infty} \frac{\theta^x e^{-\theta}}{x!} = 1$ as it is Poisson we get that $C = 1$. Also,

$$f_2(y) = \frac{\theta^y e^{-\theta}}{y!} \quad y \in \mathbb{Z}_{\geq 0}$$

Thus, $\mathbb{V}(X) = \theta$ and $\mathbb{V}(Y) = \theta$. Finally,

$$\mathbb{V}(2X + 3Y) = 4\mathbb{V}(X) + 9\mathbb{V}(Y) = 13\theta$$

EXAMPLE 3.5.11

The joint p.d.f. of X and Y is $f(x, y) = \begin{cases} x + y & x, y \in [0, 1] \\ 0 & \text{otherwise} \end{cases}$.

Find $\mathbb{V}(X + Y)$.

Solution. We know $\mathbb{V}(X + Y) = \mathbb{V}(X) + \mathbb{V}(Y) + 2\text{Cov}(X, Y)$. Recall that

$$f_1(x) = \begin{cases} x + \frac{1}{2} & x \in [0, 1] \\ 0 & \text{otherwise} \end{cases} \quad f_2(y) = \begin{cases} y + \frac{1}{2} & y \in [0, 1] \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{E}[X] = \int_0^1 x \left(x + \frac{1}{2}\right) dx = \frac{7}{12}$$

$$\begin{aligned}\mathbb{E}[X^2] &= \int_0^1 x^2 \left(x + \frac{1}{2}\right) dx = \frac{5}{12} \\ \Rightarrow \mathbb{V}(X) &= \mathbb{E}[X^2] - \mu_X^2 = \frac{5}{12} - \left(\frac{7}{12}\right)^2 = \frac{11}{144}\end{aligned}$$

We know that $\mathbb{E}[Y] = 7/12$, $\mathbb{V}(Y) = 11/144$. Now,

$$\begin{aligned}\mathbb{E}[XY] &= \int_0^1 \int_0^1 xy(x+y) dy dx = \frac{1}{3} \\ \Rightarrow \text{Cov}(X, Y) &= \mathbb{E}[XY] - \mu_X \mu_Y = \frac{1}{3} - \left(\frac{7}{12}\right) \left(\frac{7}{12}\right) = -\frac{1}{144}\end{aligned}$$

Hence,

$$\mathbb{V}(X+Y) = \mathbb{V}(X) + \mathbb{V}(Y) + 2\text{Cov}(X, Y) = \frac{11}{144} + \frac{11}{144} - \frac{2}{144} = \frac{20}{144} = \frac{5}{36}$$

DEFINITION 3.5.12: Correlation coefficient

The **correlation coefficient** of random variables X and Y is defined by

$$\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\mathbb{V}(X)}\sqrt{\mathbb{V}(Y)}}$$

REMARK 3.5.13

$\rho(X, Y)$ can only be used to characterize **linear** association between X and Y . For example, there might be exist some quadratic relationship between X and Y but $\rho(X, Y) \rightarrow 0$.

EXAMPLE 3.5.14

$Y = X^2$ and $X \sim N(0, 1)$. Note that $\rho(X, Y) = 0$, but obviously there is some relationship between X and Y .

THEOREM 3.5.15

If $\rho(X, Y)$ is the correlation coefficient of random variables X and Y , then $-1 \leq \rho(X, Y) \leq 1$

- (1) $\rho(X, Y) = 1 \iff Y = aX + b$ with $a > 0$.
- (2) $\rho(X, Y) = -1 \iff Y = aX + b$ with $a < 0$.

EXAMPLE 3.5.16

Let $f(x, y) = \begin{cases} x+y & x, y \in [0, 1] \\ 0 & \text{otherwise} \end{cases}$. Find $\rho(X, Y)$.

Solution. Recall that $\mathbb{V}(X) = \mathbb{V}(Y) = 11/144$ and $\text{Cov}(X, Y) = -1/144$. So,

$$\rho(X, Y) = \frac{-1/144}{\sqrt{11/144}\sqrt{11/144}} = -\frac{1}{11}$$

- Definition
- Linearity property
- Expectation of product in independent case

$$\mathbb{E}[g(X)h(Y)] = \mathbb{E}[g(X)]\mathbb{E}[h(Y)]$$

if X is independent of Y .

- Covariance $\text{Cov}(X, X) = \mathbb{V}(X)$. Also, $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y] \iff \text{Cov}(X, Y) = 0$.
- Correlation

3.6 Conditional Distributions

DEFINITION 3.6.1: Conditional probability (density) function

Suppose that X and Y have joint probability (density) function $f(x, y)$, and marginal probability (density) functions $f_1(x)$ and $f_2(y)$ respectively. Suppose also that the support set of (X, Y) is $A = \{(x, y) : f(x, y) > 0\}$.

