1 Review

We begin our discussion of mathematical statistics with a review of concepts from previous courses. One of these key concepts is that of probability.

Recall that a **sample space** Ω is the set of all possible outcomes of an experiment. Subsets of Ω are called **events** and the collection of all events is denoted by $\mathcal{F}$.

Definition 1.1 (probability set function)**.** Let Ω be a sample space and let $\mathcal{F}$ be the collection of all events. Let $P : \mathcal{F} \to \mathbb{R}$ be a real-valued function. Then P is a **probability set function** (also referred to as **probability measure**, **probability distribution** or simply **probability**) if it satisfies the following three conditions:

1. $0 \leq P(A) \leq 1$, for all $A \in \mathcal{F}$.
2. $P(\Omega) = 1$ and $P(\emptyset)$.
3. If $\{A_n\}$ is a sequence of events in $\mathcal{F}$ and $A_m \cap A_n = \emptyset$ for all $m \neq n$, then

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

In order to formalize quantities which depend on random events, we reintroduce the concept of a random variable and its support.

Definition 1.2 (random variable)**.** Let Ω be a sample space. A **random variable** is a function from Ω into the real numbers. The **support** (also called **space** or **range**) of X is the set of real numbers $\mathcal{S} = \{x : x = X(\omega), \omega \in \Omega\}$.

In cases where $\mathcal{S}$ is a countable set, we say that X is a **discrete random variable**. The set $\mathcal{S}$ may also be an interval of real numbers, in which case we say that X is a **continuous random variable**.

Given a random variable X, its support $\mathcal{S}$ becomes the sample space of interest. Besides inducing the sample space $\mathcal{S}$, X also induces a probability which we call the **distribution** of X.

The probability distribution of a discrete random variable is described completely in terms of its probability mass function and its support.

Definition 1.3 (pmf)**.** Let X be a discrete random variable with support $\mathcal{S}$. The **probability mass function** (pmf) of X p_X is given by

$$p_X(x) = P(X = x), \text{ for } x \in \mathcal{S}.$$

Similarly, the probability distribution of a continuous random variable is described completely in terms of its probability density function and its support.

Definition 1.4 (pdf)**.** Let X be a continuous random variable with support $\mathcal{S}$. The **probability density function** (pdf) of X is a function f_X that satisfies

$$P(X \le x) = \int_{-\infty}^{x} f_X(t)\,\mathrm{d}t$$

for all $x \in \mathcal{S}$.

The pmf of a discrete random variable and the pdf of a continuous random variable are quite different entities. The cumulative distribution function, though, uniquely determines the probability distribution of a random variable.

Definition 1.5 (cdf)**.** Let X be a random variable. Then its **cumulative distribution function** (cdf) is defined by $F_X(x)$, where

$$F_X(x) = P(X \le x).$$

One of the most important measures associated with random variables is that of expectation.

Definition 1.6 (expectation)**.** Let X be a random variable with support $\mathcal{S}$.
If X is a *continuous* random variable with pdf $f(x)$ and

$$\int_{-\infty}^{\infty} |x| f(x)\,\mathrm{d}x$$

is finite, then the **expectation** of X, denoted $E(X)$ is defined as

$$E(X) = \int_{-\infty}^{\infty} x f(x)\,\mathrm{d}x\,.$$

If X is a *discrete* random variable with pmf $p(x)$ and

$$\sum_{x \in \mathcal{S}} |x| p(x)$$

is finite, then the **expectation** of X is defined as

$$E(X) = \sum_{x \in \mathcal{S}} x p(x).$$

Sometimes the expectation $E(X)$ is called the **expected value** of X or the **mean** of X. When the mean designation is used, we often denote the expected value by μ.

Theorem 1.1 (Law of the unconscious statistician)**.** Let X be a random variable with support $\mathcal{S}_X$ and let $Y = g(X)$ for some real-valued function g.