The **conditional probability (density) function** of X given $Y = y$ is

$$f_1(x | y) = \frac{f(x, y)}{f_2(y)} \quad \text{provided } f_2(y) > 0 \quad (x, y) \in A$$

The **conditional probability (density) function** of Y given $X = x$

$$f_2(y | x) = \frac{f(x, y)}{f_1(x)} \quad \text{provided } f_1(x) > 0 \quad (x, y) \in A$$

PROPOSITION 3.6.2: Properties — Conditional Probability Function

$f_1(x | y)$ and $f_2(y | x)$ are both probability functions; that is,

$$f_1(x | y) \geq 0 \quad \text{and} \quad \sum_x f_1(x | y) = 1 \implies f_1(x | y) \text{ is a p.f.}$$

$$f_2(y | x) \geq 0 \quad \text{and} \quad \sum_y f_2(y | x) = 1 \implies f_2(y | x) \text{ is a p.f.}$$

PROPOSITION 3.6.3: Properties — Conditional Probability Function

$f_1(x | y)$ and $f_2(y | x)$ are both probability density functions; that is,

$$f_1(x | y) \geq 0 \quad \text{and} \quad \int_{-\infty}^{\infty} f_1(x | y) dx = 1 \implies f_1(x | y) \text{ is a p.d.f.}$$

$$f_2(y | x) \geq 0 \quad \text{and} \quad \int_{-\infty}^{\infty} f_2(y | x) dy = 1 \implies f_2(y | x) \text{ is a p.d.f.}$$

EXAMPLE 3.6.4

$$\text{Let } f(x, y) = \begin{cases} 8xy & 0 < y < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

Find

- (i) $f_1(x | y)$
- (ii) $f_2(y | x)$

Solution.

(i) To find $f_1(x | y)$, we need to calculate $f_2(y)$.

$$f_2(y) = \int_y^1 8xy \, dx = -4y^3 + 4y \quad 0 < y < 1$$

By definition,

$$f_1(x | y) = \frac{f(x, y)}{f_2(y)} = \frac{8xy}{4y - 4y^3} = \frac{2x}{1 - y^2} \quad 0 < y < 1$$

Given $0 < y < 1$, the support of X is $y < x < 1$.

(ii) To find $f_2(y | x)$, we need to calculate $f_1(x)$.

$$f_1(x) = \int_0^x 8xy \, dy = 4x^3 \quad 0 < x < 1$$

By definition,

$$f_2(y | x) = \frac{f(x, y)}{f_1(x)} = \frac{8xy}{4x^3} = \frac{2y}{x^2} \quad 0 < x < 1$$

Given $0 < x < 1$, the support of Y is $0 < y < x$.

EXAMPLE 3.6.5

$$f(x, y) = \begin{cases} x + y & x, y \in [0, 1] \\ 0 & \text{otherwise} \end{cases}$$

Recall that $f_1(x) = x + 1/2$ for $0 \leq x \leq 1$ and $f_2(y) = y + 1/2$ for $0 \leq y \leq 1$. Therefore,

$$f_1(x | y) = \frac{f(x, y)}{f_2(y)} = \frac{x + y}{y + 1/2}$$

Given $0 \leq y \leq 1$, the support of X is $0 \leq x \leq 1$.

$$f_2(y | x) = \frac{x + y}{x + 1/2}$$

Given $0 \leq x \leq 1$, the support of Y is $0 \leq y \leq 1$.

EXAMPLE 3.6.6

$f(x, y) = q^2 p^{x+y}$ where $x \in \mathbb{Z}_{\geq 0}$ and $y \in \mathbb{Z}_{\geq 0}$. Note we derived that $f_1(x) = qp^x$ and $f_2(y) = qp^y$. Therefore,

$$f_1(x | y) = \frac{f(x, y)}{f_2(y)} = qp^x = f_1(x)$$

$$f_2(y | x) = \frac{f(x, y)}{f_1(x)} = qp^y = f_2(y)$$

This is another way to show independence of X and Y .

THEOREM 3.6.7

Suppose X and Y are random variables with marginal probability (density) functions $f_1(x)$ and $f_2(y)$ respectively and conditional probability (density) functions $f_1(x | y)$ and $f_2(y | x)$. Suppose also that A_1 is the support set of X and A_2 is the support set of Y . Then X and Y are independent random variables if and only if either of the following holds

$$f_1(x | y) = f_1(x) \quad \forall x \in A_1$$

or

$$f_2(y | x) = f_2(y) \quad \forall y \in A_2$$

THEOREM 3.6.8: Product Rule

Suppose X and Y are random variables with joint probability (density) function $f(x, y)$, marginal probability (density) functions $f_1(x)$ and $f_2(y)$ respectively and conditional probability (density) functions $f_1(x | y)$ and $f_2(y | x)$. Then

$$f(x, y) = f_1(x | y)f_2(y) = f_2(y | x)f_1(x)$$

EXAMPLE 3.6.9: Product rule

Suppose $Y \sim \text{Poisson}(\theta)$ and $X | Y = y \sim \text{Binomial}(y, p)$. Find the marginal p.f. of X .

Before we get to the solution of this problem, let's consider a physical setup.

- Y : number of students who go to Tim Hortons in one day. Note that $Y \sim \text{Poisson}(\theta)$.
- $X | Y = y$: number of students among these y visitors

What is the distribution of X ? We guess that $X \sim \text{Poisson}(\theta p)$.

Solution.

$$f_1(x | y) = \binom{y}{x} p^x (1-p)^{y-x} \quad x = 0, 1, \dots, y$$

$$f_2(y) = \frac{\theta^y}{y!} e^{-\theta} \quad y = 0, 1, 2, \dots$$

$$\begin{aligned} f(x, y) &= f_1(x | y)f_2(y) \\ &= \left(\frac{y!}{x!(y-x)!} p^x (1-p)^{y-x} \right) \frac{\theta^y}{y!} e^{-\theta} \\ &= \left(\frac{\theta^x p^x}{x!} \right) \frac{\theta^{y-x} (1-p)^{y-x}}{(y-x)!} e^{-\theta} \end{aligned}$$

(X, Y) support is $x = 0, 1, \dots, y$ and $y = 0, 1, \dots$. Therefore,

$$\begin{aligned} f_1(x) &= \sum_y f(x, y) \\ &= \sum_{y=x}^{\infty} \left[\left(\frac{(\theta p)^x}{x!} \right) \left(\frac{(\theta(1-p))^{y-x}}{(y-x)!} e^{-\theta} \right) \right] \\ &= \frac{e^{-\theta} (\theta p)^x}{x!} \sum_{h=0}^{\infty} \frac{[\theta(1-p)]^h}{h!} & h = y - x \\ &= \frac{e^{-\theta} (\theta p)^x}{x!} e^{\theta(1-p)} \\ &= \frac{(\theta p)^x}{x!} e^{-\theta p} \end{aligned}$$

Therefore, $x = 0, 1, \dots$ and so $X \sim \text{Poisson}(\theta p)$.

EXAMPLE 3.6.10

Suppose Y has p.d.f. $f_2(y) = \frac{y^{\alpha-1}}{\Gamma(\alpha)} e^{-y}$ for $y > 0$; that is, $Y \sim \text{Gamma}(\alpha, \beta = 1)$. The conditional p.d.f. of X given $Y = y$ is

$$f_1(x | y) = ye^{-xy} \quad \text{for } x > 0, y > 0$$

Find the marginal p.d.f. of X .

Solution. Firstly, find the joint p.d.f. of (X, Y) is

$$f(x, y) = f_1(x | y)f_2(y) = ye^{-xy} \frac{y^{\alpha-1}}{\Gamma(\alpha)} e^{-y} = \frac{y^\alpha}{\Gamma(\alpha)} e^{-(x+1)y}$$

The support of X is $(0, \infty)$. Recall that the gamma function is $\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx$.

The marginal p.d.f. of X is

$$f_1(x) = \int_{-\infty}^{\infty} f(x, y) dy = \int_0^\infty \frac{y^\alpha e^{-(x+1)y}}{\Gamma(\alpha)} dy$$

Let $t = (x+1)y$, therefore $y = t/(x+1)$ and $dy = dt/(x+1)$.

$$\int_0^\infty \frac{t^\alpha}{(x+1)^\alpha \Gamma(\alpha)} e^{-t} \frac{1}{x+1} dt = \frac{1}{(x+1)^{\alpha+1} \Gamma(\alpha)} \int_0^\infty t^\alpha e^{-t} dt = \frac{1}{(x+1)^{\alpha+1} \Gamma(\alpha)} \Gamma(\alpha+1)$$

By 2.3.7, we know that $\Gamma(\alpha+1) = (\alpha)\Gamma(\alpha)$. Therefore,

$$\frac{\Gamma(\alpha+1)}{(x+1)^{\alpha+1} \Gamma(\alpha)} = \frac{(\alpha)\Gamma(\alpha)}{(x+1)^{\alpha+1} \Gamma(\alpha)} = \frac{\alpha}{(x+1)^{\alpha+1}}$$

That is, $f_1(x) = \frac{\alpha}{(x+1)^{\alpha+1}}$ and the support of X is positive.

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Recall that $f_2(y | x) = \begin{cases} \text{p.f.} & X \text{ and } Y \text{ are joint discrete} \\ \text{p.f.} & X \text{ and } Y \text{ are joint continuous} \end{cases}$

Therefore, we can define expectation of expectation based on $f_2(y | x)$.

3.7 Conditional Expectation

DEFINITION 3.7.1: Conditional expectation

The **conditional expectation** of $g(Y)$ given $X = x$ is defined as

$$\mathbb{E}[g(Y) | X = x] = \begin{cases} \sum_y g(y) f_2(y | x) & Y \text{ is discrete} \\ \int_{-\infty}^{\infty} g(y) f_2(y | x) dy & Y \text{ is continuous} \end{cases}$$

REMARK 3.7.2

• Supplementary notes: $\mathbb{E}[g(Y) | X = x]$ is denoted by $\mathbb{E}[g(Y) | x]$.

We're interested in

1. The conditional mean of Y given $X = x$ is denoted $\mathbb{E}[Y | X = x]$ since $g(Y) = Y$.
2. The conditional variance of Y given $X = x$ is denoted by $\mathbb{V}(Y | X = x)$ and is given by

$$\mathbb{V}(Y | X = x) = \mathbb{E}[Y^2 | X = x] - (\mathbb{E}[Y | X = x])^2$$

3. $\mathbb{E}[e^{tY} | X = x]$, that is, $g(Y) = e^{tY}$.

THEOREM 3.7.3: Independence

If X and Y are independent random variables then

$$\mathbb{E}[g(Y) | X = x] = \mathbb{E}[g(Y)] \quad \text{and} \quad \mathbb{E}[h(X) | Y = y] = \mathbb{E}[h(X)]$$

In other words, the conditional expression becomes an unconditional one.

EXAMPLE 3.7.4

If X and Y are independent, then

$$\mathbb{E}[Y | X = x] = \mathbb{E}[Y] \quad \text{and} \quad \mathbb{V}(Y | X = x) = \mathbb{V}(Y)$$

$$\text{Also, } \mathbb{V}(Y | X = x) = \mathbb{E}[Y^2 | X = x] - (\mathbb{E}[Y | X = x])^2 = \mathbb{E}[Y^2] - (\mathbb{E}[Y])^2$$

THEOREM 3.7.5: Substitution Rule

If X and Y be random variables and $h : \mathbb{R}^2 \rightarrow \mathbb{R}$ then

$$\mathbb{E}[h(X, Y) | X = x] = \mathbb{E}[h(x, Y) | X = x]$$

EXAMPLE 3.7.6

- $\mathbb{E}[X + Y | X = x] = \mathbb{E}[x + Y | X = x] = x + \mathbb{E}[Y | X = x]$
- $\mathbb{E}[XY | X = x] = \mathbb{E}[xY | X = x] = x\mathbb{E}[Y | X = x]$

THEOREM 3.7.7

The conditional expectation has all properties of expectation like linearity.