(a) Suppose X is discrete with pmf $p_X(x)$. If

$$\sum_{x \in \mathcal{S}_X} |g(x)| p_X(x)$$

is finite, then the expectation of Y exists and is given by

$$E(Y) = \sum_{x \in \mathcal{S}_X} g(x) p_X(x).$$

(b) Suppose X is continuous with pdf $f_X(x)$. If

$$\int_{-\infty}^{\infty} |g(x)| f_X(x) \,\mathrm{d}x$$

is finite, then the expectation of Y exists and is given by

$$E(Y) = \int_{-\infty}^{\infty} g(x) f_X(x) \,\mathrm{d}x.$$

An important application of the above theorem shows that expectation is *linear*. That is, $E(aX + b) = aE(X) + b$. It is a useful exercise to show that this is the case. Furthermore, this property can be generalized for $a_1, \dots, a_k$ real numbers and $g_1, \dots, g_k$ real-valued functions.

$$E(a_1 g_1(X) + \cdots + a_k g_k(X)) = a_1 E(g_1(X)) + \cdots + a_k E(g_k(X))$$

Expectation allows us to define a countably infinite number of measures associated with random variables, called moments.

Definition 1.7 (moment)**.** Suppose X is a random variable and m is a positive integer. The m**th moment** of X is defined to be $E(X^m)$, provided this expectation exists.

As such, the first moment of a random variable is simply its **mean** μ. It is often useful to think about moments about the mean $E((X-\mu)^m)$. We call these **central moments**. The second central moment should be familiar to you as the **variance** σ^2. We call the third central moment the **skewness** and call the fourth central moment the **kurtosis**.

Definition 1.8 (mgf)**.** Let X be a random variable such that for some $h > 0$, the expectation of e^{tX} exists for $-h < t < h$. The **moment generating function** (mgf) of X is defined to be the function $M_X(t) = E(e^{tX})$ for $-h < t < h$.

Clearly, $M_X(0) = 1$ for any random variable. Not every random variable has a mgf. For example, the mgf of the Cauchy Distribution with pdf $f(x) = \frac{1}{\pi(1+x^2)}$ is not defined. It can be shown that if the mgf of a random variable exists, then all of its moments exist.

Theorem 1.2. Let X and Y be random variables with mgfs M_X and M_Y, respectively, existing in open intervals about 0. Then $F_X(z) = F_Y(z)$ for all $z \in \mathbb{R}$ if and only if $M_X(t) = M_Y(t)$ in an open interval about 0.

Theorem 1.3. Let X be a random variable with mgf M_X, and let $a, b \in \mathbb{R}$ be fixed. Then the mgf of $Y = aX + b$ also exists and is given by

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

Theorem 1.4. Suppose X and Y are independent random variables with mgfs M_X and M_Y. Let $a, b \in \mathbb{R}$ be fixed and define $Z + aX + bY$. Then the mgf of Z exists in an open interval about 0 and is given by

$$M_Z(t) = M_X(at) M_Y(bt).$$

Theorem 1.5. Suppose X is a random variable with mgf M_X and let $M_X^{(m)}(t) = \frac{\mathrm{d}^m}{\mathrm{d}t^m} M_X(t)$.

Then the mth moment of X is given by

$$E(X^m) = M_X^{(m)}(0).$$

The above theorem should make clear why we call mgfs as such. The proof is reliant on the Taylor expansion of e^{tX}. Observe the following.

$$\begin{aligned} M_X(t) &= E(e^{tX}) \\ &= E\left(\sum_{n=0}^{\infty} \frac{t^n}{n!} X^n\right) \\ &= \sum_{n=0}^{\infty} \frac{t^n}{n!} E(X^n) \end{aligned}$$

We reintroduce some special distributions, starting with those of the discrete kind.

Definition 1.9 (binomial random variable)**.** Assume a sequence of n Bernouilli trials each with probability of success p and let X be the number of successes. Then X is a **binomial random variable** with pmf

$$p_X(x) = \begin{cases} \binom{n}{x} p^x (1-p)^{n-x} & \text{for } x = 0, 1, \dots, n \\ 0 & \text{otherwise} \end{cases}$$

We write $X \sim b(n, p)$.

If $X \sim b(n, p)$, X has support $\{0, 1, \dots, n\}$, mean $\mu = np$, variance $\sigma^2 = np(1-p)$ and mgf $M_X(t) = (1 - p + pe^t)^n$.

Definition 1.10 (negative binomial random variable)**.** Assume a sequence of Bernouilli trials each with probability of success p is performed until the rth success occurs. Let Y be the number of trials required. Then Y is a **negative binomial random variable** with pmf

$$p_Y(y) = \begin{cases} \binom{y+r-1}{y-1} p^r (1-p)^y & \text{for } y = 0, 1, \dots \\ 0 & \text{otherwise} \end{cases}$$

We write $Y \sim nb(r, p)$.

If $Y \sim nb(r, p)$, Y has support $\mathbb{Z}_{\geq 0}$, mean $\mu = \frac{pr}{1-p}$, variance $\sigma^2 = \frac{pr}{(1-p)^2}$ and mgf $M_Y(t) =$

$\left(\frac{1-p}{1-pe^t}\right)$ with $t < -\ln p$.

Taking $r = 1$, we obtain the geometric distribution.

Definition 1.11 (Poisson random variable)**.** A discrete random variable X is a **Poisson random variable** if its pmf has the form

$$p_X(x) = \begin{cases} \frac{\lambda^x e^{-\lambda}}{x!} & \text{for } x = 0, 1, \dots \\ 0 & \text{otherwise} \end{cases}$$

where $\lambda \in \mathbb{R}_{\geq 0}$. We write $X \sim \text{Pois}(\lambda)$.

If $X \sim \text{Pois}(\lambda)$, X has support $\mathbb{Z}_{\geq 0}$, mean $\mu = \lambda$, variance $\sigma^2 = \lambda$ and mgf $M_X(t) = \exp(\lambda(e^t - 1))$.

We now recall some continuous distributions.

Definition 1.12 (uniform random variable)**.** A continuous random variable X is said to be a **uniform random variable** if it has pdf

$$p_X(x) = \begin{cases} \frac{1}{b-a} & \text{for } x \in [a, b]) \\ 0 & \text{otherwise} \end{cases}$$

where $a, b \in \mathbb{R}$ are fixed. We write $X \sim U(a, b)$.

If $X \sim U(a, b)$, X has support $[a, b]$, mean $\mu = \frac{a+b}{2}$, variance $\sigma^2 = \frac{(b-a)^2}{12}$ and mgf $M_X(t) = \begin{cases} \frac{e^{tb}-e^{ta}}{t(b-a)} & \text{for } t \neq 0 \\ 1 & \text{for } t = 0 \end{cases}$.

Definition 1.13 (normal random variable)**.** A continuous random variable X is said to be a **normal random variable** with parameters $\mu \in \mathbb{R}$ and $\sigma^2 > 0$ if its pdf has the form

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}.$$

We write $X \sim N(\mu, \sigma^2)$.

If $X \sim N(\mu, \sigma^2)$, X has support $\mathbb{R}$, mean μ, variance σ^2 and mgf $M_X(t) = e^{\mu t + \frac{\sigma^2 t^2}{2}}$.

The derivation of this mgf is left as an exercise.

Theorem 1.6. Let $X_1, \dots, X_n$ be IID random variables such that $X_i \sim N(\mu_i, \sigma_i^2)$ for each $i = 1, \dots, n$. Let $Y = \sum_{i=1}^n a_i X_i$ for some set of real constants $\{a_1, \dots, a_n\}$. Then Y is also normally distributed with

$$E(Y) = \sum_{i=1}^n a_i \mu_i \quad \text{and} \quad \mathrm{Var}(Y) = \sum_{i=1}^n a_i^2 \sigma_i^2.$$

Definition 1.14 (gamma random variable)**.** A continuous random variable X is said to be a **gamma random variable** with parameters $\alpha, \beta > 0$ if its pdf has the form

$$f_X(x) = \begin{cases} \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} & \text{for } x \in \mathbb{R}_{>0} \\ 0 & \text{otherwise} \end{cases}.$$

We write $X \sim \Gamma(\alpha, \beta)$.

Taking $\alpha = 1$ yields the exponential distribution.