EXAMPLE 3.7.8

$f(x, y) = \begin{cases} 8xy & 0 < y < x < 1 \\ 0 & \text{otherwise} \end{cases}$ We've found that $f_1(x | y) = (2x)/(1 - y)^2$ for $0 < y < 1$ and $y < x < 1$.

$$\mathbb{E}[X | Y = y] = \int_{-\infty}^{\infty} x f_1(x | y) dx = \int_y^1 (x) \frac{2x}{1 - y^2} dx = \left(\frac{2}{3}\right) \frac{1 - y^3}{1 - y^2} = \left(\frac{2}{3}\right) \frac{y^2 + y + 1}{y + 1}$$

$$\mathbb{E}[X^2 | Y = y] = \int_y^1 (x^2) \frac{2x}{1 - y^2} dy = \left(\frac{2}{4}\right) \frac{1 - y^4}{1 - y^2} = \left(\frac{1}{2}\right) (y^2 + 1) \quad 0 < y < 1$$

$$\mathbb{V}(X | Y = y) = \left(\frac{1}{2}\right)(1 + y^2) - \left(\frac{4}{9}\right) \frac{(1 + y + y^2)^2}{(1 + y)^2} \quad 0 < y < 1$$

EXAMPLE 3.7.9

Suppose $Y \sim \text{Poisson}(\theta)$ and $X | Y = y \sim \text{Binomial}(y, p)$. Then,

$$\mathbb{E}[X | Y = y] = yp \quad \text{and} \quad \mathbb{V}(X | Y = y) = yp(1 - p)$$

REMARK 3.7.10

Note that $\mathbb{E}[g(Y) | X] \neq \mathbb{E}[g(Y) | X = x]$.

$\mathbb{E}[g(Y) | X]$ is a random variable because it's a function of X , denoted by $h(X)$. Its value is given by $h(x) = \mathbb{E}[g(Y) | X = x]$ for $X = x$.

How to get it? Two steps.

- Step 1: Find $\mathbb{E}[g(Y) | X = x] = h(x)$
- Step 2: Replace x with X to get the random variable $\mathbb{E}[g(Y) | X] = h(X)$.

EXAMPLE 3.7.11

Suppose $Y \sim \text{Poisson}(\theta)$ and $X | Y = y \sim \text{Binomial}(y, p)$. Then,

$$\mathbb{E}[X | Y = y] = yp \implies \mathbb{E}[X | Y] = Yp$$

These concepts lead to the Double Expectation Theorem or more commonly known as the Law of Total Expectation.

THEOREM 3.7.12: Double Expectation (Law of Total Expectation)

Suppose X and Y are random variables then

$$\mathbb{E}[g(Y)] = \mathbb{E}[\mathbb{E}[g(Y) | X]]$$

In particular, $\mathbb{E}[Y] = \mathbb{E}[\mathbb{E}[Y | X]]$.

EXAMPLE 3.7.13

Suppose $Y \sim \text{Poisson}(\theta)$ and $X | Y = y \sim \text{Binomial}(y, p)$. Find $\mathbb{E}[X]$.

Solution. By Theorem 3.7.12 we have

$$\mathbb{E}[X] = \mathbb{E}[\mathbb{E}[X | Y]] = \mathbb{E}[Yp] = p\mathbb{E}[Y] = p\theta$$

Recall that we've shown that $X \sim \text{Poisson}(p\theta) \implies \mathbb{E}[X] = p\theta$.

Last lecture:

- Conditional expectation: $\mathbb{E}[g(Y) | X = x]$
- Properties:
 - (1) Independence
 - (2) Substitution rule

(3) Linearity

- Definition of $\mathbb{E}[g(Y) | X]$
 - a random variable and function of X , denoted as $h(X)$
 - two step method to find $h(X)$
- Double expectation theorem: $\mathbb{E}[g(Y)] = \mathbb{E}[\mathbb{E}[g(Y) | X]]$

THEOREM 3.7.14: Law of Total Variance

Suppose X and Y are random variables then

$$\mathbb{V}(Y) = \mathbb{E}[\mathbb{V}(Y | X)] + \mathbb{V}(\mathbb{E}[Y | X])$$

REMARK 3.7.15

$\mathbb{V}(Y | X)$ is a random variable and function of X .

How to get it? Two steps:

1. $\mathbb{V}(Y | X = x) = \mathbb{E}[Y^2 | X = x] - (\mathbb{E}[Y | X = x])^2$.
2. Replace x with X to get the random variable $\mathbb{V}(Y | X)$.

EXAMPLE 3.7.16

$Y \sim \text{Poisson}(\theta)$, $X | Y = y \sim \text{Binomial}(y, p)$. Find $\mathbb{V}(X)$.

Solution. We know that $X \sim \text{Poisson}(p\theta)$, then $\mathbb{V}(X) = p\theta$. But we can alternatively use the Double Expectation Theorem.

$$\mathbb{V}(X) = \mathbb{E}[\mathbb{V}(X | Y)] + \mathbb{V}(\mathbb{E}[X | Y])$$

To find $\mathbb{V}(X | Y)$,

$$\mathbb{V}(X | Y = y) = yp(1 - p) \implies \mathbb{V}(X | Y) = Yp(1 - p)$$

To find $\mathbb{E}[X | Y]$,

$$\mathbb{E}[X | Y = y] = yp \implies \mathbb{E}[X | Y] = Yp$$

Therefore,

$$\mathbb{V}(X) = \mathbb{E}[Yp(1 - p)] + \mathbb{V}(pY) = p(1 - p)\mathbb{E}[Y] + p^2\mathbb{V}(Y) = p(1 - p)\theta + p^2\theta = p\theta$$

EXAMPLE 3.7.17

Suppose $X \sim \text{Uniform}[0, 1]$ and $Y | X = x \sim \text{Binomial}(10, x)$. Find $\mathbb{E}[Y]$ and $\mathbb{V}(Y)$.

$$\mathbb{E}[Y] = \mathbb{E}[\mathbb{E}[Y | X]]$$

Two steps to find $\mathbb{E}[Y | X]$.

$$\mathbb{E}[Y | X = x] = 10x \implies \mathbb{E}[Y | X] = 10X$$

$$\mathbb{E}[Y] = \mathbb{E}[10X] = 10\mathbb{E}[X] = 10 \left(\frac{1+0}{2} \right) = 5$$

$$\mathbb{V}(Y) = \mathbb{E}[\mathbb{V}(Y | X)] + \mathbb{V}(\mathbb{E}[Y | X])$$

Two steps to find $\mathbb{V}(Y | X)$.

$$\mathbb{V}(Y | X = x) = 10x(1 - x) \implies \mathbb{V}(Y | X) = 10X(1 - X)$$

$$\begin{aligned}
\mathbb{V}(Y) &= \mathbb{E}[10X(1-X)] + \mathbb{V}(10X) \\
&= 10\mathbb{E}[X] - 10\mathbb{E}[X^2] + 100\mathbb{V}(X) \\
&= 10\left(\frac{1+0}{2}\right) - 10[\mathbb{V}(X) + (\mathbb{E}[X])^2] + 100\mathbb{V}(X) \\
&= 5 - 10\left[\frac{(0-1)^2}{12} + \left(\frac{1+0}{2}\right)^2\right] + 100\left[\frac{(0-1)^2}{12}\right] \\
&= 5 - 10\left(\frac{1}{12} + \frac{1}{4}\right) + 100\left(\frac{1}{12}\right) \\
&= 5 - 10\left(\frac{1}{3}\right) + \frac{100}{12} \\
&= 10
\end{aligned}$$

EXAMPLE 3.7.18

Suppose $Y \sim \text{Poisson}(\theta)$ and $X \mid Y = y \sim \text{Binomial}(y, p)$. Find the m.g.f. of X using the Double Expectation Theorem. [We could use the formula sheet to find $M_X(t)$ since we already know $X \sim \text{Poisson}(p\theta)$]

Solution. By definition, the m.g.f. of X is

$$M_X(t) = \mathbb{E}[e^{tX}] = \mathbb{E}[\mathbb{E}[e^{tX} \mid Y]]$$

Given $Y = y$,

$$\begin{aligned}
\mathbb{E}[e^{tX} \mid Y = y] &= \sum_{x=0}^y e^{tx} \binom{y}{x} p^x (1-p)^{y-x} \\
&= \sum_{x=0}^y \binom{y}{x} (pe^t)^x (1-p)^{y-x} \\
&= (1-p + pe^t)^y
\end{aligned}$$

Therefore, $\mathbb{E}[e^{tX} \mid Y] = (1-p + pe^t)^Y$. Therefore,

$$\begin{aligned}
M_X(t) &= \mathbb{E}[(1-p + pe^t)^Y] \\
&= \sum_{y=0}^{\infty} (1-p + pe^t)^y \frac{\theta^y e^{-\theta}}{y!} \\
&= e^{-\theta} \sum_{y=0}^{\infty} \frac{[\theta(1-p + pe^t)]^y}{y!} \\
&= e^{-\theta} \exp\{\theta(1-p + pe^t)\} \\
&= \exp\{\theta p(e^t - 1)\}
\end{aligned}$$

Actually, this is the m.g.f. of $\text{Poisson}(\theta p)$.

3.8 Joint Moment Generating Functions

DEFINITION 3.8.1: Joint moment generating function

If X and Y are random variables, then

$$M(t_1, t_2) = \mathbb{E}[e^{t_1 X + t_2 Y}]$$

is called the **joint moment generating function** of X and Y if $M(t_1, t_2)$ exists for $|t_1| < h_1$ and $|t_2| < h_2$ for some $h_1, h_2 > 0$.

REMARK 3.8.2

In general, suppose X_1, \dots, X_n are random variables, then

$$M(t_1, \dots, t_n) = \mathbb{E} \left[\exp \left\{ \sum_{i=1}^n t_i X_i \right\} \right]$$

is the **joint moment generating function** if it exists for $|t_i| < h_i$ for some $h_i > 0$ where $i = 1, \dots, n$.