If $X \sim \Gamma(\alpha, \beta)$, X has support $\mathbb{R}_{>0}$, mean $\mu = \frac{\alpha}{\beta}$, variance $\sigma^2 = \frac{\alpha}{\beta^2}$ and mgf $M_X(t) = \left(1 - \frac{t}{\beta}\right)^{-\alpha}$ for $t < \beta$.

Definition 1.15 (beta random variable)**.** A continuous random variable X is said to be a **beta random variable** with parameters $\alpha, \beta > 0$ if its pdf has the form

$$f_X(x) = \begin{cases} \frac{x^{\alpha-1}(1-x)^{\beta-1}}{\mathrm{B}(\alpha,\beta)} & \text{for } x \in (0,1) \\ 0 & \text{otherwise} \end{cases}$$

where $\mathrm{B}(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$. We write $X \sim \mathrm{Beta}(\alpha, \beta)$.

If $X \sim \mathrm{Beta}(\alpha, \beta)$, X has support $(0, 1)$, mean $\mu = \frac{\alpha}{\alpha+\beta}$, variance $\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$ and mgf $M_X(t) = 1 + \sum_{k=1}^\infty \left(\prod_{r=0}^{k-1} \frac{\alpha+r}{\alpha+\beta+r}\right) \frac{t^k}{k!}$.

2 Multivariate distributions

We will often want to deal with more than one variable based on the same random experiment.

Definition 2.1 (random vector)**.** Consider a random experiment with sample space Ω. Let $X_1, X_2 : \Omega \to \mathbb{R}$ be random variables. We say that (X_1, X_2) is a **random vector**. The support of (X_1, X_2) is the set of ordered pairs $\chi = \{(x_1, x_2) : X_1(\omega) = x_1, X_2(\omega) = x_2, \omega \in \Omega\}$.

Of particular interest are events of the form $(X_1 \le x_1) \cap (X_2 \le x_2)$ for $(x_1, x_2) \in \mathbb{R}^2$.

Definition 2.2 (joint cdf)**.** Suppose that (X_1, X_2) is a random vector. The **joint cdf** of (X_1, X_2), is the function F_{X_1,X_2} defined as

$$F_{X_1,X_2}(x_1, x_2) = P(X_1 \le x_1, X_2 \le x_2).$$

From here we can extend the univariate case for the probability over intervals to rectangular subsets of $\mathbb{R}^2$.

Theorem 2.1 (Rectangular probability formula)**.** Suppose that the random vector (X_1, X_2) has joint cdf F_{X_1,X_2} and let $a_1, b_1, a_2, b_2 \in \mathbb{R}$ be such that $a_1 < b_1$ and $a_2 < b_2$. Then

$$P\left((X_1, X_2) \in [a_1, b_1] \times [a_2, b_2]\right) = F_{X_1,X_2}(b_1, b_2) - F_{X_1,X_2}(a_1, b_2) - F_{X_1,X_2}(b_1, a_2) + F_{X_1,X_2}(a_1, a_2).$$

Recall that, in general, random variables can be of the discrete type or of the continuous type. We extend this idea to random vectors.

A random vector (X_1, X_2) is said to be **discrete** if its support χ is countable. In this case both X_1 and X_2 are discrete random variables. It thus makes sense to define pmfs for discrete random vectors.

Definition 2.3 (joint pmf)**.** Let (X_1, X_2) be a discrete random vector. Then the **joint pmf** of (X_1, X_2), is the function p_{X_1,X_2} given by

$$p_{X_1,X_2}(x_1, x_2) = P(X_1 = x_1, X_2 = x_2).$$

As in the univariate case, this joint pmf satisfies the following properties.

1. $0 \le p_{X_1,X_2}(x_1,x_2) \le 1$ for all $(x_1,x_2) \in \chi$.
2. $\sum_{(x_1,x_2)\in\chi} p_{X_1,X_2}(x_1,x_2) = 1$.

Example 2.1. Suppose two dice are rolled. Let X denote the number of dots facing up on the first die and Y the number of dots on the second die. Also, let $W = \max(X,Y)$. We would like to find the joint pmf of the random vector (X,W) and the probability that $X = W$.

Solution. Let χ denote the support of (X,W). It is clear that $\chi = \{1,\dots,6\} \times \{1,\dots,6\}$. The joint pmf $p_{X,W}$ of (X,W) can be summarized by the following table.

W/X	1	2	3	4	5	6
1	$\frac{1}{36}$	0	0	0	0	0
2	$\frac{1}{36}$	$\frac{2}{36}$	0	0	0	0
3	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{3}{36}$	0	0	0
4	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{4}{36}$	0	0
5	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{5}{36}$	0
6	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{6}{36}$

It is clearly the case that $0 \le p_{X,W}(x,w) \le 1$ and $\sum_{(x,w)\in\chi} p_{X,W}(x,w) = 1$.
We can now find the probability that $X = W$. That is, that the first die has the larger number of dots. We sum along the diagonal of the above table.

$$\begin{aligned}\sum_{\substack{(x,w)\in\chi \\ x=w}} p_{X,W}(x,w) &= \frac{1}{36} + \frac{2}{36} + \cdots + \frac{6}{36} \\ &= \frac{7}{12}\end{aligned}$$

If the joint cdf F_{X_1,X_2} of a random vector (X_1,X_2) is continuous, then we say that (X_1,X_2) is **continuous**. Similarly to a joint pmf, we can also define a joint pdf.

Definition 2.4 (joint pdf)**.** Let (X_1,X_2) be a continuous random vector. Then the **joint pdf** of (X_1,X_2) is the function f_{X_1,X_2} satisfying

$$F_{X_1,X_2}(x_1,x_2) = \int_{-\infty}^{x_2}\int_{-\infty}^{x_1} f_{X_1,X_2}(u,v)\,\mathrm{d}u\,\mathrm{d}v$$

for all $(x_1, x_2) \in \mathbb{R}^2$.

As in the univariate case, the joint pdf satisfies the following properties.

1. $f_{X_1,X_2}(x_1, x_2) \geq 0$ for all $(x_1, x_2) \in \mathbb{R}^2$.
2. $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f_{X_1,X_2}(u, v)\,\mathrm{d}u\,\mathrm{d}v = 1$.

Often times, we will want to obtain the distributions of the random variables X_1 and X_2 from the joint distribution of (X_1, X_2).

Given the above setup, we may obtain the **marginal cdf** of X_1 from the following equivalent formulations.

$$\begin{aligned}
F_{X_1} &= P(X_1 \leq x_1) \\
&= P(X_1 \leq x_1, -\infty < X_2 < \infty) \\
&= \lim_{x_2 \to \infty} P(X_1 \leq x_1, X_2 \leq x_2) \\
&= \lim_{x_2 \to \infty} F_{X_1,X_2}(x_1, x_2)
\end{aligned}$$

We may also find **marginal pmfs** and **marginal pdfs**.

If (X_1, X_2) is a discrete random vector, then

$$\begin{aligned}
p_{X_1}(x_1) &= P(X_1 = x_1) \\
&= \sum_{x_2} p_{X_1,X_2}(x_1, x_2)
\end{aligned}$$

If (X_1, X_2) is a continuous random vector, then

$$f_{X_1}(x_1) = \int_{-\infty}^{\infty} f_{X_1,X_2}(x_1, x_2)\,\mathrm{d}x_2$$

Example 2.2. We revisit the previous example. We would like to find the marginal pmf of W.
Solution. We apply the definition.

W	$p_W(w)$
1	$\frac{1}{36}$
2	$\frac{3}{36}$
3	$\frac{5}{36}$
4	$\frac{7}{36}$
5	$\frac{9}{36}$
6	$\frac{11}{36}$

Example 2.3. Consider the joint pdf of (X, Y) to be

$$f_{X,Y}(x,y) = \begin{cases} cxy^2 & \text{for } 0 \le x \le 2, 0 \le y \le 1 \\ 0 & \text{otherwise} \end{cases}$$

We would like to find the value of c such that $f_{X,Y}$ is a valid pdf. We would then like to find the marginal pdfs.
For $f_{X,Y}$ to be valid, we require it to be non-negative and it must integrate to 1. The second property will be used to determine c.