REMARK 3.8.3: Applications of Joint Moment Generating Functions

- (1) From joint m.g.f. to marginal m.g.f. Given $M(t_1, t_2)$ for $|t_1| < h_1$ and $|t_2| < h_2$ with $h_1, h_2 > 0$,

$$M_X(t_1) = M(t_1, t_2 = 0) = \mathbb{E}[e^{t_1 X}]$$

$$M_Y(t_2) = M(0, t_2) = \mathbb{E}[e^{t_2 Y}]$$

- (2) Independence Property. X and Y are independent if and only if

$$M(t_1, t_2) = M_X(t_1)M_Y(t_2)$$

More generally, if X_1, \dots, X_n are independent, then

$$M(t_1, \dots, t_n) = \prod_{i=1}^n M_{X_i}(t_i)$$

EXAMPLE 3.8.4

Suppose $f(x, y) = e^{-y}$ for $0 < x < y$ is the joint p.d.f. of (X, Y) . Find the joint m.g.f. of X and Y . Are they independent? Find the marginal p.d.f. of X and Y .

Solution.

$$\begin{aligned}
 M(t_1, t_2) &= \mathbb{E}[e^{t_1 X + t_2 Y}] \\
 &= \int_0^\infty \left[\int_0^y e^{t_1 x + t_2 y} e^{-y} dx \right] dy \\
 &= \int_0^\infty e^{(t_2 - 1)y} \left[\frac{1}{t_1} e^{t_1 x} \right]_0^y dy \\
 &= \frac{1}{t_1} \int_0^\infty e^{(t_2 - 1)y} (e^{t_1 y} - 1) dy \\
 &= \frac{1}{t_1} \int_0^\infty e^{(t_1 + t_2 - 1)y} - e^{(t_2 - 1)y} dy \\
 &= \frac{1}{t_1} \left(\frac{1}{1 - t_1 - t_2} - \frac{1}{1 - t_2} \right) \\
 &= \frac{1}{(1 - t_1 - t_2)(1 - t_2)}
 \end{aligned}$$

with $t_2 - 1 < 0$ and $t_1 + t_2 - 1 < 0$. Therefore, $t_2 < 1$ and $t_1 + t_2 < 1$.

$$M_X(t_1) = M(t_1, t_2 = 0) = \frac{1}{1 - t_1}$$

which is the m.g.f. of Exponential(1).

$$M_Y(t_2) = M(t_1 = 0, t_2) = \frac{1}{(1 - t_2)^2}$$

which is the m.g.f. of Gamma($\alpha = 2, \beta = 1$). Note that the joint support is a triangle (not a rectangle), so obviously $M(t_1, t_2) \neq M_X(t_1)M_Y(t_2)$. Thus, X and Y are not independent.

EXAMPLE 3.8.5: Additivity of Poisson Random Variables

Suppose $X \sim \text{Poisson}(\theta_1)$ and $Y \sim \text{Poisson}(\theta_2)$ with X and Y independent. Prove that $X + Y \sim \text{Poisson}(\theta_1 + \theta_2)$.

Solution. We can try to find the p.d.f. of $X + Y$ (direct method). Alternatively, find $M_{X+Y}(t)$.

$$\begin{aligned}
 M_{X+Y}(t) &= \mathbb{E}[e^{tX+tY}] \\
 &= \mathbb{E}[e^{tX} e^{tY}] && X \text{ and } Y \text{ independent} \\
 &= \mathbb{E}[e^{tX}] \mathbb{E}[e^{tY}] \\
 &= \exp\{\theta_1(e^t - 1)\} \exp\{\theta_2(e^t - 1)\} \\
 &= \exp\{(\theta_1 + \theta_2)(e^t - 1)\}
 \end{aligned}$$

which is the m.g.f. of Poisson($\theta_1 + \theta_2$).

3.9 Multinomial Distribution

DEFINITION 3.9.1: Multinomial distribution

(X_1, \dots, X_k) are joint discrete random variables with joint p.f. given by

$$f(x_1, \dots, x_k) = \mathbb{P}(X_1 = x_1, \dots, X_k = x_k) = \frac{n!}{x_1! x_2! \dots x_k!} p_1^{x_1} \dots p_k^{x_k}$$

where $x_i = 0, 1, \dots, n$ ($i = 1, 2, \dots, k$). Furthermore, $\sum_{i=1}^k x_i = n$, $\sum_{i=1}^k p_i = 1$, for $0 < p_i < 1$ $i = 1, \dots, k$. Then, (X_1, \dots, X_k) follows a **multinomial distribution**.

$$(X_1, \dots, X_k) \sim \text{Multinomial}(n; p_1, \dots, p_k)$$

EXAMPLE 3.9.2: Possible Application

- there are k boxes and each box has same balls
- probability of choosing a ball from the i^{th} box is p_i for $i = 1, 2, \dots, k$.
- randomly choose n balls from k boxes.

Let $X_i :=$ number of boxes from the i^{th} box for $i = 1, 2, \dots, k$. Then,

$$(X_1, \dots, X_k) \sim \text{Multinomial}(n; p_1, \dots, p_k)$$

Note: if there are only two boxes, then $X_1 \sim \text{Binomial}(n, p_1)$.