$$\begin{aligned} \int_0^1 \int_0^2 cxy^2 \, \mathrm{d}x \, \mathrm{d}y &= 1 \\ c \int_0^1 y^2 \int_0^2 x \, \mathrm{d}x \, \mathrm{d}y &= 1 \\ c\left(\frac{1}{3}\right)(2) &= 1 \\ \frac{2}{3}c &= 1 \\ c &= \frac{3}{2} \end{aligned}$$

Such a c makes $f_{X,Y}$ a valid pdf.
We first find the marginal pdf of X.

$$\begin{aligned} f_X(x) &= \int_0^1 \frac{3}{2} x y^2 \, \mathrm{d}y \\ &= \frac{3}{2} x \int_0^1 y^2 \, \mathrm{d}y \\ &= \frac{x}{2} \end{aligned}$$

So $f_X(x) = \begin{cases} \frac{x}{2} & \text{for } 0 \le x \le 2 \\ 0 & \text{otherwise} \end{cases}$

We leave the marginal pdf of Y as an exercise.

Expectations in the multivariate case are easily extended from the univariate case to random vectors.

Theorem 2.2 (Law of the unconscious statistician (multivariate))**.** Let (X_1, X_2) be a random vector and let $Y = g(X_1, X_2)$ for some real-valued function g. Then Y is a random variable and we have the following.

(a) Suppose (X_1, X_2) is discrete with pmf $p_{X_1,X_2}(x_1, x_2)$. If

$$\sum_{x_1} \sum_{x_2} |g(x_1, x_2)| p_{X_1,X_2}(x_1, x_2)$$

is finite, then the expectation of Y exists and is given by

$$E(Y) = \sum_{x_1} \sum_{x_2} g(x_1, x_2) p_{X_1,X_2}(x_1, x_2).$$

(b) Suppose (X_1, X_2) is continuous with pdf $f_{X_1,X_2}(x_1, x_2)$. If

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |g(x_1, x_2)| f_{X_1,X_2}(x_1, x_2) \, \mathrm{d}x_1 \, \mathrm{d}x_2$$

is finite, then the expectation of Y exists and is given by

$$E(Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x_1, x_2) f_{X_1,X_2}(x_1, x_2) \, \mathrm{d}x_1 \, \mathrm{d}x_2 \, .$$

We can now that expectation is a linear operator.

Theorem 2.3 (Linearity of expectation)**.** Let (X_1, X_2) be a random vector and let $Y_1 = g_1(X_1, X_2)$ and $Y_2 = g_2(X_1, X_2)$ be random variables for some real-valued functions g_1 and g_2. Suppose that both $E(Y_1)$ and $E(Y_2)$ exist. Then for all $k_1, k_2 \in \mathbb{R}$,

$$E(k_1 Y_1 + k_2 Y_2) = k_1 E(Y_1) + k_2 E(Y_2).$$

Proof. We prove for the discrete case.

We show absolute convergence using the triangle inequality.

$$\begin{aligned}\sum_{x_1}\sum_{x_2} |k_1 g_1(x_1, x_2) + k_2 g_2(x_1, x_2)| p_{X_1,X_2}(x_1, x_2) \le |k_1| \sum_{x_1}\sum_{x_2} |g_1(x_1, x_2)| p_{X_1,X_2}(x_1, x_2) \\ + |k_2| \sum_{x_1}\sum_{x_2} |g_2(x_1, x_2)| p_{X_1,X_2}(x_1, x_2)\end{aligned}$$

But $E(Y_1)$ and $E(Y_2)$ exist, so the above is finite and $E(k_1 Y_1 + k_2 Y_2)$ exists.

$$\begin{aligned}E(k_1 Y_1 + k_2 Y_2) &= \sum_{x_1}\sum_{x_2} (k_1 g_1(x_1, x_2) + k_2 g_2(x_1, x_2)) p_{X_1,X_2}(x_1, x_2) \\ &= k_1 \sum_{x_1}\sum_{x_2} g_1(x_1, x_2) p_{X_1,X_2}(x_1, x_2) + k_2 \sum_{x_1}\sum_{x_2} g_2(x_1, x_2) p_{X_1,X_2}(x_1, x_2) \\ &= k_1 E(Y_1) + k_2 E(Y_2)\end{aligned}$$

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