PROPOSITION 3.9.3: Properties — Multinomial Distribution

If $(X_1, \dots, X_k) \sim \text{Multinomial}(n; p_1, \dots, p_k)$, then

- (1) $M(t_1, \dots, t_k) = \mathbb{E}[e^{t_1 X_1 + \dots + t_k X_k}] = (p_1 e^{t_1} + \dots + p_k e^{t_k})^n$ where $|t_i| < \infty$ for $i = 1, \dots, k$.
- (2) $X_i \sim \text{Binomial}(n, p_i)$ for $i = 1, \dots, k$.
- (3) If $T = X_i + X_j$ for $i \neq j$, then $T \sim \text{Binomial}(n, p_i + p_j)$
- (4) $\text{Cov}(X_i, X_j) = -np_i p_j$ for $i \neq j$
- (5) The conditional probability function of X_i given $X_j = x_j$ for $i \neq j$ is

$$X_i \mid X_j = x_j \sim \text{Binomial}\left(n - x_j, \frac{p_i}{1 - p_j}\right)$$

- (6) The conditional distribution of X_i given $T = X_i + X_j$ for $i \neq j$ is

$$X_i \mid X_i + X_j \sim \text{Binomial}\left(t, \frac{p_i}{p_i + p_j}\right)$$

Proof of: 3.9.3

Proof of (1): Too long for my poor soul to type. Proof requires the Multinomial Theorem.

Proof of (2): The moment generating function of X_i for $i = 1, \dots, k$ is

$$M(0, \dots, 0, t, 0, \dots, 0) = [p_i e^{t_i} + (1 - p_i)]^n \quad t_i \in \mathbb{R}$$

which is the moment generating function of a $\text{Binomial}(n, p_i)$ random variable. By 2.5.10 we have $X_i \sim \text{Binomial}(n, p_i)$ for $i = 1, \dots, k$.

Proof of (3): The moment generating function of $T = X_i + X_j$ for $i \neq j$ is

$$\begin{aligned}
 M_T(t) &= \mathbb{E}[e^{tT}] \\
 &= \mathbb{E}[e^{t(X_i + X_j)}] \\
 &= \mathbb{E}[e^{tX_i + tX_j}] \\
 &= M(0, \dots, 0, t, 0, \dots, 0, t, 0, \dots, 0) \\
 &= (p_1 + \dots + p_i e^t + \dots + p_j e^t + \dots + p_{k-1} + p_k)^n & t \in \mathbb{R} \\
 &= [(p_i + p_j)e^t + (1 - p_i - p_j)]^n & t \in \mathbb{R}
 \end{aligned}$$

which is the moment generating function of a Binomial($n, p_i + p_j$) random variable. By 2.5.10 we have $T \sim \text{Binomial}(n, p_i + p_j)$ for $i \neq j$.

Proof of (4): By (2) we have $\mathbb{E}[X_i] = np_i$, $\mathbb{V}(X_i) = np_i(1 - p_i)$, and $\mathbb{V}(X_j) = np_j(1 - p_j)$. By (3) we have $X_i + X_j \sim \text{Binomial}(n, p_i + p_j)$, so $\mathbb{V}(X_i + X_j) = n(p_i + p_j)(1 - p_i - p_j)$. Thus,

$$\begin{aligned}
 \text{Cov}(X_i + X_j, X_i + X_j) &= \mathbb{V}(X_i) + \mathbb{V}(X_j) + 2\text{Cov}(X_i, X_j) \\
 \implies n(p_i + p_j)(1 - p_i - p_j) &= np_i(1 - p_i) + np_j(1 - p_j) + 2\text{Cov}(X_i, X_j)
 \end{aligned}$$

Therefore, $\text{Cov}(X_i, X_j) = -np_i p_j$.

Proof of (5): There are x_j outcomes from the j^{th} category. Therefore, there are $(n - x_j)$ balls chosen from the remaining $(k - 1)$ boxes. We are not allowed to choose from the j^{th} box, we are only allowed to choose from the remaining $(k - 1)$ boxes. Therefore, proportionally we get the success probability as $p_i/(1 - p_j)$.

EXERCISE 3.9.4

Prove property (6) from Proposition 3.9.3.

3.10 Bivariate Normal Distribution

DEFINITION 3.10.1: Bivariate normal distribution

Suppose that X_1 and X_2 are continuous random variables with joint probability density function

$$f(x_1, x_2) = \frac{1}{2\pi|\Sigma|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \Sigma^{-1}(\mathbf{x} - \boldsymbol{\mu})\right\} \quad (x_1, x_2) \in \mathbb{R}^2$$

Also,

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{2 \times 1}, \quad \boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}_{2 \times 1}, \quad \Sigma = \begin{bmatrix} \sigma_1^2 & p\sigma_1\sigma_2 \\ p\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}_{k \times k}$$

and Σ is positive semi-definite. Also, $|\Sigma|$ is the determinant of Σ . Then, $\mathbf{X} = (X_1, X_2)$ follows a **bivariate normal distribution**, and we write

$$\mathbf{X} \sim \text{BVN}(\boldsymbol{\mu}, \Sigma)$$

REMARK 3.10.2: †

Alternatively, we could write

$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp \left\{ -\frac{1}{2(1-\rho^2)} \left[\left(\frac{x_1-\mu_1}{\sigma_1} \right)^2 + \left(\frac{x_2-\mu_2}{\sigma_2} \right)^2 - \frac{2\rho(x_1-\mu_1)(x_2-\mu_2)}{\sigma_1\sigma_2} \right] \right\}$$

PROPOSITION 3.10.3: Properties — Bivariate Normal Distribution

(1) X_1, X_2 has joint moment generating function

$$M(t_1, t_2) = \mathbb{E}[e^{t_1 X_1 + t_2 X_2}] = \exp \left\{ \mathbf{t}^\top \boldsymbol{\mu} + \frac{1}{2} \mathbf{t}^\top \Sigma \mathbf{t} \right\} \quad \forall \mathbf{t} \in \mathbb{R}^2$$

(2) Marginally,

$$M_{X_1}(t_1) = M(t_1, 0) = \exp \left\{ t_1 \mu_1 + \frac{1}{2} t_1^2 \sigma_1^2 \right\}$$

which is the m.g.f. of $N(\mu_1, \sigma_1^2)$; that is, $X_1 \sim N(\mu_1, \sigma_1^2)$. Also, $\mathbb{E}[X_1] = \mu_1$ and $\mathbb{V}(X_1) = \sigma_1^2$.

$$M_{X_2}(t_2) = M(0, t_2) = \exp \left\{ t_2 \mu_2 + \frac{1}{2} t_2^2 \sigma_2^2 \right\}$$

which is the m.g.f. of $N(\mu_2, \sigma_2^2)$; that is, $X_2 \sim N(\mu_2, \sigma_2^2)$. Also, $\mathbb{E}[X_2] = \mu_2$ and $\mathbb{V}(X_2) = \sigma_2^2$.

(3) Conditional distribution.

$$X_2 \mid X_1 = x_1 \sim N \left(\mu_2 + \frac{\rho\sigma_2(x_1 - \mu_1)}{\sigma_1}, \sigma_2^2(1 - \rho^2) \right)$$

$$X_1 \mid X_2 = x_2 \sim N \left(\mu_1 + \frac{\rho\sigma_1(x_2 - \mu_2)}{\sigma_2}, \sigma_1^2(1 - \rho^2) \right)$$

$$f_2(x_2 \mid x_1) = \frac{f(x_1, x_2)}{f_1(x_1)}$$

$$f_1(x_1 \mid x_2) = \frac{f(x_1, x_2)}{f_2(x_2)}$$

(4) $\text{Cov}(X_1, X_2) = \rho\sigma_1\sigma_2$

(5) $\rho = 0 \iff X_1$ and X_2 are independent.

(6) Linear transformations of bivariate normal are still normal.

(7) $(\mathbf{X} - \boldsymbol{\mu})^\top \Sigma^{-1} (\mathbf{X} - \boldsymbol{\mu}) \sim \chi^2(2)$

4.

$$\mathbb{E}[X_1 X_2] = \mathbb{E}[\mathbb{E}[X_1 X_2 \mid X_1]]$$

Step 1: $\mathbb{E}[X_1 X_2 \mid X_1 = x_1] = \mathbb{E}[x_1 X_2 \mid X_1 = x_1] = x_1 \mathbb{E}[X_2 \mid X_1 = x_1] = x_1 \left(\mu_2 + \frac{\rho\sigma_2(x_1 - \mu_1)}{\sigma_1} \right)$

Step 2:

$$\mathbb{E}[X_1 X_2 \mid X_1] = X_1 \left(\mu_2 + \frac{\rho\sigma_2(X_1 - \mu_1)}{\sigma_1} \right)$$

$$\begin{aligned}
\mathbb{E}[X_1 X_2] &= \mathbb{E}\left[X_1 \mu_2 + \frac{X_1 \rho \sigma_2 (X_1 - \mu_1)}{\sigma_1}\right] \\
&= \mu_2 \mathbb{E}[X_1] + \frac{\rho \sigma_2}{\sigma_1} [\mathbb{E}[X_1^2] - \mu_1 \mathbb{E}[X_1]] \\
&= \mu_2 \mu_1 + \frac{\rho \sigma_2}{\sigma_1} [\mu_1^2 + \sigma_1^2 - \mu_1^2] \\
&= \mu_1 \mu_2 + \rho \sigma_1 \sigma_2
\end{aligned}$$

Thus,

$$\begin{aligned}
\text{Cov}(X_1, X_2) &= \mathbb{E}[X_1 X_2] - \frac{\mathbb{E}[X_1] \mathbb{E}[X_2]}{\mu_1 \mu_2} = \rho \sigma_1 \sigma_2 \\
\text{Corr}(X_1, X_2) &= \frac{\text{Cov}(X_1, X_2)}{\sqrt{\mathbb{V}(X_1) \mathbb{V}(X_2)}} = \rho
\end{aligned}$$

5. We know if X_1 and X_2 are independent, then $\rho = 0$. If $\rho = 0$, e.g. $X_2 X_1 = x_1 \sim N(\mu_2, \sigma_1^2)$ and $X_1 X_2 = x_2 \sim N(\mu_1, \sigma_1^2)$ In summary: If joint bivariate normal then uncorrelated = independence.

6. Let $\mathbf{c} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix}$, then $\mathbf{c}^\top X = c_1 X_1 + c_2 X_2 \sim N$ with

$$\begin{aligned}
\mathbb{E}[\mathbf{c}^\top X] &= c_1 \mu_1 + c_2 \mu_2 \\
\mathbb{V}(\mathbf{c}^\top X) &= \mathbf{c}^\top \Sigma \mathbf{c}
\end{aligned}$$

Furthermore, $A \in \mathbb{R}^{2 \times 2}$, $\mathbf{b} = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$

$$AX + \mathbf{b} \sim \text{BVN}(A\boldsymbol{\mu} + \mathbf{b}, A\Sigma A^\top)$$

Two linear combinations of BVN is joint BVN.

7. Note $\chi^2(1) := Z^2$ where $Z \sim N(0, 1)$.

$$\chi^2(n) = \sum_{i=1}^n Z_i^2$$

where Z_1, \dots, Z_n are independent $N(0, 1)$.